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Mapping Socio-Ecological Vulnerability to Mining: A Global Composite Indicator Approach

GEO 511 Master's Thesis

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Abstract:

Mining activities have diverse and far-reaching environmental and social impacts, which are expected to intensify in the future due to the increasing global demand for raw materials. Assessing where these impacts may be most pressing requires approaches that integrate both ecological and social factors. This thesis addresses this challenge by developing a spatially explicit, global-scale composite indicator of socio-ecological vulnerability to mining impacts. The indicator is conceptually grounded in the IPCC AR6 definition of vulnerability and operationalizes the dimensions of sensitivity and lack of adaptive capacity. It combines multiple ecological and social variables to provide a comparative assessment of vulnerability at the global scale. The results reveal distinct spatial patterns of socio-ecological vulnerability. Different analyses indicate that the magnitude and ranking of vulnerability scores are influenced by methodological choices and data availability. This highlights that the resulting patterns must be interpreted with caution, particularly in regions where data limitations affect the representation of certain variables.

The study demonstrates that global-scale indicators can provide valuable insights into broader spatial patterns of vulnerability but that they also involve important trade-offs. The indicator should therefore be understood as an exploratory and comparative tool, whose results require careful interpretation in light of its conceptual and methodological limitations.

Keywords:

Socio-ecological vulnerability; mining; composite indicator; global assessment; spatial analysis

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List of Content

List of Figures v
List of Tables vi
List of Abbreviations vii
1 Introduction 1
1.1 Motivation 1
1.2 Problem statement and research questions 2
1.3 Structure 3
2 Background 4
2.1 Mining and socio-ecological vulnerability 4
2.1.1 Biodiversity and mining 4
2.1.2 Water Risk and mining 5
2.1.3 Vulnerable peoples and communities 6
2.1.4 Existing indicators 7
2.2 Vulnerability: Frameworks and definitions 8
2.3 Indicator based assessments 10
2.3.1 Indicator characteristics 10
2.3.2 How to build composite indicators 12
2.4 Vulnerability indicators 13
2.5 Research gap 15
3 Methods 17
3.1 Overall research design 17
3.2 Literature Review 18
3.3 Pilot indicator evaluation 20
3.4 Scope and spatial framework of the indicator 27
3.5 Conceptual framework of the final indicator 28
3.6 Data and data preprocessing 30
3.7 Indicator implementation 41
3.7.1 Sensitivity 42
3.7.2 Lack of adaptive capacity 42
3.7.3 Socio-ecological vulnerability 43
3.8 Indicator analysis 43
4 Results 46
4.1 Collinearity 46
4.2 Vulnerability score distribution 48
4.3 Vulnerability scores across countries 56
5 Discussion 63
5.1 Interpreting spatial patterns of socio-ecological vulnerability to mining 63

5.2 Interpretation and application ... 65
5.3 Theoretical and methodological reflection on indicator performance ... 68
5.4 Methodological and conceptual limitations ... 73
5.5 Directions for future research ... 79
6 Conclusion ... 82
7 AI statement ... 84
8 References ... 86
Personal declaration ... 93

List of Figures

Figure 1: Comparison of vulnerability definitions in the IPCC third and fourth assessment report to the fifth assessment report (Estoque et al., 2023) 10
Figure 2: Workflow (illustration by the author) 17
Figure 3: Conceptual design of pilot indicator (illustration by the author) 21
Figure 4: Conceptual design of final indicator (illustration by the author) 29
Figure 5: Biodiversity intactness map (illustration by the author), data provided by De Palma A. et al. (2025) .. 31
Figure 6: Protected areas map (illustration by the author), data provided by UNEP-WCMC & IUCN (2025) 33
Figure 7: Key biodiversity areas map (illustration by the author), data provided by BirdLife International (2025) 34
Figure 8: Water risk map (illustration by the author), data provided by Kuzma et al. (2023) 35
Figure 9: Poverty map (illustration by the author), data provided by UNDP (United Nations Development Programme) (2025b) 36
Figure 10: Indigenous Peoples' and Local Communities' map (illustration by the author, data provided by LandMark (2024) 37
Figure 11: Land rights map (illustration by the author), data provided by LandMark (2024) 38
Figure 12: Environmental Democracy map (illustration by the author), data provided by The Access Initiative (2015) 39
Figure 13: Rule of law map (illustration by the author), data provided by World Justice Project (2025) 40
Figure 14: Conflict index map (illustration by the author), data provided by ACLED (2024) 41
Figure 15: Sensitivity dimension map (illustration by the author) 49
Figure 16: Lack of adaptive capacity dimension map (illustration by the author) 49
Figure 17: Socio-ecological vulnerability to mining map (illustration by the author) 50
Figure 18: Socio-ecological vulnerability to mining, final indicator zoomed in by world region (illustration by the author) 51
Figure 19: Maps of all individual variables (illustration by the author) 52
Figure 20: Boxplots of vulnerability score distribution for baseline indicator and different scenarios omitting one variable (illustration by the author) 55
Figure 21: Mean socio-ecological vulnerability to mining per country map with different vulnerability classes (illustration by the author) 56
Figure 22: Stacked pillar diagram showing top 10 countries with highest mean vulnerability score and its variable contribution (illustration by the author) 58
Figure 23: Stacked pillar diagram showing top 10 countries with highest mean vulnerability score and its variable contribution for different scenarios omitting one variable (illustration by the author) 59
Figure 24: Scatterplots showing mean vulnerability score rankings of baseline indicators and different scenarios omitting one variable plus Spearman correlation coefficients (illustration by the author) 62
Figure 25: Stacked pillar diagram showing top 10 countries with highest mean vulnerability score and its variable contribution (illustration by the author) 64
Figure 26: Conflict index map (illustration by the author), data provided by ACLED (2024) 71
Figure 27: Scatterplots showing mean vulnerability score rankings of baseline indicators and leave-land rights/conflict-out scenarios plus Spearman correlation coefficients (illustration by the author) 72
Figure 28: Land rights variable and environmental democracy variable distribution maps (illustration by the author) 75
Figure 29: Map showing missing value counts for socio-ecological vulnerability (illustration by the author) 76
Figure 30: Mean socio-ecological vulnerability to mining per country map with different vulnerability classes (illustration by the author) 76

List of Tables

Table 1: List with candidate variables and potential datasets 20
Table 2: Conducted interviews and summarized main feedback 23
Table 3: IUCN categories for protected areas 32
Table 4: Pixel-level Spearman correlation coefficients 46
Table 5: Pixel-level variance inflation factors (VIFs) 47
Table 6: Country-level Spearman correlation coefficients 47
Table 7: Country-level variance inflation factors (VIFs) 48
Table 8: Cliff's delta and JSD values for baseline indicator and scenario comparison 53
Table 9: 50 countries with highest mean vulnerability score and their variable contribution 60

List of Abbreviations

ACLED: Armed Conflict Location & Event Data Project

AR4 / AR5 / AR6: Fourth / Fifth / Sixth Assessment Report

BII: Biodiversity Intactness Index

EDI: Environmental Democracy Index

HDI: Human Development Index

IPCC: Intergovernmental Panel on Climate Change

IPLC: Indigenous Peoples' and Local Communities

IUCN: International Union for Conservation of Nature

KBA: Key Biodiversity Areas

MCDA: Multi-Criteria Decision Analysis

MPI: Multidimensional Poverty Index

OECD: Organization for Economic Co-operation and Development

PA: Protected Areas

SES: Social-Ecological System

UN: United Nations

UNDP: United Nations Development Programme

UNDRR: United Nations Office for Disaster Risk Reduction

UNEP(-WCMC): United Nations Environment Programme (World Conservation Monitoring Centre)

VIF: Variance Inflation Factor

WDPA: World Database on Protected Areas

1 Introduction

1.1 Motivation

The global impacts of mining activities on the environment and people are of diverse nature and far-reaching. Among other things, mining can lead to biodiversity and habitat loss, pollution, water scarcity, human health risks, displacements, loss of livelihoods and conflicts (Durán et al., 2013; Luckeneder et al., 2021; Macklin et al., 2023; Manhart et al., 2019; Owen et al., 2022; Sonter et al., 2022). These impacts are likely to intensify in the future due to the projected high increase in material demand, which is needed for transition to renewable energy (UNEP, 2024). In order to address these impacts and take appropriate measures to mitigate them, it is important to assess the areas in which they are most likely to be most pressing. The following question arises: Where are people and the environment particularly vulnerable to the potential impacts of mining activities? Given the diverse nature of such impacts this assessment is no simple task. It is crucial to consider both ecological and social factors, because consequences of mining for people and the environment are highly intertwined. For example, pollution from mine sites can reduce biodiversity, which can also have a significant impact on the livelihoods of local communities. Such impacts are highly complex and dynamic and often extend far beyond the immediate surroundings of a mine (Macklin et al., 2023). This means that assessments of mining-related impacts cannot be limited to single dimensions or isolated variables. Instead, there is a need for approaches that capture the interplay between ecological conditions and social systems in a systematic way. In this context, the concept of socio-ecological vulnerability provides a useful theoretical concept, since it allows for the integration of both socio-ecological susceptibility to mining impacts and the capacity of communities to cope with and adapt to these mining-related pressures.

At the same time, existing approaches which assess mining-related impacts often remain fragmented. Many studies focus either on ecological aspects, such as biodiversity loss and water risk or on social dimensions, such as displacement and inequality. While these approaches provide important insights, they often do not account for the interactions between social and ecological systems, which are central to understand the full extent of mining-related impacts. As a result, there is a need for more integrated approaches that combine these perspectives (Hossain et al., 2023). One possible way to address this challenge is by indicator-based assessments. Composite indicators, which consist of several aggregated variables, can summarize complex issues and provide information about a phenomenon, which is not directly measurable (Beroya-Eitner, 2016; European Environment Agency, 2014). In the context of mining, spatially explicit indicators are especially valuable, as they can reveal geographical patterns and identify regions, where vulnerability may be particularly high. Additionally, a global-scale indicator is particularly useful with regards to mining activities, since they occur in various regions around the globe.

Also, it is impossible to predict with certainty where future mining activities occur. A global-scale approach enables the identification of broader spatial patterns and highlights regions, where socio-ecological vulnerability may be particularly high. Thereby, vulnerability is a pre-existing condition and can also occur in areas where mining activities are not yet fully developed. Although such an approach cannot capture local complexities in detail, it provides an important first step for understanding vulnerability in an exploratory and comparative way.

The development of spatially explicit, global-scale composite indicators comes along with many challenges and many methodological choices must be made. This highly influences the applicability of an indicator. The mentioned choices define where a composite indicator can be used and where it cannot. Against this background, this thesis sets out to develop a spatially explicit, global-scale composite indicator of socio-ecological vulnerability to mining impacts. These considerations form the basis for the following problem statement and research questions. By doing so, the aim is to identify spatial patterns of vulnerability and to critically reflect on the associated conceptual framework, methodological decisions and implications.

1.2 Problem statement and research questions

Despite extensive research on the environmental and social impacts of mining, there remains a lack of integrated, spatially explicit approaches that capture socio-ecological vulnerability in a consistent and comparable way at the global scale. Existing studies often focus on either ecological or social dimensions or are limited to specific regions, commodities or case studies. As a result, there is limited understanding of how different vulnerability factors interact across space and of how these interactions translate into broader spatial patterns. Furthermore, the development of composite indicators involves a range of conceptual and methodological decisions that can substantially influence their outcome. This creates a need for approaches that not only integrate multiple dimensions of vulnerability, but also transparently assess their underlying assumptions, limitations and potential applications. As a consequence, this thesis aims to examine the following research questions:

- RQ1: How can a spatially explicit socio-ecological indicator of vulnerability to mining impacts be developed at the global scale, and what are its conceptual and methodological limitations?
- RQ2: What kind of spatial patterns of socio-ecological vulnerability to mining emerge at the global scale based on the developed indicator?
- RQ3: Which methodological choices most strongly influence the indicator’s outcomes, and how might future research improve socio-ecological vulnerability assessments of mining?
- RQ4: What are the appropriate applications and limitations of a global socio-ecological vulnerability indicator in the context of mining governance and research?

1.3 Structure

The thesis is structured as follows. Chapter 2 provides the theoretical and conceptual background by reviewing literature on mining-related socio-ecological impacts, vulnerability frameworks and indicator-based assessments. It identifies the research gap addressed by existing literature and establishes the conceptual foundations for the indicator development. Chapter 3 presents the methodological approach, including the overall research design, the pilot indicator development, expert evaluation, data selection and preprocessing. Furthermore, the second part of Chapter 3 elaborates the conceptual and technical implementation of the final indicator. Chapter 4 presents the results of the indicator implementation, including spatial patterns of vulnerability, country-level mean vulnerabilities and sensitivity analyses. Chapter 5 discusses the results, the performance of the indicator, the interpretation context and potential applications as well as reflects on methodological and conceptual limitations. Finally, Chapter 6 concludes the thesis by summarizing key findings and highlighting the broader contributions and limitations of the study.

2 Background

This thesis is based on existing research around environmental and social indicators, environmental and social impacts of mining as well as socio-ecological vulnerability.

2.1 Mining and socio-ecological vulnerability

There is scientific evidence that mining activities have a negative effect on the environment, which accordingly leads to detrimental effects for people living around mine sites. Several publications examine these effects. This section provides an overview of mining-related impacts based on existing literature.

2.1.1 Biodiversity and mining

The impact of mining activities on biodiversity is a pressing issue. Accordingly, many studies have examined this impact. The main destructive effect of mining on ecosystems and biodiversity is the frequent and total removal of all vegetation, which directly destroys habitats (Bruno Rocha Martins et al., 2020; Chen et al., 2022; Eckert et al., 2024). This happens either directly through mineral extraction or indirectly through the construction of infrastructure such as roads and settlements needed for the mining activities (Eckert et al., 2024; Murguía et al., 2016; Sonter et al., 2018). Impacts occur on different scales and reach from rather local (mineral extraction) to regional scales (infrastructure surrounding the mine) (Murguía et al., 2016; Sonter et al., 2018). The most severe impact could result in the complete and permanent removal of ecosystems (Sonter et al., 2018). Restoration of ecosystems after closure of mine sites is complex, protracted, financially costly and long-term monitoring as well as planning is needed (Angeler et al., 2019; Bruno Rocha Martins et al., 2020; Eldridge et al., 2022; Tibbett, 2024). For example, heavy machinery used in mining processes degenerate the soil heavily by destroying soil organisms and disrupting aggregates. This degeneration of soil makes the regrowth of plants difficult or even impossible (Bruno Rocha Martins et al., 2020; Mensah et al., 2015; Tibbett, 2024). This indicates that biodiversity loss due to mining is very difficult to reverse after mining closure.

In addition to the physical degradation of habitats, the pollutants emitted by mining activities pose another problem in harming biodiversity. This includes, for instance particulate matter such as clay, silt or sand from waste rocks. This suspended matter is transported through wind or water, increases turbidity in surface water and can therefore hinder photosynthesis or suffocate fish eggs when the particles settle (Lottermoser, 2017; Wolkersdorfer & Mugova, 2022). Other examples for pollutants are substances such as arsenic, lead, mercury, zinc, cadmium and copper, which spread through surface water, and which are toxic for flora and fauna when reaching high concentrations (Macklin et al., 2023; Mensah et al., 2015; Todd et al., 2024). Another threat to biodiversity is the acidification of soil and surface water caused by acidic mine drainage, which results from the weathering of sulfide minerals brought to the surface during mining (Lottermoser, 2017). This weathering process makes conditions for vegetation and aquatic organisms hostile (Dudka & Adriano, 1997; Lottermoser, 2017; Mensah et al., 2015; Sonter et al., 2018; Wolkersdorfer & Mugova, 2022; Worrall et al., 2009). Besides lowering the pH value, acidic mine drainage also leads to a higher solubility of other pollutants from mining in the water (Manhart et al., 2019). Literature indicates that the ecological effects caused by acidic mine drainage and pollutants occur still for decades, even after mine closure (Chen et al., 2022; Durán et al., 2013; Todd et al., 2024; Wolkersdorfer & Mugova, 2022; Worrall et al., 2009).

Those impacts caused by physical degradation as well as by pollution, are present up to tens to hundreds of kilometers from the immediate mine site location (Luckeneder et al., 2021; Macklin et al., 2023; Sonter et al., 2022; WWF, 2023). This is important to consider also in relation to biodiversity issues. It implies that even though a mine does not lie immediately inside a biodiversity hotspot, it can still pose a threat to these areas if they lie within a certain distance. Additionally, several studies show that the location of mine sites relative to high-biodiversity areas is not randomly distributed. This means that mines disproportionally affect areas such as protected areas, key biodiversity areas and other biodiversity hotspots (Durán et al., 2013; Kobayashi et al., 2014; Luckeneder et al., 2021; Murguía et al., 2016; Sonter et al., 2020; WWF, 2023). Furthermore, it is expected that the impacts on biodiversity will worsen in the future, since more materials, especially metals, are needed for the transition to renewable energies (Luckeneder et al., 2021; Murguía et al., 2016; Sonter et al., 2018, 2022; Tost et al., 2020). Lastly, literature also shows that reduced biodiversity intactness makes an ecosystem more susceptible to hazards, so that an ecosystem with degraded biodiversity is even more vulnerable (Weisshuhn et al., 2018).

2.1.2 Water Risk and mining

Water plays a central role in the context of mining. Several risks must be considered in this regard, including water scarcity, water quality and hydrological alterations. Water scarcity is a relevant issue, since many mine sites are located in areas where water is already scarce (Fuentes-George, 2023; Luckeneder et al., 2021). Mining activities consume large amounts of water for pumping and for extracting minerals through water-intensive separation procedures, as well as for heating and cooling water systems (Meissner, 2021). For some materials, such as copper, predicted decreases in ore grades make water scarcity more likely, as more water will be needed to extract the minerals of interest (Meissner, 2021; Northey et al., 2017). Water consumption varies depending on the type of ore and the processing method used (Meissner, 2021).

Pollution or acidic mine drainage also increases water risk, since it can contaminate surface or groundwater. In addition of harming the ecosystems and biodiversity a deterioration of the water quality can lead to functional impairments in the human body (Todd et al., 2024). Discharge from mine sites can contaminate fresh water sources, which poses many challenges, especially in rural areas (Wolkersdorfer & Mugova, 2022). A case study from Ghana revealed that residents living close to a mine site had to drill deeper holes to reach uncontaminated groundwater, which also led to high financial costs for the people (Mensah et al., 2015). The UNEP (2024) states that the suffering water quality related to mining poses a threat to Indigenous communities.

Besides pollution and water scarcity, hydrological alterations impose water risks related to mining. Mining can permanently alter groundwater levels and river flow regimes through dewatering and continuous water discharges, which disrupts natural seasonal flow patterns and surface-groundwater interactions (Meissner, 2021; Northey et al., 2017).

Generally, literature suggests that water risk caused by mining will intensify in the future, among other reasons due to climate change. Climate change related extreme weather events and floods can further accelerate the migration of pollutants through surface runoff and groundwater (Chen et al., 2022). As a contrast, long dry periods can cause protective layers on waste dumps to crack, and when rain returns, it can rapidly wash out pollutants in a first flush (Werner et al., 2020; Wolkersdorfer & Mugova, 2022).

2.1.3 Vulnerable peoples and communities

Not all peoples and communities are equally vulnerable to the negative impacts related to mining. Literature shows that different circumstances can lead to higher overall vulnerability. Thereby, vulnerability among people and communities in mining-affected areas is strongly shaped by pre-existing social, economic, and political conditions.

Literature indicates that several groups suffer disproportionately from negative impacts caused by mining. These groups are women, children, marginalized people such as the elderly, disabled people and people of low social status because they face higher risks of income loss, health impacts and social marginalization (Mancini & Sala, 2018; Shiquan et al., 2022). Also, a variety of studies mentions the impact of mining on Indigenous People and local communities (IPLC), who are often strongly affected by mining since they are highly dependent on their land, which they need to sustain their livelihood and because it is an important part of their cultural identity (Gamu et al., 2015; Mancini & Sala, 2018; Owen et al., 2022; Villén-Pérez et al., 2020). Not only are IPLC more vulnerable to the effects of mining, but their land disproportionately intersects with mine site projects (Burton et al., 2024; Owen et al., 2022; Phillips, 2025; Villén-Pérez et al., 2020). Although IPLC are the most affected by mining, they often lack legally recognized land rights. This means they have very limited opportunities to influence how, or even if, mining activities are carried out on their land. (Phillips, 2025). One reason for this is that minerals are often state-owned, which means that local communities have no formal right to participate in contract negotiations (Phillips, 2025). Politically weak populations, like IPLC are therefore particularly vulnerable to displacement caused by mining projects (Owen et al., 2021). Poor definition of land tenure increases the probability of displacement, which is also the case for subsistence farmers and small-scale miners (Forget & Rossi, 2021; Owen et al., 2021). Thereby, displacement and resettlement can further impoverish already poor population groups, for instance when peasants must move to less fertile land (Gamu et al., 2015). Gamu et al. (2015) emphasize that the relationship between mining and poverty is highly context-dependent and there is no consistent evidence that mining universally exacerbates poverty. However, studies show that mining can worsen living conditions in specific contexts, particularly if communities are already economically marginalized, which makes them more sensitive to negative impacts (Gamu et al., 2015; Shiquan et al., 2022).

Several studies report increases in different kinds of inequality linked to mining (Forget & Rossi, 2021; Gamu et al., 2015; Shiquan et al., 2022). This includes vertical inequality, so how wealth is distributed among citizens (Forget & Rossi, 2021; Gamu et al., 2015), as well as horizontal inequality, which describes inequalities between different communities or jurisdictions (Gamu et al., 2015; Shiquan et al., 2022). Shiquan et al. (2022) conducted a study using data from the China Family Panel Studies and found a high spatial heterogeneity for mining impacts; while some groups benefit through higher incomes, others suffer from income reductions and other social and environmental externalities. This also depends on the people's capacity to resist the impacts of mining (Shiquan et al., 2022). Shiquan et al. (2022) found that while the regional economy develops, the overall impacts of mining are negative due to social and environmental externalities.

The spatial heterogeneity in how people are affected by mining is a driver of conflicts and physical violence. Conflict risks increase in mining regions, especially where horizontal inequalities or pre-existing conflicts exist (Bond & Kirsch, 2015; Gamu et al., 2015). Generally, there is a high association among mining and rising conflicts (Owen et al., 2022). Literature even suggests that conflict is a structural problem related to mining activities (Phillips, 2025). Often this co-occurrence is connected to factors such as rapid in-migration of workers, corruption, weak institutions, commodity price fluctuations, a lack of employment opportunities, loss of traditional livelihoods, health and safety of mine workers, threats to cultural integrity and environmental change (Bond & Kirsch, 2015; Phillips, 2025). Phillips (2025) recently suggested that legal frameworks around mining require further scrutiny, since they are non-transparent, limit inclusive decision-making, prioritize investor rights over environmental and human rights and therefore reinforce power asymmetries in favor of corporate actors. Phillips (2025) argues that legal mechanisms structurally perpetuate inequalities, eventually leading to conflicts. In this context, inclusive governance and the active engagement of local stakeholders are critical for reducing vulnerability (Burton et al., 2024; Ebbesson, 2010; Forget & Rossi, 2021; Gamu et al., 2015; Painter et al., 2024; Phillips, 2025; Shiquan et al., 2022; Villén-Pérez et al., 2020).

2.1.4 Existing indicators

As shown in the previous sections, mining activities have wide-ranging and diverse impacts on both the environment and human populations. A variety of studies try to describe some of these impacts using either one or a set of indicators. The list of developed indicators is very long, and some studies bring together large indicator frameworks by conducting an extensive literature review. As done by Mancini & Sala (2018), who develop a reference list of 28 typical social impacts characterizing the mining sector and who compare those against the indicators used for assessing and promoting sustainability in different contexts. Fuentes-George (2023) identifies 95 different environmental sustainability indicators used for copper production. Manhart et al. (2019) develop an indicator system that assesses the "Environmental Hazard Potential" of mining activities by integrating metrics from geology, technology and the natural environment. Marnika et al. (2015) outline 36 indicators categorized into seven groups to assess mining in protected areas by covering technical disturbance, waste management and social impacts. Worrall et al. (2009) formulate a sustainability criteria and indicator framework to evaluate the needs of legacy mine land that consists of 14 criteria and 72 indicators. Kobayashi et al. (2014) generate an indicator to quantify site-level pressure on biodiversity. Murakami et al. (2020) use an ecological footprint and a total material requirement indicator to assess the impacts of copper mines.

The literature review of existing indicators above is not fully comprehensive, since the impact of mining activities is a broad term. The scope of an indicator can vary depending on temporal resolution, spatial scale and resolution, commodity, mining methods as well as on environmental and social factors considered. The paper by Luckeneder et al. (2021) is of particular interest as it introduces the concept of ecosystem vulnerability, which can be used to assess the potential impact of metal mining on a global scale at the mine site level. With this, they provide an attempt to capture mining impacts on a more general scale. They rely on a limited set of spatial proxies, namely biome types, protected areas and water scarcity. Also, they make use of datasets containing national-level ore grade averages and mining locations. With these datasets they identify spatial patterns in terms of where mine sites are located relative to vulnerable ecosystems, which they define through the mentioned spatial proxies. While Luckeneder et al. (2021) refer to the term "ecosystem vulnerability" and while they also refer to three key dimensions of vulnerability, "exposure, sensitivity, and adaptive capacity" (IPCC, 2007), their analysis does not explicitly operationalize all of these dimensions. Also, their approach limits itself to only look at ecosystem vulnerabilities, neglecting social aspects of mining activities.

2.2 Vulnerability: Frameworks and definitions

Since the goal of this thesis is the development of an indicator describing socio-ecological vulnerability to mining impacts, a clear definition of the term vulnerability is crucial. There are several existing definitions (Beroya-Eitner, 2016; Berrouet et al., 2018; Estoque et al., 2023), whereas this thesis' focus lies on the vulnerability frameworks provided by the Intergovernmental Panel on Climate Change (IPCC), since they are grounded in extensive peer-reviewed literature and represent an internationally recognized scientific consensus. However, as there are several different definitions of vulnerability throughout the IPCC's assessment reports (AR), and it has been unclear whether subsequent reports replaced previous definitions, deciding which notion to use is not straightforward (Estoque et al., 2023). Estoque et al. (2023) show that the revised vulnerability definition from earlier AR have not been adopted by many existing vulnerability studies and that the definition therefore varies strongly among studies. Since many existing studies refer to the IPCC's definition of vulnerability given in AR4 (Estoque et al., 2023), the same definition is used for the pilot indicator in this thesis. In AR4 the term vulnerability consists of three dimensions: Exposure, sensitivity, and adaptive capacity (Estoque et al., 2023; IPCC, 2007). Exposure being the variation that a system is exposed to a hazard, sensitivity being the degree of susceptibility of a system to a hazard and adaptive capacity being the ability of a system to cope with a hazard (IPCC, 2007; Weisshuhn et al., 2018). However, after evaluating the pilot indicator through experts, it has been revised and the final indicator makes use of the updated vulnerability definition as it is described in AR5 and AR6. This definition consists of the two dimensions; Sensitivity and lack of capacity to cope and adapt (IPCC, 2022). Section 3.3 in the methods chapter elaborates this specific decision. In AR5 and AR6, vulnerability itself forms one of three dimensions and together with hazard and exposure it defines the term risk (Estoque et al., 2023; IPCC, 2022). Figure 1 by Estoque et al. (2023) illustrates the differences between the two vulnerability definitions. AR6 defines vulnerability as follows: "*Vulnerability […] is defined as the propensity or predisposition to be adversely affected and encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt"* (IPCC, 2022, p. 2927).

There are also other relevant vulnerability definitions. The United Nations Office for Disaster Risk Reduction UNDRR (2017) defines it as: *"The conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards"*. Additionally, an annotation is added to the UNDRR definition referring to the terms "Capacity" and "Coping capacity", which describe positive factors that increase the ability of people to cope with hazards (UNDRR, 2017). With that definition, the UNDRR treats susceptibility to the impacts of hazard and coping capacity separately and does not explicitly incorporate them both under the definition of vulnerability. Within the vulnerability definition itself, the UNDRR only refers to susceptibility to the impacts of harm, which is the equivalent of sensitivity as defined in the IPCC vulnerability definition.

Accordingly, the UNDRR framing conceptualizes vulnerability primarily as a set of underlying susceptibility conditions, while capacities that may reduce harm are treated as distinct but related concepts. In contrast, the IPCC's AR5/AR6 definition explicitly integrates both sensitivity and the lack of coping and adaptive capacity within the concept of vulnerability itself. For the purpose of developing a socio-ecological vulnerability indicator to mining impacts, this integrated understanding is particularly useful. Mining-related pressures often unfold gradually over time, interact with ecological and social pre-conditions and require long-term adaptation rather than short-term emergency response as for disasters (Bruno Rocha Martins et al., 2020). A definition that simultaneously captures susceptibility to harm and limitations in adaptive capacity therefore better reflects the systemic and dynamic nature of socio-ecological vulnerability in mining contexts.

While the UNDRR definition provides valuable insights into the structural conditions that increase susceptibility to hazards, its main orientation toward disaster risk reduction makes it less directly applicable to long term change processes such as land degradation, water contamination or livelihood transformation that are associated with mining activities. The IPCC AR5/AR6 definition, originally conceptualized for long term impacts caused by climate change, is therefore conceptually well suited for a socio-ecological vulnerability indicator to mining impacts.

