Quantifying, monitoring, and minimising the negative environmental impacts of mining in tropical Africa.

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Abstract

Mining activities are distributed spatially across sub-Saharan Africa (SSA) and are in close proximity to the forestlands. Deforestation and forest degradation caused by mineral excavation is underreported especially in the SSA region, which has become a mining hub, because of its abundant mineral reserves. This study focuses on the primary and secondary impact of mining on areas of biodiversity richness, the location of 469 mines were identified and mapped in SSA and a database of mining locations was created using geospatial techniques. The dynamics of these mines were assessed to quantify how much they have expanded over time from 2001 to 2020 and the hotspots of mining were identified. Proximity analysis was conducted to ascertain the level of threat the mines pose to areas of conservation interest, results showed that the mines that are < 10 km to the protected areas had doubled in size from < 50,000 ha in 2000. The abundant reserve of key minerals in SSA has made it a major mining hub, especially at the turn of the millennium when over 260 mines were created in less than 20 years. Mining caused deforestation and forest degradation, a comparative analysis was conducted using matching to compare forest losses around locations with mines (*treatments*) and locations without mines *(controls*) over time at various buffer distances from the mines, using two sets of data: the global forest change (GFC) and the tropical moist forest (TMF). The result showed that treatments had lost 726,887 ha compared to 427,700 ha in the controls. In addition, the rates of deforestation and forest degradation pre- and post-mine creation were assessed, the rates of forest loss had increased significantly from an annual average of 1,318 ha pre-mine to 2,418 ha post-mine creation, this is an indication that mining drives forest loss. The key commodities driving deforestation in SSA are gold and copper, with annual mean loss rates of 1,462 ha and 556 ha, respectively. Sustainable mining is a prerequisite for reducing deforestation and forest degradation, and the reduction of GHG emissions attributable to mineral extraction. Furthermore, the impact of mining on the forest can be minimised through forest restoration and offsetting of biodiversity loss.

Dedication

I dedicate this thesis to the almighty, the most beneficent and the most merciful Allah (swt) from whom I derive the strength and guidance to carry on in life. Secondly, to my lovely wife and kids, to my parents, my extended family, friends, colleagues, and well-wishers who are too numerous to mention here.

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Declaration

I confirm that the thesis is my own work. I am aware of the University's Guidance on the use of unfair means. This work has not been previously submitted for an award at this or any other institution. This research owes extensive acknowledgements to the intellectual contributions of my supervisors (D.P.E. and B.R.G.).

Chapter 2.

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Chapter 3.

This chapter is currently in preparation and has not yet been submitted for publication.

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Chapter 1: General Introduction

About one third of the Earth's land surface is covered by forests (Sanchez et al., 2019); they represent one of the largest terrestrial carbon sinks. It was estimated that about 45% of global carbon and 80% of terrestrial biomass is stored in them (Romijn et al. 2015; Morales-Hidalgo, Oswalt, & Somanathan, 2015), more than one billion people worldwide depend on the forest for their livelihoods (WWF 2022; Cell press, 2020). Forests play vital roles in terms of biodiversity conservation and other ecosystem services; especially the tropical forest, which constitute wide areas of rich biodiversity and species endemicity that are unique to the tropics (Poorter et al., 2015; Laurance et al., 2012). The spatial attributes of the tropical forests, coupled with its varying altitudinal zonation makes it highly diverse, with thousands of plants species and hundreds of amphibians, birds, mammals, and reptiles' species (Ribeiro et al., 2009), and many more species still unknown (Lewinsohn and Prado, 2005). Biodiversity has allowed for immense food production for the sustenance of human livelihood and natural materials for industrial use (IUCN & ICMM, 2004). Global forests are highly threatened by the various anthropogenic activities which arise from converting forestlands to other land uses, which often leads to deforestation and forest degradation (Garzuglia et al., 2018), these activities include logging, mining, agriculture, and

Natural habitats are fragmented as a result of anthropogenic activities which often trigger land use changes that threatens conservation (Senior, Hill, & Edwards, 2019), the deforestation caused by these activities are more prominent within the pantropical regions of the world, where about 52% of global permanent forest lands are found (FAO, 2016). The rate of forest loss in the tropics has become more alarming in recent years, for instance between 1990 and 2020 there was a loss of about 178 million ha of forest globally (FAO, 2020). Between 2000 and 2010, the annual net rate of deforestation was 5.25 million hectares in the neotropics (FAO, 2020) and 1.1 million ha in Insular Southeast Asia (Miettinen et. al., 2011). According to the Global Forest Watch, the world lost 42.2 million hectares of tree cover in 2020 alone (GFW, 2020). The Consequence of deforestation goes far beyond the immediate precinct of the forest, as carbon released from the felled trees contribute to global warming (Kayet et al., 2021), the carbon released from tropical deforestation was estimated to be about 2 billion tonnes of carbon annually (Gibbs et al., 2007).

Drivers of deforestation

Forests globally are highly threatened by the various anthropogenic activities which arise from converting forestlands to other land uses, leading to deforestation and forest degradation (Garzuglia et al., 2018). These activities include, but are not restricted to, logging, mining, agriculture, and infrastructure development (Kissinger et al., 2012).

Agriculture: The conversion of forests into agricultural land is a major cause of deforestation, land cover is usually converted to the land use that provides people with the highest economic return (von Thunen, 1966). Forests are often cleared to make way for crops, such as soybeans, palm oil, and cattle grazing. Agricultural expansion is identified as a main driver of deforestation in the tropics (Gibbs et al., 2010; Hosonuma et al., 2012; Rudel et al., 2009), cropland expansion was responsible for about 3.6 million hectares of deforested in the Brazilian Amazon, between 2001 and 2004 (Morton et al., 2006). Mechanised agriculture, cattle ranching, and small-scale agriculture were identified as proximate causes of deforestation in Bolivia by Müller et al 2012, resulting in the loss of 1.88 million hectares of forest between 1992 and 2004. It was estimated that Agriculture is responsible for 80% of deforestation globally (Kissinger et al., 2012). The future prices for agricultural products will determine the land available for agricultural expansion, Lambin and Meyfroidt, 2011 projected that cropland may expand by an additional 2.7-4.9 million hectares per year, based on the current population growth and subsequent enhancement of food production to meet up with increasing demand. As globalisation increased, the impact of agriculture on local forests has also changed tremendously. The ability of highly capitalised farmers to grow at large scale to supply distant markets has weakened the historically strong relationship between local population growth and forest cover (Rudel et al., 2009).

Logging: While logging is not the only driver of deforestation, it is a significant contributor. Commercial logging is responsible for about 32 million hectares of forest loss per year, which represents approximately 10% of total global deforestation (WWF, 2018). Illegal logging and legal logging for commercial purposes can cause significant damage to forest ecosystems, leading to degradation and deforestation. Selective logging is another form of systematic forest disturbance which affects intact forest cover which facilitates deforestation and forest degradation (Hethcoat et al., 2022). Forests are often logged to provide economic capital from ecological capital (Asner et al., 2006), a heavily logged forest leads to degradation and subsequently to gross deforestation due to improper management and lack of control of anthropogenic activities (Putz and Redford 2010). Logged forests have the potential to regenerate if properly managed unlike those affected by other drivers of deforestation. Logging creates road networks that greatly increase access to intact forests for farmers, ranchers, and hunters. (Laurance et al., 2001), in addition, logging greatly increase the vulnerability of forests to fires (Nepstad et al., 2008), At the end of the last millennium, the Brazilian Amazonia was losing between 10,000 to 15,000 km^2 of its forest to logging annually (Nepstad et al 1999), between 1999 and 2002 the areas logged ranged from 12,075 to 19,823 km^2 per year (Asner et al 2005). Illegal logging and unsustainable forestry practices remain a significant problem in many African countries, leading to deforestation and forest degradation (FAO, 2020). In addition, illegal logging costs Africa about $17 billion annually (Browne et al., 2022).

Infrastructure development: The volume of deforestation due to infrastructure development varies depending on the region and the type of infrastructure (Geist & Lambin, 2002). For instance, in the Amazon Forest, 96% of deforestation occurs within 5.5km of roads (Barber et al., 2014). However, some studies provide estimates of the amount of forest loss associated with specific infrastructure projects (Sloan et al., 2018). The construction of roads, dams, and other infrastructure can also lead to deforestation and degradation, as they often require the clearing of large areas of forest (Baehr, BenYishay, & Parks, 2021), between 2000 and 2012, infrastructure development in the tropics was responsible for the loss of approximately 1.7 million hectares of forest per year, with roads and highways accounting for the largest share of this loss (Laurance et al., 2014).

Fuelwood and charcoal: Trees are cut down to provide fuel for cooking, heating, and other household uses, and this has led to the loss of millions of hectares of forested land, as well as the associated loss of biodiversity, soil erosion, and increased greenhouse gas emissions. Deforestation and forest degradation caused by the production and consumption of fuelwood and charcoal is a significant environmental issue in many parts of the world. Fuelwood and charcoal are the primary sources of energy for cooking and heating in many developing countries, particularly in rural areas where access to electricity and modern fuels is limited. As a result, the demand for these fuels is high, and the unsustainable harvesting of trees for fuel has led to deforestation and forest degradation in many parts of the world. Fuelwood is the main driver of forest degradation in Africa

(Hosonuma et al., 2012). The demand for industrial wood and fuelwood increased 35% in the tropics since 1990, principally in poorer countries (Sloan & Sayer, 2015). Apart from domestic uses, charcoal is also utilized by extractive industries in the conversion of iron-ore into steel (Sonter et al., 2014),

Mining: Mining is one of the contributors to deforestation and environmental degradation, particularly in tropical forests where valuable minerals and resources are abundant (Giljum et al., 2022). The loss of forest cover and habitat destruction caused by mining activities can have serious consequences for biodiversity and local communities. Mining activities, such as oil and gas extraction, coal mining, and gold mining, often require the clearing of forests to access the minerals and materials that lie beneath the soil, resulting in deforestation and environmental degradation within and beyond the boundaries of the mines (Sonter et al., 2017). Mining associated activities and infrastructure expansion are also responsible for forest loss and degradation in the tropics (Pacheco et al., 2021; Ranjan 2019),

Deforestation and Forest Degradation in sub-Saharan Africa Afrotropic recorded an annual forest loss rate of 3.4 million ha between 2000 and 2010, the rate increased to 3.9 million ha annually during the succeeding decade (2010 to 2020) in the region. This was in contrast to the other regions of the globe, where records showed a declining trend in deforestation compared to the preceding decade, the SSA recorded a net deforestation of 74,038,200 ha (10%) of its forest cover between 2000 and 2020 (FAO, 2020). These growing forest losses and forest degradation in the Afrotropic are attributed to various anthropogenic activities in the region i.e., agriculture, urbanisation, mining, logging, and fuelwood (Edwards et al., 2014; Hosonuma et al., 2012). The Afrotropic has some of the worlds' important and unique terrestrial and aquatic habitats in the protected and reserved areas, which are home to most endangered and rare species of flora and fauna which attracts international tourism (Balmford et al., 2002; Aleman et al., 2018; Laurance et al., 2015). However, there is generally a reduction in biodiversity across the African continent and this affects ecosystems that support the habitats, because of indiscriminate deforestation and forest degradation (Aleman et al., 2018; Adam Smith Int'l., 2015).

Critical conservation and development issues in sub-Saharan Africa

The quest for better living conditions in most developing countries of the tropical regions has led to the encroachment of forestlands for the development of various industries, which in turn provides employment, trade, and some better means of livelihood to the populace (Jianhua & Jr, 2014). A typical case is the SSA where most of the countries have low incomes and rely on the land for their survival (Malinga 2018; Ndoye & Tieguhong 2004). The United Nations Food and Agriculture Organization (FAO) in its 2015 annual forest assessment, reported that there has been tremendous encroachment into the forests leading to a loss of over 84.6 million ha from 1990 to 2015. However, there are conflicting figures about the amount of forest lost generally in sub-Saharan Africa (Potapov et al., 2012) and especially from 1900 to 1980 (Aleman et al., 2018), this was due to the dearth of knowledge on forest inventory procedures and the lack of correct baseline data. Nevertheless, the advancement in knowledge has made it much easier to quantify and monitor deforestation and forest degradation accurately in present days using reliable approaches, tools, and satellite images (Aleman et al., 2018), thereby eliminating uncertainties in the outcomes. It was projected that by the year 2030 Africa would have lost 15% of its remaining production forest (d'Annunzio, et al., 2015), if the situation around the forests is not changed from the business-as-usual scenario.

1.1 Mining-induced Forest disturbances in sub-Saharan Africa

This thesis is focused on both primary and secondary deforestation and forest degradation caused by mining in SSA, with the specific objective of identifying the location of mines and quantifying the areal loss of forest cover within and beyond the footprint of the mines. The deforestation caused by mining beyond the immediate footprint is referred to here as secondary deforestation, which includes but is not limited to infrastructural development, settlements expansion, agriculture, and hunting. Mining is a major economic venture in Africa, with about 30% of known global mineral deposits spread in various parts of the continent (Edwards et al., 2014), thus, making it a hub for mineral exploration. Most mining activities globally are located within the tropical region (Swenson et al., 2011a) and expanding rapidly into the remote areas, thereby attracting major infrastructural development to support the smooth operation of the mines which in most cases causes fragmentation of habitats with high biodiversity richness. The consistent rise in the prices of minerals due to high demand globally, has been identified as another factor that has led to the expansion of existing mines and the creation of new ones exponentially (Arndt et al., 2017; Hund et al., 2013).

Mining causes about 7% of global deforestation (Hund et al., 2017), but other findings have shown that most figures for mining induced deforestation were from the primary effect at the immediate footprint of the mines (Sonter et. Al., 2017), without taking account of the secondary deforestation which occurs beyond the mine's extent, which in most cases are larger than the primary deforestation (Alvarez-Berrios and Aide, 2015). Mining and its attributable activities are among the known drivers of deforestation that have not been studied explicitly using spatial data and modern techniques (Ferretti-Gallon & Busch, 2014). Mining attributable infrastructures and settlement expansions are sometimes left out in those reports (secondary effect), whereas these are features that sprang up because of the mines' creation. The destruction done to the environment by these mines is too enormous, ranging from soil degradation to air and water pollution and forest loss which leads to anthropogenic carbon emissions (Hund et al., 2013).

1.2 Economic worth of mining in sub-Saharan Africa

The extractive industry in Africa has a current market value of $248 trillion, making it the second largest globally (African Mining IQ, 2022). Mining is a multibillion-dollar industry in SSA (Janneh & Ping, 2011), it employs millions of people directly and indirectly and contributing immensely to the gross domestic product (GDP) of countries in the region (Signé & Johnson, 2021), most SSA nations rely solely on proceeds from minerals for their revenues. Therefore, the discovery of high-value minerals such as gold, diamond and petroleum led to the abandoning of agriculture and other trades in these countries. In Nigeria for instance the discovery of petroleum in 1956 changed the narrative from an Agrarian economy to an oil-based mono economy (Odularu, 2008). This shift in paradigm is very evident in other minerals producing countries too, the Democratic Republic of Congo (DRC) depends largely on income from mining, as it plays a key role in the supply of mineral resources for global uses (Yager, 2007), its mining operations are dominated by both the large-scale mining and the artisanal and small-scale mining (ASM) which employs around 12.5 million people, the DRC has about 47% of global Cobalt reserve (Barazi et al., 2017).

In Zimbabwe, the discovery of high-value minerals such as diamond and gold shifted focus from a vibrant and highly productive agricultural-based economy in the 1990s to a mineral resources-dependent country (Malinga, 2018). The future of mining in the SSA appears to be very promising, considering the abundant reserve of untapped key minerals with high potentials for demand in the near future. This is already attracting huge investments from the existing and new industry players who are willing to join the booming mineral industry in SSA (Deloitte, 2015).

1.3 Long-term effect of forests destruction on climate change

Undoubtedly, deforestation and forest degradation contribute significantly to changing the climate globally, to remedy this challenge several initiatives have been introduced by governments and other organisations to reduce the carbon emitted from deforestation and forest degradation. Some of the initiatives are incentive based, such as the clean development mechanism (CDM) as launched by the Kyoto Protocol which allows the investment in projects that are geared towards reducing emissions in developing countries (UN, 1998). These were done through organisations such as the Carbon fund (CF), Green climate fund (GCF), Forest carbon partnership facility (FCPF) and the United Nations Reducing Emissions from Deforestation and Forest Degradation plus (UN-REDD+) (Turubanova et al., 2018; Kissinger et al., 2012). Efforts were also made on forest and landscape restoration through the Bonn challenge which is targeted at restoring 350 million hectares of forestland globally by 2030, this is expected to generate about $170 billion per annum (Laestadius, et al., 2015). The African Union with the support from other partners is building the Great green wall with the aim of restoring about 50 million ha of forestland in Sub-Saharan Africa (Sacande, et al., 2018). The~~se~~ above measures are aimed at reducing global warming which subsequently results in distortions of the climate, but it may be counterproductive or jeopardised if drastic actions are not taken to checkmate some of the overlooked deforestation caused indirectly by mining.

1.4 Thesis overview

Forests play key roles in sequestering carbon from the atmosphere and providing habitats for flora and fauna to flourish. The importance of forests in mitigating the impact of climate change cannot be overemphasised. However, the pristine forests of SSA are depleting at alarming rates; between 2000 and 2015 about 45 million ha of forest was lost in SSA (FAO, 2016). The anthropogenic activities within or in close proximity to the forest are often responsible for deforestation and forest degradation. Among the drivers of deforestation, mining seems to be neglected as it is wrongly perceived as a minor driver. In this study I mapped out the mining locations in SSA to establish how close they are to the areas of conservation interest, in addition to creating a database of mines with their years of establishment and commodity mined. Secondly, I evaluated the amount of deforestation and forest degradation the mines have caused post creation by comparing the losses around the mines to matched locations with no mines, but with similar attributes (controls). Lastly, I identified the hotspots of mining and assessed the forest losses and changes caused by key individual commodities mined at various buffer distances.

1.4.1 Chapter 2: Where are mines located in sub-Saharan Africa and how have they expanded overtime?

Mining locations across sub-Saharan Africa were identified and mapped to explore their distribution and areal extents, to then understand the potential threats that they pose to conservation. Over 200 major mines and numerous ASMs became operational between 2001 to 2020 out of the 469 mapped in the study region, with high potential of an associated increase in mining-induced land use change. The hotspots of mining activity are identified near the regions of high carbon stocks and high value to biodiversity conservation, suggesting susceptibility to deforestation and other negative environmental consequences. The objectives of this chapter were to ascertain (1) where the location of mining hotspots are in SSA? (2) what minerals are they extracting and how have these mines expanded overtime? and (3) how close are these mines to forests and protected areas?

1.4.2 Chapter 3: How much deforestation and forest degradation has been driven by the primary and secondary effects of mining?

The database of mining locations in SSA had been established in chapter 2, and it was used to identify the locations of mining activities within or in close proximity to the areas of biodiversity richness. Focus was on the mines that were created post 2000, matching technique was used to quantify the amount of forest area that was either deforested or degraded around the mines. The objectives of this chapter were to (1) evaluate the amount of deforestation and forest degradation in locations with mines (treatments) compared to locations without mines (controls) at various buffer intervals from 2001 to 2020; and (2) compare the annual rates of deforestation before and after mine creation (i.e., across time) with distance from mine (i.e., across space).

1.4.3 Chapter 4: How different mined commodities impact deforestation and forest degradation in sub- Saharan Africa.

The impacts of mining on the environment and especially on forestlands varies considerably among the minerals being mined. Variance in impacts of commodity extraction on the total deforestation and degradation was assessed using a matching protocol following chapter 3 to compare the loss/ changes in the treatments to their corresponding matched controls. The following objectives were tackled in this chapter: (1) Identify the key commodities mined and their spatial distribution; (2) evaluate the amount of deforestation and forest degradation caused by each commodity mined versus their matched controls; (3) assess the change in the rates of deforestation and forest degradation before and after the creation of mines at various buffer distances from the mines.

