Spatial data approaches for assessing the environmental and socioeconomic impacts of mining activities

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To the communities facing environmental and social injustice as a direct outcome of the excessive exploitation of natural resources.

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List of publications

This cumulative dissertation comprises three first-author papers:

1. Luckeneder, S., Giljum, S., Schaffartzik, A., Maus, V., and Tost, M. (2021): "Surge in global metal mining threatens vulnerable ecosystems", *Global Environmental Change* **69**, 102303. Available at https://doi.org/10.1016/j.gloenvcha.2021.102303.

2. Luckeneder, S., Maus, V., Siqueira-Gay, J., Krisztin, K., and Kuhn, M. (2024): "Transient economic benefit and persistent forest loss: regional impacts of mining in Brazil", under revision for *Nature Communications*.

3. Luckeneder, S., Giljum, S., Maus, V., Sonter, L.J., and Lenzen, M. (2024): "EU consumption's hidden link to global deforestation caused by mining", submitted to *Science* (under review). Working paper available at https://doi.org/10.57938/b890eed0-1ab4-43af-b577-df48f43290a6.

Author contributions

As the lead author of all three publications included in this thesis, I was actively involved in every stage of the research process. Paper 1 was conceptualised by S.G. and myself, with all authors involved in the writing and editing. The data compilation and analysis were primarily my responsibility. For Paper 2, I led the conceptualisation and conducted the empirical analysis. V.M. and T.K. supported method development, and all authors participated in writing and editing. In Paper 3, I was responsible for the conceptualisation and modelling. V.M. provided the forest loss accounts, which I integrated into the trade model, with input from S.G. and M.L. All authors contributed to the writing and editing stages.

Other relevant publications

My research output during the PhD includes more than the three first-author papers. Working on different projects with varying team arrangements and responsibilities allowed me to explore the topic from broader perspectives and reflect on it beyond the specific scope of the dissertation:

1. Maus, V., Giljum, S., Gutschlhofer, J., da Silva, D.M., Probst, M., Gass, S.L.B., Luckeneder, S., Lieber, M., and McCallum I. (2020): "A global-scale data set of mining areas", *Scientific Data* **7**, 289. Available at https://doi.org/10.1038/s41597-020-00624-w.

2. Maus, V., Giljum, S., da Silva, D.M., Gutschlhofer, J., da Rosa, R., Luckeneder, S., Gass, S.L.B., Lieber, M., and McCallum I. (2022): "An update on global mining land use", *Scientific Data* **9**, 433. Available at https://doi.org/10.1038/s41597-022-01547-4.

3. Giljum, S., Maus, V., Kuschnig, N., Luckeneder, S., Tost, M., Sonter, L.J., and Bebbington A.J. (2022): "A pan-tropical assessment of deforestation caused by industrial mining", *Proceedings of the National Academy of Sciences* **119**(38), e2118273119. Available at https://doi.org/10.1073/pnas.2118273119.

4. Cerny, M. and Luckeneder, S. (2023): "Undermined efforts? The ambiguous role of mining jobs in a just transition", *Journal für Entwicklungspolitik* **39**(3/4), 113-138. Available at https://doi.org/10.20446/JEP-2414-3197-39-3-113.

5. Kramer, M., Kind-Rieper, T., Munayer, R., Giljum, S., Masselink, R., van Ackern, P., Maus, V., Luckeneder, S., Kuschnig, N., Costa, F., and Rüttinger, L. (2023): "Extracted forests. Unearthing the role of mining-related deforestation as a driver of global deforestation". Berlin: WWF. Available at https://www.wwf.de/fileadmin/fm-wwf/Publikationen-PDF/Wald/WWF-Studie-Extracted-Forests.pdf.

6. Sonter, L.J., Maron, M., Bull, W.B., Giljum, S., Luckeneder, S., Maus, V., McDonald-Madden, E., Northey, S.A., Sánchez, L.E., Valenta, R., Visconti, P., Werner, T.T., and Watson, J.E.M. (2023): "How to fuel an energy transition with ecologically responsible mining", *Proceedings of the National Academy of Sciences* **120**(35), e2307006120. Available at https://doi.org/10.1073/pnas.2307006120.

7. Giljum, S., Maus, V., Sonter, L.J., Luckeneder, S., Werner, T.T., Lutter, S., Gershenzon, J., Cole, M., Siqueira-Gay, J., Bebbington, A.J. (2024): "Global metal mining is a growing driver of environmental change", submitted to *Nature Reviews Earth & Environment* (under review).

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After five years, completing this dissertation feels like closing a memorable chapter in my life. The Institute for Ecological Economics has become a second home for me, a place I found myself in somewhat by coincidence. My background is in economics and development studies, and environmental issues weren't originally my focus. But as I began working as a research assistant, I was drawn into ecological economic thinking, which has since deeply shaped both my work and my worldview. I am grateful to the community at the institute, where I was surrounded by researchers and mentors who continually inspired me. I also acknowledge the privilege I bring to this work, not only as an academic but as a white Austrian male, a fact I cannot overlook as I navigate my work in fields that intersect with global and societal inequalities.

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During this PhD, I've been lucky to travel and work with researchers around the world. I am especially grateful to Laura Sonter for hosting me during my time at the University of Queensland, a period that was not only productive but also the beginning of continued support and collaboration ever since. My stay in Brazil was equally unforgettable, thanks to RICHARD VAN DER HOFF, who helped me find my way through the hills of Minas Gerais and connected me with fellow researchers, making it possible to organise excursions to various mining sites.

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Sebastian Luckeneder
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Chapter 1

Introduction

Every year, billions of tonnes of earth are moved by humans for the extraction of metal ores and other minerals, shaping and profoundly changing entire landscapes and societies. During the course of this PhD, I had the chance to visit large-scale mining operations in the Brazilian state of Minas Gerais. I was struck by the size of the operations, and how, almost aesthetic in appearance, terraced steps were cut into mountainsides, winding through the hills in different shades of rock and ore. At the same time, I was confronted with the evidence of human intervention in the natural landscape and the significant effects mining had on all life in the area, which had transformed from a once lush, green terrain into a barren, rocky expanse. The environmental and societal consequences of mining are manifold and interconnected. This thesis focuses on some particular aspects of mining-induced change, aiming to deepen our understanding of the consequences of the unprecedentedly high and rapidly growing material consumption in certain parts of the world.

The rising human population, economic expansion, rapid urbanisation, and growing affluence have driven global resource consumption to unprecedented levels, pushing the world economy toward – and in some cases beyond – planetary boundaries (Steffen et al. 2015; Wiedmann et al. 2020; Watari et al. 2021; Rockström et al. 2023; UN IRP 2024). This growth is particularly pronounced for metals and minerals, which are foundational to built environment, mobility infrastructure, and energy systems (UN IRP 2024). As depicted in Figure 1.1, the global extraction of metal ores, non-metallic minerals and mined fossil fuels has doubled since the year 2000, reaching 10.0 bn tonnes, 46.4 bn tonnes, and 8.9 bn tonnes, respectively, by 2020. This corresponds to astounding 2,071 tonnes of raw material being mined every second in that year. Despite this historically high level of extraction, there are compelling reasons to expect continued acceleration in mining activities. First, the demand for housing, transport and energy infrastructure in emerging economies, especially those experiencing rapid population growth and urbanisation, remains significant (UN IRP 2024). Second, the increasing adoption of renewable energy technologies is set to considerably boost the demand for critical minerals, such as lithium, cobalt, nickel and rare earth elements, which are essential for wind turbines, solar panels, and electric vehicles (Watari et al. 2019; Watari et al. 2020). Even materials like iron, aluminium, copper, and non-metallic construction materials, which are already extracted in large volumes, will continue to be required in substantial quantities

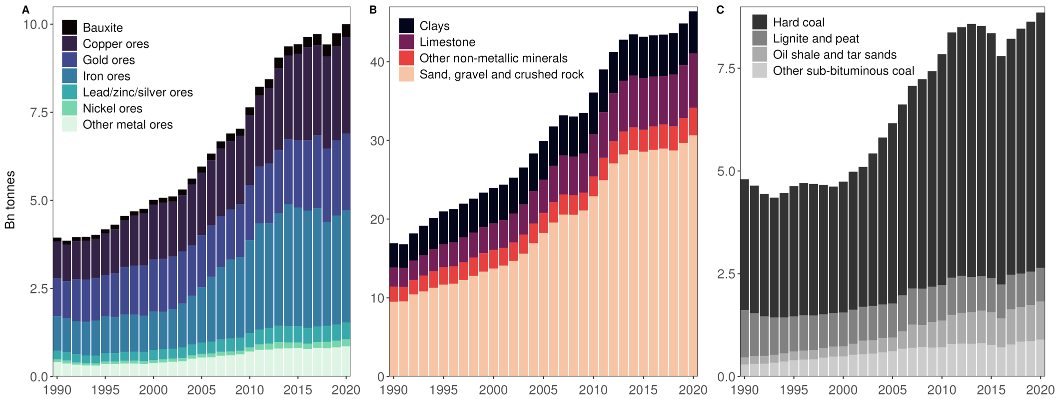

Figure 1.1: Global extraction of mined materials, 1990-2020: metallic minerals (**A**), non-metallic minerals (**B**) and mined fossil fuels (**C**). Data sourced from the UN IRP Material Flows Database, accessed via Release 057 of the GLORIA global environmentally-extended MRIO database (Lenzen et al. 2017; Lenzen et al. 2022).

for the development of renewable energy infrastructure (Lèbre et al. 2020; Hache et al. 2020). Lastly, the anticipated rise in global metal ore extraction is linked to declining ore grades (Mudd 2010; Prior et al. 2012; Calvo et al. 2016) and technological advancements that now facilitate the exploitation of previously inaccessible or lower-grade deposits. As a result, mining activities are increasingly encroaching upon ecologically sensitive regions.

Despite the global surge in mining, the anticipated rise in demand for various materials, and the well-documented social and environmental consequences, which are often explored at the level of individual case studies (Temper et al. 2015), systematic assessments of mining impacts at a global scale remain limited. Most research has concentrated on specific mining regions (e.g., Arellano-Yanguas 2011; Sonter et al. 2014; Bebbington et al. 2019; González-González et al. 2021; Kumi et al. 2023; Ladewig et al. 2024) or particular materials (e.g., Asner and Tupayachi 2016; Sovacool 2019; Siqueira-Gay and Sánchez 2021; Chen et al. 2022). Meanwhile, global metal and mineral supply chains continue to suffer from a lack of transparency and standardised accounting frameworks (Calderon et al. 2020).

A significant challenge to understanding the current state of global mining lies in persistent data gaps. There is limited information available on the exact locations of exploration and active mine sites, as well as the commodities involved, production volumes, associated waste, pollution, and resource use such as water and energy consumption (Maus and Werner 2024).

The absence of a reliable global spatial data foundation hampers efforts to assess the full scope of mining's environmental and socioeconomic impacts. Existing evaluations are often fragmented and contested. In particular, the literature on the socioeconomic effects of mining – frequently measured in terms of economic growth – produces inconclusive results, with varying outcomes depending on the indicators used, mining types, and regional contexts. While there is broader consensus about the environmental risks of mining, industry narratives commonly highlight that due diligence and environmental and social standards serve to address and prevent them (e.g., Global Tailings Review 2020; ICMM 2024a). However, the gravity of these risks is underscored by recurring disasters such as tailings dam failures (Escobar 2015; Silva Rotta et al. 2020; Torres-Cruz and O'Donovan 2023), the persistent threats to indigenous health and livelihoods (Basta et al. 2021; Mataveli et al. 2022), and the growing global opposition to mining, as evidenced by widespread environmental movements against mine development (Temper et al. 2015; Toumbourou et al. 2020; Sternberg 2020; Ivanović et al. 2023).

The systematic assessment of mining impacts is further complicated by several factors. These include confounding and interacting activities, which obscure the isolation of mining's specific effects from other economic and environmental influences, as well as the indirect and cumulative impacts that unfold across different temporal and spatial scales (Franks et al. 2013; Sonter et al. 2014). The difficulties in quantifying both direct and indirect consequences arise not only from the data deficiencies but also from the need for integrative, cross-disciplinary conceptual frameworks and established methodologies (Lechner et al. 2017; Wang et al. 2020). Despite these complexities, recent empirical studies have made significant progress in addressing the cumulative impacts of mining, such as the spread of deforestation within and beyond mining areas (Sonter et al. 2017; Giljum et al. 2022; Ladewig et al. 2024). Further progress in this field is expected, with the release of global datasets on land area covered by mining (Maus et al. 2020; Maus et al. 2022; Tang and Werner 2023) – revealing that mining activities now span over 100,000 km^2 – offering a promising foundation for global statistical assessments of the cumulative impacts of mining.

Lastly, as mining and its impacts have become globalised through international supply chains, addressing these issues requires an integration of local contexts with broader, global perspectives. The integration of developing countries into the global economy as raw material providers has peripheralised the negative environmental and social effects of international consumption (Dorninger et al. 2021; Hickel et al. 2022). Today, considerable knowledge gaps remain regarding the connections between localised mining impacts and the final demand for products and services elsewhere, which ultimately drives resource extraction and its consequences. Only recently have researchers begun to address these linkages. For example, Cabernard and Pfister (2022) studied biodiversity loss associated with mining-related land use, identifying impact hotspots and related supply chains. These gaps in knowledge – whether related to missing data, incomplete evidence of impacts, or opaque supply chains – continue to hinder efforts toward managing resources sustainably and planning for future raw material use.

1.1 Aim of the thesis

The aim of this thesis is to address the above outlined gaps in the study of mining-induced changes. Specifically, **my research aims to examine the current status and spatial distribution of global mining activities, advance the understanding of their local impacts, and trace these effects through global supply chains to the final consumption of goods and services.** To achieve this aim, the research is organised around three main assessment goals, each addressing specific research questions and explored in a dedicated research article (for an overview, see Figure 1.2):

1. **Contextual risks associated with mining expansion** (Publication 1)
    - What is the global spatial distribution of metal mining projects, and how have their patterns of expansion changed over time since the year 2000?

- To what extent does mining interfere with vulnerable ecosystems, including biodiversity-rich biomes, protected areas, and water-scarce regions?
- What are the hotspots of raw material extraction, and what risks are associated with them?

2. **Local impacts and spillover effects on neighbouring areas** (Publication 2)
   - Using the Brazilian mining sector as an example, what are the impacts of mining on regional economic growth and forest cover?
   - To what extent do these impacts of mining extend beyond municipal boundaries, affecting neighbouring areas?

3. **Spatial disconnect between where materials are extracted and where the related products are consumed that embody the environmental and social impacts of extraction** (Publication 3)
   - What is the global extent of forest loss directly attributable to mining?
   - How much of this forest loss can be linked to EU consumption patterns?
   - Which industrial sectors in the EU are most responsible for driving these impacts?

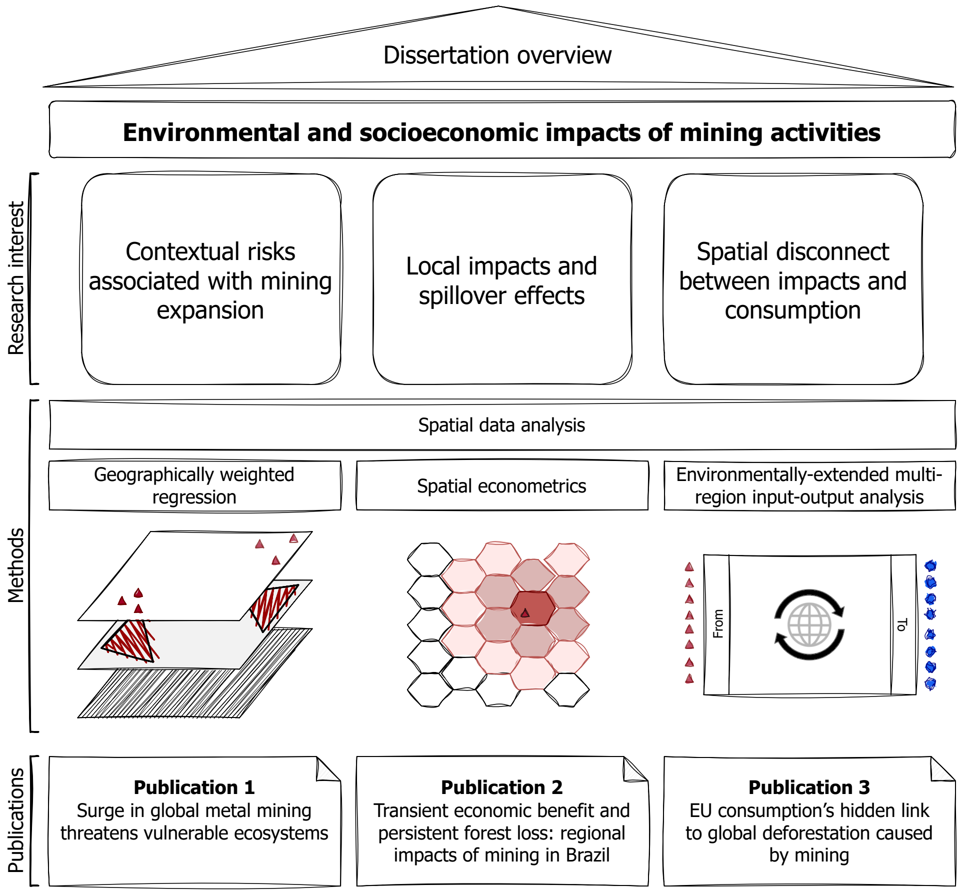

Figure 1.2: Three key aspects explored in the thesis, methods applied, and publications.

1.2 Theoretical and methodological background

This thesis has greatly benefited from collaborations with experts in human and economic geography, industrial ecology, conservation science, and mining and environmental engineering. The three publications presented share a foundation in interdisciplinary thinking, with ecological economics as their theoretical backbone. Ecological economics is an interdisciplinary area of research that integrates insights from economics, ecology, and other disciplines, acknowledging that biophysical processes underpin all economic activities. Unlike traditional economic models that primarily operate in monetary terms, ecological economics employs biophysical metrics – such as energy use, material flows, and land area – to quantify and assess economic processes. This approach recognises the biophysical limits of ecosystems and underscores the need for sustainable development to prevent the transgression of planetary boundaries (see, for example, Daly and Farley 2011; Haberl et al. 2019). By adopting the lens of ecological economics, this dissertation situates mining and its related issues within a broader understanding of the field's key concepts and paradigms. Two concepts, social metabolism and environmental justice, have been particularly instrumental in guiding the research.

Social (or socioeconomic) metabolism can serve as a paradigm to study the biophysical basis of human societies (Pauliuk and Hertwich 2015). It defines the stocks of a social system (comprised of humans, durable infrastructures and animal livestock) and describes the flows of energy and materials within and between societies and the exchanges with nature to build and maintain these stocks (Fischer-Kowalski and Haberl 1998; Fischer-Kowalski and Haberl 2015). Moreover, it highlights the social and environmental impacts of economic activities and describes how extensive resource use is driving the global economy towards exceeding planetary boundaries (Martinez-Alier and Walter 2016; Rockström et al. 2009). Mining plays a pivotal role in this regard, providing the global economy with natural resources to allow for an "extended metabolism" (Fischer-Kowalski and Haberl 1998, p. 574) that largely mobilises non-renewable resources, while simultaneously generating significant waste and pollution throughout extraction and processing.

At the intersection between ecological economics and political ecology, environmental justice, in turn, conceptualises the link between the growing metabolism of societies – mostly in the Global North and emerging economies – and the unequal distribution of environmental benefits and burdens. This imbalance gives rise to "ecological distribution conflicts", highlighting the need for equitable and inclusive solutions at both local and global scales (Martinez-Alier 2004; Martinez-Alier et al. 2016; Scheidel et al. 2018). Given mining's potential to cause extensive adverse impacts, it is a significant driver of ecological distribution conflicts. Therefore, adopting an environmental justice perspective is crucial for identifying impact hotspots, addressing and mitigating the adverse effects of mining, and promoting responsible material sourcing solutions. These concepts form essential pillars for the perspectives presented in this dissertation, aligning with its research objectives and offering a framework for understanding both the biophysical and societal dimensions of mining's impacts.

Integrating different spatial scales is crucial for a more comprehensive understanding of the dynamics of the recent mining expansion. Bridging global-scale analyses with spatially explicit approaches enables this integration. The global perspective recognises that the surge in mining is a direct result of the growing physical metabolism of the global economy, while simultaneously revealing pronounced sub-global disparities. Conversely, spatially explicit analyses are essential for linking extractive practices to specific local contexts and impacts. The integration of spatial data forms a unifying theme across the three publications of this dissertation, reflected in the methodological frameworks employed. These methods include a combination of geographic information systems (GIS) such as spatial intersection and overlay analyses, econometric techniques, and multi-region input-output (MRIO) models, each contributing distinct insights into the spatial dimensions of mining impacts (see Figure 1.2). Recent research underscores the potential of remote sensing and GIS for analysing the environmental, social, and economic impacts of mining at local, regional, and global scales (Werner et al. 2019; Werner et al. 2020; Islam et al. 2020). Notably, during this PhD, several global mining datasets became available (Maus et al. 2020; Maus et al. 2022; Tang and Werner 2023; Jasansky et al. 2023), further enriching spatial analyses. The field is advancing rapidly, with ongoing improvements in remote sensing now enabling the detection of even artisanal and small-scale mining activities (Nursamsi et al. 2024a; Nursamsi et al. 2024b). In this research, I compile several spatial datasets, combining detailed mining registers, spatial point and polygon data on mining sites, high-resolution satellite images of land cover, socio-environmental characteristics of municipalities, and statistical data at national, ecosystem, and watershed levels. The following chapters of this thesis demonstrate how these datasets are employed to effectively capture certain aspects of the complex geographical dimensions of mining impacts.

1.3 Summary of paper contributions

The first paper, titled **Surge in global metal mining threatens vulnerable ecosystems**, addresses the contextual risks posed by the expansion of global mining operations into ecologically sensitive areas. Here, contextual risks refer to the broader environmental conditions surrounding mine sites, which play a crucial role in determining the vulnerability of ecosystems and the extent of mining's impacts. To understand the local environmental and social consequences of the global expansion of mining, it is essential to study risks at a spatially explicit level. Existing global assessments have typically focused on cross-sectional data and single environmental aspects, such as biodiversity loss (Murguía et al. 2016; Sonter et al. 2018) and water scarcity (Northey et al. 2017). Building on these earlier studies, this paper presents the first comprehensive, fine-grained assessment of global metal mining activities, covering nine major metal commodities over a 20-year period.

While assuming that mining exerts pressure on all ecosystems, the paper identifies specific areal characteristics that signal particular vulnerability. We conduct a descriptive spatial analysis (it is important to note that this analysis does not aim to detect causal impact relationships), using data on the spatial and temporal distribution of mining activities for bauxite, copper, gold, iron, lead, manganese, nickel, silver, and zinc from 2,935 active mining sites worldwide between 2000 and 2019. The analysis relies on the SNL metals and mining database (SNL 2020) – despite known limitations and biases (Maus and Werner 2024), as it was the most comprehensive dataset available at the time – and combines this information at the individual mine-level with country- and commodity-specific conversion factors from

UNEP's Global Material Flow Database (UN IRP 2017a) to generate standardised accounts of extracted crude ore. Robustness checks are carried out to ensure the dataset's reliability and to confirm that it covers the most significant mining operations globally for the nine metals considered. The data is then intersected with three spatial layers serving as proxy indicators of ecosystem vulnerability: terrestrial biomes, protected areas, and water stress. The analysis reveals that the rapid expansion of mining activities is increasingly affecting vulnerable ecosystems. For instance, in 2019, 79% of global metal ore extraction occurred in five of the six most species-rich biomes, and mining volumes in tropical moist forests had doubled since 2000. Additionally, we find that half of global metal ore extraction took place within 20 km of protected areas, and regional hotspots of mining growth are identified in Latin America, Central Africa, India, and Western Australia.

Through this descriptive spatial analysis, the paper offers a comprehensive overview of the state of global mining, providing valuable insights into the locations and ore extraction rates of active mine sites and their interaction with key environmental indicators. This work sets the stage for more detailed local studies and future research on the cumulative impacts of mining, and offers recommendations for how mining companies and policymakers can contribute to impact mitigation.

The second paper of this dissertation, titled **Transient economic benefit and persistent forest loss: regional impacts of mining in Brazil**, takes a closer look at one of the hotspots identified in the first publication. The aim of this study is to assess the regional economic and environmental impacts of mining, with a particular focus on GDP growth and forest cover loss. Unlike the first paper, which emphasises contextual risks, this paper focuses on delivering empirical evidence of the actual local and regional consequences of mining activities. To achieve this, a flexible econometric model is proposed, incorporating spillover effects between municipalities. This approach is demonstrated through a case study of Brazil.

Brazil is not only a major global supplier of metal ores but also plays a crucial role in tropical forest conservation. Among several adverse mining impacts (e.g., Silva Rotta et al. 2020; Ferrante and Fearnside 2022), mining-induced deforestation stands out as a significant concern (Sonter et al. 2017). However, while there is widespread recognition of the environmental and social risks linked to mining, there remains debate over the potential economic benefits it could bring to local communities (de Castro Gentil et al. 2019; Fernandes and Araujo 2016). In this paper, we critically examine the notion of a trade-off between economic gains and environmental damage, challenging the assumption that mining consistently leads to sustained regional economic development.

By focusing on observations at the municipality level, the study offers a more localised analysis compared to broader national-level assessments of mining's macroeconomic impacts. Moreover, we distinguish between industrial mining and informal mining ("garimpo"), highlighting how these two types of operations, which are provided for in Brazilian legislation, differ in their impacts. The econometric models employed utilise spatial panel data. We use land cover data based on satellite imagery from the MapBiomas project (MapBiomas 2023), which features mining observations, complemented by various socioeconomic and biophysical variables. In total, the compiled dataset covers yearly observations from 5,262 municipalities over the period from 2005 to 2020. The econometric approach employed allows for stronger causal inferences, as it accounts for a range of regional confounding factors as well as national macroeconomic trends to isolate the specific effects of mining. Additionally, the study incorporates a spatial weighting scheme to recognise that nearby observations are interrelated.

This approach is particularly useful for investigating cumulative impacts that stem from the transmission of impacts across space, revealing how both economic and environmental effects of mining extend beyond the municipalities where mining occurs. The assumption that mining's impacts transcend municipal borders is well-founded: economically, mining operations can create local employment and multiplier effects that benefit surrounding areas, while environmentally, impacts such as deforestation can spread for instance through the development of transport and energy infrastructure related to mining, which in turn makes remote areas more accessible for other human activities. This spatially sensitive analysis provides a fresh perspective on the broader regional consequences of mining, emphasising how both benefits and harms extend beyond the boundaries of the mining municipalities themselves.

Our findings reveal that the impacts of different mining types vary and are not uniform over time, reflecting the complexity of assessing cumulative mining effects. Industrial mining operations may generate short-term economic benefits, including positive spillovers to neighbouring areas. However, these economic gains are temporary and influenced by global commodity price fluctuations. The deforestation caused by mining is closely tied to the type of mining activities and the dual legal framework governing them in Brazil. Industrial mining is associated with lower rates of forest loss in neighbouring municipalities, whereas "garimpo" mining is linked to substantial deforestation. Striking a balance between forest conservation and economic development is crucial for achieving sustainability in extractive economies and their supply chains. However, our results suggest that the relationship between these two spheres is more intricate than a straightforward trade-off. While enhancing environmental responsibility is essential, particularly in the poorly regulated informal sector, mining does not guarantee sustained economic development. Although this paper focuses on localised impacts, it provides a basis for further research. The study contributes valuable quantitative evidence to inform political discourse, relevant not only for Brazil but also for resource-rich economies worldwide. However, broader global assessments may face significant limitations due to data availability challenges.

In the third article of this dissertation, titled **EU consumption's hidden link to global deforestation caused by mining**, we bridge the gap between local environmental impacts at mine sites and the consumption of goods and services in distant regions, particularly focusing on final demand in the European Union (EU). The study traces how environmental degradation, specifically deforestation driven by mining, is embodied in international supply chains and final demand, mainly through private and government consumption, and capital formation. Knowing how local impacts are tied to global consumption is particularly important given the rise of new supply chain laws, such as the recently adopted EU Corporate Sustainability Due Diligence Directive (CSDDD), which requires large companies to monitor and ensure sustainability throughout their supply chains (European Commission 2022). The directive is especially relevant to the supply chains of metals and minerals, as many world regions, including the EU, heavily depend on imports of these resources (European Commission 2020b). However, as previously noted, traceability of local mining impacts remains a challenge in a globalised economy.

This paper addresses key knowledge gaps, focusing specifically on the environmental impact of forest loss caused by mining. Mining has increasingly been recognised as a significant local driver of deforestation, along with associated issues such as biodiversity loss and social conflicts. These impacts extend not only within the immediate vicinity of mining sites but also affect surrounding regions, amplifying the environmental and social pressures on local ecosystems and communities (Pendrill et al. 2022; Sonter et al. 2017; Giljum et al. 2022; Ladewig et al. 2024). With satellite imagery offering clear evidence of forest cover changes, forest loss within mining areas provides a valuable case study for quantitatively assessing the environmental impacts embedded in the EU's final demand for goods and services. We utilise high-resolution satellite imagery to track forest cover changes (Hansen et al. 2013) within delineated mining areas (Maus et al. 2022). This allows us to compile annual records of forest loss due to mining across extraction sites globally between 2001 and 2019. Obtained data are then incorporated into a global trade model, which facilitates the linkage of deforestation at mining sites to final demand patterns in the EU. The combination of satellite-based deforestation mapping and economic modelling therefore enables a detailed assessment of how forest loss at mine sites is tied to consumption in distant markets.

Our findings reveal that 12% of the global forest loss caused by mining activities can be attributed to final demand in the EU, with the vast majority of these impacts occurring outside the EU's borders. This highlights the disproportionate burden placed on non-EU countries as a result of EU consumption patterns. We also observe considerable variation in the intensity of mining-related deforestation across different commodities, mining regions, and European industry sectors, which enables us to propose targeted strategies for policymakers and industries to mitigate the environmental impacts of resource consumption. These strategies not only outline pathways for the EU to adopt more environmentally responsible sourcing practices, but also address the implications for material suppliers. However, we also recognise limitations such as, while our analysis focuses on forest loss, mitigating deforestation could result in trade-offs with other environmental or social impacts. Moreover, our findings underscore the need for international cooperation to achieve global sustainability targets, as final demand in other major economies such as the USA, China, and India also contributes significantly to mining-related impacts.

Chapter 2

Surge in global metal mining threatens vulnerable ecosystems

Abstract: Mining activities induce profound changes to societies and the environment they inhabit. With global extraction of metal ores doubling over the past two decades, pressures related to mining have dramatically increased. In this paper, we explore where growing global metal extraction has particularly taken effect. Using fine-grain data, we investigate the spatial and temporal distribution of mining of nine metal ores (bauxite, copper, gold, iron, lead, manganese, nickel, silver and zinc) across approximately 3,000 sites of extraction worldwide between 2000 and 2019. To approach the related environmental implications, we intersect data of global mining with terrestrial biome categorisations, protected areas, and a water pressure index on the watershed-level. We find that 79% of global metal ore extraction in 2019 originated from five of the six most species-rich biomes, with mining volumes doubling since 2000 in tropical moist forest ecosystems. We also find that half of global metal ore extraction took place at 20 km or less from protected territories. Further, 90% of all considered extraction sites correspond to below-average relative water availability, with particularly copper and gold mining occurring at high rates in areas with significant water scarcity. Our study has far-reaching implications for future global and local policy and resource management responses to mitigate the negative effects of the expected expansion of metal mining.

2.1 Introduction

Mining plays an ambiguous role for society. It has become indispensable to the model of economic growth currently pursued in industrialised, mineral-based societies. But it is also among the most environmentally and socially hazardous human activities. Its harmful consequences for the environment and its catalysing association with social conflicts are well-documented (Scheidel et al. 2020; Conde 2017; Bebbington et al. 2008; Bridge 2004).

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Unprecedented and rapidly growing extraction of metals and minerals during the past two decades (Schandl et al. 2017; Schaffartzik et al. 2014b) and the projected increase in material demand (UN IRP 2019; OECD 2019) are alarming signs that associated impacts will intensify in the future.

The surge in global metal mining signifies an increased production of metal commodities through establishing new mining projects, physical expansion of existing sites and intensifying and optimising the extraction process. It is part of an overarching trajectory of globally increasing resource use, referred to as the Great Acceleration (Steffen et al. 2015), which is pushing the global economy's metabolism up against Planetary Boundaries (Rockström et al. 2009). Differences in growth dynamics of the extractive sector are apparent, with countries and regions unequally contributing to this global trajectory (Dorninger et al. 2021; Schaffartzik et al. 2016). Local mining expansion and intensified production, as well as related impacts in the immediate surroundings of the sites of extraction, are closely coupled to overarching global change, calling for a "multilevel perspective" (Gibson et al. 2000) to understand the environmental and social implications of mining's worldwide growth. By studying the local expressions of the global surge in mining in a spatially explicit manner, we seek to advance the empirical understanding and conceptual framing across levels of scale.

This paper presents and contextualises a detailed assessment of how metal mining volumes are distributed across almost 3,000 mining projects worldwide, covering nine metal ores (bauxite, copper, gold, iron, lead, manganese, nickel, silver and zinc) in the period 2000–2019. We explore whether the development of global metal mining has particularly affected vulnerable ecosystems around the world and identify hotspots of raw material extraction and ecosystem impact. We assume extraction gains to be associated with additional pressures, because production volumes are likely related to the areal extent of mining sites (Werner et al. 2020) and intensified use of heavy machinery. Based on our large-scale empirical assessment, we discuss the environmental implications of the expected increase in mining activities. We pave the way for in-depth local studies and future assessments of the cumulative magnitude and transmission of impacts, and summarise how mining companies and policies can contribute to impact mitigation.

In order to gauge the potential impact of mining on ecosystems, we focus on ecosystem vulnerability. Vulnerability has been debated in sustainability science under definitions such as "the degree to which a system, subsystem, or system component is likely to experience harm due to exposure to a hazard, either a perturbation or a stress/stressor" (Turner et al. 2003, p. 8074). In their extensive review, Weißhuhn et al. (2018) suggest the term ecosystem vulnerability as being preferable to ecological, environmental, or other notions of vulnerability and propose a framework with "exposure", "sensitivity", and "adaptive capacity" defining the degree of vulnerability. They stress that such a perspective on vulnerability is biocentric (Birkmann and Wisner 2006) rather than anthropocentric, because it understands environmental systems as being affected by natural and anthropogenic drivers, instead of being sources of hazards that influence human systems. In employing this concept in the context of intensified mining, we investigate whether the acknowledgement of ecosystem vulnerability deters extraction.

For the purposes of this paper, we assume that mining activities exert pressure on all ecosystems, but that certain areal characteristics can be identified which are considered to signal particular vulnerability. Our study uses three spatial layers as proxy indicators for ecosystem vulnerability: terrestrial biome categorisations, protected areas, and water scarcity. Subsequently, we connect these layers with spatio-temporal patterns of extraction at the mine level. In doing so, we combine approaches from previous work dealing with single environmental layers and their respective links to mining. Murguía et al. (2016) and Sonter et al. (2018) demonstrate how mining relates to biodiversity loss. Durán et al. (2013) find that metal mining activities undermine the role of protected areas as a key policy tool for conservation. Regarding an intersection of mining sites with water scarcity indicators, Northey et al. (2017) find that the exposure of areas to water risk is especially high in the case of copper mining. Recently, studies have also investigated the areal extent of mines, either based on estimations, such as Tost et al. (2020), or by the use of satellite imagery (Werner et al. 2020; Maus et al. 2020). These studies focus on cross-sectional analyses of a specific selection of metals, such as four key metals in Durán et al. (2013) or of the locations of base metal resources in Northey et al. (2017). Our study builds upon these approaches to provide the first fine-grained assessment of metal mining regions on a worldwide scale, covering nine major metal commodities across a 20-year period.

We find that the rapidly expanding mining sector exerts increasing pressures on ecosystems recognised as vulnerable. Our results show that there is a substantially skewed distribution in terms of extraction volumes, i.e. extraction per mine is not evenly distributed around a certain value, but a minority of mines reports much higher figures than the mass. Further, regional hotspots of mining growth have emerged during the observed time period, in particular in Latin America, Central Africa, India, and Western Australia. Due to the multilevel approach, our findings have substantial implications for future global and local policy responses, supporting calls for a stricter set of rules for accessing primary resources.

2.2 Material and methods

2.2.1 Mining data and environmental spatial layers

We utilised mine-specific production data from the SNL Metals and Mining Database[1] (SNL 2020). Projects were considered for which SNL reported any mining of bauxite, copper, gold, iron, lead, manganese, nickel, silver or zinc within the time period 2000–2019, in total summing up to 2,935 individual mines. Focusing on the 21st century obviously presents a limitation, but it allows to cover the entire period of what might be considered the "second great acceleration" (Görg et al. 2020) of resource use at the global level.

Except for bauxite, iron and manganese, which are listed as ores (gross weight), metal production is reported as metal content (net weight). In order to construct a homogeneous measure of extracted crude ore that is used as an input from the natural environment to the economic system, we applied country- and commodity-specific conversion factors from UNEP's Global Material Flow Database (UN IRP 2017a) to all net weight commodities. This measure, referred to as "extraction" or "metal ore" in the following, corresponds to the actual amount of extracted material exerting pressure on the environment instead of a

[1] This database, offered by Standard and Poor's (S&P) Market Intelligence, provides extensive operative and financial information on thousands of mining projects based on company reports.

final product after several processing steps.[2] Figure 2.1 provides a summary of the data and illustrates variations in extraction volumes and increasing extraction rates for the nine metal ores. For more detail, see Appendix A.1.

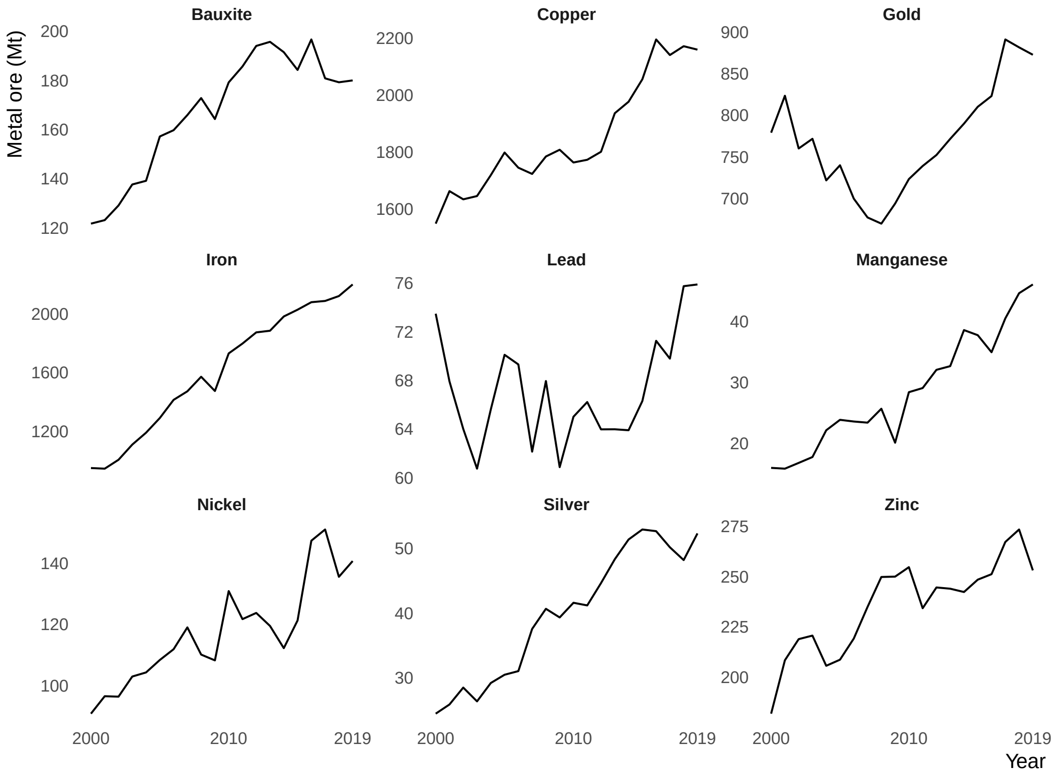

Figure 2.1: Global extraction of bauxite, copper, gold, iron, lead, manganese, nickel, silver and zinc ores based on SNL (2020) and UN IRP (2017) conversion factors. Please note the differences in scale on the y-axes. See Table A2 in the Appendix for underlying data.

We considered this set of base and precious metals in our study because of their extensive industrial use. Next to construction materials, coal and crude oil, iron, bauxite and copper ore feature the highest extracted mass among mineral resources (Murguía et al. 2016). Schaffartzik et al. (2016) name iron and aluminium (we consider bauxite) being quantitatively most important. Together with other metals in smaller amounts including lead, manganese and copper they form the "skeleton of industrial development" (ibid.: 103). Similar selections are made, for example, by Durán et al. (2013) and Northey et al. (2017), additionally including zinc and nickel. We furthermore consider the precious metals gold and silver, because of the high prevalence of such mining facilities (Murguía et al. 2016) and persistent exploration expenditure due to high market value (Ali et al. 2017). Other metals with growing demand, such as cobalt or rare earth metals, were not covered in our analysis as they were poorly reported in the database at hand.

We are aware that assuming national averages as ore grades introduces uncertainty in the data. As a validation of coverage and quality, we compared annual metal extraction accord-

[2]Waste rock is excluded because this information is not yet available for global analyses, but it would be extremely valuable to researchers and policy makers. We expect that an inclusion of over- and interburden might allow for a better approximation of the potential disruption to the local system.

ing to our dataset (based on reports of production from individual mines) with official UNEP IRP statistics (based on national accounts). In the Appendix (Figure A1), we demonstrate that our extraction data provides reliable coverage, mimicking extraction trends reported by other sources. Largest gaps between our modified SNL aggregates and UNEP IRP figures occur because of country-level irregularities, most notably regarding China. For the case of iron, approximately 1,500 Megatonnes (Mt) of Chinese iron ore extraction in 2017 is missing in the SNL data compared to UNEP IRP. Moreover, we illustrate that assumptions about ore grades influence extraction estimates for individual mines (Table A3, Figures A2 and A3). For comparison, we considered copper mines of four countries and mine-specific ore grades available from Mudd and Jowitt (2018). The exercise suggests that assumed national averages are conservative, as they rather lead to under-estimating extraction, and that estimates from both approaches correlate well. However, we must also note that we found substantial deviations for some extraction countries, such as Peru, where estimates of the considered sample sum up to 350 Mt when utilising individual ore grades while they only amount to 90 Mt using the UNEP average grade.