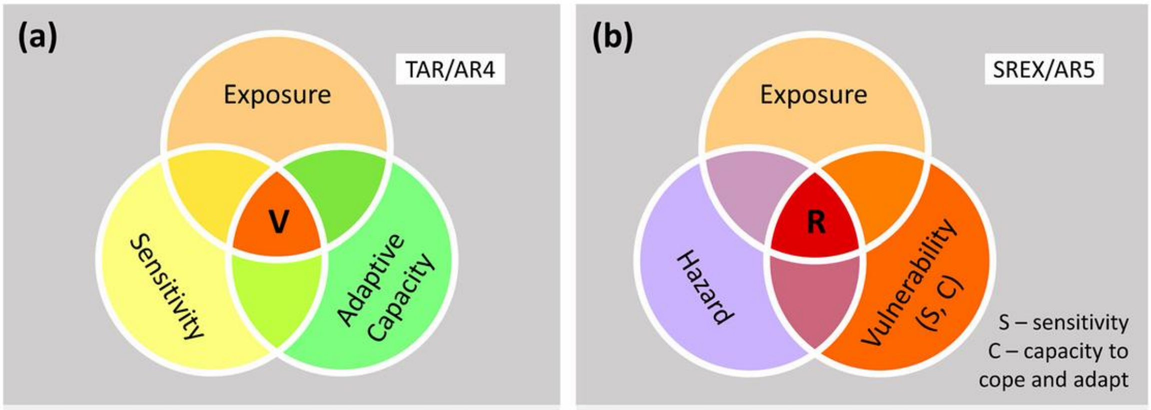

Figure 1: Comparison of vulnerability definitions in the IPCC third and fourth assessment report to the fifth assessment report (Estoque et al., 2023)

2.3 Indicator based assessments

2.3.1 Indicator characteristics

Indicators are a widely used tool to provide information about a phenomenon, which is not directly measurable. Thereby indicators aim to describe complex issues and help a variety of actors, such as policymakers, in identifying broader patterns and trends (Beroya-Eitner, 2016; Maggino, 2017; Niemeijer, 2002). Indicators are applied across many fields, including both social indicators, which focus on societal conditions and processes (Maggino, 2017) as well as environmental indicators, which provide information on environmental problems, help to evaluate their urgency and answer the questions of what is happening to the environment and why (European Environment Agency, 2014). Additionally, indicators describing socio-ecological systems are used, following the recognition that social and natural systems are coupled and must be looked at together (Beroya-Eitner, 2016). As for the indicators' characteristics and quality requirements, the following discussion primarily draws on environmental indicator research, whose quality criteria are conceptually transferable to socio-ecological systems.

Indicators can be assigned to different categories that are formulated by the European Environment Agency. These categories should help to structure thinking about the interplay between the environment and socio-economic activities and together they form the DPSIR (driving force, pressure, state, impact, and response) framework (European Environment Agency, 2014). The European Environment Agency explain it like this: *"[…] social and economic developments drive (D) changes that exert pressure (P) on the environment. As a consequence, changes occur in the state (S) of the environment, which lead to impacts (I) on human health, ecosystem functioning and the economy. Finally, societal and political responses (R) affect earlier parts of the system, directly or indirectly"* (European Environment Agency, 2014, pp. 15–16). This kind of framework is in line with the ones used by other organizations such as the Organization for Economic Co-operation and Development (OECD) or the United Nations (UN) and it helps to select indicators as well as to communicate results of indicator-based assessments (European Environment Agency, 2014).

The construction of meaningful, robust and easy interpretable indicators is far beyond trivial. Accordingly, a lot of literature addresses the question of what constitutes a good indicator. The OECD pioneered the systematic formulation of quality requirements for environmental indicators and structured them into the dimensions of policy relevance, analytical soundness and measurability (OECD, 1993). This structure is likewise employed by the European Environment Agency (2014) reflecting a shared and widely accepted framework for evaluating environmental indicators.

With regards to policy relevance, indicators are expected to provide a representative picture of environmental conditions, pressures or societal responses, while remaining simple and easy to interpret. They should be capable of capturing temporal trends, respond to environmental change and human activities and enable comparisons across regions or countries. Furthermore, effective indicators should be applicable at national or regionally significant scales and include reference values or thresholds that allow users to assess the significance of observed indicator values. From a scientific perspective, indicators must be analytically sound, meaning that they are theoretically well grounded, scientifically robust and ideally aligned with internationally accepted standards. They should also be suitable for integration with analytical tools such as economic models, forecasting approaches or information systems. Finally, indicators must be supported by measurable and reliable data. This requires that the underlying data is available or obtainable at a reasonable cost, well documented with known quality, and updated regularly using transparent and consistent procedures. (European Environment Agency, 2014; OECD, 1993)

It is important to mention that indicators are more than raw data and can be seen as "purposeful statistics", since they are developed with a certain goal and are therefore always connected to a conceptual model (Maggino, 2017). Maggino et al. (2017, p. 88) therefore argue: *"Developing indicators is a normative exercise per definition, since indicators are related to a conceptual definition of the phenomenon of interest and since a phenomenon can be defined in different ways. Consequently, in order to describe a phenomenon different groups of indicators can be selected".* This is important to consider, especially when indicators should provide quick and easily interpretable answers to important questions. Contextualization of an indicator as well as a transparent construction process are crucial, since the same indicator can have reverse meanings depending on the socio-economic context and thereby might be misinterpreted or even misused (Birkmann, 2007; OECD, 2008).

2.3.2 How to build composite indicators

Often indicators are not based on a single variable, but they are put together out of several different indicators building a set. This function of many variables is called a composite indicator (Burgass et al., 2017; European Environment Agency, 2014). Composite indicators can summarize complex issues using several dimensions and are easier to interpret than several individual indicators (Burgass et al., 2017; OECD, 2008).

Constructing a composite indicator begins with the development of a theoretical framework, which is the most critical step (OECD, 2008). This is necessary to build a conceptual model and to come up with a clear definition of the measured phenomenon, which is crucial for the whole process (Maggino, 2017; OECD, 2008). In a subsequent step, the theoretical framework must be used to identify subgroups, hereafter referred to as “dimensions”, and to select their respective variables (OECD, 2008). Such a nested structure enhances the understanding of the key drivers underlying the composite indicator and can facilitate the determination of relative weights among different components (OECD, 2008).

The selection of variables and the data representing them should be based on different criteria. The handbook on constructing composite indicators of the OECD (2008, p. 23) stresses that *“the strengths and weaknesses of composite indicators largely derive from the quality of the underlying variables”*. Variables should be selected based on their relevance, analytical soundness and on data availability. Data availability can be a major constraint when developing composite indicators, where the use of proxy data is a viable option when facing data scarcity. However, selecting data is a delicate issue, since poor data can lead to weak results. When making compromises within the indicator development, transparency about the specific choices is essential. (OECD, 2008)

Besides selecting variables and suitable data, other decisions must be made during the indicator construction. Since the selected variables typically differ in units and scales, normalization is a necessary step to make them comparable and to avoid certain variables disproportionately influencing the composite result due to their measurement scale (Maggino, 2017; OECD, 2008). Normalization can be conducted in a variety of ways, such as rankings, standardization with z-scores or using Min-Max normalization (OECD, 2008). Subsequently, the normalized variables must be aggregated and optionally weighted to form higher-level dimensions and ultimately the single composite score of the final indicator (Maggino, 2017; OECD, 2008).

The aggregation of multiple variables into a composite indicator is closely related to approaches from multi-criteria decision analysis (MCDA), which provides a methodological framework for combining multiple criteria into a single evaluative measure (Greco et al., 2016). In MCDA, particular attention is paid to weighting schemes and aggregation rules, as these determine the extent to which trade-offs and compensation between criteria are permitted (El Gibari et al., 2019; Greco et al., 2016). Simple additive aggregation, which is commonly applied in composite indicator construction, allows for compensability between variables, meaning that lower values in one criterion can to some extent be balanced by higher values in another (Gan et al., 2017). Alternative MCDA approaches propose non-compensatory or partially compensatory aggregation rules to limit such trade-offs. However, these schemes often require more detailed preference information and stakeholder input, which may not be available or feasible in large-scale assessments (e.g. global scale) (El Gibari et al., 2019). In line with the OECD handbook, the choice of aggregation method should therefore be based on the underlying theoretical framework (OECD, 2008). This again illustrates that the construction of an indicator is a normative process and several choices must be made. These choices always have a subjective component, which makes transparency a guiding principle for this process. Assumptions and limitations must be communicated clearly to make sure that the indicator remains credible and fit for its intended purpose (OECD, 2008).

Lastly, one important part of the indicator construction is its validation. To examine the validity of the internal structure of the indicator, including its dimensions and variables several methods can be applied. The OECD handbook recommends the use of exploratory multivariate analysis as a diagnostic tool to examine whether variables grouped within the same indicator dimension exhibit coherent statistical behavior, to identify variables that provide overlapping information and to detect dominant variables that may disproportionately influence the composite result (OECD, 2008). In this context, multivariate analysis does not constitute a validation of the indicator against a ground truth but rather serves as a tool to assess internal coherence and structural consistency. This understanding aligns with the conceptualization of validation of Rykiel (1996) in model development, who emphasizes that validation refers to the suitability of a model for its intended purpose rather than its ability to represent an objective truth. Consequently, the examination of internal structure contributes to the credibility and interpretability of the composite indicator by ensuring that its construction is theoretically justified, transparent, and fit for purpose, rather than empirically "proven" in an absolute sense. According to Rykiel (1996), there are several validation procedures. Face validity, which is the consultation of experts, is thereby also an important aspect mentioned in the OECD handbook. It says that experts and as many stakeholders as possible should be involved to increase the robustness of the indicator (OECD, 2008; Rykiel, 1996).

2.4 Vulnerability indicators

Since vulnerability is a condition that is not directly measurable and is inherently complex, a composite indicator is well suited to describe it. To build this kind of indicator, one must rely on proxy variables and aggregation procedures. Villa & McLeod (2002) argue that global vulnerability assessments necessarily represent a compromise between scientific rigor and practical feasibility, resulting in "least disappointing" approximations that are nevertheless essential for environmental decision-making. Indicators therefore serve as simplified representations of complex systems that remain useful for policy and decision-making (Beroya-Eitner, 2016). Indeed, some existing indicators describe different types of vulnerability, including ecological, social, and socio-ecological vulnerability (Beroya-Eitner, 2016; Berrouet et al., 2018; Kim et al., 2025; Painter et al., 2024; Villa & McLeod, 2002).

Social vulnerability indicators focus on social, economic, and political drivers that exacerbate environmental risks and therefore help to understand the broader conditions in which people live and that may worsen the consequences of disasters or environmental hazards (Mah et al., 2023; Painter et al., 2024). Social vulnerability indicators describe the interplay of diverse social elements, which shape people's capacity to prepare for, respond to and recover from such events (Kim et al., 2025). Such indicators are crucial in many fields including disaster risk management, health, environmental and climate change as well as land use and urban planning (Kim et al., 2025; Mah et al., 2023; Painter et al., 2024). Despite their wide application, social vulnerability indicators also face several limitations. Many existing indicators rely primarily on secondary quantitative datasets, such as census data and are therefore typically constructed through deductive variable selection rather than participatory or stakeholder-based approaches (Mah et al., 2023; Painter et al., 2024). As a result, these indicators often reflect observable demographic characteristics that are associated with vulnerability rather than the underlying structural processes that make these demographic groups vulnerable in the first place, such as political marginalization or institutional inequalities (Painter et al., 2024). This can limit the extent to which such indicators support interventions aimed at addressing the root causes of vulnerability rather than only identifying populations that are statistically correlated with higher risk. Also, many social vulnerability indicators do not show temporal dynamics of vulnerability but only provide snapshots of current vulnerability, which is neglecting the temporal character of it (Painter et al., 2024). Additionally, environmental variables are rather underrepresented within social vulnerability indicators and only a few indicators include variables such as air and water quality, natural hazards or pollution and waste (Kim et al., 2025). Besides social vulnerability indicators, there are also indicators focusing on ecological vulnerability. Ecological vulnerability is the potential of an ecosystem to regulate its response to stressors and refers to ecosystem disturbance, system damage and the ability of system restoration (Hou et al., 2022; Weisshuhn et al., 2018). Ecological vulnerability has historically received less attention than social vulnerability in the vulnerability literature, although research in this area has expanded in recent years (Beroya-Eitner, 2016).

The existence of social as well as ecological vulnerability indicators raises the question whether approaches exist that integrate perspectives into a composite socio-ecological vulnerability indicator. Indeed, recent research emphasizes a transition away from "siloed" perspectives towards Social-Ecological System (SES) frameworks (Berrouet et al., 2018; Hossain et al., 2023). Within an SES framework, vulnerability is the degree to which an integrated system, consisting of societal and biophysical subsystems, is likely to experience harm due to exposure to a hazard or process, such as climate change or land-use transformation (Berrouet et al., 2018). The SES framework considers changing social conditions such as poverty as well as ecological conditions such as land and water use and thereby recognizes social and ecological systems as complex structures that interact with each other (Hossain et al., 2023). For example, environmental degradation caused by resource extraction can alter ecosystem functioning and ecosystem services, which may affect local livelihoods and thereby influence the vulnerability of communities that depend on these ecosystems. Hossain et al. (2023) emphasize that it is crucial to consider dynamics that arise from the interactions between social and ecological systems when it comes to adaptation efforts. While Hossain et al. (2023) mainly address climate change adaptation, this reasoning can also be applied to other forms of environmental alterations such as land degradation or, as in the case of this thesis, to mining activities. To understand vulnerability to environmental hazards, it is therefore beneficial to adopt an integrated perspective that considers both social and ecological variables and their potential interactions.

Literature furthermore emphasizes that vulnerability indicators are inherently context-dependent, and their interpretation depends on the socio-economic and environmental setting in which they are applied (Birkmann, 2007). This underlines the importance of spatially explicit indicator design, transparent methodological choices as well as clearly communicated assumptions and limitations.

2.5 Research gap

Despite the extensive body of literature documenting the environmental and social impacts of mining, important gaps remain, particularly with respect to how these impacts are integrated and assessed across broader spatial scales. As previous sections show, existing research provides substantial knowledge on mining-related ecological degradation, water risks and social impacts such as displacements, inequality and conflicts. Likewise, vulnerability research has produced a wide range of social and ecological vulnerability indicators. However, these strands of literature often remain conceptually and methodologically separate. Social vulnerability indicators tend to focus primarily on demographic, socio-economic and political conditions, while ecological vulnerability indicators concentrate on ecosystem disturbance, degradation and recovery potential. Approaches that explicitly combine both perspectives into an integrated socio-ecological vulnerability perspective remain comparatively scarce.

This gap is particularly relevant in the context of mining, since mining activities affect ecosystems and human communities simultaneously and through interacting processes. While several indicator frameworks have been developed to assess mining-related impacts, most are either sector-specific, limited to particular commodities or regions or focus on only one dimension of vulnerability. Approaches such as the one by Luckeneder et al. (2021) represent an important step toward spatially explicit assessments of mining-related vulnerability. However, they operationalize vulnerability only partially and restrict their focus to ecosystem-level proxies without incorporating social sensitivity and adaptive capacity. Consequently, there is currently no globally consistent and spatially explicit indicator that captures socio-ecological vulnerability to mining impacts in an integrated and transparent manner. This thesis addresses this gap by developing a composite indicator that combines ecological and social variables of vulnerability, grounded in IPCC vulnerability frameworks. Thereby this indicator aims at providing a comparative analysis of relative socio-ecological vulnerability to mining impacts at the global scale.

3 Methods

First, this chapter presents the overall research design. Subsequently, the literature review process is presented. Next, the conceptualization of the pilot indicator is shown and the expert feedback on the results of the pilot indicator is summarized. This is followed by a presentation of the study scope and the conceptual design of the revised indicator. Afterwards, the used datasets are listed together with their preprocessing steps, which is followed by the indicator's implementation. The last part of this chapter describes the methods used to analyze the resulting spatial indicator.

3.1 Overall research design

This section presents the overall research design by providing an overview of the most important steps. These steps are described in more detail in the following sections. The overall workflow is shown in Figure 2.

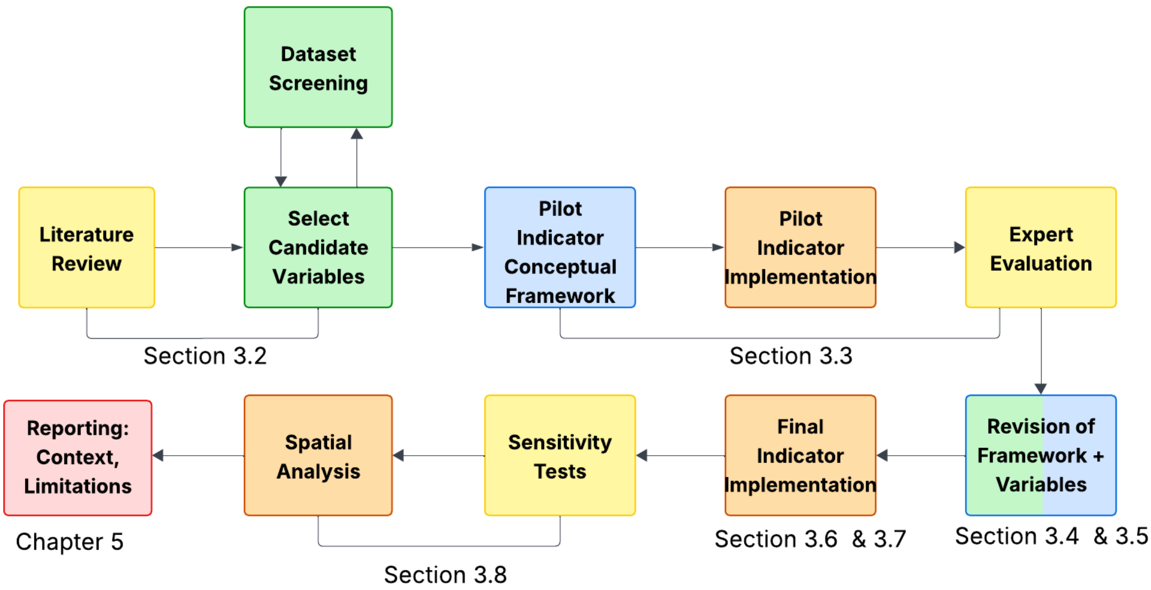

Figure 2: Workflow (illustration by the author)

Literature collection and variable candidate selection

As a first step, literature around socio-ecological impacts caused by the mining industry was collected. The collected studies were used afterwards to decide on potential variables to include in the indicator. Section 3.2 describes this process in more detail.

Pilot indicator and evaluation

Based on the selected literature, potential available datasets were inspected and variables were defined based on theory provided by literature as well as on practical constraints given by data availability. A pilot indicator was calculated, and the preliminary results were shown to experts in order to evaluate them. More information on the expert consultations and resulting changes of the pilot indicator are given in section 3.3.

Final indicator and analysis

After the expert's feedback the pilot indicator was revised, and a new conceptual framework was developed. The conceptual framework was then implemented and the results analyzed. This was done through sensitivity tests and general spatial analysis. Section 3.5 to 3.8 describe this part of the methods.

3.2 Literature Review

The literature review was conducted primarily with google scholar. Articles were selected based on the following criteria:

- They develop or implement indicators to describe impacts related to mining activities (or activities with similar effects) detrimental to ecosystems
- Work on a regional or global scale
- Do not rely on in situ measurements
- Do not examine a single mine site/case

Based on this structured literature review of 19 peer-reviewed studies, candidate variables were identified and listed by preliminarily allocating them to different dimensions of vulnerability. Additionally, possible datasets representing these variables were listed to narrow down the candidates for inclusion in a global-scale vulnerability indicator. The list resulting from this literature review can be found in Table 1. The goal of this list is to define a preliminary conceptual framework of a pilot indicator which can then be evaluated by experts. For this pilot indicator the goal initially was to describe ecosystem vulnerability, instead of socio-ecological vulnerability.

EXPOSURE

VARIABLE	Proxy / Dataset	Rationale	Key references
PROXIMITY TO MINES / MINE-AFFECTED AREA	Global mine polygons	Exposure decreases with distance from mining sites; captures direct and indirect impacts	(Eckert et al., 2024; Kobayashi et al., 2014; Tang & Werner, 2023)
MINING INTENSITY (ORE GRADE, PRODUCTION, METAL TYPE, MINING METHOD)	Mine-specific attributes	Lower ore grades and higher production increase waste, water use, and emissions	(Dudka & Adriano, 1997; Kobayashi et al., 2014; Priester et al., 2019)

EXPOSURE

VARIABLE	Proxy / Dataset	Rationale	Key references
CUMULATIVE MINING EXPOSURE	Mine polygons (density)	Multiple nearby mines increase cumulative environmental pressure	(Kobayashi et al., 2014; Sonter et al., 2018)
DOWNSTREAM EXPOSURE WITHIN CATCHMENTS	HydroSHEDS v1	Pollution and sediment transport affect downstream ecosystems	(Macedo et al., 2022)

SENSITIVITY

VARIABLE	Proxy / Dataset	Rationale	Key references
WATER STRESS	AWARE index (WULCA)	Water-scarce regions are more sensitive to water-intensive mining	(Luckeneder et al., 2021; Manhart et al., 2019)
LITHOLOGY / MINERALOGY	Global ecological land units	Determines acid mine drainage risk and geochemical buffering	(Lottermoser, 2017; Northey et al., 2017)
PROTECTED AREA STATUS	WDPA	Protected ecosystems assumed to be more sensitive to disturbance	(Kobayashi et al., 2014; Luckeneder et al., 2021)
BIOCLIMATE	Global ecological land units	Climate conditions influence weathering rates and AMD risk	(Northey et al., 2017; Wolkersdorfer & Mugova, 2022; Younger & Wolkersdorfer, 2004)
LANDFORMS / SLOPE	Global ecological land units	Steep terrain may increase erosion and contaminant transport	(Manhart et al., 2019)
ACCIDENT HAZARD (FLOODS, LANDSLIDES, EARTHQUAKES)	Global hazard datasets	Natural hazards increase likelihood of mining accidents	(Manhart et al., 2019)
VASCULAR PLANT DIVERSIT	Global vascular plant richness maps	Proxy for biodiversity and ecological value	(Murguía et al., 2016;

ADAPTIVE CAPACITY

VARIABLE	Proxy / Dataset	Rationale	Key references
REGROWTH POTENTIAL (BIOCLIMATE AND VEGETATION)	Global ecological land units	Climate and vegetation influence recovery speed	(Weisshuhn et al., 2018)
ECOSYSTEM CONNECTIVITY	Global ecological land units, fragmentation indices	Connectivity supports recolonization and ecological memory	(Weisshuhn et al., 2018)
ECOLOGICAL DIVERSITY	Biodiversity proxies	Functional redundancy increases buffering capacity	(Weisshuhn et al., 2018)
SOIL AND WATER STABILITY	Global ecological land units / hydrological proxies	Stable abiotic conditions support resilience	(Lottermoser, 2017)
DISTURBANCE HISTORY	-	Ecosystems with past disturbance experience may recover better	(Weisshuhn et al., 2018)
FINANCIAL CAPACITIES	GDP, restoration funds	Long-term monitoring necessary for restoration, very costly	(Angeler et al., 2019; Bruno Rocha Martins et al., 2020)
ENVIRONMENTAL REGULATIONS	National regulation indices	Regulations crucial to mitigate negative impacts of mining	(Luckeneder et al., 2021)
DEMOCRACY AND ENVIRONMENTAL PROTECTION	VDem data	Under certain conditions democracy can work in favor of the environment	(J. Von Stein, 2022)

Table 1: List with candidate variables and potential datasets

3.3 Pilot indicator evaluation

This section describes the pilot indicator and its evaluation, which preceded the implementation of the final indicator. Figure 3 shows the conceptual framework of the pilot indicator. The pilot indicator is conceptualized to describe ecosystem vulnerability to mining and is based on three dimensions: Exposure, sensitivity and adaptive capacity. Together they form an indicator that describes ecosystem vulnerability to mining impacts. The combination of the variables consists of a simple additive aggregation to build the dimensions. However, for the dimensions the additive aggregation only applies to exposure and sensitivity. Adaptive capacity, on the other hand, is subtracted in the aggregation process to form the indicator. This reflects the idea that higher exposure and sensitivity increase vulnerability, whereas higher adaptive capacity mitigates it. This conceptual framework is still based on the old Intergovernmental Panel on Climate Change (IPCC) definition of vulnerability, as provided in assessment report (AR) 4 (IPCC, 2007).

As for the different variables, several things are worth mentioning with regards to the pilot indicator. First, there is a group of variables that are mine specific and connected to the mine location and therefore form the dimension of exposure. The data is provided by a satellite-based dataset including mine polygons around the world by Tang & Werner (2023). The variable of proximity expresses the distance of an area to the next mine site. The proximity score decreases with distance from the mine site. If several mines are close by, the proximity score is increased cumulatively. The variable pollution of surface water consists of a flow accumulation score that indicates where pollutants produced by mine sites potentially accumulate. It takes mine sites as sources and analyses the pollutants' flow direction using a digital elevation model. The pollutant accumulation decreases with distance from the mine sites.

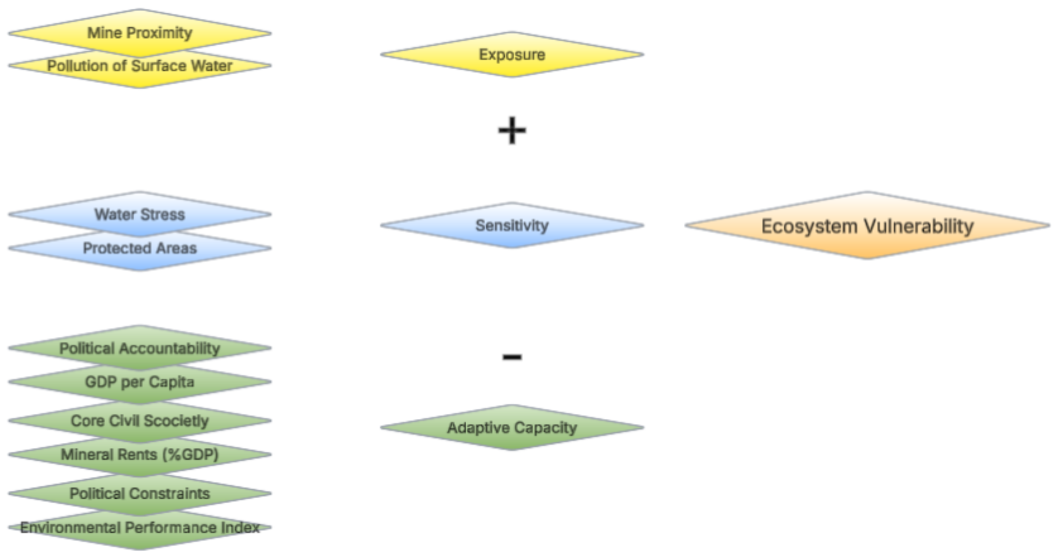

Figure 3: Conceptual design of pilot indicator (illustration by the author)

Second, the variables are clearly separated with respect to what they describe; for sensitivity the variables are ecosystem related while they are policy and economy related within the adaptive capacity dimension. Sensitivity consists of the two variables water scarcity and protected areas (PA). The adaptive capacity dimension tries to capture how political and economic conditions in a country help ecosystems to better cope with the impact of mining. This conceptualization is based on connections between democracy and environmental protection, which are found in literature. The dimension of adaptive capacity includes six variables that are combined pairwise and is based on the work of J. Von Stein (2022). It includes:

- Political Accountability and GDP per capita: If political accountability is high, which means that politicians are held accountable for their actions through clean elections, it is more likely that environmental protection is high. This is only the case if environmental protection is what citizens want, which is more likely if individual prosperity is higher.
- Civil Society and Mineral Rents: Environmental protection is strengthened by a strong civil society, though the effect depends on which actors hold the most power and influence within it. In the context of mining, the level of mineral rents (% of GDP) can be an important factor. When mineral rents are high, a country's economy is heavily dependent on mineral extraction. In such cases, actors from the mining sector may hold significant power within civil society, potentially limiting its capacity to advocate for environmental protection
- Political Constraints and Environmental Performance: When political constraints are high in a country, it is likely that changes in law are difficult. This could indicate that when environmental performance of a country is already good and political constraints are high, it is difficult to change the laws, which would have a detrimental effect on the environment. On the other hand, if environmental performance is already low, high political constraints make it difficult to change laws in favor of the environment.

The pilot indicator as conceptualized in Figure 3 was implemented and presented to experts of different backgrounds. Interviews were conducted with experts from academia, civil society, and the private sector to critically assess the conceptual design, data choices, and applicability of the vulnerability indicator. The interviews lasted between 30-60 minutes. Table 2 lists the different interviews and summarizes the main feedback points.

For most interviews a short presentation or a pre-sent summary served as a common starting point, outlining the conceptual design of the pilot vulnerability indicator, the selected data and preliminary results in the form of maps and country-level statistics. In several cases, the presentation was iteratively refined from interview to interview to incorporate feedback from earlier interviews. The interviews were then guided by a set of prepared questions, which were adapted to the disciplinary background and expertise of each interviewee, resulting in interviews of varying degrees of structure.

The interview AC-3 followed a different format, as it focused on highly specific questions related to mineral occurrence, geological constraints and the interpretation and limitations of the mine location dataset, rather than on the overall indicator design and results. It therefore did not include the full presentation of the conceptual design.