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Chapter 2: Where are mines located in sub-Saharan Africa and how have they expanded overtime?

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2.1 | Abstract

Mining is a multi-billion-dollar industry spread across sub-Saharan Africa (SSA). From major to small-scale and artisanal mines, SSA is now the global epicentre for investors in the extractive industry. Here, 469 mines were identified and mapped across SSA to explore their distribution and areal extents, and to then understand the potential threats that they pose to conservation. The dominant eight commodities in SSA are gold, copper, iron, limestone, uranium, diamond, bauxite, and petroleum, making up 405 mines and occupying 85% of the 305,500-ha total areal extent. Mining expanded substantially between 2000 and 2018, with 260 (58%) new mines created and major areal expansion of many older mines. Hotspots of mining activity are apparent in the copper-belt of the Democratic Republic of Congo and Zambia, Ghana, and the Niger-delta region of Nigeria. These mining 'hotspots' are distributed in close proximity to regions of high carbon stocks and high value to biodiversity conservation, with the areal extent of mines more than doubling between 2000 and 2018 to 119,200 ha within 10 km of a protected area, suggesting susceptibility to deforestation, forest degradation and other negative environmental consequences. The identification of mines and their changing spatial extent is imperative for use in monitoring future encroachments in SSA and to conservation and habitat recovery. Furthermore, Africa needs to introduce sustainable mineral development policies to safeguard and protect its forests, especially reducing the frequency of protected area downgrading, downsizing and degazettement (PADDD) events.

Keywords: Mining locations, sub-Saharan Africa, ecological zones, protected areas, biodiversity conservation.

2.2 | Introduction

Mining is an important industry globally. It is a multibillion-dollar industry (Janneh & Ping, 2011) in sub-Saharan Africa (SSA), and a key source of employment and income for governments of most countries in the region. Mineral resources such as metals (including precious commodities [e.g., gold and PGM] and industrial commodities [e.g., copper, bauxite, tin, and iron-ore]), gemstones, limestone, and many other industrial minerals, e.g., manganese and uranium (Taylor et al., 2009), can be found in large quantities and good quality within the tropical region of SSA, making it among the world's major mineral producers (Yager et al., 2015; Kinnaird, Nex, & Milani, 2016). In addition, the region is increasingly recognised as being petroleum rich.

The global demand for mineral and petroleum resources is increasing (Hammarstrom et al., 2006), attracting the major mining players to SSA where they invest heavily and develop infrastructure (Janneh & Ping 2011; Edwards et al., 2014). This investment has led to an unprecedented upsurge in mining activities in SSA. For instance, Chinese investments in African mining grew from $15 billion to $150 billion between 2000 and 2012 (CDF, 2016; Platform, 2016), while Canada, Australia, Brazil, and others have also increased their investments within the last 20 years by an additional $50 billion in over 600 mining projects in Africa (Edwards et al., 2014; Weng et al., 2013; Woods and Lane, 2015). Though these huge investments are often (but not always, i.e., if they cause the 'resource curse') laudable from a socio-economic perspective, they also pose great threats to biodiversity conservation and climate change-mitigating carbon-stocks in the tropical regions of Africa.

In sub-Saharan Africa, artisanal and small-scale mining (ASM) occurs profusely, in part because of the prevalent poverty rate of the region. In most cases, ASM operates in very inaccessible locations within the forest (Durán, Rauch, & Gaston, 2013). Nonetheless, mineral extraction is not counted as a major driver of deforestation (Sonter et al., 2017; Alvarez-Berrios and Mitchell Aide, 2015), because it occupies areas perceived as small when compared to other drivers of deforestation, especially agricultural expansion (Kissinger et al., 2002; Ferretti-Gallon & Busch, 2014). The need to conserve forests and protected areas from mining by monitoring encroachments and its associated activities cannot be overemphasised. A key necessity therefore is to thoroughly inventory known existing mining locations, with emphasis on their proximity to forest and protected landscapes.

Previous studies have enumerated the occurrences of minerals on the continent (Durán et al., 2013; Edwards et al., 2014a). For instance, Edwards et al. (2014a) identified over 4,000 mineral occurrences in the Congo region, although the vast majority of such occurrences will not represent a mineable deposit. Not much is known about the present-day distribution of active mines, with very few geodatabases (e.g., MMSD Nigeria, USGS, globalforestwatch.org and Africaopendata.org) with comprehensive data about mining locations and dynamics. The lack of both coordination of the numerous field datasets and adding it up to interpret the full impacts of mining are some of the challenges faced in studying the secondary impacts of mining, such as deforestation and population immigration (Chatham House, 2015).

Some past studies on mining-induced deforestation in Africa were done at national level (e.g., DRC, (Schure, Ingram, Chupezi, & Ndikumagenge, 2011); Nigeria, (Merem et al., 2017)), others were commodity specific (e.g., gold, (Klubi, Abril, Nyarko, & Delgado, 2018). Furthermore, a review of previous baseline surveys on ASM in some African countries (Heemskerk, Drechsler, Noetstaller, & Hruschka, 2004) showed a lack of reckonable data on the size and location of mines. The need for spatially accurate digital maps of the location and size of active and abandoned mines is principal, as part of enhanced measures for monitoring forest encroachment.

Key to quantifying the potential impacts of mines on environmental conservation is to understand whether their distribution overlaps with important habitats and protected areas. In the Peruvian Amazon, for example, gold mines were expanding at a rate of 2,170 ha per annum before 2008, but this suddenly rose to 6,150 ha per annum after the 2008 global economic crisis (Asner et al., 2013) with ~15,500 ha of forest lost to mining between 2003 and 2009 (Swenson et al., 2011). More broadly, across the Neotropics ~168,000 ha of forest was lost to gold mining sites from 2001 to 2013 (Alvarez-Berrios & Mitchell Aide, 2015), while between 2001 and 2014, districts in India that produced coal, iron and limestone lost about 44,800 ha more forest cover. However, Ranjan (2019) showed that not all mineral extractions caused deforestation in India with, for instance, some of the districts that produced dolomite and manganese recording an increase in the forest area or an insignificant reduction.

Vulnerable to mining expansion are forests, both protected and unprotected, in regions where there are high concentrations of mineral occurrences (Edwards et al., 2014), and especially within countries where political influence plays a leading role in mineral licensing. For instance, Golden

Kroner et al. (2019) showed that between 1960 and 2018, globally there were 3749 events (2898 between 2008 and 2018) of protected area downgrading, downsizing, and degazettement (PADDD), of which 62% are caused by resource extraction. The Amazonia region had 440 events, with the Ecuadorian government removing over 200,000 ha of land between 1990 and 2013 from PAs to allocate them for mining (Qin et al., 2019). Within SSA, the Democratic Republic of Congo enacted 41 PADDD events between 1960 and 2018 to enable mineral extraction (Golden Kroner et al., 2019). These among other factors were suggested to have led to forest cover loss in the DRC (Butsic et al., 2015), such events have occurred more broadly across SSA (Edwards et al., 2014).

In this study, the critical information gap about the spatial location and distribution of mines across SSA was addressed, and in turn identified the hotspots of mining and their proximity to areas of high biodiversity value. The areal extents of individual mines were delineated and measured to show their current extents using recently acquired high-resolution imageries (World Imagery ESRI, 2019) for 2009 to 2019. The data was used to address the following questions: (Q1) Where are mining hotspots in SSA? (Q2) What minerals are being extracted and how have these mines expanded overtime? (Q3) How close are these mines to forests and protected areas?

2.3 | Methods

2.3.1 Description of Study Area and Workflow

The study covers the tropical forest and woodland savannah regions of sub-Saharan Africa, comprising thirty-seven countries as defined by the Food and Agricultural Organization (FAO, 2015). The study region (Figure 2.1a) covers an area of 2,025 million ha, which is ~67% of the entire African continent and has an estimated population of over 1 billion people (World Bank, 2018). Ecologically, there are four main lowland ecological zones (ecozones) in the region (Figure 2.1b): tropical rainforest (TRF), tropical moist deciduous forest (TMDF), tropical dry forest (TDF), and tropical shrublands (TSL) at the transition zones into the Sahara to the north and the Kalahari to the south. In addition to lowland ecozones, there is also the tropical montane system (TMS) with high elevations and mixed vegetation mostly found in Ethiopia, Kenya, Rwanda, Burundi, DRC, Cameroon, and Nigeria.

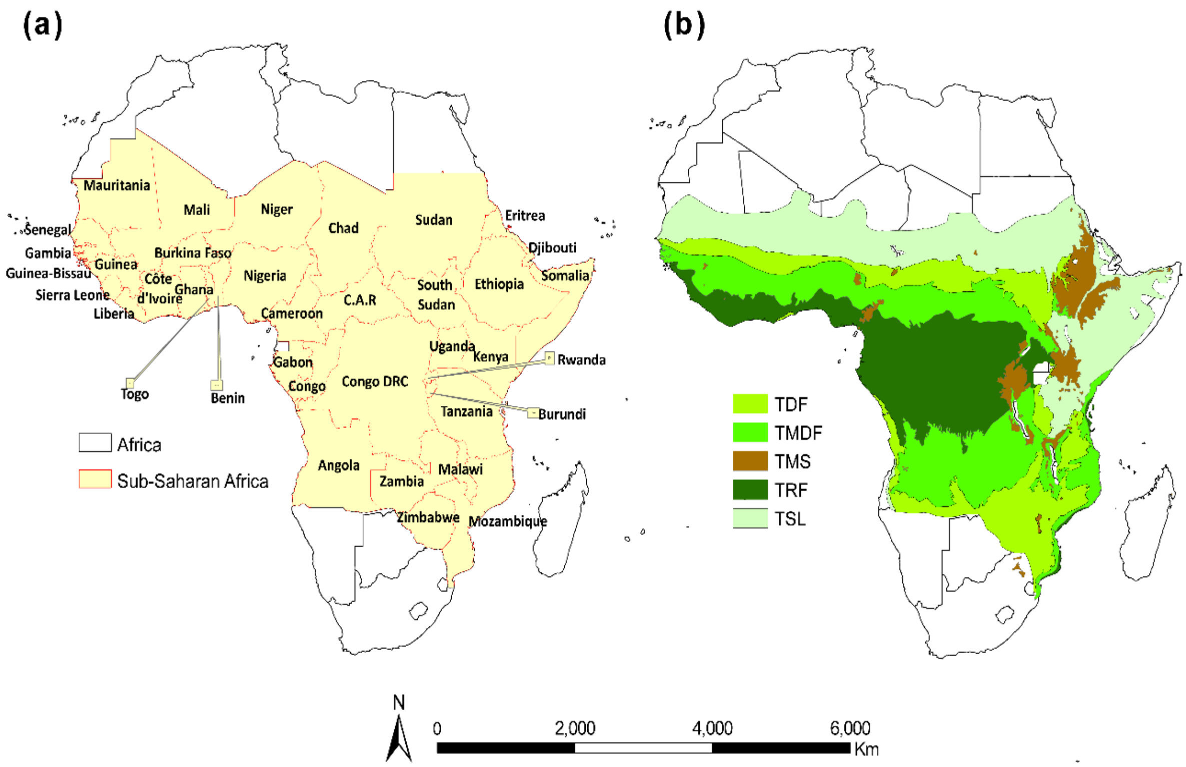

Figure 2. 1

(a) Map of the countries covered in the study, (b) Ecological map of sub-Saharan Africa as defined by the Food and Agricultural Organization (FAO, 2016), tropical rainforest (TRF), tropical moist deciduous forest (TMDF), tropical dry forest (TDF), tropical montane system (TMS) and tropical shrublands (TSL).

To address the research questions, a workflow was drawn (Figure 2.2) on how to move from the input to processing and output stages, and a loop for backward movement when the need arose for quality control (QC) and validation. This resulted in three final outputs [MLD_SAF], [MDB_SAF_QC] and [MDB_PD_pre-2000 and post-2000], and one preliminary output [MDB_SAF_prelim].

2.3.2 Mine Locations: Secondary Input Data, Quality Control

The input data used for the study (Figure 2.2) were derived from various sources (Table 1) in a range of file formats. As a consequence of the acquisition approaches used in each case, these data often exhibited: (i) omissions (e.g., several mines in Africa were missing entirely); (ii) incomplete statistics (e.g., type of mineral mined, and dates open/closed); (iii) unreliable location data (e.g., unclear mine locations and names); and (iv) some mineral occurrences were also listed as mines. As a result, detailed quality checks were undertaken on all mine locations, thus data listed in Table 1 (from ML1 to ML6) were cleaned and subsequently standardised into a format for use elsewhere (e.g., Excel, ArcMap, and R). Quality checks were carried out thoroughly on the data to check for errors in the data such as repetitions, inaccurate and unmatched locations, and incorrect spellings.

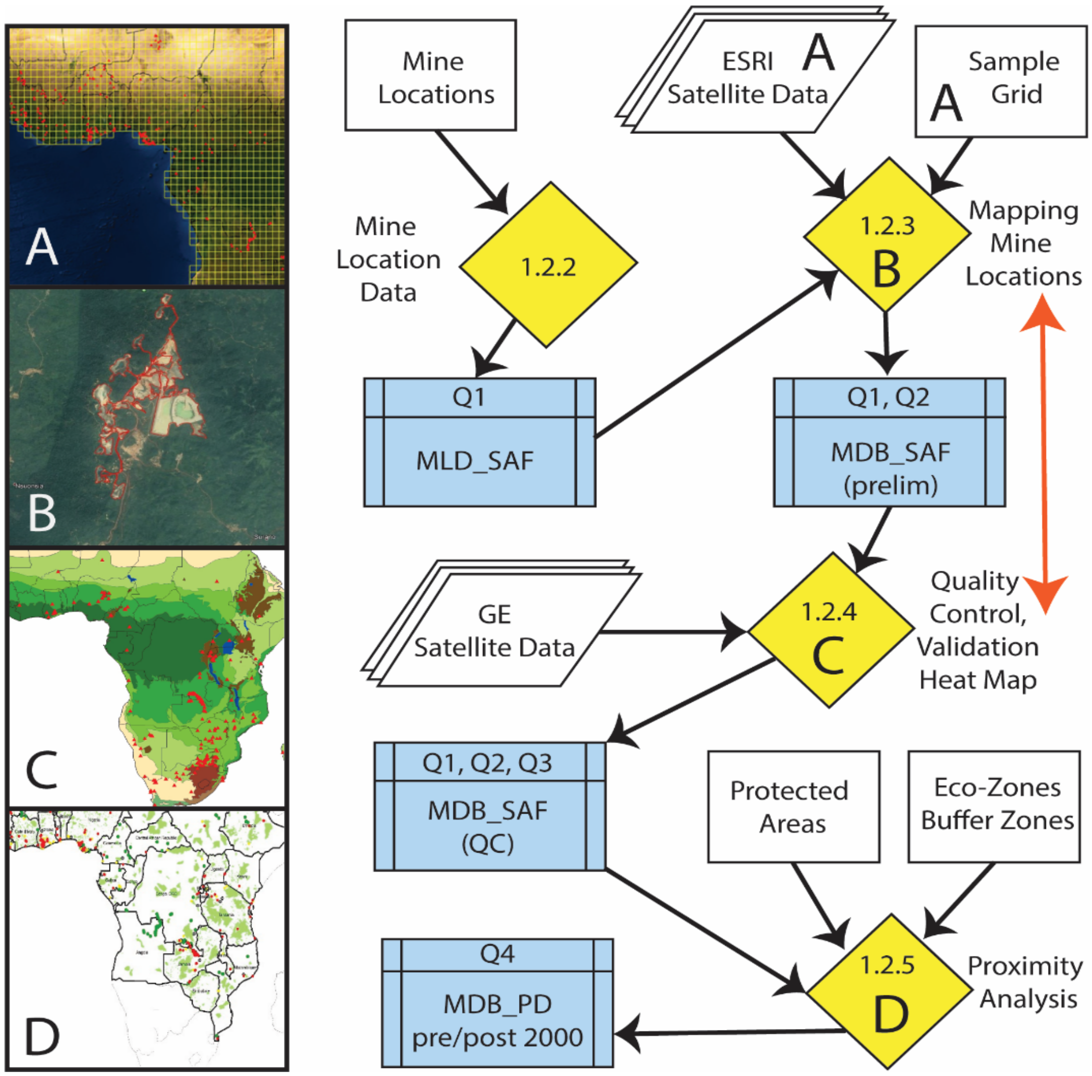

Figure 2. 2

Flow diagram highlighting key stages taken in the workflow and the outputs to address the research questions; a). (Q1) Where are mining locations and hotspots in SSA? b & c). (Q2) What minerals are being extracted and how have these mines expanded overtime? d). (Q3) How close are these mines to forests and protected areas?

The checks were done by searching the internet, especially the websites of mine operators and other relevant stakeholders in the mining industry, to verify the names of the mines and commodities mined. At the end of the QC process, the irrelevant and redundant entries were rejected, and some of the locations were mineral occurrences that are not yet operational (e.g., data labelled ML1 in Table 1). The resulting output was a Mine Location Database for Sub-Saharan Africa [MLD_SAF]; **(**see stage **A** in Figure 2.2). This was used to derive associated point shapefiles which encompassed the following attributes: the commodity mined, the mine operator, the year established and the geo-location.

Table 1.

List of data sources used in the workflow outlined in Figure 2.2 [ML = Used in the determination of mine locations MLD_SAF and compilation of the mine database MDB_SAF_prelim; QC = used as part of the quality control and checking procedures required to generate MDB_SAF_QC]

Use	Source	Data Type	Years
ML1	USGS	Mineral facilities operators	2006 to 2010
ML2	MMSD-Nigeria	Mines in Nigeria	Up to 2017
QC	British Geological survey	Mineral deposits	Up to 2018
QC	ESRI	High resolution imageries	2009 to 2019
ML3	Mining-atlas.com	List of mines	Up to 2018
ML4	OpenAFRICA.com	List of mines	Up to2016
ML5	IndustryAbout.com	List and coordinates of mines	Up to 2018
ML6	Mindat.org	location of mineral deposits	Up to 2017
QC	Global Forest Watch	Cadastre of mine fields	Up to 2017
QC	Google Earth	High and medium resolution imageries	Availability (online)

2.3.3 Mapping of mine locations: Digitising polygons for each mine footprint

The input data for stage **B** (see figure 2.2) were: (i) the [MLD_SAF] database; (ii) 100 km x 100 km sample grids; and (iii) high resolution World Imagery base map which are ESRI-derived satellite data (Figure 2.2). The digitization of the areal extent of mines were undertaken using ESRI-derived high-resolution World Imagery (World Imagery ESRI, et.al, 2019). These data comprise satellite imagery with spatial resolutions ranging from 0.3 m (e.g., IKONOS) to 15 m (e.g., SPOT) and dates of acquisition from 2009 to 2019 (World Imagery ESRI, et.al, 2019). Automated classification approaches, such as the use of Support Vector Machine (SVM), can be used to map mines in smaller regions (e.g., Isidro et al., 2017) where mining locations are known. However, the use of these and similar methods over large areas is not straightforward, and an entirely automated method for identifying mining locations with high accuracy is yet to be established (Lobo et al. 2018). Thus, considering the size of the study area and the difficulty of adopting reliable automated processes using available data, a more systematic manual encoding method was adopted. This was specifically designed to avoid misclassification of mining locations where land uses with similar spectral values (such as airstrips, roads, construction sites and areas cleared for agriculture) were apparent (Isidro et.al., 2017).

The basis of this approach is similar to that used by Swenson et.al (2011), whereby the exact spatial locations of mines and their actual areal extents were derived across SSA. For this study, the Swenson et.al (2011) approach was developed further to allow mine digitising to take place at a consistent scale of 1:5000 to reduce known errors associated with excessive overshooting of polygons and to create a reliable baseline inventory of mines polygon. To facilitate this, a sample grid of 100 x 100 km was devised to cover the entire study region (see Figure 2.2a).