Difficulties to fully consider artisanal and informal mining on a global scale impose a limitation, again suggesting that the data we used represent under- rather than over-estimations of material extraction. The environmental pressures related to small-scale mining will be at least as strong and possibly farther-reaching compared to larger mines considered in our study (Asner et al. 2013; Caballero Espejo et al. 2018).

Exposure to environmental complexity was assessed by spatially intersecting extraction data with terrestrial biome categorisations (accessed from Resolve 2017 based on Dinerstein et al. 2017). Biomes are defined as communities of plants and animals occurring together under certain climate conditions (Resolve 2017). They systematically subsume the richness of an area's ecosystem in terms of variety in and number of species. As another proxy for anthropocentrically recognised rich, special, or endangered biodiversity, we considered a spatial layer on protected areas (UNEP-WCMC and IUCN 2020). We calculated the distance to the closest protected area for each mine. Third, we considered the Available Water Remaining (AWARE) index (WULCA 2019) as an indicator for water risk exposure (annual average at watershed level). It represents water availability after the demand of ecosystems and humans is met. While a variety of spatial water indices exists with each providing a somewhat different perspective on the interactions between water resources and mining (Northey et al. 2017), we chose this index for two main reasons. First, it provides spatial coverage for the entire set of considered mines except for Nalunaq mine in Greenland. Second, the AWARE index was designed to reflect potential water deprivation by other users of water – a suitable indicator given that mines utilise water in a number of processes. The index further features a convenient interpretation: It is limited between 0.1 and 100, where 1 corresponds to the world average and 10, for instance, represents water availability that is ten times less than the world average.

2.2.2 Approaches to analysing global distribution and extraction trends

We implemented three analytical steps in order to evaluate the surge in global metal mining between the years 2000 and 2019. We first assessed annual spatial distribution and concentration of global metal ore extraction. Second, we performed spatial overlay analyses to determine the extent to which increased production particularly occurs in recognisably sensitive areas with regard to species richness, need of protection, and water availability. In doing so, we also addressed differences in extraction patterns across the nine commodities. Third, to detect the most critical developments and based on our findings from the layer analyses, we performed an assessment of hotspots among the three environmental layers. An illustration of our workflow is provided in Figure 2.2.

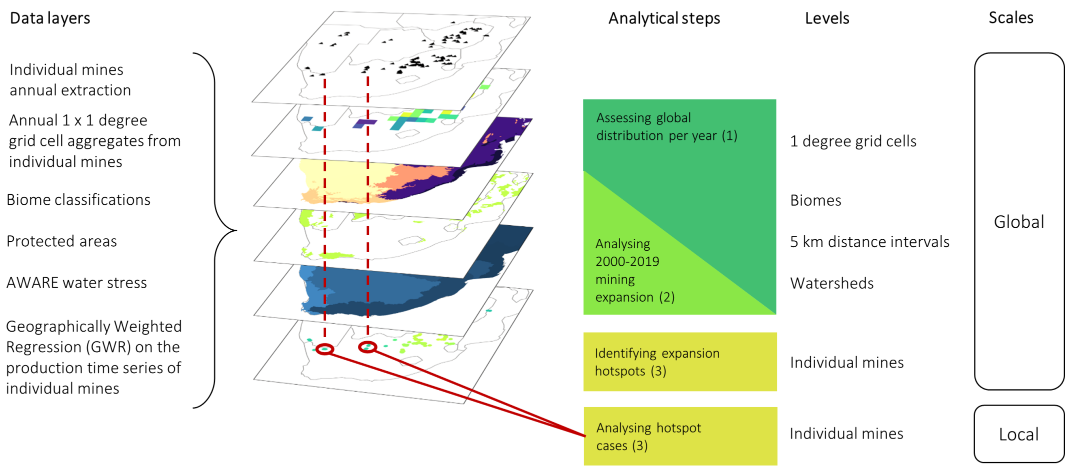

Figure 2.2: Workflow of this study, highlighting utilised spatial data, analytical steps 1–3, and respective operational level and scale of each stage. Dashed red lines represent links across layers, and solid red lines indicate syntheses of information.

To facilitate visual interpretation, we aggregated annual metal mining into 1×1 degree cells (corresponding to approximately 110 km at the equator) by summing up the total ore extraction across all nine metals. This simplification serves as an initial, high-level picture of the spatial distribution of global metal ore extraction. It cannot point out potential environmental impacts that occur in direct and up to only a few km proximity to mines, nor does it reflect the actual number and specifics of mining projects such as type and scale within each grid cell. However, recent studies show that assuming biodiversity (Sonter et al. 2020) and deforestation (Sonter et al. 2017) effects within at least a 50 km wide radius around mines is reasonable, and hence the map provides a first estimate of potentially negatively affected areas and indicates the corresponding extraction volumes (for a more conservative grid of 0.5 and 0.1 degrees see Figures A5 and A6 in the Appendix). In order to intersect mining activities with regional environmental structure, we overlaid all mine sites with the three different spatial layers mentioned above and aggregated annual extraction volumes into the respective layer categories.

Trends in the extraction volumes were estimated employing a geographically weighted regression (GWR) model, modelling log-transformed extraction at the mine level as a function of time (see Appendix A.2 and Brunsdon et al. (1996) for more detail regarding GWR). GWR captures the spatial structure within the data and yields spatially varying parameter estimates. In contrast to estimating a trend for each single spatial observation, GWR incorporates the information of surrounding mines weighted by geographical distance and hence reflects potential compound effects of mining on the environment in areas where multiple sites are close to each other. Extractive industries can have different relationships across regions such as networks of mines expanding in emerging mining regions, regional boosts in investment and new technologies or multiple mines being closed in certain areas as a consequence of decreased (economic) feasibility of mining. While the GWR approach makes it possible to depict sub-national densification clusters by reflecting heterogeneity within countries, it comes at the cost that it smooths over individual outlier cases within the clusters (using spatial weights assigned to proximate mining projects) that might also have critical impacts on the environment.

2.3 Results

The main findings of our study include global spatially explicit extraction volumes, the distribution of mining sites, and their intersection with terrestrial biomes, distance to protected areas and water risk classifications over the period 2000–2019. We also identify particular hotspots of mining intensification and expansion.

2.3.1 Spatial distribution of metal mining

Relative to the total earth surface, only a small area is used for mining. In a recent paper, Maus et al. 2020 estimated the global mining area at around 57,300 km^2, approximately the size of Croatia or Togo. In Figure 2.3, we show all mining activities projected into 1×1 degree cells.[3] Among the mining cells, we observe strong heterogeneity regarding extraction volumes and a highly skewed distribution, i.e. a small fraction of mining areas reporting very large extraction volumes and vice versa. For 2019, about 95% of all mining areas indicate less than 25 Mt and half of the observations less than 1.3 Mt of extraction per cell, while a small fraction of cells yields extraction of up to 279 Mt.

Mining activities are spatially concentrated in Western Australia, Southern Africa, and along the Andes and into the Central and North American ranges of the American Cordillera. Furthermore, we find significant activities in Brazil, West Africa, India, China and Southeast and Central Asia. For China, we observe a considerable number of mining sites, but we also find that almost 80% of the observed cells show extraction volumes not larger than 2 Mt. Maus et al. (2020) also highlight that mining in China is characterised by many – on average smaller – mining areas, while Australia reaches a comparable total areal extent with fewer, but larger mining sites. Certain clusters appear in strong concentrations within countries, such as in Brazil or along the Zambian and Congolese border. This fact is vital to consider for the discourse about mining and its impacts, as well as for global material flow analyses. Sizeable copper flows, for example, originate from the DR Congo, with extraction occurring only in a few mines in the very south of the country. Likewise, in Brazil, 90% of all iron ore extracted in 2019 can be attributed to only ten mining sites within the states of Pará and Minas Gerais.

The unequal distribution of extraction intensity across all mining regions shows a similar pattern across commodities, but on different scales regarding volumes, the number of mining regions and the degree of concentration. For more detail, see Figure A7 in the Appendix,

[3] 2000, 2010, 2015 and 2019 maps separate by metal are available in Appendix A.3. For an evaluation of how the counts of mining cells have changed per commodity, see Figure A4.

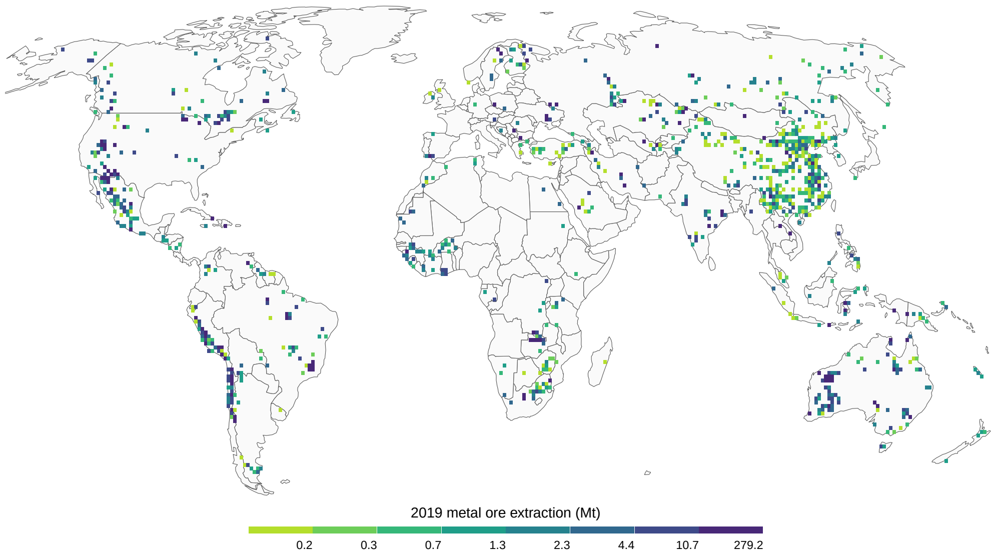

Figure 2.3: Global 2019 metal ore extraction (in Mt) grouped by 8 quantiles on a 1 degree resolution (i.e. about $110\,km \times 110\,km$ at the equator) using a Robinson map projection. Based on SNL (2020) and UN IRP (2017) conversion factors.

where we resampled extraction data to 0.25 degree resolution and ordered the cells by their extraction volumes for all nine metals.

In Figures 2.4A-C, we map the three environmental layers and indicate how mining sites are distributed across them. With regard to terrestrial biome classifications, most mines are located in temperate broadleaf & mixed forests (627 observations), tropical & subtropical moist broadleaf forests (594) and deserts & xeric shrublands (448), while only 39 sites lie in the tundra biome. The histogram in 2.4B illustrates that 92% of all mines are located within a distance of 250 km to a protected area. More than a third of the 2,935 mines are in a range of 20 km, and 4.2% of all mining sites (i.e. 123 mines) are located within designated protected territories. Lastly, we detect that, on the one hand, only 280 mines, i.e. 9.5% of our full sample, are located in watersheds of above-average water availability. On the other hand, 13% of mines lie within areas of an index score higher than 60 (corresponds to 4.1 on the figure's logarithmic scale), i.e. within high water risk regions such as various Central and Eastern Asian deserts, the Chihuahuan Desert, and Southeast Australian temperate forests and savannas.

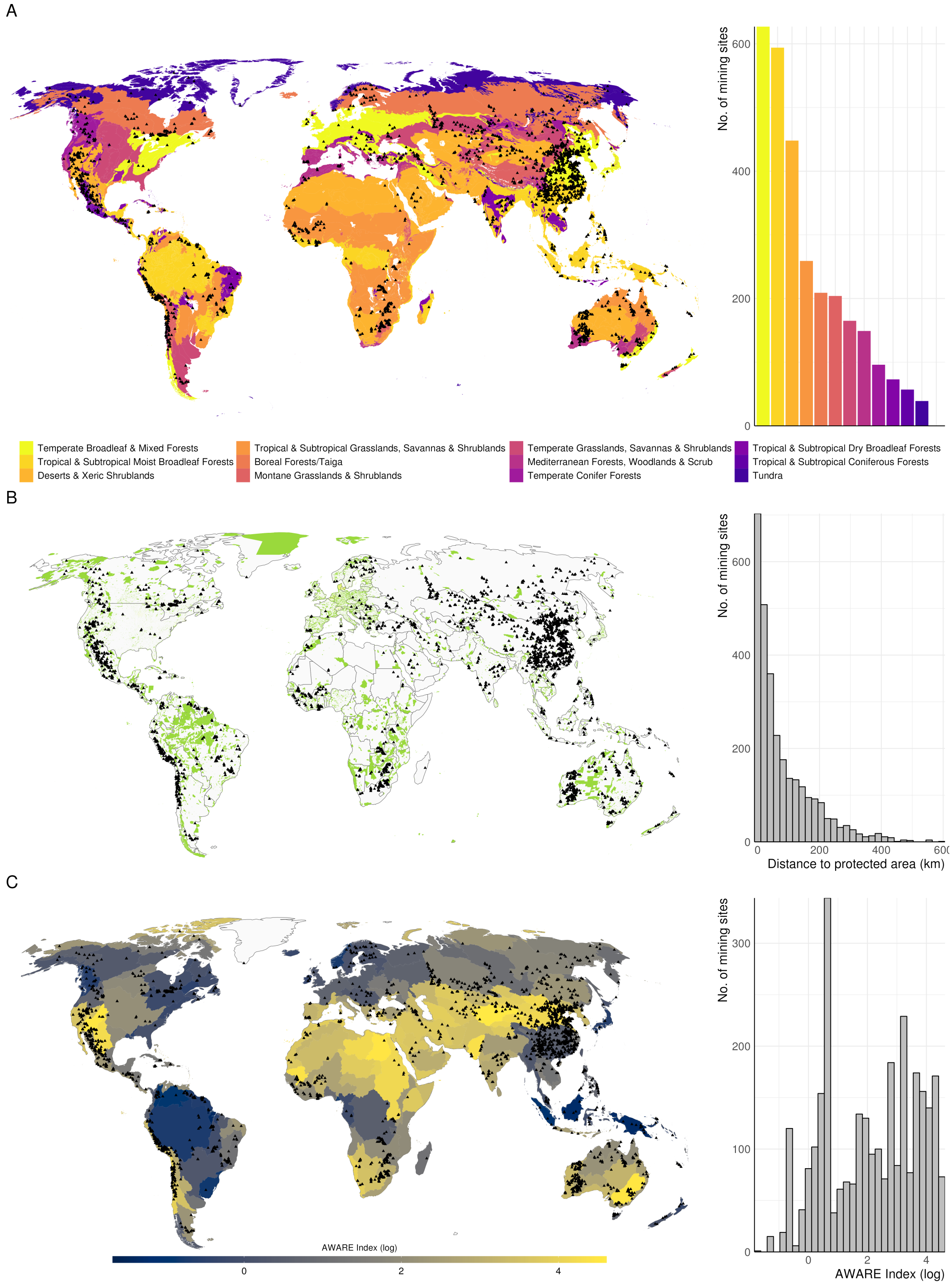

Figure 2.4: Mining sites considered in this study (based on SNL 2020) and their distribution across terrestrial biomes (based on Resolve 2017, **A**), protected areas (based on UNEP-WCMC and IUCN 2020, **B**), and AWARE water stress index classifications (log-transformed, based on WULCA 2019, **C**) using Robinson map projections.

2.3.2 Surge in global metal mining in environmentally vulnerable regions

Having explored the uneven distribution of mining activities across the globe, we evaluated the intensification and expansion of mining against the backdrop of perceivable regional vulnerability to the harmful consequences of extractive practices. Figure 2.5 illustrates how extraction volumes have developed in relation to the regional characteristics of the area in which they occur. It is important to note that "regional" in this sense refers to a wider understanding than specific localised features in the immediate surroundings of mines. Heterogeneity in space that occurs at more granular levels is not assessed here. Not only extraction volumes (see Section 2.3.1) but also biomes exhibit notable variation in size: the Mediterranean forests, woodlands & scrub biome extends over only 1.5% of global land surface while boreal forests/taiga are the largest biome covering 12%. We hence evaluated both absolute numbers (left panels in Figure 2.5; in Mt) and relative trends (right panels; using 2000 as the base year) for the three spatial layers.

Figure 2.5A shows that, in absolute values, deserts and xeric shrublands (DesXS) were the most exploited terrestrial biome during the past twenty years. In 2019, 2,241 Mt of metal ores were mined there, followed by tropical and subtropical moist broadleaf forests (TropSubMBF, 911 Mt) and temperate broadleaf and mixed forests (TempBMF, 614 Mt). Upon ranking all biomes according to their richness in species[4], we find that five of the six most complex terrestrial biomes jointly were the origin of 79% of total metal ore extracted in 2019. Next to the three biomes mentioned above, these five include montane grasslands and shrublands (MontGS) and tropical and subtropical grasslands, savannas and shrublands (TropSubGSS). While this pattern has not altered over the past twenty years and the ranking across biomes remained mostly unchanged since 2000, we see that extraction has changed in relative terms within biomes. The right panel of Figure 2.5A shows that mining has intensified over time in all biomes except temperate conifer forests (TempCF) and MontGS. In TropSubMBF, the biome richest in species, metal ore extraction has increased by a factor of 2.1, due to, among others, the expansion of mining activities in the Central Range Papuan montane rain forests (New Guinea), the North Western Ghats moist deciduous forests and the Malabar Coast moist forests (India), and the Borneo lowland rain forests (Indonesia).

Nature reserves are a political instrument for protecting specific territories from anthropogenic environmental destruction. However, it is likely that the designation of conservation areas also accounts for current and potential future minerals extraction in some countries. As a second spatial layer, we examined the proximity of mining activities to protected areas. Figure 2.5B depicts global extraction up to 50 km from such areas. In 2019, 50% of all global metal ore extraction took place within a 20 km boundary around protected territories, and 480 Mt (8%) were mined within officially protected zones. Similar to mining within biomes, we find that this is a pattern that has not changed fundamentally since 2000. But it has intensified. While the high concentration of metal ore extraction within a buffer of 20 km around protected areas appears to be a stable finding for the period considered in our study, it is the mining *within* protected areas that surged. Over the twenty-year period, mining in protected areas has risen from 225 Mt to 480 Mt, a 113% increase. Further, the figure

[4]We based the ranking on the Millennium Ecosystem Assessment (2005), where species richness (the number of species in a given area) is referred to as the most common measure of biodiversity.

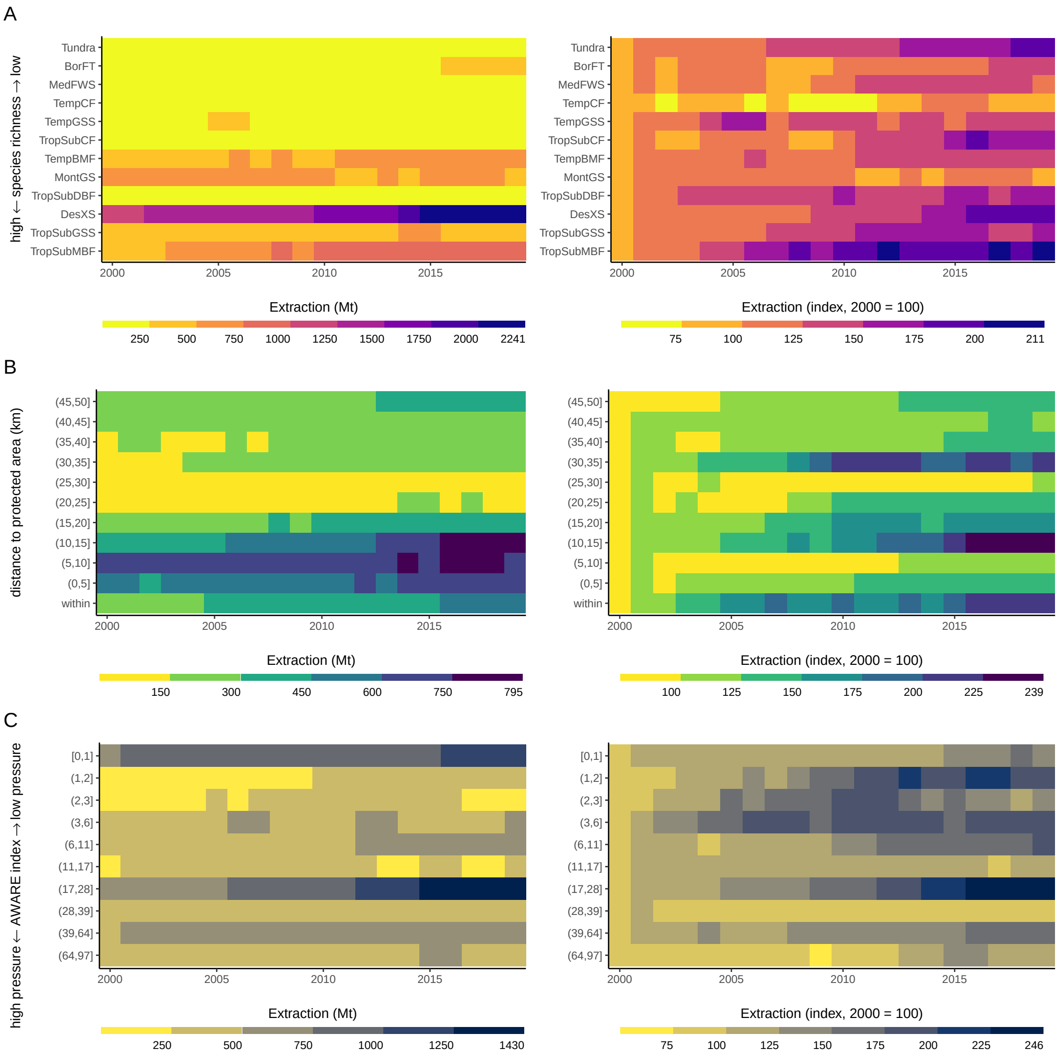

Figure 2.5: Total (left) and relative (right) extraction volumes within biome classifications (**A**), 5 km proximity buffers to protected areas (**B**), and available water remaining (AWARE) decile intervals (**C**); 2000–2019; based on SNL (2020) and UN IRP (2017) conversion factors.

suggests that there was a significant surge in mining in the 10-15 km range from protected areas.

The large increase of mining activities in protected areas is partly explained by new sites. Over the full period analysed in this study, 123 mines were detected within protected zones. The number of mining sites in such zones increased from 55 in 2000 to a peak of 96 in 2012 and since then oscillated between 80 and 90. One prominent example of a new project within a protected area is the expansion of mining in the Carajás National Forest in the state of Pará, Brazil, located in the Xingu-Tocantins-Araguaia moist forests ecosystem. In 2016, the Brazilian multinational corporation Vale opened the Serra Sul (also known as S11D) mine as the largest project in the company's history (Vale 2016). In 2019, 73 Mt of iron ore were mined at this site. Other mines within the area, which was declared national forest of the state Pará in 1998, have already existed longer, yet increased their extraction significantly at the beginning of the 21st century. For example, the N5 iron ore mine increased its production from 11 Mt in 2001 to 54 Mt in 2013 and the N4W mine from 15 Mt in 2001 to almost 40 Mt in 2012.

Some mines are not located within, but directly border on protected areas. The Indonesian Grasberg copper and gold mine, one of the world's largest mining projects, is such an example. Its concession area immediately neighbours Lorentz National Park, designated World Heritage Site in 1999. The mine is related to the pollution of rivers and lakes in that area due to riverine tailings disposal (Martinez-Alier 2001). Lorentz National Park is the largest national park in South-East Asia. It has an outstanding biodiversity and comprises a number of fragile ecosystems, such as subalpine areas, tropical rainforest, and mangroves (UNESCO 2020).

Supporting the choice of terrestrial biomes as one category indicating ecologically complex and vulnerable regions, nine out of the ten largest extraction projects that lie within protected areas (identified by accumulated mined volumes) are located in TropSubMBF or TropSubGSS. Only the Grasberg mine in Indonesia belongs to the MontGS biome. Eight of these nine mines in tropical regions are located in Brazil (seven of which are iron ore mines and one is a bauxite mine).

The third layer intersection was conducted with regard to water stress, using the normalised AWARE index with a score of 1 representing the available water remaining in a watershed as corresponding to world average and scores above 1 corresponding to less water availability relative to the global average. Figure 2.5C illustrates annual extraction in Mt at the AWARE decile level. While in 2019, 1,080 Mt (18 %) of metal ore were extracted in the decile with high relative water availability, i.e. watersheds with an AWARE score smaller or equal to 1, 90% of all considered extraction sites are located within watersheds that have below-average relative water availability. Considering that the consumption-weighted average AWARE index is 43, meaning that the majority of economic activity and water consumption affects regions where the index exceeds 1, we find that 1,034 Mt (17 %) were extracted in watersheds with an AWARE score higher than this weighted average. In the most critical category, the 64 to 97 decile, 472 Mt were mined in 2019, of which approximately one third was mined in the Chihuahuan desert in Mexico and the United States. Largest extraction volumes and highest growth rates are measured for watersheds with AWARE scores between 17 and 28. These include major mining hubs such as the Escondida copper mine in the Chilean Atacama desert, iron ore production in the Australian Pilbara shrublands, and copper mining in the Kazakh semi-desert.

2.3.3 Differences across metal types

We next highlight differences across metals in Figure 2.6. From top to bottom, this figure depicts the environmental layers and from left to right, it represents the nine metals considered in this study. We illustrate how the composition of extraction volumes per metal has developed between 2000 and 2019. Regarding biomes (2.6A), the five categories with highest species richness – TropSubMBF, TropSubGSS, DesXS, tropical and subtropical dry broadleaf forests (TropSubDBF) and MontGS – are separately shown while all other biome categories are aggregated as "other". Charts in 2.6B show distance to protected areas in incremental steps of 5 km each up to 20 km proximity and remaining sites grouped into a residual category. In 2.6C, AWARE index categorisations are depicted. We stress the five most critical water scarcity deciles and subsume the other half of all observations under AWARE scores between 0 and 10.7. Note that the levels of extraction volumes differ widely, with iron, copper and gold ore being mined in the largest amounts.

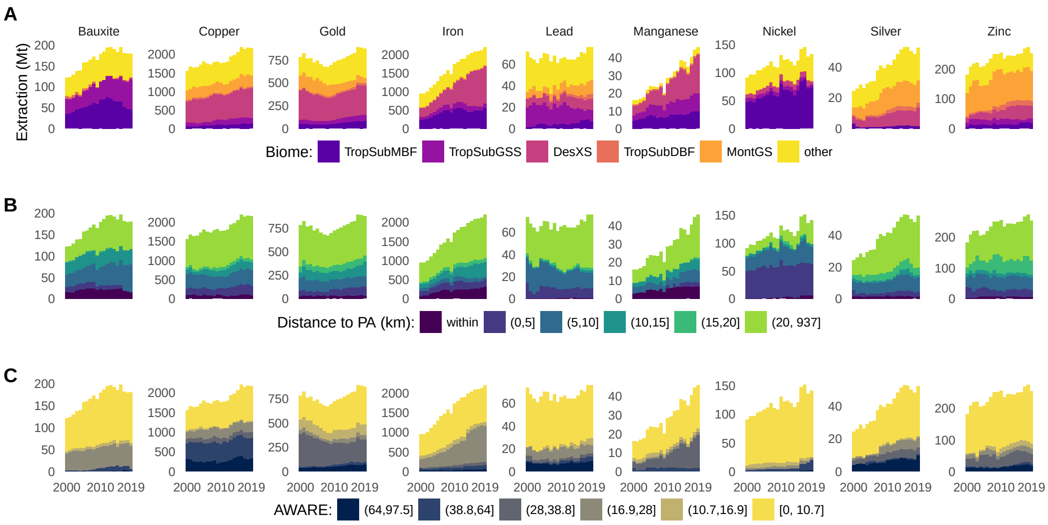

Figure 2.6: Extraction volumes by commodity and selected biomes (**A**), distance to protected area (**B**), and AWARE index (**C**); 2000–2019; based on SNL (2020) and UN IRP (2017) conversion factors.

Highest increases in global extraction are reported for iron and manganese ores. In 2019, more than 75% of iron ore were mined either in TropSubMBF, TropSubGSS or DesXS biomes. This share has grown since 2000, when 60% were mined in these three categories, mostly (but not only) because of extraction gains in DesXS. Manganese, which is predominantly used as an input for steel production, reaches an even higher share of production stemming from these critical biomes of about 90%. This proportion has not significantly changed since 2000, but absolute volumes have risen from 16 Mt in 2000 to 46 Mt in 2019. Furthermore, similar to iron ore and bauxite, manganese ore is, to a notable extent, mined within protected areas. A prominent example are manganese mining operations at Groote Eylandt: Australia's fourth-largest island is entirely part of Anindilyakwa Indigenous Protected Area. Extraction volumes at Groote Eylandt have more than quadrupled between 2000 and 2019, and in 2019, the mine extracted about three quarters of Australian manganese ores.

Besides bauxite, iron, and manganese, nickel ores are most notably mined in TropSubMBF. While bauxite mining decreased in TropSubMBF from 76 Mt in 2012 to 45 Mt in 2019, and shifted to TropSubGSS (49 Mt in 2012 and 72 Mt in 2019), the mining of nickel ores in TropSubMBF has been increasing during the past two decades. In 2019, about 55% of global nickel ore extraction took place in the species-richest tropical biome, 66% of which can be attributed to only two mining sites in the Indonesian Sulawesi lowland rain forests, Sorowako and Pomalaa. Sulawesi island has been suffering from massive deforestation in recent decades, with nickel mining known as one among several significant drivers (Supriatna et al. 2020). In addition, nickel mining is almost entirely conducted within a 20 km distance to protected areas, and about half of all ore is extracted at 5 km or less from protected areas. However, in contrast to bauxite and iron ore mining, nickel is hardly mined *within* protected areas.

The world's largest copper and gold deposits are located in DesXS, and hence large mining projects are located in this biome, such as Escondida and Chuquicamata in Chile, or Morenci and Bingham Canyon mines in the USA. The fact that copper and gold ores are predominantly mined in desert ecosystems is reflected by water pressure indicators, as becomes evident in Figure 2.6C. Approximately 40% of all copper ore is mined inside the two highest AWARE deciles. While gold ore extraction shows a decreasing trend in the third highest decile of scores around 30, iron ore extraction substantially increased for regions with AWARE scores between 17 and 28. These include several Australian iron ore mines located in the Pilbara shrublands, such as Hope Downs, the Sino-Iron project, and Roy Hill, which may have significant impact on groundwater and surface water in that area (WA Government 2009). Nickel mining tends to affect mostly areas with low AWARE scores. However, we also notice a rapid increase in the second decile since 2016.

2.3.4 Regional hotspots

One of the innovations of our study is to show regional mining patterns over time based on spatially explicit accounts of metal ore extraction. In order to estimate regional trends, we conducted a GWR analysis. As noted in Section 2.2.2, the framework of a GWR considers both reported volumes for each mine and volumes for respective neighbouring mining sites, with more weight given to closer operations. We hence obtained trend estimates for each mining location not only accounting for the mine itself, but also for surrounding activities, enabling us to provide an overview of the trends across agglomerations of mining projects. In Figure 2.7, we present all positive 2000–2019 trend estimates for total metal ore extraction. We limit results shown on the map to only positive coefficients in order to highlight hotspots of increased production, the focus of this study. A map including negative GWR trend coefficients and metal-specific maps are provided in Appendix A.2. Table 2.1 lists selected hotspots with their respective GWR coefficients, biome, distance to the nearest protected area, AWARE score, and average annual extraction.

On the one hand, GWR results reveal global hotspots of densification, i.e. positive trend coefficients for mining regions where extraction volumes have on average increased. We find positive coefficients for 1272 site observations. The regions with the highest extraction growth rates (between 7% and 10% per year) are located in mining clusters in Peru, the DR Congo, Zambia, India, China, and in Western Australia. Highest average annual growth is reported for iron ore and bauxite sites in Odisha, Eastern India. On the other hand, 1659 site observations yield negative trend coefficients and can therefore be interpreted as regions with decelerating extraction. In the following, we highlight some examples, connecting to other findings from the previous sections.

Countries along the Andean Range tend to be strongly involved with mining. For Peru, we can identify mining intensification in the south of the country, whereas extraction volumes on average decreased in the north. The densification hotspots are represented in Table 2.1 by the example of the five mines with highest growth coefficients inside Peru. They are located in the Central Andean puna and Sechura desert ecoregions, and lie within areas reaching a particularly high AWARE score of 28.27. Significant mining intensification at

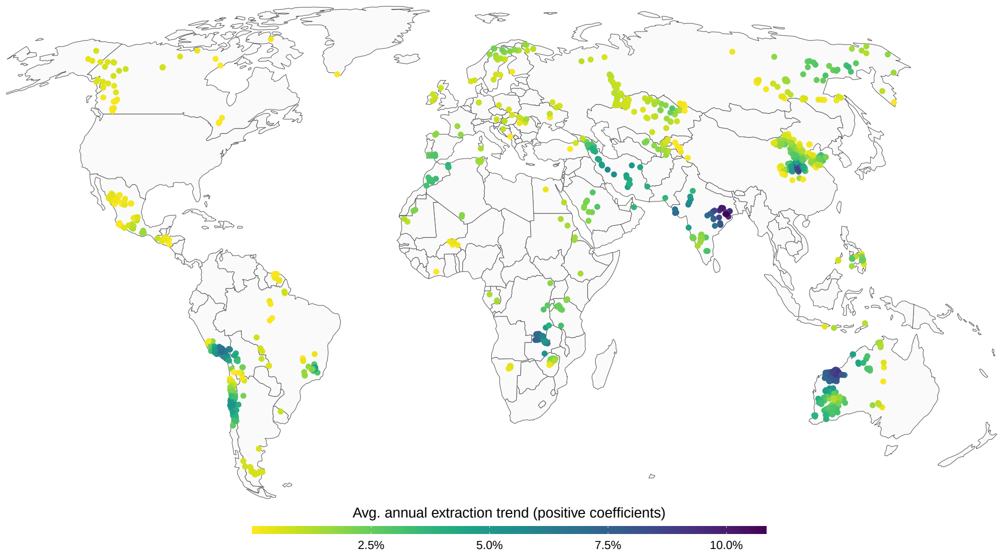

Figure 2.7: Mining sites with positive trends in metal ore extraction between 2000 and 2019. The linear coefficients were estimated for each mining location using GWR. The map is a Robinson projection. Based on SNL (2020) and UN IRP (2017) conversion factors. Technical notes on GWR are provided in Appendix A.2.

these hotspots is cause for concern because Peruvian regions suffering from water scarcity are shown to be particularly vulnerable to ecological distribution conflicts related to mining and water competition (Salem et al. 2018; Bebbington and Williams 2008).

For Brazil, we find substantial extraction growth in the state of Minas Gerais (up to 5% p.a.), while mining regions outside Minas Gerais stagnated on average. Four out of the five Brazilian mines with the highest growth coefficients are located no farther than 5 km away from natural reserves (e.g. Serra do Gandarela National Park). Furthermore, many projects of that hotspot are large-scale and situated in species-rich tropical biomes. One of the most serious threats to the environment and people in that region are tailings dam failures of large mining projects. Vale's Mina Córrego do Feijão, for example, gained notoriety due to the dam disaster near the municipality of Brumadinho in January 2019, releasing around 12 million cubic meters of tailings and killing at least 259 people (Freitas and Almeida 2020). Brazil has hundreds of such tailings dams, most of them in the state of Minas Gerais (do Carmo et al. 2017). Brucutu mine, extracting almost 18,000 Mt ore per year on average and with an average extraction intensification of 5.2%, is such an example, and it is located in proximity to the previous tailings dam failure. In 2019, as a response to the Brumadinho dam disaster, disposal of tailings at the Laranjeiras dam, part of Brucutu mine, was temporarily suspended due to safety concerns. In November 2015, Minas Gerais had already experienced a major environmental accident, when two dams at Samarco minining complex (4.9% average annual extraction expansion) collapsed, causing 19 casualties and far-reaching contamination of rivers, eventually spreading pollutants over more than 600 km (do Carmo et al. 2017).

With average annual growth rates of approximately 7%, the strongest intensification of mining activities in Africa is found in the border region between Zambia and the DR Congo, known as the Central African Copperbelt. The highly mineralised region lies in the

Country	Mine	β [%]	Biome	Dist. PA [km]	AWARE	μ [kt]
Peru	Ares	7.27	Montane Grasslands & Shrublands	19.80	28.27	1529.51
	Santa Rosa	7.19	Deserts & Xeric Shrublands	20.18		95.54
	Orcopampa	7.18	Deserts & Xeric Shrublands	21.52		2639.23
	Arcata	7.11	Montane Grasslands & Shrublands	4.89		729.17
	Shila-Paula	7.08	Montane Grasslands & Shrublands	53.93		295.81
Brazil	Brucutu	5.22	Trop. & Subtrop. Moist Broadleaf Forests	14.69	3.14	17958.33
	Sao Bento	5.12	Trop. & Subtrop. Moist Broadleaf Forests	4.08		367.65
	Gongo Soco	5.05	Trop. & Subtrop. Moist Broadleaf Forests	1.49		5464.29
	Samarco	4.87	Trop. & Subtrop. Grasslands, Savannas & Shrublands	1.92		17827.88
	Alegria	4.84	Trop. & Subtrop. Grasslands, Savannas & Shrublands	3.05		12720.52
DR Congo	Kamoto	7.21	Trop. & Subtrop. Grasslands, Savannas & Shrublands	18.15	1.67	2762.92
	Metalkol RTR	7.21		22.47		1846.24
	Mutoshi	7.20		33.32		248.28
	Kolwezi	7.20		24.66		1359.43
	Tilwizembe	7.16		48.99		48.87
Zambia	Trident - Sentinel	7.42	Trop. & Subtrop. Grasslands, Savannas & Shrublands	5.22	7.43	16301.33
	Lumwana	7.16		0.00		10431.14
	Kansanshi	6.85		10.77		21100.96
	Muliashi North	5.80		5.72		3224.72
	Baluba	5.78		4.50		1621.13
India	Malangtoli	10.83	Trop. & Subtrop. Moist Broadleaf Forests	59.15	16.90	573.33
	Silijora-Kalimati	10.71		50.01		87.10
	Unchabali	10.70		45.90		1284.75
	Dubna	10.62		50.85		11.86
	Khondbond	10.62		44.61		748.19
Australia	Spinifex Ridge	9.14	Deserts & Xeric Shrublands	88.89	27.19	765.14
	Corunna Downs	9.13		120.61		512.00
	Bamboo Creek	9.11		79.34		5.12
	Nullagine	9.06		147.96		1155.92
	Mt Webber DSO	8.97		78.24		3783.89

Table 2.1: Mines selected by highest five coefficients (β) from GWR (average growth p.a.) per hotspot country. Dist. PA indicates distance to nearest protected area, μ indicates average annual ore extraction based on SNL (2020) and UN IRP (2017) conversion factors. Empty cells in biome and AWARE column indicate constant characteristic for all five mines.

TropSubGSS biome, more precisely the Central Zambezian miombo woodlands. It is known for its vast copper deposits, but is also the habitat for a great variety of wildlife such as large mammals. The adverse effects of mining expansion in the Copperbelt, especially on forests and forest livelihoods, are evident. Moving millions of tonnes of earth, industrial copper mining has directly and indirectly caused significant environmental change due to extensive forest clearings, pollution of soil, air and water, and population pull effects of mining towns (Mwitwa et al. 2012; Peša 2020). Our results show that Zambian mining hotspots are located in particularly close proximity to protected areas. Moreover, Lumwana mine with an average annual growth coefficient of 7.16% lies partly within Acres No. 105 National Forest.

The SNL (2020) data supports that metal mining has become a major industry in India. Growth rates of metal ore extraction such as bauxite and iron ore are exceptionally high in the eastern territories and the northwest. Yet, GWR results stress substantial extraction growth for some of the country's less prominent (and smaller in size) mining projects. While India's largest projects, such as the Chhattisgarh Group, Sesa Goa, and Noamundi iron mine, extract between 15 Mt and 25 Mt of metal ore per year (and results yield coefficients between 2% and 9%), average annual ore extraction for the mines listed in Table 2.1 lies between 0.01 and 1.3 Mt. Extraction volumes of these iron ore and bauxite sites, however, grow at remarkably swift rates of about 10%, i.e. the highest rates observed globally. They are located in the tropical East Deccan moist deciduous forests, which offer a spacious and rich habitat for a great number of species, including endangered large vertebrates (Wikramanayake et al. 2002). Extensive extraction gains in this area, as they are observed, hence endanger conservation of a still-intact habitat.

In the Global North, trend estimates for mines located in the Unites States and eastern Canada indicate an average decline of mining activities, while slight intensification is found for the Canadian Rocky Mountains. For Europe, we find almost entirely positive trend coefficients, indicating growing metal extraction volumes within Europe, although at generally low levels of absolute extraction. A geographical divide is apparent in Australia. Large iron ore sites in Western Australia are the drivers for intensification rates up to almost 10% and make the region a global hotspot, while sites across the eastern half of the continent show an average decline by about 2.5% per year. Highest coefficients are reported for mines in Pilbara, which hosts some of the world's largest iron ore mines. Among others, Mount Webber direct shipping iron ore mine is located at that hotspot, with a growth coefficient of almost 9%. The large mining complex, opened in 2014, continuously increased annual extraction volumes and mined more than 7 Mt of ore in 2019. Australian mining activities also demonstrate that the movement of vast amounts of earth not only causes pollution and degradation of ecosystems and loss of biodiversity, but also destroys cultural and spiritual heritage. The mining expansion in Pilbara, for example, disturbs significant Indigenous sites. In May 2020, Anglo-Australian multinational Rio Tinto was blamed for destroying the Aboriginal heritage of 46,000 year old Juukan Gorge rock shelters in order to expand Brockman 4 mine (EJatlas 2020).

2.4 Discussion

2.4.1 Mining's socio-ecological impacts

In contrast to other frameworks that conceptualise the socio-ecological crisis and possible responses at high levels of aggregation and abstraction (e.g. Rockström et al. 2009), our results demonstrate concretely *where*, from 2000 to 2019, the surge in global mining has been implemented. What we demonstrate in particular is that increased production occurs to a large extent in areas requiring protection. Almost 80% of global metal extraction in 2019 occurred in the world's most species-rich biomes, 90% of mining sites were in areas of relative water scarcity, and almost 50% of extraction occurred at less than 20 km distance or even within protected areas. By highlighting that these are especially vulnerable areas, it is not our intention to suggest that mining should be expanding "elsewhere", in areas that are supposedly less vulnerable. Instead, we interpret the degree to which mining occurred in areas that – by indirect or direct stipulation - *should* be protected to demonstrate the environmental unsustainability of the current mode of expansion.