ID	SECTOR/ AFFILIATION	ROLE/ EXPERTISE	INTERVIEW FORMAT/DATE	MAIN FEEDBACK THEMES
NGO-1	NGO (human rights)	Environmental justice, mining impacts, corporate accountability	Individual interview, in person, 28.10.2025	Different IUCN categories for WDPA should be weighted differently; GDP per capita does not reflect inequality and regional differences; Mineral rents is not a good proxy; environmental performance index too generic; missing inclusion of Indigenous People, consider including conflict related variable, consider filtering for countries where the mining industry has high significance, thereby strengthening exposure dimension; Global South mining hotspots missing in results; caution about what results based on raw vulnerability scores show; define target audience; reflect on own position
NGO-2	NGO (con-servation)	Biodiversity conservation, environmental impacts of mining	Group interview (3 participants), online, 14.11.2025	Key mining countries (e.g. Brazil, Indonesia) are missing among most vulnerable countries; PA insufficient as biodiversity proxy; missing inclusion of Indigenous People; missing conflict variable; pollution of surface water calculation unsuitable; keep water risk; consider inclusion of infrastructure in exposure layer; strengthen adaptive capacity (e.g. through governance, corruption); consider including land rights; mineral rents probably not a relevant variable; add variable on environmental policies
AC-1	Academia (Political Ecology)	Governance, extractive conflicts	Individual interview, online, 17.11.2025	Define target audience; rethink logic of subtraction of adaptive capacity; be careful about colonial continuities (e.g. corruption as variable); consider global power asymmetries; keep water stress (very important); reconsider using GDP and mineral rents; consider rule of law (access to law) as variable; include conflict as variable
AC-2	Academia (GIS/natural resources)	Spatial modelling	Individual interview, in person, 17.11.2025	Reconsider additive index logic and consider multiplicative index; rethink separation of sensitivity and adaptive capacity variables (unclear variable assignment); reconsider global index due to missing comparability of different ecosystems; missing biodiversity and deforestation variables; consider spatial resolution differences (country-level vs. spatially explicit)
AC-3	Academia (Natural Sciences / Geology)	Mineral resources, extractive processes	Individual interview, in person, 18.11.2025	Emphasized distinction between resources and reserves; no absolute geological limits for mineral extraction but strong economic and technological constraints; warned against using reserves/resources as proxies (not possible to map this sufficiently); caution against overinterpreting satellite-based mining data; amount of acidic mine drainage cannot be determined based on lithology alone
PR-1	Private Sector (reassurance/ consulting)	Mining-related sustainability, environmental and social risk assessment	Individual interview, online, 28.11.2025	Reconsider exposure dimension, since location with existing mines are now more vulnerable than locations with no mines; include key biodiversity areas or similar layers, since PA not sufficient for biodiversity; keep water stress/risk, because its linked to social impacts as well; consider colonial continuities, include rather conflict, rule of law, Indigenous People instead of GDP and mineral rents; consider including human rights with regards to land rights and labor rights; define target audience

Table 2: Conducted interviews and summarized main feedback

Based on the feedback gathered from the expert interviews a series of adjustments was applied to the conceptual framework of the indicator. Several interviewees criticized the dimension of exposure due to different reasons. The results of the pilot indicator identified a variety of most vulnerable countries, which did not match the results of other studies and therefore did not reflect actual mining hotspots (NGO-1, NGO-2). AC-3 considered the satellite-based dataset on which exposure was built as not appropriate since it does not reflect reality sufficiently. When asked AC-3 further emphasized that it is not a viable option to model the probability of occurring current or future mine sites based on geology maps that indicate mineral deposits. The difference between resources, which are the actual minerals occurring in the earth's crust, and reserves, the mineral deposits that could potentially be extracted in an economically und technically feasible manner, was explained. According to AC-3, resources are not the limiting factor when it comes to mineral extraction, however the reserves are what matters. It is not possible to model reserves available since this is dependent on many factors and exploration is complex, costly and takes often many years. Following, these insights AC-3 implicated that it is not possible to use geological data to model potential exposure. Furthermore, the exposure dimension raised questions, as the presence of mine sites in an area makes it more vulnerable to mining impacts than areas without mining activity. However, this logic can be confusing in some cases, since one could also argue that more pristine areas with no prior mining activities are more vulnerable to the impacts of newly established mine sites (PR-1). Lastly, NGO-2 questioned the calculation of one of the two exposure variables. The calculation of surface water pollution is complex and dependent on many different factors, which seemed to be oversimplified in the pilot indicator (NGO-2). In response to the substantial criticism of the exposure dimension, the final framework places greater emphasis on pre-existing socio-ecological conditions rather than direct representations of mining activities, which also aligns with more recent vulnerability definitions provided by the IPCC (IPCC, 2022). The dimension of exposure is therefore neglected in the revised indicator.

Feedback also concerned the conceptual separation between the dimension of sensitivity and adaptive capacity. On the one hand, experts argued that separating ecosystem-related variables from policy and economic variables appears artificial and lacks theoretical significance (AC-2). On the other hand, it was perceived to be problematic that adaptive capacity is subtracted to build the final vulnerability layer and can therefore explicitly compensate for variables that increase vulnerability within the sensitivity dimension (AC-1). Since the pilot indicator includes only ecosystem related variables for sensitivity and only political and economic variables for adaptive capacity, this would imply that political and economic variables can directly and fully compensate for the negative impacts of ecosystem related variables. However, AC-1 argues that it is more useful to have an indicator that considers political, social and environmental factors all together and have an additive aggregation to avoid this kind of compensation. To take this feedback into account, the dimension of adaptive capacity was reformulated and is subsequently described as "lack of adaptive capacity", which aligns with more recent vulnerability definitions (IPCC, 2022). To further respond to the feedback regarding an artificial separation of the variables, both sensitivity and lack of adaptive capacity were revised based on other points of criticism raised in the interviews. This modification is described below.

As for sensitivity, several experts emphasized the importance of water risk, being environmentally as well as socially relevant and that it should be kept in the indicator (NGO-2, AC-1, PR-1). However, water risk was not only deemed important in terms of water scarcity but also water quality (PR-1). Regarding the PA variable, experts agreed that this is an important variable since the World Data Base on Protected Areas (WDPA) (UNEP-WCMC & IUCN, 2025) is the most complete dataset on PA (PR-1), however it was not considered to be sufficient to represent biodiversity richness. PR-1 suggested adding another layer such as key biodiversity areas (KBA) (BirdLife International, 2025). This was suggested since the determination of KBA is less political than it is for PA in the WDPA and based more on scientific reasoning. NGO-1 additionally suggested weighing different IUCN categories differently for the PA variable, because not all categories have the same protection status. NGO-2, as well as AC-2, stressed the importance to adequately include biodiversity within the indicator, since it is one key aspect of mining impacts and PA alone are not sufficient to capture that. NGO-2 suggested using a measure of habitat fragmentation. AC-2, however, pointed out that habitat fragmentation is far too complex to calculate, especially for a global indicator and suggested using a very widely used and easily applicable biodiversity metric such as the biodiversity intactness index (De Palma et al., 2024). Additionally, AC-2 emphasized the importance of deforestation when it comes to mining impacts and suggested including a variable on this.

Generally, the pilot indicators' operationalization of the adaptive capacity dimensions was not approved by the experts and many suggestions for improvement were made. While experts confirmed the importance of social and political factors for vulnerability of mining impacts, they questioned the connection between democracy and economic conditions with a reduced vulnerability of ecosystems. Generally, it seemed that this connection was not what the experts found to be intuitively most relevant. However, it was emphasized that social vulnerability is of high importance and an indicator accounting for social as well as ecological concerns would probably provide more valuable insights (AC-1, NGO-2, PR-1). Furthermore, experts pointed out that the variable selection in the pilot indicator risks reproducing colonial continuities and that global power asymmetries must be considered when operating with country-level democracy indicators as done in the pilot indicator (NGO-1, NGO-2, AC-1, PR-1). In their opinion, such indicators do often not provide a nuanced understanding and result in a pattern of Global North versus Global South, which does not reflect reality. Additionally, variables such as GDP per capita or mineral rents were criticized. NGO-1 stressed that GDP per capita does not provide any insights on existing inequalities and how wealth is distributed within a country. According to several experts, mineral rents seem to be an irrelevant indicator, since it is not clear with what conditions high or low mineral rents are connected (NGO-1, NGO-2, AC-1). Other variables seemed to be far more relevant. One of those variables is conflict. It was mentioned by NGO-1, NGO-2, AC-1 and PR-1 with the explanation that the co-occurrence of mining and conflicts is very high. Furthermore, access to law, so how people can claim their rights, was mentioned as an important aspect and the use of a rule of law index was suggested (AC-1, PR-1). This is also closely connected to land rights, which is a pressing issue concerning mining activities. How well land rights are secured is considered to be important by NGO-2 and PR-1. This is especially important considering Indigenous People (PR-1). Several experts noted the lack of variables representing Indigenous People's presence or rights (NGO-1, NGO-2, AC-1, PR-1).

Following this feedback on both the sensitivity and adaptive capacity dimension, different variables were added, replaced or exchanged between dimensions to sharpen their differentiation. For sensitivity, the variable of KBA and biodiversity intactness index (BII) were added to represent biodiversity issues more accurately. As for the water stress variable, the variable was renamed to water risk and another underlying dataset was chosen, which consists of an extensive water risk framework and also considers aspects such as water quality. Additionally, to account for social factors within the sensitivity dimension, a variable on the presence of Indigenous Peoples' and Local Communities' (IPLC) land was added. Furthermore, the variable of poverty was added to this dimension to provide a more nuanced picture than relying solely on GDP per capita, which was previously located in the adaptive capacity dimension. The adaptive capacity dimension, as mentioned before, was renamed to "lack of adaptive capacity" and based on the thorough feedback, received new variables. These include land rights, environmental democracy, rule of law and conflict. Through these adaptations the indicator aims to also account for factors defining social vulnerability. It differs substantially from the pilot indicator, which aims to describe ecosystem vulnerability only. This adjustment addresses feedback, underlining that environmental and social factors both are important for vulnerability with regards to mining and that some of these factors overlap and cannot be separated. Further descriptions of the adapted indicator design and variables as well as data used are provided in section 3.5 and 3.6.

Other feedback concerned the conceptual aggregation of the different dimensions. This was questioned by AC-2 who argued that multiplicative aggregation is more common for risk assessments. While multiplicative approaches are common in risk assessments, where risk is conceptualized as a function of hazard, exposure and vulnerability, and which therefore becomes zero when either hazard or exposure is absent (IPCC, 2022), this logic is not considered appropriate for the present indicator. The aim of the indicator is to assess vulnerability as an inherent condition, independent of the actual occurrence of mining activities. Additionally, a multiplicative aggregation would disproportionately suppress the overall vulnerability score if there were very low values in one dimension. This would risk obscuring high vulnerability in individual dimensions.

Lastly, feedback on a more general scale concerned the definition of a target audience for such an indicator. Different experts mentioned that it is crucial to think about the target audience and the implications this has for how the indicator is interpreted and used (NGO-1, AC-1, PR-1). NGO-1 and

PR-1 emphasized that caution must be taken, because an indicator like this just provides scores as raw numbers. For example, in the planning of new mining sites, a relatively low vulnerability score in one area compared to others does not imply that mining activities can be considered acceptable. This is particularly important in cases where such areas overlap with protected areas or other sensitive environments. These examples raised by the experts are crucial and will be discussed more closely in section 5.4.

3.4 Scope and spatial framework of the indicator

The indicator developed in this thesis describes socio-ecological vulnerability to the impacts of mining activities. “Mining activities” thereby encompass a broad range of processes and cover all steps within a mine life cycle: from its exploration, opening and closing. It also includes further processing steps of ores such as smelting. It concerns the production of all different kinds of commodities and does not focus on particular ones. The indicator itself does not include mining specific data. Therefore, the vulnerability scores do not provide information whether an area actually suffers from mining activities. It provides an estimate of how relatively vulnerable this area is with regard to potential mining activities.

The indicator is calculated on a global scale. It covers all terrestrial areas around the world except Antarctica by using a land mask. Raster layers and maps are provided at 5000 meters resolution in a world cylindrical equal area projection (EPSG:6933). This projection is used, because it preserves the correct relative size of landmasses which makes it suitable for thematic maps. The datasets used are given on different scales, ranging from country-level indicators to sub-country-level datasets such as protected areas or Indigenous Peoples’ land. A uniform grid-based resolution is therefore required to harmonize these different input layers consistently. The selected resolution of 5000 meters allows sub-country-level datasets to retain meaningful spatial patterns while avoiding a false impression of precision when downscaling coarser inputs, such as country-level data. At the same time, a finer resolution would substantially increase computational costs without adding informational value. Consequently, the 5000-meter grid should be understood as an analytical support for integrating heterogeneous data sources rather than as a representation of site-specific conditions.

As for the temporal resolution, datasets from different years are used due to data availability. The indicator is not intended to capture changes in vulnerability over time, but rather to provide a spatially explicit representation of the current or recent state of socio-ecological vulnerability. Most datasets represent conditions around 2024 and 2025, while individual datasets originate from earlier years; 2015, 2020 and 2023. These temporal discrepancies are considered acceptable given the largely structural nature of the included variables and the global scope of the assessment. Potential limitations of this temporal heterogeneity are discussed in the limitations section.

From a conceptual perspective, the indicator integrates elements of the DPSIR framework by primarily operationalizing pressure and state indicators that describe underlying environmental and socio-economic and political conditions relevant to mining impacts (Burkhard & Müller, 2008; European Environment Agency, 2014). At the same time, its overall structure is aligned with established vulnerability frameworks as defined by the IPCC AR6, where vulnerability is conceptualized as a function of sensitivity and lack of capacity to cope and adapt (IPCC, 2022). This conceptual alignment provides the basis for the indicator’s structure and guides the selection and aggregation of variables, which is described in detail in section 3.6 to 3.7.

3.5 Conceptual framework of the final indicator

Figure 4 illustrates the conceptual framework of the socio-ecological vulnerability indicator developed in this thesis. The final conceptual framework reflects both the theoretical foundations outlined in Chapter 2 and insights gained from expert feedback during the evaluation of the pilot indicator provided in section 3.3. In line with established vulnerability frameworks (IPCC, 2022), vulnerability is conceptualized as a multidimensional condition resulting from the interaction of sensitivity and lack of adaptive capacity. Higher values in both dimensions correspond to higher vulnerability, meaning that variables are conceptualized consistently with respect to their contribution to increased susceptibility or reduced capacity to cope. This framing is particularly suitable for mining-related impacts, as mining simultaneously affects ecological systems and human communities through interacting ecological and socio-economic processes.

The sensitivity dimension captures the degree to which socio-ecological systems are susceptible to harm from mining-related pressures. Mining activities simultaneously affect ecological systems and human communities through interacting biophysical and socio-economic processes, which makes this dimension particularly relevant for capturing such combined effects. The biodiversity intactness index (BII), protected areas (PA) and key biodiversity areas (KBA) reflect the ecological importance and vulnerability of ecosystems. The presence of PA or KBA results in higher sensitivity scores. BII is inversely related, as higher intactness implies lower susceptibility of the ecosystem to degradation. BII quantifies the proportion of an ecosystem’s original biodiversity that remains under current conditions. In the context of vulnerability assessment, higher intactness therefore suggests greater ecosystem conditions and functional integrity, which aligns with lower susceptibility to additional disturbances such as mining.

Indigenous peoples’ and local communities’ (IPLC) lands are included to account for communities that are highly connected with their land and nature and further depend on it to sustain their livelihoods. This makes these groups more sensitive to the impacts caused by mining. Lastly, water risk and poverty further capture underlying environmental and socio-economic conditions that increase susceptibility to harm. Both water risk and poverty reduce buffering capacity of ecosystems and people respectively and thereby they amplify the impacts of environmental change caused by activities such as mining.

The lack of adaptive capacity dimension represents structural constraints that limit the ability of societies to cope with and respond to mining impacts. Land rights, the environmental democracy (EDI), and rule of law capture formal and informal governance structures that shape access to decision-making, legal protection and resource control. Secure land rights can strengthen the capacity of communities to defend their livelihoods and territories, while environmental democracy reflects the extent to which populations can participate in environmental decision-making and access relevant information. Similarly, the rule of law reflects the effectiveness of legal institutions and the enforcement of regulations, which is particularly relevant in the context of environmental governance and resource extraction.

Conflict is included as an indicator of social instability and weakened institutional capacity, which can further undermine adaptive responses and exacerbate vulnerability. This is especially important, because mining is highly correlated with conflict (Phillips, 2025). When conflict is already present, additional pressure through mining activities makes the system even more fragile. Together, these variables describe the structural conditions that influence whether negative impacts caused by mining can be managed and mitigated.

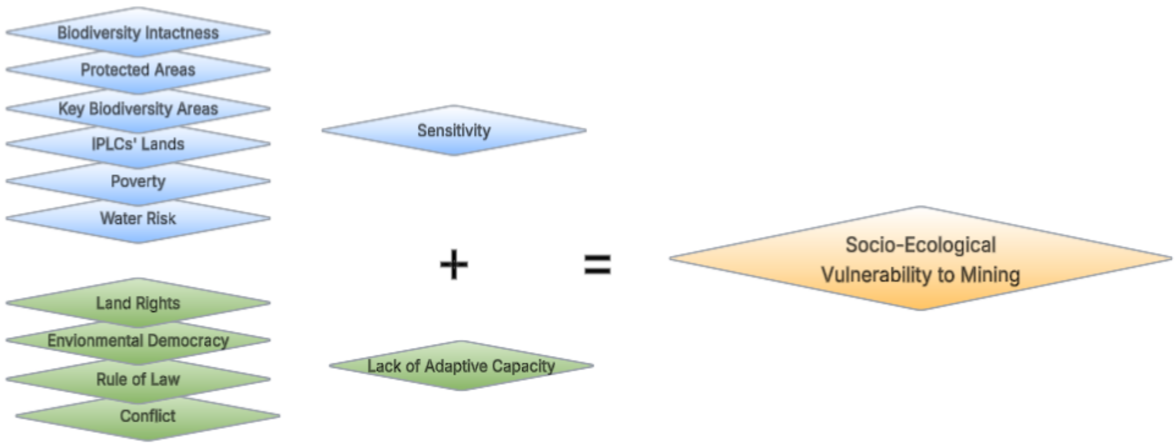

Figure 4: Conceptual design of final indicator (illustration by the author)

Variables within each dimension are normalized and aggregated using a simple additive approach, resulting in one composite layer for sensitivity and one for lack of adaptive capacity. These two-dimension layers are subsequently summed up to generate the final indicator of socio-ecological vulnerability to mining. Higher values of the aggregated dimensions correspond to higher overall vulnerability. This aggregation approach allows for partial and relative compensability between variables, meaning that higher values in one variable can be balanced to some extent by lower values in another within the same normalized scale. However, this differs from subtractive aggregation, where one component is directly offset against another. It also differs from multiplicative aggregation, where very low values in one variable can disproportionately lower the overall score. While this represents a normative assumption, it is consistent with the exploratory and comparative purpose of the indicator and with common practice in composite indicator construction at the global scale.

By separating sensitivity and lack of adaptive capacity into two distinct but complementary dimensions, the conceptual framework allows for a differentiated perspective on vulnerability. The selected variables do not aim to exhaustively represent all possible pathways through which mining affects socio-ecological systems. They rather serve as spatially explicit proxies for the key processes and conditions related to mining impacts identified in literature. The framework does not explicitly model causal relationships between different variables but rather represents a simplified and static approximation of socio-ecological vulnerability based on available spatial proxies. With that, the indicator attempts to provide estimates of general socio-ecological vulnerability to mining impacts and does not focus on specific commodities or mining methods. This enables a consistent global assessment of socio-ecological vulnerability around the globe.

3.6 Data and data preprocessing

This section presents the used datasets in detail. For data preprocessing all datasets were harmonized. Sub-country-level explicit datasets were reprojected to a world cylindrical equal area projection (EPSG:6933) and rasterized to a raster of 5000 meters resolution. Country-level datasets were first joined with country boundary polygons (Esri, 2025) and subsequently also rasterized to the same projection and resolution as the sub-country-level datasets. All datasets were processed so that the values range between 0 and 1, with zero representing lowest sensitivity and lack of adaptive capacity respectively, and one representing highest sensitivity and lack of adaptive capacity. Some of the datasets were already within this range; or between 0 and 100. In the latter case the values were simply divided through 100 to transform values to match the range 0-1. Other datasets had to be transformed, since high scores did not match the theoretical framework which requires that high scores represent high sensitivity or lack of adaptive capacity. Some variables had to be normalized using a min-max normalization. For some of the sub-country-level datasets, values had to be applied, since the polygons in the datasets only contain boundaries of certain features (e.g. KBA). Detailed variable-specific transformations are described below.

Biodiversity Intactness Index (BII)

The BII is a metric that provides an estimated percentage of the original number of species and their abundance that remains in any given area, despite human impacts (De Palma A. et al., 2025). It thereby reflects both how many species remain and how similar the ecosystem is to its natural, undisturbed state. The index is derived from a large global database of biodiversity observations combined with spatial data on human pressures such as land use and population density and is subsequently modelled using statistical approaches to estimate biodiversity responses across different environments (De Palma A. et al., 2025). The underlying global database compiles millions of biodiversity observations from over 1000 peer-reviewed studies, providing broad taxonomic and geographic coverage (De Palma A. et al., 2025). This dataset was selected to integrate biodiversity explicitly in the indicator construction as well as because it was recommended as a commonly used dataset during the expert interviews. Also, the BII reflects an ecosystem's ability to continue to function resiliently, with lower values indicating potential reductions in ecosystem functioning (De Palma A. et al., 2025). In the context of a vulnerability indicator to mining impact this means an ecosystem can be considered as more vulnerable if BII is low indicating a reduced resilience of the ecosystem.

To generate the BII layer, the BII raster dataset for the year 2020 (v2.1.1), which is the most recent available, was used directly as provided. The values in this raster represent modelled estimates of biodiversity intactness for 2020 based on observed biodiversity data and spatially explicit human pressures. The dataset provides global gridded estimates of BII at a spatial resolution of 5 arc minutes (approximately 10 km at the equator), expressed as percentage values between 0 and 100. Therefore, they were divided by 100 to match the 0-1value range. The intactness scores were then inverted so that higher intactness values correspond to lower sensitivity. This was done by subtracting the BII values from 1. The resulting raster was aligned to meet the chosen resolution of 5000 meters and the preferred projection. The final biodiversity intactness layer is visualized in Figure 5.

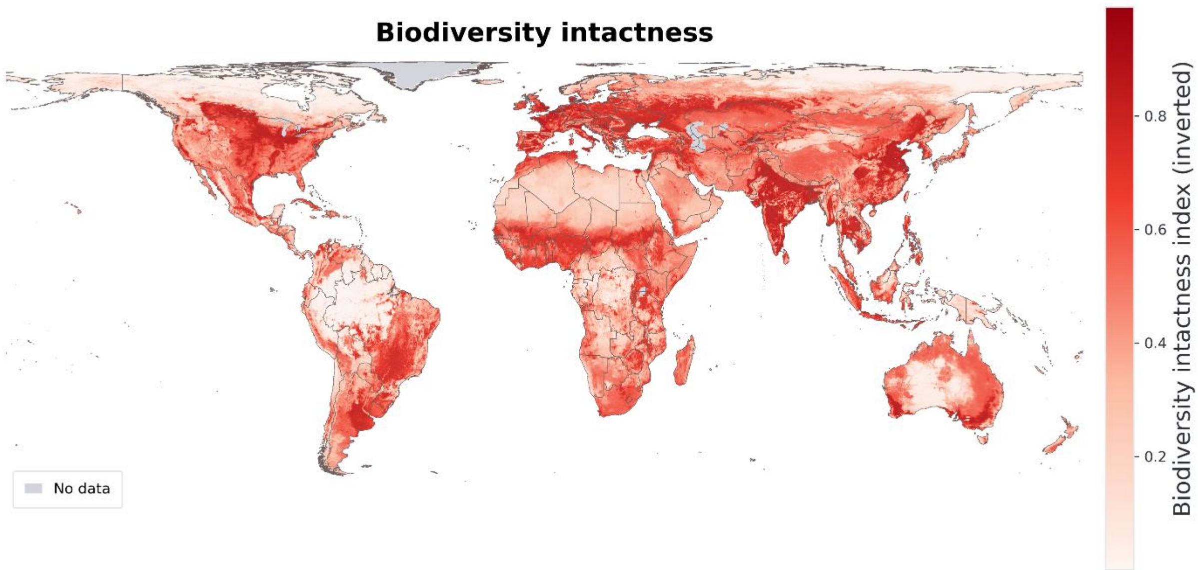

Figure 5: Biodiversity intactness map (illustration by the author), data provided by De Palma A. et al. (2025)

Protected Areas (PA)

The World Database on Protected Areas (WDPA) was used to generate the PA layer. The WDPA is a global dataset compiling nationally designated PA reported by governments and other stakeholders, providing the most comprehensive global inventory of PA currently available (UNEP-WCMC & IUCN, 2025). PA polygons were first filtered to keep only terrestrial and coastal sites, excluding marine-only protected areas to ensure consistency with the terrestrial scope of the analysis.

Each PA was assigned a weight based on its International Union for Conservation of Nature (IUCN) management category (UNEP-WCMC, 2019). These weights should reflect the relative sensitivity of different protection regimes to mining-related disturbances, with stricter protection categories assumed to be more sensitive due to their higher ecological integrity and lower tolerance for human intervention. Weights and main category characteristics can be seen in Table 3. The weighting of PA categories is necessarily normative, reflecting assumptions about the relative sensitivity of different protection regimes to mining-related disturbances. Also, as found during the expert interviews, the IUCN categories can be ambiguous with regards to the question of what activities are allowed within a certain PA (PR-1). Additionally, PA designations and IUCN categories may reflect political, institutional or governance considerations that do not always align perfectly with ecological importance. Furthermore, the completeness and accuracy of WDPA data may vary across countries, since reporting depends on national submissions, and designated protection does not necessarily reflect effective on-the-ground enforcement (UNEP-WCMC & IUCN, 2025). To mitigate this limitation, the sensitivity dimension incorporates KBA as well in a separate variable. This should ensure that areas of high ecological value are captured beyond formal protection status.

Following the weighting, the PA polygons were rasterized, so that each cell contains a score reflecting the category-based weighting. The resulting layer is visualized in Figure 6.

CATEGORY	IMPLICATIONS FOR SENSITIVITY TO MINING	SENSITIVITY
IA – STRICT NATURE RESERVE **IB – WILDERNESS AREA**	Pristine or near-natural ecosystems; minimal human footprint; sensitivity high	1.00
II – NATIONAL PARK **III – NATURAL MONUMENT OR FEATURE**	Mostly natural ecosystems managed for conservation and recreation; strong ecological integrity but some controlled use allowed	0.90
IV – HABITAT / SPECIES MANAGEMENT AREA	Actively managed for specific species or habitats; some interventions and local disturbances occur	0.70
V – PROTECTED LANDSCAPE/SEASCAPE **VI – PROTECTED AREA WITH SUSTAINABLE USE OF NATURAL RESOURCES**	Landscapes/seascapes with sustainable use; ecosystems already modified; therefore, probably some resilience to human activity	0.40
NOT ASSIGNED	Intermediate sensitivity, since category is unknown	0.5

Table 3: IUCN categories for protected areas

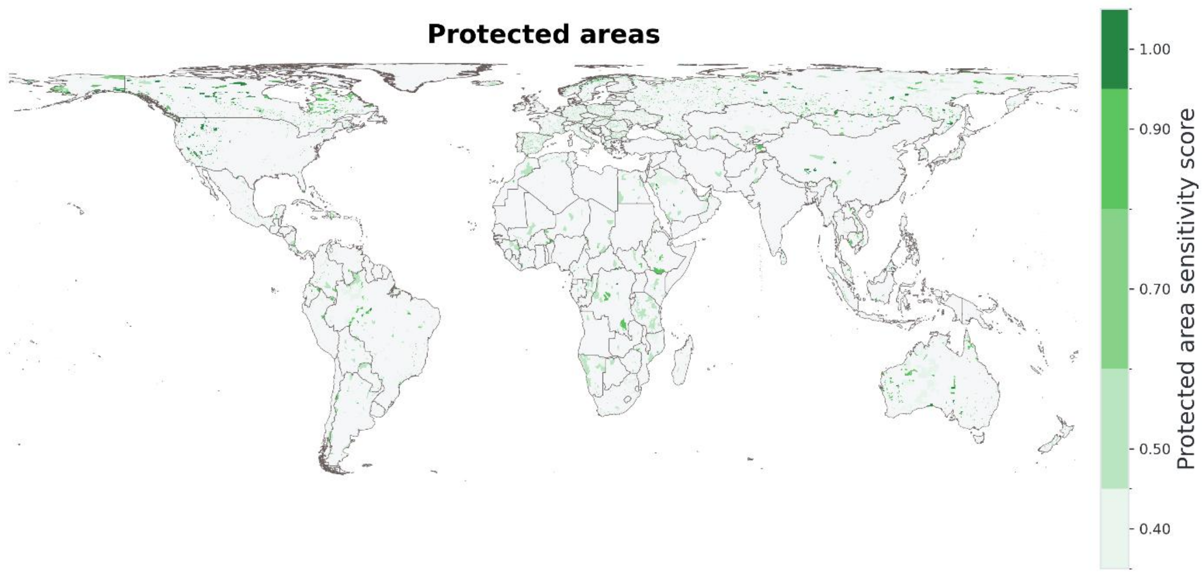

Figure 6: Protected areas map (illustration by the author), data provided by UNEP-WCMC & IUCN (2025)

Key Biodiversity Areas (KBA)

The variable of KBA consists of polygon data with sites contributing significantly to the global persistence of biodiversity and which are identified based on globally standardized criteria such as the presence of threatened or geographically restricted species, ecological integrity or irreplaceability (BirdLife International, 2025). It was chosen for this indicator to complement the PA variable, since KBA are only based on the ecological value of areas and are not susceptible to political constraints. This was found during the expert interviews (PR-1). Also, this variable further strengthens the representation of biodiversity aspects within the indicator. The KBA layer was created by assigning a score of 1 to all polygons, thereby treating the presence of a designated key biodiversity area as a binary indicator of high ecological sensitivity. A differentiated weighting was not applied, as the KBA designation itself already reflects a standardized global assessment of ecological importance based on internationally agreed criteria (BirdLife International, 2025). Introducing additional internal weighting would have required further normative assumptions without a clear empirical basis. As the analysis was limited to terrestrial areas, the use of country boundaries as a mask implicitly excluded marine KBAs from the dataset. Next, the vector layer was rasterized and is visualized in Figure 7.