These grids were manually encoded as follows:

(a) The spatial locations of mines derived from [MLD_SAF] were used as the starting reference for the manual mine encoding method. From this, the mines were digitised systematically in an eastward direction by moving from western sub-Saharan Africa (e.g., Senegal), to eastern countries (e.g., Somalia) through the central parts of the tropical African region and down to the southernmost countries (e.g., Mozambique).

(b) Each grid square was systematically scanned and surveyed for (i) both existing and new mine occurrence, and (ii) to check/validate all mine locations flagged in [MLD_SAF].

(c) Grid squares were categorised as either (MY) symbolising that the quadrat had been mapped and a mine was found within the quadrat, or (MN) mapped but no mine was found within the quadrat. At this stage, all mines were digitised as polygons and attribute data was generated in each case.

(d) This method yielded an additional 134 mines that were not initially listed on the [MLD_SAF] database. To accommodate these, live updates to the core mining database took place. For these sites, the Google Earth coordinates were used to investigate if they were actually mining sites. Where positive evidence was obtained (e.g., infrastructure, equipment, proximal settlements, rapid land-use change), these were entered into the known mine location data, and tagged accordingly.

(e) Upon digitising all the polygons, the resulting output was the sub-Saharan Africa Mine database [MDB_SAF_prelim], created with various attribute fields specifically, coordinates (dd), size (ha), year opened/closed, type of mineral mined method of mining and status (active/abandoned) for easy analysis and access to current information (see Figure 2.2).

2.3.4 Validation and cross-checking of mine location polygons, and heat maps

At this stage the [MDB_SAF_prelim] data were validated, and cross checked using other readily available high-resolution remote sensing data spanning multiple years. The process ultimately involved directly intercomparing mine location footprints from the [MLD_SAF] database with available resources Google Earth (data spanning 1972 to present); these data were used for the good availability of cloud free, multi-temporal, high spatial resolutions imagery. At this stage, additional information about each mine (including name of mine, commodity, the operator, and other relevant attributes) were also checked and updated by searching internet resources exhaustively using the names of settlements in close proximity to the defined mine footprint. This process was also used to update any missing information apparent in the [MDB_SAF_prelim] database, especially dates of mine establishment, dates of mine closure and the present operational status of the mines.

Using this approach, the digitised polygons of the mines were themselves validated manually via Google Earth to check for any changes in the size of the polygons resulting from likely mine expansion over time as some of the ESRI World Imagery scenes for some locations were either older or coarser in resolution than the Google Earth scenes and vice versa. At the end of stage **C**, the [MDB_SAF_QC] database includes additional attributes: such as area, commodity, time/date, precise location, and mine operator (see Figure 2.2).

Finally, the polygons of the mining locations were imported into ArcMap and converted to point shapefiles, before using the density tool in the spatial analyst to generate a kernel density map (heat map) with a radius of 185 km from each point, this was classified into seven classes with an interval of five points. This output denotes the spatial concentration of mines in the study area and clearly reveals the regions with high and low mine density.

2.3.5 Estimating mine proximity to forests and protected areas.

Input data for this part of the workflow (stage **D; Figure 2.2**) included (i) [MDB_SAF_QC], (ii) data from FAO eco-zones, and (iii) data from WDPA (see Figure 2.2; Table 1). Proximity analysis was conducted on these data to ascertain how close the mine footprints identified in [MDB_SAF_QC] were to key protected areas and regions of conservation interest within the region. The analysis was undertaken using two time slices that allowed analysis of: (i) mines created before the year 2000, and (ii) mines created post-2000. This was done to see if any increased risk from recent mining activity was apparent – i.e., whether new mines (post-2000) were being created significantly closer to PAs than older (pre-2000) mines.

Overall, the proximity analysis was undertaken using the following approach:

(a) The world database of protected areas (WDPA; IUCN, 2016) was initially cleaned to remove any non-relevant or redundant data - i.e., those PAs whose status includes, ‘not reported’, ‘proposed’ and ‘recommended’, plus others that were not within the study area. Overall, (as per Durán et al., 2013) only those PA polygons that were deemed directly relevant to the study were utilised. In addition, the dataset of the Ecological Zones of Africa (FAO, 2015) was also added to the workflow to operate as a guide for the identification of both forest and non-forest zones.

(b) The three thematic layers (SAF_MDB_QC, FAO_Eco-zones and WDPA) were input into the *near tool* of the proximity analysis toolset (ESRI ArcGIS 10.6) to calculate the nearest distance (in a range from 0 to 100 km) from the boundaries of the mines to the nearest PAs within specified ecozones.

(c) Buffer zones were then created from the above process based on the distance between mines and PAs, and these zones were ascribed to four key vulnerability categories as follows: (i) *red zone* for mines that are at the distance of (0<10 km) to the boundaries of the PAs; (ii) *amber zone* for mines that are at a distance of (>10<20 km) to the PAs; (iii) brown zone for mines that are at a distance of (>20<30 km); (iv) *grey zone* for mines that are at a distance of (>30<40 km); and (v) *green zone* for mines that are at a distance of (>40<100 km) to the PAs. The colours assigned to the zones provides some guide as to the level of vulnerability of forest/protected areas in that zone to mining-induced deforestation. The outer limit of 100 km distance from PAs was chosen because it was assumed that the secondary effect of mining (e.g., infrastructure development) might not be properly ascertained at distances of above 100 km; except in a few exceptional cases where mines are to be linked to the ports for export of commodities through the construction of hundreds of kilometres of roads and rails (e.g., Simandou in Guinea and Mbalam in Cameroon). The output data from stage **D** of the workflow were defined as [MDB_PD_Pre2000 and MDB_PD_Post2000] database (Figure 2.2).

(d) In addition to the proximity data, a series of attributes were also extracted, including the type of commodity mined, year of establishment, and other statistics (e.g., size of the polygons according to commodity mined).

2.4 | Results

2.4.1 Where are the mines located?

The locations of 469 mines were mapped in this study area, of which 134 (29%) mines were not present in other readily accessible databases to the conservation community. The hotspots of mines were identified in the DRC, Nigeria, and Ghana, with other concentrations of mines in Guinea, Zambia, and Zimbabwe (Figure 2.3a). These six countries accounted for 52% of the mines mapped in SSA. The least mined locations were Malawi, Djibouti, and Guinea Bissau with only five mines in combination.

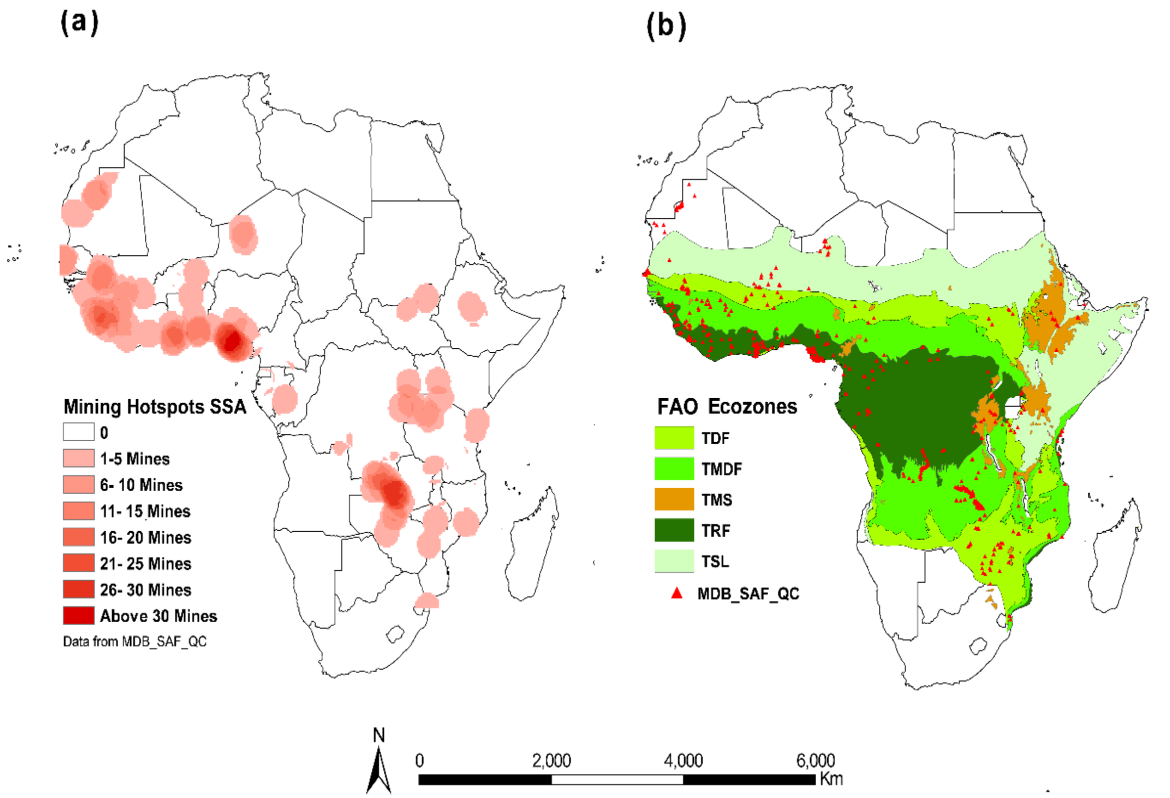

Figure 2. 3

(a) Mining hotspots for 2018 showing DRC, Zambia, Nigeria, Ghana, and Guinea as the main hubs of mining activities in sub-Saharan Africa. Hotspots were identified using the kernel density map with a radius of 185 km from each mining location and classified into 7 regular classes at 5 points intervals**. (b)** The spatial distribution of the location of mines in the various ecozones of sub-Saharan Africa as defined by the FAO.

A total of 322 mines are located within the two important ecozones where most of Africa's intact habitats are situated: the TRF and the TMDF having 42% and 32% of mines, respectively (Figure 2.3b). Additionally, the TDF ecozone, which is also considered as an important ecozone in conservation based on its canopy cover and tree species, had 68 mines where gold is the main commodity.

The TSL ecozone may be regarded as the least important ecozone in terms of habitat and ecosystem conservation, because of the sparse tree cover, a large expanse of savanna and grassland and a lack of endemic species. This ecozone had only 33 mines. The TMS ecozone had the least number of mines (27), most of which were mines for limestone, uranium, and phosphate, which is potentially positive given the high endemism in these montane regions.

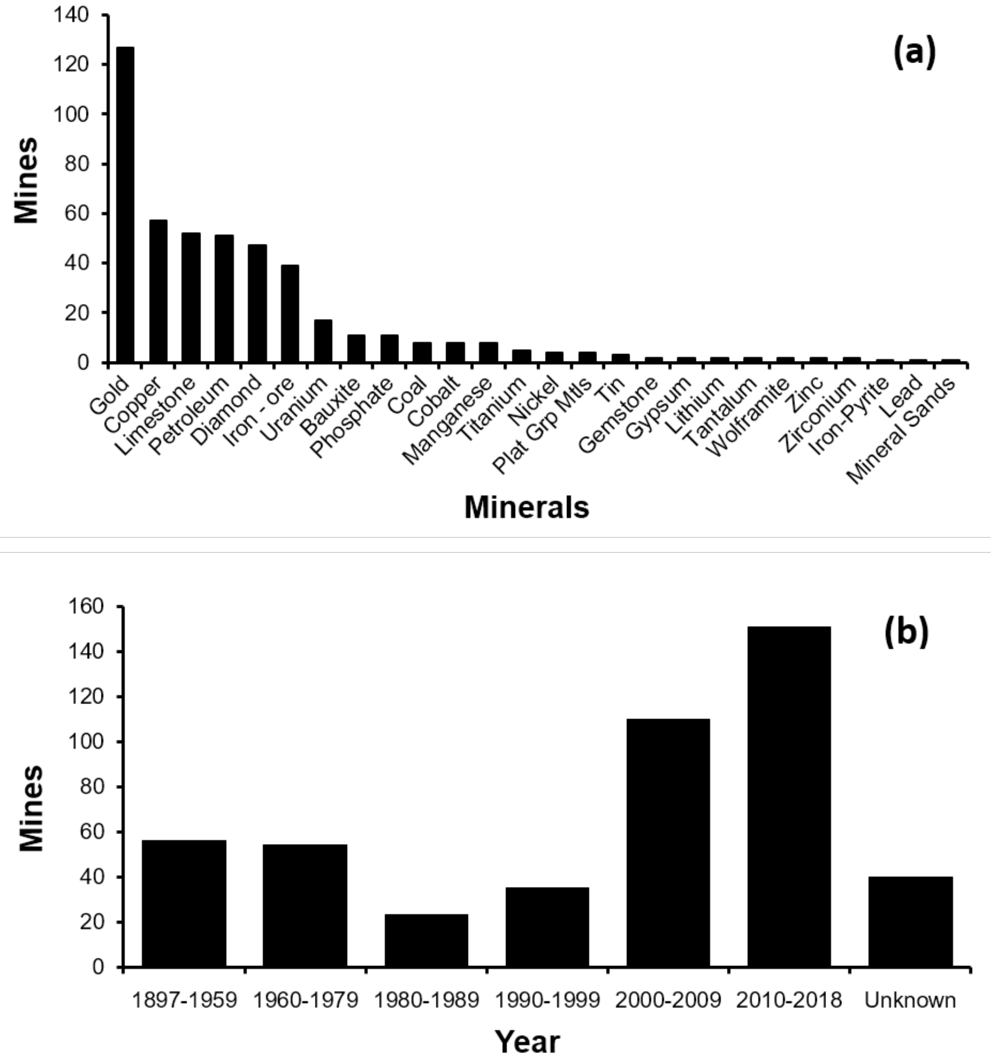

Figure 2. 4

(a) The distribution of the number of mining sites mapped by commodity mined, **(b)** The number of mines created overtime in the study area (based upon records of mining initiation).

2.4.2 What minerals are being extracted and how have the mines expanded overtime?

In total 26 minerals were mapped, occupying a land area of about 305,500 ha (Figure 2.4a). The top six by number included the low bulk-high value commodities gold (25%) and diamond (10%), the high bulk-low value commodities copper (13%), limestone (10%) and iron (7%), and petroleum (12%), making a total of 377 mines. These six commodities accounted for 75% of the total areal extent of mines mapped. The results showed that commodities with the least number of mines in the SSA are lithium, tantalum, and iron-pyrite, which each had only 1-3 mines. Gold is the most mined commodity, with the highest number of mining sites (127) spread across the region (Figure 2.4a) and occupying a land area of about 32% (99,800 ha) of the total areal extent of mines mapped in SSA. Important minerals such as bauxite, iron-ore, coal, gemstones, cobalt, and tantalum are also mined in enormous quantities in the study area, among others.

Two hundred and sixty (58%) of the mines in the study area were established between the year 2000 and 2018 (Figure 2.4b). Within this time period, copper and limestone had 35 and 25 new mining locations, respectively, while iron-ore and diamond had 27 new locations each. Furthermore, with the use of historic data from Google Earth, it was discovered that most of the existing mines for high-value commodities (e.g., gold, and diamond) that were created pre-1980 have expanded remarkably during the period under review (2000-2018). For example, the Tarkwa gold mine in Ghana, which used to be less than 300 ha in areal extent in the 1980's, has expanded to over 3,000 ha, and the Thsibwe diamond mine in the DRC, which used to be 50 ha in the 1980's, had become over 400 ha. Overall, there was a total expansion of 189,200 ha in the areal extent of mines in SSA in the period under review, with gold having the largest expansion by area with an additional 77,000 ha in land area.

It was found that in total the DRC had the highest number of mines (63), while Zambia had the largest areal extent representing 13.2% (40,300 ha) of the total area mined in SSA. Many new extractive projects came on board in the period under review. Some of the notable new ones were uranium (e.g., Niger; Dasa Mine 2017) and limestone (e.g., Zimbabwe; Dangote – Ndola 2015 and Nigeria; Obu/Okpella 2017), as well as petroleum and gas explorations in six new locations (e.g., South Sudan had four new projects; Palouge 2003 and Thar-Jath 2002).

2.4.3 How close are the mines to forests and protected areas?

Over time, it can be seen that a consistently substantial proportion of the reported mining activities occurred in close proximity to PAs (Figure 2.5 a, b, c). Indeed, there was a substantial increase in mining area since the year 2000 in each category of buffer zones, especially in the red zone (0<10 km from PAs; Figure 2.5 a, b), which shows that this zone remains a constant focus for mining activities (Figure 2.5c), with the areal extent of mines having more than doubled from 49,800 ha pre-2000 to 119,200 ha for those created post 2000; with a corresponding 250% increase in total number of mines. For instance, gold mining extent had expanded from 4,400 ha to 23,300 ha in this zone. The occurrence of mineral commodities mined in the red zone have also significantly increased in number in the period under review, most prominently: copper (from 13 to 29 mines), diamond (from 15 to 27 mines), gold (which rose from 15 to 48 mines) and iron-ore (from 7 to 27 mines). In the amber zone, there was a substantial increase in the number of mines from 33 in 2000 to 67 by 2018, resulting in an increase in areal extent by 250% in the zone (Figure 2.5b).

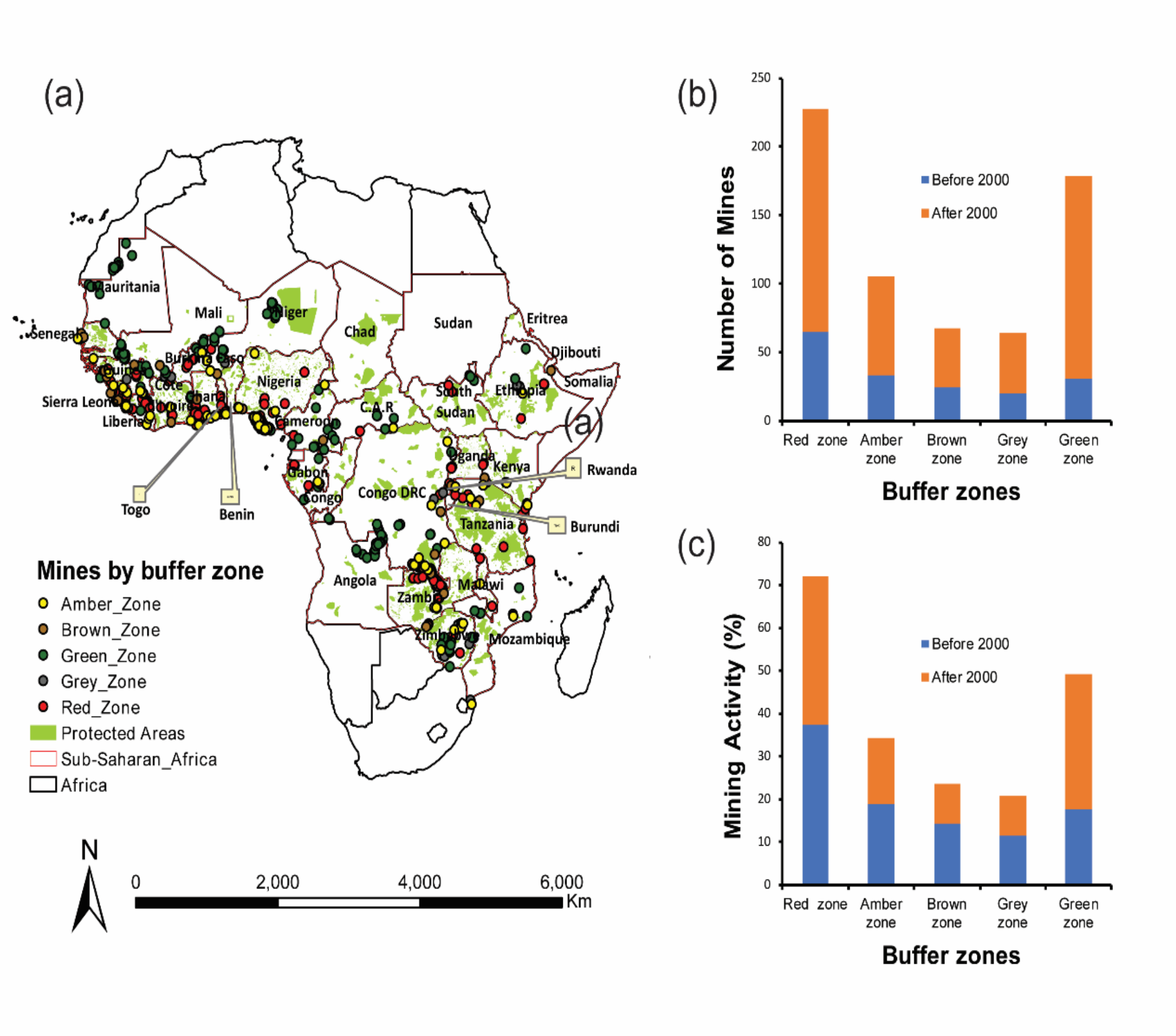

Figure 2. 5

Mines and their proximity to protected areas. (a) A map of the study area showing the proximity of mines to the PAs (via different buffer zones) in 2019 (b) The distribution of total mine numbers in the different buffer zones of proximity to the forests and protected areas, noting increased mine numbers in the post-2000 period for all buffer zones, and (c) the distribution of the relative proportion of mines (mine numbers expressed as a proportion of the total) in each buffer zone for the two time-slices, noting the consistent appearance of mining activity in the red buffer zone regions. Labels are: (i) red zone is for mines that are at a distance of (0<10 km), (ii) amber zone is for mines that are at a distance of (>10<20 km), (iii) brown zone is for mines that are at a distance of (>20<30 km); (iv) grey zone is for mines that are at a distance of (>30<40 km); and (v) green zone is for mines that are at a distance of (>40<100 km) to the PAs.