The findings of this paper compare well with previous, often cross-sectional, studies, while contributing to the literature by offering annual estimates and trends for the nine metals at hand. Northey et al. (2017), for example, also find highest average AWARE scores for copper, medium water risks for lead-zinc resources, and nickel to be mined predominantly in areas that are exposed to less water risks. While the shares of copper, lead and zinc mining in critical categories are stable, we do, however, detect a recent surge in nickel mining for higher AWARE scores. Durán et al. (2013) find that 7% of mines in their sample overlap with protected areas and 27% lie within a 10 km boundary. Our findings are slightly more conservative, but just as alarming. We furthermore complement the findings of Durán et al. (2013) by the observation that extraction volumes have considerably increased within protected areas since 2000. A comparison with Murguía et al. (2016) shows that results are sensitive to the choice how to proxy biodiversity. Our findings are in line with their study regarding bauxite, while our approach does not support their conclusions that silver mining showed a high concentration in “high diversity zones” (ibid: 416).

The global approach applied in this study also entails some uncertainties and limitations. Using crude ore extraction estimates instead of often reported net-metal contents more accurately quantifies pressures that are exerted by the mining industry on the environment and hence our estimates also serve as better indicators with regard to potential impacts. A drawback to our crude ore approach is that assumptions on average ore grades place substantial variances around these estimates. However, we argue that such uncertainties affect the conclusions of this work less, because we can assume high correlation between our estimates and actual extraction volumes from conducted robustness checks. Introducing mine-specific conversion factors can thus be assumed to have level effects on our global-scale results rather than causing substantial changes of our findings on the distributional structure and trends of global mining activities.

Further, by keeping a global scope while utilising broad categories of associated vulnerability, we provide only a crude assessment about where environmental impacts may be more severe than elsewhere. This approach is beneficial as it serves as an early warning mechanism through a trend analysis of the global mining sector, helping to identify potential high-impact areas. Nevertheless, we need to stress that we can only illustrate threats to the environment in terms of *potential* impacts or a contextual risk. Estimating *actual* impacts would require more locally specific data such as actual mine practices and more precise information on (changes in) the mines’ immediate surroundings. Species-richness, for instance, serves as broad indicator, while biodiversity and hence also impacts are heterogeneous across space within the same biome.

Our study thus provides signposts to where more in-depth local studies are needed that consider the interplay of regional circumstances at the site- and case level. On the one hand, we support efforts to evaluate the impacts of the global surge in mining based on investigations that are tied to specifically selected cases. On the other hand, there is great need for more quantitative studies on the magnitude of impacts induced by the entire mining industry. Any expansion of mining constitutes a trade-off for other human and non-human uses or values attached to land and resources. More accurate assessments of mining projects’ propensities to exert additional pressures such as biodiversity loss, deforestation, water and air pollution as well as social conflicts could help constructing spatially varying impact measures. These indicators could then be used for global assessments of mining impacts and industry monitoring. Importantly, more knowledge is needed about the nature and the extent of the spatial transmission and the temporal persistence of mining-induced environmental change. Such improvements will help not only to anticipate the consequences of increased metal production, but also to evaluate current progress towards more sustainable technologies and better regulations, as well as to better consider competing stakeholder interests.

Our research points mostly towards the potential environmental impacts of mining expansion where it occurs. Simultaneously, designating land (and resources in a much wider sense) to be used for mining precludes many other human uses or the non-use of that land. Environmental justice movements opposing mining have raised numerous issues from the loss of land and water for subsistence uses to local air and water pollution and the destruction of cultural values (Martinez-Alier 2001; Temper et al. 2015). The categories we utilised may often proxy the risk of social disruption just as much as they indicate environmental vulnerability. Conflicting use and pollution of water is a frequent cause for resistance of local communities against mining projects, even though mining operators insist that technologies would guarantee sustainable use of water resources and concrete water monitoring plans would already be in place at major mining projects (Bebbington and Williams 2008). Geological conditions determine that the deposits of some metals are predominantly mined in areas where water is scarce. Our study illustrates the massive extraction of copper and iron ores in desert ecosystems and areas of below-average water availability, which inevitably raises questions about potential conflicting uses of water and strategies to prevent future social disruptions in affected regions. Similarly, protected areas secure livelihoods and cultural values for many indigenous populations. We did not distinguish between indigenous lands and other protected areas in this study and we did not consider informal mining, which is evidently affecting protected lands in many regions (see, e.g., Asner and Tupayachi 2016). However, our results suggest that public resistance against mining operations may rise due to increased production within and close to protected areas and we hence highlight the need for investigating and monitoring social dynamics around such areas.

2.4.2 Implications for mining companies and policies

Accelerated global extraction of metals and minerals particularly threatens vulnerable ecosystems and selected regions emphasised in this study. To reduce associated risk in the short and medium term, the impacts of mining itself need to decrease. There is no doubt that the mining industry has already developed and implemented improvements in environmental management processes and impact mitigation systems, such as progressive rehabilitation throughout the life cycle of a mine. While considerable advancements were also made in regulatory systems (e.g. cumulative environmental impact assessment policies and improved regional planning), environmental minimum standards and better sustainability practises and performance must be realised at the mine sites (IRMA 2020) and above and beyond corporate level commitments, as e.g. demanded by the International Council on Mining and Metals (ICMM 2020).

Evaluating, challenging and improving this ongoing transition also includes critically reviewing and reforming national environmental regulations. Our work contributes to such a discourse by pinpointing regions with expansive dynamics and alarming developments such as a surge in extraction within protected areas. These insights could be used for more accurately targeting regional policies. As shown in Section 2.3.4, areas with highest extraction growth rates are, with the exception of Australia, located in low- and middle-income countries of the Global South including Brazil, the DR Congo, India and China. These countries score lower in the OECD Environmental Policy Stringency Index as compared to industrialised countries (OECD 2021). However, according to this composite measure, nations such as China and India have put significant efforts in improving environmental standards, while the index stagnates at very low levels for Brazil. The Central African Copperbelt also marks a challenging region with substantial room for improvements at the policy and company level. Even though forms of protective laws and regulations were established in the 1990s in Zambia and in the 2000s in the DR Congo, this change in environmental management practices remained rather a change on paper, while mining companies intensified extractive operations based on a dominantly economic and technocratic rationale (Peša 2020). Concrete opportunities for action include rethinking mining governance such that it avoids unnecessary large-scale infrastructure, averts opening up untouched spaces to settlement, considers cumulative impacts across space (such as watershed regions) and over time and involves most affected populations in the decision making (Bebbington et al. 2020). National and sub-national governments are integral parts of the International Resource Panel's "Sustainable Development Licence to Operate" framework (UN IRP 2020), which makes a strong case for policy coherence along multiple levels that is grounded on robust laws and regulations: National governments have the opportunity to define broad national development goals and to require mining activities being aligned to these. They can do so, for instance, through the use of auctioning, given that government policy objectives are clarified and made publicly available well in advance of the auction. Sub-national and local governments, in turn, have the ability to actively collaborate in local development planning and to steer negotiations regarding trade-offs between the environmental, economic and social dimensions of mining operations.

The shared knowledge as to the distribution and the contextual risk of increased mining, to which we have contributed with our research, turns the decision to expand mining anywhere into an informed decision to inflict negative impacts on the environment and human communities. Any expansion therefore arguably requires tight governance of which metals can be extracted, not just when and where, but also *for what purpose* and *by what means*. One possible solution how both of these aspects could be controlled better might be more vertical integration of mining in global supply chains, making these less complex and more transparent, which should be advantageous to consumer facing downstream companies, e.g. in the automotive or electronics sectors.

2.4.3 The global drivers of accelerated mining

While our results have clear implications for mining companies and related regulation, the global framework in which mining actors operate needs to be equally considered, when discussing options to reduce the socio-ecological impacts of mining. Given that any expansion of mining has detrimental environmental and social impacts, it seems straightforward to call for a halt to mining expansion, as has, in fact, been the request throughout various environmental justice movements (e.g. Temper et al. 2015). However, this claim is in stark contrast to expected future trends. Global demand for metal ores is expected to significantly increase in the coming decades (Elshkaki et al. 2018) mostly due to the build-up of global material stocks (Krausmann et al. 2017; Krausmann et al. 2020) and the expansion of low-carbon infrastructures, such as wind and solar energy and battery storage capacities (Elshkaki and Shen 2019; Watari et al. 2020). It will be impossible to sustain increasing levels of consumption in those areas while simultaneously curbing the negative environmental and social impacts of metal mining.

The increasing metabolic inequalities of current growth trajectories also play an important role. Global supply and use chains currently direct the additional resources gained by metal mining to places of already high or rapidly increasing consumption and material wealth (Dorninger et al. 2021). High-income and some middle-income economies engage in net-appropriation of raw materials and without net-imports would not be able to pursue their models of industrialised growth. While the mature industrialised economies have largely exhausted their domestic resource base, countries in the earlier phases of capitalist industrialisation continue to hinge their economic “development” on extractivist agendas (Gudynas 2010), taking on roles of global suppliers of primary commodities while foregoing the higher value added associated with refinement and manufacturing (UNCTAD 2019). As a consequence, final consumers are in many cases geographically distant from resource extraction and the related impacts (Schaffartzik et al. 2016; Gudynas 2010). Due to these “tele-connections” between production and consumption, the systemic character behind ecological distribution conflicts needs to be addressed from a global perspective, acknowledging pertinent patterns of ecologically unequal exchange (Dorninger et al. 2021; Xu et al. 2020b).

2.5 Conclusion

To date, there is no reason to expect the expansion of metals and minerals extraction to halt in the near future. In contrast, the accelerated build-up of global material stocks and the development of new and supposedly more sustainable technologies will create growing markets for metal ores.

In this study, we investigated and contextualised metal ore extraction of the past two decades. We illustrated the types and amounts of commodities extracted, along with a detailed assessment of their geographical location. Backed by the rich empirical evidence that mining activities induce hazardous changes to the environment, we considered areas around mining sites to be more strongly at risk and reflected how severe mining pressures may impact ecosystems, in particular those already recognisable as vulnerable. It is remarkable that, compared to the total global surface, relatively few and small areas supply the metallic basis for the entire industrialised world. However, based on what we know so far about the impacts of minerals extraction on the environment and their spatial transmission, it seems highly likely that indirect effects distant from mines may be extensive. We found that the intensification of extraction shows distinct regional patterns, which increase the pressure on vulnerable ecosystems in several biomes across the globe. In order to preserve both livelihoods and habitats to many, often rare and endangered species, particularly tropical ecosystems of vast biodiversity require stronger protection from interference through mining. The increase of metal mining in vulnerable and protected areas shown in our study points to the challenge of reversing current unsustainable trends in resource extraction.

Metals are point resources and do not occur ubiquitously. Rather than implying that there is no choice but to mine them where they do occur, we have argued that this in fact supports an even stronger case for reducing resource consumption, first and foremost of the world’s wealthiest economies, in order to protect vulnerable ecosystems and their inhabitants. Further pursuing this agenda can be supported by the type of information we have sought to develop for this article, including the spatially explicit mapping, the historical contextualisation and the assessment of the status quo of resource development and its transformative potential. Aggregate global conceptualisations and targets must be integrated with in-depth knowledge of local-level consequences of mining expansion. For the examples of selected hotspots of mining expansion, we demonstrated that many of them are unambiguously related to local socio-environmental risk and disasters.

Further investigating and monitoring the spatial and temporal evolution of metal mining can serve as an early warning mechanism and will help to anticipate potentially hazardous developments and better-inform mining management and policy making. Our results have implications for the way we organise the biophysical basis of our economic systems, because they underline that reoccurring local ecological distribution conflicts all across the globe are not to be solved at the case level. Instead, they are consequences of an expansion systematically affecting species-rich, water-scarce, complex, fragile and hence vulnerable ecosystems.

Chapter 3

Transient economic benefit and persistent forest loss: regional impacts of mining in Brazil

Abstract: Environmental and social risks in mining regions often juxtapose promises of local economic growth. Brazil, a major global mineral supplier and conservation leader, has pursued resource-led development despite mining's threat to its forests. Yet, the efficacy of this development strategy is uncertain. Here we investigate mining's impact on deforestation and regional economic growth in Brazil. We find substantial effects of mining on deforestation rates for less regulated concessions, while the associated boost in regional Gross Domestic Product (GDP) is transient. The shortly-waning economic benefit correlates strongly with global mineral prices, suggesting that Brazil's extractive industries have failed to deliver lasting local economic advantages. Our results challenge the perception that mining inherently drives regional economic development. As global demand for minerals rises, especially for the energy transition, strategic mining investments must be revised to prioritise sustained local progress, nature conservation and well-being.

3.1 Introduction

Global mining activities cover more than 100,000 km^2 of land (Maus et al. 2022; Tang and Werner 2023), leading to significant environmental and social impacts both directly at the mine sites and in their surrounding areas (Giljum et al. 2022; Sonter et al. 2020; Bebbington et al. 2018a). Yet, minerals and fossil fuels are indispensable for various aspects of human society, such as housing, energy, transport, and communication infrastructure. This creates a tension between domestic economic opportunities and the associated social

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and environmental risks (Bebbington et al. 2008; UN IRP 2017b; Martinico-Perez et al. 2018). Consequently, there are fundamental uncertainties regarding the compatibility of mining with sustainable development (Dubiński 2013; Alves et al. 2021).

Brazil is not only among the world's leading suppliers of iron, gold, copper, and bauxite but also a significant hub for tropical forest conservation. Among the various adverse consequences associated with mining (Escobar 2015; Silva Rotta et al. 2020; de Souza Porto and Rocha 2022; Ferrante and Fearnside 2022; Siqueira-Gay et al. 2020; Rorato et al. 2020), mining-induced deforestation is especially pronounced in Brazil (Sonter et al. 2017). Forest loss is caused directly at the mine sites, such as at the actual extent of open-pits and forest clearing for on-site mining facilities, waste rock dumps and tailings ponds, but also indirectly due to transport, storage, processing and energy infrastructure build-up outside designated mining areas, as well as population pull effects and related urban and agricultural expansion (Giljum et al. 2022). Alarmingly, the country's mining territory expanded from 187 thousand ha in 2005 to 351 thousand ha in 2020 (MapBiomas 2023, Figure 3.1), posing threats to areas vital for forest conservation and biodiversity (Sonter et al. 2017; Siqueira-Gay and Sánchez 2021; Luckeneder et al. 2021). This is of particular concern due to the resultant loss of natural habitats and destruction of carbon sinks, which could undermine efforts to meet global climate targets (Gatti et al. 2021).

While there is broad consensus about the environmental and social risks of mining in Brazil, opinions diverge regarding the potential economic advantages that mining could bring (de Castro Gentil et al. 2019; Fernandes and Araujo 2016). Historically, Brazil's extractive sector and institutions have portrayed both industrial and informal mining as pivotal to the economic development of its resource-rich peripheral territories (de Castro Gentil et al. 2019), often in forested remote regions. Some studies support this view, showing that mining can spur regional economic development through job creation, local procurement, and associated local spillovers (Aragón and Rud 2013; Arias et al. 2013; Aragón et al. 2015). However, this perspective is countered by research that points to the negative economic implications of resource wealth according to the "resource curse thesis". Such studies argue that the presence of abundant natural resources can hinder the growth of sectors like manufacturing, education, and health – sectors which are vital for sustained growth (Auty 1993; Sachs and Warner 2001; Humphreys et al. 2007; Manzano and Gutiérrez 2019; Owen et al. 2021). Notably, for Brazil, empirical evidence remains inconclusive as to whether mining catalyses sustained local economic development.

This study investigates the impact of mining on deforestation and regional economic growth in Brazil at the municipality level. Moreover, it differentiates between industrial and wildcat mining, known as "garimpos" (Figure 3.1D), both provided for in Brazilian legislation (Appendix B.1). By doing so, it offers a focused analysis that contrasts with broader assessments of macroeconomic mining impacts on national indicators (Sachs and Warner 2001; Havranek et al. 2016). A regional focus is warranted to understand the extent to which economic activities, such as mining, benefit the local economies that constitute the concrete living environment of the population. Moreover, it is warranted as a means to understand the spatial distribution of the gains and losses from such activities. We employed panel-structure Bayesian spatial econometric models, regressing 5-year average annual Gross Domestic Product (GDP) growth rates on a set of determinants for economic growth, augmented with land cover information and mine locations. The same setup was

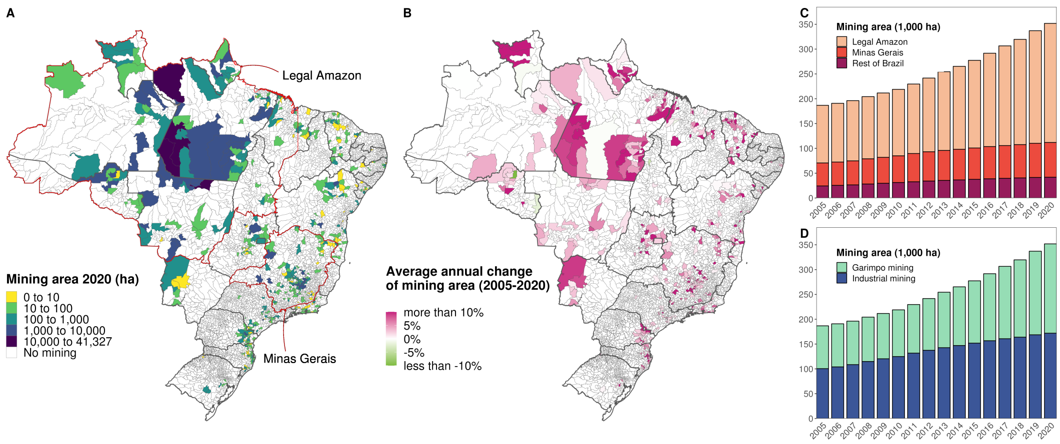

Figure 3.1: **Brazilian mining area.** Land cover classified as "mining" (MapBiomas 2023). Total area in ha per municipality in 2020 and indication of the Legal Amazon and Minas Gerais (borders in red) **(A)**, average annual change of mining area between 2005 and 2020 in % **(B)**, 2005-2020 mining area by region in 1,000 ha **(C)** and 2005-2020 mining area by mining regulation type in 1,000 ha **(D)**.

replicated to assess the effects of mining on forest loss. Besides its advantage of explicitly accounting for and evaluating the spatial spillovers that are central to this work, our spatial econometric approach offered a robust statistical framework that considered various national and local drivers of regional GDP and forest loss. This approach contrasts with experimental approaches or before-after control-impact assessments, which need careful monitoring of both impact and control groups over time. All models relied on a consistent set of georeferenced data, sourced from remotely sensed land cover data products (MapBiomas 2023), Brazil's socioeconomic statistics (IBGE 2023a; IBGE 2023b; FIRJAN 2018) and biophysical records (CRU 2021; USGS 2021), spanning 5,262 municipalities from 2005 to 2020. Our findings reveal significant mining effects on deforestation rates in less regulated concessions, whereas the surge in regional GDP proves transient and eventually becomes negative.

3.2 Results

3.2.1 Effects of mining on regional GDP

The Brazilian economy is widely influenced by mineral extraction. Throughout the study period, the economic growth of all Brazilian municipalities showed a strong correlation with global metals and minerals prices. However, our focus diverged from this overarching relationship between mining and the country's economic performance as we explore regional disparities observed between mining and non-mining municipalities. Descriptive statistics suggest nuanced dynamics between these two categories, as mining municipalities tend to have outperformed non-mining municipalities during periods of ascending commodity prices and vice versa (Figure 3.2). Differences were notable in 2004 and 2010, when increases in metals and minerals prices coincided with 4.0 percentage points (pp) and 3.1 pp higher GDP growth rates, respectively, in mining as compared to non-mining municipalities, and in 2015 and 2016, when mining municipalities fell back by 2.6 pp and 2.8 pp, respectively, suggesting greater vulnerability to the recessionary pressures within these areas. Nevertheless, these observations necessitated further scrutiny within a controlled modelling framework, isolating the effects of mining at the municipality level by accounting for national macroeconomic trends and potential overarching and regional confounding factors.

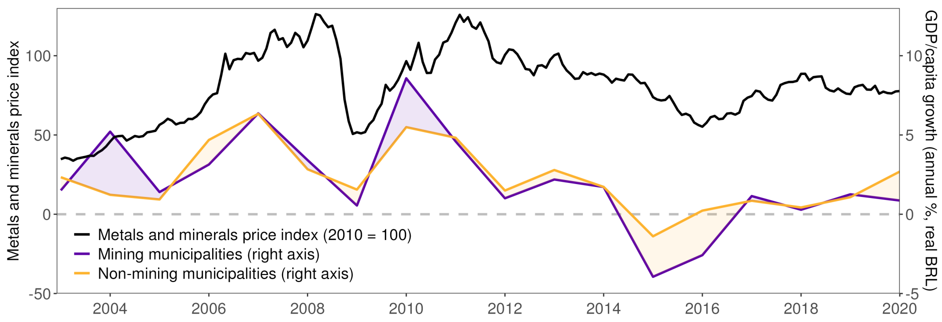

Figure 3.2: **Mining, commodity prices and the GDP.** Global prices of metals and minerals (World Bank 2023a) and median annual growth rates of GDP per capita in real Brazilian Real (IBGE 2023a; IBGE 2023b; World Bank 2023b) for mining and non-mining municipalities.

Figure 3.3 depicts mining impact estimates, i.e. the estimated differences in GDP growth in pp between mining and non-mining regions after having accounted for several observed drivers of economic growth, as well as overarching yet unobserved economic factors, such as national policy schemes and world market commodity prices that may have influenced municipalities regardless of their exposure to mining (see Methods for details). We used the presence of industrial and garimpo mining within a municipality as the mining indicator to facilitate the interpretation of results. In Appendix B.6, we show that mining intensity in terms of mining area within each municipality does not change our main conclusions (Figures B5 and B6). Each panel shows median impact estimates surrounded by 95 % certainty intervals for the respective years or multi-year periods (pooled impacts for pre-2010 and post-2010 time frames) in two colours. The darker colour represents direct impacts within mining municipalities and the lighter colour indicates the magnitude of spillover effects of mining across municipality borders. All impacts indicate estimated average differences as compared to non-mining, non-neighbouring municipalities, keeping all other municipality characteristics in the model constant.

The findings in Figure 3.3A reveal that the local economic effects of industrial mining activities were ambivalent for Brazil across the 5,262 municipalities. The extent and direction of direct and indirect (spillover across municipality borders) impacts of industrial mining varied significantly between the two time periods, previous to 2010 and since 2010 (see right panel in Figure 3.3A). Before 2010, industrial mining led to an average direct boost in GDP growth rates as compared to non-mining lying between 1.5 pp and 1.9 pp with additional spillover between 1 pp and 2.0 pp with 95 % certainty. The spillover indicates that municipalities near municipalities with industrial mines experienced a positive additional GDP growth (1.5 pp on average) relative to those without mining municipalities in their surroundings. However, this spillover effect on neighbour municipalities turned negative after 2010 (lower than -0.1 pp with 97.5 % certainty). The direct effect of mining is not conclusive after 2010, as the average effect could be either positive or negative, between -0.2 pp and 0.1 pp.

Analysing yearly effects (left panel in Figure 3.3A), mining showed mainly positive direct stimulus and spillover before 2010, which is in line with the pooled estimates. The following years showed more intricate results, with the uncertainty ranging from positive to negative

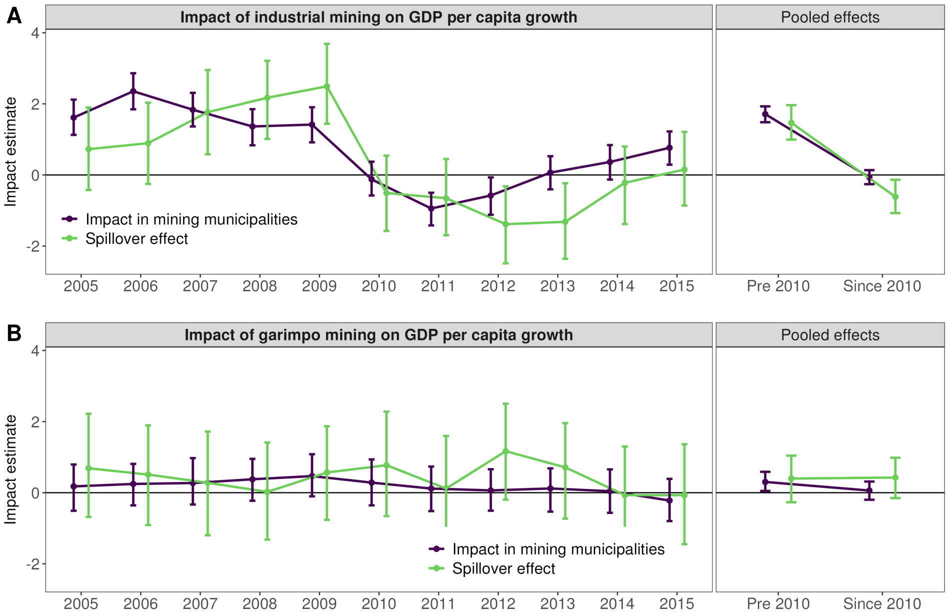

Figure 3.3: **Regional GDP impact estimates.** Impacts of binary industrial **(A)** and garimpo **(B)** mining indicator on 5-year average annual GDP per capita growth. Left panels show yearly estimates, right panels show pooled (pre 2010 and since 2010) estimates. Estimates were obtained from 20,000 Markov chain Monte Carlo iterations, with the first 10,000 being discarded as burn-in. Points denote posterior means, error bars show 95 % posterior credible intervals.

values in several years. Yet, the average estimates of yearly effects were mostly negative with distributions centred on values that were lower than those observed in years preceding 2010. By 2012, effects were consistently negative and lower than -0.07 pp and -0.3 pp with 97.5 % certainty for direct and spillover effects, respectively. The estimates indicate significant drops from 1.4 pp direct and 2.5 pp spillover effects in 2009 to -0.9 pp direct and -0.7 pp spillover effects in 2011. After 2011, the negative impacts slowly faded, and eventually, the direct effect turned positive again in 2015 (0.8 pp), while the spillover effect remained ambiguous with an average effect lying between -0.9 pp and 1.2 pp for the same year.

Contrasting industrial mining, garimpo mining showed weaker and less conclusive effects on GDP throughout the entire observation period. A small positive direct impact only for the period before 2010 was observed (0.3 pp on average) as depicted in the right panel in Figure 3.3B. The annual direct and spillover effects were all centred around zero (see the left panel in Figure 3.3B) with uncertainty on the effects ranging from negative to positive values for every observed year, which suggests negligible effects of garimpos on the GDP of Brazilian municipalities. The complete set of regression output including all predictors is provided in Appendix B.4.

3.2.2 Mining-induced forest loss

Figure 3.4 shows that Brazilian mining municipalities experienced higher forest loss rates than non-mining municipalities (36.7 % difference in medians between 2003 and 2020). Again, the figure merely suggests a positive link between mining and increased forest loss rates, however, without considering any hidden, potentially correlated deforestation drivers. We therefore followed the statistical approach introduced above, ensuring control over both observable and latent factors that could confound the relationship between mining and forest loss.

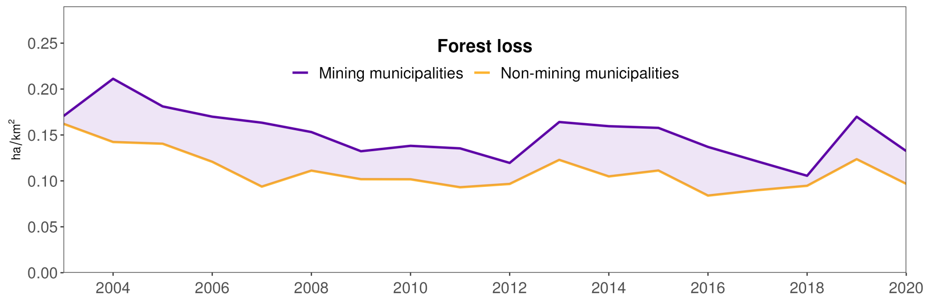

Figure 3.4: **Mining and forest loss.** Median annual forest loss rates (ha forest loss per km^2 municipality area, zero forest loss municipalities excluded) for mining and non-mining municipalities (MapBiomas 2023).

In contrast to the GDP growth, which predominantly demonstrated effects from industrial mining, forest loss was associated with garimpo mining, especially in the earlier years of the observation period, as seen in Figure 3.5. Note that the figure mirrors the presentation of Figure 3.3, displaying direct and spillover impact estimates within 95 % uncertainty intervals. Prior to 2010, municipalities with garimpo operations faced an average loss of 0.03 ha more forest per km^2 compared to areas without. Even more pronounced, municipalities neighbouring areas with garimpo activities saw a notable spillover effect, experiencing an average increase in forest cover loss by 0.32 ha per km^2, as emphasised in the right panel of Figure 3.5B. In absolute terms, impact estimates suggest a direct forest loss of 894 ha per year associated with garimpos and 4,320 ha spillover effect, as depicted in the right panel of Figure 3.5D.

However, post-2010 data, as indicated in the right panels of Figure 3.5B,D, offer less consistent findings. The relative forest loss due to garimpos appears to have become less impactful for this period. Yet, the annual effects of garimpo on forest loss in neighbouring municipalities persisted in the most recent years of the time series, as evident from the left panel of Figure 3.5B. Absolute losses reduced, too, in the post-2010 period, with garimpo mining causing an estimated annual loss of 270 ha and a corresponding spillover effect of 1,077 ha in neighbouring areas. Interestingly, industrial mining municipalities exhibited a consistent protective effect (pre and post-2010) on neighbouring municipalities' forests in both absolute and relative terms (Figure 3.5A,C). However, in the municipalities hosting the actual industrial mines, the data is inconclusive, leaving it uncertain whether industrial mining has a detrimental or protective impact on forests.

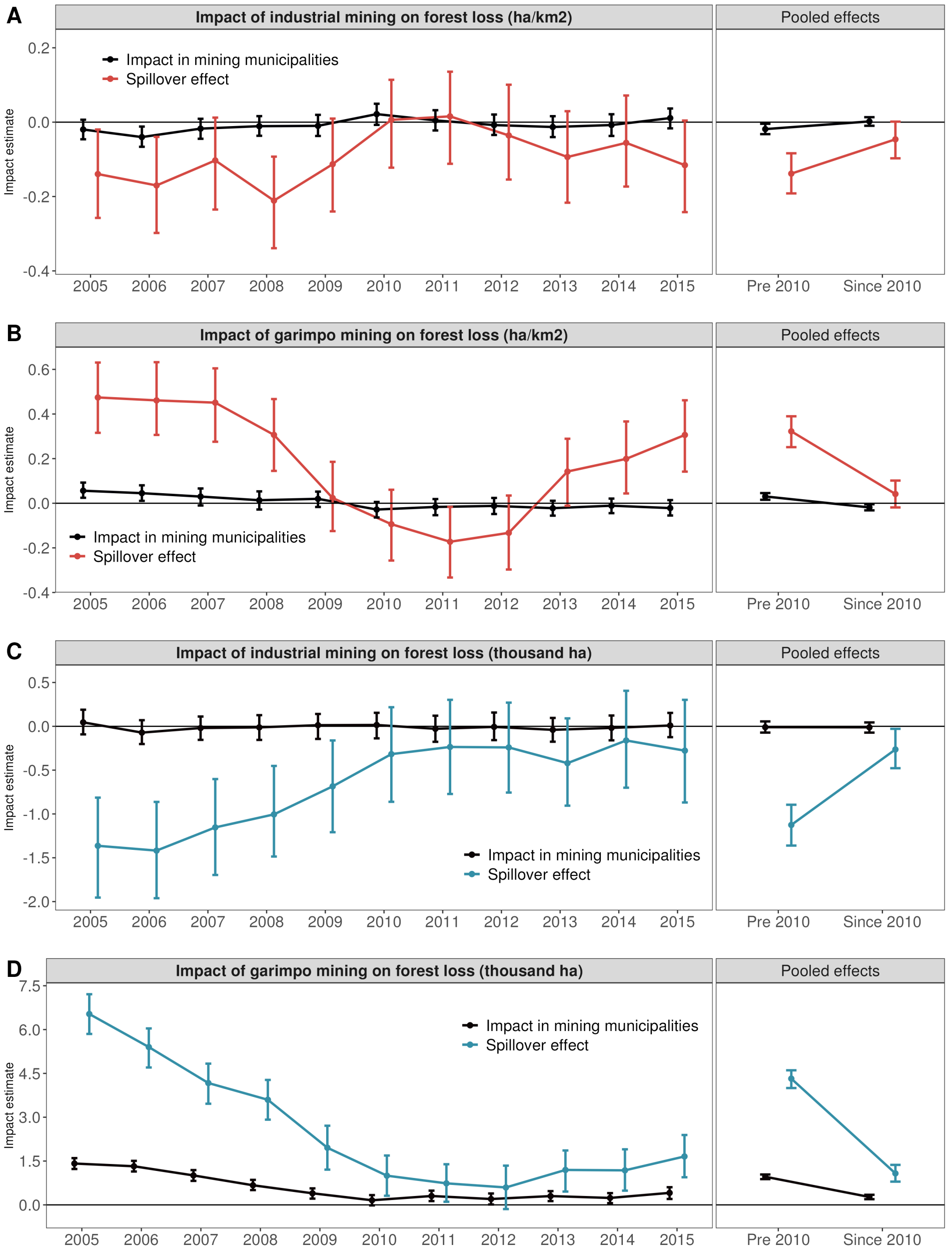

Figure 3.5: **Regional forest loss impact estimates.** Impacts of binary industrial **(A)** and garimpo **(B)** mining indicator on forest loss in ha per km^2 of municipality area. Impacts of binary industrial **(C)** and garimpo **(D)** mining indicator on forest loss in thousand ha. Left panels show yearly estimates, right panels show pooled (pre 2010 and since 2010) estimates. Estimates were obtained from 20,000 Markov chain Monte Carlo iterations, with the first 10,000 being discarded as burn-in. Points denote posterior means, error bars show 95 % posterior credible intervals. Forest loss was defined as negative changes in natural forest formation based on (MapBiomas 2023).

3.3 Discussion

Our results suggest that economic stagnation and crisis (tied to Brazil's dependence on global commodity prices) had a distinct influence, causing a turnaround in the relationship between mining and regional economies. Before 2010, a beneficial global environment (high prices and demand for materials) translated into regional economic growth within and close to industrial mining municipalities, i.e. the revenues from mining as well as multiplier effects remained local to a notable extent. These findings contrast the negative relationship that is typically found in cross-country comparisons (Sachs and Warner 2001) and suggest a strong positive economic impact of mining that diffuses across municipality borders for example via labour markets (Alves et al. 2021). The presence of positive spillovers indicates the existence of diffused backward linkages such as via commuting workers and the emergence of "mining clusters" that exhibit endogenous development and diversification of the industrial mix due to agglomeration effects (Arias et al. 2013). However, a growing extractive sector also interferes with other, potentially more sustainable, local economic structures such as small-scale agriculture or manufacturing and creates dependence on the mining industry (Aragón et al. 2015). When the commodity price bubble bursts and the subsequent economic crisis kicks in, the cycle reverses and by the same backward linkages leads to downward development in both mining municipalities and their neighbours.

The negligible economic stimulus of garimpos aligns with their frequently illegal nature, as profits generated often evade official record-keeping. Despite estimations indicating significant employment provided by garimpos, such as the presence of approximately 200,000 garimpeiros in the Brazilian Amazon (Bebbington et al. 2018b), the generated profits may bypass official economic indicators. Furthermore, this observation implies a lack of economic multipliers that would typically arise if garimpo mining profits were were to flow into local consumption or investment.

Our results show that the deforestation impact of mining strongly depends on the type of mining activities and the (in the Brazilian case dual) legal framework they are embedded in. While industrial mining was associated with lower forest loss rates in neighbouring municipalities, less stringent legal requirements, such as no restrictions on mining techniques, opened the floodgates to adopting environmentally hazardous practices for holders of garimpo concessions. Indeed, garimpos increasingly adopted methods and machinery of large-scale industrial exploration and thus departed from the original purpose of the "Garimpeira Mining Permission" (Manzolli et al. 2021; Cozendey et al. 2022). This development is a major explanation for why we found strong forest loss impacts for garimpos, and it indicates a need for the creation of efficient policies tailored to address the circumvention of environmental protection laws. Moreover, geographical patterns differ between garimpo and industrial mining with the former being conducted mostly in the Brazilian Amazon and industrial mining dominating elsewhere such as in the state of Minas Gerais (see Appendix B.1). Since garimpos are the primary cause for mining-induced forest loss, prioritising their regulation can lead to rapid progress in forest conservation. Recognising that gold mining constitutes the core of garimpo activities in Brazil, it might be an aspiration to halt gold extraction entirely (Lezak et al. 2022). Such a step, however, will require broad international political cooperation and is likely to encounter fierce opposition from industry stakeholders.

Finding a balance between forest loss and economic development is a central endeavour in making extractive economies and related supply chains more sustainable. Yet, our results revealed a more complex situation than a simple trade-off between the two spheres. While improved environmental responsibility must be achieved especially in the poorly regulated informal sector, there is generally no guarantee for mining-induced economic development.

While industrial mining benefits municipalities and their neighbours during boom phases, local mining economies can also experience bust phases with stronger negative impacts. This raises the question of which policies can mitigate negative economic impacts while retaining the positive economic stimulus during boom periods. Creating resilience to temporary (as found in this paper) or long-term (as discussed in the resource-curse literature) downturns is key to guaranteeing the economic sustainability of mining activities. Long-term strategic planning is needed in this regard, including far-sighted concepts of how to use, save and invest mining rents for the benefit of local communities and how to reduce the local economies' dependence on the mining sector. Currently, mining rents still often fail to benefit citizens, primarily because largest profit shares accrue to mining companies. This situation is compounded by continued appropriation of rents at the central level, inefficient use of financial transfers by subnational and local governments, and a lack of downward accountability and transparency regarding the use of public finances (Arellano-Yanguas 2011). Moreover, mining operations require strategies addressing socioeconomic perspectives for mined-out areas.

Revenues from taxes and royalties are considered contributing factors to the socioeconomic development of mining regions. The Brazilian CFEM (Financial Compensation for the Mineral Exploration) tax, for example, generates income for mining municipalities based on the volume and value of extracted material (Alves et al. 2021). Moreover, local procurement and employment effects are frequently argued by the mining industry to foster regional economic development (ICMM 2024b). We showed that these economic dynamics strongly correlate with external factors such as world market prices. Municipalities may depend strongly on incomes and jobs from the mining industry, causing a reversal of the above-stated effects due to recoiling mining activities, job losses, diminished tax revenues, and a sluggish reorientation of local economic structures in times of falling market prices.

Our findings raise concerns about the alignment of mining with several of the United Nations' Sustainable Development Goals (SDGs). While the expansion of the mining sector is anticipated to provide essential resources for the global energy transition (Sonter et al. 2023) with positive effects mainly on SDGs 7 (affordable and clean energy) and 13 (climate action), the regions tasked with this supply must cope with the multifaceted social and environmental challenges posed by mining. These challenges have been expected to be offset by the inherently inclusive and sustainable economic growth outlined in SDG 8 (Monteiro et al. 2019). Yet, our results indicate that relying on mining to realise this particular SDG may be misguided.

To conclude, our findings support the concerns raised earlier that the continued expansion of the extractive sector can increase deforestation and related pressures on Brazilian forests, particularly the Amazon, while likely failing economic promises (van der Hoff and Rajão 2020; Diele-Viegas et al. 2020; Siqueira-Gay et al. 2020; Rorato et al. 2020). The study thus contributes to a better-informed political debate by delivering much-needed quantitative evidence with relevance not only for Brazil but for resource-rich economies globally.

3.4 Methods

3.4.1 Econometric framework

To assess the economic and environmental impacts across the entire Brazilian mining sector, we adopted a well-established econometric approach, building on the extensive literature that examines the effects of natural resource extraction on socioeconomic indicators (Havranek et al. 2016). This empirical methodology, also used to analyse the determinants of economic growth (Crespo Cuaresma et al. 2014; Ertur and Koch 2007) and the causal pathways of deforestation (Busch and Ferretti-Gallon 2017; Kuschnig et al. 2021) is well-suited for investigating macro-level dynamics at the regional scale. It allowed us to isolate the effects of mining by controlling for various observable and unobservable confounding factors, i.e. factors affecting both the presence of mining and the outcomes of interest (economic growth and forest loss), thereby also accounting for dynamics that may influence both mining and non-mining municipalities.

In light of the potential effects of mining activities on neighbouring areas, we aimed to account for the spatial spread of impacts across geographical locations. Combining well with the spatial nature of the mining data at hand, this study employed a spatial econometric approach. Spatial models explicitly consider the non-randomness of observations across space, thus addressing the bias and misleading inference that may result from spatial dependence (Baltagi and Pirotte 2010). Several applied contributions found strong evidence that socioeconomic and environmental observations were subject to spatial dependence at regional level, including economic growth (López-Bazo et al. 2004; LeSage and Fischer 2008; Crespo Cuaresma et al. 2014; Resende et al. 2016) and deforestation (Robalino and Pfaff 2012; Kuschnig et al. 2021).

We employed panel-structure spatial models, using data for 5,262 Brazilian municipalities over the course of 16 years. The computation of five-year average growth rates (see below) resulted in 57,882 observations. Spatial panel models account for spatial correlations and, at the same time, offer extended possibilities to consider time- or region-specific idiosyncratic effects (Elhorst 2010). Incorporating time-specific fixed effects, for example, accounts for factors influencing the dependent variables in specific years of the sample. The models can thereby consider trends affecting municipalities regardless of their exposure to mining, such as national (e.g., macroeconomic conditions, environmental and economic policies) and global (e.g., commodity price fluctuations) factors. We estimated the models using Bayesian methods following the standard Markov Chain Monte Carlo (MCMC) estimation framework as proposed for spatial econometrics (LeSage and Pace 2009). The exact estimation procedure is presented in Appendix B.3. As a measure of uncertainty, we report 95 % Bayesian credible intervals.

Economic growth

The underlying principle is to regress growth rates of countries or regions on income (usually GDP) at the initial period of a certain growth window as well as on a number of further determinants of growth. Typically, these include information on population growth, human capital stock and sectoral structure such as gross value added or employment across economic sectors (LeSage and Fischer 2008; Crespo Cuaresma et al. 2014).