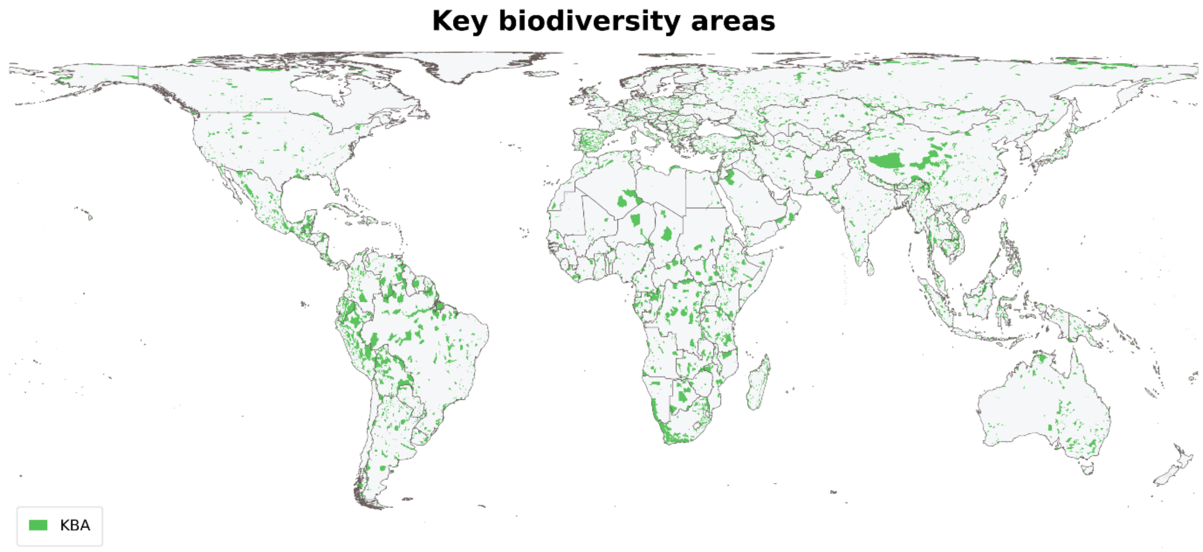

Figure 7: Key biodiversity areas map (illustration by the author), data provided by BirdLife International (2025)

Water Risk

To build the water risk layer for the sensitivity dimension, the overall water risk indicator with default weighting by the Aqueduct 4.0 framework was used. This indicator aggregates multiple dimensions of water-related risk into a single composite indicator. The overall water risk indicator was selected in order to capture a broad representation of physical water quantity (e.g., water stress, depletion, variability), physical water quality (e.g., wastewater treatment and eutrophication) and regulatory and reputational risks (e.g., governance, access to water and sanitation). With this, the water risk indicator does not focus on individual hydrological hazards alone. It is therefore intended to support broad, cross-regional comparisons by summarizing multiple dimensions of water-related risk into a single, easily interpretable metric. Aqueduct water risk indicators are calculated at the hydrological sub-basin level (HydroBASINS level 6), based on gridded inputs at 5 arc minutes resolution (approximately 10 km at the equator). The baseline indicator in the dataset represents long-term water risk conditions derived from a 40-year time series (1979–2019). Values are estimated using temporal smoothing and trend extraction to approximate conditions around 2019 rather than providing an annual snapshot. (Kuzma et al., 2023)

Raw overall water risk values were normalized using min–max normalization:

$$W' = \frac{W - W_{\min}}{W_{\max} - W_{\min}}, \tag{1}$$

where W is the original water risk value for a given hydrological sub-basin, $W_{\min}$ and $W_{\max}$ are the minimum and maximum values observed globally and W' is the resulting normalized value within the interval $[0,1]$. Min–max normalization was used in order to preserve the relative ranking of water risk across different sub-basins while ensuring numerical comparability with other sensitivity variables which are also normalized to the $[0,1]$ range.

Different weighting options for the water risk indicator were provided within the Aqueduct 4.0 framework. Default weighting was chosen to maintain methodological consistency with the standard Aqueduct framework and to avoid introducing additional normative assumptions through specific weighting schemes such as industry-specific ones.

The normalized water risk layer was rasterized. The result is visualized in Figure 8.

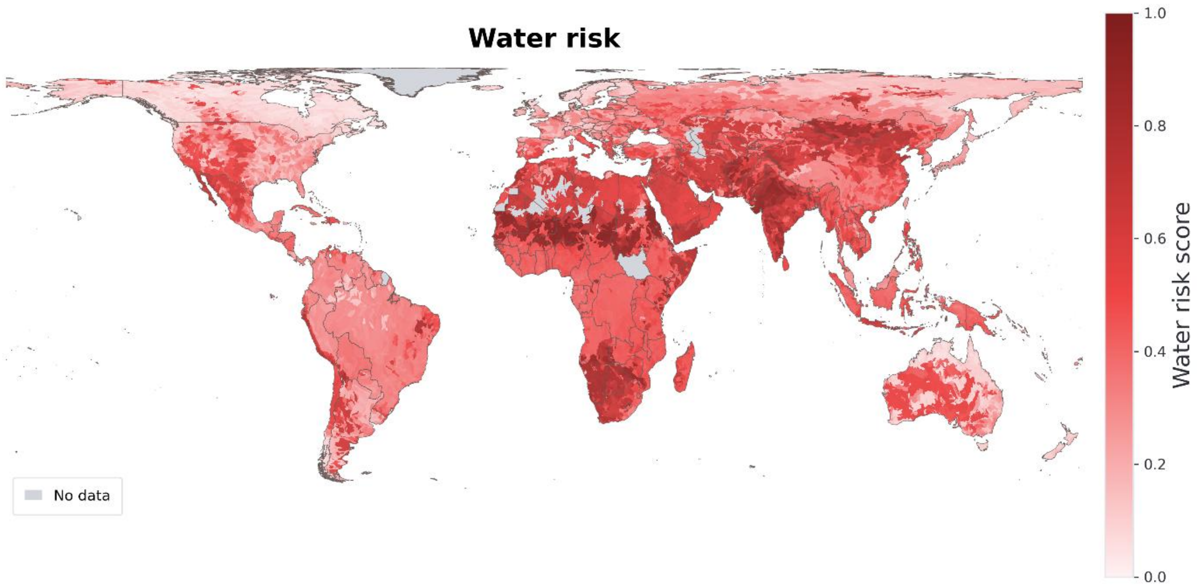

Figure 8: Water risk map (illustration by the author), data provided by Kuzma et al. (2023)

Poverty

To build the poverty layer related to the sensitivity dimension, the Human Development Index (HDI) developed by the United Nations Development Programme UNDP (2025b) was used. The HDI was chosen since other, potentially more specific poverty-related datasets have much shorter spatial coverage globally with many countries having missing values. This applies for example for the Multidimensional Poverty Index (MPI) which was recently published by (UNDP, 2025a). It contains values for 109 countries whereas the HDI contains values for 193 countries. The two datasets include similar proxies, although the MPI includes more variables, which are more specifically linked to poverty. Specifically, the MPI includes nutrition, years of schooling, school attendance, child mortality, cooking fuel, housing, sanitation, electricity, drinking water and assets. The HDI includes much broader variables, namely life expectancy at birth, expected years of schooling, mean years of schooling and gross national income per capita. Since spatial coverage is substantially higher for HDI than for MPI, HDI was chosen although it contains fewer specific proxies. The HDI is a composite index designed to capture key dimensions of human development, combining indicators of health, education and standard of living into a single measure. The HDI is calculated as the geometric mean of normalized indices. While the HDI is not a direct measure of poverty, it provides a widely used proxy for socio-economic vulnerability, particularly in global comparative analyses.

First, the index, which is already provided at a 0-1 range, was inverted, so that higher values of the HDI correspond to lower sensitivity. The resulting dataset was merged with country boundary geometries through ISO codes and subsequently rasterized to produce the final poverty layer visualized in Figure 9.

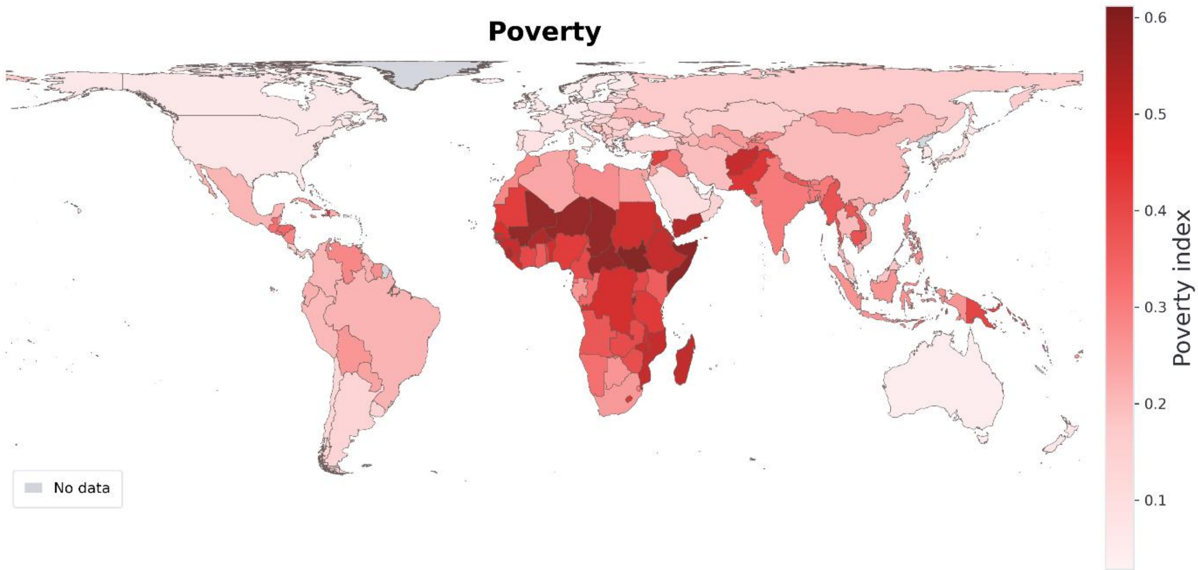

Figure 9: Poverty map (illustration by the author), data provided by UNDP (2025b)

Indigenous Peoples' and Local Communities' Lands (IPLC lands)

Sub-country-level data provided by LandMark (2024) were used to build the layer representing IPLC lands. The dataset includes polygon features delineating legally recognized IPLC territories, point features indicating the locations of IPLC lands where spatial extents are not explicitly defined and indicative areas that may lack formal recognition or complete boundary delineation. The dataset consolidates geospatial information from multiple local, national, and regional mapping initiatives, including contributions from Indigenous organizations, civil society and existing spatial datasets.

To account for the lack of areal representation in the point data, IPLC point features were buffered by 5000 meters. This buffering was applied to approximate the spatial footprint of IPLC lands. The goal of this step is to reduce the risk of underrepresenting their presence when rasterizing the IPLC layers at a 5000 meters resolution in a later step. The buffered point features were then merged with polygon datasets representing both recognized and indicative IPLC lands. The resulting merged polygon layer was used as a binary mask, assigning a value of 1 to areas intersecting IPLC lands to indicate higher sensitivity.

It is important to mention that the absence of data representing IPLC lands does not necessarily mean that no IPLC live there, since this can also be caused by a data gap, limited documentation or lack of formal recognition (LandMark, 2024). Although this is an important limitation of the data, the

LandMark data still provides a good assessment of IPLC land location, especially on a global scale. The dataset is continuously updated as new information becomes available.

Finally, the IPLC layer was rasterized and is visualized in Figure 10.

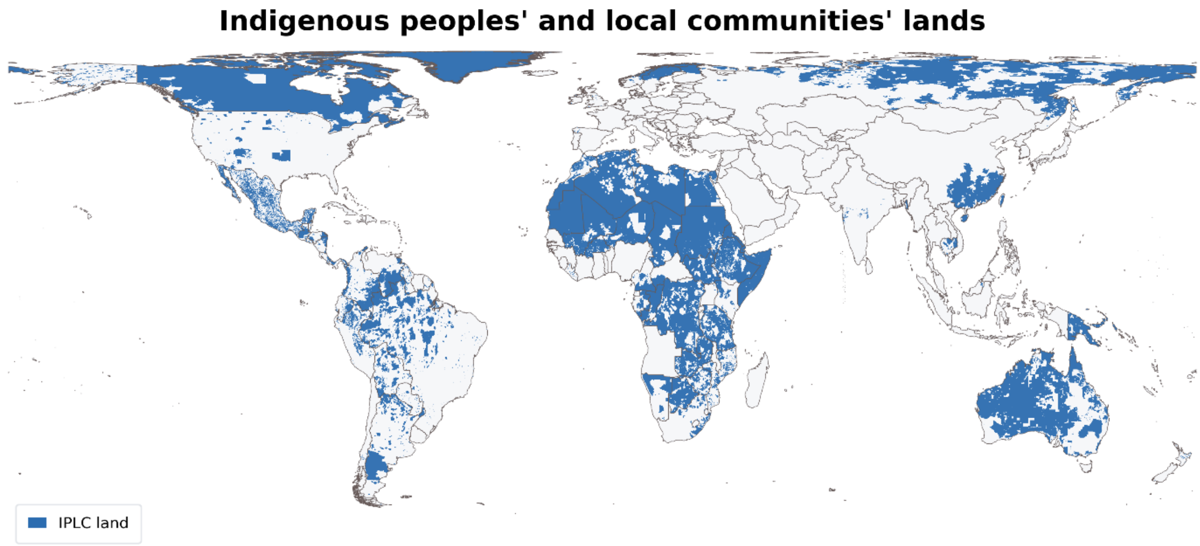

Figure 10: Indigenous Peoples' and Local Communities' map (illustration by the author, data provided by LandMark (2024)

Land Rights

To build the layer representing the land rights variable related to the lack of adaptive capacity dimension, the country-level composite indicator of tenure security in national law provided by LandMark (2024) was used. This indicator assesses the extent to which national legal frameworks recognize and protect the collective land and resource rights of IPLC. The indicator is provided as a cross-sectional dataset, representing a snapshot of land tenure conditions across countries at the latest available reference point.

This dataset was chosen for several reasons. First, it ensures conceptual consistency with the sensitivity dimension of the indicator, which already relies on LandMark data for mapping IPLC lands. Using the same source for both the spatial representation of IPLC territories and the country-level assessment of land tenure security allows for a coherent treatment of land-related vulnerability across dimensions. Second, the LandMark indicator is explicitly designed to assess tenure security from the perspective of IPLC, focusing on the legal recognition and protection of collective land and resource rights (LandMark, 2024). The dataset is developed through close collaboration with Indigenous organizations, local communities and civil society partners and aims to improve the visibility of land rights issues at the global scale (LandMark, 2024). This orientation makes the indicator particularly suitable for capturing aspects of adaptive capacity that are directly relevant to communities most affected by extractive activities. In the context of this thesis, the use of the LandMark dataset also helps to partially counterbalance the reliance on more conventional governance and development indicators, such as rule of law or HDI, that are often criticized for reflecting Global North-centric institutional models.

The indicator of land rights had to be normalized using min-max normalization. This calculation was conducted in the same manner as for the water risk variable given in formula (1). Following the normalization the resulting values were merged with country boundary geometry, which was then rasterized. The resulting layer is visualized in Figure 11.

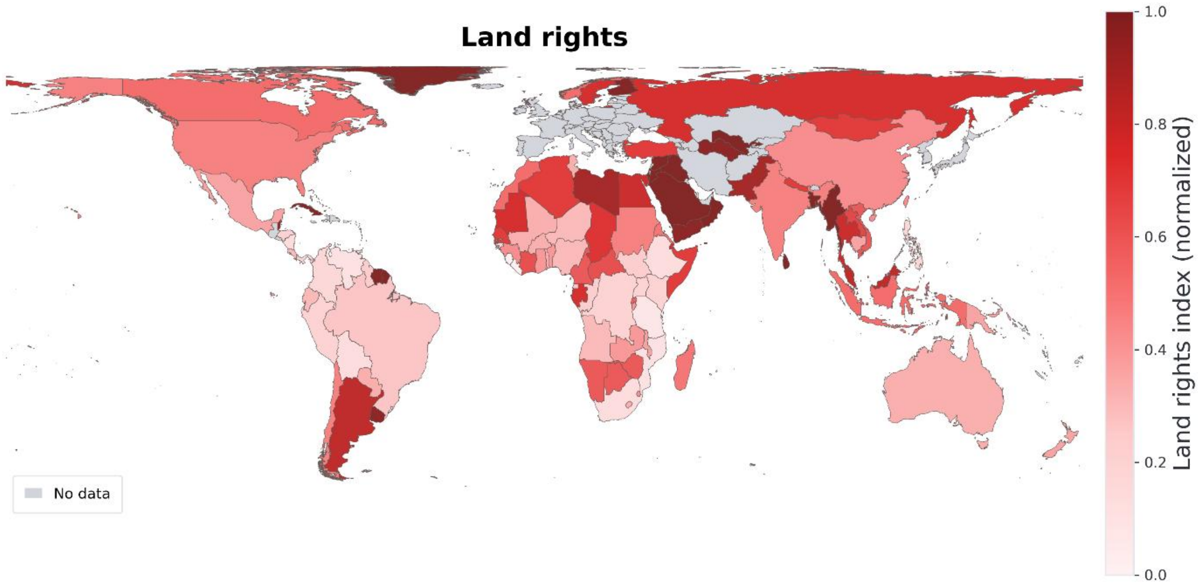

Figure 11: Land rights map (illustration by the author), data provided by LandMark (2024)

Environmental Democracy Index (EDI)

The variable of environmental democracy was constructed using the environmental democracy index (EDI), which is a measure of how well a country's laws protect the public's rights to access environmental information, participate in environmental decision-making, and seek justice in environmental matters (The Access Initiative, 2015). It was chosen for this indicator in response to expert feedback and literature emphasizing the access to legal processes and meaningful stakeholder participation are of particular importance in the context of mining, where decisions often have far-reaching social and environmental consequences and affect groups with limited political power.

The EDI is a project of the Access Initiative and partner organizations and it is based on 75 legal indicators (Worker & De Silva, 2015). These indicators are scored using predefined criteria, with legal indicators typically evaluated on a scale from 0 to 3 and are subsequently aggregated into overall country scores by averaging across indicators, guidelines and thematic pillars (Worker & De Silva, 2015). The index is structured around the United Nation Environment Programme Bali Guidelines, which ensures alignment with internationally recognized principles of access to information, public participation and access to justice in environmental governance. The EDI *"[...] measures the degree to which countries have enacted legally binding rules that provide for environmental information collection and disclosure; public participation across a range of environmental decisions; and fair, affordable, and independent avenues for seeking justice and challenging decisions that impact the environment"* (Worker & De

Silva, 2015, p. 4). These aspects are highly relevant for mining-related conflicts, as limited access to information or legal boundaries can substantially constrain the ability of affected communities to respond to environmental degradation or contest harmful projects (Burton et al., 2024; Ebbesson, 2010; Forget & Rossi, 2021; Gamu et al., 2015; Painter et al., 2024; Phillips, 2025; Shiquan et al., 2022; Villén-Pérez et al., 2020).

Within the lack of adaptive capacity dimension, the EDI variable complements the rule of law indicator (see below) by capturing a more specific aspect of governance. While the rule of law index reflects overall institutional quality and legal enforcement, the EDI focuses explicitly on environmental decision-making processes and access rights. Including both variables therefore allows the indicator to distinguish between general legal capacity and the more specific ability of societies to engage with environmental governance.

To build the layer representing the variable of EDI the country-level composite EDI first had to be normalized using a min-max normalization. This calculation was conducted in the same manner as for the water risk variable given in formula (1). Subsequently, the normalized values were merged with country boundary geometry and then rasterized. The resulting layer is visualized in Figure 12. It is apparent that this variable has a larger number of countries with no data. This issue is discussed in section 5.4.

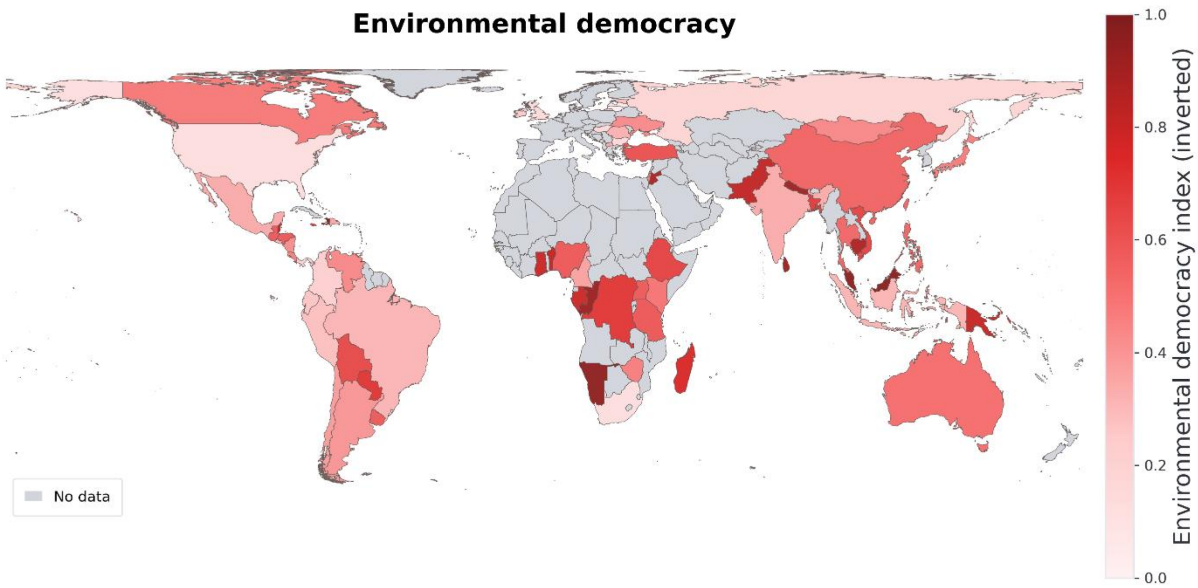

Figure 12: Environmental Democracy map (illustration by the author), data provided by The Access Initiative (2015)

Rule of Law

To build the layer representing the rule of law variable related to the lack of adaptive capacity dimension, the country-level composite rule of law index by the World Justice Project (2025) was used. This index is built on different dimensions, including constraints on government powers, absence of corruption, open government, fundamental rights, order and security, regulatory enforcement, civil justice and criminal justice. The index is constructed by aggregating many sub-indicators into these dimensions, which are then combined into an overall country score. Data is collected through questionnaires answered by experts and the general public in each country, making the World Justice Project (WJP) index one of the most comprehensive global efforts to measure the rule of law. There are different existing rule of law indicators and the choice of the WJP indicator was based on several considerations.

A study by Versteeg & Ginsburg (2017) comparing different rule of law indicators found that although their conceptualization differs considerably, the indicators have a high correlation. This suggests that the selection of a specific rule of law indicator is unlikely to fundamentally alter broad spatial patterns in a composite vulnerability assessment. At the same time, the WJP index stands out in its data collection approach by supplementing expert assessments with nationally representative household surveys, whereas most other indicators rely exclusively on expert-based evaluations (Versteeg & Ginsburg, 2017). Furthermore, the WJP indicator applies the broadest conceptualization of rule of law including a high number of variables. This aligns with the objective of this thesis to capture structural constraints on societies' ability to prevent, manage and respond to mining-related impacts.

First, index values by the WJP were inverted to ensure that high values of this variable reflect higher lack of adaptive capacity. Subsequently, the data were merged with country geometry and rasterized. The resulting layer is visualized in Figure 13.

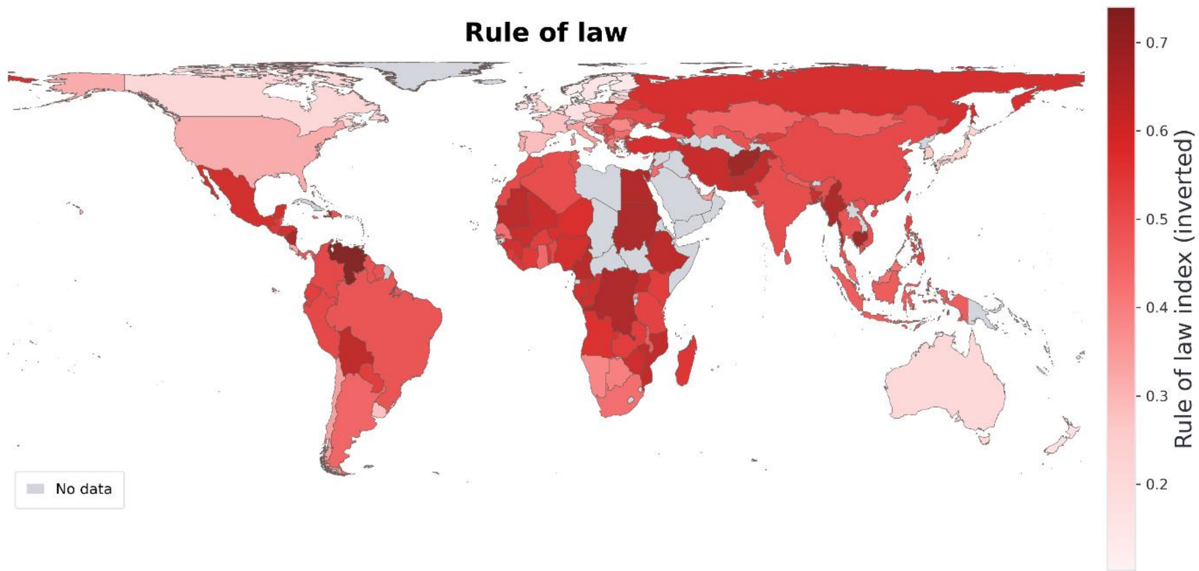

Figure 13: Rule of law map (illustration by the author), data provided by World Justice Project (2025)

Conflict

To build the layer representing the conflict variable related to the lack of adaptive capacity dimension, the country-level composite conflict index by ACLED (Armed Conflict Location & Event Data) (2024) was used. This conflict index is constructed as a composite measure combining multiple dimensions of conflict including deadliness, danger to civilians, geographic diffusion and the number of armed groups

(ACLED, 2024). The conflict index was included because conflict strongly constrains adaptive capacity and is frequently mentioned in the literature and by experts as a key factor shaping vulnerability in mining contexts. Mining activities often co-occur with conflict, particularly in regions with weak governance or contested land and resource rights (Phillips, 2025). Even when conflict is not directly caused by mining, widespread violence and instability can intensify the social and environmental impacts of extractive activities.

While the ACLED index does not capture mining-specific conflict, it provides a useful proxy for broader conditions of instability that reduce societies' capacity to manage additional pressures. For this reason, it is a relevant component related to the lack of adaptive capacity dimension in a global vulnerability assessment.

To incorporate the conflict index in the indicator, it first had to be normalized using a min-max normalization. This calculation was conducted in the same manner as for the water risk variable given in formula (1). Subsequently, the normalized conflict index values were merged with country boundary geometry and rasterized. The resulting layer is visualized in Figure 14.

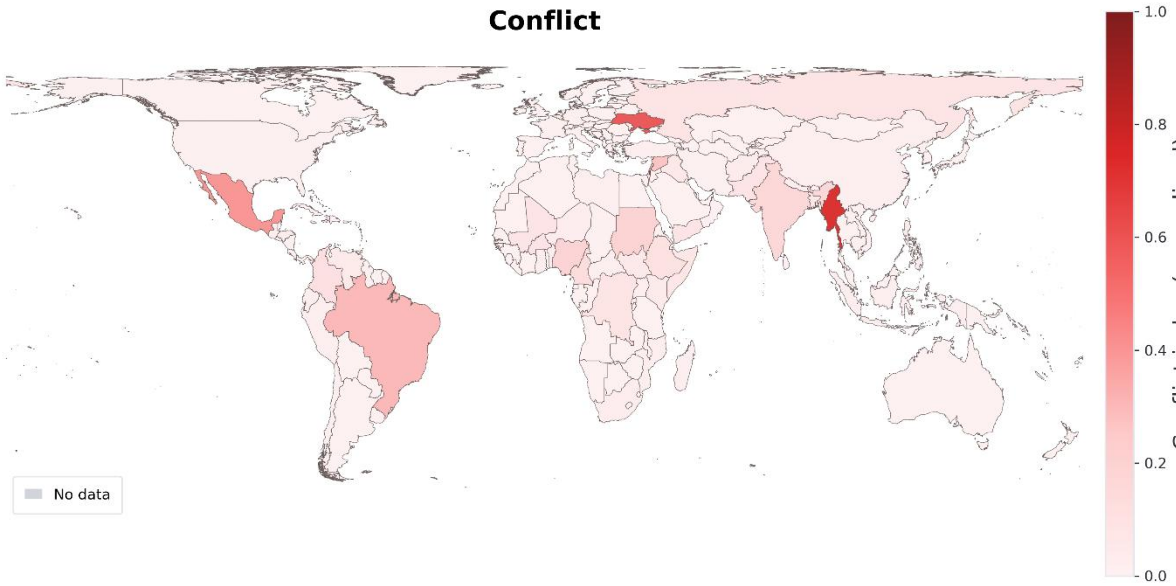

Figure 14: Conflict index map (illustration by the author), data provided by ACLED (2024)

3.7 Indicator implementation

This section describes the indicator implementation in detail describing construction of the individual dimensions. The data preprocessing as well as the indicator's implementation was conducted in Python using standard geospatial and numerical libraries (e.g. rasterio, geopandas, numpy). For the traceability of the different steps and calculations, all code scripts can be found in the following GitHub repository: https://github.com/jabren00/Global-Indicator-for-Socio-Ecological-Vulerability-to-Mining-Impacts-Master-s-Thesis.git

3.7.1 Sensitivity

The dimension of sensitivity was implemented through a simple additive aggregation of the raster layers representing six variables: Biodiversity intactness (BII) X_1, protected areas (PA) X_2, key biodiversity areas (KBA) X_3, Indigenous Peoples' and local Communities' (IPLC) lands X_4, poverty X_5 and water risk X_6. Because not all variables are available for all regions globally, the sensitivity score was computed on a per-pixel basis using only the datasets available at each location. This approach prevents the composite score from becoming undefined in areas where some variables are missing. However, this means that the number of variables included in the calculation can vary between regions, which may affect the comparability of results. All raster layers were first aligned and if necessary, transformed to ensure consistent directionality, such that higher values correspond to higher vulnerability. If the variables were not already normalized to a common scale ranging from 0 to 1, normalization was performed using min-max scaling, transforming all variables to a common range between 0 and 1 based on their global minimum and maximum values (see Section 3.6). Sensitivity *S* was then calculated as:

$$S = \frac{1}{n}\sum_{i=1}^{n} X_i \qquad X_i \epsilon [0,1] \tag{2}$$

where *S* is the sensitivity value for a given raster pixel, *n* is the number of available variables at that pixel, and X_i represents the normalized value of the *i*-th variable. This calculation results in a pixel-level sensitivity score between 0 and 1. The sensitivity *S* is therefore the arithmetic mean of the collection of variables X_i.