The brown zone is considered as the transition zone between the areas with high vulnerability and the areas of low vulnerability to mining-induced deforestation and habitat degradation. An increase of 19 new mining locations were found in this zone, with the grey and green zones having a total of 44 and 147 mining locations, respectively, in all the phases of the analysis (pre- and post-2000; Figure 2.5a). Generally, from the post 2000-era analysis, an increase of 270% was discovered in the number of mining locations (Figure 2.5b), translating to about expansion in the areal extent of mines in the study area by 189,200 ha.

2.5 | Discussion

The results have established that mining sites are located in most parts of sub-Saharan Africa, regardless of the ecological region. However, the proximity of mines to areas of high environmental value suggests that they pose significant threats to forest and ecosystem conservation in SSA, especially considering the rapid rates of expansion of existing mines and the creation of new ones. Over 200 major mines and numerous ASMs have been established within the last 20 years in the study region, with high potential of an associated increase in mining-induced deforestation and degradation in SSA. This study fills a core need for an accurate database of mining hotspots (Figures 2.3 & 2.4), enabling the continuous monitoring of identified mining hotspots that can help to reduce deforestation caused by mine encroachment.

2.5.1 Mine expansion

The findings revealed that 58% of mines in the study area were established between the year 2000 and 2018 (figure 2.5) and most of those established pre-2000 had expanded significantly. This development can be attributed to the growth in mineral demand and as a direct manifestation of the recent huge investments in the mining sector of Africa (Janneh & Ping, 2011; Edwards et al., 2014b; Woods & Lane, 2015). Incidentally, the last two decades were the era when the global economy rose from about \$33 trillion to over \$80 trillion (*World Bank*, 2018), and coincidentally the period when Africa's forests were depleted by over 45 million ha (FAO, 2015), with mining identified as one driver of deforestation.

In the Neotropics, gold mining has expanded rapidly into new regions between 2001 and 2013, with 168,000 ha of forest lost to the new mines created (Alvarez-Berrios & Mitchell Aide, 2015), with existing Huepetuhe, Delta-1 and Guacamayo gold mines in south-western Peru expanding by over 500,000 ha between 1999 and 2012 (Asner et al., 2013). Such a greater rate of expansion may be expected in the future in sub-Saharan Africa, especially if deposits are exhausted elsewhere.

The areal extent of most mines for commodities such as gold, copper, iron-ore, diamond, and uranium are larger than 1,000 ha, including all structures within the mining sites (see also: Durán et al., 2013; Swenson et al., 2011; Alvarez-Berrios & Mitchell Aide, 2015). However, these classes of mines are also likely to have attracted the expansion and creation of new settlements around them, in addition to the artisanal and small-scale mining activities thriving around their vicinities, which remain an unquantified major potential negative consequence for the environment (Spittaels & Hilgert, 2013). Poor dwellers in such settlements are likely to hunt for food and extract enormous quantities of fuelwood, extirpating wildlife and resulting in local deforestation or degradation.

The activities of ASM and the informal miners are scattered around the region. Their mostly far smaller areal extent (Asner et al., 2013; Hund et al., 2013; Heemskerk et al., 2004) means that measuring the size of these mines (and indeed locating them) using optical satellite imagery is often not feasible (e.g., Landsat; Nigeria-SAT & SENTINEL), especially when working at a large area with the presence of tree canopies around the mines (Asner et al., 2013). The exceptions may be in those cases where the ASM are concentrated within one vicinity, creating a large aggregate areal extent. For example, the Banankoro diamond mine in Guinea and the Asankrangwa belt mines in Ghana, which stretches down the entire length of the Ofin river, making it the largest ASM gold mine in Ghana and the SSA at large.

2.5.2 Conservation impacts

Many mines were located close to areas of conservation concern. This finding mirrors those of Edwards et al. (2014) who found 964 mineral occurrences inside or within a distance of 10 km of the protected areas of Central Africa and of Durán et al. (2013) who found that, globally, 482 mines for metals (bauxite, copper, iron, and zinc) are within or at a distance of up to 10 km from protected areas. However, this study represents a major advance, in that it deals with mines and not occurrences, and covers most of SSA rather than solely the Congo Basin (as per Edwards et al., 2014). This study has also identified 200 more mines than Durán et al. (2013) in the study region, who were only able to study four mineral types and focused on designated protected areas.

In addition, they were unable to detect impacts in the west and central Africa regions where a concentration of mines with proximity to areas of concern were identified, both PAs and forests more generally.

Mines have advanced towards areas of conservation interest overtime: of great concern are mines within the green buffer zone in countries including Nigeria, Angola, and the DRC where the Chinese and others are increasingly investing in gold, copper, limestone, and gemstones (e.g., Schure, et al., 2011; Edwards et al., 2014; Executive Research Associates (Pty) Ltd, 2009). These may represent substantial upcoming threats because of the ongoing prospecting and exploration for minerals in nearby locations that are more proximate to areas of conservation concern. This is likely to attract more infrastructure development and bring in ASM miners.

There is a dearth of strong laws in the region and lack of commitment on the governments of most countries in the SSA on the need to maintain and protect the PAs (Edwards et al. .2014). For instance, the DRC government granted mining concessions in locations that overlapped with important protected areas in the region; in 2018, it proposed to enact PADDD to downsize two of its important PAs (Virunga and Salonga National Parks) by about 400,000 ha to enable mineral extraction in the area (Qin et al., 2019).

The encroachment of mining and its related activities within or near to PAs will likely significantly negatively affect the capacity of PAs to perform their core conservational functions (Dudley, 2010), with changes in habitat landscapes close to PAs having direct influence on the ecosystem within PAs (Laurance et al., 2012). Furthermore, in most cases, new mines require new infrastructures which leads to linear clearing of forests the effect of which can be enormous (Laurance et al., 2009). In tropical Africa, for instance, hunting of animals in primary forest has increased in close proximity to roads and is driving the most endangered species towards extinction (Laurance et al., 2009) at the same time as impacting tree seed dispersal and recruitment (Terborgh et al., 2008).

2.6 | Conclusion

In total, 469 mines were identified and mapped across SSA to explore their distribution and areal extents, and to then understand the potential threats that they pose to conservation. Hotspots of mining activity are in close proximity to regions of high carbon stocks and high value to biodiversity conservation, suggesting susceptibility to deforestation and other negative environmental consequences. Without effort by conservationists, policymakers, and international funders of mining to bring renewed rigour to environmental standards, there is significant danger that mining in SSA will result in major conservation losses, both within and outside of PAs. In particular, we need a much more robust approach to the increasing frequency of PADDD events to make way for mining.

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Chapter 3: How much deforestation has been driven by the primary and secondary effects of mining?

3.1 | Abstract

Sub-Saharan Africa (SSA) has become a mining hub, attracting major players in the mining industry because of its abundant mineral reserves. A key question is, to what degree does the creation of new mines and expansion of existing ones generate off-site deforestation and forest degradation? Firstly, a comparative analysis was performed to quantify deforestation and forest degradation between 2001 to 2020 at 0-10 km buffer distance by matching locations with mines (treatments) and those with no mines (controls) but with similar environmental attributes, and then assess the rates of annual change before and after the mines were created. Using the global forest change (GFC) dataset revealed that mining caused 726,887 ha of deforestation, 41% more than the matched controls, equating to a mean annual loss of 36,500 ha in treatments versus 21,384 ha in controls. For mines created between 2009 and 2011 (the median years), the rates of deforestation increased by 2,100 ha per year (307%) after mine creation. Mining drives substantial deforestation beyond the spatial extent of the mine, indicating the urgent need for the mining sector to account for these broader environmental costs in their impact assessments, carbon accounting, and associated investments in conservation protection.

3.2 | Introduction

Sub-Saharan Africa (SSA) has an enormous volume of high-grade minerals across the region (Edwards et al., 2014a), making it a mining hub and global epicentre of mine expansion. Coupled with the global rise in demand for precious metals, gemstones, and industrial minerals, mining has become a major source of revenue for most countries globally (World Bank, 2016) and a means of livelihood for local inhabitants. SSA has recorded remarkable increases in mining investments by major industry players over the last 2 decades (Janneh & Ping 2011; Weng et al., 2014), and in 2018, the region produced minerals worth about $350 billion (Republic of Austria, 2020).

The unprecedented financing into the mining sector, has led to the creation of new mines post 2000 as well as major expansion of existing ones. Some of these mines are expanding into areas of high biodiversity value, causing environmental loss and major risks for conservation e.g., Artisanal mining (Ahmed et al., 2020; Barazi et al., 2017; Edwards et al., 2014; Weng et al., 2014; Schure et al., 2011). Mining is not regarded as a foremost cause of primary deforestation, because the area of land involved in some cases is relatively small (Chakravarty, Ghosh, & Suresh, 2011), yet mining-induced habitat disruptions are being underestimated or neglected in some countries (Alvarez-Berrios & Mitchell Aide, 2015; Sonter et al., 2017), despite evidence from satellite images (Swenson et al., 2011; Asner et al., 2013). Mining causes deforestation, forest degradation and associated habitat fragmentation, and the subsequent loss of intact terrestrial habitats, which houses a hyperdiversity of tropical species (Frelich, 2014.; Sonter et al., 2017; Curtis et., al. 2018; Tegegne et al., 2016; Lobo et al., 2016). For instance, in the Neotropics, gold mining was responsible for the loss of ∼130,300 ha of tropical moist forest biome (TMFB) between 2007 and 2013 (Alvarez-Berrios & Mitchell Aide, 2015). In the South-eastern Peruvian Amazon alone, gold mines expanded threefold between 2008 and 2012 to 6,154 ha per year (Asner et al., 2013), causing 64,586 ha of forest loss from 2010- 2017, which is twice the area lost in the previous 26 years (1985-2009) (Caballero et al., 2018). In Indonesia, ~220,000 ha of forest land was lost between 2001 and 2016 as a result of increased mining activities in the country (Austin et al., 2019), mining induced deforestation increased 2.77 times from 2000 to 2008 in Guyana (Chakravarty, Ghosh, & Suresh, 2011).

These studies focused on the core mine area, yet mining causes and facilitates environmental losses outside of the mine boundaries largely due to deforestation during the construction of mining support infrastructure (roads, rails, seaports, workers settlements), in addition to subsequent deforestation by the mining settlements for agricultural activities(Edwards et al., 2014; Durán, Rauch, & Gaston, 2013; Sonter et al., 2017) and forest degradation (within-forest impacts) via selective logging for timber or fires. These 'secondary' impacts of mining can occur in distant forests and intact habitats. For example, in the Brazilian Amazon between 2005 and 2015, mining caused ∼1.2 million ha of deforestation at distances of 0-70 km away from the boundary of mining leases relative to matched controls (Sonter et al., 2017). In addition, the coal mines in Kalimantan in Indonesian Borneo, caused secondary deforestation at distances up to 50 km in radius from the centre of the mine (Sievernich et al., 2021).

Two key unknowns are the severity of secondary impacts of mining on deforestation and on forest degradation in Sub-Saharan Africa. In this study, the severity of mining-induced losses and changes from deforestation and forest degradation were assessed. The database of 225 mines which were created post 2000 in SSA (Ahmed et al, 2020) was utilised, i deployed a suite of geospatial environmental data and tools (ArcGis, Google Earth Engine (GEE), QGIS) combined with statistical matching techniques using R package (*Matchit*). Doing so, two core objectives were tackled: **(1)** evaluate the amount of deforestation and forest degradation from 2001 to 2020 in the locations with mines (*treatments)* compared to locations without mines (*controls*) at various buffer intervals; and **(2)** compare the annual rates of deforestation before and after mine creation (i.e., across time) with distance from mine (i.e., across space).

3.3 | Materials and Methods

3.3.1 Study Region

This study covers sub-Saharan Africa, with prominence on the Afrotropic region which comprises of four ecological zones (ecozones): the tropical rainforest (TRF), tropical moist deciduous forest (TMDF), tropical dry forest (TDF), and tropical shrubland (TSL). These ecozones cover a land area of 1,300 million ha (Fig. 3.1), which is 64% of SSA's total land area coverage comprising 37 countries (FAO, 2016). The region is endowed with the largest mineral reserves and deposits globally (Edwards et al., 2014a), and with a population of ∼1.1 billion (World Bank, 2020). SSA is faced with political and socio-economic challenges including arm conflicts and environmental degradation which has made it one of the most economically impoverished regions in the world (IMF, 2021).

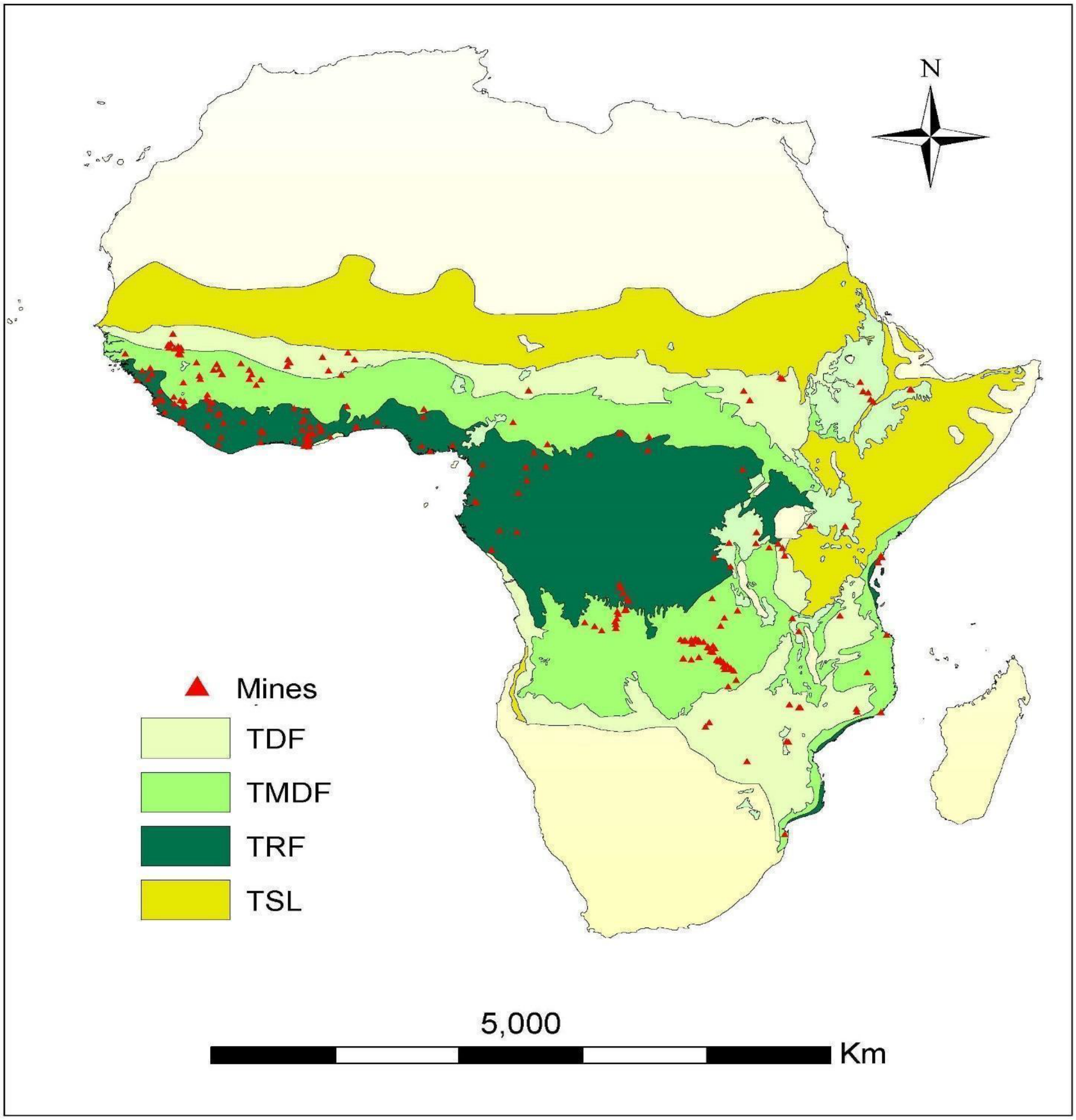

Figure 3. 1

Map of the study region showing mine locations in red dots and the ecological zones of sub-Saharan Africa as defined by the Food and Agricultural Organisation (FAO, 2016), tropical rainforest (TRF), tropical moist deciduous forest (TMDF), tropical dry forest (TDF) and the tropical shrublands (TSL).

3.3.2 Forest, deforestation, and forest degradation in sub-Saharan Africa

Forest

The most common definition of forest used in many countries of SSA is an area of >0.5 ha with >10% canopy cover of trees at >5 m height, or trees with potential to grow to these thresholds (FAO, 2006). Forests may thus include natural primary habitats and secondary habitats consisting of newly planted trees, naturally regenerating forests, and forestry plantations. Forest types in SSA are mainly the evergreen forest, deciduous forest, bamboo, mangrove forest, and plantation forest, among others.

Deforestation

When a forested land has been converted into a non-forest, the land is said to have been deforested and where there is a decline in the capacity of the forest to produce (Quy et al. 2018). Though the definition of deforestation varies by regions and studies, Hosonuma et al. (2012) depicted deforestation as the conversion from forest into other land uses, thereby assuming that the forest is not anticipated to regrow without artificial means. In this study, the measures of deforestation incorporate definitions following Hansen et al (2013) *"Forest loss as a stand-replacement disturbance or the complete removal of tree cover canopy at the Landsat pixel scale"* and Vancutsem et al (2021) *"Deforestation is the permanent conversion of forest into non-forested land and was observed over more than 2.5 years and no vegetative regrowth was detected"*.

Forest degradation

Forestlands where habitats had been disrupted and tree cover canopy fragmented can be referred to as degraded forests (FAO, 2010). Such *forest degradation* often results in reduced quality of ecosystem goods and services provided by the forest (Nick et al., 2014), but such degradation is transient because forests may recover with time (Hosonuma et al. 2012). When the altered forest is observed for a maximum period of 2.5 years with no notable change, the area is termed as degraded forest (Vancutsem et al., 2021). Defining forest degradation could also be a complex task, as there are diverse perspectives on which forest characteristics are the most significant (Thompson et al., 2013).

The transition from undisturbed forest to deforested land cover usually takes place when the intact forest has been degraded by anthropogenic activities and subsequently deforested over time. Matricardi et al 2020 reported that the size of degraded forest in the Brazilian Amazon was greater than the deforested land between 1992 to 2014, thereby making it an important metric for monitoring and evaluating forest change. Although difficulty lies in the fact that the degradation of forests is a gradual process that usually comprises small modifications that are hard to quantify, particularly with the moderate level of detail offered by satellite imagery commonly utilized in worldwide forest monitoring systems.