Following the literature on economic growth and spatial spillover (Ertur and Koch 2007; LeSage and Fischer 2008), and in line with the framework demonstrated for the Brazilian case (Resende et al. 2016), we employed a panel-structure spatial Durbin model (SDM) of the form:

$$\boldsymbol{y}_t = \rho \boldsymbol{W}\boldsymbol{y}_t + \boldsymbol{X}_t\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}_t\boldsymbol{\theta} + \boldsymbol{\xi}_t + \boldsymbol{\epsilon}_t, \qquad \boldsymbol{\epsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{\Omega}), \;\; \boldsymbol{\Omega} = \sigma^2 \boldsymbol{I}_n, \tag{3.1}$$

where $\boldsymbol{y}_t$ denotes an $n \times 1$ vector of regional economic growth rates at time t. As advocated in earlier literature (Caselli et al. 1996), we used five-year periods as growth windows to smooth over short-term business cycle influences and calculated the respective average annual growth rates $\boldsymbol{y}_t = [ln(\boldsymbol{Y}_{t+5}) - ln(\boldsymbol{Y}_t)]/5 * 100$, with $\boldsymbol{Y}_t$ denoting per capita GDP at time t (results were robust against variations in growth windows, see Figure B7). $\boldsymbol{X}_t$ is an $n \times k$ matrix of k exogenous country characteristics in the initial period. These include prominent determinants of economic growth such as initial income, population density, education and indicators for industrial structure, but also information on mining activities, land use and land use change. We used interaction terms between binary mining indicators and yearly dummy variables in order to obtain year-specific effects of the presence of industrial and garimpo mining. Additionally, in order to obtain pooled effects for the time before and after 2010, respectively, we ran another model interacting the binary mining indicators with dummy variables of the respective period. The choice of the year 2010 for separation is based on our yearly coefficient results. The error term $\boldsymbol{\epsilon}_t$ was assumed to follow a multivariate Normal distribution with zero mean and a diagonal variance-covariance matrix $\boldsymbol{\Omega}$ with constant variance σ^2. $\boldsymbol{W}$ is an $n \times n$, non-negative, row-standardised spatial weights matrix. Its elements impose a structure of spatial dependence upon observational units, setting $w_{ii} = 0$ and $w_{ij} > 0$ if regions i and j are defined as neighbours ($i, j = 1, \ldots, n$). The exact specification of $\boldsymbol{W}$ is presented and illustrated in Appenix B.2 and Figure B4. Characteristically for an SDM, the regression equation includes the spatially-lagged dependent variable $\boldsymbol{W}\boldsymbol{y}_t$ as well as the spatially-lagged regional characteristics $\boldsymbol{W}\boldsymbol{X}_t$ as explanatory variables. The $k \times 1$ vectors of the unknown parameters $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ correspond to $\boldsymbol{X}_t$ and $\boldsymbol{W}\boldsymbol{X}_t$ respectively, and ρ (where the sufficient stability condition $|\rho| < 1$ is satisfied for row-standardised $\boldsymbol{W}$, LeSage and Pace 2009) is a scalar, measuring the magnitude of spatial autocorrelation. If $\rho = 0$, we obtain a growth regression model with spatial lags in $\boldsymbol{X}$ (SLX), where regional growth rates are independent, but $\boldsymbol{W}\boldsymbol{X}$ is still considered. The model collapses into a classical linear model in the case where both $\rho = 0$ and $\boldsymbol{\theta} = 0$. Finally, the model considers a time-specific constant $\boldsymbol{\xi}_t$, capturing year-specific confounding factors such as commodity price dynamics and domestic business cycles.

Forest loss

This model type was designed to assess the effects of mining on forest loss, where again we used municipalities as observation units. Forest loss is expected to be subject to significant spatial spillover (Robalino and Pfaff 2012; Busch and Ferretti-Gallon 2017; Kuschnig et al. 2021), which is why we employed an SDM of the form

$$\tilde{\boldsymbol{y}}_t = \lambda \boldsymbol{W}\tilde{\boldsymbol{y}}_t + \tilde{\boldsymbol{X}}_t\boldsymbol{\delta} + \boldsymbol{W}\tilde{\boldsymbol{X}}_t\boldsymbol{\gamma} + \boldsymbol{\nu}_t + \boldsymbol{\mu}_t, \qquad \boldsymbol{\mu}_t \sim N(\boldsymbol{0}, \tilde{\boldsymbol{\Omega}}), \;\; \tilde{\boldsymbol{\Omega}} = \tilde{\sigma}^2\boldsymbol{I}_n, \tag{3.2}$$

where the dependent variable $\tilde{\boldsymbol{y}}_t$ denotes a vector of cleared land within each municipality. In the $n \times \tilde{k}$ matrix $\tilde{\boldsymbol{X}}_t$ we considered economic growth directly as a control variable instead of including the full set of growth determinants. Other control variables remained the same as in the growth specification, because most determinants of economic growth overlap with indicators used for explaining forest loss (Busch and Ferretti-Gallon 2017). Mining again entered the model in the form of interaction terms between binary mining indicators and year and period dummy variables, respectively. Similar to the growth model, $\boldsymbol{\nu}_t$ denotes a time-specific constant and we again assumed a normally distributed error term $\boldsymbol{\mu}_t$ with constant variance $\tilde{\sigma}^2$. The $k \times 1$ vectors $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$ correspond to $\tilde{\boldsymbol{X}}_t$ and $\boldsymbol{W}\tilde{\boldsymbol{X}}_t$ respectively and λ is the spatial coefficient. The spatial weights matrix $\boldsymbol{W}$ and the properties of the spatial model remain the same as in Equation 3.1.

Direct and spillover impacts

Assuming independence of observations, the estimation coefficients of conventional (non-spatial) linear models can be typically interpreted as marginal changes in the dependent variable due to shifts in one of the explanatory variables. In this regard, spatial models require additional steps because we explicitly impose dependence among observations, implying that the partial derivatives of the dependent variable in region i with respect to an explanatory variable in region j are potentially non-zero and therefore cause feedback effects. Calculating average direct, indirect (i.e. spillover) and total impacts was proposed as a solution to this issue (LeSage and Pace 2009): First, transforming Equation 3.1 (without loss of generality, the same derivation holds for Equation 3.2) to

$$\boldsymbol{y}_t = (\boldsymbol{I}_n - \rho\boldsymbol{W})^{-1}(\boldsymbol{X}_t\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}_t\boldsymbol{\theta} + \boldsymbol{\xi}_t + \boldsymbol{\epsilon}_t), \tag{3.3}$$

we derive n^2 partial derivatives of a particular explanatory variable k as

$$\frac{\partial y_i}{\partial x_{jk}} = \boldsymbol{S}_k(\boldsymbol{W})_{ij} = (\boldsymbol{I}_n - \rho\boldsymbol{W})^{-1}(\boldsymbol{I}_n\beta_k + \boldsymbol{W}\theta_k)_{ij}, \tag{3.4}$$

where infinite feedback effects are captured through the spatial multiplier $(\boldsymbol{I}_n - \rho\boldsymbol{W})^{-1}$. The impact matrix is then summarised by calculating the average total effect as the average over all entries in $\boldsymbol{S}_k(\boldsymbol{W})_{ij}$, the average direct effect as the average when only considering its main diagonal, and the average indirect effect as the difference between the two. An interpretation of average direct effects is then given by the average response of the dependent to independent variables over the sample of observations and hence similar to regression coefficients from classical linear models. The average spillover can be interpreted as the cumulative average response of a region's dependent variable to a marginal change in an explanatory characteristic across all other regions.

3.4.2 Data

We compiled a balanced panel data set, covering 5,262 Brazilian municipalities over the period 2005-2020. Data were collected from various sources and, if necessary, aggregated to the municipality level. Municipalities, the lowest administrative divisions in Brazil, are occasionally split or merged and hence their total number varies. In order to keep a balanced panel with a constant number of spatial observations, we followed previous research (Resende et al. 2016) and only considered municipalities with unchanged geographical extent over the sample period. An overview of the variables used in this study is presented in Table B1.

The dependent variable in the growth models was the five-year average annual growth rate of GDP per capita, which was computed from yearly per capita GDP in BRL at current purchasing power parities as reported by the Brazilian Institute for Geography and Statistics, IBGE (2023a; 2023b). In the last year of the panel, 2015, this measure therefore comprises economic growth between 2015 and 2020. We selected five-year growth windows as a suitable measure for mid-term economic effects (Caselli et al. 1996). We were aware that other studies emphasise poverty and distributional effects of mining (Arellano-Yanguas 2011; Loayza and Rigolini 2016). However, we needed to resort to GDP growth in our study, because alternative socioeconomic indicators that would allow for a broader understanding of human well-being are difficult to obtain for this level of geographical detail, especially for a yearly panel. GDP per capita therefore served as a key indicator for *economic* development, despite its limitations such as only covering market transactions and not describing income distribution.

Considered municipalities varied in size from 3.57 km^2 to 159,533 km^2 (mean = 1,541 km^2, sd = 5,683 km^2). In the forest loss models, we used relative and absolute measures for the dependent variable, i.e. the decrease in natural forest formation (a) as annual change relative to municipality size in ha per km^2 and (b) as annual change in absolute ha. The data was calculated from municipality-level land cover statistics as provided by the MapBiomas project (MapBiomas 2023). In contrast to the five-year windows used in the economic growth specification, our focus shifted to annual changes in forest cover. This decision stemmed from our assumption that no adjustments for business cycles were necessary, given deforestation occurring at immediate events without significant recovery periods.

The essential municipality characteristic for this study was the presence of mining activities. Mining entered the models as binary indicators for the presence of industrial and garimpo mining within a municipality in a certain year. Detailed yearly geospatial data on Brazilian land area covered by mining was taken from MapBiomas (2023). We transformed their continuous metric (ha per municipality) to a binary variable for simpler interpretation of effects. Results were robust with only minor exceptions against an alternative specification using mining area in ha as an indicator for the actual mining intensity (see Figures B5 and B6). Instead of land cover information about mining, the CFEM tax would have been another indicator for active mining activities. However, we refrained from using the CFEM as an explanatory variable, as the tax income directly enters municipality GDP, i.e. the dependent variable, creating identification issues in the econometric model.

We considered land use change dynamics as control variables in all models. Using satellite data on the conversion of land, e.g. from natural forest formation to pasture or from grassland to agriculture, is an efficient approach for observing economic activity and environmental transformation at the same time. Our data was obtained from MapBiomas (2023), providing yearly land transition information from 30 m resolution satellite images aggregated to the level of Brazilian municipalities. We utilised land cover classifications at the second sub-categorical level and considered forest formation and forest plantation for the case of forest, grassland as non-forest natural formation, and agriculture and pasture for farming. Other categories such as wetlands, non-vegetated areas and bodies of water were omitted since they had minor relevance for our analysis. In order to be consistent with the five-year GDP growth horizon, we computed the average change in ha over five years. Land use change from any category to forest formation was not considered as a covariate, because it marks a transformation that is only viable over a longer time horizon.

Initial land cover was considered as a proxy for the land cover conditions at the beginning of either a window of GDP growth or a one-year forest loss period. We again used data from MapBiomas (2023). In order to reflect the variation in municipality area, this variable entered the models as shares of natural forest, forest plantation, grassland, agriculture and pasture relative to the total municipality area.

The remaining covariates were motivated by economic growth theory (see the respective literature below), and by following a meta-analysis for the case of the forest loss models (Busch and Ferretti-Gallon 2017). We considered initial income in terms of per capita GDP in the initial year of a growth window as a proxy for physical capital, which is a major determinant of economic growth in the neoclassical growth framework (Solow 1956). A negative relationship between initial stock of physical capital and economic growth, which is explained by diminishing returns to capital accumulation, is a well-established stylised fact in the empirical literature known as the convergence hypothesis. In addition, a number of studies show that the convergence hypothesis holds for direct impacts in spatial econometric growth frameworks, while spillover effects from the flows of capital, goods, knowledge and people between regions are shown to be positive, implying that poorer regions benefit from having highly capitalised neighbours (López-Bazo et al. 2004).

Endogenous growth theory highlights the role of human capital as a key driver of innovation processes such as technological change (Lucas 1988; Romer 1990). However, whether indirect effects are positive or negative is uncertain, because positive economic effects from knowledge spillover and brain drain channels may counteract each other. We proxied human capital using the FIRJAN education index (FIRJAN 2018), an index for Brazilian municipalities on a scale from 0 (worst) to 1 (best) measuring both schooling coverage and quality. The education index was only available from 2005, constraining our sample to this starting year.

Population growth was another component taken from the neoclassical growth framework. Following this theory, a positive impact of population growth would hold for absolute income growth at the national scale, but not for the growth of per capita income due to capital dilution. Therefore, unless higher output exceeds population growth, we would expect a negative effect. For subnational entities, this relationship is unclear, because one part of the population dynamics are migration patterns, which may vary across scale levels (Resende et al. 2016). We obtained population counts per municipality from the IBGE and computed population growth again at five-year average rates. Population counts for 2007 and 2010 were interpolated due to missing data.

In line with numerous other studies, we used population density as a proxy for agglomeration externalities (Resende et al. 2016). Population agglomeration effects have been considered in the economic geography literature. Denser populated (i.e. urban) regions are associated with positive effects on productivity growth, because they show higher rates of technological progress (Fingleton 2001). However, this relationship may not hold for poor districts in low and middle income countries, where strong urbanisation is caused by extensive population growth without having any substantial effects on labour productivity.

We followed previous research (LeSage and Fischer 2008) and included the gross value added (GVA) in the agriculture, industry and service sectors as control variables in order to proxy the industrial structure of municipalities.

The forest loss regressions followed a similar structure as the growth regression, with small adjustments. Instead of initial income, population growth and density, human capital and the sectoral mix variables, we directly used the five-year average annual economic growth rates as a proxy for economic activity. The empirical literature is inconclusive regarding the direction of the effect that income may have on forest cover (Busch and Ferretti-Gallon 2017), yet this proxy subsumes a set of deforestation drivers that are related to any other anthropogenic activity besides the mining and other land use change effects. Forest cover change accounts were only included in the GDP growth models, as they effectively define the dependent variables in the forest loss models.

Final control variables for economic growth and forest loss were the biophysical characteristics precipitation and elevation.

The data was compiled using the **dplyr** (Wickham et al. 2021), **tidyr** (Wickham 2021), **readxl** (Wickham and Bryan 2019), **stringi** (Gagolewski 2021), **sf** (Pebesma 2018), **raster** (Hijmans 2021), **geobr** (Pereira and Goncalves 2022), **exactextractr** (Baston 2022) and **elevatr** (Hollister et al. 2021) R packages (R Core Team 2024). Code and data for the complete reproducibility of the results are provided at https://doi.org/10.5281/zenodo.11634331.

Chapter 4

EU consumption's hidden link to global deforestation caused by mining

Abstract: The integration of metals and minerals into global supply chains leads to mining impacts that manifest far from the location of final consumption. To address these distant impacts, new legal frameworks are emerging that require companies to exercise due diligence across their entire supply chains. However, accurately quantifying local mining impacts and tracing them from production to consumption remains challenging. This study examines global flows of forest loss within mine sites from 2001 to 2019, with a focus on final demand in the European Union. By integrating satellite imagery with a multi-region input-output framework, we find that 12% of global forest loss caused by mining is linked to EU consumption, with 89% of these impacts occurring outside EU borders. The study identifies variations in impact intensities across global mining areas, commodities, and European industry sectors, offering actionable strategies and highlighting challenges for responsible material sourcing in consumer and producer regions.

4.1 Introduction

Global demand for mined materials has reached unprecedented levels and continues to rise, driven by increasing affluence, extensive infrastructure development, rapid urbanisation, and the shift towards renewable energy sources (JRC 2023; UN IRP 2024). While coal mining remains the cornerstone of energy systems in many regions, a substantial increase in the extraction of metals and minerals critical for the energy transition is inevitable (Ali et al. 2017; Sovacool et al. 2020; Xu et al. 2020a). For instance, constructing an electric vehicle requires six times more minerals than a conventional car, and building an onshore wind power plant needs nine times the mineral resources compared to a gas-fired power plant

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(IEA 2021). Considering the adverse impacts of mining, much needed technological solutions to decarbonise industrialised societies therefore paradoxically risk endangering natural ecosystems (Sonter et al. 2018; Sonter et al. 2020; Luckeneder et al. 2021; Luderer et al. 2019) and contribute to climate change (Azadi et al. 2020), if no adequate steps towards more responsible mining practices are taken (Ali et al. 2017; Sonter et al. 2023; Azadi et al. 2020).

Metals and minerals enter global supply chains and end up in industrial production and final consumption distant from extraction sites. Many countries, including those in the European Union (EU), heavily rely on these resource imports. For instance, EU's import reliance ranges from 60% for nickel, zinc and aluminium to over 70% for iron ore, cobalt and manganese and nearly 100% for platinum (European Commission 2020b). This dependency raises concerns about the reliable and unhindered access to critical raw materials (Hool et al. 2023), as well as the human rights violations and environmental damage associated with extraction elsewhere (Wiedmann and Lenzen 2018). To secure mineral resources while safeguarding human rights and achieving global environmental goals, comprehensive initiatives and legal frameworks are essential. These should address social and environmental risks throughout the entire supply chain, incorporating scope-3 reporting and stringent law enforcement to assess, mitigate and disclose impacts effectively.

To promote responsible practices among EU companies throughout their supply chains, the European Council achieved consensus on the Corporate Sustainability Due Diligence Directive (CSDDD) in March 2024. This directive is part of EU's "Green New Deal" and a broader strategy to address the impacts and opportunities within supply chains, complementing other initiatives such as the Batteries Regulation (European Parliament 2023b), the Corporate Sustainability Reporting Directive (European Parliament 2022), and the regulation on deforestation-free products (European Parliament 2023a). The CSDDD requires companies to identify actual and potential adverse impacts in their supply chains and to apply due diligence in order to prevent these impacts (European Commission 2022). The directive is crucial for material sourcing, covering supply chains for minerals that have previously been excluded from existing or proposed EU due diligence instruments, such as the Conflict Minerals Regulation (European Parliament 2017). Additionally, it aligns with various emerging global disclosure frameworks and standards with similar objectives, including those by the OECD (2023) and the Taskforce on Nature-related Financial Disclosures (TNFD 2023).

However, traceability remains a challenge for all supply chain initiatives, particularly for mined materials. Information on mining-related environmental impacts embodied in European imports is currently almost entirely missing. First, there is a significant knowledge gap regarding the quantification of local environmental impacts that the extraction of these materials causes. Only recently, studies have started to systematically assess the extent to which mining contributes to deforestation (Ladewig et al. 2024; Giljum et al. 2022; Sonter et al. 2017), water scarcity (Meißner 2021) and biodiversity loss (Cabernard and Pfister 2022). Second, policymakers, companies and researchers have encountered difficulties in tracing these impacts along global trade networks. While progress has been made with agricultural supply chains regarding the spatial and sectoral resolution of global footprint assessments (Bruckner et al. 2019; Escobar et al. 2020; zu Ermgassen et al. 2020), many supply chains of non-renewable resources remain opaque and nontransparent, providing a key barrier for change.

To address these existing research gaps, we choose forest loss caused by mining as the environmental impact of interest, as deforestation is a major driver of other negative impacts, such as biodiversity loss (Gibson et al. 2011). We assess forest loss within land area occupied by mining and subsequently connect this information to a global trade model. It is well-explored that agriculture is the dominant driver of deforestation (Curtis et al. 2018; Pendrill et al. 2019; Pendrill et al. 2022), and direct deforestation impacts from mining are comparatively smaller (Giljum et al. 2022). However, three quarters of agricultural expansion into forested areas are driven by domestic demand within producer countries (Pendrill et al. 2019), while mined materials are predominantly embodied in global supply chains (Wiedmann and Lenzen 2018). Moreover, mining has increasingly come into focus as an important driver of deforestation in local contexts, with substantial indirect effects surrounding extraction sites (Pendrill et al. 2022; Sonter et al. 2017; Giljum et al. 2022; Ladewig et al. 2024). While the EU has implemented biodiversity and forest strategies to combat deforestation and forest degradation (European Commission 2020a; European Commission 2021), these measures primarily focus on intra-European environmental issues. Only the regulation on deforestation-free products (European Parliament 2023a) explicitly addresses the origins of imported products, but it does not consider metals or minerals. Given the likely heterogeneity of mining impacts on forests across different regions and the EU's reliance on specific areas for its supply chains, companies, policymakers, and consumers would benefit greatly from better understanding these impacts to promote more sustainable production and consumption patterns. As satellite imagery provides robust evidence of forest cover change, forest loss caused by mining is an excellent case study for a concrete, quantifiable exploration of the environmental impacts embedded in the EU's final demand for products and services.

4.2 Results

By integrating high-resolution satellite imagery depicting forest cover (Hansen et al. 2013) with delineations of mining areas (Maus et al. 2022), we derived annual records of forest loss caused by mining across extraction sites worldwide from 2001 to 2019. These records comprise all cleared areas within the boundaries of mining operations, encompassing open cuts, tailings dams, waste rock dumps, water ponds, and processing plants as of 2019 (Maus et al. 2022). It is important to note that our investigation focuses on the immediate, or 'direct', repercussions of forest loss, specifically referring to the deforestation within the confines of mining areas resulting from the establishment or expansion of extraction sites, as well as associated on-site infrastructure and processing facilities. Our analysis therefore portrays a conservative estimate of the total impact, as mining activities have been empirically linked to considerable deforestation in the broader vicinity through 'indirect' pathways, such as the development of transportation and energy infrastructure, as well as population pull effects (Sonter et al. 2017; Giljum et al. 2022; Ladewig et al. 2024).

Accumulated 2001-2019 global forest loss caused by mining amounted to 13,224 km^2, which is depicted in Figure 4.1 at 2 degrees resolution (approximately 220 km at the equator), revealing a pervasive occurrence of forest loss caused by mining across nearly all regions worldwide. While 92% of the mapped tiles show forest loss of less than 10 km^2, regions with exceptionally high rates, ranging up to 767 km^2, were identified. These hotspots are located in South America (e.g., Figure 4.1A), Ghana (Figure 4.1B), Russia, Myanmar, and Indonesia (Figure 4.1C), as well as in Canada, the United States, and Australia (see Figure C2 in Appendix C).

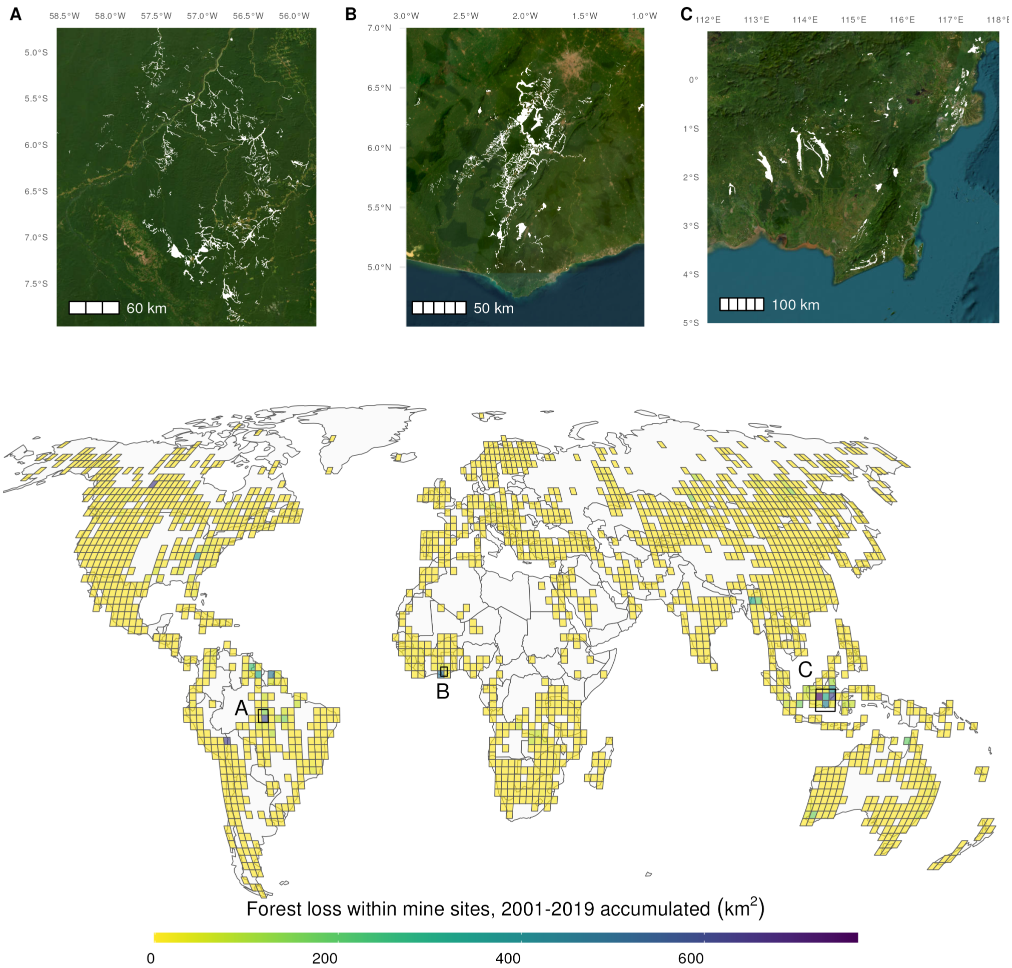

Figure 4.1: Accumulated 2001-2019 forest loss caused by mining at 2 degrees resolution using a Robinson map projection. Areas were obtained by intersecting mining area polygons (Maus et al. 2022) and forest cover maps from the Global Forest Change (GFC) dataset (Hansen et al. 2013). Zoom-in maps highlight mining areas (white) in the Brazilian Amazon (**A**, 750 km^2 forest loss caused by mining within shown mining areas, mostly artisanal gold mining), Southern Ghana (**B**, 499 km^2, other non-ferrous ores, bauxite and gold mining), and Indonesian Borneo (**C**, 2,467 km^2, mostly coal mining).

4.2.1 Forest loss intensities vary across countries and materials

Utilising mine-specific information on historical commodity production sourced from the S&P Capital IQ Pro Metals and Mining database (S&P 2024), we estimated forest loss within mining areas driven by the extraction of specific commodities. In case of coupled production (different metals contained in the crude ore), we applied commodity price-weights to allocate forest loss between metals (see Section 4.4.1). We aggregated this information across a range of key commodities, i.e. bauxite (aluminium ore), hard coal, lignite and peat, copper ores, gold ores, iron ores, lead/zinc/silver ores, nickel ores, other non-ferrous ores, tin ores, and uranium ores.

Global forest loss caused by mining, as illustrated in Figure 4.2B, mirrors the notable upsurge in metals and minerals extraction depicted in Figure 4.2A. Over the span from 2001 to 2012, there was a substantial acceleration in material extraction of the 11 analysed commodity groups, escalating from 9.3 bn tonnes to 15.2 bn tonnes. Correspondingly, mining-related forest loss exhibited a marked increase from 237 km^2 in 2001 to 1,234 km^2 in 2012. Post-2012, forest loss rates appeared to stabilise, maintaining a yearly average of approximately 856 km^2, while extraction of the selected commodities experienced only marginal growth. Nonetheless, it is important to note that dynamics across commodities (Figure C3) and countries varied significantly, with notable outliers at the upper end (Figures C5 and C6).

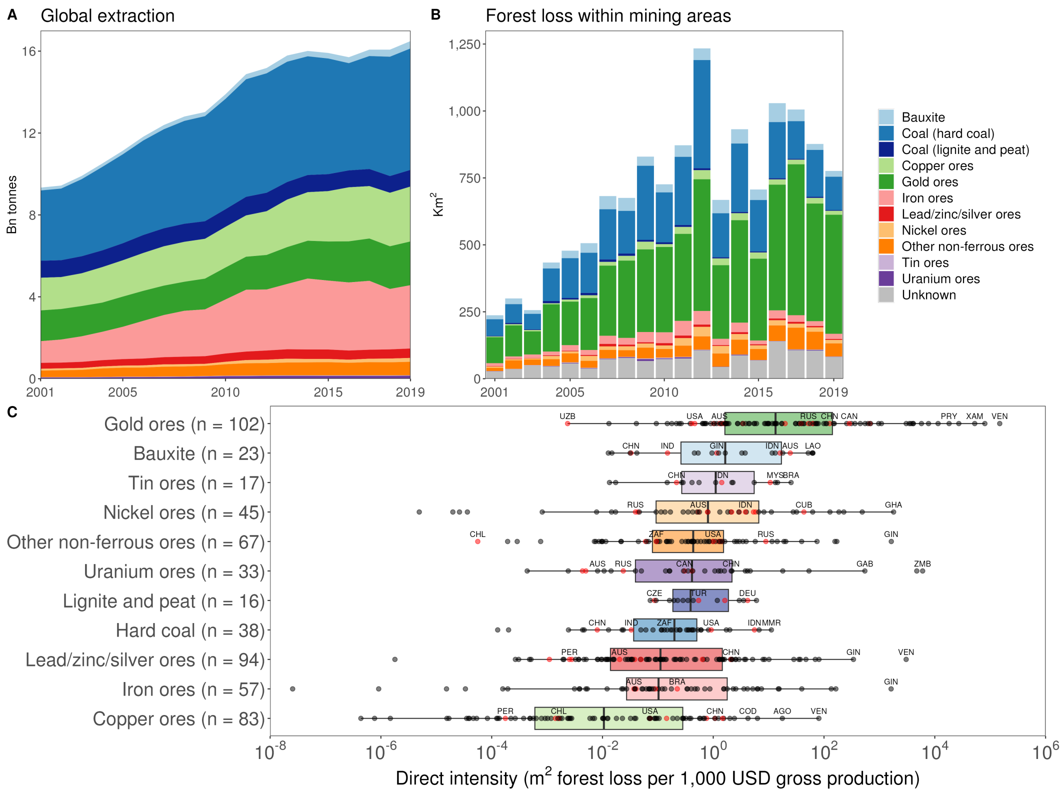

Figure 4.2: Global 2001-2019 extraction of selected metals and coal in billion tonnes (Lenzen et al. 2022; Lenzen et al. 2017) (**A**). Yearly forest loss (in km^2) within mining polygons by commodity (**B**). Direct intensities in m^2 of forest loss per 1,000 USD output by primary extraction sector (**C**; Points denote 2001-2019 country average, red points indicate major producers together responsible for more than 70% of global production per commodity, n is the number of countries observed where respective mining activities were recorded. Outliers for Belgian hard coal were omitted.).

The largest shares of accumulated forest loss caused by mining during the period from 2001 to 2019 can be attributed to the extraction of gold ores (43%) and various forms of coal (hard coal, lignite and peat; 26%), followed by the aggregated group of "other non-ferrous ores" (6%), bauxite (5%), and iron ore (4%) (Figure C4). This forest loss occurred predominantly in Indonesia, Brazil and other South American countries, Australia, Canada, Russia, and the United States. Approximately 10% of the observed forest loss could not be conclusively linked to any of the key commodities.

It is important to understand the magnitude of forest loss impacts relative to the scale of each country's respective extraction sectors. Direct forest loss intensities, denoting the spatial extent of forest loss in relation to gross production of specific primary extraction sectors, exhibit significant variation across commodities and global regions. The boxplots depicted in Figure 4.2C illustrate that country-specific coefficients span a broad spectrum for all commodities. The highest median intensities were observed for gold ores (median = 13.3 m^2 per 1,000 USD, mean = 3,7, sd = 17,587), followed by bauxite (1.7, 14.6, 22.3), tin (1.1, 4.6, 7.2), and nickel ores (0.8, 68.1, 278), while the smallest average intensities were associated with copper ores (0.01, 1.5, 9.1). While 90% of intensities fell below 43 m^2 per 1,000 USD output within the respective sector, outliers were notable (see Figures C5-C8 in Appendix C for more detailed depiction of yearly forest loss and gross production). In Venezuela, gold ores were, for instance, associated with 35 ha, and lead/zinc/silver ores with 1.8 ha forest loss per 1,000 USD in 2012, respectively, and Guinean iron ore displayed values of 1.4 ha per 1,000 USD in 2018.

Although some of these average intensities at the country level involve minor mining producers, Figure 4.2C also reveals that major producing countries (represented by red dots, constituting 70% of global production per commodity) span various intensity levels. For instance, among the top three bauxite producers – Australia, China, and Guinea (USGS 2024) – direct forest loss intensities were 24.6, 0.03, and 1.2 m^2 per 1,000 USD, respectively.

4.2.2 EU final demand causes 12% of global forest loss within mine sites

Raw materials, especially metallic minerals, integrate into international trade networks and global supply chains. By linking the data on mining-related forest loss outlined above to the global multi-region input output (MRIO) model GLORIA (Lenzen et al. 2017; Lenzen et al. 2022), we obtained footprint-type indicators to portray local environmental impacts at extraction sites that are embodied in the final demand (mainly private and government consumption, and capital formation) of products and services elsewhere. In our case, we derived forest loss occurring at extraction sites that is incorporated in consumption across various world regions and industry sectors (see Section 4.4.2, Figure C9). In total, 1,416 km^2 of forest loss within mining areas were attributable to the final demand in the EU between 2001 and 2019. Figures 4.3A and 4.3B show that 89% of this impact occurred outside the EU, primarily associated with material flows originating from the Americas (626 km^2), Indonesia (227 km^2), Russia (159 km^2), Ghana (75 km^2), and Australia (73 km^2).

The EU ranked second in terms of consumption-driven forest loss, following China (2,058 km^2) and ahead of the United States (1,332 km^2) and Japan (753 km^2). EU demand thus contributed to 12% of global forest loss caused by mining between 2001 and 2019. Table C1 in Appendix C shows a full list of countries and per capita values.

Variations existed concerning the materials associated with forest loss impacts attributed to EU consumption. As illustrated in Figure 4.3B, the EU's mining-related forest loss footprint in Indonesia and Russia was predominantly linked to gold ores (102 km^2 and 72 km^2, respectively) and coal (114 km^2 and 56 km^2), while Brazilian forest loss was mostly

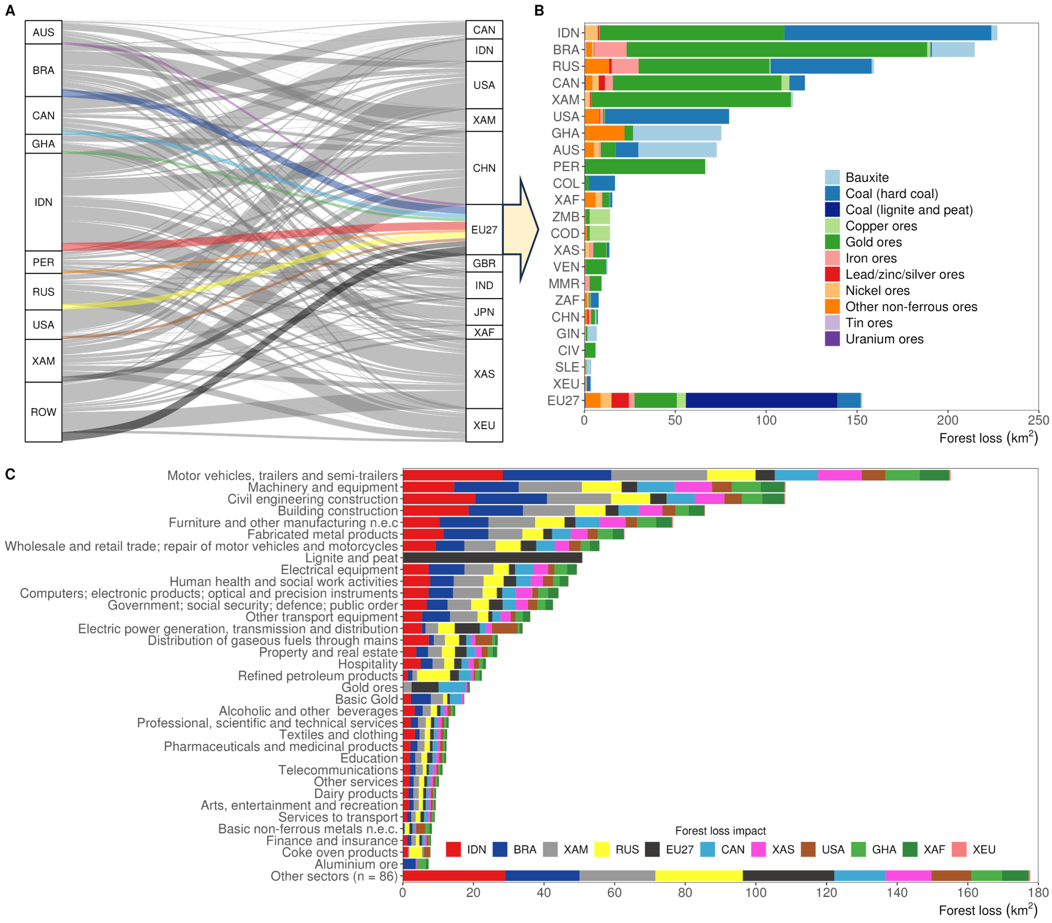

Figure 4.3: Global flows from local occurrence of forest loss caused by mining (production perspective) to where products and services associated with this forest loss are consumed (consumption/footprint perspective). Colours highlight EU-27 consumption (**A**). Mining-related forest loss associated with EU-27 consumption by impact region and mined commodity (**B**). Mining-related forest loss associated with EU-27 consumption by EU-27 industry sector and impact region (**C**).

due to gold ores (165 km^2) and smaller yet considerable portions of bauxite (24 km^2) and iron ores (18 km^2). Gold extraction also dominated forest loss dynamics in Peru (66 km^2), Venezuela (11 km^2), and Cote d'Ivoire (6 km^2). Bauxite emerged as a significant factor in Ghana (49 km^2) and Australia (43 km^2). In Guinea (5 km^2) and Sierra Leone (3 km^2), mining-related forest loss linked to EU demand was almost entirely associated with bauxite. Copper-related forest loss occurred primarily in Zambia and the Democratic Republic of Congo (11 km^2, respectively). Apart from Indonesia, coal embodied in EU consumption (mostly as a source of energy and as an ingredient in steel production) was a prominent factor of forest loss at extraction sites in the USA (68 km^2), Russia (56 km^2), and Colombia (14 km^2), but mostly within the EU itself. Almost two thirds of the 153 km^2 forest loss related to extraction and consumption inside the EU were due to the extraction of coal, particularly in Germany (66 km^2), Romania and Poland (11 km^2, respectively). EU consumption of nickel – essential for enhancing battery performance, longevity and energy density (IEA 2021) – notably contributed to forest loss in Indonesia (6.7 km^2), with subsequent impacts observed in the EU (5.9 km^2), Canada (3.5 km^2) and Australia (2.9 km^2), as well as the 'Rest of Africa' (XAF, 3 km^2) and 'Rest of Americas' (XAM, 2.9 km^2) regions.

One quarter of the EU's forest loss footprint was attributed to just three industrial sectors: automotive manufacturing, machinery and equipment production, and civil engineering construction, i.e. a subset of the construction industry focused on large-scale infrastructure projects such as the construction of roads, dams and railways. The GLORIA dataset provides a detailed sectoral breakdown encompassing 120 distinct industry sectors, facilitating a thorough analysis of impacts within national economies. Figure 4.3C illustrates forest loss embodied in EU's final demand, categorised by industry sector. Among these sectors, the automotive industry in the EU had the most significant impact, accounting for 155 km^2. 19.8% of this area was traced to Brazil, 18.2% to Indonesia, and 17.5% to the 'Rest of Americas' aggregate region. Notably, only 3.5% of the mining-related forest loss impact linked to the EU's automotive industry occurred within the EU itself.

The locations of forest loss associated with the final demand across EU's industrial sectors generally showed a proportional relationship to overall mining-related forest loss levels (see Figure C4), with some notable exceptions. For example, the electric power generation sector had a larger forest loss impact within the EU and in the USA, likely due to the use of coal for energy production, and refined petroleum products left a substantial footprint in Russia.

Comparing the sectoral distribution of EU's footprint with other major material-consuming economies reveals considerable regional disparities. For instance, Chinese consumption predominates the forest loss footprint in the construction, machinery, and electrical equipment sectors (Figure C10) and the United States exhibits the largest footprint in electric power generation, notably fuelled by domestically mined coal, as well as in government, security, and defense sectors (Figure C11). Japan's footprint is disproportionately large in the professional, scientific, and technical services sector. Conversely, the EU footprint is relatively modest in the construction sectors, electric power generation, and electrical equipment (Figure C12).

4.3 Discussion

In recent years, supply chain initiatives have gained prominence due to the increasing awareness that a globalised economy can mask the local environmental and social consequences of raw material extraction behind international trade flows. However, our understanding of the effects of mining and the quantification of these impacts embodied in traded goods remains limited, primarily due to the complexity and opacity of these supply chains. Here, we present conclusions and actionable strategies to minimise negative impacts derived from our findings.

4.3.1 EU's pathways to environmentally responsible sourcing

The varying intensities of forest loss underscore the importance of considering such heterogeneity in formulating effective mining and supply chain management strategies. This study offers insights into sourcing alternatives with lower deforestation impacts, aligning with legal frameworks like the EU CSDDD. By identifying hotspots of supplier impacts and variations in forest loss intensities, our findings can help prioritise areas for intensified environmental impact assessment and inform EU stakeholders' investment strategies. It thereby facilitates the integration of environmental considerations with economic and legal decision factors, ensuring that suppliers are held accountable for their environmental impacts. We illustrate potential alternatives in selecting supplier countries in Figure 4.4, where we present forest loss caused by mining embodied in EU consumption and associated forest loss intensities relative to the production capacities of extracting countries. Ideally, the EU would source from countries located in the top left quadrant of each panel, indicating high production capacities at low forest loss intensities.