3.7.2 Lack of adaptive capacity

The dimension of lack of adaptive capacity was implemented through a simple additive aggregation of the raster layers representing four variables: Land rights Y_1 , environmental democracy index (EDI) Y_2, rule of law Y_3 and conflict Y_4. Since not all variables are available for all regions globally, the lack of adaptive capacity score was computed on a per-pixel basis using only the datasets available at each location, following the same approach as described for the sensitivity dimension. All raster layers were first aligned and if necessary, transformed prior to ensure consistent directionality, such that higher values correspond to higher vulnerability. Furthermore, the raster datasets were normalized to a common scale ranging from 0 to 1 using min–max scaling. Lack of adaptive capacity *A* was then calculated as:

$$A = \frac{1}{m}\sum_{i=1}^{m} Y_i \qquad Y_i \epsilon [0,1], \tag{3}$$

where *A* is the lack of adaptive capacity value for a given raster pixel, *m* is the number of available variables at that pixel, and Y_i represents the normalized value of the *i*-th variable. The lack of adaptive capacity *A* is therefore the arithmetic mean of the collection of variables Y_i.

3.7.3 Socio-ecological vulnerability

The final vulnerability indicator V was calculated as the arithmetic mean of the sensitivity S and lack of adaptive capacity A dimensions:

$$V = \frac{1}{2}(S + A), \quad V \epsilon [0,1], \tag{4}$$

where both S and A are normalized raster layers with values ranging from 0 to 1. This formulation assigns equal importance to sensitivity and adaptive capacity in determining overall vulnerability. Substituting the definitions of S and A, the vulnerability indicator can be expressed as:

$$V = \frac{1}{2}\left(\frac{1}{n}\sum_{i=1}^{n} X_i + \frac{1}{m}\sum_{i=1}^{m} Y_i\right), \tag{5}$$

where X_i represents the normalized sensitivity variables, Y_i represents the normalized lack of adaptive capacity variables, n is the number of sensitivity datasets available for a given raster pixel, and m is the number of lack of adaptive capacity datasets available at that pixel.

To contextualize the calculation of the vulnerability, a raster layer showing the count of missing variables was produced (see 5.4). For each raster pixel, the total missing count was calculated as the sum of missing sensitivity and lack of adaptive capacity datasets. This layer was generated only for pixels located within country boundaries, and pixels with missing information were assigned no-data values.

3.8 Indicator analysis

To analyze the results of the socio-ecological indicator, several approaches were used. First, the different variables were examined with respect to collinearity to see if variables correlate and are therefore redundant. Collinearity was assessed at both the pixel and country-levels, to account for the fact that the indicator is computed at the pixel level and partially interpreted at the national scale. A random sample of up to 150’000 valid pixels was drawn globally using a window-based sampling approach, excluding no-data values and only including terrestrial areas. This ensures that samples are spatially distributed across the study area rather than clustered. Given the 5000 meters spatial resolution of the raster data, this sample size represents a substantial proportion of all valid land pixels worldwide and is sufficient to robustly estimate collinearity. To avoid disproportionate influence of large countries, the number of sampled pixels per country was capped at 2000 pixels. Spearman correlation coefficients were computed on the sampled pixel values and variance inflation factors (VIFs) were calculated. VIF values were interpreted using common thresholds, where values above 5 indicate moderate multicollinearity and values above 10 indicate strong multicollinearity, suggesting potential redundancy among variables (O’Brien, 2007). Country-level collinearity was assessed by calculating national mean indicator values from the sampled pixels. Only countries represented by at least 50 sampled pixels were kept, ensuring stable estimates. Spearman correlation coefficients and VIFs were then computed across countries using the national mean indicator values. This two-scale approach allows for identifying both local (pixel-level) and aggregated (country-level) relationships between variables, which may differ due to spatial averaging effects.

For a visual inspection of vulnerability, sensitivity and lack of adaptive capacity scores, the final indicator as well as the two dimensions were plotted using an equal area projection and a red color ramp with dark red indicating higher scores. The use of an equal-area projection ensures that spatial patterns are not visually distorted by differences in area representation across latitudes. To support this visual assessment of the distribution of vulnerability scores, boxplots were created. This was not only done for the actual indicator (herein after referred to as baseline indicator), but also for different scenarios of the indicator. In total, ten different scenarios of the indicator were calculated. Thereby, each scenario leaves one of the ten variables included in the indicator out. For each scenario one boxplot was built to examine how the distribution of vulnerability scores changes, if variables are omitted. To support the visual examination of the boxplots, Mann-Whitney U test were conducted to confirm that the differences in the vulnerability score distributions between the baseline indicator and different scenarios are statistically significant (Mann & Whitney, 1947). Additionally, the non-parametric effect size measure Cliff's delta was calculated to quantify the amount of difference between each scenario and the baseline indicator (Macbeth et al., 2011). Cliff's delta is defined as the difference between the probability that a value from one group exceeds a value from another group and the probability of the complement (Cliff, 1993). In this case this means Cliff's delta δ is the difference between the probability that a value in the baseline indicator B is higher than in the scenario σ and the probability that a value in the baseline indicator is lower than in the scenario:

$$\delta = P(B > \sigma) - P(B < \sigma), \qquad -1 \leq \delta \leq 1 \tag{6}$$

The values of δ can range from -1 to 1, whereas 0 means a complete overlap between two groups of values, -1 that all values in group B are lower than in group σ and 1 that all values in group B are higher than in group σ (Cliff, 1993). Thus, Cliff's delta helps to estimate how strongly the vulnerability scores vary from the baseline indicator to each scenario. In addition to examining whether the distributions of the baseline indicator and the scenarios differ significantly, and how strong this difference is with regard to higher and lower values, the Jensen-Shannon distance JSD was calculated to determine the extent to which the overall distribution shapes differ. This metric is based on the Jensen-Shannon divergence (Lin, 1991). Thus, JSD captures differences in overall distributional shape, which are not reflected in rank-based effect sizes like the Cliff's delta. It is defined as:

$$JSD(B\|\sigma) = \sqrt{\frac{D(B\|m)+D(\sigma\|m)}{2}}, \quad 0 \leq JSD(B\|\sigma) \leq 1, \tag{7}$$

Where m is the mixture distribution of B and $\sigma: m = \frac{1}{2}(B + \sigma)$ and D is the Kullback-Leibler divergence (SciPy, 2008). JSD therefore measures how differently the two distributions relate to their average (mixture) distribution. If the distributions are similar, combining them does not change the overall variability, resulting in a low distance. If they differ strongly, the combined distribution becomes more variable, leading to higher distance. JSD can reach from 0 (equality) to 1 (maximal distance). Together all these approaches (boxplots, Mann-Whitney U, Cliff's delta, and JSD) allow to identify variables within the indicator that have a strong influence on the distribution of vulnerability scores.

Furthermore, the indicators results were more closely examined on the country-level. This approach is justified for several reasons. First, five out of ten variables are based on country-level data, which means that a substantial share of variation of vulnerability scores arise between countries and not necessarily within their boundaries. Furthermore, many of the variables, such as access to law and socio-economic conditions, are shaped by national policies and institutions. Finally, as the indicator is designed for global application, country-level analysis facilitates comparison across regions and supports interpretation. To compare the countries, the mean vulnerability score of pixels within country boundaries was calculated. Additionally, the contribution of each variable to the mean was calculated to enable an estimation of why countries have the vulnerability scores they do. Variable contributions were derived from the normalized values prior to aggregation, allowing for a decomposition of the composite score into its underlying components. To visualize these results, the ten countries with highest mean vulnerability were plotted in a stacked pillar diagram, which shows the mean vulnerability as well as the contribution of its variables. This visualization facilitates interpretation by linking overall vulnerability scores to their underlying drivers.

To conduct sensitivity tests of the indicators results concerning country means, the same scenarios as described above were used. Mean vulnerability scores were calculated for each country for ten scenarios, where always a different variable was omitted. Here again, contribution to mean vulnerability of each variable was calculated. For each scenario, the ten most vulnerable countries with their respective variable contributions were plotted in a stacked pillar diagram. Moreover, Spearman correlation was calculated to compare each scenario with the baseline indicator. This allows to see whether the ranks of countries (most to least vulnerable) vary strongly if one variable is omitted. Spearman correlation was chosen, since the analysis focuses on relative ordering rather than absolute values. Additionally, the country ranks of the indicator were compared to the country ranks of the pilot indicator using Spearman correlation once more. This comparison provides insight into how methodological refinements between the pilot and final indicator affect the relative positioning of countries.

4 Results

This section presents results obtained in this master thesis. First, collinearity among the different variables of the indicator is discussed. Second, the distribution of vulnerability scores is presented, including different indicator scenarios. Third, the vulnerability scores on country-level are examined by again considering different scenarios to test the indicator's sensitivity. Fourth, the indicator's results on country-level are compared to the pilot indicator's results.

4.1 Collinearity

Collinearity among indicator variables was assessed at both pixel and country-levels using Spearman correlation coefficients and variance inflation factors (VIFs). Pixel-level correlations (Table 4) indicate generally weak to moderate linear relationships among most variables. However, some variables experience very strong positive correlation. The strongest correlation coefficients are observed among socio-economic and governance-related variables. In particular, poverty shows very strong positive correlations with rule of law (r = 0.772) and conflict (r = 0.714). Furthermore, conflict and rule of law show a very strong positive correlation (r = 0.788) as well. As for the correlation of ecological variables, the biodiversity intactness index (BII) and water risk show a moderate correlation (r = 0.57). Water risk also shows moderate to strong positive correlations with poverty (r = 0.626), rule of law (r = 0.437) and conflict (r = 0.446). The only two variable pairs that shows a moderate negative correlation are BII and Indigenous People's and local communities' (IPLC) lands (r = -0.407) and water risk and IPLC' lands (r = -0.346). Correlations among other variables, including protected areas (PA), key biodiversity areas (KBA), land rights and environmental democracy index (EDI) are rather weak, suggesting limited spatial redundancy at the pixel scale.

	BII	PA	KBA	Water risk	Poverty	IPLC lands	Land rights	EDI	Rule of law	Conflict
BII	**1.0**	-0.167	-0.021	0.57	0.286	-0.407	-0.155	0.211	0.157	0.203
PA	-0.167	**1.0**	0.124	-0.08	-0.044	-0.011	-0.02	-0.055	-0.045	-0.046
KBA	-0.021	0.124	**1.0**	0.113	0.169	-0.096	-0.116	0.036	0.12	0.092
Water risk	0.57	-0.08	0.113	**1.0**	0.626	-0.346	-0.198	0.224	0.437	0.446
Poverty	0.286	-0.044	0.169	0.626	**1.0**	-0.298	-0.179	0.094	**0.772**	**0.714**
IPLC lands	-0.407	-0.011	-0.096	-0.346	-0.298	**1.0**	0.015	0.155	-0.213	-0.283
Land rights	-0.155	-0.02	-0.116	-0.198	-0.179	0.015	**1.0**	-0.157	0.199	-0.043
EDI	0.211	-0.055	0.036	0.224	0.094	0.155	-0.157	**1.0**	-0.054	-0.264
Rule of law	0.157	-0.045	0.12	0.437	**0.772**	-0.213	0.199	-0.054	**1.0**	**0.788**
Conflict	0.203	-0.046	0.092	0.446	**0.714**	-0.283	-0.043	-0.264	**0.788**	**1.0**

Table 4: Pixel-level Spearman correlation coefficients

As for the VIFs commonly used cut-off values that indicate concerning multicollinearity are 5-10 (O'Brien, 2007). Since pixel-level VIFs (Table 5) remain below 2.1 for most variables, multicollinearity is weak. However, poverty as well as rule of law variables are comparatively higher, with VIF = 4.39 and VIF = 4.16 respectively. Nevertheless, they stay below 5 and therefore still indicating weak multicollinearity.

VARIABLE	VIF
POVERTY	4.39
RULE OF LAW	4.16
WATER RISK	2.06
EDI	1.79
BII	1.65
LAND RIGHTS	1.53
CONFLICT	1.39
IPLC LANDS	1.37
KBA	1.08
PA	1.05

Table 5: Pixel-level variance inflation factors (VIFs)

At the country-level, correlation coefficients are generally less extreme since there are no very strong correlations observable (Table 6). However, more of the variables experience moderate positive as well as negative correlation. Once more, the variable of poverty shows strong positive correlation with water risk (r = 0.632) and rule of law (r = 0.617). Water risk shows strong positive correlation with BII (r = 0.597). BII shows rather strong negative correlations with IPLC's lands (r = -0.577). Except for KBA and the land rights variables, all other variables experience moderate positive or negative correlation with at least two variables.

	BII	PA	KBA	Water risk	Poverty	IPLC lands	Land rights	EDI	Rule of law	Conflict
BII	1.0	-0.461	-0.286	0.597	0.326	-0.577	0.241	0.276	0.039	0.135
PA	-0.461	1.0	0.253	-0.408	-0.173	0.398	-0.256	-0.024	-0.149	-0.406
KBA	-0.286	0.253	1.0	-0.142	-0.059	0.131	-0.357	0.032	0.075	-0.189
Water risk	0.597	-0.408	-0.142	1.0	0.632	-0.251	0.142	0.365	0.266	0.17
Poverty	0.326	-0.173	-0.059	0.632	1.0	0.032	-0.232	0.447	0.617	0.361
IPLC lands	-0.577	0.398	0.131	-0.251	0.032	1.0	-0.425	-0.192	0.339	0.004
Land rights	0.241	-0.256	-0.357	0.142	-0.232	-0.425	1.0	0.295	-0.31	-0.283
EDI	0.276	-0.024	0.032	0.365	0.447	-0.192	0.295	1.0	0.143	-0.319
Rule of law	0.039	-0.149	0.075	0.266	0.617	0.339	-0.31	0.143	1.0	0.421
Conflict	0.135	-0.406	-0.189	0.17	0.361	0.004	-0.283	-0.319	0.421	1.0

Table 6: Country-level Spearman correlation coefficients

Country-level VIF values (Table 7) are overall slightly higher than at the pixel level, however the maximum VIF of poverty (VIF = 3.51) is lower than the maximum of the pixel level VIF's. With that, the VIF's remain for the pixel as well as for the country-level below commonly used thresholds for concern (O'Brien, 2007). Overall, the results indicate moderate collinearity among some lack of adaptive capacity indicators. However, this provides no evidence of severe redundancy at both spatial scales.

VARIABLE	VIF
POVERTY	3.51
BII	2.28
WATER RISK	2.27
RULE OF LAW	2.13
LAND RIGHTS	2.07
EDI	1.98
IPLC LANDS	1.79
PA	1.58
KBA	1.46
CONFLICT	1.33

Table 7: Country-level variance inflation factors (VIFs)

4.2 Vulnerability score distribution

The spatial distribution of the sensitivity and lack of adaptive capacity dimension and overall socio-ecological vulnerability to mining is shown in Figure 15 to Figure 17. The visual inspection of the sensitivity map (Figure 15) shows sub-national heterogeneity, reflecting the sub-country-level nature of some of the underlying variables, namely BII, KBA, PA, IPLC lands and water risk. Elevated sensitivity values are observed across parts of West, Central and East Africa, Southeast Asia as well as portions of South America. These regions are characterized by the spatial coincidence of multiple sensitivity components. In contrast, lower sensitivity values dominate much of Europe, North America, North Asia and parts of Oceania.

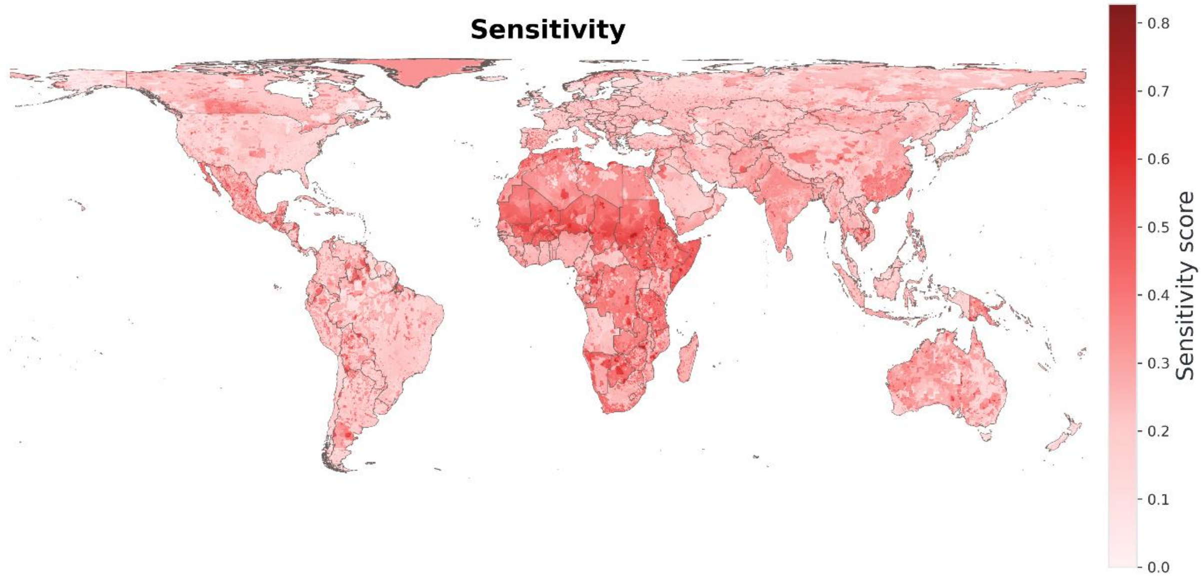

Figure 15: Sensitivity dimension map (illustration by the author)

The visual inspection of the lack of adaptive capacity map (Figure 16) exhibits clear national-level patterns, with homogeneous values within countries, which is due to the nature of all four underlying variables that are given on the country-level. However, there are significant differences among regions. Higher lack of adaptive capacity scores are observed across large parts of Central and South Africa, South and Southeast Asia as well as parts of North, Central and South America. In much of Europe, the USA, Oceania as well as parts of Central Asia comparatively lower scores of lack of adaptive capacity dominate.

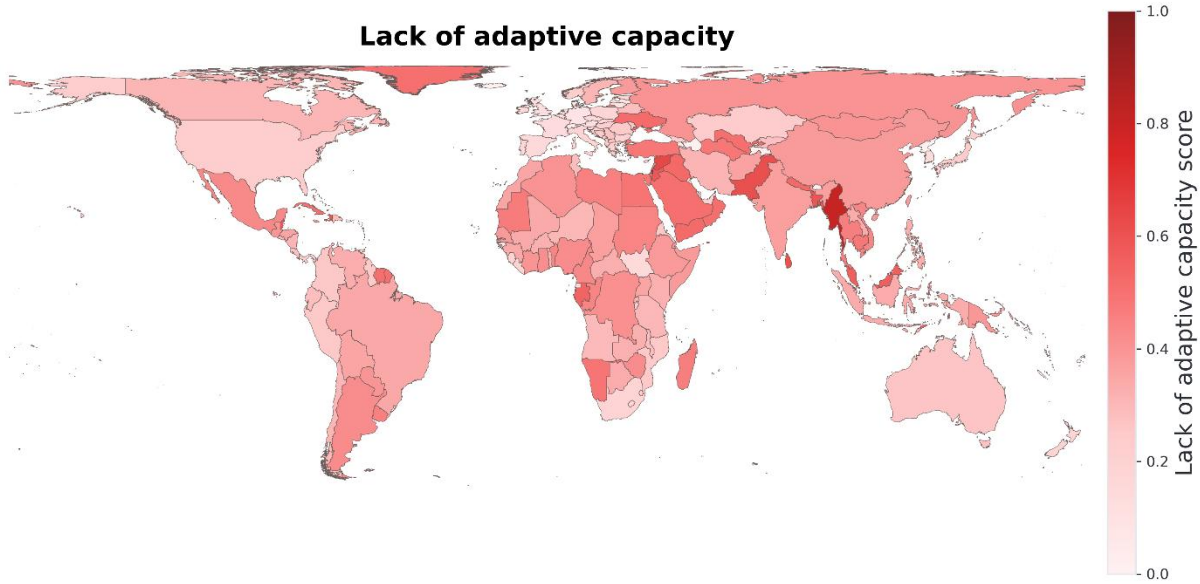

Figure 16: Lack of adaptive capacity dimension map (illustration by the author)

The combined socio-ecological vulnerability map (Figure 17) integrates these two dimensions and displays both country-level contrasts and fine-scale spatial variation. Regions with high vulnerability scores generally coincide with areas where high sensitivity overlaps with high lack of adaptive capacity, resulting in vulnerability hotspots in parts of Africa, Southeast Asia, South America as well as Mexico.

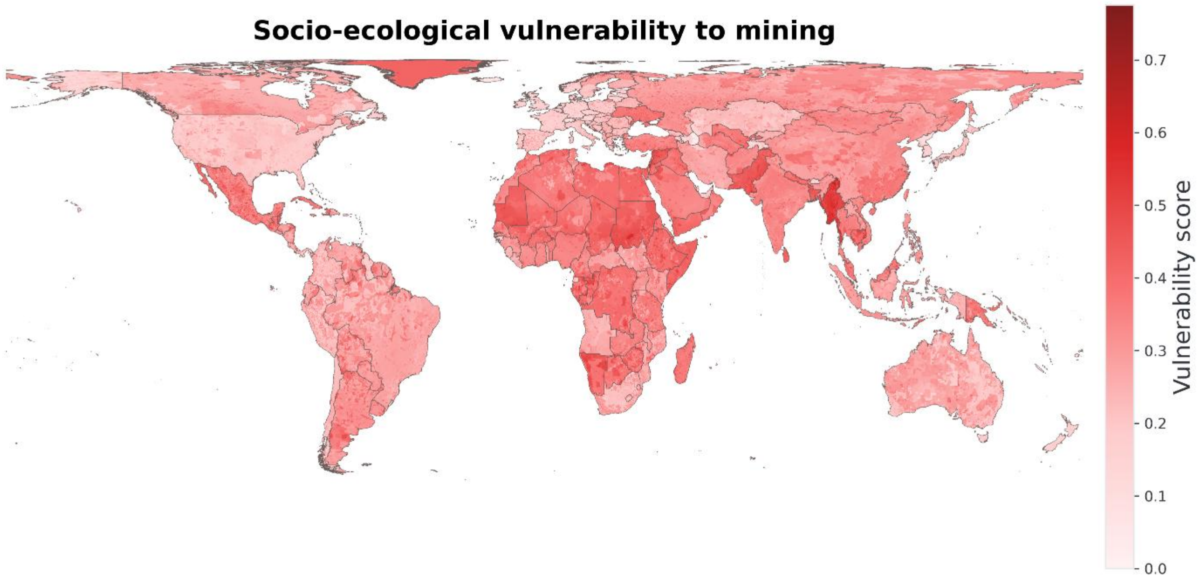

Figure 17: Socio-ecological vulnerability to mining map (illustration by the author)

For better visibility Figure 18 depicts the raster layer of the final composite indicator zoomed in by world region. This allows for a better visual inspection of spatial patterns. It is evident from the figure that there is also a certain degree of local heterogeneity with regard to vulnerability scores. Although half of the variables are provided at country-level, the sub-country-level can also be explored using the provided indicator. To facilitate the identification of the underlying variables within the global vulnerability map, Figure 19 depicts all individual variable maps within a grid chart. This helps to understand the spatial patterns of vulnerability since it allows to trace vulnerability scores back to the contributing variables.

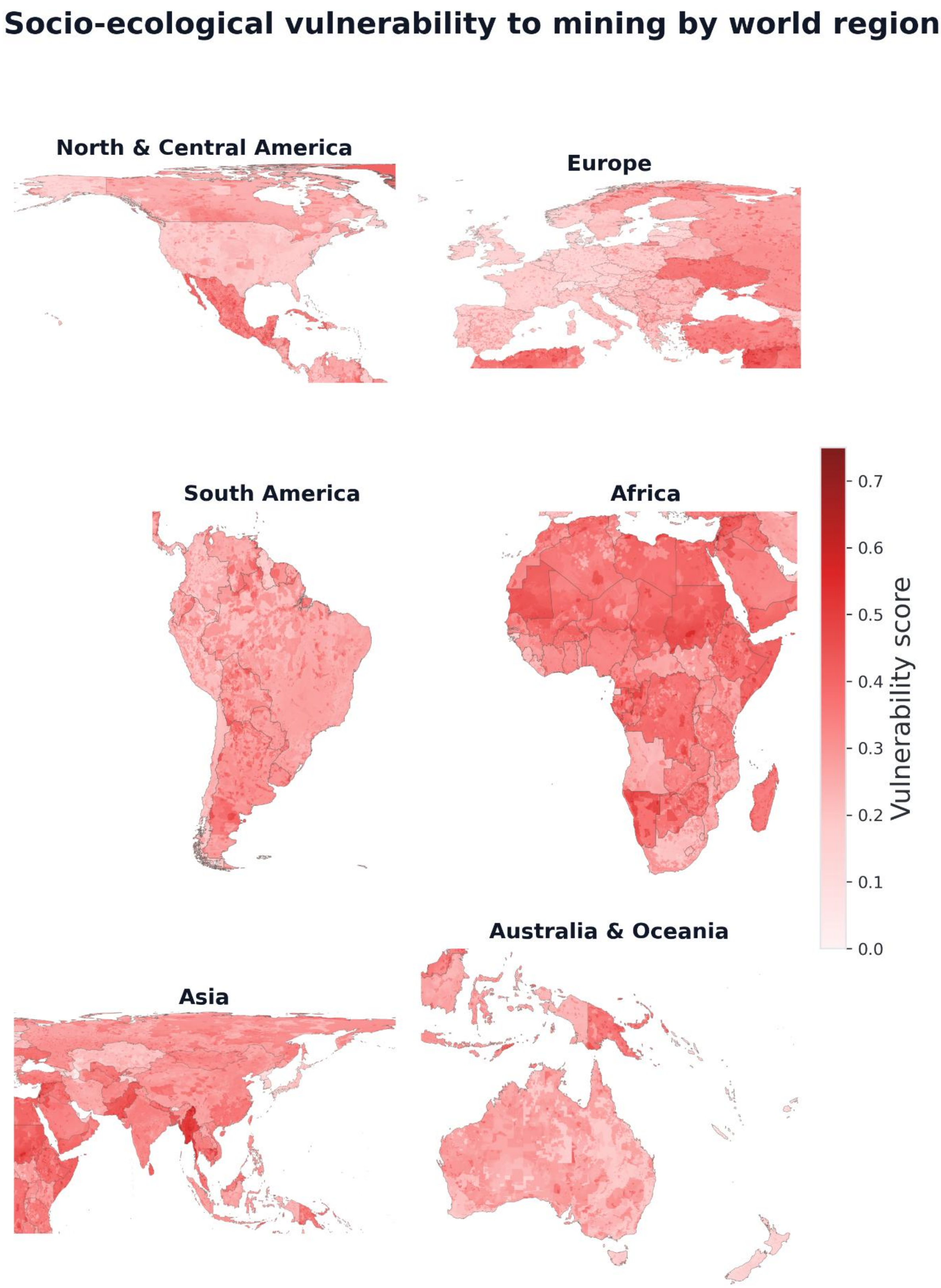

Figure 18: Socio-ecological vulnerability to mining, final indicator zoomed in by world region (illustration by the author)

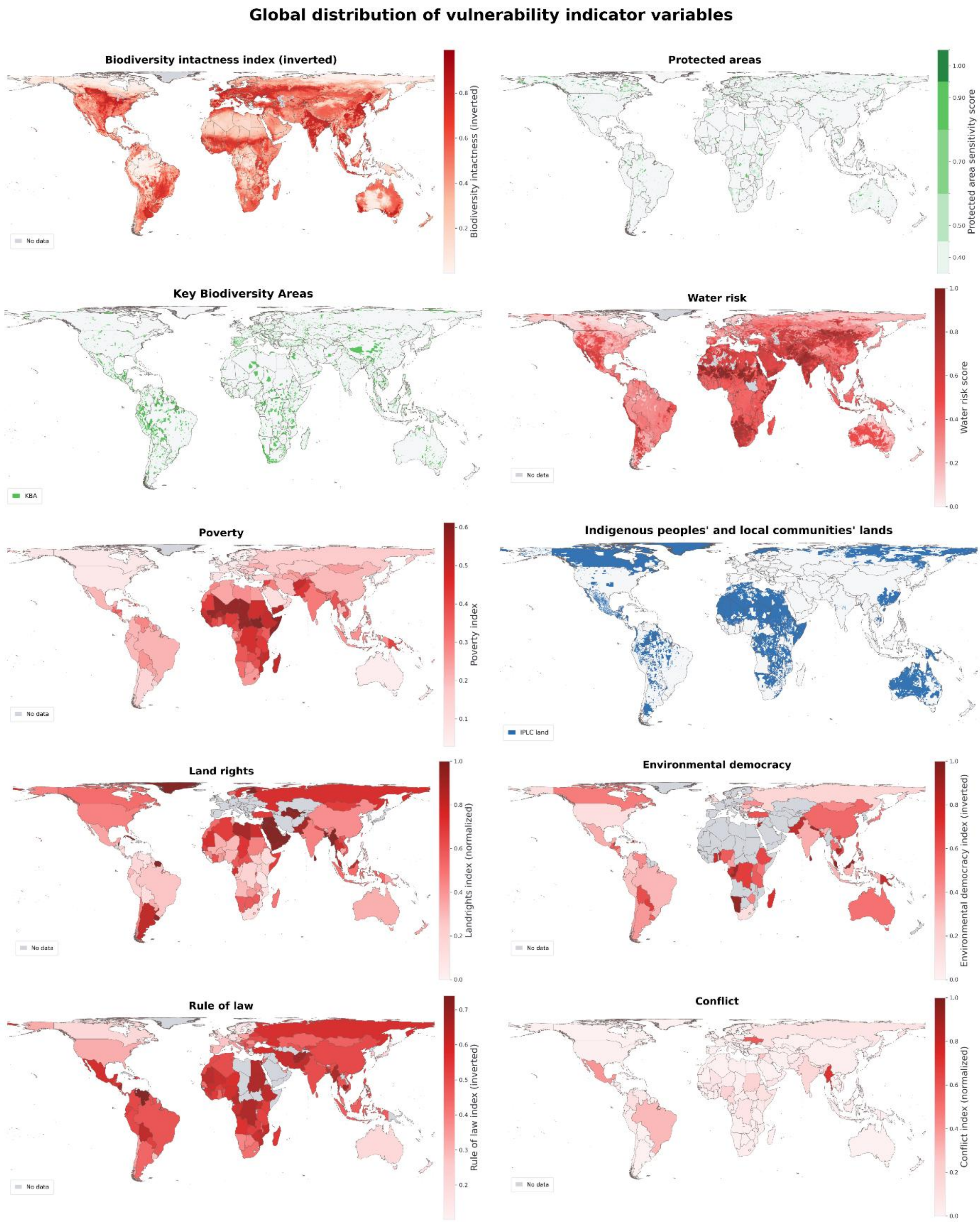

Figure 19: Maps of all individual variables (illustration by the author)

The distribution of vulnerability scores across all raster pixels is summarized in Figure 20 using boxplots for the baseline indicator and for scenarios in which individual variables are left out. Additionally, summary statistics were calculated for each scenario to support the interpretation of the distributions. Furthermore, the application of non-parametric methods allowed distribution comparison, including hypothesis testing, effect size estimation and distributional distance measurements.