3.3.3 Data and Broad Approach

To evaluate the effect of mining on environmental losses in the study area, The counterfactual scenario was assessed by comparing deforestation and forest degradation in the locations with mines versus those without mines. To achieve this, the open-access, high-resolution maps of the 21st-Century Global Forest Change (GFC) dataset (Hansen et al. 2013), and the freely available Tropical Moist Forest (TMF) dataset from (Vancutsem et al., 2021) were used. The GFC dataset comprises various forest layers, i.e., *tree cover 2000, loss year, loss,* and *gain*. The GFC dataset was used to extract the tree cover statistics for the baseline year of the study *(TC_2000)* at 10% canopy threshold, the *loss* and *loss year* layers were also used to extract the annual forest cover loss statistics from 2001 to 2020. The GFC dataset has been used by numerous studies for monitoring and reporting of forest dynamics especially in the tropics (Galiatsatos et al., 2020).

In addition, the TMF dataset was used, which is most suitable for calculating the annual change in degraded forest because of its improved capability and temporal resolution when monitoring forest over time (Silva et al. 2021). The TMF dataset offers a comprehensive description of the changes in land cover over a period of time, starting from the baseline year and extending up to the year 2020. This dataset is composed of multiple layers representing various categories of forest, including moist forest, wet forest, and rain forest. Notably, the dataset encompasses the four distinct Global Ecological Zones (GEZs) that are commonly found in Sub-Saharan Africa, namely “tropical rainforest”, “tropical moist forest”, “tropical mountain system”, and “tropical dry forest”. Mines created post 2000 and are within the forested area of SSA (*n=225*) from Ahmed et al., 2021, were used to generate the buffer rings at 1 km to 10 km radius from the centroid of the mines (i.e., 0-1 km, 1-2 km, and so on to 9-10 km). Mine locations (*treatments)* were matched with non-mining (*controls)* locations of similar biophysical and social traits (matching variables). The amount of deforestation and forest degradation over time were compared between the *treatments* and their corresponding matched *controls*. In addition, the rates of annual change in deforestation and forest degradation post mine creation were computed within the treatments.

3.3.4 Matching Analysis

Matching studies of deforestation typically seek to compare areas that have experienced deforestation with areas that have not, to identify the causal effects of deforestation on various outcomes (Braber et. al., 2018; Sonter at al., 2017). In this study, the matching statistical technique was utilised in evaluating the impact of having a mine close to the forest and not having a mine by comparing forest loss between the treatment and matched control locations. The goal of using matching analysis is to identify control locations that are as similar as possible to treatment locations in terms of key characteristics that may influence deforestation. In this study, the locations were matched using key variables that may influence deforestation.

To do this, it is important to select suitable variables for use in the matching process. Previous studies have shown some of the variables that are likely to influence forest disruptions (Curtis et al., 2018; Ferretti-Gallon & Busch, 2014; Laurance et al., 2012), and are categorised into the following: (i) Geographic Characteristics; (ii) Land Use and Land Cover; (iii) Socioeconomic Factors; (iv) Environmental Factors; and (v) Political and Institutional Factors. Some of the variables may include, elevation, terrain, vegetation, climate, land use, and population density. Table 2 shows how they impact deforestation and their relevance to this study.

Table 2.

Useful variables in matching studies of deforestation and their relevance to this study.

Category	**Variables**	**Impact on deforestation**	**Relevance to this study**
Geographic Characteristics	Elevation	Lowlands are more suitable for agriculture (Oakleaf et al., 2019; Tegegne et al., 2016; Laurance et al., 2014).	Derived TWI and TPI are two factors that would determine the suitability of the area to agriculture when mining is established.
	Slope	Determinant for land suitability for agriculture, housing and infrastructure development (Bavaghar, 2015; Ahmadi, 2018; Kayet et al., 2021).	The steeper the slope the less suitable for crop production, similar to TPI,
	Soil type	Soil quality determines its suitability for crop production. This leads to forest loss. (Witcover et al., 2006; Ahmadi, 2018; Kayet et al., 2021).	Not of much significance to this study.
	Distance to roads	Forests nearer to roads are more susceptible to deforestation (Bavaghar, 2015; Laurance et al., 2009; L.S. Ng et al., 2020; Rosa et al., 2013)	An important variable but was not used in this study due to the scale of the study region and the accuracy of data.
	Distance to waterways	Forests nearer to waterways are susceptible to degradation and deforestation (Aleman, Jarzyna, & Staver, 2018).	Not of much significance to this study

Land Use and Land Cover	Forest type	Primary and secondary forest may have different rates of distortion due to their varied biodiversity richness (J. Barlow et al., 2012; Gardner et al., 2009; WWF, 2021).	An important variable for comparing rates of forest loss in different locations, VCF data was used.
	Agriculture	Forestland suitable for agriculture is most likely to be converted (Müller et al., 2012; Laurance et al., 2014).	As a key driver of deforestation, it is a significant variable
	Urbanization	Settlements often expand into forests (Barbier, 2013; Chakravarty et al., 2011; Jianhua & Jr, 2014)	Settlements are most likely to grow towards the forestlands, making it an important variable
Socioeconomic Factors	Population density	The growth in population may lead to expansion of settlements into the forests (Potapov et al., 2012; Ferretti-Gallon & Busch, 2014; Morales-Hidalgo et al., 2015).	A key variable used in this study, an increase in population density would lead to the expansion of settlements, agriculture, and infrastructure.
	Poverty levels	The income of people around the forest may decide the fate of the forest as most may resolve to cutting down the trees for economic gains (den Braber et al.,2018; Ferretti-Gallon & Busch, 2014; Lamb et al.,2005; Witcover et al., 2006).	An important variable for comparing how the inhabitants may destroy the forest to earn a living.

	Access to amenities and infrastructure	Accessibility to alternative sources of energy may save the forest from being used as a source of fuelwood and charcoal for domestic uses. (Hosonuma et al., 2012; Sloan & Sayer, 2015; Thompson et al., 2013).	An important variable for comparing the standards of living among settlements, and how it contributes to deforestation.
Environmental Factors	Climate	Continuous change in climate may lead to aridity and subsequent forest loss (Laurance, 1998; Creese & Pokam, 2016).	An important variable for comparing rates of forest loss in different years
	Rainfall	Rainfall patterns may cause drought, prolonged droughts can stress trees and increase their susceptibility to diseases and insect infestations may lead to degradation (Kayet et al., 2021; Nepstad et al., 2008; Müller et al., 2012).	An important variable for comparing rates of forest loss in different years and at various locations
	Temperature	Higher temperatures can increase the risk of forest fires. (Kayet et al., 2021; Nepstad et al., 2008; et al., 2018).	An important variable for comparing rates of forest loss in different years and at various locations

	Natural disasters	Earthquakes and landslides can cause distortion in the forests (Sar et al., 2018).	Not a relevant variable in this study
Political and Institutional Factors	Land tenure	Forest on lands with poorly defined tenure rights may lead to deforestation (Laestadius et al., 2015; Ferretti-Gallon & Busch, 2014; Forrest et al., 2015; Tegegne et al., 2016; Geist & Lambin, 2002)	Not a relevant variable in this study
	Government policies	Weak government policies will always lead to illegal activities which causes deforestation (Newman et al., 2018; Hund et al., 2017)	An important variable in measuring how certain policies can have impact over forests
	Protected areas	Forest within protected areas are less likely to be depleted. (Forrest et al., 2015; Mascia et al., 2014; Andam et al., 2008)	An important variable in measuring and comparing the impact of policies and controls over forest

The variables selected for this research were: *(a) elevation* derived from the digital elevation data at 225 m spatial resolution (GMTED2010, from the USGS), *(b) vegetation cover* from the vegetation continuous fields (VCF, from MODIS) for the year 2000 at 250 m spatial resolution from (DiMiceli et al., 2015), the *(c) topographic positioning* i*ndex* (TPI) and *(d) topographic wetness index* (TWI) both indexes were generated using the digital elevation data in the QGIS 3.18, and *(e) population density,* using the 1 km Gridded Population of the world Density for 2000 (CIESIN, 2018). These variables were used in the matching analysis to identify control locations that are as similar as possible to treatment location. They were selected based on the criteria listed in Table 2 and their suitability and relevance. Based on previous research and scientific understandings, the variable selection process is best done without using the observed outcomes (Andam et al 2008; Rubin, 2001; Braber et. al., 2018; Sonter et al., 2017).

These variables are believed to be relatively constant during the period under review, even though the population density data which is dynamic and the only endogenous variable which is found to transform rapidly (Lemma 2020). Matching was used because of its ability to eliminate bias in the selection and pairing of treatment and control units (Andam et al., 2008) and is suitable in balancing covariates (Ho et al., 2011). It is widely applied in the assessment of causal inference (Imbens, 2004; Stuart, 2010) and in conservation studies (Schleicher et al., 2019). By carefully selecting control locations that are as similar as possible to treatment locations, we can better isolate the effects of mining on deforestation and draw more reliable conclusions about its impact. Several matching methods were applied using the *Matchit* package in R, the Genetic matching method was adopted because it yielded better covariate balances (Stuart, 2010; Ho et al, 2007; Rubin, 2007).

Genetic matching uses an algorithm that best matches each covariate and balances the output optimally (Diamond and Sekhon, 2006). The propensity scores matching (PSM) was used to facilitate the construction of matched sets with similar distributions and summarised all of the variables into one scalar grouping of individuals with similar scores (Rosenbaum and Rubin,1983; Stuart, 2010).

Propensity score: $[P(X) = \Pr(d=1|X)]$ (1)

Where *P* indicates the **Propensity score,** *X* is the covariate value**, Pr** is the probability and ***d*** is the unit in the *treatment and control* groups.

The Control points:

Random points were generated (*n=30,000*), they were evenly distributed across the SSA region at a minimum interval of 10 km for use as *controls* following (Devenish et al,. 2022). The subset of the control points by country was created, subsequently, country specific matching without replacement was performed to pair the matched treatments and controls that fall within the same country. This was to avoid bias and eliminate the error of wrongfully matching treatments with controls across (sometimes several) country boundaries, given that mining and habitat protection laws and regulations differ by country.

Assessing the balance of matching:

The quality of outputs from the matching analysis were checked using the covariate balance, this was assessed using the *cobalt* package in R (Greifer, 2021). We diagnosed the balance using the standardized mean differences (SMD) as suggested by Schleicher et al., (2019), Zhang et al. (2018), and Stuart (2010). A better balance with few large numbers will yield less bias in treatment effect estimates; SMD values of < 0.25 were used as acceptable balance for treatments and controls (Stuart et al., 2013).

$$\mathbf{SMD} = \frac{\underline{X}_1 - \underline{X}_2}{\sqrt[2]{(S_1^2 + S_2^2)/2}} \qquad \mathbf{(2)}$$

where $\bar{X}_1$ and $\bar{X}_2$ are sample means, while S_1^2 and S_2^2 are sample variance for both the treatments and controls.

3.3.5 Evaluating the impact of mining on deforestation and degradation over time and across various buffer intervals.

I evaluated the amount of forest lost and the expansion of degraded forest in the treatment and control locations, with the hypothesis that control locations are unaffected by mining as indicated by Sonter et al (2017), hence the counterfactual. The GFC and the TMF datasets were used, both were generated from Landsat images at medium spatial resolution of 30 metres and suitable temporal resolutions. Even though the GFC dataset had some temporal discrepancies, it is still a good dataset for measuring deforestation due to its good spatial resolution (Palahi et al., 2021). The forest degradation layer of the TMF dataset (*DegradedForest*) was used, which encompasses the closed evergreen forest area that has been temporarily disturbed by anthropogenic activities. The paired matched points were utilised to create buffer rings at 1 km intervals for distances of 1 to 10 km radius from the centroid of the points; these buffer rings were used to measure forest loss and degradation at various distances from the points. Using the *Google Earth Engine* (GEE) open-source tool, both the tree cover for the baseline year *(TC_2000)* and the annual forest loss were extracted from the GFC dataset for 2001 to 2020, for individual buffer rings for the treatments and controls (*Table S1*). The 10% tree canopy cover threshold was adopted as the average for the study area to balance the disparity in national forest definitions by the various countries in the SSA region (FAO, 2010).

The forest layers of the TMF dataset have different labelling from that of the GFC dataset, however, the aggregation of three layers of the TMF dataset (*degraded forest, forest regrowth*, and *undisturbed forest)* for the year 2000 can be equated to the tree cover 2000 (TC_2000) layer of the GFC dataset, considering the 10 % tree canopy cover for an area >0.5 ha and height of >5m. These buffer rings were used to extract the forest cover for the baseline year from the TMF data and subsequently extracted annual deforestation and degraded forest from 2001 up to 2020 for both treatments and controls using the same buffer rings generated above for analysis and comparison with the GFC dataset.

Using the TMF dataset, we calculated the ***actual*** amount of forest that was degraded annually for the treatment and control locations to analyse the extent of forest degradation. This was done by subtracting the degraded forest value of the preceding year from the degraded forest value of the current year. Specifically, the formula used was:

$$\mathbf{Xa_{year} = (Xd_{year} - Xd_{year-1})} \quad \text{… (3)}$$

Xa_{year} = actual degraded forest in year X,

Xd_{year} = degraded forest value in current year,

Xd_{year-1} = degraded forest value in the previous year.

For instance, the ***actual*** degraded forest for 2002 was determined by subtracting the degraded forest value in 2001 from the degraded forest value in 2002. To assess the normality of the data, a normality test was performed, and the obtained p-value was < 0.05 for both control and treatment locations. This indicates that the data is not normally distributed. Therefore, the *Mann-Whitney U test* statistical technique, which is most suitable for analysing non-asymmetric data, was implemented.

The test was used to evaluate whether there is a significant difference in forest loss and the deforestation + forest degradation between the control and the treatment locations. The null hypothesis *(*H_0*: there are no significant differences in forest loss/ degradation between the controls and treatments).* The p-value was compared to the significance level of 0.05 to either accept or reject the null hypothesis.

<u>Regression model (Generalized additive model)</u>

To analyse the relationship between mining and deforestation, the Generalized additive model (GAM) , a likelihood-based regression model was adopted. The GAMs are useful for modelling non-linear relationships between variables and for handling large datasets with multiple predictors (Hastie and Tibshirani, 1986); the mgcv package (Woods, 2021) in R was used to fit the model. GAM has the ability to give a sensible prediction and confidence interval, especially considering the variation in the dataset used for this study due to the new mines which obviously have few years data. GAM was also used to model the proportion of initial forest cover that was deforested within the buffer rings before and after the creation of mines, and to estimate and predict the proportion of forest area loss in treatment locations relative to the controls for each buffer ring i.e., 0-1 km, 1-2 km, 2-3 km, etc. I used both datasets (GFC and TMF) to identify at what distance the mines have a more severe impact on forest disruption and modelled the trend of loss/ changes in deforestation and forest degradation. In summary, a GAM is a powerful tool for forecasting future deforestation rates, especially when there are non-linear relationships between the response (deforestation) and (mining) predictor variables. By carefully collecting and analysing historical data, fitting a robust model, and evaluating the accuracy of forecasts, we can better understand the drivers of deforestation and make informed decisions about how to prevent or mitigate its impacts.

3.3.6 Change in the rates of deforestation and forest degradation before and after the mine creation (i.e., across time) with distance from mine (i.e., across space).

A comparative analysis of change in the rates of annual deforestation and forest degradation was done, by quantifying the rates of deforestation from *n-years* before mines were created to *n-years* after mine creation. The difference in the annual mean of both *(before* and *after)* is the change in deforestation rates post-mine creation for the study area. In the analysis of all the mines (*n=225*), some mines were less than 4 years old (i.e., 1, 2 or 3 years old) making it difficult to fit them into the GAM model, considering the sparse data available. To address this issue, a supplementary analysis was conducted using the median years of the study (2009, 2010, and 2011) to create a subset of the data, which consisted of 51 mines, representing 23% of the total mines. The subset of the treatments allows for sufficient data (i.e., ~10 years before/after) and a better understanding of whether the rates of deforestation have increased significantly after the creation of the mines. The datasets used in the study were non-normally distributed (with a p-value < 0.05), this means that the data did not conform to the normal distribution pattern. To test whether there were significant changes in forest loss or degradation after the creation of mines, I employed a non-parametric test (*Mann-Whitney U test),* to compare two groups of data to determine whether there is a significant difference between them. The null hypothesis (H_0) states that there are no significant changes in forest loss or degradation after the creation of mines. In this context, if the p-value obtained from the Mann-Whitney U test is greater than 0.05, then the null hypothesis would be accepted, indicating that there is no significant difference between the rates of forest loss or degradation before and after mine creation. Conversely, if the p-value obtained is less than 0.05, then the null hypothesis would be rejected, suggesting significant changes in forest loss or degradation after the creation of mines.

3.4 | Results

3.4.1 Impacts of mining on total deforestation and forest degradation.

Deforestation in the controls versus treatment locations (GFC). The analysis conducted on deforestation for the two decades revealed that there was a cumulative loss of 1,210,600 ha of forest cover within the sum of the 0-10 km buffers from the matched treatment plus control points using the GFC dataset. The study found that the cumulative deforestation recorded at the treatment locations was 726,887 ha (Figure 3.2A), indicating a loss of 12.6% of the total tree cover within the treatment buffers. On the other hand, the cumulative forest loss within the control buffers was 427,699 ha (8% of the tree cover 2000). The results showed that net deforestation was significantly higher in the treatment locations compared to their matched controls, the average annual rate of deforestation was 3,231 ha in the treatment locations versus 2,149 ha in the matched control locations (Figure 3.2B, W = 19297, p-value = 0.00001297. Therefore, the null hypothesis was rejected (H_0*: there are no significant differences in forest loss in the controls and treatments)* and it was concluded that there was a significant difference in deforestation between the controls and treatments in the period under review.

The subset analysis, focusing on the 51 mines created between 2009-2011 revealed that the average annual rate of net deforestation in the treatments from the time of mine creation to 2020 was 3,213 ha, while the control locations had an average net deforestation of 1,755 ha. Further analysis of the median deforestation values for both the treatments and controls showed a significant difference with the treatments having a median deforestation of 2,408 ha this differs significantly from the median deforestation of the controls which was 1,158 ha (Figure 3.2C, W = 807, p-value = 0.0009686). The null hypothesis was also rejected since the $p\text{-value} < 0.05$, which means that there was a significant difference in deforestation between the controls and treatment locations.