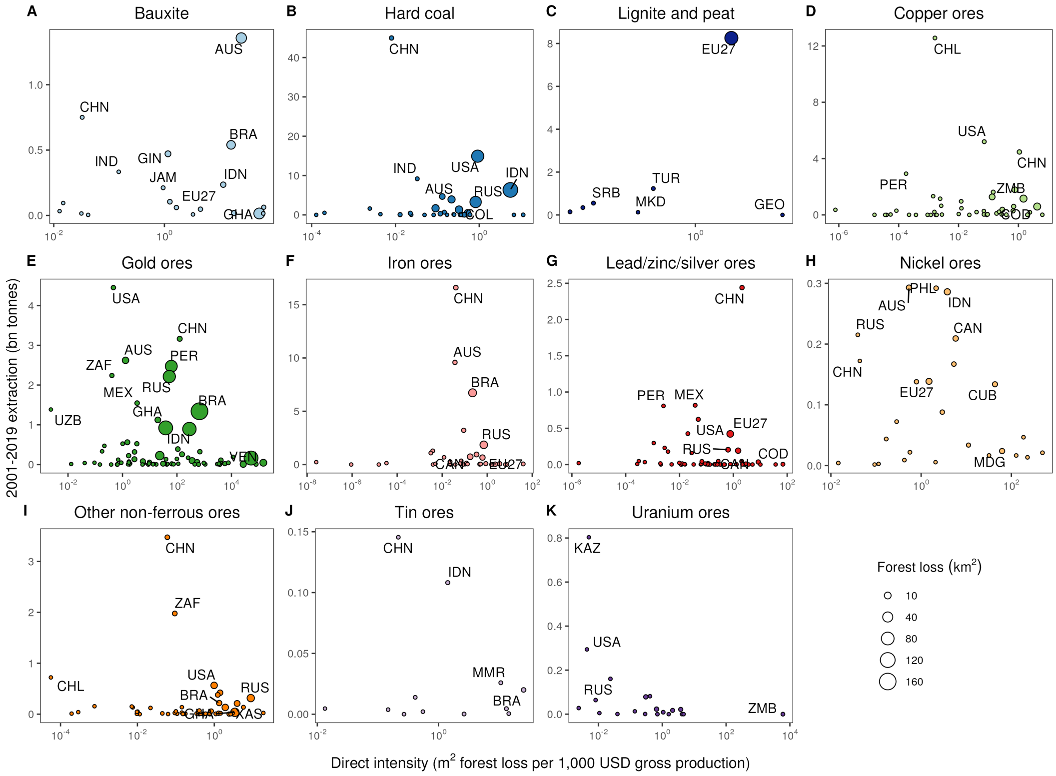

Figure 4.4: Forest loss caused by mining embodied in EU-27 consumption by commodity and impact region. Dot sizes illustrate the scale of forest loss, x-axis indicates 2001-2019 country average direct intensity (m^2 per 1,000 USD) and y-axis indicates 2001-2019 accumulated extraction (bn tonnes) in each country.

Our findings also support private sector and institutional decision-making by identifying industrial sectors within the EU with significant forest loss impacts. The EU's automotive industry is a key player for change and deserves prioritised attention. While decarbonisation will reduce coal-related impacts, the rising demand for electric vehicles will increase the extraction of other materials (Xu et al. 2020a; IEA 2021). Consequently, due diligence must be exercised by stakeholders, particularly within the automotive sector. Anticipating these impacts can also facilitate a more progressive discussion. Beyond responsible material sourcing and mitigating related environmental and social impacts, the sector and modes of living require a substantial transformation, including rethinking transport and logistics systems towards public transport and sharing concepts (Bärnthaler et al. 2023).

To minimise further forest loss, the EU could pursue several pathways. One involves shifting to suppliers with lower deforestation intensity. For example, prioritising Chinese coal over Indonesian sources could reduce deforestation impacts. A more sustainable scenario would not only shift the origin of materials but also seek to avoid or replace high-impact materials altogether. In the context of the energy transition, this would mean relying on technologies that do not depend on coal. However, this approach must also consider the increased demand for other materials that also have high deforestation intensities, such as nickel. Another pathway involves reducing total material consumption in specific industries, for instance through ambitious recycling strategies or alternative transportation methods. The actual dynamics of these approaches are intricate, influenced by factors such as geopolitics, uncertainty about future technologies and material demand, mining feasibility, and the long lifespan of mining operations. Given these challenges, interdisciplinary collaboration is essential to steer a globally fair and just energy transition. To support this effort, future research must systematically assess material demand and its associated socio-environmental impacts and integrate this information into modelled scenarios.

4.3.2 Implications for material suppliers

A rigorous implementation of supply chain initiatives such as the CSDDD will significantly impact commodity producers. Cautious sourcing decisions could incentivise national governments of producer countries to establish appropriate socio-ecological legal and economic frameworks, ensuring they remain significant trade partners for the EU. This externalisation of the EU's standards beyond its jurisdiction through market mechanisms has been referred to as the "Brussels Effect" (Bradford 2015). For instance, Figure 4.4 suggests that the Australian bauxite industry would need to better manage its environmental impacts to comply more effectively with EU standards. Failure to do so could result in corporations operating in or exporting to the EU being forced to shift their material sourcing to other bauxite suppliers, such as China or Indonesia. Consequently, to remain competitive in the EU market, supplier countries might need to either improve their environmental impact mitigation strategies or specialise in the production of minerals with lower environmental impacts. However, especially regarding intermediate traded products, the pressure to adopt more sustainable and responsible procurement would be most effective only if actors disclosed their sourcing information. Moreover, the EU might miss the intended outcome if producers turned their attention to alternative markets (Vasconcelos et al. 2024). The effectiveness of supply chain initiatives therefore also depends on the balance between international competition and cooperation. More sustainable outcomes can only be achieved with the development of transparent and comprehensible supply chains, a goal that remains currently unmet.

Other important aspects are that commodity production has increasingly shifted towards the Global South, and that coal remains the most important energy source globally for electricity generation (IEA 2023). Some regions depend heavily on mining activities, providing employment and income for millions of people, while at the same time causing social and environmental disruption (Bebbington et al. 2008). This structural dependence means that any significant changes to the industry can have profound socioeconomic implications for these communities. As evidenced in palm oil debates, countries have been critical of EU supply chain regulations, arguing that such regulations amount to green protectionism and unfairly push them out of the EU market (Kinseng et al. 2023). Therefore, increasing support by the EU to resource extraction countries in the Global South is necessary to apply better management strategies that help mitigate mining impacts. The EU will need to work closely with various stakeholders in mining countries, including civil society, to jointly develop solutions for adhering to new regulations.

4.3.3 Limitations to supply-chain-wide forest protection plans

In 2008, the European Commission issued the ‘Communication on Deforestation’, proposing ambitious objectives: halting global forest cover loss by 2030 and reducing gross tropical deforestation by at least half by 2020 (European Commission 2008). Our findings highlight the necessity for policies that improve the accountability of EU companies for mining-related environmental impacts occurring in their supply chains outside the EU. These issues are not addressed by the EU's biodiversity (European Commission 2020a) and forest strategies (European Commission 2021), nor by the EU regulation on deforestation-free commodities and products ('Deforestation Regulation', European Parliament 2023a), which, despite its comprehensive supply chain perspective, does not cover forest loss caused by abiotic material extraction. We thus argue that the implementation of the CSDDD presents a crucial opportunity to complement the EU Deforestation Regulation. This would address the environmental impacts of mining, such as forest loss, beyond European borders, enabling the EU to take responsibility for extraction-related impacts driven by its consumption.

However, there are limitations to consider. First, our analysis focused solely on forest loss, but decisions aimed at minimising mining-related forest loss may entail trade-offs with other impacts. For instance, shifting bauxite production from Australia, where forest loss intensity is high and contributes significantly to the EU's deforestation footprint, to China, where deforestation impacts are lower, might overlook other socio-environmental concerns, such as soil pollution and associated health risks (Li et al. 2014). Similarly, in Peru and Chile, where copper ores show relatively low forest loss intensities, copper extraction occurs in desert ecosystems with different environmental priorities, including significant water and energy demands. Understanding these complexities is crucial for informed policy and corporate decisions. While intensity metrics provide initial indicators of risk, local contextual factors warrant consideration in comprehensive impact assessments.

Second, there are fundamental limitations to national supply chain policies. Even with the optimal implementation of the EU's CSDDD and biodiversity and forest strategies, only about 12% of global forest loss caused by mining could have been mitigated. This indicates that the EU alone cannot reverse global forest loss trends and underscores the imperative for international action and cooperation to achieve global zero-deforestation targets despite many challenges (Vasconcelos et al. 2024). Consistent implementation of policies like the CSDDD can inspire other consumer regions to adopt similar measures, potentially steering the global economy towards greater sustainability. This will require political will and may incur higher costs.

In conclusion, this study successfully elucidated the mining-related forest loss embedded within the supply chains of EU consumption, but it is crucial to stress that it has addressed only one impact dimension. As the demand for mineral resources continues to grow, the development of methods and assessments that account for the full spectrum of embodied mining impacts will become increasingly important. Future research and policy must therefore advance beyond single-issue analyses, adopting a comprehensive approach that integrates environmental, social, and economic factors. The findings of this study place particular responsibilities on the Global North and emerging economies such as China and India. Their collective efforts will be instrumental in establishing sustainable global supply chains and ensuring a more responsible use of the planet's resources.

4.4 Methods

We calculated forest loss caused by mining globally at the mine site level for the period 2001-2019 and connected this information to an environmentally-extended multi-region input-output (EE-MRIO) framework. An overview of the workflow is shown in Figure C1 in Appendix C.

4.4.1 Measuring forest loss caused by mining

Data: We measured deforestation caused by mining by overlaying spatial data on mining areas and annual forest cover loss. By integrating this information with data on mining operations, we were able to identify specific commodities and production activities associated with forest loss.

We used the global mine area dataset by Maus et al. (2022) as an indicator for land area covered by mining. The dataset is based on visual interpretation of satellite imagery and features 44,929 spatial polygons, adding up to 101,583 km^2 of land area used by large-scale and artisanal and small-scale mining infrastructure, such as open cuts, tailings dams, waste rock dumps, water ponds, and processing plants.

Forest loss was obtained from the Global Forest Change (GFC) dataset (Hansen et al. 2013), which provides yearly information on tree cover and tree loss at 1-arcsecond resolution (approximately 30 by 30 m at the equator) on a global scale. We classified any pixel with detected tree cover loss and an initial tree cover greater than 25% as deforestation, consistent with established literature (Pendrill et al. 2022). We did not distinguish between partial and complete canopy removal, as mining activities typically result in extensive surface modification and the complete removal of existing vegetation.

To identify the commodities and production linked to deforestation, we applied the Hcluster algorithm (Müllner 2013) to cluster mining area polygons with the coordinates of mines from the S&P Capital IQ Pro Metals and Mining database (S&P 2024). The algorithm clusters geographically close spatial features, connecting mining areas (polygons) with the S&P database coordinates (points). The clusters were defined using a single parameter of the Hcluster algorithm, the maximum tree depth, which was set at 10 km to account for the mining infrastructure spread over the regions, as indicated in the literature (Maus et al. 2022; Werner et al. 2020). This approach often links multiple commodities to a single mining area, reflecting the fact that many sites extract several commodities (Nassar et al. 2015) and multiple S&P properties can be part of a single cluster. Consequently, the same deforestation area may be linked to several commodities.

Geospatial assessment and allocation procedure: We initially intersected the forest cover loss data at 1-arcsecond resolution with the mining polygons to compute the annual forest loss within each mining polygon between 2001 and 2019. The year 2019 was selected as the endpoint because the mining polygons dataset is derived from 2019 cloudless mosaic satellite imagery. It is reasonable to assume that the forest area cleared within the 2019 mining extents was directly attributed to mining activities such as mine expansion or infrastructure development.

Subsequently, we followed the results from the Hcluster algorithm to identify the specific commodities associated with each mining area. To allocate forest loss areas to the respective commodities, we tested four different allocation methods: equal shares, reported primary commodities, extraction mass, and commodity prices. The allocation methods are summarised in Figure C13. For this study, we employed the price-weighted allocation method for forest loss accounts, with detailed results presented in Figure C17. However, a comparison of allocation methods indicates that the forest loss accounts and related findings are robust regardless of the allocation method chosen (see Figure C14-Figure C16).

4.4.2 Environmentally-extended multi-region input output analysis

The forest loss accounts were then integrated in an environmentally-extended multi-region input output (EE-MRIO) framework. EE-MRIO models are extensively utilised to examine a broad spectrum of environmental issues, including carbon emissions (Minx et al. 2009), raw materials (Wiedmann et al. 2015), land use (Hubacek and Giljum 2003) and water resources (Lutter et al. 2016) embodied in the production and consumption of goods and services. These models facilitate the assessment of environmental impacts from both production and consumption perspectives.

The production perspective attributes impacts to the regions and sectors where they occur, whereas the consumption (or footprint) perspective attributes impacts to the final consumption of products and services at the end of global supply chains. Consequently, MRIO models provide a direct link between the impacts of metals and minerals extraction around mine sites and the consumption of goods and services occurring elsewhere. Among their numerous applications, MRIO analysis was recently employed to demonstrate global biodiversity loss associated with mining-related land use (Cabernard and Pfister 2022).

Data: We used Release 057 of the GLORIA global environmentally-extended MRIO database (Lenzen et al. 2022), constructed in the Global MRIO Lab (Lenzen et al. 2017). It features 160 countries and 4 rest of the world accounts, each divided into 120 industry sectors to describe the structure of the global economy. We harnessed the availability of 11 primary extraction sectors: bauxite (aluminium ore), copper ores, gold ores, iron ores, lead/zinc/silver ores, nickel ores, other non-ferrous ores, tin ores, uranium ores, hard coal, and lignite and peat.

Model: The EE-MRIO setting, based on a generalised version of the open IO model, leverages the fundamental input-output balance, which states that the total output of an economy is the sum of all intermediate and final consumption (Leontief 1941; Lenzen 2001; Schaffartzik et al. 2014a). Let $\boldsymbol{Z}$ be an $n \times n$ matrix representing the *intermediate demand* between n industry sectors, and let $\boldsymbol{y}$ be an $n \times 1$ vector of the *final demand* for products (or services) from n sectors. Thus, the total output x_i of a sector i equals the sum of the respective row entries $\sum_{k=1}^{n} \boldsymbol{Z}_{ik}$ plus y_i.

Additionally, let $\boldsymbol{A}$ be the $n \times n$ *direct requirement matrix* (or *technology matrix*), where the element $\boldsymbol{A}_{ij}$ indicates the inputs required from industry i by industry j to produce one unit of total output of sector j. From the relationships:

$$\boldsymbol{x} = \boldsymbol{Z}\boldsymbol{\iota}_n + \boldsymbol{y} \tag{4.1}$$

where $\boldsymbol{\iota}_n$ is a vector of size n consisting of ones, and

$$\boldsymbol{A} = \boldsymbol{Z}\hat{\boldsymbol{x}}^{-1} \Rightarrow \boldsymbol{Z}\boldsymbol{\iota}_n = \boldsymbol{A}\boldsymbol{x} \tag{4.2}$$

where $\hat{\boldsymbol{x}}$ indicates a matrix diagonalising $\boldsymbol{x}$, it follows that:

$$\boldsymbol{x} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{y} \Rightarrow \boldsymbol{x} = (\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{y} = \boldsymbol{L}\boldsymbol{y} \tag{4.3}$$

where $\boldsymbol{L}$ is the *total requirements matrix*, or Leontief inverse, reflecting both direct and indirect intermediate requirements of each sector to produce one unit of final demand for a respective product or service.

Until now, the model and its components are purely described in monetary terms. However, in this study, we employ an environmentally extended version of the MRIO framework (Kitzes 2013), requiring the addition of information on environmental inputs. Let $\boldsymbol{e}^\intercal$ be a $1 \times n$ *direct intensity vector* of environmental inputs (e.g., tons of material, hectares of land, cubic meters of water) associated with one monetary unit of output from each sector. The environmental footprint $\boldsymbol{f}$ associated with the final demand for products and services (consumption perspective) is then defined as:

$$\boldsymbol{f} = \boldsymbol{e}^\intercal \boldsymbol{L} \odot \boldsymbol{y} \tag{4.4}$$

where $\boldsymbol{f}_i$ represents all the environmental inputs required by sector i to provide goods and services to final consumers.

In this study, we investigate the environmental impact of forest loss attributable to the production of metals and coal. Based on the forest loss accounts described in the previous section, which we aggregated to the 11 domestic primary extraction sectors considered in the GLORIA database, we constructed a direct intensity vector $\boldsymbol{e}^\intercal$, which serves as an "environmental extension" to our model. This vector denotes the area of forest loss per monetary output for each specific metal and coal extraction sector featured in the MRIO model, thereby representing the "forest loss intensities" associated with mining sectors across different countries. The environmental extension, expressed in area per 1,000 USD, is illustrated in Figure 4.2C and Figure C8. Further elaboration on the components used for constructing $\boldsymbol{e}^\intercal = \frac{\text{forest loss (area)}}{\text{total output (USD)}}$ can be found in Appendix C (Figure C5, Figure C7).

Limitations All models, including the EE-MRIO model applied in this study, are simplifications of the complex realities they aim to represent. These simplifications, while necessary for managing the complexity of global economic structures, inherently introduce certain limitations that must be acknowledged.

Primary limitations stem from the general assumptions of the MRIO framework (Kitzes 2013). These well-known assumptions include the treatment of economic sectors as homogeneous entities with standardised products, maintaining constant input-output structures, and simplifying environmental pressures. We are aware that such assumptions do not fully capture the heterogeneity and non-linear dynamics present in real-world economic and environmental interactions. Nonetheless, these model types have proven valuable for capturing global trends and relationships.

Regarding the spatial resolution of forest loss accounts in relation to national data in GLORIA, aggregating high-resolution forest loss data unavoidably sacrifices spatial detail, which may impact result accuracy. The model operates under the assumption that subnational forest loss patterns and trade flows align with national averages. Thereby, the model is unable to consider subnational regions' trade flows with other global regions, but integrates them into national trade (Wiedmann and Lenzen 2018). This approach can obscure important details, such as when resources from one region in country A are predominantly consumed in country B, while the same resources from another region in country A – potentially with different environmental impacts – are predominantly consumed in country C.

These limitations need to be considered when interpreting the results of this study. They highlight the necessity for further research to refine EE-MRIO models, particularly by integrating high-resolution spatial data with subnational and international trade flows, and accounting for regional and temporal variability in environmental impacts.

Chapter 5

Conclusion

Mining activities have far-reaching impacts on the environment and societies. Over recent decades, mining's expansion has exemplified an extended social metabolism, in which global resource extraction has not only accelerated but has also reached into previously undisturbed and increasingly fragile territories. As demand continues to surge, new frontiers of extraction such as deep sea mining and emerging technological innovations are likely to introduce new challenges and risks.

This thesis has examined mining activities from the perspectives of ecological economics, specifically addressing how the pressures of the global economy affect local ecosystems and regional economies. By exploring three primary dimensions – the risks associated with expanding mining into vulnerable ecosystems, the local impacts and spillover effects of extraction, and the geographical disconnect between extraction and consumption – it provides a comprehensive view across multiple spatial scales. But what overarching conclusions emerge from the presented data and statistical exercises? A **central takeaway** from this research is that integrating geographic data with advanced spatial statistics and modelling provides a clearer understanding of the impacts of resource extraction, enabling policymakers, businesses, and communities to better anticipate and manage future extraction pressures. The findings highlight the importance of a global, integrated approach, as local environmental and social impacts are directly tied to global consumption patterns, trade systems, and inherent inequalities. This thesis thus presents approaches for linking sub-national contexts with global perspectives, offering a roadmap to identify priority areas for further work on local contexts of ecosystem vulnerabilities, social dynamics, and pathways toward responsible resource governance.

The **three main chapters** of this dissertation, presented as standalone research articles, each contribute from distinct angles. The first paper provides a broad, spatially explicit overview of global mining expansion for major metals over the past two decades, during which extraction rates have doubled. It reveals how this rapid expansion has intensified pressures on ecosystems classified as vulnerable, underscoring unsustainable trends in current resource extraction. The second paper narrows the focus to Brazil, examining the regional economic and environmental impacts of mining at the examples of GDP growth and forest cover change. By highlighting the multifaceted socioeconomic and environmental effects of mining, the study demonstrates that economic benefits and ecological degradation are no straightforward trade-offs. It calls for a cautious approach to development narratives that does not unconditionally prioritise economic gains. The third and final paper traces the impacts of resource extraction to final demand, linking forest loss from mining activities to industries and consumption within the European Union. By revealing the environmental costs embedded in EU supply chains, this paper provides a foundation for policies aimed at mitigating these impacts through more transparent and responsible sourcing practices.

Notably, this thesis demonstrates the utility of quantitative approaches in assessing environmental and socioeconomic impacts of mining, exemplified through forest loss and GDP growth as key metrics. However, many other critical impacts, such as pollution, biodiversity loss, water scarcity, and environmental distribution conflicts, remained empirically unexplored. By focusing on a specific set of impacts, this work lays the groundwork for future research to address these additional dimensions, and potentially develop methods to capture indirect and cumulative effects across diverse temporal and spatial scales.

Together, the three studies emphasise the need for both demand- and supply-side measures to curb resource consumption and mitigate the adverse impacts of mining. They advocate that future resource governance must incorporate tight regulatory measures and that consumption patterns must be geared towards efficiency and sufficiency. This aligns with the recommendations of the UN International Resource Panel, which, in its Global Resources Outlook (UN IRP 2024) argues that demand-side interventions promoting resource efficiency and sustainable consumption must complement supply-side reforms like responsible sourcing practices.

This thesis offers several actionable recommendations to improve environmental and social outcomes in the mining sector. However, these **policy recommendations** by no means cover the entire scope of action and instead supplement and support existing calls in the literature, such as the four actions towards ecologically responsible mining proposed by Sonter et al. (2023) and the calls for a reimagined infrastructure governance agenda for extractive industries (Bebbington et al. 2018a; Bebbington et al. 2020). Although some environmental management practices, including progressive rehabilitation, minimum environmental standards, and sustainability guidelines, have been implemented by key stakeholders, the findings from the three studies underscore the need for further action at both local and global levels to address mining's complex impacts.

The first paper, for example, emphasises the need for robust monitoring systems to anticipate the impacts of rising metal production and to track progress toward sustainable technologies and regulatory improvements. It calls for greater corporate transparency, requiring detailed, locally specific data on mining practices and changes in the surrounding environment. These data can serve as indicators for global assessments of mining impacts and more effective industry monitoring. The paper also stresses the urgency of critically reviewing, reforming, and enforcing current national environmental regulations, for instance in light of escalating extraction activities in protected areas. The second paper's analysis of Brazil's mining sector importantly suggests that targeted regulation of industrial mining, in contrast to informal "garimpo" activities, can yield better environmental outcomes. It underscores the need for more sustainable solutions, particularly for gold mining, suggesting that its limited societal benefits may warrant halting such activities. The paper also highlights the risks of local economies becoming overly dependent on the extractive sector, which may undermine more sustainable economic structures. To address these issues, it advocates for long-term strategic planning, including the prudent management of mining rents to benefit local communities, reducing economic reliance on mining, and developing strategies to support resilience in mined-out areas. This thesis further cautions that national environmental and social standards, as well as policies within associations of nations like the EU, may be insufficient, as international competition and limited corporate transparency create obstacles to advancing sustainable resource management. This issue is particularly highlighted in the third paper, which seeks to inform policy initiatives like the EU's Corporate Sustainability Due Diligence Directive (CSDDD) that target the reduction of environmental and social impacts of large companies across their supply chains. By illustrating that even flawless CSDDD implementation may be insufficient, the study calls for stronger international cooperation, legal alignment, and global standards for responsible mining, as well as policies supporting a fair and just transition, particularly for resource-producing regions in the Global South. However, the study also offers practical recommendations for the EU, including sourcing alternatives with lower deforestation impacts and investment strategies to hold suppliers accountable for their environmental footprints.

Overall, this dissertation offers innovative insights into particular aspects of mining-induced change. Many pressing challenges remain, however, and timely action is essential, as, every day, the global economy's ongoing reliance on newly mined resources brings further environmental change, fuels distribution conflicts, and nudges the planet closer to its ecological limits. Addressing uncertainties around where and how mining will expand in response to growing demand and technological advances will be crucial. Current research is progressing in this direction, aiming to reliably model such developments in the near future.

Looking ahead, **future research** must further integrate local impact assessments with global perspectives to equip policymakers with the knowledge needed for sustainable resource management that is both environmentally responsible and socially just. This thesis identifies several key areas where further work is needed. First, developing more comprehensive datasets that reduce reliance on corporate disclosures, particularly through the use of advanced remote sensing technologies, will be crucial. Additionally, there is a need for new empirical frameworks that go beyond single-issue analyses to better capture the multidimensional impacts of mining. Equally important is the development of methods to assess the cumulative and indirect effects of mining, including modelling spatial connectivities and the temporal dynamics of mining impacts. Such approaches will enable more precise and preventative mining management that addresses potential harms before they materialise. Finally, refining supply chain models – such as by increasing sectoral resolution – will be instrumental for accurately tracing the flow of metals and minerals from extraction to final demand. This will be key to understanding and reducing the global footprint of high-impact industries, including renewable energy technologies. While this research offers important insights into addressing massive challenges, it underscores the need for a collective, interdisciplinary approach that engages stakeholders such as local communities, the mining industry, and consumers. Enhancing our understanding of mining impacts and the policies needed to address them is essential to providing the material basis for well-being while safeguarding the planet and all its communities.

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Appendices

A Supplementary Information Paper 1

A.1 Data

Raw data and gap filling

- We downloaded individual mine "production" data for all metals considered in this study from the SNL Metals & Mining Database (SNL 2020). The download was conducted in May 2020.
- Note that by "production" SNL refers to metal content (i.e. net weight) for all commodities considered in this study except bauxite, iron, and manganese, where "production" denotes mostly ores.
- We filtered for "production" > 0 and $2000 \leq$ "year" ≤ 2019.
- We used "production" (and hence mostly net weight values) as our baseline because this variable offered most complete global coverage. Based on this baseline, we estimated respective metal ore extraction in a second step.
- For gap filling of bauxite, iron, and manganese data, we downloaded "ore processed" data from the SNL Metals & Mining Database and again filtered for "production" > 0 and $2000 \leq$ "year" ≤ 2019.
- For bauxite, iron and manganese mines where no "production" but only "ore processed" was reported, we added these volumes to our data. We avoided double counting by only considering reported values where either of the three commodities was listed as "primary commodity".
- We converted all values to tonnes.

Applying UNEP conversion factors

- For copper, lead, zinc, nickel, gold and silver, we estimated extracted gross weight volumes by applying the same conversion factors as they were used for the construction of UNEP's Global Material Flows database (UN IRP 2017a).
- We divided net weight volumes by country- and metal-specific conversion factor estimates as summarised in Table A1. Data in the table of factors does not solely represent the estimation factors as used in the compilation of the last version of the IRP database, as a range of additional conditions were applied. Furthermore it does

not represent the set of estimation factors used in the current IRP database version upcoming in 2021, which have been compiled on a different basis.

Commodity	Min	25%	Median	Mean	75%	Max
Copper	0.2300	0.5200	0.9050	6.6894	0.9900	100.0000
Gold	0.0001	0.0003	0.0004	0.0006	0.0006	0.0075
Lead	0.5230	2.4000	4.1785	3.8419	5.3250	5.9479
Nickel	0.2000	1.2000	1.9800	23.8447	3.0000	100.0000
Silver	0.0129	0.0300	0.0300	13.2675	0.0300	100.0000
Zinc	0.9000	4.8300	4.8300	5.3597	5.0000	14.9669

Table A1: Summary statistics of UN IRP (2017) conversion factors utilised in this study; in %; n = 146 countries

Limitations

- Polymetallic ores are difficult to attribute to single metals on an aggregated scale (West et al. 2020; Tost et al. 2020). We hence decided to build upon SNL's "production" values. This means that an upward bias might be introduced for metals that frequently occur as by-products, such as lead and silver. A comparison of aggregated accounts with UNEP's Global Material Flows database values for"domestic extraction" yields a good fit (see Figure A1), but it must be noted that the same difficulties in data compilation applied to the UNEP data.

- It is still to be expected that our data are conservative estimates due to mining sites being missed out by SNL, and the impossibility of fully recording artisanal and informal mining operations on a global scale.

- Bias regarding specific regions can be introduced if specific regions are systematically differently covered by SNL. We noticed high uncertainty for Chinese mining sites. For 2017, our SNL-based approach yields significantly smaller mining volumes of approximately 1,500 Mt of iron ore and 16 Mt of manganese ore less than reported in the UNEP data. Therefore, we refrained from interpreting any results with regard to China in our study.

- By assuming national averages as conversion factors between reported metal content and estimated ore extraction, we accept a considerable degree of uncertainty in the data. Especially for larger amounts, small variations in ore grades may already lead to significant deviations in extraction estimates. To help quantifying this effect, we compared our data with estimates from individual mine conversion factors. In a small case study, we selected copper as the metal of interest and reduced the analysis to Australia, Chile, Peru and Zambia. We used mine-specific ore grades available from the supplementary information of Mudd and Jowitt (2018) and matched this data with our list of mines from SNL (2020). We then computed and contrasted extraction volumes for 2015 based on both national ore grade averages and individual grades as summarised in Table A3 and Figures A2 and A3. For our sample, we find some substantial deviations based on ore grade assumptions, but also that corresponding extraction estimates correlate well. We tend to rather under- than overestimate extraction volumes compared to the mine-specific approach. Most significant deviations are found for Peru, in total resulting in a 2015 national estimate of 350 Mt using individual ore grades vs. only 90 Mt using the UNEP average grade of 1.8% for the considered 25 mines. The deviation relates to large Peruvian copper mines, where individual grades were reported to be considerably lower than the assumed national average.

While data on individual ore grades was published in previous works for a number of metals (e.g. Mudd et al. 2017 and Mudd and Jowitt 2018), no extensive, harmonised and openly available global database on a large range of metals is yet available. We concluded that an approximation approach was most suitable for our analysis, because a harmonisation of existing material and potential extensions would have been beyond the scope of our analysis. For future research, we can only highlight the importance of simple access to harmonised data, at best using unique mine identifiers such as geocodes, as well as the great potential that lies in the combination of statistical reports and additional information – most notably from satellite imagery – to estimate resource extraction and environmental impacts.

Data summary

	Bauxite			Iron			Nickel		
Year	Content [Mt]	Ore [Mt]	Avg. CF	Content [Mt]	Ore [Mt]	Avg. CF	Content [Mt]	Ore [Mt]	Avg. CF
2000		121.6154			947.1160		1.0615	90.7601	1.1696
2001		123.0441			942.9956		1.1675	96.4668	1.2102
2002		129.0004			1003.5283		1.1581	96.3204	1.2023
2003		137.5569			1107.2741		1.1257	102.9003	1.0940
2004		139.0460			1188.4307		1.2034	104.2362	1.1545
2005		157.0885			1288.8093		1.3179	108.3051	1.2168
2006		159.6403			1412.6257		1.3912	111.8240	1.2441
2007		165.7980			1471.0586		1.3946	118.9655	1.1723
2008		172.7108			1570.4442		1.3668	110.0675	1.2418
2009		164.1642			1473.1348		1.2117	108.1768	1.1201
2010		179.0968			1729.9033		1.3130	130.8332	1.0036
2011		185.5672			1797.0445		1.3983	121.6595	1.1494
2012		193.9284			1873.5024		1.4826	123.6844	1.1987
2013		195.6001			1884.6442		1.5683	119.4311	1.3132
2014		191.3867			1982.1119		1.4927	112.1712	1.3307
2015		184.1518			2028.2689		1.5901	121.2229	1.3117
2016		196.5633			2079.5212		1.9519	147.2955	1.3252
2017		180.7309			2088.0441		1.9468	150.9611	1.2896
2018		179.1387			2121.3685		1.7581	135.4898	1.2976
2019		179.8947			2200.5818		1.7047	140.6466	1.2121

	Copper			Lead			Silver		
Year	Content [Mt]	Ore [Mt]	Avg. CF	Content [Mt]	Ore [Mt]	Avg. CF	Content [Mt]	Ore [Mt]	Avg. CF
2000	12.2515	1548.7819	0.7910	2.4742	73.4762	3.3674	0.0121	24.3872	0.0497
2001	13.2027	1662.8676	0.7940	2.3648	67.9017	3.4827	0.0124	25.8121	0.0479
2002	13.3412	1634.0790	0.8164	2.2746	63.9930	3.5545	0.0128	28.4287	0.0452
2003	13.4605	1645.5423	0.8180	2.1611	60.7282	3.5587	0.0120	26.2915	0.0457
2004	14.3323	1718.9156	0.8338	2.2411	65.5983	3.4165	0.0130	29.1373	0.0445
2005	14.7312	1798.2449	0.8192	2.4112	70.0962	3.4398	0.0137	30.4154	0.0451
2006	14.3985	1745.0136	0.8251	2.3780	69.3035	3.4313	0.0137	30.9785	0.0443
2007	14.4107	1723.1330	0.8363	2.1538	62.1263	3.4668	0.0156	37.5112	0.0415
2008	14.8674	1784.3460	0.8332	2.4212	67.9368	3.5639	0.0162	40.6294	0.0398
2009	15.4026	1808.0036	0.8519	2.2115	60.8515	3.6343	0.0154	39.2870	0.0391
2010	14.9656	1763.2787	0.8487	2.4010	65.0003	3.6938	0.0169	41.5637	0.0407
2011	15.0256	1772.7691	0.8476	2.4330	66.2090	3.6747	0.0169	41.1528	0.0411
2012	15.4355	1800.8653	0.8571	2.2999	63.9610	3.5958	0.0180	44.6081	0.0403
2013	16.7593	1936.0821	0.8656	2.3584	63.9676	3.6869	0.0190	48.3043	0.0394
2014	16.9550	1976.3345	0.8579	2.3561	63.8887	3.6879	0.0195	51.3607	0.0379
2015	17.6478	2055.1359	0.8587	2.4430	66.2898	3.6854	0.0200	52.9119	0.0378
2016	18.9348	2194.8312	0.8627	2.7065	71.2459	3.7988	0.0187	52.6527	0.0355
2017	18.6524	2140.1618	0.8715	2.6314	69.7795	3.7710	0.0183	50.1524	0.0365
2018	19.1758	2171.1827	0.8832	2.8638	75.7409	3.7811	0.0177	48.1747	0.0368
2019	19.1717	2159.0821	0.8880	2.8802	75.8814	3.7956	0.0191	52.3006	0.0366

	Gold			Manganese			Zinc		
Year	Content [Mt]	Ore [Mt]	Avg. CF	Content [Mt]	Ore [Mt]	Avg. CF	Content [Mt]	Ore [Mt]	Avg. CF
2000	0.0020	778.7653	0.0003		16.0008		6.8875	181.7657	3.7892
2001	0.0021	823.0934	0.0002		15.8721		7.9238	208.3392	3.8033
2002	0.0019	759.7741	0.0003		16.8121		7.7954	218.8607	3.5618
2003	0.0020	771.4307	0.0003		17.7732		7.8499	220.6174	3.5582
2004	0.0019	721.4750	0.0003		22.1492		7.7205	205.5910	3.7553
2005	0.0019	739.6501	0.0003		23.8596		7.8932	208.6280	3.7834
2006	0.0018	699.6095	0.0003		23.5832		8.2997	219.1344	3.7875
2007	0.0018	676.9916	0.0003		23.3960		8.6860	234.8893	3.6979
2008	0.0018	669.5606	0.0003		25.6741		8.6200	249.7848	3.4510
2009	0.0019	693.6454	0.0003		20.1129		8.3403	249.9667	3.3366
2010	0.0019	723.0663	0.0003		28.3813		8.7602	254.6770	3.4397
2011	0.0020	738.7320	0.0003		29.0540		8.4787	234.2322	3.6198
2012	0.0020	751.9583	0.0003		32.0360		8.7385	244.5789	3.5729
2013	0.0021	771.3372	0.0003		32.6361		8.3261	243.9494	3.4130
2014	0.0022	789.6254	0.0003		38.5364		8.4008	242.3071	3.4670
2015	0.0022	809.8479	0.0003		37.7014		8.3547	248.4502	3.3627
2016	0.0022	822.7619	0.0003		34.9103		8.5889	251.1772	3.4195
2017	0.0023	890.6802	0.0003		40.4473		8.8472	267.2152	3.3109
2018	0.0024	881.1796	0.0003		44.5664		9.5039	273.4248	3.4759
2019	0.0024	872.2883	0.0003		45.9968		9.1315	253.0751	3.6082

Table A2: Annual aggregates of the data considered in this study. Content is obtained from SNL (2020). Ore is based on SNL and country- and commodity-specific conversion factors from UN IRP (2017). The average conversion factor (CF, in %) depicted in this table follows from content and ore figures.

Comparison with UNEP country aggregates

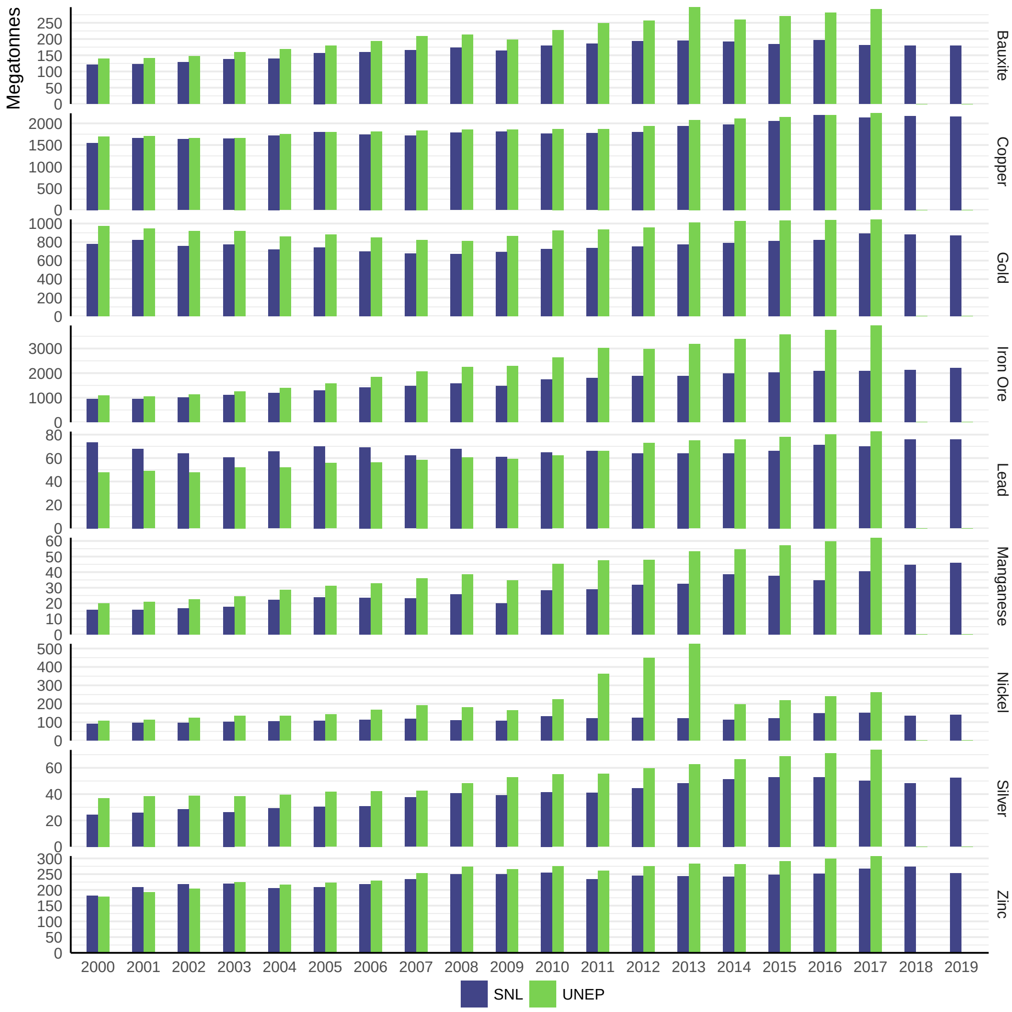

Figure A1: Globally aggregated crude ore extraction of the commodities covered in this study. Comparison of the utilised data (based on mine accounts by SNL 2020) and UNEP's national statistics (UN IRP 2017a). UNEP 2015–2017 are projections; no data yet available for 2018 and 2019. Large deviations for nickel in 2011–2013 are driven by BGS (2021) (used as a source for UNEP's domestic extraction statistics) reporting an extreme production increase for Indonesia over this period (followed by a rapid drop in 2014). This development is apparently not reflected in the SNL data.

Ore grade estimates for copper

Country	Ore UNEP	Ore MJ	ρ	CF UNEP	CF MJ min	CF MJ median	CF MJ mean	CF MJ max	n
Australia	105.77	157.74	0.60	1.01	0.11	1.06	1.40	5.65	24
Chile	527.55	1006.94	0.98	1.00	0.27	0.53	0.63	1.64	30
Peru	90.51	346.10	0.89	1.80	0.07	0.45	0.53	1.38	25
Zambia	88.00	88.50	0.83	0.99	0.51	2.06	1.82	4.11	12

Table A3: Copper extraction estimates ('Ore', in Mt) for 2015 based on SNL (2020) and conversion factors (CF, %) from (a) UN IRP (2017) (UNEP) and (b) Mudd and Jowitt (2018) (MJ); ρ = Pearson correlation coefficient between extraction estimates from both approaches; n = number of observations using semi-automatised matching of mining properties by their names.

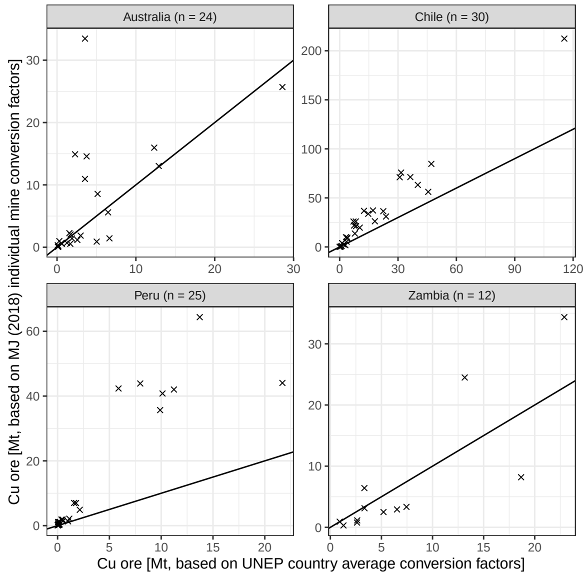

Figure A2: 2015 copper extraction estimates for each mine: UN IRP (2017) vs. Mudd and Jowitt (2018) conversion factors. Solid line indicates 45 degrees.

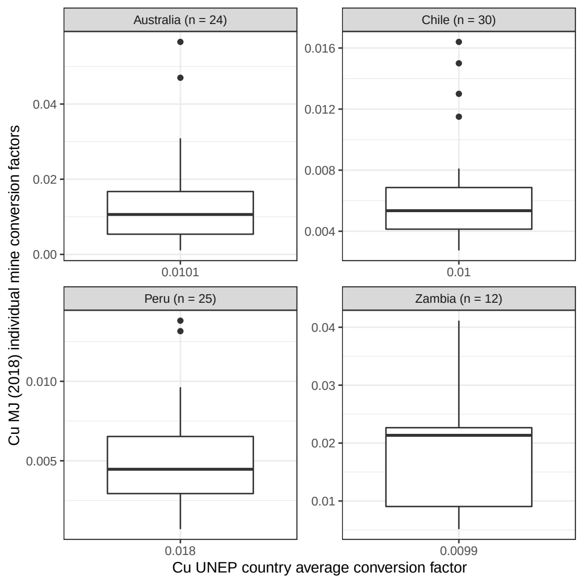

Figure A3: National average UN IRP (2017) copper ore grades vs. mine-specific grades from Mudd and Jowitt (2018).