Under the baseline scenario including all variables, vulnerability scores have a mean value of approximately 0.30. The mean and median vulnerability scores are very similar, which indicates that vulnerability values are broadly centered and not dominated by extreme outliers. This is further supported by the relatively low variance (0.006), indicating a compact distribution. In addition, the low skewness of the baseline distribution (0.09) suggests only slight asymmetry. The 90th percentile is approximately 0.41. This shows that the upper 10% of pixels reach noticeably higher vulnerability values than the global average. While the index is theoretically bounded between 0 and 1, the observed values occupy a narrower range with most values not being higher than 0.51 as indicated by the upper whiskers. The maximum vulnerability observed is 0.78. However, this concerns only a small number of pixels and therefore, these scores are not visible in the boxplot.

SCENARIO	CLIFF'S DELTA	JSD
CONFLICT	-0.375	0.351
LAND RIGHTS	0.267	0.252
BII	0.102	0.217
RULE OF LAW	0.159	0.192
PA	-0.141	0.191
KBA	-0.110	0.171
IPLC'S LANDS	0.093	0.168
WATER RISK	0.105	0.154
EDI	0.036	0.144
POVERTY	-0.021	0.090

Table 8: Cliff’s delta and JSD values for baseline indicator and scenario comparison

Leaving individual variables out leads to relatively small changes in the overall distribution of vulnerability scores. The observed differences between the baseline indictor distribution and the distribution of each scenario were tested using a Mann-Whitney U test, resulting in $p < 0.0001$ for all scenarios. The differences between the baseline distribution and each scenario distribution are therefore statistically significant. Mean vulnerability values across leave-one-out scenarios range from around 0.26 to around 0.37. The 90th percentile varies between approximately 0.38 and 0.53. The largest increase in vulnerability occurs when conflict is omitted, resulting in a substantially higher mean (0.37 compared to 0.30 in the baseline), a higher variance (0.012 compared to 0.006 in the baseline), a substantially stronger right-skewness (0.66 compared to 0.09 in the baseline) and a marked increase in the upper tail of the distribution with the 90th percentile at approximately 0.53 compared to 0.41 in the baseline. This indicates that while most pixels shift to moderately higher vulnerability levels, a subset of pixels reaches particularly high values, leading to a more pronounced upper tail. This observation is supported by Cliff’s delta and JSD. For the scenario where conflict is omitted Cliff’s delta is -0.375, indicating that a considerable number of values in the baseline indicator are lower than in the leave-conflict-out scenario. In addition, the high JSD value (0.351) indicates a rather strong change in the overall distributional shape.

Similarly, the exclusion of PA and KBA leads to noticeable upward shifts in both the mean vulnerability and the higher end of the distribution, with mean values increasing to approximately 0.32 and 90th percentiles rising to about 0.44 and 0.43, respectively. These shifts are consistent with the negative Cliff's delta values for these scenarios (-0.141 and -0.110), indicating higher vulnerability values compared to the baseline, while the corresponding JSD values (0.191 and 0.171) suggest moderate changes in distributional shape.

In contrast, the omission of land rights and rule of law results in the strongest decreases in vulnerability scores, with mean values dropping to approximately 0.26 and 0.28, respectively, and 90th percentiles falling to approximately 0.38 and 0.39. This indicates that these variables contribute substantially to higher vulnerability levels in the baseline indicator. This is supported by positive Cliff's delta values (0.267 and 0.159), indicating that vulnerability values in these scenarios tend to be lower than in the baseline. At the same time, relatively high JSD values (0.252 and 0.192) indicate that these scenarios also involve notable changes in the overall distributional shape.

Other variables, including BII, EDI, IPLC lands, poverty, and water risk, lead to comparatively smaller changes when excluded, with mean values remaining close to the baseline. This is reflected in mostly negligible Cliff's delta values, indicating limited directional shifts. Meanwhile JSD values vary for these variables in the range of approximately 0.09 to 0.22. BII, IPLC lands, water risk and EDI still show moderate JSD values suggesting that these variables still influence distributional shape. In contrast, poverty shows a very low JSD (0.09), indicating a weak influence on distributional shape.

Overall, the similarity of the distributions across scenarios indicates that no single variable dominates the vulnerability calculation alone and that the indicator is robust to the exclusion of individual components. This pattern is in line with the indicator's construction, as vulnerability scores are meant to reflect the combined influence of several factors rather than being driven by a single variable. However, at the same time, the stronger shifts observed for conflict, PA and KBA highlight their comparatively greater influence on higher vulnerability values, while governance-related variables such as land rights and rule of law tend to reduce overall vulnerability levels when omitted.

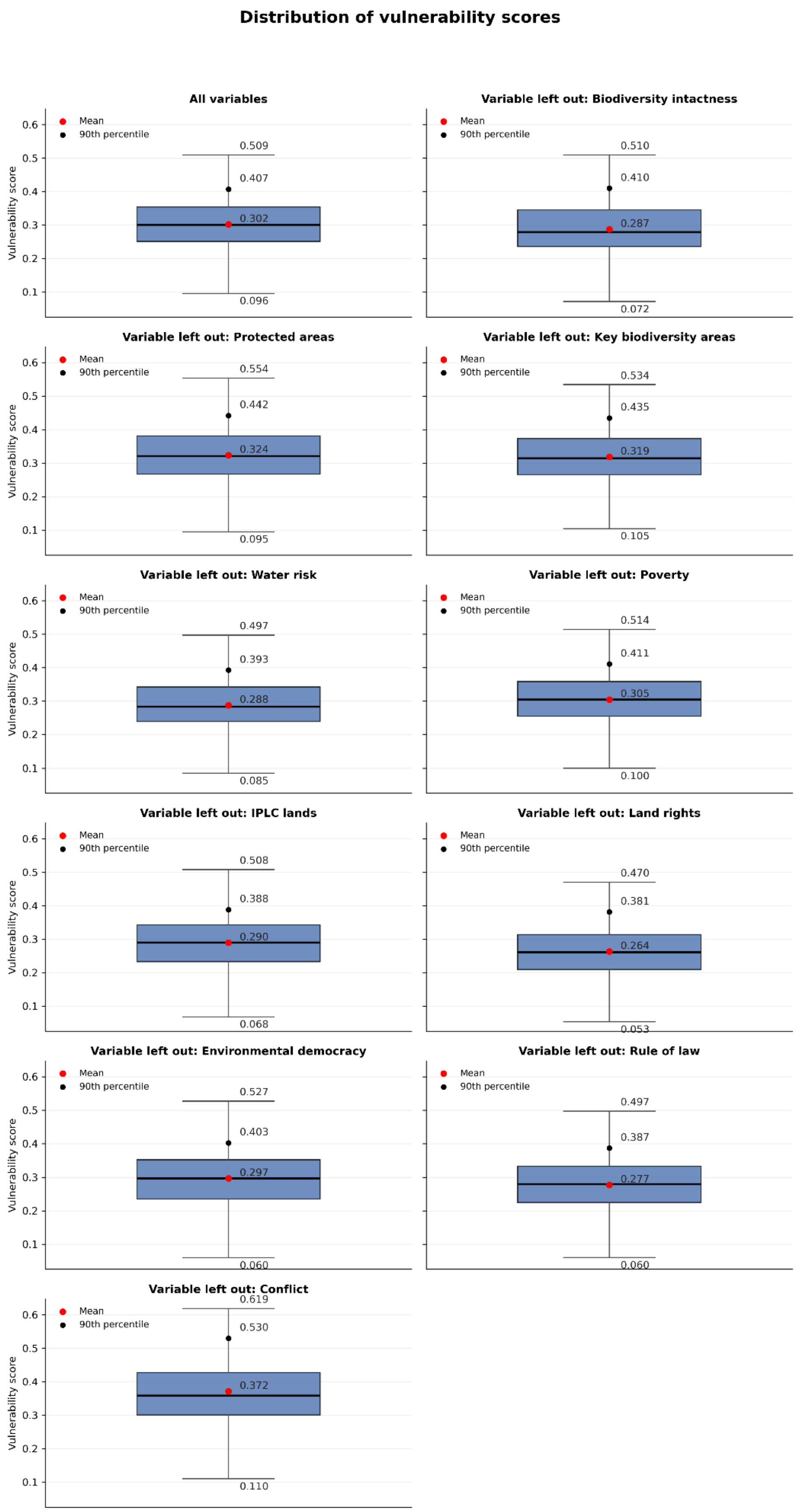

Figure 20: Boxplots of vulnerability score distribution for baseline indicator and different scenarios omitting one variable (illustration by the author)

4.3 Vulnerability scores across countries

Since many variables are provided on the country-level, the inspection of socio-ecological vulnerability mean scores per country is of interest. Figure 21 depicts the world map by assigning each country to a vulnerability class based on its mean vulnerability score. This is done by applying a quantile classification scheme with five classes (very low, low, moderate, high, very high). A quantile classification is appropriate, as the indicator is intended as a comparative tool, enabling the relative positioning of countries within the global distribution of socio-ecological vulnerability. Among the countries in the very low vulnerability class are mostly small island states and overseas territories, which are not directly visible in the map due to their size. Other countries with very low vulnerability are Iceland, Switzerland, Brunei Darussalam, Azerbaijan and North Korea. The low vulnerability class consists of many European Countries, the USA, Japan, South Korea, Bhutan, New Zealand, Guyana, Equatorial Guinea, Guinea-Bissau and again a variety of small island states and overseas territories. Countries classified as having moderate vulnerability are geographically diverse, including parts of Southern and Eastern Europe (e.g. Italy, Greece, and Poland), Latin America (e.g. Chile and Peru), Central Asia (e.g. Kazakhstan), Asia (e.g. Indonesia and Malaysia), Canada, Australia as well as some countries in Africa (e.g. South Africa and Angola). The high vulnerability class includes many countries in Latin America (e.g. Brazil, Argentina and Venezuela), Africa (e.g. Kenya, Uganda, Tanzania, Morocco) and large parts of Asia (e.g. India, China, Thailand). The very high vulnerability class is strongly concentrated in Africa (e.g. Congo DRC, Chad, Somalia, Algeria), as well as in most parts of and around the Arabian Peninsula, in parts of Central Asia (e.g. Pakistan and Uzbekistan), some countries in Southeast Asia (e.g. Myanmar and Cambodia) and Central America (e.g. Mexico and Guatemala). These countries represent the upper end of the global vulnerability distribution.

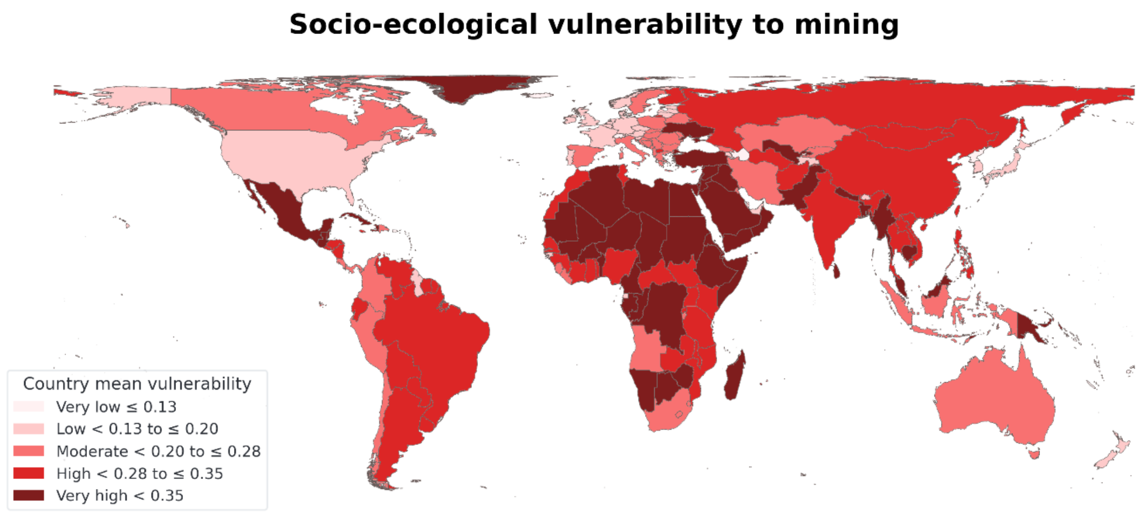

Figure 21: Mean socio-ecological vulnerability to mining per country map with different vulnerability classes (illustration by the author)

Figure 22 presents the ten countries with the highest mean socio-ecological vulnerability to mining, along with the relative contributions of individual sensitivity and lack of adaptive capacity variables. Across these countries, vulnerability arises from differing combinations of contributing factors. In some cases, such as Syria and Palestine, the high vulnerability score is mainly driven by one variable, where Palestine is a clear outlier compared to the rest of the countries since conflict increases the vulnerability score from about 0.1 to 0.6 resulting in the highest mean vulnerability. For the other countries vulnerability is rather driven by a combination of different variables. Generally, rule of law and land rights seem to be variables that account for substantial contributions for many of the countries. Additionally, conflict as well as EDI contribute to a handful of countries a comparatively high share of overall vulnerability. Although water risk and poverty contribute a relatively low share of overall vulnerability, they nevertheless contribute to all ten countries clearly to overall vulnerability, which does not apply to the other variables. Considering the sub-country-level variables, KBA and especially IPLC lands contribute in some cases substantial shares. PA on the other hand, does not seem to play a crucial role in any of the countries. These results highlight considerable heterogeneity in the composition of vulnerability among the highest-ranking countries.

Table 9 additionally shows the 50 countries with highest mean vulnerability scores. As in Figure 22, it is apparent that mean vulnerability scores do not vary strongly, however more variability can be found among the variable's contributions. Additionally, Table 9 reveals which variables are missing for each country, which is important for the interpretation of the results. Missing variables are marked as zero, except for the sub-country-level PA, KBA and IPLC land datasets. In these cases, a value of zero indicates that these features cover zero percent of the country's area. When examining Table 9 it is apparent that many countries have missing values for some of the variables. This is important for the results' interpretation. The issue of missing values is discussed in detail in Section 5.4. Furthermore, Table 9 shows that among the 50 countries with the highest mean vulnerability almost all are countries of the Global South from different regions.

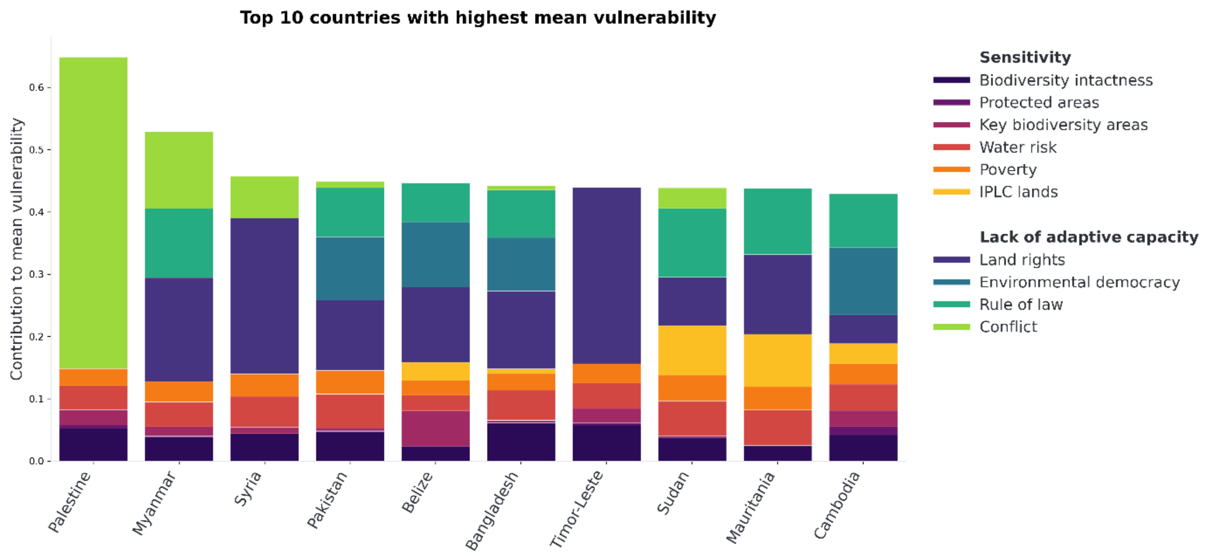

Figure 22: Stacked pillar diagram showing top 10 countries with highest mean vulnerability score and its variable contribution (illustration by the author)

Figure 23 shows the stacked variable contributions for the top-ranked countries under a series of leave-one-out scenarios, in which individual variables were excluded from the vulnerability calculation. This indicates how sensitively the indicator reacts if its construction is slightly changed. The magnitude of overall vulnerability stays roughly the same for all scenarios with a maximum mean vulnerability around 0.6. The most striking scenario is the one where the conflict variable is left out. This highly alters the variables' contributions to vulnerability, with land rights being the variable contributing by far the most for all top ten countries. Such a clear pattern is not visible for the other scenarios, where the left out variable affects the results less strongly. This aligns with the pixel level vulnerability score distribution as presented in Figure 20, where the largest increase in vulnerability occurs when conflict is omitted, resulting in substantially higher vulnerability scores for most of the pixels.

As for the countries counting to the ten most vulnerable ones, there is variation for all scenarios compared to the baseline indicator as well as compared to other scenarios. However, several countries show up more than once. This goes especially for Palestine and Myanmar which are the two countries with the highest mean vulnerability for all scenarios except for where the conflict variable is left out. Also, Syria is listed among the top ten for nine out of ten scenarios. Bangladesh, Belize, Haiti and Sudan appear in seven out of ten scenarios and all of them are also counting to the most vulnerable countries in the baseline indicator. As for the rest of the countries, half appears in more than one scenario whereas the other half only appears once.

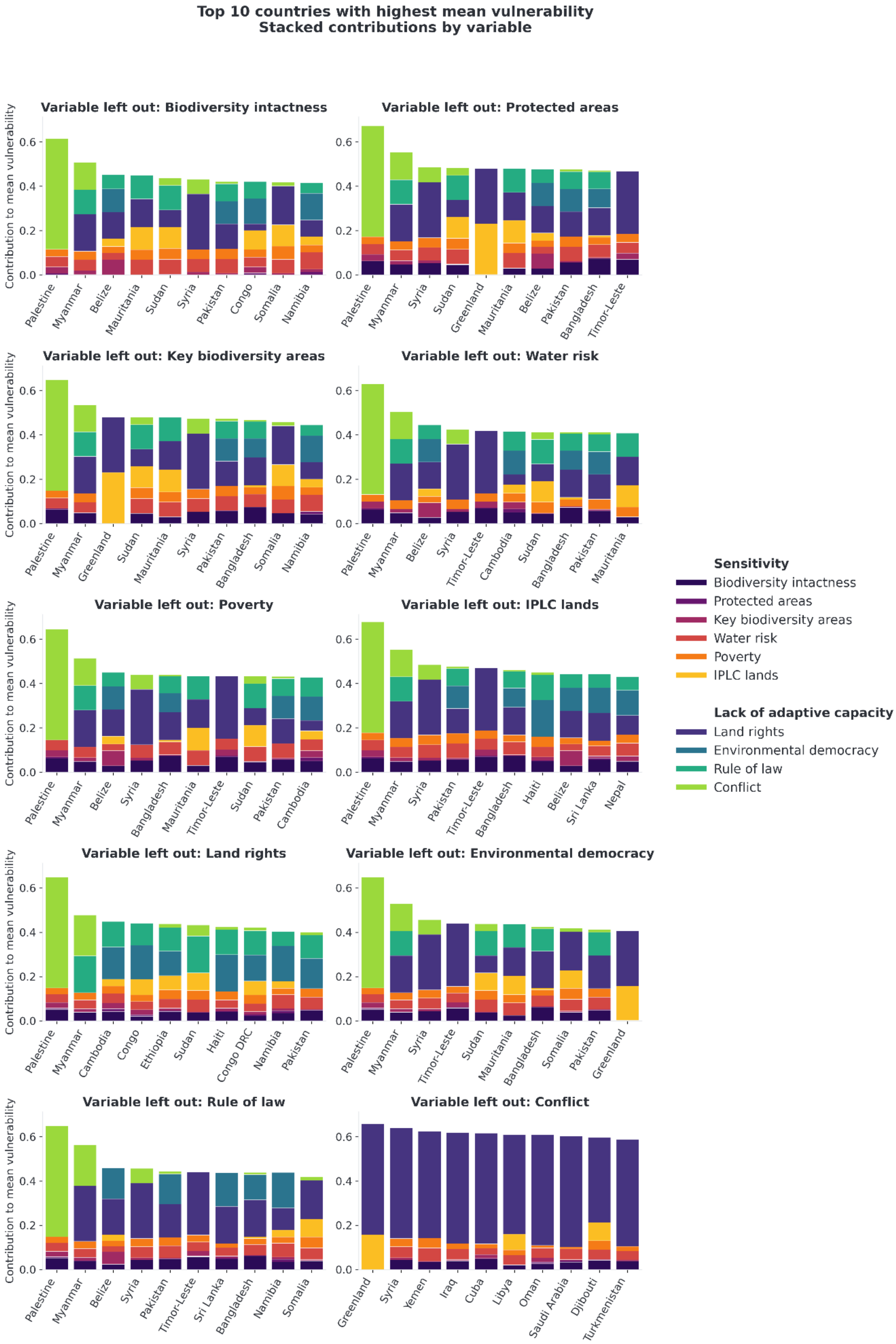

Figure 23: Stacked pillar diagram showing top 10 countries with highest mean vulnerability score and its variable contribution for different scenarios omitting one variable (illustration by the author)

COUNTRY	MEAN	BII	PA	KBA	WATER RISK	POVERTY	IPLC LANDS	LAND RIGHTS	EDI	RULE OF LAW	CONFLICT
PALESTINIAN TERRITORY	0.65	0.05	0.01	0.02	0.04	0.03	0.00	0.00	0.00	0.00	0.50
MYANMAR	0.53	0.04	0.00	0.01	0.04	0.03	0.00	0.17	0.00	0.11	0.12
SYRIA	0.46	0.04	0.00	0.01	0.05	0.04	0.00	0.25	0.00	0.00	0.07
PAKISTAN	0.45	0.05	0.00	0.00	0.05	0.04	0.00	0.11	0.10	0.08	0.01
BELIZE	0.45	0.02	0.00	0.06	0.02	0.02	0.03	0.12	0.10	0.06	0.00
BANGLADESH	0.44	0.06	0.00	0.00	0.05	0.03	0.01	0.13	0.09	0.08	0.01
TIMOR-LESTE	0.44	0.06	0.00	0.02	0.04	0.03	0.00	0.28	0.00	0.00	0.00
SUDAN	0.44	0.04	0.00	0.00	0.06	0.04	0.08	0.08	0.00	0.11	0.03
MAURITANIA	0.44	0.02	0.00	0.00	0.06	0.04	0.08	0.13	0.00	0.11	0.00
CAMBODIA	0.43	0.04	0.01	0.03	0.04	0.03	0.03	0.05	0.11	0.09	0.00
HAITI	0.42	0.04	0.00	0.01	0.04	0.04	0.00	0.00	0.17	0.11	0.01
NAMIBIA	0.42	0.03	0.01	0.01	0.06	0.03	0.03	0.08	0.12	0.05	0.00
SRI LANKA	0.42	0.05	0.01	0.01	0.04	0.02	0.00	0.13	0.11	0.06	0.00
SOMALIA	0.42	0.04	0.00	0.01	0.05	0.05	0.08	0.17	0.00	0.00	0.02
GREENLAND	0.41	0.00	0.00	0.00	0.00	0.00	0.16	0.25	0.00	0.00	0.00
GABON	0.41	0.02	0.00	0.02	0.03	0.02	0.04	0.10	0.10	0.07	0.00
CONGO	0.41	0.02	0.01	0.02	0.04	0.03	0.07	0.03	0.11	0.08	0.00
CHAD	0.41	0.04	0.00	0.01	0.06	0.05	0.07	0.18	0.00	0.00	0.00
DJIBOUTI	0.40	0.04	0.00	0.00	0.04	0.04	0.08	0.19	0.00	0.00	0.00
NEPAL	0.40	0.04	0.00	0.02	0.05	0.03	0.00	0.09	0.11	0.06	0.00
YEMEN	0.40	0.04	0.00	0.00	0.06	0.04	0.00	0.24	0.00	0.00	0.02
EGYPT	0.40	0.02	0.00	0.00	0.04	0.02	0.06	0.13	0.00	0.11	0.00
ETHIOPIA	0.40	0.04	0.00	0.01	0.04	0.04	0.06	0.02	0.08	0.08	0.01
JORDAN	0.40	0.03	0.00	0.01	0.05	0.02	0.00	0.13	0.11	0.06	0.00
BURKINA FASO	0.39	0.06	0.00	0.00	0.05	0.05	0.07	0.06	0.00	0.09	0.01
LIBYA	0.39	0.02	0.00	0.00	0.04	0.02	0.07	0.22	0.00	0.00	0.00
CONGO DRC	0.39	0.02	0.01	0.01	0.04	0.04	0.06	0.03	0.09	0.08	0.01
MALI	0.39	0.04	0.00	0.00	0.05	0.05	0.08	0.06	0.00	0.10	0.01
ZIMBABWE	0.38	0.05	0.00	0.01	0.05	0.03	0.03	0.08	0.06	0.08	0.00
UKRAINE	0.38	0.06	0.01	0.00	0.03	0.02	0.00	0.00	0.07	0.09	0.10
IRAQ	0.38	0.04	0.00	0.01	0.05	0.03	0.00	0.25	0.00	0.00	0.01
GUATEMALA	0.38	0.03	0.00	0.04	0.03	0.03	0.05	0.00	0.10	0.09	0.00
BOTSWANA	0.38	0.04	0.00	0.02	0.06	0.02	0.07	0.10	0.00	0.07	0.00
ISRAEL	0.38	0.04	0.00	0.03	0.03	0.01	0.00	0.17	0.08	0.00	0.02
UZBEKISTAN	0.37	0.04	0.00	0.01	0.05	0.02	0.00	0.17	0.00	0.08	0.00
MADAGASCAR	0.37	0.04	0.00	0.01	0.04	0.04	0.00	0.06	0.09	0.07	0.00
ERITREA	0.37	0.04	0.01	0.01	0.06	0.04	0.08	0.13	0.00	0.00	0.00
LEBANON	0.37	0.06	0.00	0.03	0.05	0.02	0.00	0.00	0.00	0.14	0.07
MALAYSIA	0.37	0.03	0.01	0.01	0.02	0.02	0.00	0.10	0.12	0.05	0.00
NIGER	0.37	0.03	0.00	0.01	0.06	0.05	0.07	0.05	0.00	0.10	0.00
MEXICO	0.37	0.04	0.00	0.02	0.04	0.02	0.04	0.05	0.04	0.07	0.05
PAPUA NEW GUINEA	0.37	0.02	0.00	0.01	0.03	0.04	0.07	0.06	0.13	0.00	0.00
CUBA	0.37	0.05	0.00	0.02	0.03	0.02	0.00	0.25	0.00	0.00	0.00
BENIN	0.36	0.05	0.00	0.01	0.04	0.04	0.00	0.05	0.10	0.07	0.00
ALGERIA	0.36	0.02	0.00	0.01	0.04	0.02	0.07	0.12	0.00	0.09	0.00
OMAN	0.36	0.03	0.01	0.02	0.04	0.01	0.00	0.25	0.00	0.00	0.00
CAMEROON	0.35	0.03	0.00	0.01	0.04	0.03	0.03	0.08	0.05	0.08	0.02
TURKIYE	0.35	0.05	0.00	0.02	0.03	0.01	0.00	0.09	0.08	0.07	0.00
SAUDI ARABIA	0.35	0.03	0.01	0.00	0.05	0.01	0.00	0.25	0.00	0.00	0.00
THAILAND	0.35	0.05	0.00	0.01	0.04	0.02	0.00	0.10	0.07	0.06	0.00

Table 9: 50 countries with highest mean vulnerability score and their variable contribution

Figure 24 compares country vulnerability rankings under the baseline indicator with rankings obtained from each leave-one-out scenario using Spearman correlation. Across all scenarios, country rankings remain highly correlated with the baseline rankings. Spearman correlation coefficients range from ρ=0.836 (leave land rights out) to above ρ =0.996 (leave poverty out).