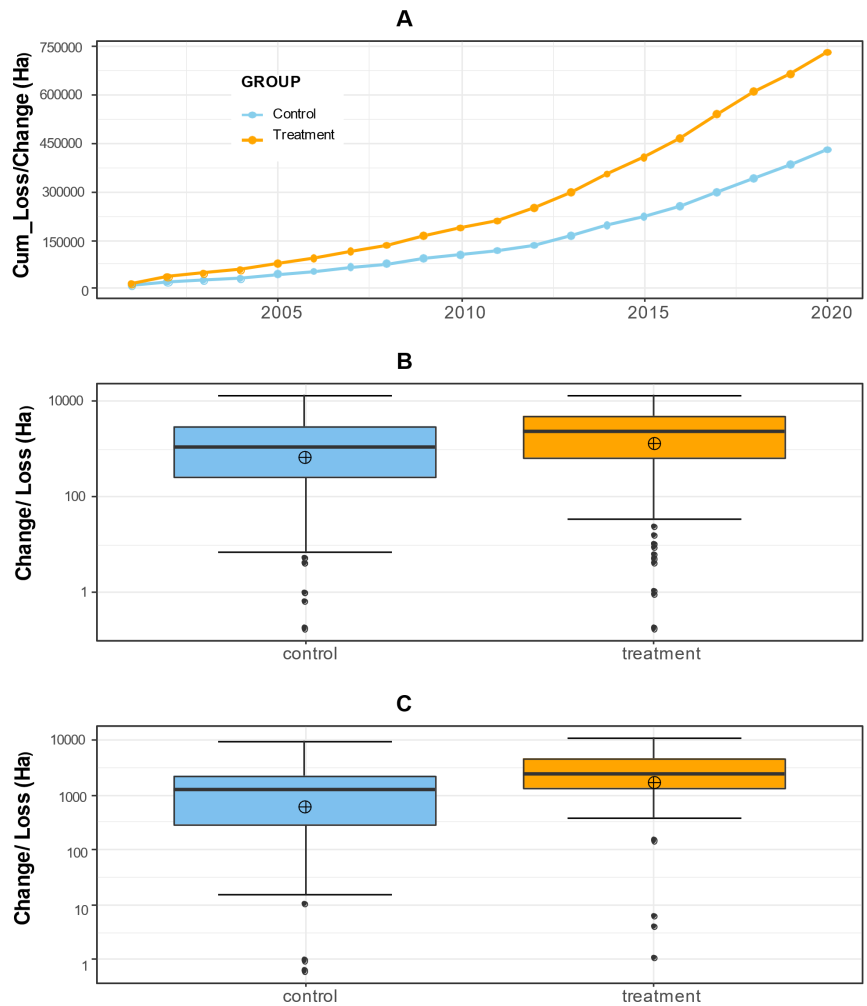

Figure 3.2

The impacts of mines on deforestation in sub-Saharan Africa from 2001 to 2020. Plots showing the cumulative forest loss in controls and the treatment locations using the **GFC** dataset, deforestation **(A)** and the mean and median loss/ change for all the 225 mines and their matched controls (**B**). While plot **C**is the mean and median of the subset analysis of 51 mines (*Mann Whitney U-Test p-value < 0.05*).

Proportion of forest area deforested through time in the treatment locations within the 10 km buffer (GFC). Here, the proportion of forest area that was deforested over time in the treatment locations within the 10 km buffer was analysed and modelled using the GAM. This was achieved by dividing the annual net deforestation by the total forest area in the buffer as shown in Figure 3.3, the proportion of forest area deforested for most mines at -10 years since mine creation was < 0.1, while at 0 years it was 0.1and > 0.25 at 15 years and above in most of the treatments.

However, at the same time there were mines who recorded negative losses (forest gain) through the years post mine creation.

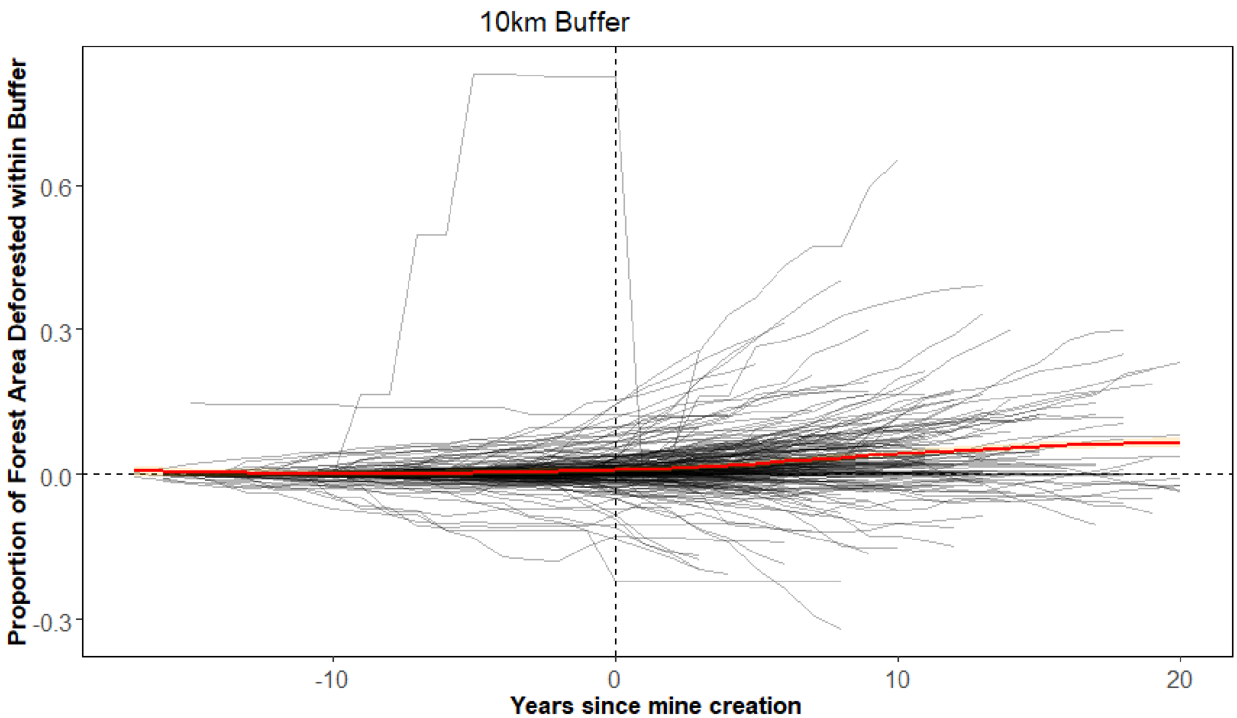

Figure 3.3

Proportion of buffer forest cover deforested (GFC). GAM plot for estimated proportion of forest area deforested through time (years before and after mine creation) within a 10 km buffer of treatment locations, the black lines refer to the 225 mines and the red horizontal line represents the fitted GAMs at the confidence intervals.

Proportion of initial forest cover deforested (GFC). Estimating the proportion of initial forest cover deforested in the treatment locations relative to the controls for the periods of 5 years pre-mine creation up to 10 years post-mine creation, using the GFC dataset revealed that the proportion of initial forest cover (*treecover_2000*) deforested at 5 years pre-mine creation was 1.8%, 0.4%, and -0.1% at the 0-1 km, 1-2 km, and the 9-10 km buffer rings, respectively (Figure 3.4A). At the year of mine creation, the proportion deforested was 5.8 % at the 0-1 km buffer ring and it declined further down to 0.7% at the 9-10 km buffer ring (Figure 3.4C). In comparison, during the 5 years post-mine creation it was observed that within the 0-1 km buffer ring the proportion of deforestation was 13.5%, the 1-2 km buffer ring was 8%, and it was 5% at the 2-3 km buffer ring. Thereafter, the severity of deforestation declined to a rate of 3% at the 3-4 km buffer ring and then stabilised to a rate of < 3% between the 4-5 km and 9-10 km buffer rings (Figure 3.4E). At 10 years post-mine creation, the proportion of initial forest cover deforested stood at 17%, 8%, and 4% at the 0-1 km, 1-2 km, and 5-6 km buffer rings, respectively, the trend remained at 3% from the 6-7 km to the 9-10 km buffer rings (Figure 3.4G). The GFC dataset revealed that there was substantial loss/ change of forest cover in the treatments relative to the controls, in most cases deforestation decreases with an increase in distance from the treatment locations at 95% confidence interval.

Proportion of initial forest cover deforested + degraded (TMF). Using the TMF dataset it showed that the proportion of initial forest cover deforested + degraded at 5 years pre-mine creation was 0.04% to 0.01% from the 0-1 km buffer ring up to the 9-10 km buffer ring (Figure 3.4B). The changes at the year of mine creation were not significantly high as the proportion of change was 0.1% at the 0-1 km buffer ring; this declined to 0.05% at the 2-3 km buffer ring and declined steadily to 0.03% at the 9-10 km buffer ring (Figure 3.4D). The changes that occurred post-mine creation were not substantial, as the proportion of change at 5 years post-mine creation was 0.18% at the 0-1 km buffer ring; this declined to 0.1% at the 2-3 km buffer ring and declined further at the 9-10 km buffer ring to 0.08% (Figure 3.4F). After 10 years of mine creation, the proportion of forest cover that were deforested + degraded was 0.22% at the 0-1 km buffer ring and declined further down to 0.08% at the 9-10 km buffer ring (Figure 3.4H). The TMF dataset showed no significant change in deforestation + degradation from the periods before mine creation versus post-mine creation at 95% confidence intervals.

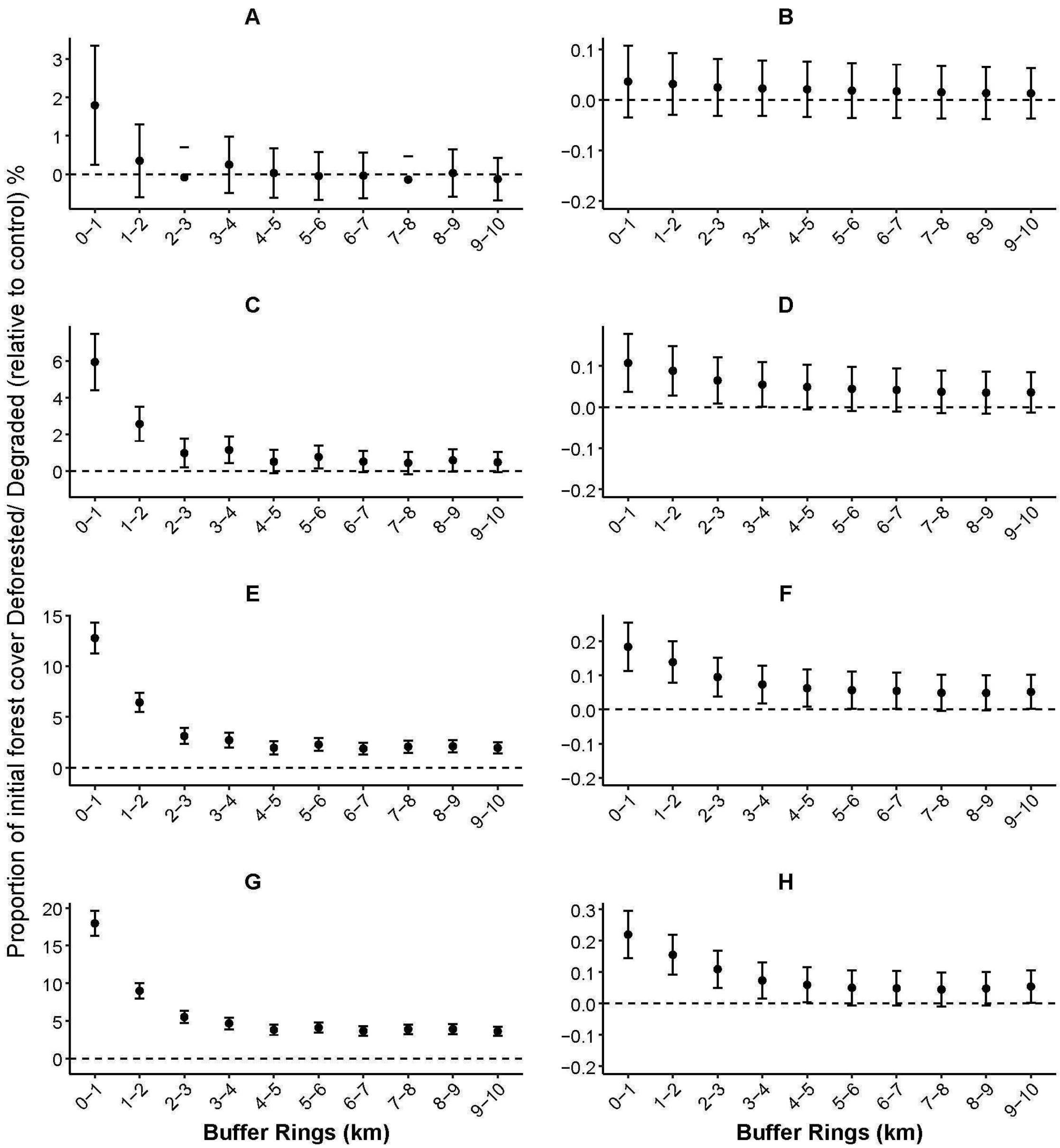

Figure 3.4

Proportion of initial forest cover deforested/ degraded relative to control (%) [GFC and TMF]. Plots from the GAM regression for 5 years pre-mine (**A, B**), year of creation (**C, D**) and 5 years post-mine creation (**E, F**), and 10 years post-mine creation (**G, H**) within the 0-1 km, 1-2 km, …, 9-10 km buffer rings in SSA from 2001 to 2020. We used the GFC dataset **(A, C, E, G)** to estimate the proportion of initial forest cover deforested pre and post mine creation in SSA, and the TMF dataset was used to estimate the proportion of forest cover deforested + degraded over the same period **(B, D, F, H)**. The error bars represent the 95% confidence intervals of the estimated proportion of initial forest cover loss/changed (derived from the upper and lower CIs of the buffer rings), the dotted line marks the reference points and the values below zero indicate a negative forest cover loss/ change (i.e., forest gain).

3.4.2 Change in rates of deforestation and forest degradation before and after the mine creation (i.e., across time) with distance from mine (i.e., across space).

The rates of deforestation before and after mine creation (GFC). The annual rates of deforestation were calculated and compared for before and after mine creation using the GFC dataset. The results showed that the mean annual rate of deforestation before the commencement of mining operations was 1,058 ha, the forest loss doubled to 2,172 ha post mine creation (Figure 3.5A, W = 32042, p-value = 1.072e-06). The statistical analysis suggests that the creation of mines is responsible for the increment in the rates of deforestation in the treatment, thereby rejecting the null hypothesis (H_0).

Here, I calculated and compared the rates of deforestation before and after mine creation, using the GFC dataset and the subset of mines *(n=51)* that were created in the median years of the study. The results showed that the average annual deforestation in the treatments before mines were created was 831 ha compared to the mean of 2,100 ha after mine creation (Figure 3.5B, W = 1934, p-value = 2.27e-05). The statistical analysis confirms that the creation of mines has caused more deforestation in the treatment locations as shown above, thereby the null hypothesis (H_0) was rejected.

The rates of deforestation plus forest degradation before and after mine creation (TMF). Rates of annual mean loss/change in deforestation + forest degradation before and after mine creation revealed a significant increase after mine creation from an average of 1,159 ha pre-mine creation to an average of 2,186 ha afterwards (Figure 3.5C). The result was validated using the Mann-Whitney U test to test (*W = 22177, p-value = 0.02251),* which indicates that the null hypothesis (H_0) should be rejected. Therefore, it can be inferred that there is a significant change in the rates of deforestation plus forest degradation after mine creation.

Analysis of the subset of mines (n = 51) that were created between 2009-2011,showed that the annual mean rate of deforestation + forest degradation was 1,200 ha before the creation of mines and 1,605 ha post mine creation. The statistical analysis showed that the p-value > 0.05 at 95% C.I. (Figure 3.5D, *W = 1335, p-value = 0.8197*) therefore the *null hypothesis* was accepted, contrary to the result in Figure 3.5C using the 225 mines.

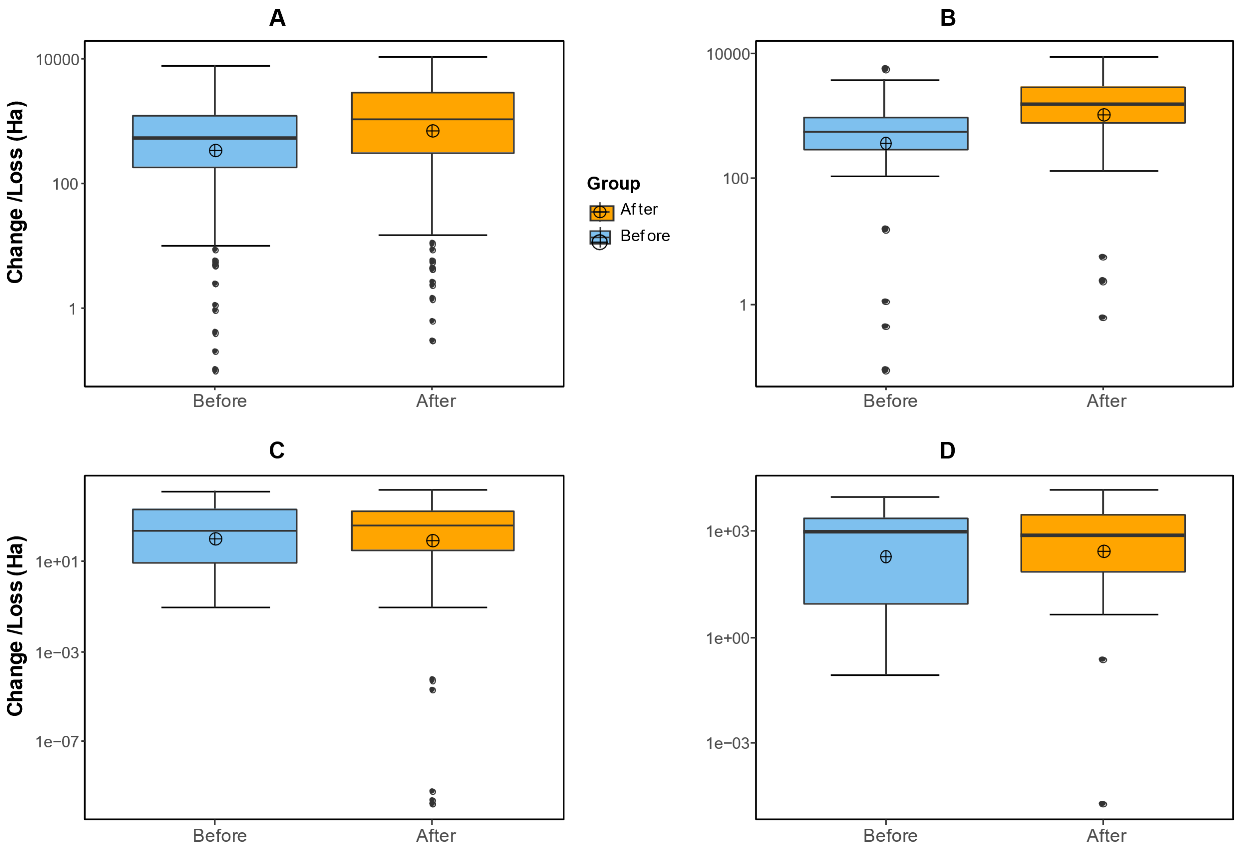

Figure 3.5

Change in rates of deforestation and deforestation + forest degradation before and after the mine creation. Plots showing the difference in the annual mean rates of deforestation before and after the creation of mines in sub-Saharan Africa from 2001 to 2020. The metrics calculated were the rates of deforestation before and after mine creation using the GFC dataset **(A, B),** using the TMF dataset. I computed the rates of deforestation + degradation **(C, D)** before and after mine creation**.** I analysed for all the 225 mines **(A, C)** and the subset for the mines (*n=51*) created at the median years of the study **(B, D**).

3.5 | Discussion

This study aimed to compare the secondary effect of mining on deforestation and forest degradation by matching treatments versus controls and analysing the rates of loss before and after the creation of mines within two decades. Here, I used covariates which are established to either cause or aid deforestation and forest degradation by proxy and are homogeneous in both the treatments and matched control locations of the study region. This drew similarities to previous studies i.e., Sonter et al. (2017), who quantified the extensive deforestation driven by mining in the Brazilian Amazon, Andam et al. (2008), who assessed the effectiveness of protected area networks in reducing deforestation and Davis et al. (2020), who assessed the Tropical Forest loss enhanced by large-scale land acquisitions. The cumulative forest loss for the treatments versus the corresponding controls were compared side by side, the results showed that the impact of mining extends beyond the immediate footprint of the mines to a distance of up to 10 km. The outcomes of the analysis derived from the GFC dataset revealed a total difference of 302,291 ha in deforestation between the treatment locations versus controls locations. Using the TMF dataset, a cumulative change of 1.02 million ha was recorded in deforestation + degradation between 2001 to 2020, out of which 55% occurred within the treatment locations. However, this study was restricted to mines established post-2000 due to the unavailability of reliable forest cover data for the study region pre-2000.