Counts of 1 degree resolution mining cells

Using 1 degree resolution grid cells (i.e. about $110\,km \times 110\,km$ at the equator) and grouping by commodity, we compared annual grid cell counts with average extraction volumes per cell. Grid aggregates were chosen instead of point data because we were interested in a regional spread rather than an expansion of already existing agglomerations of sites. In doing so, we were able to draw development paths (i.e. a scatter plot with chronologically connected points) in order to relate densification and spatial spread for each metal.

Figure A4 compares the annual counts of 1 degree mining cells with average extraction per observation for the timeline between 2000 and 2019. We can observe three different development patterns, highlighted by different colours. Most commodities show a significant increase in counts, indicating a substantial spatial expansion of mining activities. Only the occurrences of manganese and bauxite stagnate, while significant gains in mining intensity can be observed (purple). Bauxite extraction per mining grid increased by 122%, and the extraction of manganese ores by 278% between 2000 and 2019. For nickel, lead, zinc, copper and gold ores, we observe an increase of grid counts and hence a spatial spread, while the average extraction per observation has fallen (green). Iron and silver ore extraction also indicate a spatial spread, but on top of that they yield a slight expansion of average extraction intensities (blue).

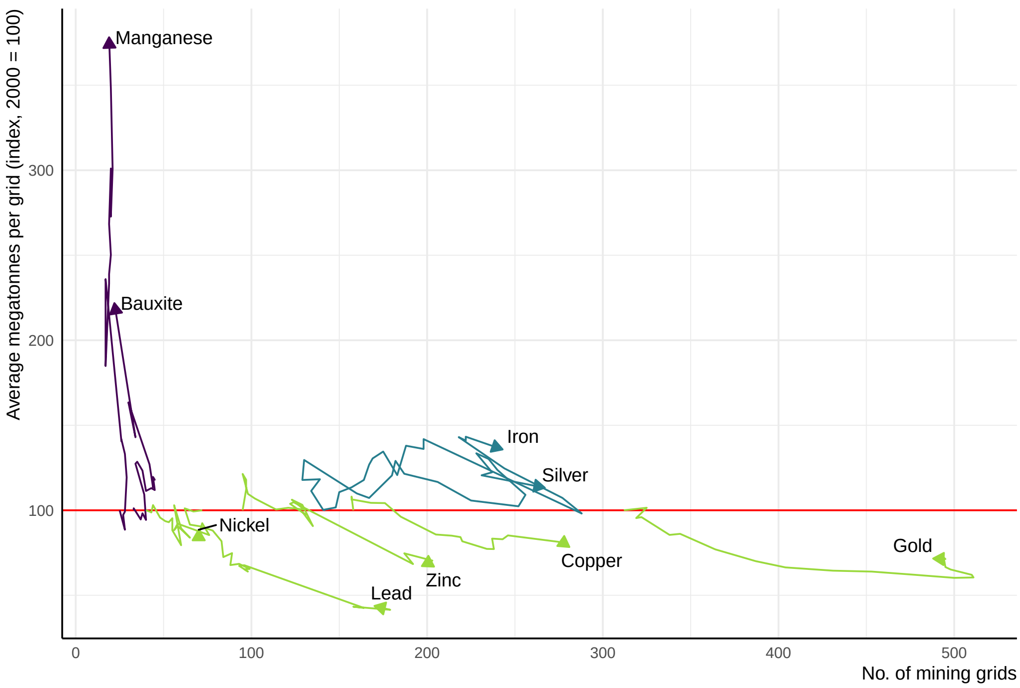

Figure A4: 2000-2019 development of the counts of 1 degree resolution mining grid cells and average extraction volumes per cell (index, 2000 = 100); starting and end points of arrows denote the years 2000 and 2019, respectively; based on SNL (2020) and UN IRP (2017) conversion factors.

Alternative (more granular) grid cell aggregates for 2019

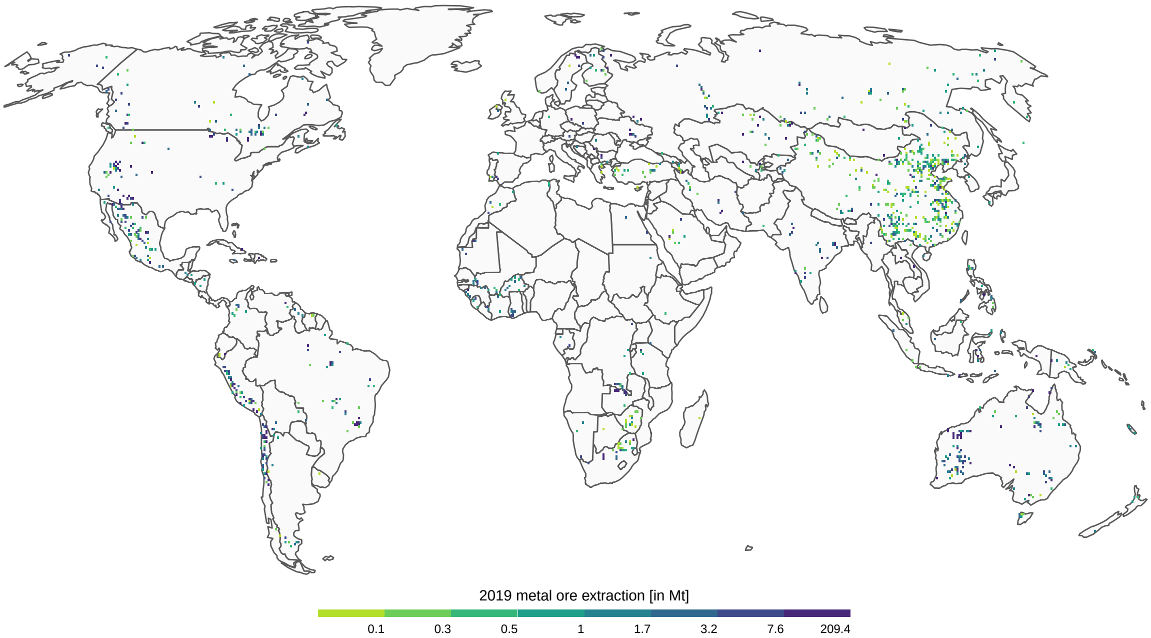

Figure A5: Global 2019 metal ore extraction (in Mt) grouped by 8 quantiles on a 0.5 degree resolution (i.e. about 55 $km \times 55\,km$ at the equator) using a Robinson map projection. Based on SNL (2020) and UN IRP (2017) conversion factors.

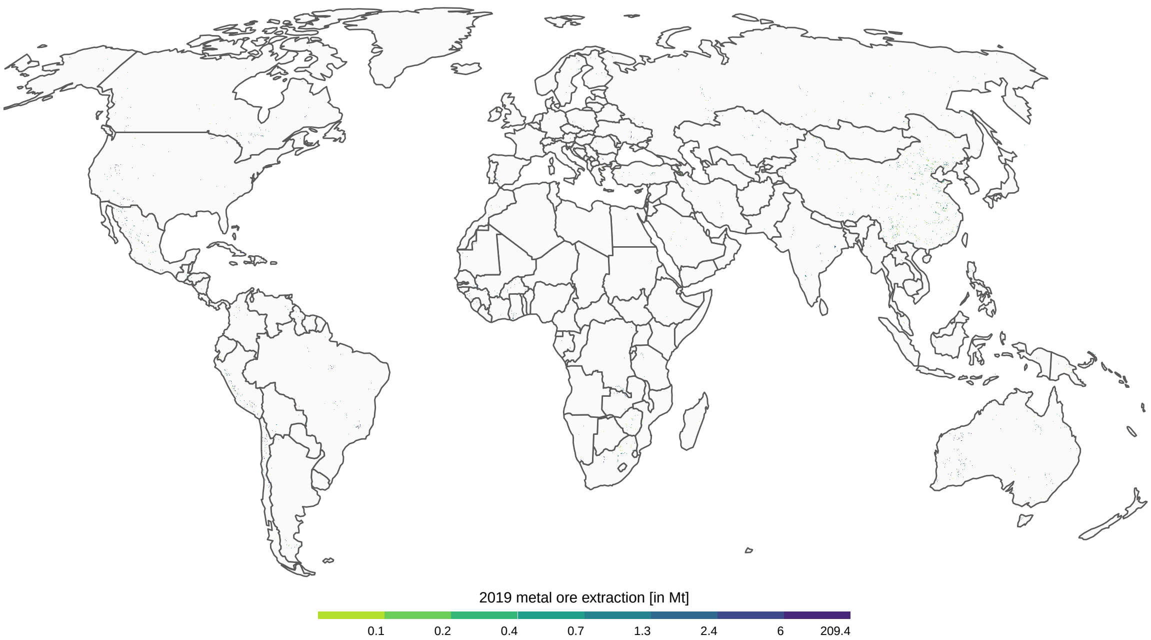

Figure A6: Global 2019 metal ore extraction (in Mt) grouped by 8 quantiles on a 0.1 degree resolution (i.e. about 11 $km \times 11\,km$ at the equator) using a Robinson map projection. Based on SNL (2020) and UN IRP (2017) conversion factors.

Distribution across mining cells

Elaborating the distribution of extraction volumes across mining grid cells, we moved to a more granular level by dividing the 1×1 degree cells into quarters. Subsequently, we ordered them from highest to lowest extraction volumes and show them as bar charts per commodity in Figure A7.

In 2019 (Figure A7 right column), 39% of the reported global total of 180 Mt of mined bauxite ore were extracted in only two Australian mining regions, one being located south of Perth and the other along Cape York Peninsula's Gulf of Carpentaria coast. 6% (131 Mt) of all copper ore (2159 Mt) came from a single $28\,km \times 28\,km$ cell in Chile's Antofagasta region, and 50% from 25 out of 360 copper mining regions worldwide. For gold, where we counted the largest number of observations (699 mines located in 626 different grids), we find that more than 20% of ore were extracted in only seven grids. Iron ore was to a large majority mined in a small number of Australian and Brazilian mining sites with more than 50% of 2019 global supply of 2201 Mt stemming from only 13 mining grids. Global lead extraction added up to 76 Mt originating from 212 different grid cells, 7% of which were mined in one small area in the East Kazakhstan Region and more than 20% coming from merely 4 regions. Manganese ore was mined in only 24 grid cells in 2019 with the largest site located near Kuruman, South Africa, producing 21 of the total of 46 Mt. Three regions, two next to Lake Matano, Indonesia, and the sites around Moa, Cuba, together accounted for more than 50% of the 141 Mt of nickel that were mined in 2019. 52 Mt of silver were extracted in 323 different 0.25×0.25 degree regions, the top 3 grids (located in Mexico, Poland and Bolivia) accounting for 12 Mt. Global zinc extraction added up to 253 Mt, with its highest concentration at the Peruvian Antamina mine, satisfying 12% of worldwide demand. Overall, our data based on SNL (2020) and UN IRP (2017) add up to 6 bn tonnes of ore extracted in 2019. Total extraction could be aggregated into 2,239 0.25×0.25 degree grid cells, and 20% of it into only 10 mining grids. Comparing 2000 (Figure A7 left column) and 2019 values indicates that the distributional patterns have not changed considerably, but the extraction volumes have. We find, for example, a 187% increase in the extraction of manganese ores, 132% in iron ores and a 114% increase in the extraction of silver ores.

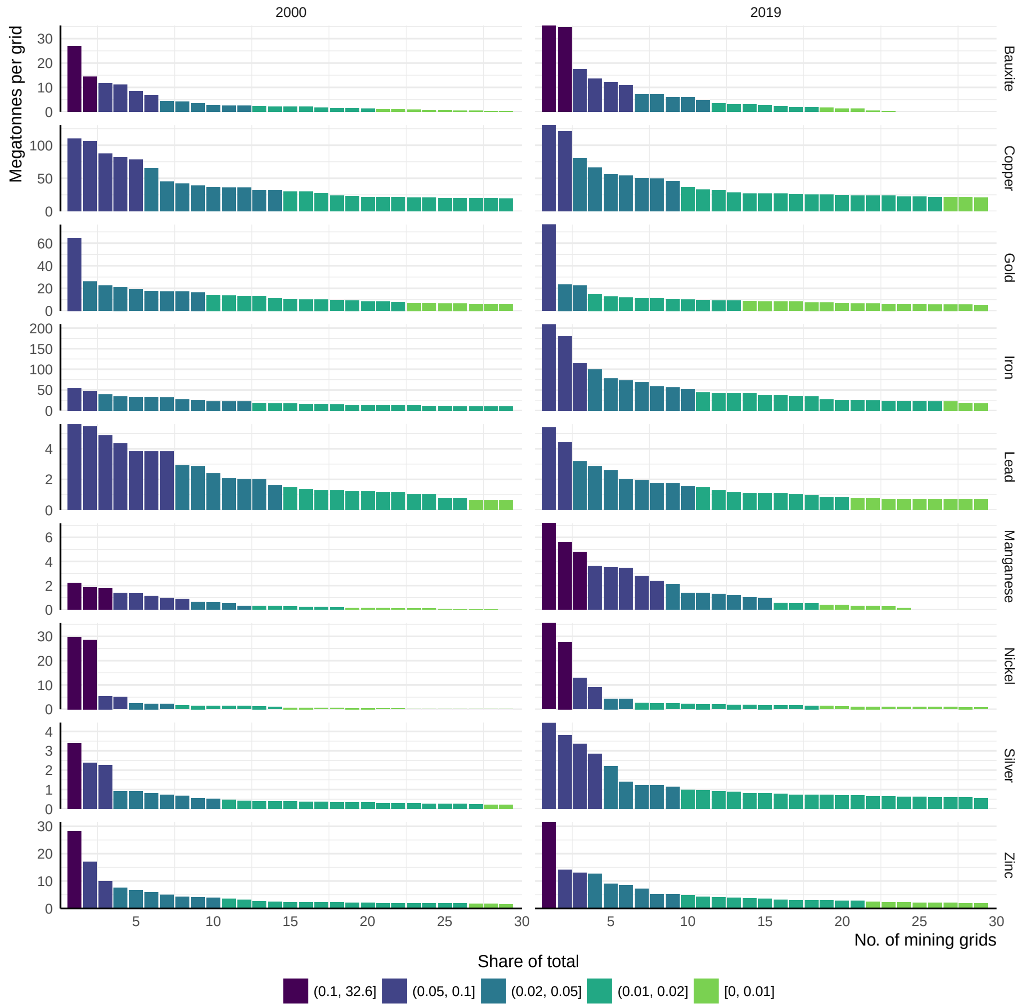

Figure A7: Metal ore extraction on a 0.25 degree resolution (i.e. about 28 $km \times 28\,km$ at the equator) based on SNL (2020) and UN IRP (2017) conversion factors.

A.2 Geographically weighted regression

We used a geographically weighted regression (GWR, Brunsdon et al. 1996) to estimate the trends in metal ore extraction for each mining location $s = 1, \ldots, n$, such that

$$y(s) = \boldsymbol{X}(s)\boldsymbol{\beta}(s) + \epsilon(s) \tag{A1}$$

where the dependent variable $y(s)$ denotes the log-transformed extraction volume of a mine at location s. The row vector of explanatory variables $\boldsymbol{X}(s)$ at location s includes only two elements in our application, first being a 1 allowing for an intercept and the second indicating the respective year. $\boldsymbol{\beta}(s)$ is a column vector of the corresponding regression coefficients and $\epsilon(s)$ the random error at location s following a Gaussian distribution. The vector of estimated parameters in a GWR model at location s is derived as

$$\hat{\boldsymbol{\beta}}(s) = [\boldsymbol{X}'\boldsymbol{W}(s)\boldsymbol{X}]^{-1}\boldsymbol{X}'\boldsymbol{W}(s)\boldsymbol{y}, \tag{A2}$$

where X is the design matrix of explanatory variables and $\boldsymbol{W}(s)$ a diagonal weights matrix of dimension n that is calculated for each calibration location s. The elements of $\boldsymbol{W}(s)$ are obtained from the kernel function

$$w_j(s) = exp(-1/2(d_{sj}/h)^2), \tag{A3}$$

where d_{sj} is the distance between locations s and j and h is the bandwidth parameter obtained via cross-validation across all the calibration locations. In order not to put weight on observations that are very far away, only the nearest 1% of all locations from the sample were considered for constructing the weights. All calculations were conducted in R (R Core Team 2024) utilising functions from the **spgwr** package (Bivand and Yu 2020) that were modified in a way such that the calculations could be run on multiple cores in parallel.

Mapping positive and negative coefficient estimates

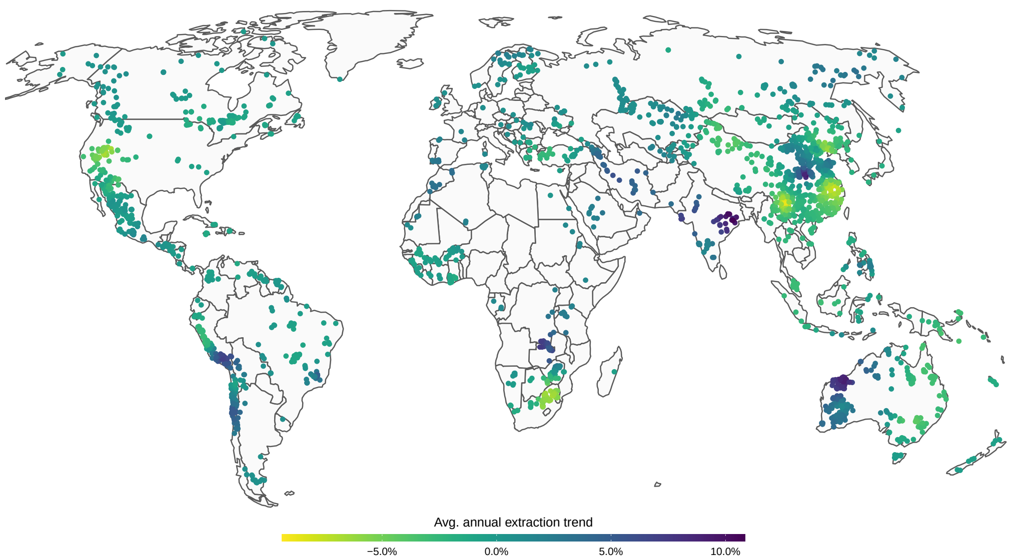

Figure A8: 2000-2019 global extraction trends in metal mining, i.e. linear coefficient estimates at point locations obtained from GWR; based on SNL (2020) and UN IRP (2017) conversion factors.

Global GWR maps separate by metal are provided for download in the online version of the article at https://doi.org/10.1016/j.gloenvcha.2021.102303.

A.3 Further results

Global ore maps separate by metal and for the years 2000, 2010, 2015 and 2019 are provided for download at https://doi.org/10.1016/j.gloenvcha.2021.102303.

B Supplementary Information Paper 2

B.1 The Brazilian mining sector

Mining activities vary in size of operation, workforce and their degree of mechanisation. In Brazil, mining titles are issued to companies, cooperatives and individuals by the National Mining Agency as part of the licensing procedures for mining initiatives. Thereby, the Brazilian mining legislation distinguishes between concessions for large-scale commercial mines and the "Garimpeira Mining Permission" (Manzolli et al. 2021). Originally designed in 1989 to accommodate artisanal and small-scale alluvial mining, this permission sought to recognise and protect miners using rudimentary tools. However, mining techniques within this sector have evolved, albeit often retaining a lower degree of mechanisation, relying on a less specialised workforce and lacking permanent infrastructure. Despite these changes, the regulatory framework for the Garimpeira Mining Permission remains relatively relaxed and decentralised compared to the industrial mining concessions, facilitating "industrial or near-industrial-scale mineral exploration under a weaker regulatory framework" (Cozendey et al. 2022, p. 2). Showing exceptional expansion since 2008, "garimpos" (wildcat miners) today constitute a sector of comparable scale to the highly industrialised commercial mining sector in terms of land utilisation (MapBiomas 2021). These operations, primarily focused on gold mining, frequently operate outside legal boundaries, resulting in significant socio-environmental ramifications (Manzolli et al. 2021).

Brazil's centre of industrial mining is the state of Minas Gerais, where 145 municipalities (17% of the state) were subject to mining activities in 2020. However, the intensification of mining has mostly occurred in the Legal Amazon area, where huge industrial mining projects such as the Carajás iron ore complex or the Paragominas bauxite mine as well as garimpo mining activities along Amazonian river banks (Maus et al. 2022) have expanded. The surge in mining in the Amazon – in 2020, 68 out of every 100 ha mined in Brazil – suggests a shift in the socioeconomic and environmental characteristics of mining areas, such as increased disturbance of pristine forest ecosystems and indigenous communities in the Legal Amazon. Figure B1 depicts how mining area was distributed across Brazilian biomes in 2005, 2010, 2015 and 2020.

Having its economy firmly oriented towards the export of natural resources, Brazil has experienced significant economic ups and downs in the past two decades. Economic expansion took place between 2000 and 2011, and it is no coincidence that global commodity prices were rising during most of that time, which is known as the 2000s commodities boom. However, after having recovered from the global financial crisis, commodity prices fell steadily between 2011 and 2016. A decrease in demand, especially from the Chinese market, and falling mining revenues led to a deep recession in 2014.

B.2 Spatial weights matrix

Spatial econometric models operationalise spatial dependence using weights matrices. These are in most cases constructed by exploiting information on geographic contiguity or distance between spatial units (see, e.g., Anselin 2013 for further information on spatial weights matrices). In this study, we used a $k = 5$ nearest neighbours specification as illustrated in Figure B4, defining the neighbours of a municipality as the five closest spatial units next to this municipality (measured at municipality centroids). In a fist step, neighbourhood was defined as a binary indicator. Subsequently, the matrix was row-standardized by dividing each cell of the matrix (either a 0 or a 1) by its respective row sum, such that the entries of each row add up to one. The specification implies positive entries in the matrix for neighbouring observations, but also that the matrix is not symmetric. The spatial weights matrix was computed and visualised using the **sf** (Pebesma 2018) and **spdep** (Bivand et al. 2013) packages in R (R Core Team 2024).

It is not our intention to capture the exact spatial relations between Brazilian municipalities (it would be impossible to come up with such a measure), but to model spatial dependence in a realistic yet parsimonious way. We are aware that the row-standardization implies that the spatial lag ($\boldsymbol{Wy}$ and$\boldsymbol{WX}$) is a weighted average of observations, which is a simplification of spatial dependence (Plümper and Neumayer 2010), but the transformation ensures the stability condition that the spatial parameter is bound between -1 and 1 (LeSage and Pace 2009). Furthermore, while there are other, in some sense less simplifying, approaches in defining neighbourhood such as trade and investment links or shared characteristics such as languages instead of geographic distance, we stick to using geographic proximity as a proxy for connectivity. Most non-geographic connectivity specifications are rather suitable for cross-country studies or demand complex municipality-level trade models due to patchy municipality-level flow data. Due to the strong heterogeneity regarding municipality size, we preferred a k-nearest neighbours specification over a contiguity or inverse distance specification. As shown in Figures B8 and B9, impact estimates are robust against alternative $k = 4$, 7, and 10 nearest neighbours definitions. However, the spatial parameter ρ varied depending on the choice of k, with 0.29, 0.37 and 0.44 in the economic growth model, 0.65, 0.72 and 0.74 in the relative forest loss specification and 0.56, 0.69 and 0.76 in the absolute forest loss model.

B.3 MCMC estimation

We used Bayesian Markov-chain Monte Carlo (MCMC) techniques in order to estimate the unknown parameters of the spatial Durbin models (SDM). The interested reader is referred to LeSage and Pace (2009) and Kuschnig (2022) for more information on estimating Bayesian spatial econometric models. Weakly informative multivariate Gaussian priors, centred on zero with a large variance of 10^4, were used for the parameters β, θ, δ and γ. The disturbance parameters σ^2 and $\tilde{\sigma}^2$ were drawn from inverse Gamma distributions $IG(0.01, 0.01)$ using weakly influential shape and scale parameters. For the spatial autocorrelation parameters ρ and λ, we used prior distributions defined on the interval $(-1, 1)$ and centred on zero as suggested in LeSage and Parent (2007):

$$\rho, \lambda \sim \frac{1}{Beta(a_0, a_0)} \frac{(1+\rho)^{a_o-1}(1-\rho)^{a_o-1}}{2^{2a_0-1}} \tag{B1}$$

with hyperparameter value $a_0 = 1.01$.

The conditional posterior distributions for the parameters β, θ, δ, γ, σ^2 and $\tilde{\sigma}^2$ follow known forms and were obtained using standard Gibbs sampling. The conditional distributions of the spatial parameters, however, are not reducible to well-known distributions. We thus used the Griddy Gibbs approach proposed by Ritter and Tanner (1992) in order to sample for ρ and λ. MCMC estimation results were obtained from 20,000 iterations and discarding the first 10,000 as burn-ins. Models ran for robustness checks were obtained from 2,000 iterations discarding the first 1,000. Estimations were performed in R (R Core Team 2024). The diagnostics by Geweke (1992) were used to confirm convergence of the sampler using the **coda** (Plummer et al. 2006) R package.

B.4 Regression results

Economic growth models

In addition to mining impacts, the economic growth models indicate how transformations from one land cover category to another relate to the economic growth rates of municipalities. Tables B2 and B3 summarise the related results (LUC control variables).

We can further interpret the effects of initial land cover classifications, i.e. the characteristics of municipalities at the beginning of a 5-year growth window. The results suggest a positive direct effect of agriculture. Moreover, findings reveal that agricultural land, forest plantation and pasture were associated with negative indirect effects.

The impact estimates of the growth models are completed by a number of further control variables, which are briefly summarised as follows: We found significant evidence of growth convergence, which is indicated by the negative direct impact estimate for initial income, which exceeds counterbalancing positive spillover effects from high-income neighbours. This finding is in line with the theoretical and empirical growth literature (López-Bazo et al. 2004; Resende et al. 2016). For human capital, effects were in opposite direction, again conforming to earlier works, but indirect effects were comparably less clearly negative (LeSage and Fischer 2008; Resende et al. 2016). For population growth and population density, we found negative direct impacts, as well as a positive indirect effect for population density. Regarding the sectoral structure, positive (direct and indirect) links were found for initial GVA in the service sector, while municipalities with large shares in the agriculture and industry sectors tended to grow at lower rates. Lastly, we turn the attention to ρ, the spatial parameter, confirming the presence of spatial dependence with an estimate of 0.32.

Forest loss models

Regardless of defining forest loss as ha per km^2 (Tables B4 and B5) or in absolute terms (Tables B6 and B7), initial natural forest area was most clearly associated with forest loss. Regarding other land cover and land cover change control variables, insights were less conclusive.

Drawing our attention to the remaining control variables, results reveal that GDP growth was negatively related with forest loss in the absolute forest loss definition, while no effects were found for the relative forest loss measure. The biophysical variables precipitation and elevation played no major role, except from the finding that municipalities at higher altitudes showed lower absolute forest loss. Lastly, note that forest loss exhibits strong spatial dependence ($\rho = 0.68$ for ha per km^2 and $\rho = 0.62$ for absolute ha), supporting the need for spatial regression approaches.

B.5 Supplementary figures

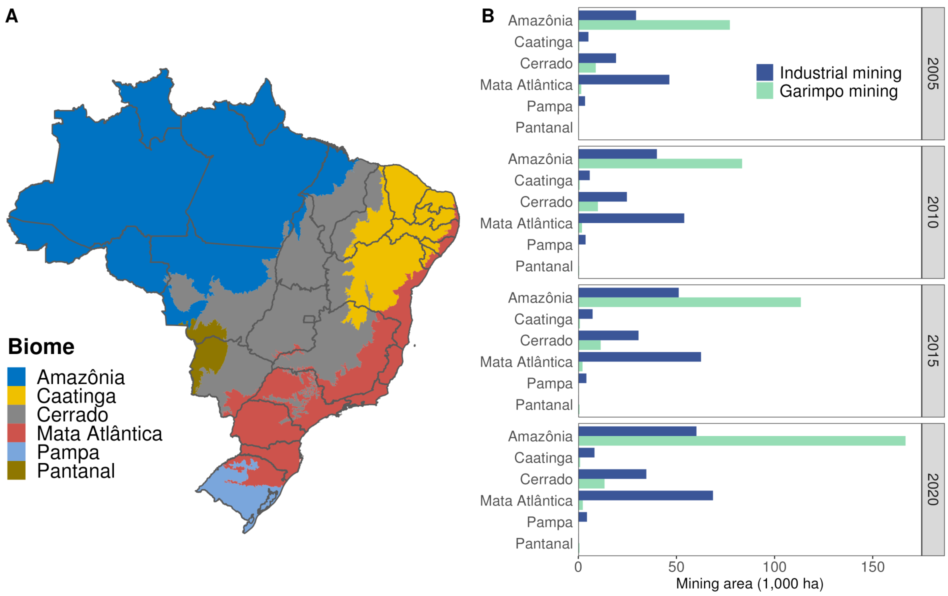

Figure B1: **Brazilian biomes and mining area.** The six terrestrial biomes of Brazil and state borders **(A)**. Mining area (in 1,000 ha) within Brazilian biomes in 2005, 2010, 2015 and 2020 **(B)**. Data: IBGE via the **geobr** (Pereira and Goncalves 2022) R package and MapBiomas (2023).

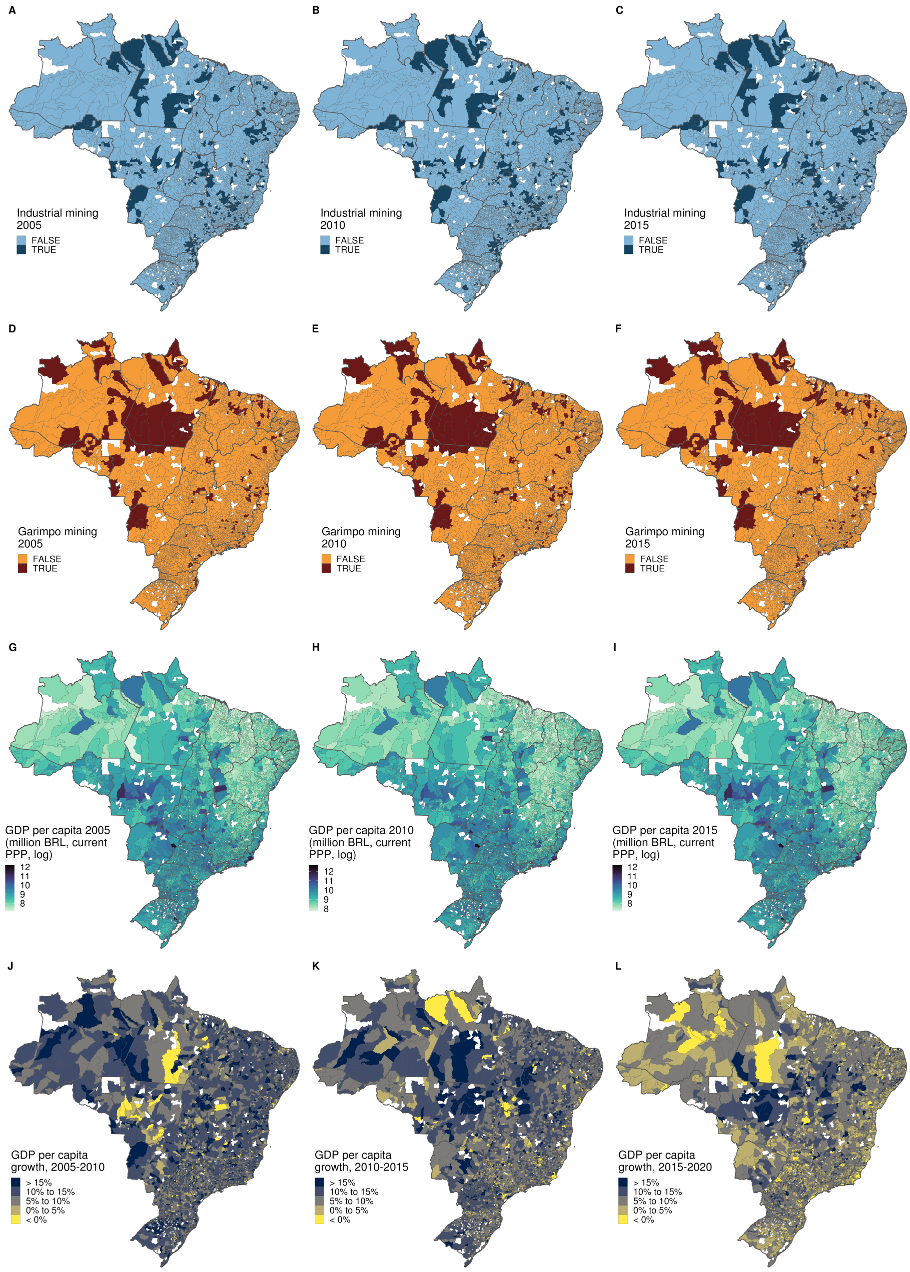

Figure B2: **Selection of variables used in the analysis (2005, 2010, 2015).** Industrial mining binary indicator **(A-C)**, garimpo mining binary indicator **(D-F)**, GDP per capita **(G-I)** and GDP per capita 5-year average annual growth rates **(J-L)**. White areas were not considered in the study due to changes of municipality borders during the sample period.

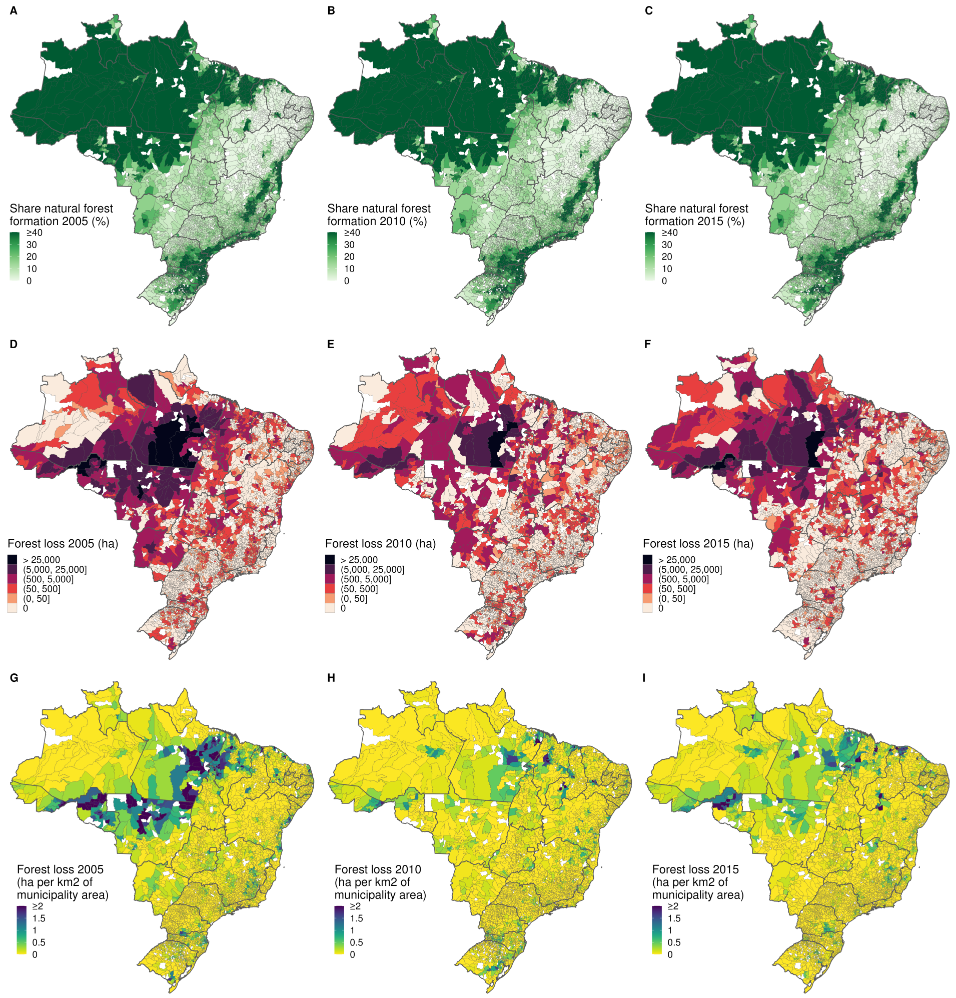

Figure B3: **Selection of variables used in the analysis (2005, 2010, 2015).** Share of area covered by natural forest formation **(A-C)**, absolute forest loss, i.e. decrease in natural forest cover in ha **(D-F)** and relative forest loss, i.e. decrease in natural forest cover relative to municipality area in ha per km^2 **(G-I)**. White areas were not considered in the study due to changes of municipality borders during the sample period.

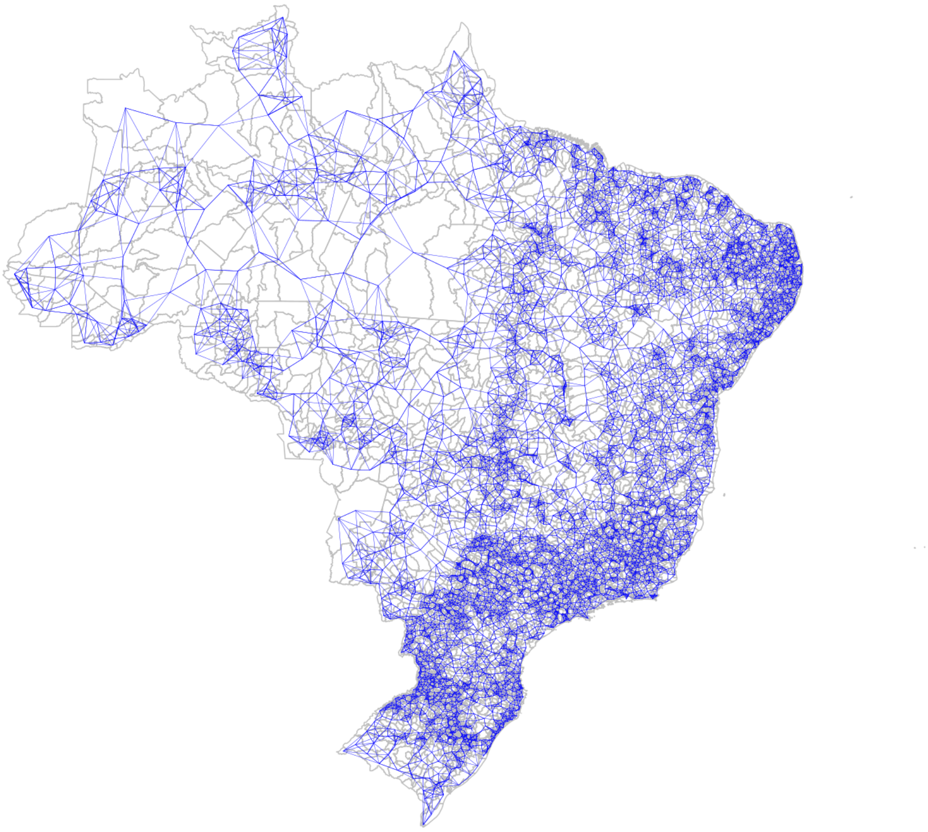

Figure B4: **Spatial weights matrix.** Visualisation of the $k = 5$ nearest neighbours spatial weights matrix employed in this study. Blue lines indicate neighbourhood, grey lines show municipality borders.

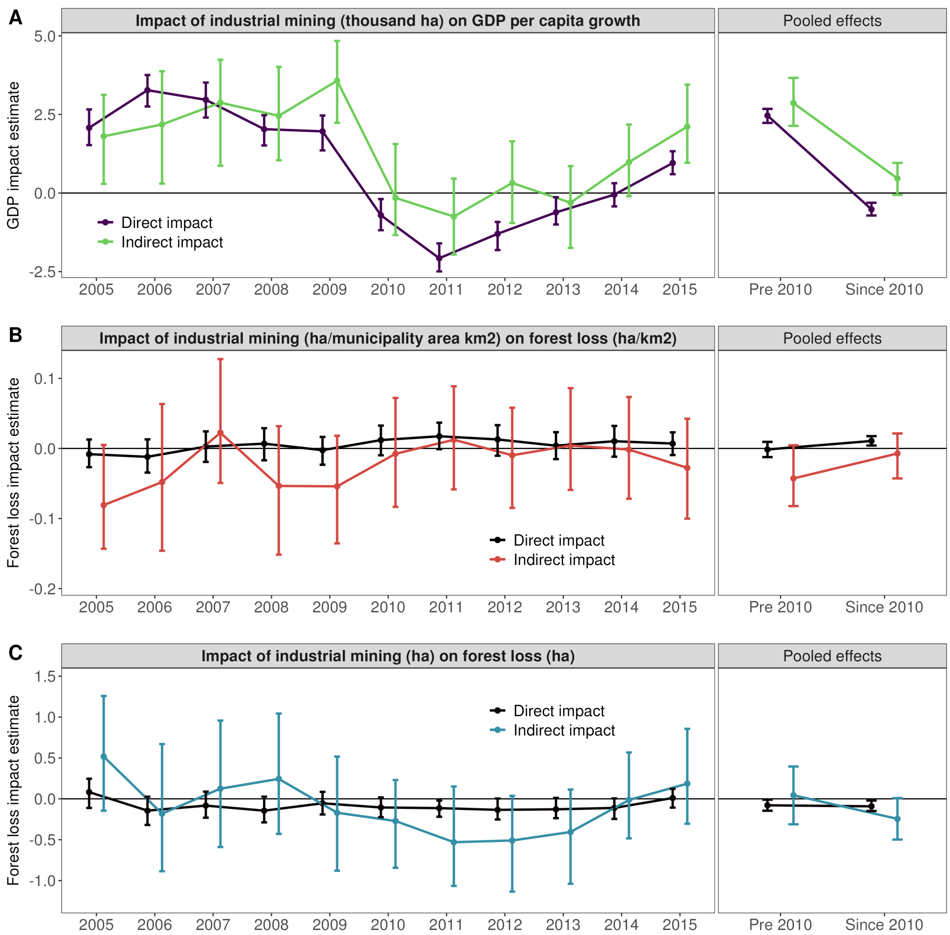

Figure B5: **Direct and indirect impact estimates of industrial mining.** Impacts of industrial mining measured in ha on 5-year average annual GDP per capita growth **(A)**, forest loss in ha per km^2 **(B)** and forest loss in ha **(C)**. Left panels show yearly estimates, right panels show pooled (pre 2010 and since 2010) estimates. Estimates were obtained from 2,000 Markov chain Monte Carlo iterations, with the first 1,000 being discarded as burn-in. Points denote posterior means, error bars show 95% posterior credible intervals.