Some individual countries exhibit notable rank shifts when specific variables are excluded. The three countries that experience the strongest shift are labeled and marked as orange. Among the countries with the strongest rank shift is Palestine in the leave-conflict-out scenario, which has a rank difference of about 170. This illustrates again the strong influence of the conflict variable on the mean vulnerability of Palestine. Other strong shifts are found in the leave-land-rights-out scenario, where Cuba, Oman and Saudi Arabia show rank shifts around 150. Despite these rank shifts the overall ordering of countries is largely preserved. This indicates a high degree of consistency in country-level vulnerability rankings across alternative indicator constructions. The same comparison of country ranks using Spearman rank correlation was applied for the country ranks of the pilot indicator and the revised baseline indicator. Since the conceptual design of these two indicators differ substantially, it is not surprising that the Spearman correlation coefficient was very low (ρ=0.21), indicating a weak correlation of country ranks among these two indicators.

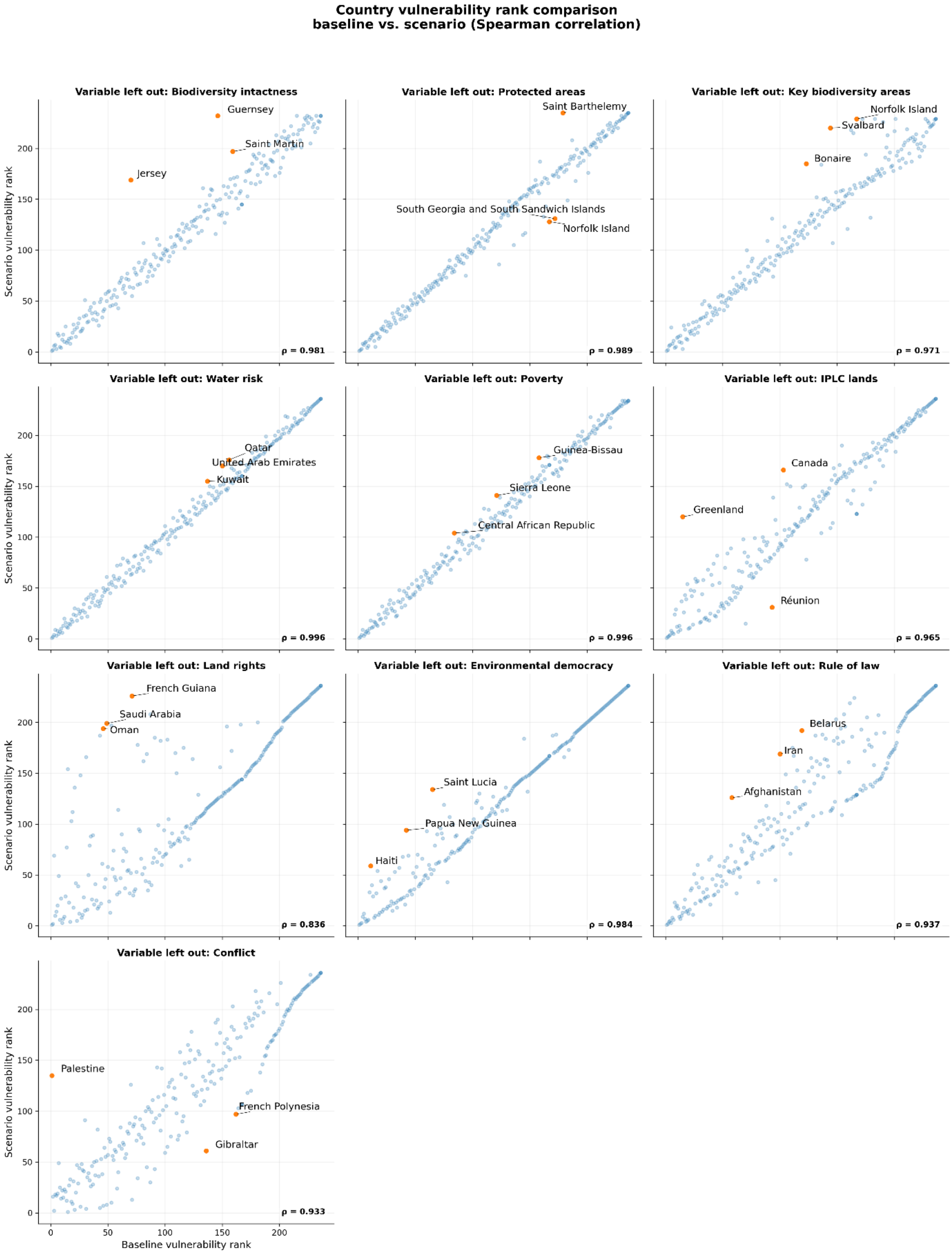

Figure 24: Scatterplots showing mean vulnerability score rankings of baseline indicators and different scenarios omitting one variable plus Spearman correlation coefficients (illustration by the author)

5 Discussion

The aim of this thesis is to answer the question of how a socio-ecological indicator describing vulnerability to mining activities can be developed on a global scale (RQ1). It also wants to answer the question of which spatial patterns occur with regards to socio-ecological vulnerability (RQ2). Furthermore, this thesis wants to critically reflect on the methodological choices that influence the indicator's results and on how future research could improve socio-ecological vulnerability assessments of mining (RQ3). Lastly, it wants to address appropriate applications as well as limitations of a global socio-ecological vulnerability indicator in the context of mining governance and research (RQ4). This chapter discusses these questions based on the developed indicator presented in this thesis. It does so first by examining the actual results of the indicator and spatial patterns that come along with them. Second, it reflects on the theoretical and methodological performance of the indicator: Are the development process as well as the characteristics of the indicator consistent with common guidelines on indicator development? Third, the interpretation context of the indicator is discussed. What does this indicator exactly show? What are its implications? What inherent characteristics does it have compared to similar existing indicators? And lastly, how can an indicator like this be used in a policy, research or extractive sector context? This last question builds the bridge to the subsequent section, which focuses on the limitations of the indicator, including both methodological limitations such as data gaps and conceptual limitations. The chapter concludes by outlining directions for future research.

5.1 Interpreting spatial patterns of socio-ecological vulnerability to mining

The visual inspection of the global indicator map (Figure 17) reveals spatial heterogeneity in socio-ecological vulnerability to mining impacts across the globe. High vulnerability scores are not randomly distributed but cluster in regions where ecologically and socially sensitive systems coincide with social, economic, and governance-related constraints. This pattern reflects how ecological and social drivers of vulnerability overlap in specific regions rather than being uniformly distributed across the globe. Some regions of the globe experience overall higher vulnerability scores. It is therefore essential to interpret these patterns in their broader socio-ecological context and to consider limitations related to data availability and scale (see section 5.4).

Besides the overall distribution of vulnerability scores, it is interesting to look at mean vulnerability scores across different countries. This is particularly meaningful, since half of the variables are only available on the country-level. When examining the contributing variables for the countries with the highest vulnerability scores it is apparent that these countries rank highly for different reasons, rather than because the same factors are dominant in all cases. Generally, it can be said that the variables related to the lack of adaptive capacity dimension are contributing the most to high vulnerability scores.

Palestine, for example, stands out because it ranks among the most vulnerable countries largely due to an extremely high value in the conflict variable, which strongly increases the lack of adaptive capacity (Figure 25). This underlines that the results do not imply high vulnerability due to mining-specific pressures but rather reflect a broader context of instability, under which any additional environmental pressure would likely exacerbate existing conditions. Similar patterns can be observed in other high-ranking countries, where vulnerability emerges either from high ecological and social sensitivity, severe governance constraints or a combination of both. These differences highlight the importance of interpreting vulnerability scores by considering their underlying components. With that, the indicator allows to not only identify potential vulnerabilities but also reasons as for why a certain country or region experiences high vulnerability scores. However, this interpretation is limited to the included dimensions and variables and does not capture other factors that may also contribute to vulnerability.

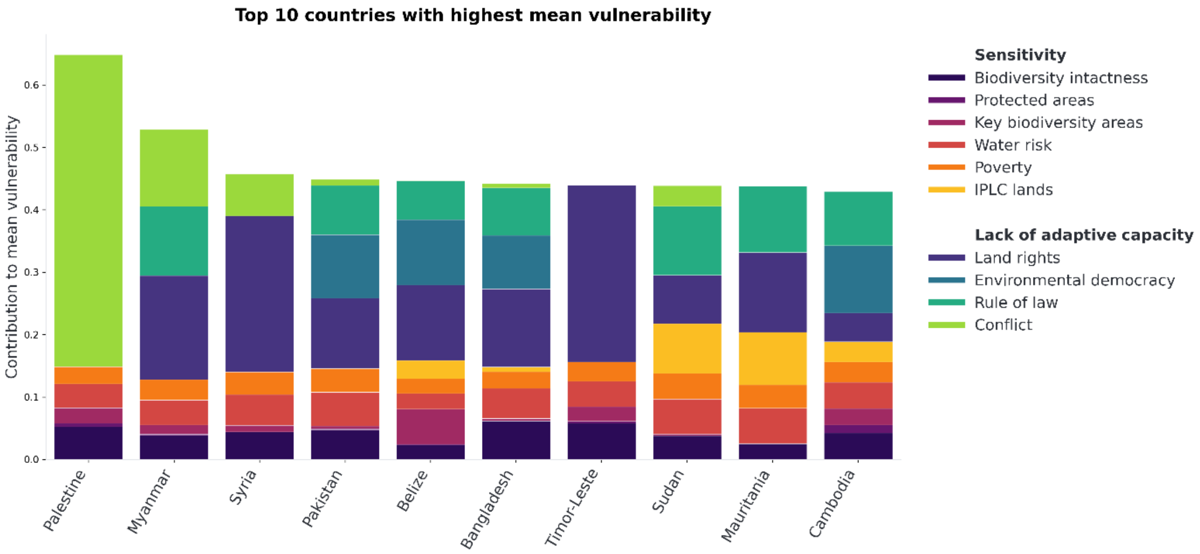

Figure 25: Stacked pillar diagram showing top 10 countries with highest mean vulnerability score and its variable contribution (illustration by the author)

As for the countries, it is striking that among the 50 countries with the highest mean vulnerability almost all are countries of the Global South from different regions (Table 9). Therefore, the indicator suggests that countries of the Global South tend to be more vulnerable relative to countries of the Global North. This spatial pattern must be interpreted with caution since there are several reasons potentially leading to this result. They concern the selection of variables as well as existing data gaps. Section 5.4 elaborates on these limitations.

The concentration of vulnerability scores within a narrower range than 0-1 is expected for a composite indicator that aggregates multiple normalized variables, because extreme values across all variables rarely coincide spatially. As a result, vulnerability scores should be interpreted in relative terms rather than as absolute measures. Values closer to the upper end of the observed range therefore indicate comparatively high socio-ecological vulnerability, even if they do not reach the theoretical maximum of the index.

Overall, the results demonstrate that distinct spatial patterns of socio-ecological vulnerability to mining do emerge on the global scale. However, they must be interpreted in relative and context-dependent terms.

5.2 Interpretation and application

For every indicator it must be clear how the results have to be interpreted. A global indicator like the one developed in this thesis relies on a high number of large-scale datasets that are aggregated to one measure. This is why there is necessarily a certain level of abstraction and generalization. However, when interpreted by acknowledging the indicator's context, it can provide valuable insights regarding different problems. Therefore, this section aims to provide the necessary context to interpret the indicator developed in this thesis.

The necessary level of abstraction is not simply a methodological weakness of the indicator, but a general characteristic of vulnerability assessment. Vulnerability is not directly measurable and represents a complex condition shaped by multiple interacting social and ecological factors. Composite indicators are therefore a common and appropriate way to approximate vulnerability, as they make it possible to combine proxy variables into a single measure. At the same time, such indicators necessarily depend on aggregation procedures and simplified representations of reality. As Villa & McLeod (2002) argue, global vulnerability assessments always involve a compromise between scientific rigor and practical feasibility. In this sense, the indicator developed in this thesis should not be understood as a precise measurement of real-world vulnerability, but the indicator is meant to serve as an exploratory and comparative tool to examine socio-ecological vulnerability to the impacts of mining on a global scale. It thereby reflects pre-existing socio-ecological vulnerability rather than the presence, intensity, or impacts of mining activities themselves. This means for example that areas can have the exact same vulnerability score although one area has already experienced intensive mining activities while the other area has not.

Ultimately, the indicator allows comparison of different regions. However, caution is advised here, since comparing different locations solely on the vulnerability score could have profound consequences, for instance when decisions on new mine sites are based on these comparisons. This leads to a further important question. When speaking of the interpretation context it is important to consider potential target audiences. Who makes use of an indicator like this and for what purpose? It is important for the indicator developer to consider what the indicator might be used for and by which actor. Not only because an indicator should be useful and relevant but also to avoid misinterpretation or even misuse (Birkmann, 2007; OECD, 2008).

For a socio-ecological vulnerability indicator in the context of mining different target audiences may be considered. From policy makers, academic researchers, non-governmental organizations or civil society actors, consultant agencies to mine operators; all these actors could potentially make use of an indicator like this. These different actors operate within distinct institutional, political and economic contexts and may pursue fundamentally different objectives. Consequently, the same indicator may be interpreted in very different ways depending on the user and the purpose for which it is applied. This is important for the indicator's interpretation and construction. Since composite indicators are normative by nature, they can reflect the objectives and priorities of particular target groups. For example, an indicator developed from the perspective of environmental justice or biodiversity conservation might assign greater importance to variables such as protected areas (PA) or Indigenous Peoples' and local communities' (IPLC) lands, whereas an indicator designed for operational or investment-oriented purposes might emphasize other factors and therefore produce different spatial patterns. This underlines that methodological choices such as variable selection, weighting, aggregation and normalization are not neutral and must be communicated transparently. These considerations are important to keep in mind when discussing how the indicator may be applied by different actors in practice.

For academic research, the indicator can serve as a tool to explore global patterns of socio-ecological vulnerability and to contextualize mining-related impacts within broader structural conditions by referring to the different components of vulnerability. For non-governmental organizations and civil society actors, it may support advocacy efforts by highlighting regions where mining-related pressures intersect with high existing vulnerabilities. In this way, high vulnerability scores might support demands for a more thorough due diligence of mine operators. This kind of use of the indicator was also mentioned during the expert interviews.

As for policy makers, the indicator can be a measure to identify regions where mining activities would interact with high pre-existing vulnerability and where stronger regulatory oversight, other precautionary approaches or social and environmental support may be required. In this sense, the indicator may help to inform high-level policy discussions on mining governance and sustainability standards by highlighting structural vulnerability patterns that need particular attention.

The indicator must not be used as a decision-making tool when it, for example comes to approving or rejecting new mining operations. As the impacts of mining can also be highly heterogenic on the local level (Shiquan et al., 2022), relying on an aggregated indicator can lead to overlooking important aspects. The same goes for operational or decision-making purposes of the private sector, such as selecting locations for new mining projects or assessing the acceptability of mining activities in specific areas. A lower relative vulnerability score does not imply that mining impacts would be negligible or socially acceptable in a certain region and is therefore not sufficient to justify a mining project. Similarly, a higher score does not imply that mining activities are inherently unjustifiable. Mining, especially small-scale mining, can also be an important source of income for the local population (Gamu et al., 2015), which means to ban mining projects in an area by solely relying on the high vulnerability score would also fail to do justice to the complexity of the prevailing conditions. Interpreting vulnerability scores in this way risks oversimplifying complex local realities and may obscure site-specific environmental and social circumstances that cannot be captured at the global scale.

The indicator's primary function lies in identifying regions where heightened attention, precaution, and further in-depth assessment are needed, rather than in providing definitive guidance on whether mining should or should not occur. Clear communication of this interpretation context is crucial to ensure that the indicator contributes constructively to research and governance debates without reinforcing insufficiently researched or oversimplified decision-making.

Compared to existing vulnerability indicators, the indicator developed in this thesis has several distinct characteristics. First, it explicitly combines social and ecological variables within a single framework, thereby following a towards Social-Ecological System (SES) perspective. This distinguishes it from approaches such as the one of Luckeneder et al. (2021), which assess spatial relationship between mine sites and vulnerable ecosystems by focusing solely on ecosystem-related proxies, namely biome types, protected areas and water scarcity. While such approaches provide important insights into ecological exposure, they do not account for the social and institutional conditions that shape how impacts are experienced and managed. The indicator developed in this thesis extends this perspective by incorporating social and governance-related variables such as IPLC lands, poverty, land rights, rule of law environmental democracy index and conflict. In doing so, it responds to a key limitation identified in the literature, namely the tendency of vulnerability assessments to remain siloed and to insufficiently integrate ecological and socio-economic dimensions (Berrouet et al., 2018; Hossain et al., 2023; Smith & Diedrich, 2024). By explicitly linking these dimensions, the indicator enables a more comprehensive representation of vulnerability as a product of interacting social and ecological processes.

Second, the indicator is specifically designed to assess vulnerability to mining impacts, whereas most existing vulnerability indicators address vulnerability in the context of general hazards or specific extreme events such as floods, earthquakes or pandemics (Kim et al., 2025; Painter et al., 2024). As shown by recent reviews, social vulnerability indicators are intended for broad application rather than a specific use case (Painter et al., 2024). At the same time, it is important to note that many social vulnerability indicators rely on a relatively similar set of socio-economic and demographic variables across different context (Kim et al., 2025). While this reflects a certain level of consensus on key drivers of vulnerability, it also points to a tendency towards standardization and replication in indicator construction (Painter et al., 2024). In contrast, the indicator developed in this thesis expands the set of variables to include governance-related and spatially explicit environmental aspects, thereby moving beyond commonly used indicator sets and capturing additional aspects of vulnerability that are particularly relevant in the context of mining.

Third, it is implemented as a spatially explicit global indicator. With that it allows for consistent comparisons across regions worldwide while still capturing some sub-national variation. In contrast to many existing indicators that are either highly localized or applied at national scale for a certain region, this approach provides a balance between global comparability and spatial differentiation. At the same time, the indicator shares key characteristics with other global composite indicators. It relies on proxy variables and aggregated and normalized data, which introduces a level of abstraction and reflects common methodological trade-offs. As highlighted in the literature, such approaches often depend on secondary data and standardized indicator sets, which can limit their ability to fully capture context-specific dynamics (Painter et al., 2024).

5.3 Theoretical and methodological reflection on indicator performance

This section reflects on the performance of the socio-ecological vulnerability indicator in light of established theoretical criteria for indicator development. As outlined in chapter 2, indicators are not neutral representations of reality, but normative constructions designed to serve a specific analytical or policy-oriented purposes (Maggino, 2017). This is well illustrated by the comparison between the pilot and final indicator. Despite both aiming to capture vulnerability to mining impacts, they show a very low correlation and produce substantially different spatial patterns and country rankings. This divergence highlights how strongly indicator outcomes depend on underlying conceptual and methodological choices, such as the definition of vulnerability, the selection of variables and the aggregation logic. In this sense, different indicator designs do not simply measure the same phenomenon differently but effectively construct different representations of vulnerability. In light of this, the performance of an indicator can be further evaluated based on the quality requirements of policy relevance, analytical soundness and measurability (European Environment Agency, 2014; OECD, 1993). Accordingly, the indicator is not evaluated in terms of absolute accuracy, but with respect to fitness for purpose, transparency and interpretability.

Policy relevance is a central quality criterion for environmental indicators and refers to their ability to meaningfully inform policy discussions while remaining transparent and interpretable (OECD, 1993). In this context, the socio-ecological vulnerability indicator developed in this thesis meets several key requirements, while others are only partially fulfilled due to data-related constraints rather than conceptual limitations. First, the indicator performs well since it allows the identification of spatial patterns of socio-ecological vulnerability to mining activities on the global scale. Thereby, the indicator can help to identify areas where mining activities are more likely to interact with socio-ecological conditions that increase the risk of severe harm to the environment and to people. With the aggregated vulnerability scores the indicator provides a clear measure that is easy to interpret. The use of a limited number of clearly defined variables and a transparent additive aggregation allows users to understand how vulnerability scores are constructed and to trace high scores back to their contributing components. The indicator also allows comparisons across regions and countries, as all variables are harmonized to a common spatial resolution and normalized to a consistent scale.

With respect to responsiveness to environmental change and human activities, as well as the capturing of temporal trends the indicator is conceptually capable of reflecting such dynamics but does not yet do so. The current implementation represents a snapshot based on the most recent available datasets. The indicator could theoretically be recalculated and updated if the required datasets became available. In terms of spatial scope, the indicator operates at the global scale while remaining applicable to regional and national contexts. Although several variables are available only at the country-level, their combination with sub-country-level data allows the identification of some subnational vulnerability patterns. However, the indicator is clearly designed for global-scale analysis, and while it allows the identification of broad subnational patterns, more detailed regional analyses would benefit from the use of region-specific datasets. Finally, the indicator does not define explicit thresholds or reference values that would allow users to assess vulnerability in absolute terms (European Environment Agency, 2014; OECD, 1993). Instead, vulnerability scores are relative and must be interpreted in comparison to other regions. As a result, the indicator cannot determine whether a given level of vulnerability is objectively high or low in absolute terms, which restricts its use in defining intervention thresholds or policy targets.

The quality requirement of analytical soundness (OECD, 1993) is largely fulfilled for the herein developed indicator. The conceptual design is theoretically well grounded and applies clear definitions of the main concepts such as vulnerability, sensitivity and lack of adaptive capacity. The adoption of the Intergovernmental Panel on Climate Change (IPCC) assessment report (AR) 6 definition (IPCC, 2022) of vulnerability provides a theoretically robust foundation and resolves conceptual ambiguities identified during the pilot phase. Additionally, by using the IPCC AR6 definition of vulnerability, the indicator is aligned with internationally accepted scientific standards, and the definition is widely recognized across climate, environmental and risk-related research communities (Estoque et al., 2023). Furthermore, the indicator is constructed in a transparent manner including transparent aggregation and normalization.

The choice of additive aggregation without weighting represents an important methodological decision, as the weighting and aggregation of index components are critical steps in composite indicator construction (Gan et al., 2017). Additive aggregation was selected because it allows the indicator to capture vulnerability independent of the presence of individual specific factors. If one variable or dimension is zero, the other variables still contribute to the vulnerability score. In this sense, additive aggregation reflects a compensatory logic, in which variables are treated as substitutable to some extent (Gan et al., 2017). Additionally, Gan et al. (2017) show that additive aggregation is the most frequently used aggregation methods for composite indicators. In contrast, multiplicative aggregation would imply that very low values in one variable or dimension can disproportionately reduce the overall score or even drive it towards zero (Gan et al., 2017). This would not be appropriate in this context, because vulnerability is a pre-existing condition that does not disappear if one variable is low. At the same time, additive aggregation allows variables to contribute jointly to the final score, while still keeping the structure transparent and interpretable because the contributions of the different variables are traceable. This traceability of individual variables contributing to the overall vulnerability is often missing in vulnerability indicators, which complicates the identification of specific vulnerability drivers (Kim et al., 2025). No explicit weighting scheme was applied. This reflects the intention to avoid introducing additional normative assumptions about the relative importance of variables, which is particularly difficult on the global scale. Instead, all variables are treated equally. Equal weighting is a commonly applied approach when no clear basis for differentiation exists, although it remains a debated choice (Gan et al., 2017; Kim et al., 2025). This decision does not imply that all variables are equally important. However, it keeps the indicator open for further refinement, as alternative weighting schemes could be applied in future research. A min-max normalization approach was used to transform all variables to a common range between 0 and 1. This method preserves the relative differences between values, which makes sense, since the indicator is meant as a comparative tool.

Analytical soundness, as defined by the OECD (1993), further refers to the theoretical and scientific robustness of an indicator and is supported here by diagnostic analyses of its internal structure, such as collinearity assessments and sensitivity analyses. Overall, the results indicate the presence of moderate to strong correlations among several socio-economic and governance-related variables within the dimension of lack of adaptive capacity. These relationships are not unexpected, as variables such as poverty and rule of law capture closely related underlying structural conditions and partly measure similar aspects of socio-economic development and governance. While this leads to a degree of overlap between variables, the variance inflation factors (VIF) remain below commonly applied thresholds for critical multicollinearity (O'Brien, 2007). This suggests that no single variable dominates the indicator construction. At the same time, the results highlight that some variables contribute similar information, which should be considered when interpreting the indicator and represents a potential area for refinement in future research.

Sensitivity analyses through the removal of individual variables did not lead to dramatic changes of vulnerability patterns, which is consistent with the observed overlap between some variables. At the same time, the results indicate that certain variables, particularly conflict, have a comparatively strong influence on the structure of vulnerability. When conflict is omitted, the relative contribution of other variables, especially land rights, increases substantially, leading to noticeable shifts in the composition of vulnerability scores. The leave-conflict-out scenario vulnerability score distribution differs substantially from the baseline indicator distribution, which was shown by Cliff's delta and JSD results (Table 8). Cliff's delta indicated that vulnerability scores tend to be higher in the scenario and JSD showed that there is considerable shift in the distribution shape. When examining the map that visualizes the conflict variable (Figure 26) it is apparent that most countries have very low scores compared to some extreme outliers with very high scores.

Figure 26: Conflict index map (illustration by the author), data provided by ACLED (2024)

As a result, the inclusion of conflict slightly lowers vulnerability scores for most countries, as it contributes only marginally to the aggregated value in most cases while still being equally weighted in the averaging process. When conflict is omitted, this dampening effect disappears and the remaining variables contribute relatively more strongly, leading to an overall increase in vulnerability scores across many countries. At the same time, the removal of a variable with a highly uneven distribution, such as conflict, alters the balance between observations. In this case, this leads to a more skewed distribution and a more pronounced upper tail. This explains the substantial differences observed between the baseline and the leave-conflict-out scenario in both effect size and distributional distance. While conflict represents the most pronounced case, other variables show similar but less pronounced effects. In particular, governance-related variables such as land rights and rule of law lead to consistent decreases in vulnerability when omitted, while biodiversity-related variables such as protected areas and key biodiversity areas result in moderate increases. However, these effects are smaller in magnitude and do not alter the overall robustness of the indicator.

In addition to the distributional sensitivity analysis, the comparison of country rankings across scenarios provides further insight into the robustness of the indicator. Despite observable changes in distributional shape and effect sizes, country rankings remain highly consistent, as indicated by high Spearman rank correlation coefficients across all leave-one-out scenarios ($\rho \geq 0.836$). This suggests that while the omission of individual variables can influence the magnitude and distribution of vulnerability scores, it has only a limited effect on the relative ordering of countries. Even in cases where individual countries experience notable rank shifts, such as in the leave-conflict-out or leave-land-rights-out scenarios, the overall ranking structure remains largely preserved (Figure 27). This supports the indicator's robustness for comparative country-level analysis.

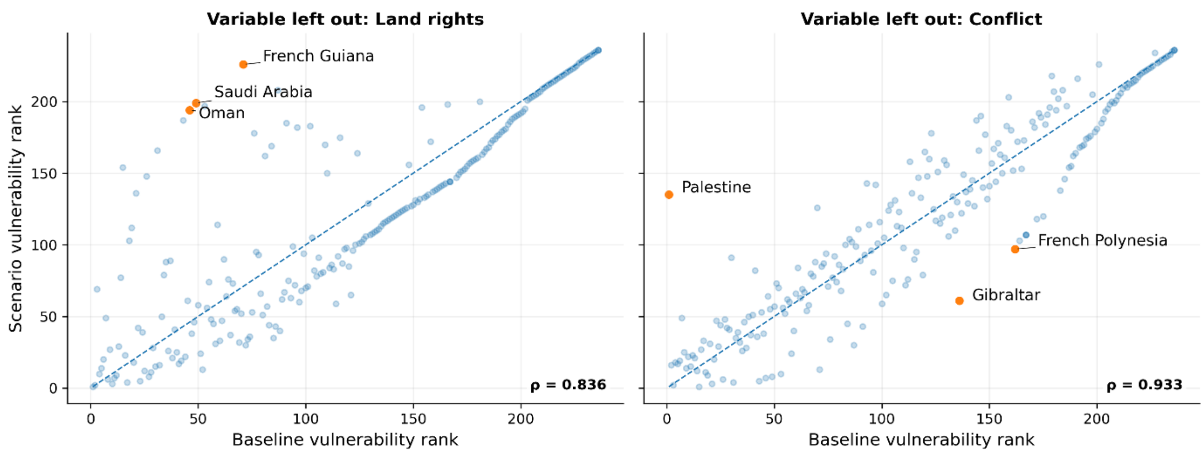

Figure 27: Scatterplots showing mean vulnerability score rankings of baseline indicators and leave-land rights/conflict-out scenarios plus Spearman correlation coefficients (illustration by the author)

Not only the internal consistency checks such as collinearity tests or sensitivity analysis serve as validation for this indicator. The conceptual design as well as the variable selection is informed by an extensive literature review and refined through expert consultation to enhance face validity (Rykiel Jr., 1996). However, it must be emphasized that the final indicator results were not again evaluated by experts. The expert consultation served only for the adaptation of the pilot indicator. Another expert consultation could not take place due to time constraints. Nevertheless, consultation with eight experts from five institutions representing academia, civil society and the private sector enabled a complete revision of the pilot indicator.