The annual average deforestation rates in the study locations increased by 83% post-mine creation compared to 1,318 ha pre-mine creation (GFC). At local scale, there was a cumulative deforestation of 7,880 ha at the Akyem mine in Ghana and 53% of this was lost in the 7 years post-mine creation, which was similar to the figure by World Bank (2019). The trend was similar using the TMF dataset, where the rate increased by 34% post-mine creation, these significant losses, and changes in forest cover throughout Central Africa confirms the existence of the impacts of mining on forest loss as observed by Sonter et al (2017). Forest cover loss/ change in the treatments were marginally higher compared to control using the GFC dataset. For instance, the proportion of loss at 5 years pre-mine creation ranged between -1% to 1.8% within the 0-1 km up to the 9-10 km buffer rings. This is similar to the trend recorded in the DRC from 2005-2010 (Potapov et al., 2012). However, these changed drastically after mine creation, within the 0-1 km buffer ring the proportion of loss was 13.5% and 17% at 5- and 10-years post-mine creation, respectively. Deforestation dropped to about 3% at the 9-10 km buffer ring for post-mine creation years, an indication that forest loss declines with an increase in buffer ring distance.

TMF dataset showed that between 2006 and 2010 deforestation was 73% of the total forest change (deforestation + forest degradation). However, from 2016 to 2020 there was a reversal in the inclination of change, as 62% of the disruption was recorded as degraded forest. Although there was a decline in the annual mean rates of change (forest degradation) in a few treatment locations towards the end of the study period, this was as a result of transformation of those areas into deforested land after 2.5 years of observation as degraded forest (Vancutsem et al., 2021). This is an indication that existing mines will continue to cause forest degradation at a higher proportion than deforestation, as has been recorded at individual mines previously i.e., Teberebie mine in Ghana and mine and Twangiza Mine in the Democratic republic of Congo. Matricardi et al 2020, also reported that the area affected by forest degradation is now greater than deforestation in the Brazilian Amazon.

3.5.1 Impacts of mine expansion on forest conservation

One-fourth of Earth's functional mines are located within a 10 km radius of protected or conservation areas globally (Hund et al., 2013). The findings of this study revealed there was a surge in deforestation within one to three years after the creation of mines, especially those created after 2008 which corresponds to the global financial crisis (Grant & Wilson, 2012; Megevand, 2013). The expansion and establishment of mines have severe consequences on conservation and ecological integrity of forests and the environment more broadly (Davis et al., 2020). Furthermore, the observed increase in the average rates of deforestation in SSA between 2008 and 2012 aligns with the result of Turubanova et al., (2018) who also recorded a peak deforestation in the DRC in 2010.

The mining industry in Africa attracted huge investments at the beginning of the millennium and increased immensely after the 2008 global financial crisis (Alvarez-Berrios & Mitchell Aide, 2015). In 2018 alone, the region produced minerals worth a staggering $350 billion (Republic of Austria, 2020). It is noteworthy that the results of recent studies indicate that forest loss in the region reached its peak in 2017, with the results from this study showing a loss of 73,161 ha in that year. These financial inflows thus have negative consequences on the forest and biodiversity conservation in SSA, as a result of heightening expansion of mines into forested land and development of mining supporting infrastructure, such as roads, rail, seaports, housing, and other support services (Hund et al., 2013; Chakravarty, Ghosh, & Suresh, 2011).

In SSA, a variety of roads and railways are currently under construction to connect the mines to industries and seaports that are situated several kilometres away (Laurance et al., 2009; Weng et al., 2013). For instance, the Lobito Road corridor, which is a significant transportation network in Central Africa. This corridor connects the copper belt region of the DRC and Zambia to the seaport in Lobito, Angola, cutting through the vast tropical forest (AfDB, 2017; Weng et al., 2013). The associated 'secondary' deforestation as a result of mining activities is of great concern, particularly since mine owners are inclined to negate responsibility for such disruptions. This issue poses significant threats to the ecological stability and sustainability of the environment in Sub-Saharan Africa.

3.5.2 Role of Monitoring and Conclusions

The study illustrates a core role for the application of geo-spatial techniques and utilisation of available data to quantify deforestation and forest degradation spatially explicitly in the Afrotropic. The study has added to the prior literature in the application of matching techniques to compare changes in the forest landscape among treatments and controls, unlike others who only quantified deforestation in the mining locations (Merem et., al 2017; Nunda 2013) without comparing them to controls. Mines for all types of commodities were also covered here, unlike previous studies who looked at deforestation caused by a single commodity (e.g., gold; Alvarez-Berrios & Mitchell Aide, 2015; Swenson et al., 2011). A major remaining question is how the type of commodity mined alters deforestation or forest degradation, which may be expected given that different commodity classes (e.g., low-value, high-bulk vs high-value, low-bulk) require different infrastructures (Werner et al., 2019). This assessment was also a major advancement because it included the use of two high-resolution satellite products (the GFC and the TMF). This approach can guide the monitoring, reporting, and verification of forest changes and carbon loss studies, and in the study of other drivers of deforestation.

In conclusion, this study demonstrates that mining-induced deforestation is a major conservation concern. Given the scale of the problem, it is essential to strengthen environmental and mining laws in sub-Saharan Africa, which will go a long way in curbing deforestation and forest degradation in the region. However, this may be a tough task for governments, considering their reliance on minerals mining for revenues. Forest restoration efforts need to be intensified by the authorities upon the mining operators after the abandonment of mining sites. Such restoration activities would kick-start the long-term process of forest regeneration provided former mining areas are protected from other anthropogenic activities that tend to follow abandoned mining sites e.g., agriculture, tourism, logging etc. It is therefore crucial for governments and other stakeholders to work collaboratively towards sustainable mining practices and forest conservation in Sub-Saharan Africa.

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Chapter 4: How different mined commodities impact deforestation and forest degradation in sub- Saharan Africa

4.1 | Abstract

The demand for minerals in sub-Saharan Africa (SSA) is driving deforestation and forest degradation, however the effect of mining on the forest varies by commodities mined. Therefore, it is imperative to quantify the specific impact caused by different commodities mined in SSA, focusing on mining hotspots where the density of mines exceeds 12 within a 100 km radius. The 5 key commodities analysed in this region are copper, diamond gold, iron-ore, and limestone. The correlation between commodity type and the rates of deforestation was investigated by matching treatments and controls and using a paired t-test. The generalised additive model (GAM) was utilised to examine both pre-mine and post-mine creation scenarios. Results from the global forest change (GFC) dataset showed that gold mines had caused 246,420 hectares of deforestation within the 10 km buffer zone, and copper mines were responsible for the deforestation of 172,751 hectares. The tropical moist forest (TMF) dataset showed a change of 58,216 ha of deforestation plus forest degradation around the mines for copper within the 10 km buffer zone, compared to 9,795 ha in the matched controls. The global demand for minerals will continue to drive deforestation and forest degradation, especially the mines for key minerals. It is crucial for mineral excavation to be conducted in a sustainable and ecologically viable manner, with industries responsibly sourcing minerals to minimize or eliminate their impact on forests.

4.2 | Introduction

The extraction of minerals and metals through mining is the source for almost all the raw materials used for production globally (ICMM, 2014). Mining of the Earth's mineral resources continues to drive the global economic growth directly and indirectly (Ranjan 2019). In sub-Saharan Africa (SSA), mining is a significant source of income for governments and a means of livelihood for many of the populace in the region (Janneh & Ping, 2011). According to current state of knowledge, about 30% of global mineral resources are located within the African continent (USGS, 2018) the Afrotropic is prominent for its occurrence of several minerals in abundance (Edward et al., 2014), such as precious minerals, metals, and other industrial commodities [e.g., bauxite, gold, gemstones, copper, tin, and iron-ore etc.] which can be found in large quantities and in good quality. Mining in the region is dominated by both the large-scale mine operators (LSM), as well as the artisanal and small-scale mines (ASM) (Taylor et al., 2009) depending on the commodity. Despite its economic importance, mineral extraction generates direct or indirect negative impacts on the environment and the forest in particular.

Over the past two decades, there has been a significant increase in the demand for minerals on a global scale (Hammarstrom et al., 2006; World bank, 2019). This may be connected to the rapid industrial and technological growth worldwide, as well as the associated demand for the relevant minerals to power these emerging sectors (Chatham House, 2020). In fact, there remains a large gap in the supply of minerals for various industries, with metals such as copper and iron being identified as key energy transition metals (ETMs) which are predicted to be in high demand as low-carbon energy technologies continue to emerge (Lèbre et al., 2020). Despite efforts to promote resource efficiency through recycling and reusing of metals and their associated products. These actions remain very inadequate in reducing the demand for mineral commodities and move towards a more sustainable and circular production (Ali et al., 2017; El-Mahallawi and El-Raghy, 2013).

Investments in mining have also increased substantially in the SSA region over the past two decades (Republic of Austria, 2020), with projections indicating that there will be even more finances for the sector in the nearest future (Barazi et al., 2017; Weng et al., 2014). As a result, it is imperative to examine the impact of mining on the environment, especially the forest, which is most often affected by mining activities.

The presence of significant deposits of some important minerals in close proximity of the critical forest landscapes poses a considerable risk of deforestation and forest degradation (Devenish, 2022; Maddox et al., 2019). This combination of factors contribute to approximately 10-15% of carbon dioxide emissions in the tropics (Nakakaawa et al. 2011), as well as causing biodiversity loss (Edwards et al. 2014; Boadi et al., 2016). In the past two decades, it was reported that the mining industry has expanded remarkably into biodiversity-rich ecosystems, exacerbating direct and indirect forms of deforestation and forest degradation (Luckeneder et al 2021).

Recent analyses have revealed the alarming extent of deforestation caused by mining activities in sub-Saharan Africa (SSA). Within a 10 km buffer zone around mine footprints, a total of 726,887 ha of forest have been lost due to 225 mines in the region (Chapter 3). However, the approach of using a matching protocol that contrasts mine locations with control locations reveals that mining activities have driven an additional 243,174 ha of deforestation above the controls using the GFC dataset. Analysing the impact of mining on deforestation beyond its immediate precinct (so called, 'secondary' impacts of mines), revealed that 93% of the deforestation occurred beyond 2 kilometres from the mines.

The impacts of mining on the environment and especially on forestlands varies considerably among the minerals being mined (World bank, 2019), especially in terms of the secondary and cumulative impacts of mining via infrastructural developments, population immigration, and associated development. In the SSA region, mining of the low-value high-bulk commodities such as iron-ore, copper, and bauxite are done at industrial-scale by the LSM operators, as these mines require the construction of major infrastructure for operation to commence. For example, the Vale mine in Mozambique extended and completed the construction of a 912 km railway which traversed through the tropical forest from the Moatize mine to Nacala port, for the export of minerals and other commodities. However, mining of the low-bulk high-value commodities attracts both the LSM and ASM operators. The proliferation of informal (sometimes referred to as ASM) miners in the SSA region is very worrisome to conservation, as the locations for mining of high-value commodities are easily accessible by footpaths. For instance, gold and diamond often attract large numbers of such miners, for example, the Geita mine in Tanzania attracted over 35,000 workers (mostly ASM) between the year 1987 and 1997 (Merket, 2019). It is thus imperative to analyse the differential impacts of mined commodities on deforestation and forest degradation.

In order to comprehensively examine the varying impacts of commodity extraction on deforestation and forest degradation in sub-Saharan Africa, a detailed assessment was conducted, encompassing spatio-temporal (before and after) dimensions. The study primarily focused on the five crucial commodities mined within the Afrotropic region, as outlined by Ahmed et al. (2020): namely, gold, copper, diamond, limestone, and iron-ore. To facilitate a rigorous analysis, a matching protocol was employed, following the established methodology outlined in Chapter 3, which entailed comparing the extent of forest loss or changes in the treatment areas with their corresponding matched controls.

The following interconnected objectives were tackled: (1). Identify the key commodities being mined and delineate their spatial distribution across the sub-Saharan African landscape. This preliminary step provided essential insights into the geographical patterns and concentrations of mining activities pertaining to each specific commodity; (2). Evaluate and quantify the magnitude of deforestation and forest degradation directly attributed to the extraction of each individual commodity, in comparison to their respective matched controls. This rigorous assessment allowed for a comprehensive understanding of the distinct environmental impacts associated with the mining operations for different commodities; (3). Assess the temporal dynamics of deforestation and forest degradation. Specifically, the investigation aimed to analyse and compare the rates of these detrimental processes before and after the establishment of mines at varying buffer distances from the mining sites. By examining temporal changes, the study aimed to ascertain the specific effects of mine creation on the surrounding forested areas over time.

By pursuing these comprehensive objectives, the study aimed to shed light on the intricate relationship between commodity extraction and the associated environmental consequences (deforestation and forest degradation), ultimately contributing to a more nuanced understanding of the challenges and implications posed by mining activities in sub-Saharan Africa.

4.3 | Data and Methodology

4.3.1 Scope and limitation

The study focused on analysing the extent of deforestation and forest degradation specifically attributed to different commodities within the Afrotropic region between 2001 and 2020. The scope of the study was confined to mines situated within or in close proximity to the Afrotropic region, considering the unique ecological and geographical characteristics of this area. By narrowing down the study to this specific area, it was aimed to provide a more localized and contextually relevant understanding of the environmental consequences associated with mining operations. Furthermore, the study was also limited to mines that were created post 2000. This temporal restriction was imposed due to practical constraints, such as the limited availability of reliable geospatial data with sufficient resolution for mines created prior to 2000 in the sub-Saharan Africa (SSA) region.

4.3.2 Data

The freely available high-resolution global forest change (GFC) dataset developed by Hansen et al (2013) was utilised for the analysis of deforestation patterns. To assess deforestation + forest degradation, the tropical moist forest (TMF) dataset from Vancutsem et al (2021) was employed. . The sub-Saharan Africa mine database compiled by Ahmed et al (2020) provided the necessary mines for the analysis. To extract forest cover and forest loss/ change statistics from the GFC and TMF datasets, this research leveraged on the capabilities of the Google Earth Engine (GEE) platform. For statistical analysis and modelling purposes, we utilized R (version 4.2.1), a widely used programming language and software environment. Additionally, we employed ArcGIS 10.7, a comprehensive geographic information system (GIS) software, for proximity analysis and mapping of mining hotspots. This approach allowed me to investigate the specific contributions of different commodities and mining operations to environmental changes in this area, while considering the unique ecological and geographical characteristics of the region.

It is important to note that the availability and utilization of reliable geospatial data prior to the year 2000 posed practical challenges for the study. Therefore, the analysis was focused on mines established after the year 2000 in the sub-Saharan Africa (SSA) region, where adequate and trustworthy data were accessible. By setting this temporal restriction, it was aimed to ensure the accuracy and reliability of the findings while acknowledging the limitations imposed by data availability.

4.3.3 Study Area

The sub-Saharan Africa region, encompassing 37 countries, spans a vast area of 2,025 million hectares (Figure 4.1). Within this expansive region, it boasts the second largest tropical rainforest in the world, covering approximately 64% of the sub-Saharan Africa (SSA) territory, as documented by Potapov et al. (2012). This remarkable expanse of lush rainforest contributes significantly to the region's ecological diversity and global carbon sequestration efforts. Apart from its rich natural resources, the sub-Saharan Africa region is known for its abundance of key mineral deposits, as highlighted by Edwards et al. (2014). These minerals play a crucial role in various industries, driving economic activities such as agriculture, mining, timber production, fishing, and more. However, alongside the potential economic benefits, the extraction and exploitation of these minerals have had significant ramifications for the region.

Unfortunately, the sub-continental region has recently gained notoriety due to its involvement in armed conflicts, often triggered by the presence of valuable minerals in the affected areas. The study conducted by Butsic et al. (2015) sheds light on this disturbing trend. These conflicts, driven by the allure of high-value minerals, have not only ravaged mining communities but also spilled over into non-mining areas, resulting in widespread violence and instability. The devastating consequences of these conflicts extend far beyond immediate casualties and destruction. They have detrimental effects on political stability and impede economic development, exacerbating the already precarious socio-economic conditions prevalent in the region. As a result, the sub-Saharan Africa region finds itself among the most impoverished regions globally, grappling with persistent economic hardships that hinder progress and quality of life for its inhabitants.

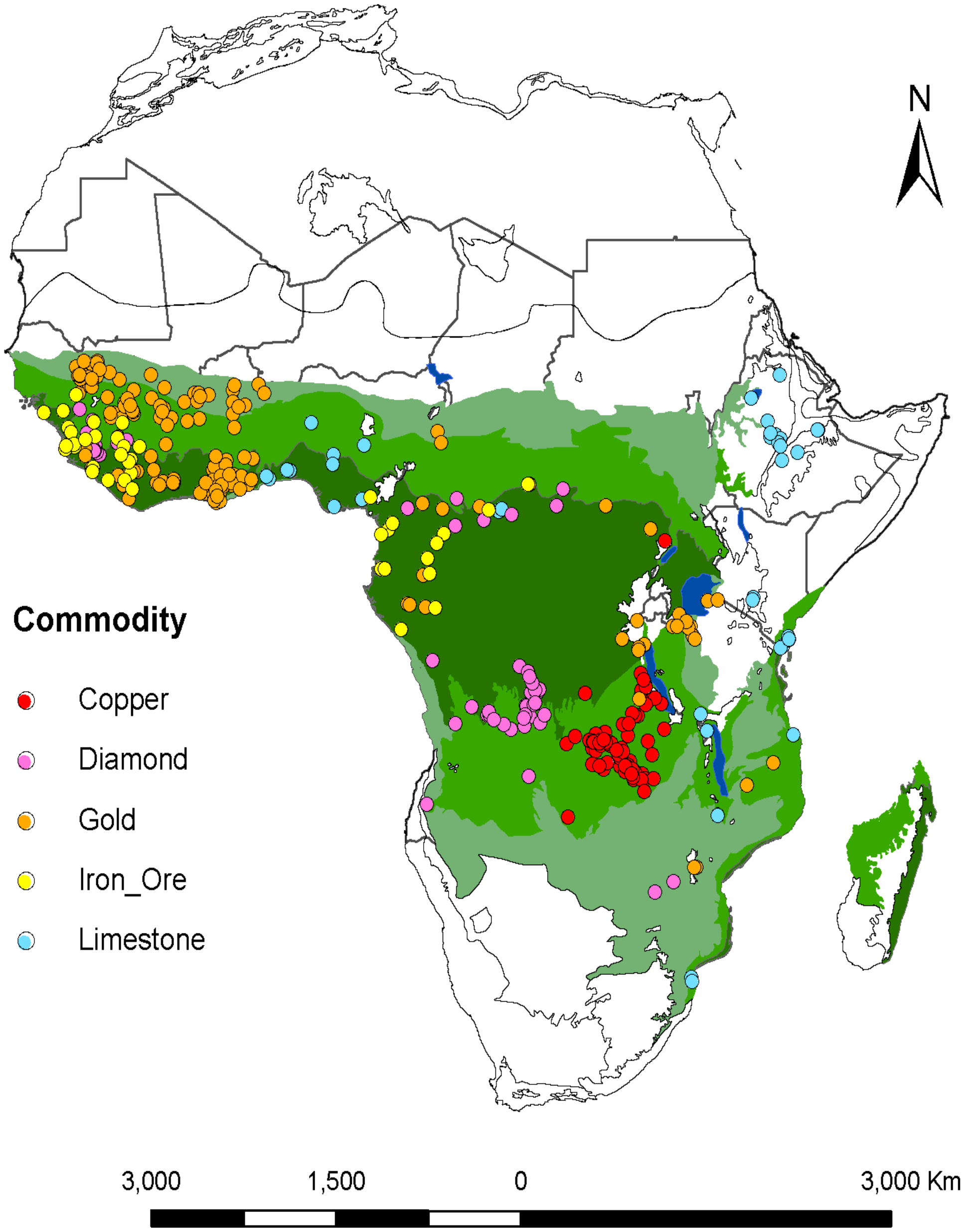

Figure 4.1

Map of the study region showing mining locations for the 5 key commodities mined (copper, diamond, gold, iron-ore, and limestone), and the ecological zones of sub-Saharan Africa.