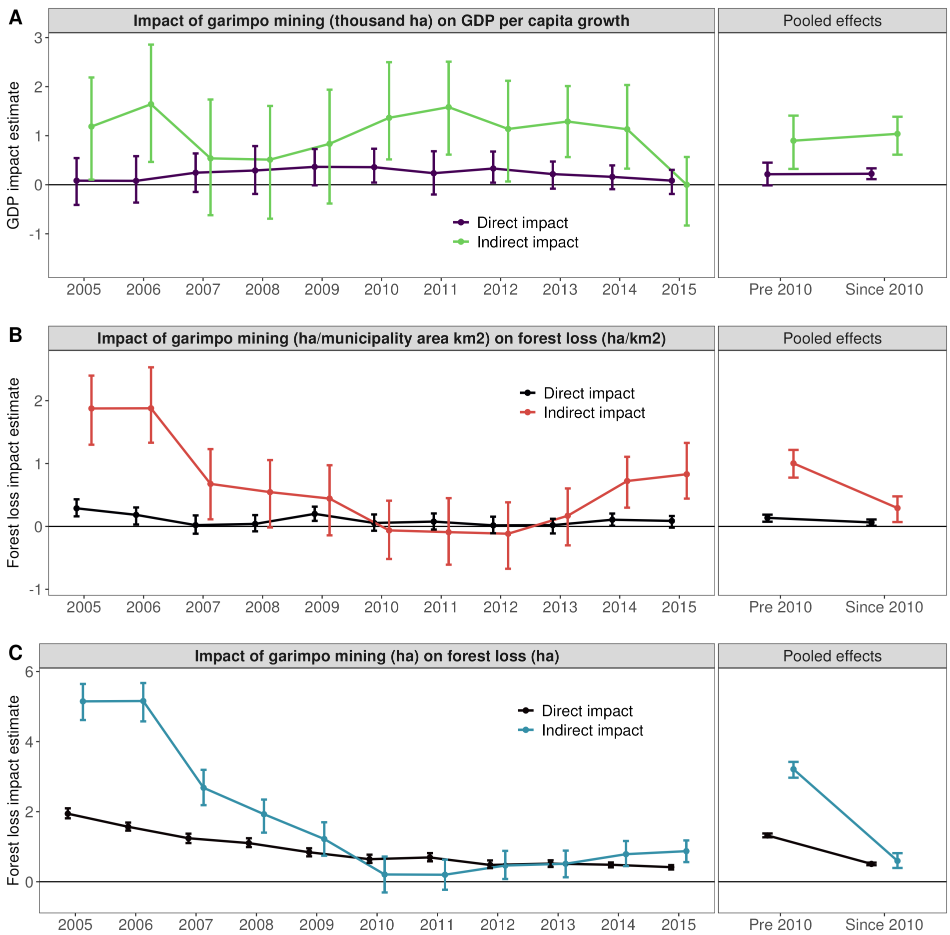

Figure B6: **Direct and indirect impact estimates of garimpo mining.** Impacts of garimpo mining measured in ha on 5-year average annual GDP per capita growth **(A)**, forest loss in ha per km^2 **(B)** and forest loss in ha **(C)**. Left panels show yearly estimates, right panels show pooled (pre 2010 and since 2010) estimates. Estimates were obtained from 2,000 Markov chain Monte Carlo iterations, with the first 1,000 being discarded as burn-in. Points denote posterior means, error bars show 95% posterior credible intervals.

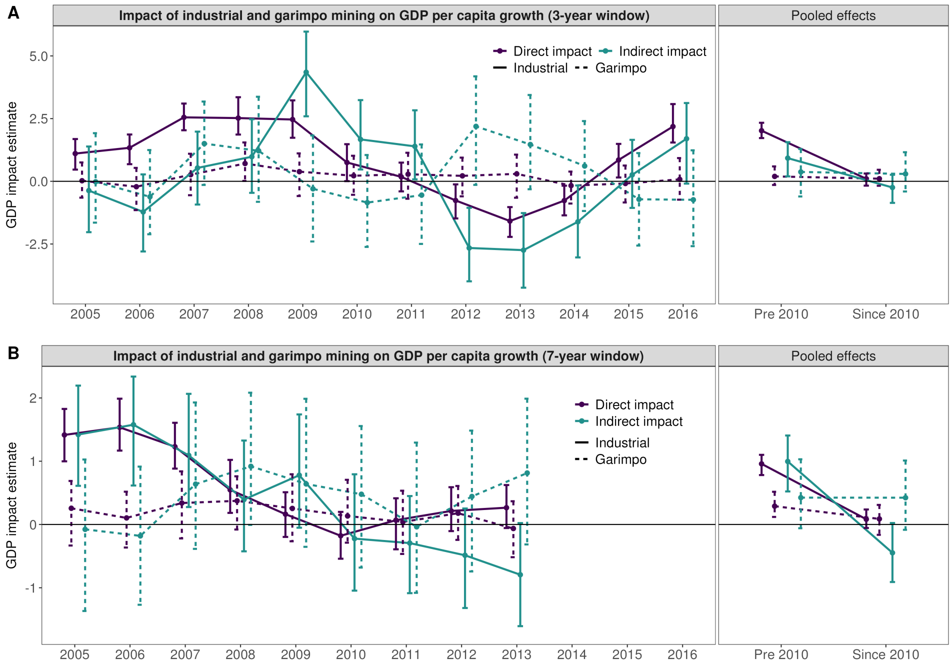

Figure B7: **Direct and indirect impact estimates.** Impacts of binary mining indicator on 3-year average GDP per capita growth **(A)** and 7-year average GDP per capita growth **(B)**. Left panels show yearly estimates, right panels show pooled (pre 2010 and since 2010) estimates. Estimates were obtained from 2,000 Markov chain Monte Carlo iterations, with the first 1,000 being discarded as burn-in. Points denote posterior means, error bars show 95% posterior credible intervals.

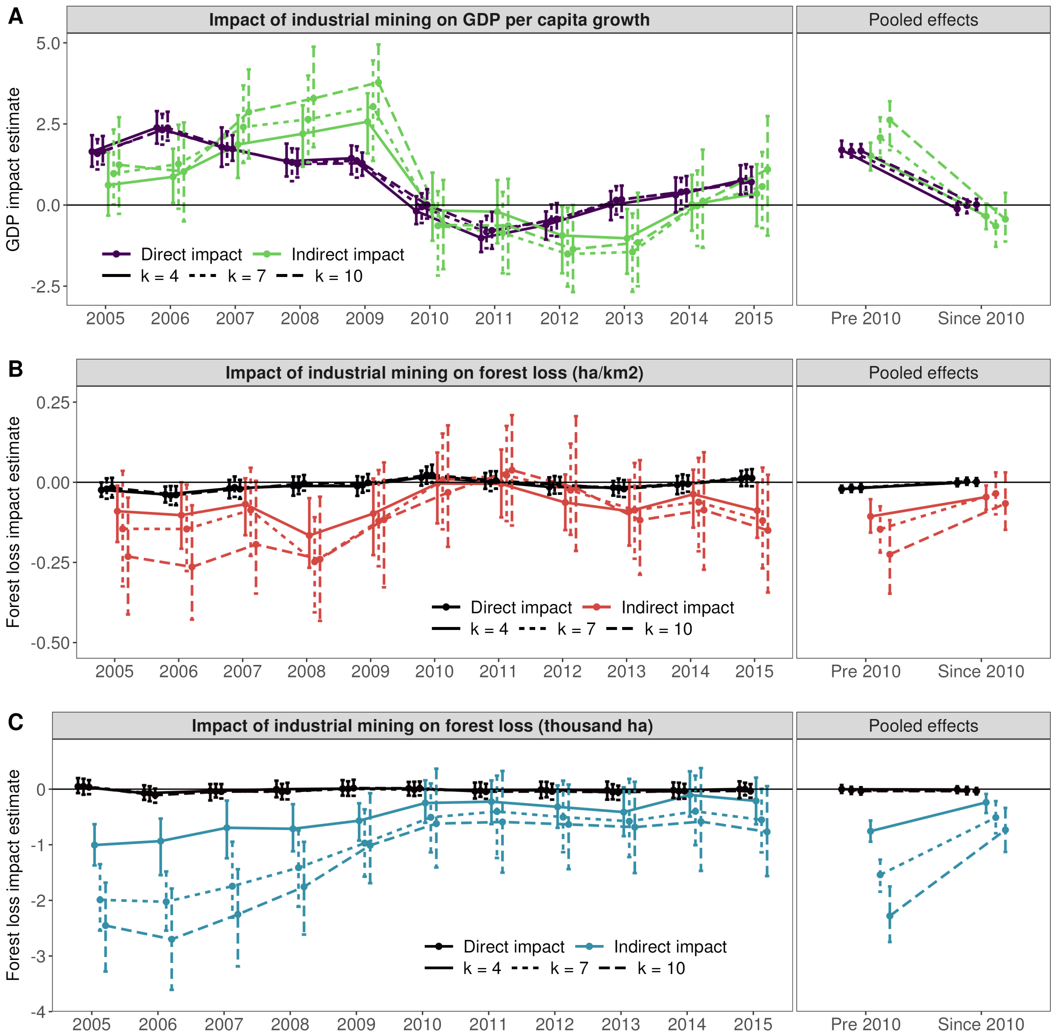

Figure B8: **Direct and indirect impact estimates of industrial mining.** Impacts of binary industrial mining indicator on 5-year average GDP per capita growth **(A)**, forest loss in ha per km^2 **(B)** and forest loss in thousand ha **(C)**. Left panels show yearly estimates, right panels show pooled (pre 2010 and since 2010) estimates. Different linetypes show results using $k = 4$, $k = 7$ and $k = 10$ nearest neighbours spatial weights matrices. Estimates were obtained from 2,000 Markov chain Monte Carlo iterations, with the first 1,000 being discarded as burn-in. Points denote posterior means, error bars show 95% posterior credible intervals.

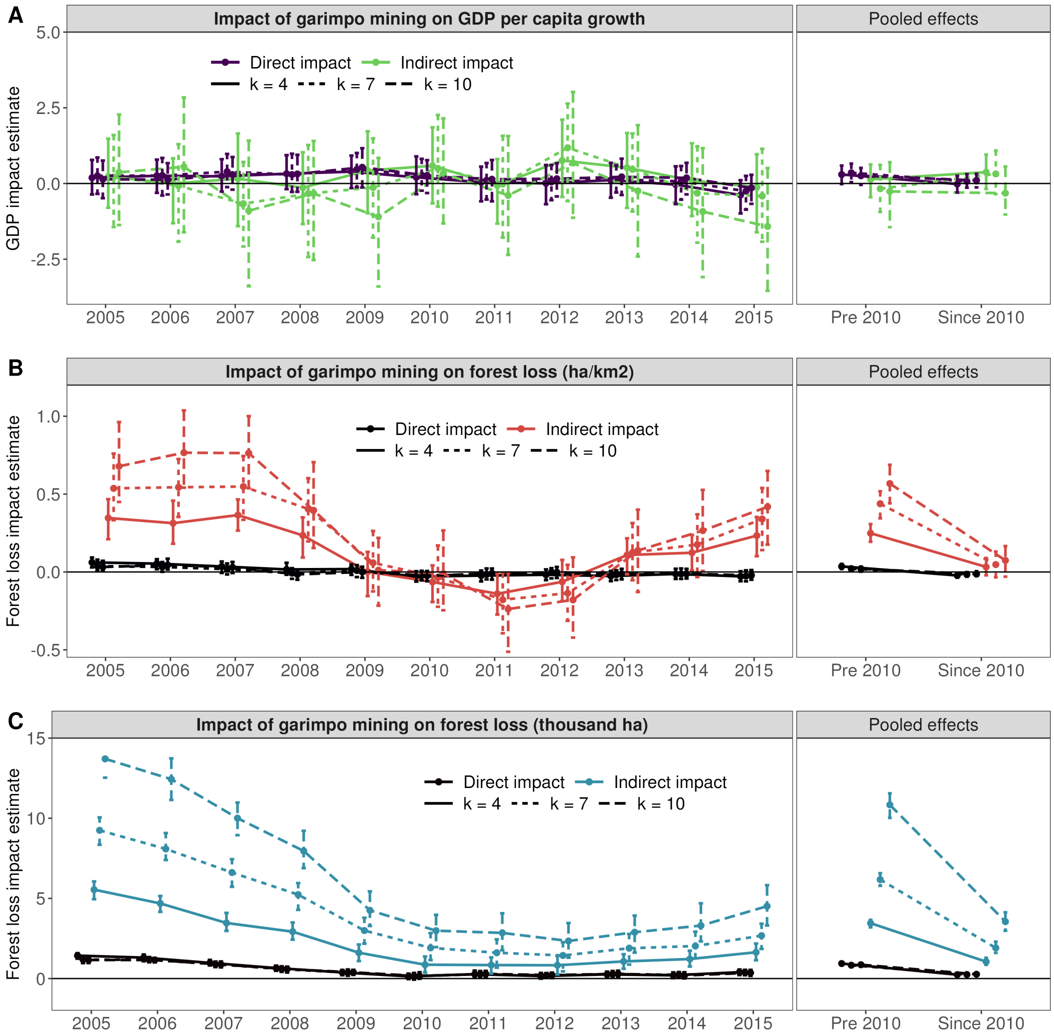

Figure B9: **Direct and indirect impact estimates of garimpo mining.** Impacts of binary garimpo mining indicator on 5-year average GDP per capita growth **(A)**, forest loss in ha per km^2 **(B)** and forest loss in thousand ha **(C)**. Left panels show yearly estimates, right panels show pooled (pre 2010 and since 2010) estimates. Different linetypes show results using $k = 4$, $k = 7$ and $k = 10$ nearest neighbours spatial weights matrices. Estimates were obtained from 2,000 Markov chain Monte Carlo iterations, with the first 1,000 being discarded as burn-in. Points denote posterior means, error bars show 95% posterior credible intervals.

B.6 Supplementary tables

Variable	Description	GM	FLM
Economic growth	Five-year average annual growth rate of gross domestic product per capita. *Source:* IBGE (2023a; 2023b)	D	I
Forest loss (relative)	Annual decrease in natural forest formation relative to municipality area (ha/km^2). *Source:* MapBiomas (2023)		D
Forest loss (absolute)	Annual decrease in natural forest formation (ha). *Source:* MapBiomas (2023)		D
Mining industrial	Presence of industrial mining within municipality, binary indicator. *Source:* MapBiomas (2023)	I	I
Mining garimpo	Presence of garimpo mining within municipality, binary indicator. *Source:* MapBiomas (2023)	I	I
Land use change (LUC^{1,2})	Land use change from classification LUC^1 to LUC^2 for the classifications forest formation, forest plantation, grassland, agriculture and pasture (5-year average change in ha, log). *Source:* MapBiomas (2023)	I	I
Initial natural forest	Share classified as forest formation. *Source:* MapBiomas (2023)	I	I
Initial forest plantation	Share classified as forest plantation. *Source:* MapBiomas (2023)	I	I
Initial grassland	Share classified as grassland. *Source:* MapBiomas (2023)	I	I
Initial agriculture	Share classified as agriculture. *Source:* MapBiomas (2023)	I	I
Initial pasture	Share classified as pasture. *Source:* MapBiomas (2023)	I	I
Initial income	Per capita gross domestic product (million BRL, current PPP, log). *Source:* IBGE (2023a; 2023b)	I	
Human capital	Education index from 0 (worst) to 1 (best): schooling coverage (pre-school attendance) and quality in elementary school. *Source:* FIRJAN (2018)	I	
Population growth	Population growth rate (%). *Source:* IBGE (2023a)	I	
Population density	Population density (thousand per km^2). *Source:* IBGE (2023a)	I	
GVA agriculture	Gross value added in agriculture (million BRL, current PPP, log). *Source:* IBGE (2023b)	I	
GVA industry	Gross value added in industry (million BRL, current PPP, log). *Source:* IBGE (2023b)	I	
GVA services	Gross value added in services (million BRL, current PPP, log). *Source:* IBGE (2023b)	I	
Precipitation	Precipitation yearly average (standardised). *Source:* CRU (2021)	I	I
Elevation	Average elevation (m). *Source:* USGS (2021)	I	I

Table B1: **Variables used in the analysis** (measured at the beginning of the respective growth/forest loss window). GM and FLM indicate use of variables in growth and forest loss models, respectively. D denotes dependent and I denotes independent variables. Variables are mapped in Figures B2 and B3.

Variables	Avg. direct impact 2.5%	PM	97.5%	Avg. spillover 2.5%	PM	97.5%
Industrial mining 2005	1.127	**1.614**	2.119	-0.423	0.725	1.898
Industrial mining 2006	1.847	**2.355**	2.861	-0.252	0.894	2.033
Industrial mining 2007	1.363	**1.834**	2.310	0.581	**1.766**	2.952
Industrial mining 2008	0.835	**1.364**	1.850	1.013	**2.172**	3.210
Industrial mining 2009	0.917	**1.416**	1.904	1.442	**2.493**	3.688
Industrial mining 2010	-0.578	-0.124	0.374	-1.576	-0.508	0.543
Industrial mining 2011	-1.419	**-0.943**	-0.500	-1.696	-0.654	0.448
Industrial mining 2012	-1.119	**-0.577**	-0.069	-2.487	**-1.385**	-0.318
Industrial mining 2013	-0.406	0.065	0.528	-2.359	**-1.318**	-0.233
Industrial mining 2014	-0.130	0.365	0.841	-1.380	-0.220	0.800
Industrial mining 2015	0.289	**0.765**	1.224	-0.861	0.152	1.211
Garimpo mining 2005	-0.508	0.177	0.793	-0.683	0.687	2.219
Garimpo mining 2006	-0.356	0.246	0.810	-0.910	0.510	1.896
Garimpo mining 2007	-0.333	0.272	0.973	-1.196	0.279	1.720
Garimpo mining 2008	-0.227	0.378	0.951	-1.318	0.023	1.412
Garimpo mining 2009	-0.103	0.467	1.082	-0.763	0.569	1.869
Garimpo mining 2010	-0.356	0.284	0.937	-0.658	0.774	2.281
Garimpo mining 2011	-0.517	0.116	0.735	-1.296	0.116	1.597
Garimpo mining 2012	-0.506	0.065	0.660	-0.196	1.168	2.503
Garimpo mining 2013	-0.532	0.119	0.685	-0.728	0.713	1.959
Garimpo mining 2014	-0.566	0.043	0.656	-1.479	-0.068	1.299
Garimpo mining 2015	-0.798	-0.220	0.388	-1.447	-0.068	1.363
$\text{LUC}^{Agriculture,ForestPlantation}$	0.007	**0.069**	0.123	-0.020	0.127	0.285
$\text{LUC}^{Agriculture,Grassland}$	-0.146	**-0.075**	-0.001	-0.042	0.167	0.369
$\text{LUC}^{Agriculture,Pasture}$	-0.041	-0.009	0.021	0.176	**0.249**	0.322
$\text{LUC}^{NaturalForest,Agriculture}$	-0.004	0.066	0.133	0.128	**0.292**	0.477
$\text{LUC}^{NaturalForest,ForestPlantation}$	-0.005	0.032	0.069	-0.088	0.001	0.087
$\text{LUC}^{NaturalForest,Grassland}$	-0.121	**-0.070**	-0.018	-0.186	-0.057	0.079
$\text{LUC}^{NaturalForest,Pasture}$	-0.033	0.000	0.033	-0.080	-0.033	0.020
$\text{LUC}^{ForestPlantation,Agriculture}$	0.037	**0.105**	0.177	-0.196	-0.003	0.247
$\text{LUC}^{ForestPlantation,Grassland}$	0.016	**0.106**	0.199	-0.540	**-0.292**	-0.039
$\text{LUC}^{ForestPlantation,Pasture}$	-0.031	0.017	0.062	-0.249	**-0.122**	-0.000
$\text{LUC}^{Grassland,Agriculture}$	0.021	**0.079**	0.140	-0.124	0.033	0.191
$\text{LUC}^{Grassland,ForestPlantation}$	-0.087	-0.023	0.043	-0.313	**-0.152**	-0.007
$\text{LUC}^{Grassland,Pasture}$	-0.055	-0.011	0.031	0.067	**0.165**	0.264
$\text{LUC}^{Pasture,Agriculture}$	0.017	**0.042**	0.068	-0.063	-0.007	0.047
$\text{LUC}^{Pasture,ForestPlantation}$	-0.001	0.035	0.068	-0.180	**-0.103**	-0.034
$\text{LUC}^{Pasture,Grassland}$	0.070	**0.112**	0.159	-0.108	-0.006	0.096
Initial agriculture	2.340	**2.906**	3.501	-1.861	**-1.043**	-0.335
Initial natural forest	-0.715	-0.222	0.259	-0.087	0.611	1.309
Initial forest plantation	-0.539	0.984	2.534	-8.319	**-5.272**	-2.207
Initial grassland	-1.209	-0.139	0.857	-0.511	1.295	3.169
Initial pasture	-0.201	0.171	0.605	-1.617	**-1.089**	-0.551
Initial income	-2.992	**-2.880**	-2.757	1.760	**2.000**	2.238
Human capital	2.143	**2.745**	3.300	-2.572	**-1.726**	-0.931
Population growth	-0.474	**-0.452**	-0.427	-0.086	-0.029	0.024
Population density	-0.485	**-0.381**	-0.279	0.181	**0.369**	0.555
GVA agriculture	-0.113	**-0.058**	-0.010	-0.146	-0.056	0.042
GVA industry	-0.419	**-0.360**	-0.305	-0.775	**-0.630**	-0.495
GVA services	0.475	**0.545**	0.614	0.251	**0.413**	0.568
Precipitation	0.091	**0.430**	0.792	-0.517	-0.145	0.205
Elevation	-0.001	**-0.001**	-0.000	-0.000	0.001	0.001
ρ	0.313	**0.320**	0.323			
Observations	57,882					

Table B2: **Average direct and indirect impact estimates on economic growth with yearly mining effects.** Panel-structure (2005-2020) spatial Durbin model including time fixed effects. Dependent variable is 5-year average annual GDP per capita growth rate. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean. Time-specific intercepts were excluded for more concise summary tables.

Variables	Avg. direct impact 2.5%	PM	97.5%	Avg. spillover 2.5%	PM	97.5%
Industrial mining × pre 2010	1.483	**1.710**	1.929	0.995	**1.469**	1.963
Industrial mining × since 2010	-0.259	-0.068	0.136	-1.072	**-0.614**	-0.135
Garimpo mining × pre 2010	0.049	**0.303**	0.588	-0.268	0.398	1.043
Garimpo mining × since 2010	-0.198	0.061	0.314	-0.151	0.427	0.984
$\text{LUC}^{Agriculture,ForestPlantation}$	0.005	**0.064**	0.124	-0.023	0.114	0.278
$\text{LUC}^{Agriculture,Grassland}$	-0.147	**-0.078**	-0.005	-0.015	0.178	0.363
$\text{LUC}^{Agriculture,Pasture}$	-0.038	-0.008	0.022	0.174	**0.239**	0.307
$\text{LUC}^{NaturalForest,Agriculture}$	0.002	**0.067**	0.133	0.109	**0.275**	0.434
$\text{LUC}^{NaturalForest,ForestPlantation}$	-0.006	0.034	0.072	-0.080	-0.001	0.080
$\text{LUC}^{NaturalForest,Grassland}$	-0.129	**-0.073**	-0.023	-0.182	-0.049	0.082
$\text{LUC}^{NaturalForest,Pasture}$	-0.033	0.000	0.035	-0.077	-0.030	0.024
$\text{LUC}^{ForestPlantation,Agriculture}$	0.028	**0.106**	0.189	-0.184	-0.005	0.205
$\text{LUC}^{ForestPlantation,Grassland}$	0.009	**0.105**	0.196	-0.558	**-0.286**	-0.032
$\text{LUC}^{ForestPlantation,Pasture}$	-0.029	0.018	0.066	-0.243	**-0.115**	-0.008
$\text{LUC}^{Grassland,Agriculture}$	0.021	**0.081**	0.144	-0.133	0.021	0.176
$\text{LUC}^{Grassland,ForestPlantation}$	-0.096	-0.024	0.044	-0.296	-0.145	0.000
$\text{LUC}^{Grassland,Pasture}$	-0.054	-0.013	0.030	0.075	**0.163**	0.266
$\text{LUC}^{Pasture,Agriculture}$	0.015	**0.042**	0.069	-0.070	-0.009	0.047
$\text{LUC}^{Pasture,ForestPlantation}$	0.002	**0.036**	0.069	-0.162	**-0.102**	-0.040
$\text{LUC}^{Pasture,Grassland}$	0.069	**0.111**	0.154	-0.111	-0.014	0.079
Initial agriculture	2.356	**2.944**	3.528	-1.902	**-1.145**	-0.388
Initial natural forest	-0.700	-0.210	0.259	-0.062	0.602	1.294
Initial forest plantation	-0.584	1.034	2.654	-7.869	**-5.065**	-2.150
Initial grassland	-1.077	-0.081	0.909	-0.539	1.253	2.882
Initial pasture	-0.213	0.173	0.576	-1.551	**-1.053**	-0.506
Initial income	-2.992	**-2.894**	-2.785	1.824	**2.044**	2.260
Human capital	2.196	**2.757**	3.296	-2.686	**-1.764**	-0.915
Population growth	-0.472	**-0.450**	-0.428	-0.060	-0.005	0.053
Population density	-0.484	**-0.380**	-0.278	0.188	**0.373**	0.540
GVA agriculture	-0.112	**-0.060**	-0.007	-0.139	-0.045	0.032
GVA industry	-0.410	**-0.356**	-0.302	-0.718	**-0.591**	-0.477
GVA services	0.476	**0.542**	0.607	0.232	**0.371**	0.510
Precipitation	0.040	**0.435**	0.795	-0.561	-0.172	0.238
Elevation	-0.001	**-0.001**	-0.000	-0.000	0.001	0.001
ρ	0.313	**0.321**	0.333			
Observations	57,882					

Table B3: **Average direct and indirect impact estimates on economic growth with pooled mining effects.** Panel-structure (2005-2020) spatial Durbin model including time fixed effects. Dependent variable is 5-year average annual GDP per capita growth rate. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean. Time-specific intercepts were excluded for more concise summary tables.

	Avg. direct impact			Avg. spillover		
Variables	2.5%	PM	97.5%	2.5%	PM	97.5%
Industrial mining 2005	-0.046	-0.020	0.007	-0.258	**-0.140**	-0.020
Industrial mining 2006	-0.066	**-0.040**	-0.012	-0.298	**-0.170**	-0.040
Industrial mining 2007	-0.045	-0.017	0.009	-0.235	-0.103	0.012
Industrial mining 2008	-0.037	-0.011	0.016	-0.339	**-0.211**	-0.093
Industrial mining 2009	-0.037	-0.010	0.020	-0.240	-0.113	0.010
Industrial mining 2010	-0.007	0.022	0.050	-0.122	0.006	0.114
Industrial mining 2011	-0.022	0.005	0.032	-0.112	0.016	0.136
Industrial mining 2012	-0.034	-0.008	0.021	-0.154	-0.036	0.101
Industrial mining 2013	-0.040	-0.013	0.016	-0.217	-0.094	0.029
Industrial mining 2014	-0.037	-0.008	0.021	-0.173	-0.056	0.072
Industrial mining 2015	-0.017	0.011	0.037	-0.242	-0.116	0.004
Garimpo mining 2005	0.025	**0.056**	0.093	0.316	**0.474**	0.631
Garimpo mining 2006	0.011	**0.045**	0.080	0.306	**0.461**	0.632
Garimpo mining 2007	-0.010	0.030	0.066	0.276	**0.451**	0.605
Garimpo mining 2008	-0.028	0.014	0.053	0.145	**0.306**	0.467
Garimpo mining 2009	-0.017	0.020	0.052	-0.125	0.023	0.186
Garimpo mining 2010	-0.064	-0.028	0.006	-0.257	-0.094	0.061
Garimpo mining 2011	-0.054	-0.017	0.019	-0.333	**-0.173**	-0.016
Garimpo mining 2012	-0.048	-0.012	0.024	-0.297	-0.133	0.035
Garimpo mining 2013	-0.056	-0.022	0.011	-0.011	0.142	0.289
Garimpo mining 2014	-0.044	-0.011	0.021	0.044	**0.199**	0.367
Garimpo mining 2015	-0.055	-0.022	0.014	0.142	**0.306**	0.462
$\text{LUC}^{Agriculture,Grassland}$	-0.020	**-0.016**	-0.011	-0.092	**-0.071**	-0.048
$\text{LUC}^{Agriculture,Pasture}$	-0.003	-0.002	0.000	-0.021	**-0.013**	-0.006
$\text{LUC}^{Grassland,Agriculture}$	-0.001	0.003	0.007	0.012	**0.030**	0.047
$\text{LUC}^{Grassland,Pasture}$	-0.006	**-0.004**	-0.002	-0.024	**-0.013**	-0.002
$\text{LUC}^{Pasture,Agriculture}$	0.002	**0.003**	0.005	0.014	**0.021**	0.027
$\text{LUC}^{Pasture,Grassland}$	-0.006	**-0.004**	-0.002	-0.006	0.004	0.015
Initial agriculture	0.022	**0.052**	0.081	-0.248	**-0.198**	-0.139
Initial natural forest	0.298	**0.324**	0.349	-0.129	**-0.077**	-0.025
Initial forest plantation	0.178	**0.260**	0.332	-0.475	-0.220	0.025
Initial grassland	0.031	**0.087**	0.139	-0.061	0.077	0.238
Initial pasture	0.112	**0.134**	0.159	-0.187	**-0.149**	-0.109
GPD growth	-0.000	-0.000	0.000	-0.000	0.002	0.004
Precipitation	-0.029	-0.011	0.006	0.007	**0.026**	0.047
Elevation	-0.000	0.000	0.000	-0.000	**-0.000**	-0.000
ρ	0.682	**0.683**	0.692			
Observations	57,882					

Table B4: **Average direct and indirect impact estimates on forest loss (relative) with yearly mining effects.** Panel-structure (2005-2020) spatial Durbin model including time fixed effects. Dependent variable is annual forest loss in ha per km^2. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean. Time-specific intercepts were excluded for more concise summary tables.

Variables	Avg. direct impact 2.5%	PM	97.5%	Avg. spillover 2.5%	PM	97.5%
Industrial mining × pre 2010	-0.032	**-0.019**	-0.004	-0.192	**-0.138**	-0.084
Industrial mining × since 2010	-0.010	0.002	0.013	-0.097	-0.046	0.001
Garimpo mining × pre 2010	0.016	**0.030**	0.046	0.251	**0.322**	0.390
Garimpo mining × since 2010	-0.032	**-0.019**	-0.004	-0.019	0.042	0.102
$\text{LUC}^{Agriculture,Grassland}$	-0.020	**-0.015**	-0.010	-0.085	**-0.064**	-0.042
$\text{LUC}^{Agriculture,Pasture}$	-0.003	-0.001	0.000	-0.018	**-0.011**	-0.004
$\text{LUC}^{Grassland,Agriculture}$	-0.001	0.003	0.006	0.008	**0.027**	0.045
$\text{LUC}^{Grassland,Pasture}$	-0.006	**-0.004**	-0.001	-0.022	**-0.012**	-0.003
$\text{LUC}^{Pasture,Agriculture}$	0.002	**0.003**	0.005	0.013	**0.019**	0.025
$\text{LUC}^{Pasture,Grassland}$	-0.006	**-0.004**	-0.002	-0.004	0.005	0.014
Initial agriculture	0.024	**0.054**	0.082	-0.242	**-0.191**	-0.136
Initial natural forest	0.301	**0.325**	0.350	-0.145	**-0.094**	-0.048
Initial forest plantation	0.185	**0.260**	0.339	-0.421	-0.218	0.014
Initial grassland	0.041	**0.089**	0.136	-0.089	0.068	0.204
Initial pasture	0.112	**0.134**	0.158	-0.190	**-0.150**	-0.110
GPD growth	-0.000	-0.000	0.000	-0.001	0.001	0.004
Precipitation	-0.030	-0.011	0.009	0.004	**0.025**	0.046
Elevation	-0.000	0.000	0.000	-0.000	**-0.000**	-0.000
ρ	0.682	**0.684**	0.692			
Observations	57,882					

Table B5: **Average direct and indirect impact estimates on forest loss (relative) with pooled mining effects.** Panel-structure (2005-2020) spatial Durbin model including time fixed effects. Dependent variable is annual forest loss in ha per km^2. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean. Time-specific intercepts were excluded for more concise summary tables.

	Avg. direct impact			Avg. spillover		
Variables	2.5%	PM	97.5%	2.5%	PM	97.5%
Industrial mining 2005	-91.944	45.129	189.290	-1954.223	**-1363.383**	-813.796
Industrial mining 2006	-202.148	-71.758	69.726	-1961.346	**-1418.089**	-862.576
Industrial mining 2007	-154.620	-19.495	111.552	-1696.175	**-1153.626**	-601.917
Industrial mining 2008	-155.163	-12.036	127.141	-1485.776	**-1005.008**	-451.998
Industrial mining 2009	-144.017	12.859	140.786	-1208.347	**-684.992**	-161.499
Industrial mining 2010	-137.420	15.238	154.110	-861.309	-317.252	217.734
Industrial mining 2011	-176.807	-28.325	120.963	-772.050	-235.558	302.126
Industrial mining 2012	-157.501	-6.616	157.102	-755.966	-240.873	270.009
Industrial mining 2013	-175.737	-40.159	95.518	-905.569	-420.590	90.622
Industrial mining 2014	-159.909	-18.319	123.247	-700.557	-161.604	405.318
Industrial mining 2015	-123.732	9.447	153.102	-869.033	-277.748	302.010
Garimpo mining 2005	1227.782	**1414.852**	1600.504	5850.678	**6533.633**	7209.794
Garimpo mining 2006	1141.991	**1321.678**	1506.368	4702.490	**5401.747**	6039.590
Garimpo mining 2007	820.756	**1008.252**	1190.399	3461.671	**4170.754**	4834.288
Garimpo mining 2008	506.281	**671.025**	855.624	2917.193	**3597.413**	4276.368
Garimpo mining 2009	213.332	**396.417**	564.436	1206.289	**1955.346**	2709.012
Garimpo mining 2010	-17.637	157.322	334.031	311.625	**999.067**	1689.094
Garimpo mining 2011	129.737	**303.535**	486.863	106.890	**736.572**	1390.477
Garimpo mining 2012	12.791	**200.332**	389.792	-143.582	595.887	1342.507
Garimpo mining 2013	129.471	**300.765**	470.097	455.390	**1195.890**	1861.831
Garimpo mining 2014	59.590	**237.209**	402.335	486.674	**1181.654**	1901.449
Garimpo mining 2015	201.229	**410.488**	604.331	945.200	**1656.988**	2391.562
$LUC^{Agriculture,Grassland}$	9.153	**33.842**	58.775	-103.593	-9.258	83.516
$LUC^{Agriculture,Pasture}$	28.935	**37.218**	46.490	-5.579	29.307	59.170
$LUC^{Grassland,Agriculture}$	7.572	**25.015**	41.484	-16.339	52.440	127.013
$LUC^{Grassland,Pasture}$	44.473	**56.614**	68.660	54.285	**102.261**	148.788
$LUC^{Pasture,Agriculture}$	37.736	**44.652**	52.414	10.670	**39.175**	67.348
$LUC^{Pasture,Grassland}$	21.233	**33.281**	45.826	-26.402	19.101	64.960
Initial agriculture	-163.642	-12.195	145.012	335.194	**557.485**	785.222
Initial natural forest	1441.874	**1577.793**	1706.876	231.428	**499.560**	728.522
Initial forest plantation	-453.614	-18.952	408.902	-3085.650	**-2034.482**	-992.611
Initial grassland	-396.308	-143.635	102.473	-1819.123	**-1075.841**	-325.443
Initial pasture	-430.151	**-316.819**	-206.106	674.124	**852.157**	1050.888
GPD growth	-6.972	**-4.466**	-2.220	-12.176	-2.535	7.114
Precipitation	-64.158	37.438	135.231	-158.783	-56.487	51.512
Elevation	-0.569	**-0.441**	-0.297	-0.041	0.134	0.302
ρ	0.612	**0.619**	0.622			
Observations	57,882					

Table B6: **Average direct and indirect impact estimates on forest loss (absolute) with yearly mining effects.** Panel-structure (2005-2020) spatial Durbin model including time fixed effects. Dependent variable is annual forest loss in absolute ha. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean. Time-specific intercepts were excluded for more concise summary tables.

Variables	Avg. direct impact 2.5%	PM	97.5%	Avg. spillover 2.5%	PM	97.5%
Industrial mining × pre 2010	-71.788	-9.985	55.858	-1360.717	**-1125.525**	-894.899
Industrial mining × since 2010	-72.068	-11.446	44.099	-478.004	**-264.168**	-28.745
Garimpo mining × pre 2010	881.149	**962.731**	1040.071	3998.943	**4320.267**	4606.542
Garimpo mining × since 2010	194.227	**270.467**	345.013	795.179	**1076.780**	1368.642
$LUC^{Agriculture,Grassland}$	11.739	**34.454**	54.629	-95.878	-2.113	93.660
$LUC^{Agriculture,Pasture}$	28.873	**38.151**	46.658	1.151	**35.021**	69.055
$LUC^{Grassland,Agriculture}$	8.035	**24.533**	39.667	-29.851	43.966	123.638
$LUC^{Grassland,Pasture}$	43.251	**56.432**	69.081	61.050	**106.488**	151.651
$LUC^{Pasture,Agriculture}$	36.213	**43.790**	51.247	5.258	**34.152**	63.230
$LUC^{Pasture,Grassland}$	20.270	**32.761**	45.117	-29.907	14.417	57.654
Initial agriculture	-170.907	-11.291	143.358	301.200	**543.993**	797.984
Initial natural forest	1439.536	**1570.441**	1700.503	257.323	**484.305**	745.181
Initial forest plantation	-480.375	-21.418	375.416	-3027.473	**-2006.050**	-775.361
Initial grassland	-390.913	-132.273	135.340	-1843.508	**-1065.684**	-349.820
Initial pasture	-437.845	**-317.685**	-194.894	659.665	**844.444**	1038.289
GPD growth	-6.755	**-4.504**	-2.183	-12.369	-2.764	6.715
Precipitation	-54.937	46.105	144.649	-171.035	-63.031	47.172
Elevation	-0.590	**-0.439**	-0.305	-0.050	0.134	0.308
ρ	0.612	**0.623**	0.632			
Observations	57,882					

Table B7: **Average direct and indirect impact estimates on forest loss (absolute) with pooled mining effects.** Panel-structure (2005-2020) spatial Durbin model including time fixed effects. Dependent variable is annual forest loss in absolute ha. Estimates printed in bold type are statistically different from zero based on the 95 percent posterior credible interval. PM denotes posterior mean. Time-specific intercepts were excluded for more concise summary tables.

C Supplementary Information Paper 3

C.1 Supplementary figures

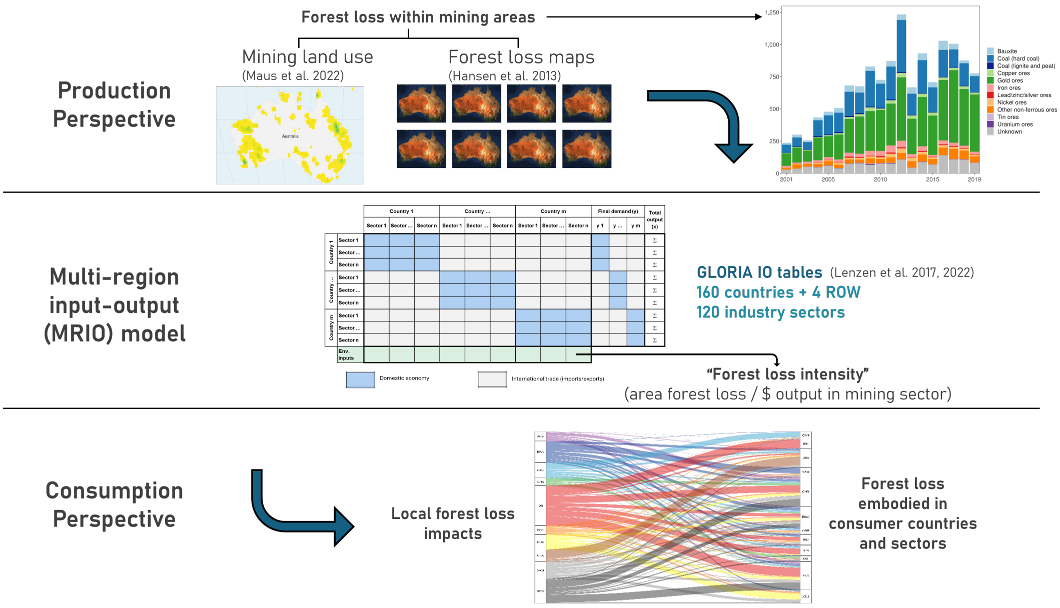

Figure C1: **Schematic workflow.** Linking local forest loss (Maus et al. 2022; Hansen et al. 2013) and the global MRIO model GLORIA (Lenzen et al. 2017; Lenzen et al. 2022) to assess forest loss embodied in final consumption.

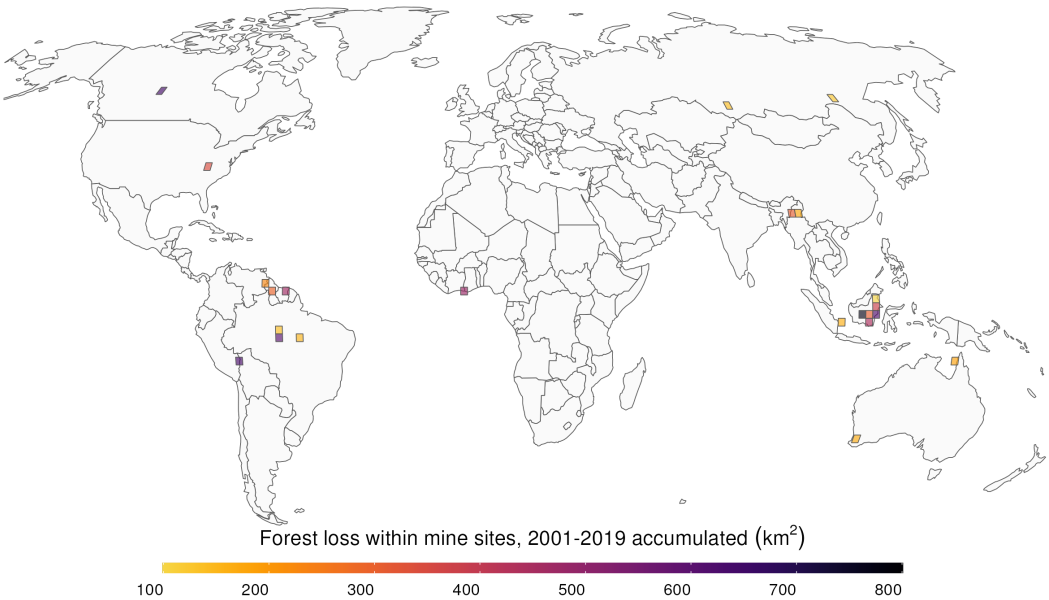

Figure C2: Accumulated 2001-2019 forest loss caused by mining at 2 degrees resolution using a Robinson map projection. Filtered for tiles with forest loss larger than 100 km^2. Areas were obtained by intersecting mining area polygons (Maus et al. 2022) and forest cover maps from the Global Forest Change (GFC) dataset (Hansen et al. 2013).