Lastly, the indicator is well suited to be included in analytical tools and models. This is due to its hierarchical and transparent construction, which allows to develop slightly altered indicator versions and the calculation with different scenarios or weights. Due to the indicator's nature, consisting of raster data with global coverage, it is designed to be integrated into geographic information systems and provides a basis for combination with other spatial datasets. This aligns with the requirement of analytical soundness that indicators should be applicable in modelling and information systems (OECD, 1993).

Ultimately, the quality requirement of measurability of indicators (OECD, 1993) is fulfilled since the indicator is built only on open-source data that are readily available. The variables are represented by datasets that are widely used by different actors, such as researchers, NGOs and the private sector. All datasets are properly and transparently documented and with one exception, namely the environmental democracy index, they are updated at regular intervals. Nevertheless, as for most indicators' certain trade-offs between data availability and data suitability had to be made. Section 5.4 discusses this issue in more depth.

Taken together, the indicator largely meets established quality requirements for policy relevance, analytical soundness and measurability. An indicator that fulfills all these requirements entirely is considered to be an ideal indicator, however not every indicator necessarily has to meet all of them in practice (OECD, 1993). Naturally, the indicator in this thesis also has inherent trade-offs and does not fully meet all criteria. The next section elaborates on these limitations.

5.4 Methodological and conceptual limitations

The developed indicator meets several important limitations, which are discussed in this section. First, the issue of data availability must be considered for a variety of reasons. The variable selection in a composite indicator is highly dependent on the available data. This is particularly true for global indicators, where consistent datasets covering large spatial extents are required. As a result, the development of such indicators often involves pragmatic choices and compromises. This was also reflected in the expert interviews. The expert from the private sector provided more straightforward feedback than that from academia and NGO experts. Specifically, the private sector suggested particular datasets, explaining that it relies on this type of data, which covers large areas of the globe, to produce risk assessments for the mining industry (PR-1). This highlights that in applied contexts assessments often rely on available data and require a certain degree of pragmatism. In contrast, experts from academia and NGOs expressed more caution regarding data selection and raised broader questions about the meaningfulness of global-scale indicators like this (NGO-1, NGO-2, AC-1, AC-2). Does it make sense to make a global scale indicator for mining vulnerability if conditions are so different that it might not be covered through global scale datasets? This is a valid concern, but it does not negate the value of developing transparent exploratory indicators at the global scale. Moreover, such indicators are already used in practice, especially in the private sector (PR-1). They can also be a useful tool for policy making and this is why it is important to still try to develop indicators like this. Therefore, while data availability necessarily leads to compromises in variable selection, the development of such indicators remains meaningful. However, it is crucial to ensure transparency about these compromises (Birkmann, 2007; OECD, 2008). As for this indicator, several such compromises have been made.

First, the variable of poverty is based on the Human Development Index (HDI) and not the Multidimensional Poverty Index (MPI) as it is described in section 3.7.1. This illustrates that there can be trade-offs between data quality and data availability when working on the global scale. While the MPI would provide a more nuanced representation of poverty, its limited spatial coverage makes it difficult to integrate it consistently into a spatially explicit global indicator. The HDI was therefore used as a proxy. Similar compromises were made for other variables. Several indicators rely on country-level data (e.g. rule of law or environmental democracy index), which were downscaled to a uniform grid of

5000 meters. While this allows integration with other spatial datasets on a global scale, it introduces a mismatch in spatial resolution. This mismatch must be considered when interpreting the indicator since otherwise it could lead to the assumption that the indicator provides sub-national information for all variables. Taken together this highlights a broader limitation of global indicator approaches, which necessarily prioritize variables that are available on a global scale over those that may be conceptually more precise.

Data availability is not only an issue with regards to what dataset is available but also with regards to missing values within a dataset. When working on a global scale it is very unlikely to get global coverage for all included variables with no data gaps. While some variables included in this indicator appear to have no or only minor data gaps, some country-level variables have a high number of countries with no values as can be seen in Figure 29. As described in section 3.7, a vulnerability score was calculated for every pixel based on the available datasets at this location. This means that a vulnerability score is visible, although some of the datasets might have missing values.

The dimension of sensitivity exhibits few data gaps occurring predominantly in the water risk variable. This rather small gap can be explained by the nature of the datasets used. Three out of the six sensitivity variables are based on sub-country-level datasets that indicate the presence of specific features, namely PA, KBA and IPLC lands. In such datasets, the absence of a mapped feature does not necessarily constitute a data gap in the conventional sense, since values are not missing but rather indicate that a given feature is not recorded at a particular location. At the same time, caution is required when interpreting feature absence, particularly for IPLC lands. As emphasized by LandMark (2024), the absence of IPLC territories in the dataset does not necessarily imply the absence of IPLC on the ground but may reflect incomplete documentation or ongoing data collection. These datasets can therefore be considered “living” datasets that are continuously updated as new information becomes available. Despite this limitation, the LandMark dataset currently represents the most comprehensive and globally consistent source of spatial information on IPLC lands.

The dimension of lack of adaptive capacity exhibits much larger data gaps. All variables in this dimension are country-level data and for a handful of countries three out of four variables are missing. Most missing values stem from the variables land rights and environmental democracy (Figure 28). The land rights variable is missing for almost all European countries as well as for Central Asian countries. The environmental democracy variable has missing values for most of Europe, Central Asia as well as Africa, where especially North and West Africa are missing. These data gaps are particularly relevant in the context of the additive aggregation approach applied in this indicator. Since vulnerability scores are calculated based on the available variables at each location, missing values reduce the number of contributing variables and thereby implicitly increase the influence of the remaining ones. As a result, the relative importance of individual variables may differ between countries depending on data availability. This can affect the comparability of vulnerability scores, as countries with fewer available variables may have scores that are driven by a more limited set of factors. While this approach allows for the inclusion of all available data, it requires careful interpretation, especially in regions with substantial data gaps.

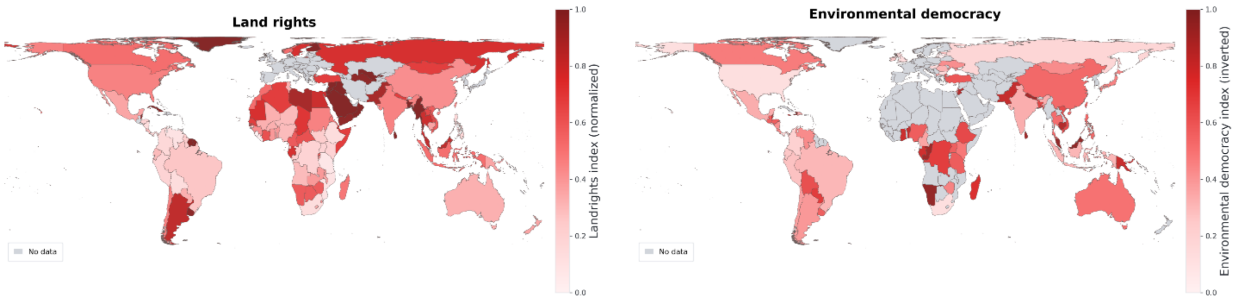

Figure 28: Land rights variable and environmental democracy variable distribution maps (illustration by the author)

Figure 29 illustrates the spatial distribution of missing values across all ten variables of the final vulnerability indicator. It thereby predominantly reflects patterns visible in the missing count of the lack of adaptive capacity dimension, since this dimension has the largest data gaps. When considering the dominant missing count within each country (the value covering the largest share of its area), it becomes evident that most countries are characterized by relatively low missing variable counts. A high number of countries has a dominant missing count of zero (50 countries), while the majority of countries has a dominant missing count of one (100 countries). Countries with a dominant missing count of two are also relatively common (54 countries), while higher missing counts occur less frequently. 31 countries have a missing count of three. Besides a variety of small island states and oversea territories, which are not visible in Figure 29 due to the map-scale, countries with a dominant missing count of three are Armenia, Azerbaijan, Bahrain, Bhutan, Cyprus, Iceland, Palestine, South Sudan, Switzerland and Tajikistan. Besides some small island states and oversea territories only the two countries of North Korea and French Guiana have a dominant missing count of four. Lastly, only small island states and oversea territories have a dominant missing count of five, except for Greenland and a small region around the Caspian Sea that also has a missing count of five. However, the latter does not represent an actual data gap. It results from the country boundary layer used, in which the Caspian Sea is not represented as a separate polygon. As a result, the sea area is assigned to surrounding countries, which creates the appearance of missing values for overlaying datasets that do not contain data for water bodies.

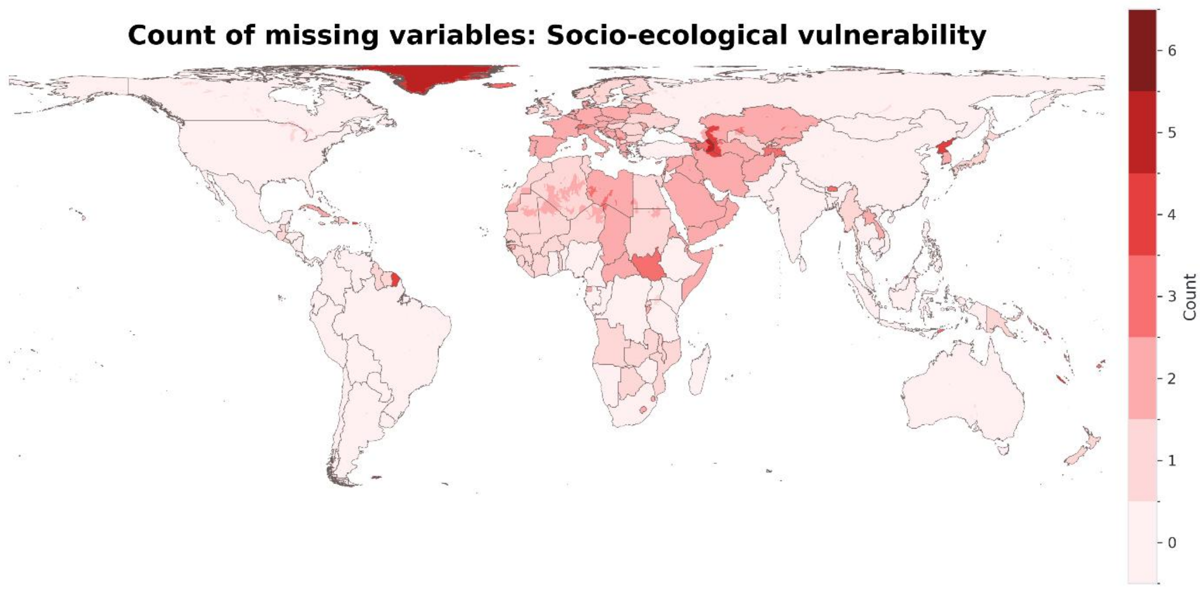

Figure 29: Map showing missing value counts for socio-ecological vulnerability (illustration by the author)

The concentration of missing values in specific regions, which is illustrated in Figure 29, raises important questions not only about data availability but also about the interpretation of resulting vulnerability scores. Some of the countries with very low mean vulnerability scores (Figure 30) such as Iceland, Switzerland or North Korea are also among the countries with highest data gaps. This illustrates quite clearly that vulnerability scores must be interpreted with care.

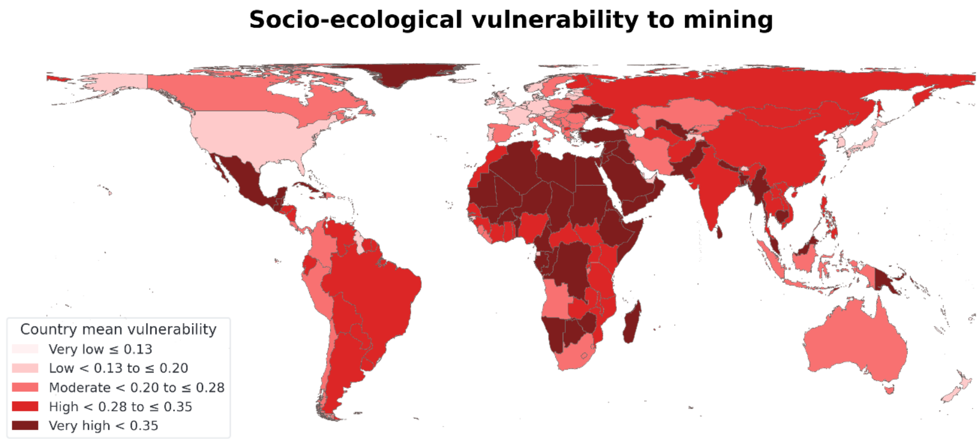

Figure 30: Mean socio-ecological vulnerability to mining per country map with different vulnerability classes (illustration by the author)

As for European countries, the missing values of land rights and environmental democracy result in a lack of adaptive capacity score primarily defined by rule of law and conflict. Since European countries generally perform well on these variables, this leads to comparatively low vulnerability scores. While this outcome is methodologically consistent with the indicator's aggregation logic, it requires critical reflection regarding the underlying assumptions on which the selected variables are based. Several experts consulted during the development of the indicator highlighted the risk that global governance or democracy indicators may reproduce Western-centric norms and institutional models (AC-1, NGO-1, PR-1). These indicators are often rooted in legal and political frameworks that emerged in the Global North and may not adequately capture alternative governance arrangements or informal mechanisms of social regulation present in other regions. Similar concerns have also been raised in the literature, which points out, that global indicators often rely on available datasets and deductive approaches, potentially leading to uneven representation across regions (Mah et al., 2023; Painter et al., 2024). This concern also applies to the rule of law indices. Rule of law is considered to be culturally contingent and dependent on time and on place, which implies that globally standardized measures may only partially reflect governance realities in different socio-political contexts (Versteeg & Ginsburg, 2017). A similar issue arises with the use of the HDI as a proxy for poverty in the sensitivity dimension. Despite its widespread acceptance, the HDI also reflects normative assumptions about development and well-being that may obscure internal inequalities and context-specific vulnerabilities. It is therefore not surprising that both the poverty and the rule of law variable have a comparatively high Spearman correlation coefficient and a high VIF as both indices reflect closely related aspects of socio-economic conditions and governance. While this overlap points to a degree of redundancy between the variables, it also mirrors a common pattern in global indicators, where different measures often end up describing similar underlying development dynamics (AC-1, PR-1). As many of these measures are shaped by development and governance concepts originating in the Global North, their use in global indicators may systematically emphasize differences between Global North and Global South contexts, leading to broad regional patterns in vulnerability scores. Although the concept of the revised indicator tries to respond to the expert feedback by including variables such as IPLC lands, land rights or environmental democracy, the final results still show a spatial pattern that points out differences between the Global North and the Global South.

One reason for this pattern may lie in the absence of variables, such as land rights or environmental democracy for many European countries. This may create an asymmetry in data availability, where governance challenges in the Global South are more extensively quantified, while similar issues in the Global North remain less explicitly captured. As a result, vulnerability in certain regions may appear lower not necessarily because adaptive capacity is higher in practice, but because fewer dimensions of vulnerability are formally measured.

These limitations do not invalidate the indicator, however, they highlight the structural constraints inherent in big data global-scale assessments. With that they underscore the importance of interpreting vulnerability scores always by considering its context. Global composite indicators like this cannot replace regional, participatory and qualitative studies This limitation is often faced by social vulnerability indicators developed in various fields and so Painter et al. (2024) points out that qualitative methods such as interviews with affected communities are crucial but rarely used methods to complement or construct indicators. Most social vulnerability indicators are constructed deductively, by relying on existing indicators and quantitative methods only, which happens at the expense of inductively constructed concepts of vulnerability (Painter et al., 2024). In this context, the indicator developed in this thesis also follows a predominantly deductive approach, as it relies on existing large-scale datasets and established indicator frameworks. Nevertheless, expert interviews were conducted during the development process to critically reflect on the conceptual design, variable selection and interpretation of results. With that, a limited participatory and qualitative component was included. This does not replace the consultation of affected communities, however, it represents an attempt to complement purely deductive indicator construction. In addition, efforts were made to include data sources that are not exclusively based on top-down approaches. For example, the LandMark dataset incorporates participatory mapping by different groups including from Indigenous organizations. Still, these elements address the structural limitations of global datasets only in a very limited manner and do not overcome the biases discussed above. Thereby the indicator can for example help to decide which areas should be scrutinized more closely using qualitative approaches. Additionally, the development of a global composite indicator as presented here can serve in identifying data gaps, justifying demands for more transparency and reflecting on potential colonial continuities in order to eventually come up with more balanced indicators.

Another limitation of the indicator concerns the temporal as well as the already briefly discussed spatial resolution. As for the temporal resolution the indicator is describing the current state of socio-ecological vulnerability, meaning it does not reveal evolution over time. “Current” means that the most recent datasets are used, even though they were released at slightly different times. The indicator combines living datasets that are updated regularly, such as IPLC lands, with datasets based on indices that are recalculated periodically. It also contains data from a one-time project, namely the environmental democracy index, which was implemented in 2015 and has not been updated. This temporal heterogeneity represents a limitation, as it means that not all variables reflect exactly the same reference year. However, its effect is mitigated by the fact that the majority of datasets used in the indicator stem from recent years, primarily 2023, 2024, and 2025. As a result, the indicator provides a reasonably up-to-date snapshot of socio-ecological vulnerability at the global scale, even though it cannot account for temporal dynamics or recent changes in governance or socio-environmental conditions. However, this limitation is often found with regards to social vulnerability indicators and is criticized in the literature since it ignores the fluid character of vulnerability (Painter et al., 2024).

As for the spatial resolution, it must be emphasized that the indicator makes use of datasets with different scales including several country-level datasets as well as sub-national spatial datasets. This means that vulnerability scores can vary on the sub-country-level if features such as PA, KBA, IPLC lands are present or if biodiversity intactness or water risk varies within the country. While these variables provide valuable insight at the sub-country-level, the remaining variables are only available at the country-level and therefore do not reveal regional variations within countries. This reflects a combination of downscaling and implicit upscaling within the indicator construction. Country-level variables are downscaled to the spatial resolution of 5000 meters, which assumes a uniform distribution within national boundaries. At the same time, sub-national datasets are effectively aggregated within the composite indicator, as their detailed spatial variability is combined with coarser information. This creates a mismatch in spatial representation across variables. In order to combine datasets with different spatial resolutions into a single composite indicator, a harmonization of scale is required (Stein et al., 2001). Downscaling country-level variables enables their integration with higher-resolution spatial data and thereby allows for a consistent global analysis. Without such an approach, many relevant socio-economic and governance-related variables could not be included in a spatially explicit assessment. A spatial resolution of 5000 meters was chosen for the vulnerability score in order to preserve details of the polygon and raster sub-national datasets. However, this may create a misleading impression regarding the scale of the country-level variables and obscure the fact that half of the variables do not provide information at the sub-country-level. Also, it represents a constraint on the meaningfulness of the indicator, particularly given the high spatial heterogeneity of socio-economic conditions related to mining (Shiquan et al., 2022). For instance, some groups can benefit from mining activities due to employment opportunities, while others might be resettled and lose their livelihoods. This spatial heterogeneity is not captured by the indicator, which underscores once more that it serves as a comparative and exploratory tool rather than providing precise statements on the current state of vulnerability at specific locations. In other words, although the indicator has a nominal resolution of 5000 meters, this apparent level of spatial detail should be treated with caution, as the inclusion of country-level variables limits the interpretability of results at this scale.

Finally, a more general conceptual limitation that applies to global-scale composite indicators like the one developed in this thesis must be addressed. It concerns the comparability of fundamentally different socio-ecological systems at the global scale and was also addressed during the expert consultation. By aggregating vulnerability across diverse contexts, the indicator enables comparisons between regions with very different environmental and social characteristics, such as arid desert regions and tropical rainforests. While this enables a consistent global overview, it is necessarily an abstraction from context-specific conditions. As a result, vulnerability scores should be understood as relative measures within this indicator, not as direct statements about how severe mining impacts would be in absolute terms or how they would manifest in different ecosystems. A high score in a desert and a high score in a rainforest therefore do not imply the same types or magnitudes of mining impacts. This is a general limitation of global comparative indicators and highlights the need to complement them with local or site-specific assessments.

5.5 Directions for future research

This thesis provides a first step toward a spatially explicit, global-scale assessment of socio-ecological vulnerability to mining impacts. Building on this work, several directions for future research can be identified that could further refine the indicator, deepen its analytical capacity and expand its applicability.

First, an analysis of temporal dynamics would be of great interest in order to see how vulnerability changes over time. Are there areas where the situation exacerbates or do certain measures lead to a vulnerability reduction? Since many of the variables included are updated on a regular basis a recalculation of the index for different time periods seems feasible. Such analysis over time could provide valuable insights into the effectiveness of policy interventions and broader socio-ecological trends.

Besides adding temporal dynamics, increasing the spatial resolution is another promising direction. Mining impacts have especially with regards to social impacts a high spatial heterogeneity (Shiquan et al., 2022). Therefore, it would be interesting to try to include more sub-country-level data concerning social factors to gain more insights into sub-national level. Since such datasets are rarely available on a global scale, the application of the conceptual framework of the indicator on different specific regions seems to be a viable option. Thereby, the variables could also be adjusted to the respective context of a region and depending on local conditions, more context-specific variables such as deforestation could be applied. Moreover, the indicator could also be developed further by applying different weighting schemes for the variable or the dimensions. With that, different normative assumptions with regards to socio-ecological vulnerability could be explored and it could be compared how they alter the indicator's results. Another option would be to calculate different scenarios by including other pressures and to examine if and how vulnerabilities change. In light of the expected intensification of climate change, such a study would be of interest.

Vulnerability is one component of the term risk as defined by the IPCC AR6 (IPCC, 2022). The development of indicators describing the other two components, namely hazard and exposure, and the combination of the three concepts within one composite indicator describing risk to mining would be another potential future research direction. This would, of course, require that sufficient mining-related data is available. Integrating the vulnerability indicator with spatial data on existing or planned mining activities could support risk-oriented assessments while maintaining conceptual clarity between underlying vulnerability and actual impacts. Such work would benefit from interdisciplinary collaboration across environmental sciences, political ecology and economics.

Finally, participatory approaches offer an important direction for future research. The engagement with Indigenous Peoples, local communities, policymakers, civil society organizations and the private sector are of high importance when it comes to refining the indicator and to contextualize its interpretation. Such participatory approaches could enhance the indicator's relevance, legitimacy and ethical robustness. This would help to ensure that global-scale assessments contribute constructively to debates on mining governance, environmental justice and sustainable resource use rather than reinforcing existing power asymmetries.

Overall, it can be said that there are still many promising directions for future research around the indicator development on mining impacts and there are many ways in which the indicator developed in this thesis can be conceptually adapted. The availability of open source and high-quality data will likely be decisive in determining whether this potential can be exploited.

6 Conclusion

This thesis sets out to develop a spatially explicit, global-scale indicator of socio-ecological vulnerability to mining impacts and to critically reflect on its conceptual framework, methodological choices, as well as potential applications and limitations. Overall, the findings of this thesis demonstrate that it is possible to develop a spatially explicit socio-ecological vulnerability indicator on the global scale, although this process necessarily involves certain trade-offs. The indicator incorporates a clearly defined vulnerability framework based on the IPCC AR6 definition of vulnerability and is constructed by operationalizing the two dimensions of vulnerability, namely sensitivity and lack of adaptive capacity. It includes social as well as ecological variables and thus plays an important role in addressing the current gap in vulnerability indicators that take both factors into account. The indicator reveals clear spatial patterns of vulnerability, particularly between regions of the Global North and Global South, since the countries most vulnerable to mining impacts tend to be located in the Global South. It also appears that different scenarios of the indicator, where individual variables are left out, lead to similar countries being the most vulnerable ones. However, these results must be interpreted with care since conceptual and methodological choices as well as data availability strongly influence the outcomes of an indicator like this. Therefore, it is not sufficient to solely consult resulting products derived from this work, such as maps or raster files. These products must only be used by considering the context of their construction. This highlights that the interpretation of the indicator requires a thorough understanding of its underlying conceptual framework and methodological construction. The vulnerability scores presented in this thesis should therefore not be understood as absolute values, but rather as relative measures that reflect underlying socio-ecological conditions within the constraints of the chosen approach.

In this context, the development of the indicator can be understood not only as a technical procedure, but also as a conceptual and normative process in which a range of assumptions and simplifications are inevitably made. Decisions regarding variable selection, data sources, normalization and aggregation directly influence the resulting patterns and must therefore be considered as integral parts of the indicator itself rather than as neutral methodological steps. The involvement of experts in the development of the conceptual design of the indicator aimed at supporting this normative process by including actors out of different fields and backgrounds. Despite their different backgrounds, the feedback from experts in NGOs, academia and the private sector did indeed have many similarities, which were very helpful for the process and may lead to a more robust indicator. At the same time, the analysis of different indicator scenarios by leaving individual variables out indicates that general spatial patterns remain relatively robust. Still, the specific ranking and magnitude of vulnerability scores changed substantially for a few scenarios, which underlines again that methodological choices matter.

As for the main limitations of a highly quantitative and global scale approach as the one presented here, the indicator does not capture local vulnerabilities, that are especially in the context of mining spatially heterogenic. Although the indicator captures some spatial patterns on the sub-national level, their reliability must be questioned since half of the variables are only available on the country-level and therefore do not provide information for the indicator’s spatial resolution of 5000 meters. Also, the indicator does not follow a participatory or inductive approach within its construction. Instead, it relies primarily on secondary quantitative datasets and a deductive variable selection based on existing literature, expert consultation and data availability. As a result, it does not capture context-specific drivers of vulnerability. It does not include local knowledge and lived experiences of people affected by mine sites. Therefore, the indicator would highly benefit from a more inductively informed conceptual design, which includes the knowledge of multiple stakeholders.

Taken together, these limitations highlight that the indicator should not be interpreted as a precise representation of local realities, but rather as a generalized and comparative approximation of socio-ecological vulnerability at the global scale. While it can reveal broader spatial patterns and provide valuable insights for large-scale assessments, its results must be complemented with more detailed, context-specific analyses in order to fully understand vulnerability in specific locations.

In terms of its application, the indicator can serve as an exploratory tool to identify regions where socio-ecological systems may be particularly susceptible to mining-related impacts. It can support comparative assessments and help to highlight areas where more detailed, context-specific analyses are needed. However, it is not suitable for site-specific decision-making or for evaluating the feasibility of individual mining projects, since this would neglect local dynamics that cannot be captured within a global-scale indicator.

Overall, this thesis demonstrates both the potential and the limitations of using composite indicators to assess socio-ecological vulnerability to mining. It contributes to the existing literature by integrating social and ecological dimensions within a spatially explicit framework and by critically reflecting on the implications of methodological choices. Future research could build on this work by incorporating more context-specific data and further investigating how vulnerability evolves over time.

7 AI statement

During the process of this thesis, the use of AI supported several steps. For which steps and how AI was used is described in this section. First, ChatGPT was used to correct the Python code needed to calculate the results. A prepared or partly prepared code was used in the prompt together with an explanation of what the code is intended to do. The resulting code was subsequently checked and understood, by asking questions back via a prompt to get detailed explanations on the code. The code was then altered manually if needed and complemented with comments to ensure comprehensibility. A code that was once partly produced or corrected through ChatGPT and that was similar for the calculation of different parts of the thesis, was then reused and adapted manually (e.g. rasterization of vector layers or generation of plots with the same characteristics). Therefore, ChatGPT was besides the official documentation of different Python packages and existing prior knowledge, the basis for most of the coding. However, it was used in a thoughtful and reflective manner to ensure that the results are meaningful, transparent and accurate. To standardize the code scripts and prepare them for the GitHub repository, ChatGPT was asked to put the jupyter notebooks in the same format and style without changing any of the code.

Furthermore, ChatGPT was used for the grammatical and stylistically correction of some parts of the text. Such a correction was applied to individual sentences or small paragraphs, that did not quite match the desired tone, structure or clearness. In these cases, the prompt consisted of a draft sentence/paragraph, an explanation of what the sentence/paragraph should mean and a question of how this can be written in a smoother/more scientific/more appropriate or clearer language. The results were inspected to make sure that the meaning of the sentence/paragraph did not change and if the language was appropriate. To deal with issues related to English grammar, phrases or words, the AI tool of DeepL AI write was used. For this the draft sentences were entered and compared with the suggested adjustments.

With regards to the expert interviews, the anonymized interview transcripts were entered together with a prompt asking to summarize the interviews in ChatGPT. Furthermore, other prompts were entered to clarify specific questions regarding the interviews. The results were verified by checking the transcripts again manually.

Lastly, the website Google NotebookLM was used to support the literature review. This helped to get an overview of the papers that were read, since it makes it possible to ask questions about defined sources and offers the function to find information again within a given paper. For example, it was used to collect definitions of a term in all relevant papers.

In the end of the working process, ChatGPT was asked to compare the final discussion chapter with the background and results chapter and suggest things that could still be added to connect theory, results and discussion more explicitly. However, this prompt resulted in only minor adjustments such as small transitional sentences. Many of the suggestions were too repetitive and were therefore not considered to provide any added value. Finally, the list of abbreviations was generated using ChatGPT by asking it to filter out all abbreviations from the text.

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Personal declaration

I hereby declare that the submitted thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the thesis.

Date, Place: 22.04.2026, Zürich Signature: J. Brem