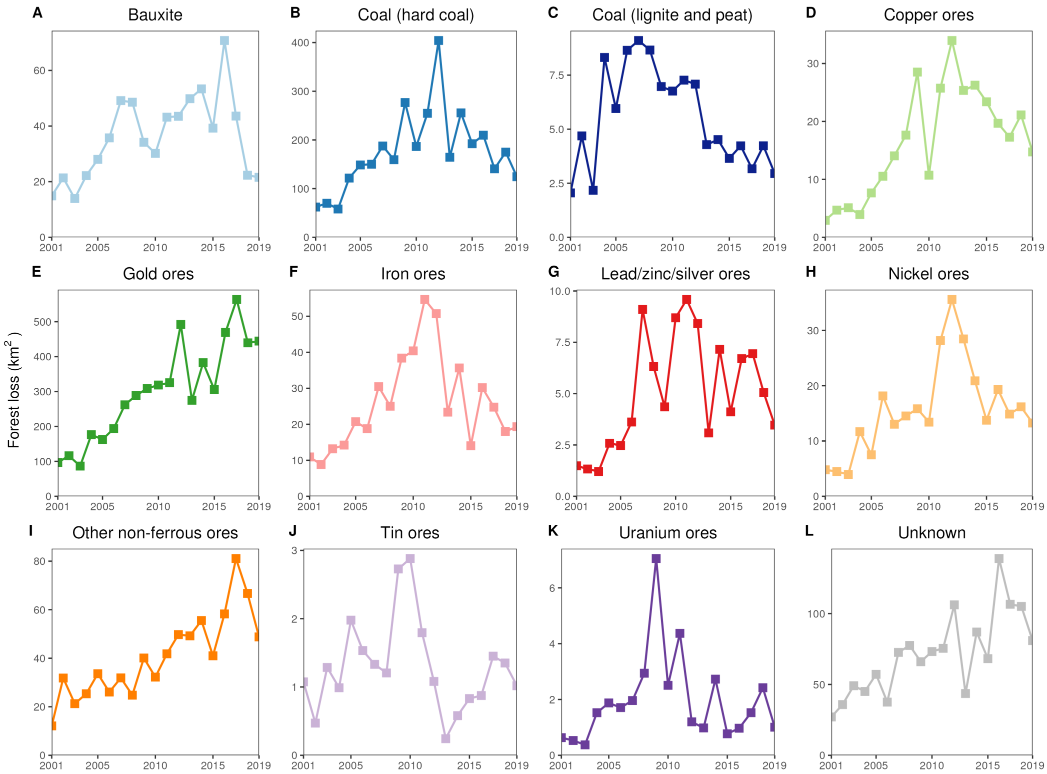

Figure C3: Yearly forest loss (in km^2) within mining polygons by commodity, 2001-2019.

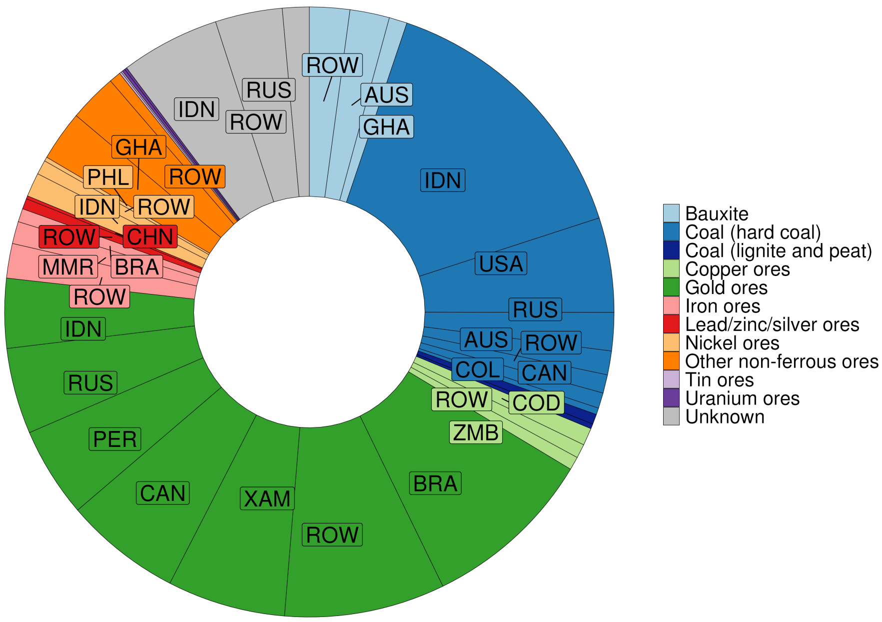

Figure C4: Accumulated 2001-2019 forest loss within mining polygons by commodity and country.

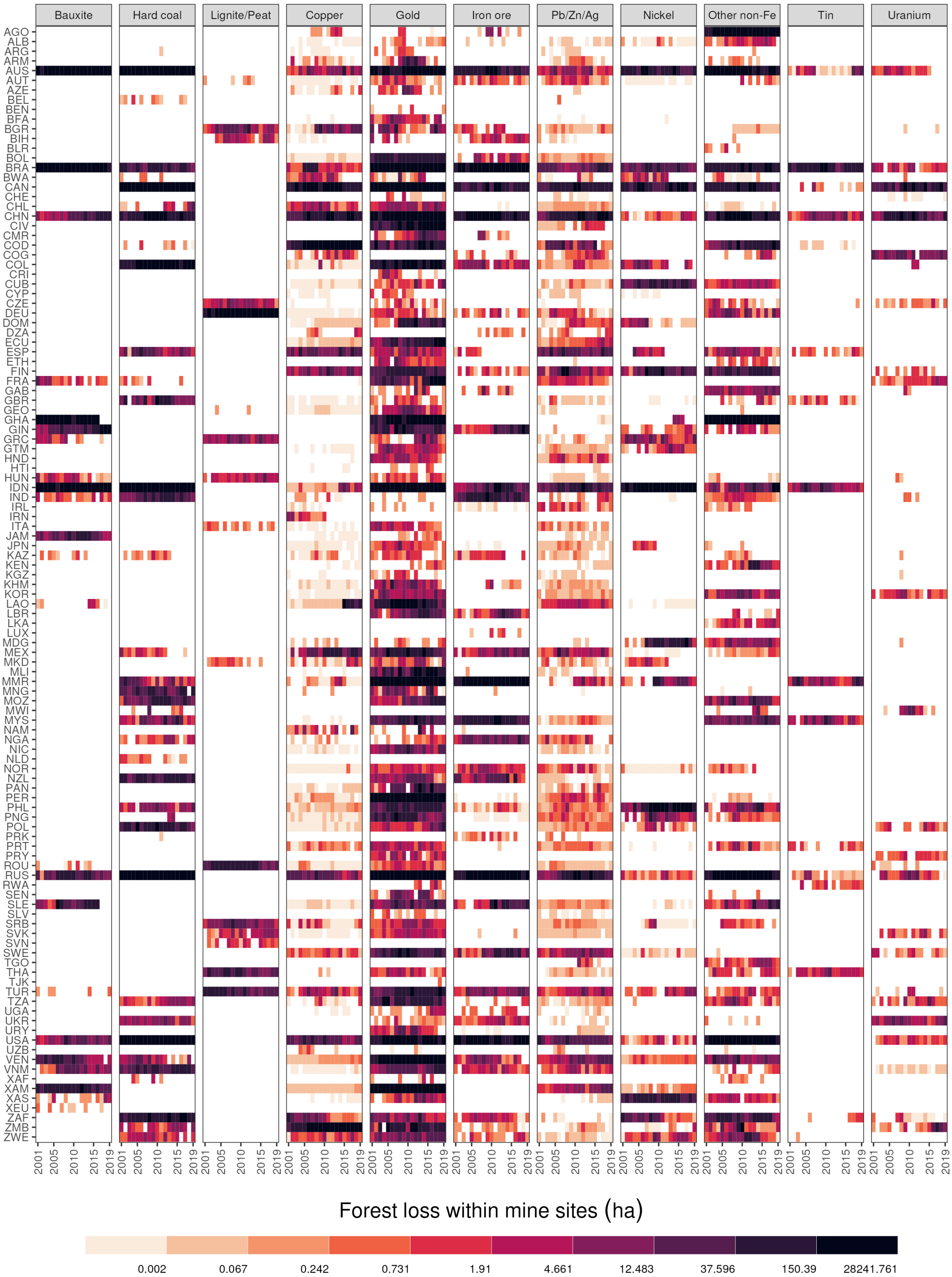

Figure C5: Yearly forest loss in hectares, by region and commodity, 2001-2019.

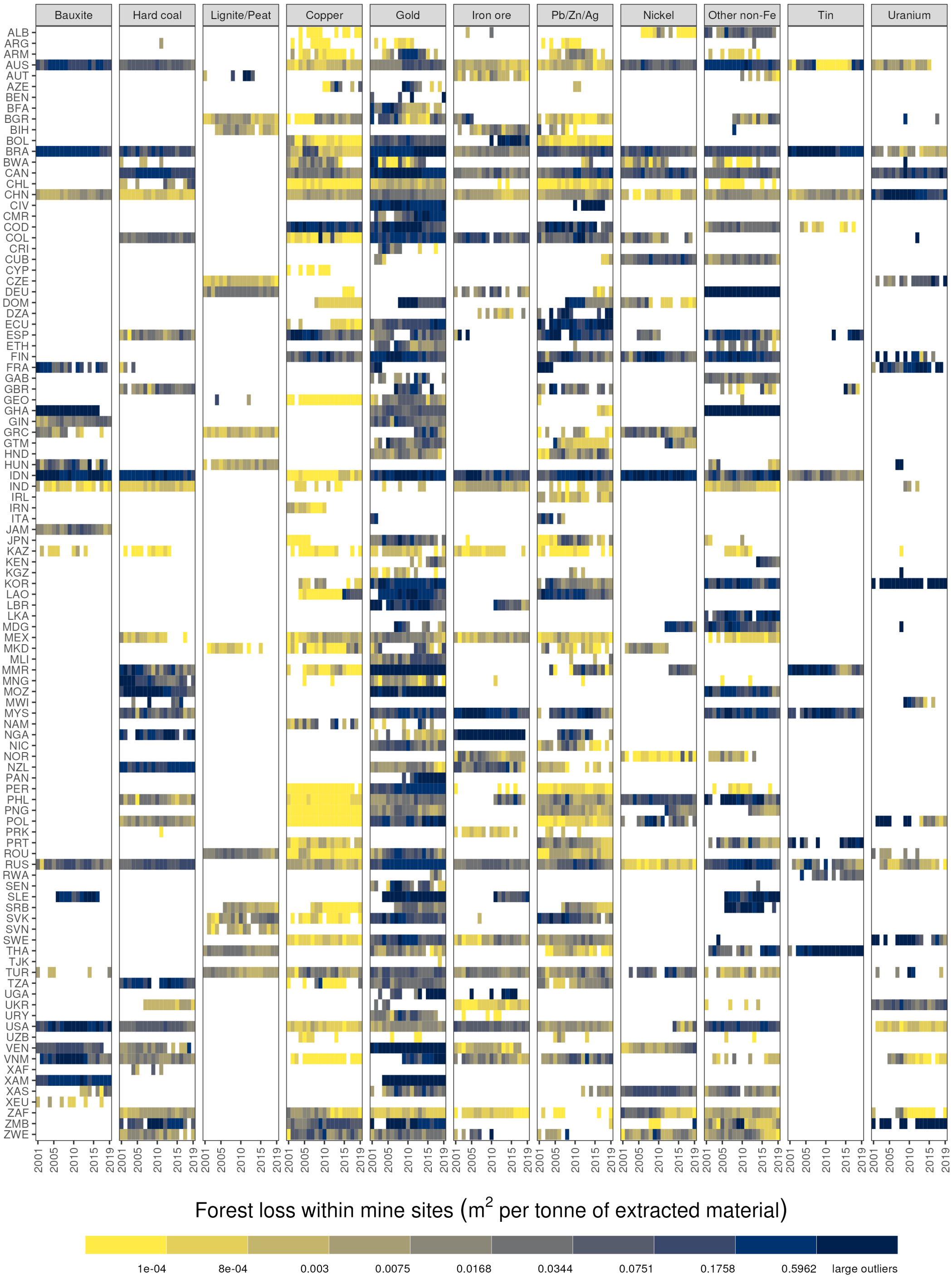

Figure C6: Yearly forest loss in m^2 per extracted tonne of material, by region and commodity, 2001-2019.

Figure C7: Total output per extraction sector calculated from the GLORIA IO tables (Lenzen et al. 2017; Lenzen et al. 2022). 2001-2019, billion USD.

Figure C8: Direct intensities in m^2 of forest loss per 1,000 USD output of each extraction sector and year.

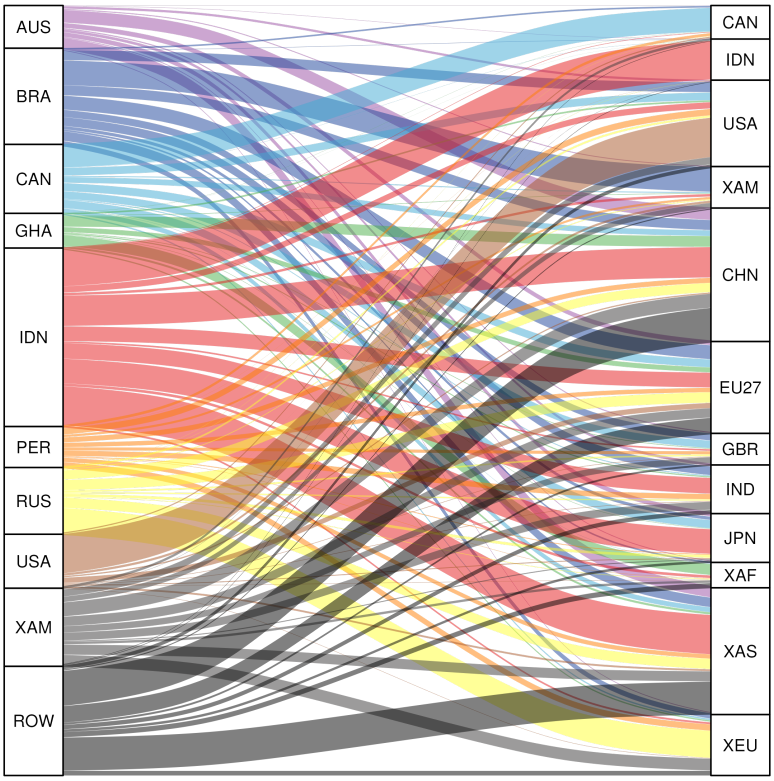

Figure C9: Production (left) and consumption (right) perspective of accumulated 2001-2019 forest loss caused by mining.

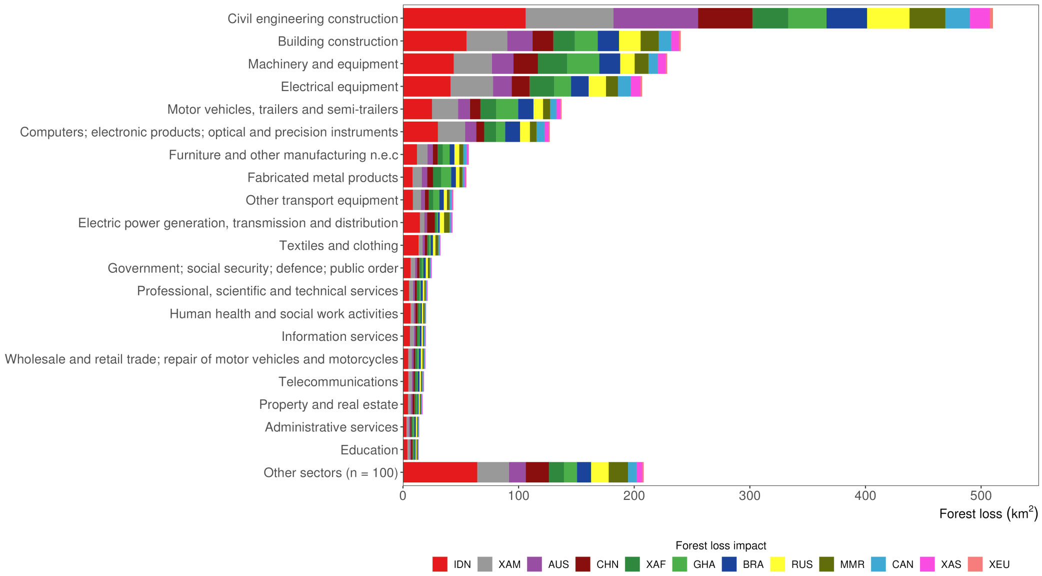

Figure C10: Forest loss caused by mining embodied in the consumption of Chinese industry sectors by world region where forest loss occurs.

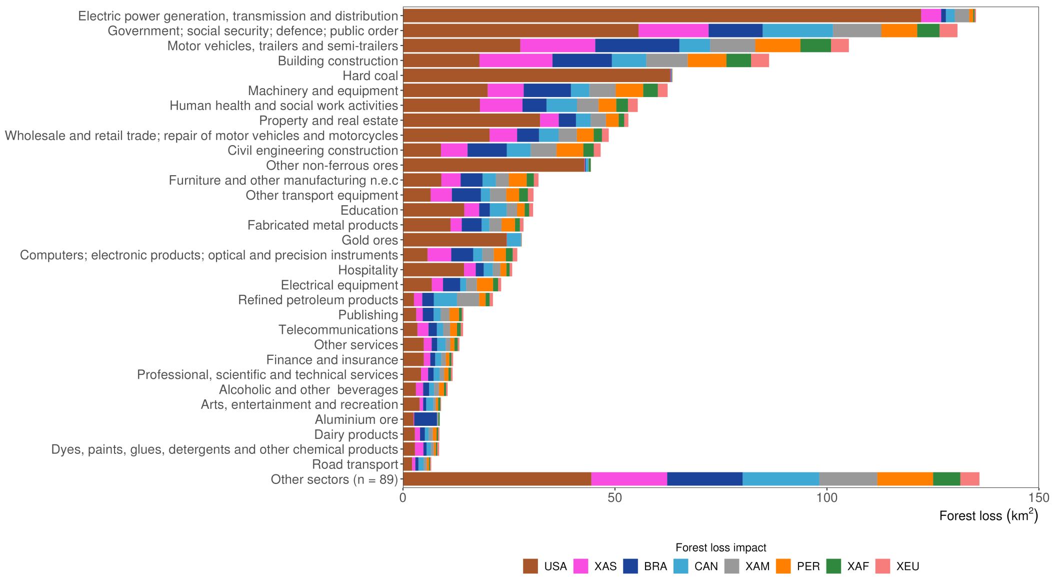

Figure C11: Forest loss caused by mining embodied in the consumption of US industry sectors by world region where forest loss occurs.

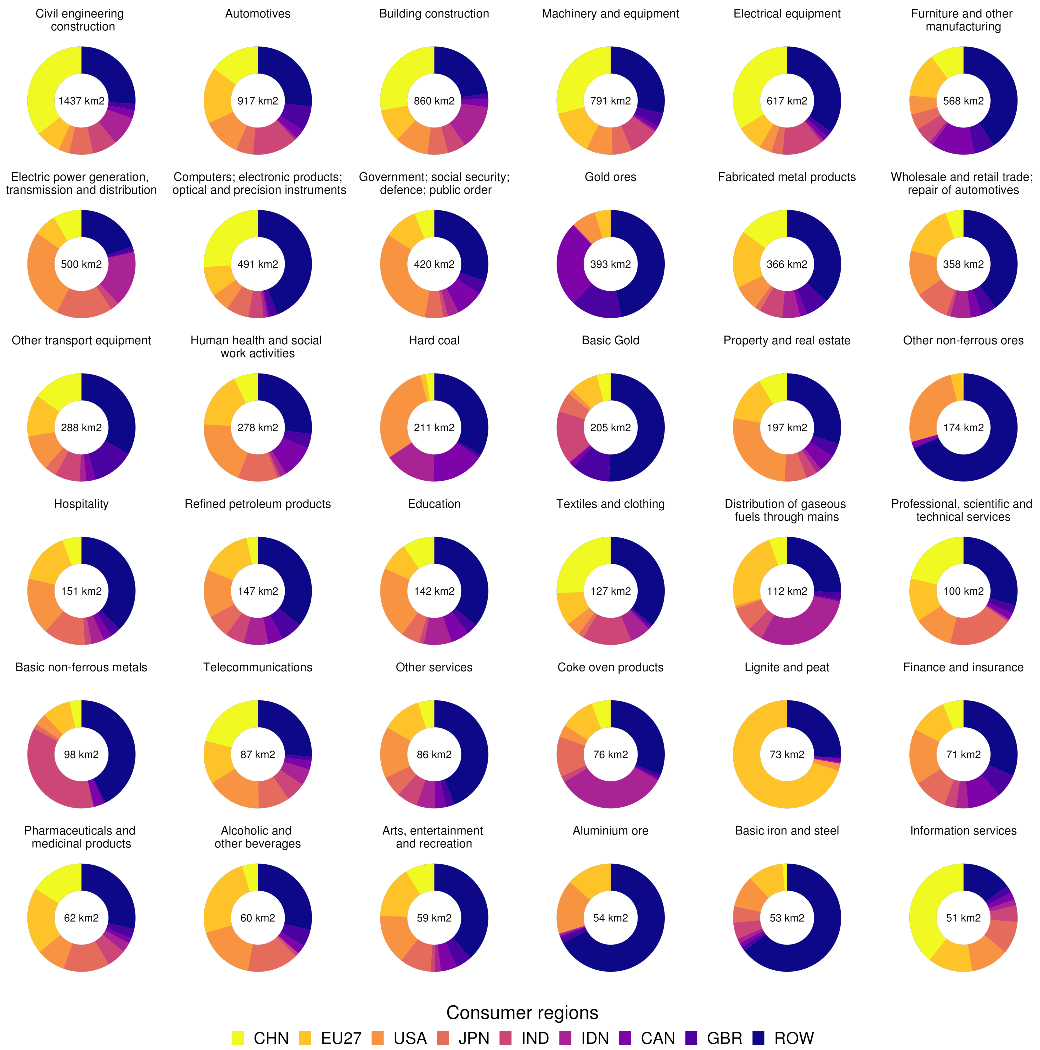

Figure C12: Forest loss caused by mining embodied in consumption, by industry sector and consumer region.

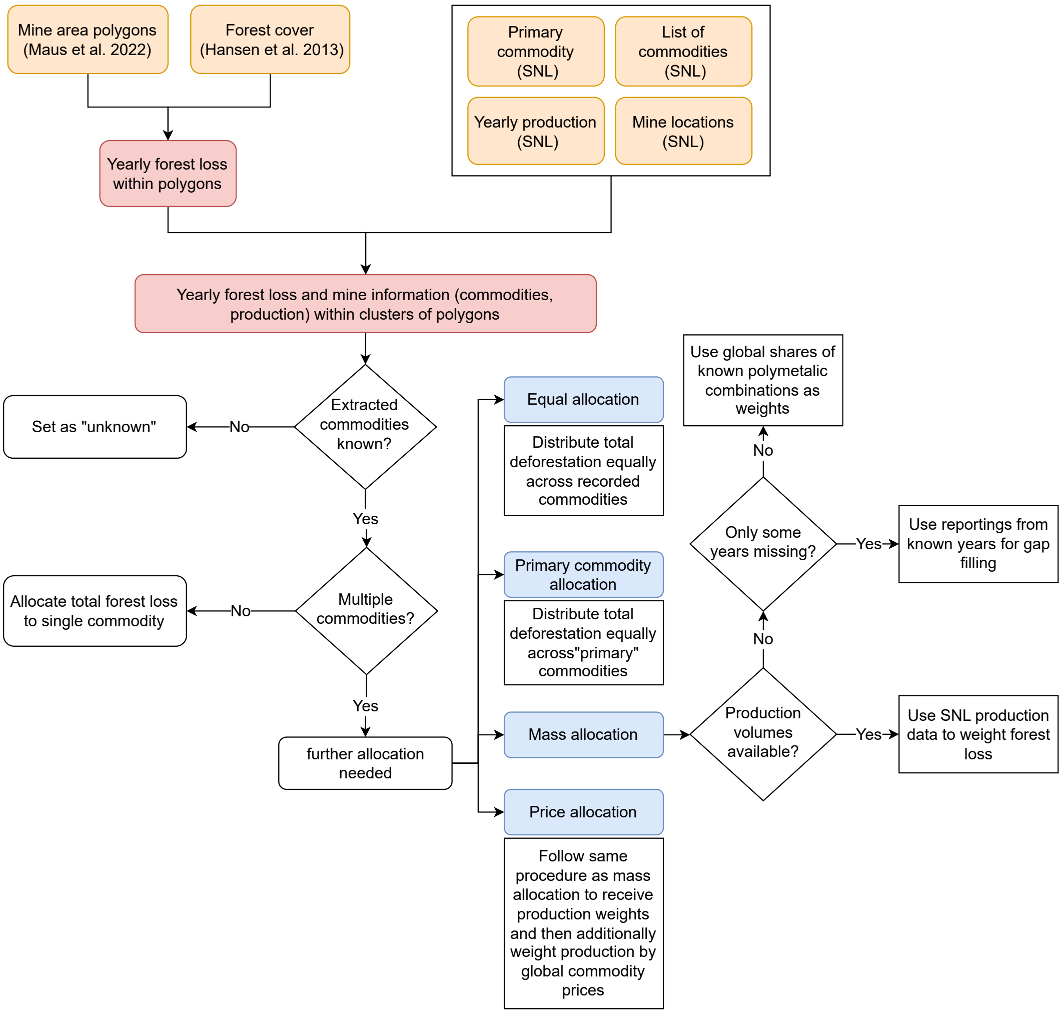

Figure C13: Allocation of forest loss withing mine sites to respective commodities.

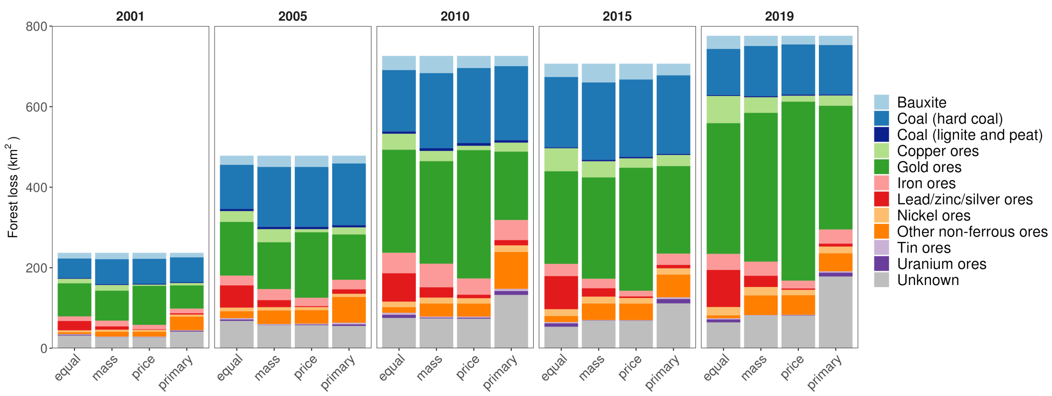

Figure C14: Yearly forest loss (in km^2) within mining polygons, by commodity and allocation type, 2001, 2005, 2010, 2015 and 2019.

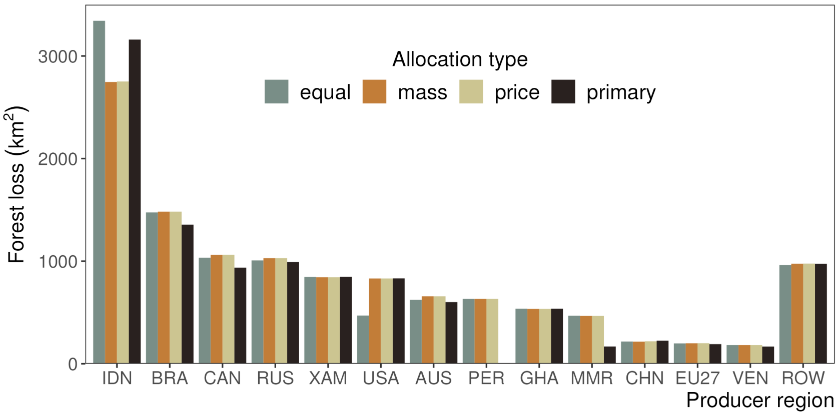

Figure C15: **Production perspective by allocation type.** Production perspective of accumulated 2001-2019 forest loss within mine sites by allocation type.

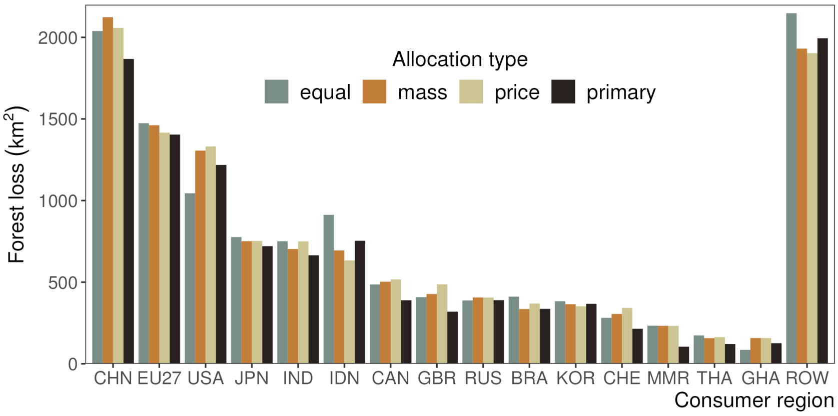

Figure C16: **Consumption perspective by allocation type.** Consumption perspective of accumulated 2001-2019 forest loss within mine sites by allocation type.

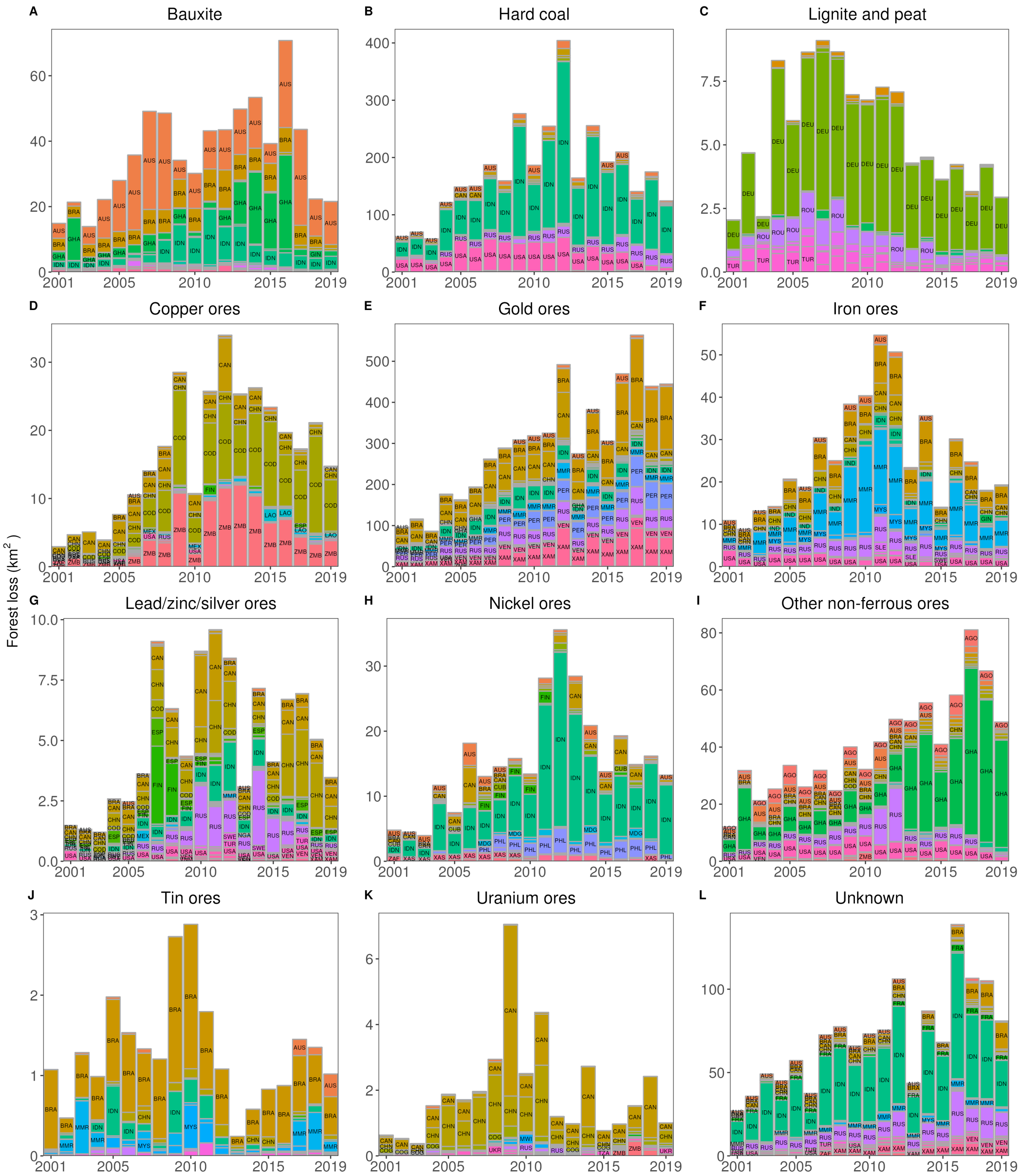

Figure C17: Forest loss within mine sites (in km^2) by extracted commodity, price allocation, 2001-2019.

C.2 Supplementary tables

Country	Prod. (km^2)	Prod. (m^2/cap)	Cons. (km^2)	Cons. (m^2/cap)
CHN	219.04	0.16	2,057.57	1.46
EU27	200.43	0.45	1,416.34	3.17
USA	831.39	2.53	1,331.74	4.06
JPN	0.43	0.00	752.51	5.94
IND	20.68	0.01	749.84	0.54
IDN	2,751.34	10.21	633.42	2.35
CAN	1,063.20	28.28	516.82	13.74
GBR	7.63	0.11	486.99	7.29
RUS	1,029.13	7.13	405.80	2.81
BRA	1,483.14	7.00	368.91	1.74
KOR	2.84	0.05	352.71	6.81
CHE	0.05	0.01	342.22	39.91
DEU	72.48	0.87	333.26	4.01
MMR	466.52	8.80	232.24	4.38
ESP	12.92	0.27	202.60	4.30
ITA	0.44	0.01	195.04	3.27
THA	5.95	0.08	163.09	2.29
GHA	534.80	16.97	157.59	5.00
FRA	13.98	0.21	153.46	2.28
SGP	0.00	0.00	147.54	25.87
AUS	657.57	25.95	147.28	5.81
TUR	23.57	0.28	116.62	1.40
MEX	25.77	0.21	109.77	0.88
MYS	35.00	1.07	108.98	3.32
XEU	0.01		108.79	
HKG	0.00	0.00	106.60	14.20
SAU	0.00	0.00	96.28	2.69
PHL	43.58	0.39	92.56	0.84
NLD	0.07	0.00	90.63	5.22
ZAF	38.63	0.66	87.09	1.50
VNM	16.73	0.17	60.05	0.63
ARE	0.00	0.00	59.71	6.48
BEL	0.03	0.00	55.51	4.83
SWE	19.94	1.94	48.06	4.68
POL	14.11	0.37	45.96	1.21
KAZ	0.40	0.02	44.58	2.41
FIN	37.33	6.76	35.32	6.40
AUT	0.59	0.07	31.97	3.60
IRL	0.22	0.04	30.12	6.10
PER	632.37	19.27	29.39	0.90
ROU	11.73	0.61	29.01	1.50
IRN	0.20	0.00	28.67	0.33
SRB	3.93	0.57	28.30	4.08
COL	79.41	1.58	26.77	0.53
XAM	843.36		25.46	
BGR	6.61	0.95	24.98	3.58
CZE	1.33	0.12	22.98	2.15
PAK	0.00	0.00	22.77	0.10
VEN	182.01	6.28	22.69	0.78
KWT	0.00	0.00	21.34	4.80
GRC	4.71	0.44	20.04	1.87
PRT	1.27	0.12	18.40	1.79
NZL	13.43	2.70	18.08	3.63
ISR	0.00	0.00	17.39	1.92
NOR	1.06	0.20	16.99	3.18
UKR	2.88	0.06	16.42	0.37
HUN	1.18	0.12	16.16	1.65
DNK	0.00	0.00	15.80	2.72
CHL	2.31	0.12	15.62	0.82
BGD	0.00	0.00	15.12	0.09
NGA	4.37	0.02	14.58	0.07
TZA	12.43	0.21	13.93	0.23
ARG	0.04	0.00	13.65	0.30
BLR	0.03	0.00	13.46	1.43
SVK	1.24	0.23	13.19	2.42
EGY	0.00	0.00	11.51	0.11
KHM	1.65	0.10	10.50	0.65
MAR	0.00	0.00	10.11	0.28
SDN	0.00	0.00	10.03	0.23
QAT	0.00	0.00	9.61	3.42
HRV	0.00	0.00	9.40	2.31
OMN	0.00	0.00	8.72	1.90
LKA	0.32	0.01	8.65	0.40
COD	151.59	1.69	8.63	0.10
IRQ	0.00	0.00	8.13	0.20
XAS	13.56		7.93	
DZA	0.15	0.00	7.88	0.18
LBY	0.00	0.00	7.04	1.07
SVN	0.16	0.08	6.76	3.24
BHR	0.00	0.00	5.99	4.01
ZMB	114.39	6.22	5.83	0.32
AGO	66.86	2.07	5.43	0.17
UGA	0.23	0.01	5.24	0.12
⋮	⋮	⋮	⋮	⋮
NPL	0.00	0.00	5.02	0.17
LUX	0.03	0.05	4.66	7.52
LBN	0.00	0.00	4.48	0.77
XAF	0.09		4.30	
MOZ	14.75	0.49	4.22	0.14
JOR	0.00	0.00	3.90	0.36
SYR	0.00	0.00	3.72	0.19
TUN	0.00	0.00	3.53	0.29
KEN	2.12	0.04	3.50	0.07
AZE	0.70	0.07	3.44	0.34
DOM	9.63	0.89	3.39	0.31
CYP	0.06	0.05	3.38	2.75
MKD	0.87	0.42	3.28	1.58
LTU	0.00	0.00	3.23	1.16
ZWE	6.14	0.40	3.17	0.21
PAN	8.44	1.99	3.10	0.73
GIN	31.40	2.44	3.07	0.24
COG	2.74	0.49	2.96	0.53
UZB	0.02	0.00	2.95	0.09
PNG	11.37	1.19	2.79	0.29
YEM	0.00	0.00	2.75	0.09
GTM	1.28	0.08	2.73	0.16
CUB	9.93	0.88	2.57	0.23
TKM	0.00	0.00	2.51	0.41
BOL	16.32	1.39	2.49	0.21
ECU	15.33	0.88	2.47	0.14
LAO	32.43	4.50	2.33	0.32
GEO	1.01	0.27	2.29	0.61
ETH	0.57	0.01	2.28	0.02
EST	0.00	0.00	2.28	1.72
CIV	37.25	1.42	2.23	0.09
CRI	0.15	0.03	2.22	0.44
URY	1.08	0.31	2.18	0.63
MLT	0.00	0.00	2.13	4.22
LVA	0.00	0.00	2.04	1.07
BIH	1.19	0.35	1.97	0.59
SEN	1.53	0.10	1.70	0.11
ISL	0.00	0.00	1.66	4.61
SLV	0.04	0.01	1.65	0.26
PRY	0.58	0.09	1.38	0.21
GAB	2.18	0.97	1.27	0.57
HND	1.07	0.11	1.24	0.12
BRN	0.00	0.00	1.23	2.81
CMR	1.73	0.07	1.18	0.05
AFG	0.00	0.00	1.17	0.03
NAM	0.89	0.36	1.11	0.45
LBR	7.12	1.43	1.10	0.22
GNQ	0.00	0.00	1.04	0.67
ARM	1.79	0.63	1.01	0.36
MWI	1.17	0.06	1.00	0.05
MNG	7.54	2.33	0.99	0.31
MLI	16.62	0.81	0.97	0.05
SLE	19.57	2.43	0.87	0.11
TJK	0.00	0.00	0.82	0.09
PSE	0.00	0.00	0.82	0.17
MDG	9.51	0.35	0.81	0.03
NIC	2.14	0.32	0.81	0.12
BWA	1.06	0.42	0.77	0.31
TCD	0.00	0.00	0.70	0.04
PRK	0.07	0.00	0.69	0.03
RWA	0.21	0.02	0.65	0.05
TGO	0.58	0.07	0.63	0.08
ALB	0.39	0.14	0.60	0.21
BFA	0.62	0.03	0.58	0.03
BEN	0.01	0.00	0.57	0.05
MDA	0.00	0.00	0.53	0.20
SDS	0.00		0.52	
JAM	5.33	1.90	0.51	0.18
HTI	0.02	0.00	0.45	0.04
DJI	0.00	0.00	0.42	0.39
BHS	0.00	0.00	0.42	1.04
MRT	0.00	0.00	0.42	0.10
BTN	0.00	0.00	0.32	0.41
KGZ	0.08	0.01	0.27	0.04
NER	0.00	0.00	0.27	0.01
BDI	0.00	0.00	0.16	0.01
ERI	0.00	0.00	0.14	0.04
CAF	0.00	0.00	0.10	0.02
BLZ	0.00	0.00	0.08	0.21
GMB	0.00	0.00	0.05	0.02
SOM	0.00	0.00	0.00	0.00
DYE	0.00		0.00	

Table C1: Accumulated 2001-2019 forest loss caused by mining. Production perspective in km^2 and m^2 per capita, and consumption perspective in km^2 and m^2 per capita. Country indicates single countries, except for EU27 (EU countries aggregated) and "rest of" Europe (XEU), Americas (XAM), Asia (XAS), and Africa (XAF) accounts. Per capita values were calculated using 2019 statistics from the **gt** (Iannone et al. 2024) R package.