Table 3. Commodities and number of mines in SSA

Commodity	*Number of mines*
Bauxite	6
Limestone	22
Coal	4
Cobalt	2
Copper	39
Diamond	27
Gemstone	1
Gold	78
Graphite	2
Iron-ore	20
Phosphate	1
Manganese	4
Nickel	3
Petroleum	6
Lithium	2
Tantalum	2
Tin	1
Titanium	2
Uranium	1
Zinc	1
Mineral Sands	1

4.3.4 Matching and post-matching analyses

Matching was applied, in the assessment of commodity induced deforestation and deforestation + forest degradation, by comparing the losses and changes occurring in mining and non-mining locations. Matching is a suitable statistical tool for causal inference (Imbens, 2004; Stuart, 2010) and in conservation studies (Schleicher et al., 2019). I matched locations with mines (treatments) to corresponding locations that do not have mines (controls) but have the same or very similar characteristics and environmental variables. The variables used are homogeneous in the study region and are suitable for studying forest disruptions as shown in previous studies (Andam et al 2008) and chapter three of this research. These variables include: (a) *elevation* derived from the digital elevation data at 225 m spatial resolution (GMTED2010, from the USGS); (b) *vegetation* cover from the vegetation continuous fields (VCF, from MODIS) for the year 2000 at 250 m spatial resolution from (DiMiceli et al., 2015); (c) *population density*, using the 1 km Gridded Population of the world density for year 2000 (CIESIN, 2018), (d) *topographic positioning index* (TPI), and (e) the *topographic wetness index* (TWI), both indices were derived using the digital elevation data in QGIS 3.18.

Post-matching statistical analysis.

To assess the differences in total deforestation and deforestation plus forest degradation between the treatment and control groups for each commodity, I conducted statistical tests. Specifically, I employed the paired t-test to determine if there was a significant difference in total loss/change between the treatment group and the matched controls. My hypothesis, denoted as Ho, stated that there would be no difference in the mean values between the treatments and controls. Furthermore, I utilized the analysis of variance (ANOVA) statistical technique to examine whether there were any significant differences in the amount of extra deforestation caused by commodities compared to the control group. The null hypothesis (Ho) in this case was that there would be no significant difference between the means of the variables (control vs treatment) concerning extra loss/change. In addressing the second objective, which involved examining the rates of loss/change before and after mine creation, I employed a generalized additive model (GAM). This model enabled me to investigate whether the rates of deforestation varied over time and space for the different commodities.

By employing these statistical methods, I aimed to determine the presence of significant differences in deforestation and forest degradation between the treatment and control groups. These analyses allowed me to assess the impact of different commodities and mining operations on the environment, providing valuable insights into the rates and patterns of deforestation in relation to time and spatial factors.

4.3.5 Identifying the key commodities, their spatial distribution, and mining hotspots in SSA.

The database of mines from Ahmed et., al 2020, was utilised to identify the types of commodities being extracted in the study area. Based on the number of mines per commodity and the extent of deforestation and forest degradation associated with these commodities, the key commodities were identified. This was achieved by considering two factors, firstly, the number of mines per commodity, which indicated the level of mining activity for each specific commodity. Commodities with a higher number of mines were given more weight in the analysis. Secondly, the size of deforestation and forest degradation associated with each commodity. The spatial distribution of mines helped in identifying the mining hotspots in the study area. This information helped in understanding the environmental impact of the mining activities and prioritize the commodities that had the greatest contribution to deforestation and forest degradation.

4.3.6 Evaluate and compare the amount of deforestation and forest degradation caused by each commodity mined versus their matched controls.

To conduct this evaluation, the analysis was narrowed down to the mines for the key commodities identified above. Then assessed the deforestation and forest degradation around these mines. The total losses and changes from 2001 to 2020 at 4 km, and 10 km buffer distances were calculated, the choice of buffer distances was based on previous findings in the study (chapter 3), it showed that impact of mining on deforestation is more severe within 0 to 4 km distance from the mines. Additionally, the study set a limit of a 10 km buffer for this particular analysis. The GFC and TMF datasets were used to analyse and compare the difference in forest change between the control and treatment locations for each commodity, i hypothesised that commodity type is not responsible for forest disruption if the means of both variables (treatment and control) are equal we should accept the null hypothesis (H_0) when p-value > 0.05.

4.3.7 Difference between the amount of extra deforestation and forest degradation caused by individual key commodities (relative to control).

The differences in the extra deforestation and forest degradation caused by individual commodities were calculated by subtracting the total changes in forest cover observed in the control areas from the total changes observed in the treatment areas within the 4 km and 10 km buffers around the mines. The mean of these differences were then computed, this provided an average measure of the additional impact caused by each commodity relative to their control areas. To assess the statistical significance of these means, the analysis of variance (ANOVA). ANOVA was employed as a statistical test to determine whether these differences were statistically significant or simply due to random variation. The statistical significance of the means provides insights into whether the additional deforestation and forest degradation caused by individual commodities were significantly different from the control areas. This analysis helps to identify commodities that have a more pronounced impact on deforestation and forest degradation, compared to others.

4.3.8 Deforestation and forest degradation of initial forest area caused by commodity mining within the various buffer distances at 10 years pre-mine and post-mine creation relative to controls.

Here, the rates of loss and change pre-mine and post-mine creation were quantified for each of the five key commodities within the 4 km and 10 km buffer distances. To assess these rates, the GFC and the TMF datasets were utilized. In addition, the study employed the generalized additive model (GAM) to compute the proportion of forest area that experienced disruption within the buffers. This helped to estimate the proportion of forest that was affected by mining activities from a certain number of years before mine creation to a certain number of years after mine creation. This analysis provided insights into the patterns and extent of forest disruption caused by each commodity, considering both the pre-mine and post-mine creation periods.

4.4 | Results

4.4.1 The spatial distribution of mines and the mining hotspots for the key commodities mined in SSA.

In this study, the focus here was on the spatial distribution of mines and mining hotspots for key commodities in Sub-Saharan Africa (SSA). It began by identifying the number of mines associated with each of the 21 commodities listed in Table 3, as enumerated by Ahmed et al. in 2020. The mines were then grouped according to the commodity they were associated with, I computed the annual deforestation and deforestation plus forest degradation within 4 km and 10 km buffer distances from these mines. To narrow down the analysis, I selected commodities that had cumulative deforestation greater than 25,000 hectares from 2001 to 2020, as determined using the Global Forest Change (GFC) dataset (as shown in Figure 4.2a). This threshold was set to identify commodities that had a significant impact on deforestation and forest degradation.

Out of the 21 commodities, a total of six commodities met the deforestation threshold and were included in the analysis. These commodities were bauxite, copper, diamond, gold, iron-ore, and limestone. Together, they accounted for 85% of the mines in the study area and were responsible for 91% of the total deforestation observed in the treatment locations during the study period. However, bauxite was dropped from further analysis as it had only six mines, which would not be suitable for statistical analyses and modelling of loss/change considering the spatial and temporal aspects of the study.

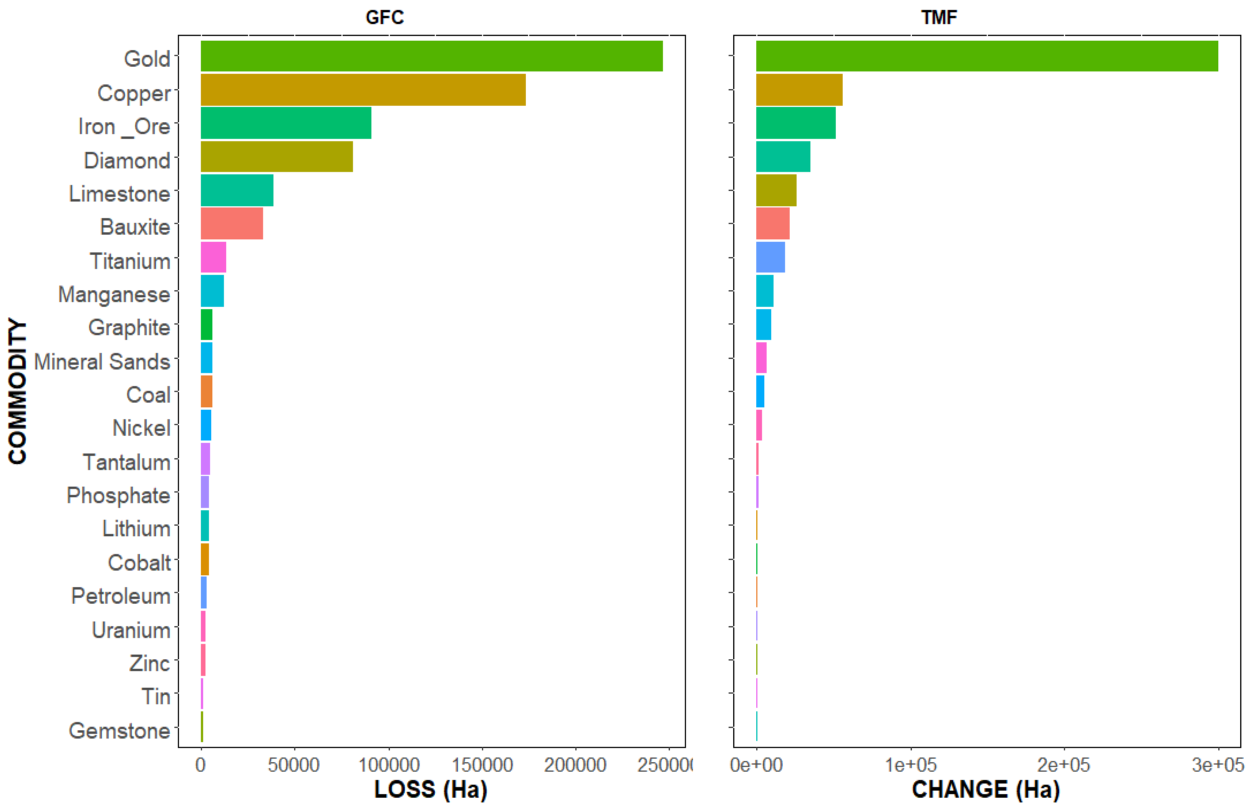

Figure 4.2

Deforestation by commodity mined in SSA at 10 km buffers using the global forest change dataset **(GFC),** and deforestation plus forest degradation by commodity mined using the tropical moist forest dataset **(TMF)**.

4.4.2 Mining hotspots in sub-Saharan Africa

The hotspots for mining in the study region were identified, based on the concentration of mines within the 100 km buffer zone. Central Africa exhibited a higher concentration of mines (>20) within an area of 10,000 hectares, particularly in the southern parts of the Democratic Republic of Congo (DRC) and the north of Zambia, known as the Central African Copperbelt (Luckeneder et al., 2021). These regions are characterized by a significant presence of mining activities. The west Africa sub-region also showed a concentration of mines (>16) within the defined buffer area, specifically in countries such as Ghana, Guinea, and Liberia (Figure 4.3). These areas have a notable number of mining hotspots, indicating the intensity of mining activities in those regions. Other parts of the SSA had varying numbers of mines within the defined buffer ranging from 3 and 15 mines.

Interestingly, many of these mining hotspots are located in close proximity (<100 km) of the Afrotropic forests, particularly the Congo and the Guinean forests.

This proximity suggests a potential impact of mining activities on these important forest ecosystems. It is worth noting that some of these mines in the identified hotspots produce multiple commodities, especially the metal ore mines (Maus et al., 2020). However, for the purpose of this study, the focus was on the main commodity or ore (by volume) being mined in these locations. For example, at the Kansanshi mine in Zambia, where gold, copper and cobalt are extracted from the same location, copper was considered as the main commodity. Figure 4.3 illustrates the mining hotspots for the five key commodities identified in the study, providing a visual representation of the spatial distribution of these mining activities within sub-Saharan Africa.

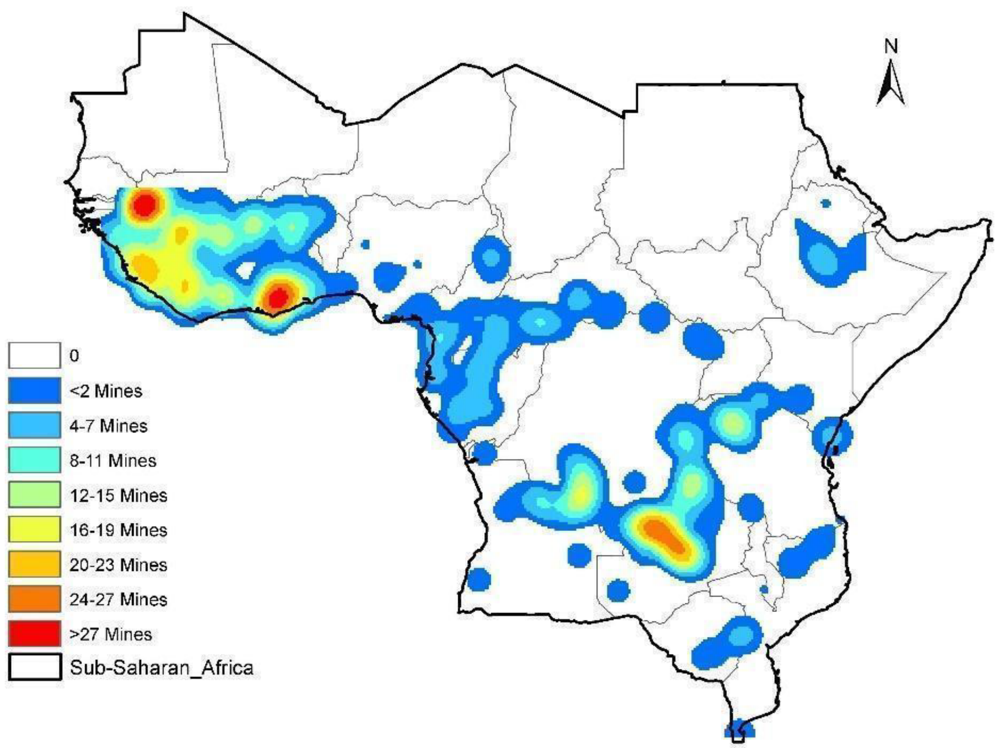

Figure 4. 3

Mining hotspots in sub-Saharan Africa, showing locations with density of >2 mines within the 100 km radius of each other, the colours indicate the density of mines within the designated radius with dark green having the least mines and dark red having the highest number of mines.

4.4.3 Evaluate the amount of deforestation and forest degradation caused by the key commodities mined versus their matched controls.

In evaluating the amount of deforestation and forest degradation caused by the key commodities mined in Sub-Saharan Africa (SSA) compared to their matched control areas, the study found that these key commodities were responsible for a significant portion of the total deforestation in the region. The results of this study revealed that, the total deforestation caused by the 21 commodities mined in SSA from 2001 to 2020 at the 10 km buffer distance, was 726,887 hectares as previously discussed in Chapter 3. Out of this total, the 5 key commodities mentioned above accounted for 86% of the deforestation. Analysing the distribution of forest loss by commodity using the GFC dataset, the study revealed that gold mining had the highest deforestation impact. Within a 4 km buffer distance, gold mining caused 46,574 ha of deforestation. Within a 10 km buffer distance, the impact increased to 246,420 ha. These figures demonstrate the significant deforestation associated with gold mining activities.

The TMF dataset showed that, at the 10 km buffer distance, gold mining accounted for 64% of the total deforestation plus forest degradation, while copper mining accounted for 13% of the total.. The results of the analysis indicated that there were significant differences in the mean of the total loss/change between the control areas and the treatment areas for each commodity. This suggests that the mining activities had a discernible impact on deforestation and forest degradation. Below is the breakdown of the results from the analysis of loss/change by commodity for both datasets (GFC and TMF).

| Copper:

In the case of copper mining in SSA, the study found that there were significant differences in the amount of deforestation and forest degradation between the mining sites and their matched control areas. According to the analysis using the Global Forest Change (GFC) dataset, the 39 copper mines in the study area exhibited a mean deforestation of 839 hectares (ha) per mine within a 4 km buffer distance from 2001 to 2020. In contrast, the corresponding control locations had a mean deforestation of 285 ha during the same period. The difference in deforestation between the mining sites and control areas was statistically significant (p-value = 0.00000292, 95% *confidence interval*) (Figure 4.4A).Similarly, within a 10 km buffer distance, the copper mines caused a mean deforestation of 4,429 ha, whereas the matched control areas had a mean deforestation of 1,761 ha. Again, this difference was found to be statistically significant (p-value = 0.00000108, 95% *confidence interval*) (Figure 4.4B).

The analysis also considered the combined impact of deforestation and forest degradation using the tropical moist forest (TMF) dataset. It was found that copper mines caused a mean change of 7,031 ha more deforestation plus forest degradation than the control areas within a 4 km buffer distance (p-value = 0.0458, 95% confidence interval) (Figure 4.4C). Within a 10 km buffer distance, the difference increased to 48,420 ha more deforestation plus forest degradation caused by copper mining compared to the control areas (p-value = 0.0271, 95% confidence interval) (Figure 4.4D).

| Diamond.

The diamond mines in SSA resulted in a total deforestation of 14,702 hectares (ha) and 80,302 ha within the 4 km and 10 km buffers, respectively, based on the analysis using the Global Forest Change (GFC) dataset from 2001 to 2020. On average, each diamond mine contributed to a deforestation of 544 ha within the 4 km buffer and 2,974 ha within the 10 km buffer in the treatment areas. In comparison, the corresponding control areas experienced a total deforestation of 7,388 ha within the 4 km buffer and 53,170 ha within the 10 km buffer during the same period using the GFC dataset. The statistical tests showed a significant result at the 4 km buffer (p-value = 0.0009926, 95% confidence interval) and also a significant result at the 10 km buffer (p-value = 0.024, 95% confidence interval) (Figure 4.4A and 4.4B) for deforestation using the GFC dataset. This suggests that the difference in forest loss between the diamond mining sites and the control areas was statistically significant at both the 4 km buffer and 10 km buffer distances.

The analysis also considered the combined impact of the total deforestation plus forest degradation using the TMF dataset, the diamond mines caused a loss of 2,806 ha at the treatment locations compared to 11,903 ha at the control locations within the 4 km buffer. Within the 10 km buffer, the changes were 25,562 ha for the treatments and 81,500 ha for the controls. The statistical tests for total deforestation plus forest degradation were statistically significant at both buffer distances, with p-values of 0.035 (95% confidence interval) for the 4 km buffer and 0.031 (95% confidence interval) for the 10 km buffer (Figure 4.4C and 4.4D).

| Gold

Gold mining in SSA resulted in significant forest losses. Within the 4 km buffer distance, gold mines caused deforestation of 11,038 hectares (ha), while within the 10 km buffer distance, the deforestation extent increased to 246,420 ha. On average, each gold mine accounted for a loss of 597 ha within the 4 km buffer and 3,159 ha within the 10 km buffer. The statistical analysis revealed a significant result at the 4 km buffer (p-value = 0.00234, 95% confidence interval), indicating that the difference in forest loss between the gold mining sites and the control areas was statistically significant (Figure 4.4A). However, at the 10 km buffer, the result was statistically insignificant (p-value = 0.0496, 95% confidence interval) (Figure 4.4B), suggesting that the difference in forest loss between gold mining sites and control areas was not statistically significant at this distance.

Analysing the TMF dataset, the study found that gold mines caused a total deforestation plus forest degradation that was 8,269 ha higher than the control areas within the 4 km buffer, and 61,919 ha higher within the 10 km buffer. However, the statistical tests for deforestation plus forest degradation were not statistically significant within both the 4 km buffer (p-value = 0.3, 95% confidence interval) and the 10 km buffer (p-value = 0.16, 95% confidence interval) (Figure 4.4C and 4.4D).

| Iron-ore

The total deforestation caused by the iron-ore mines in SSA was 11,038 ha and 90,562 ha at the 4km and 10 km buffers respectively from 2001 to 2020, the mean deforestation per mine was 551 ha for the 4 km buffer and 4,528 ha for the 10 km buffer. The corresponding controls had total deforestation of 10,336 ha at the 4 km buffer and 63,531 ha for the 10 km buffer during the same period. The statistical test showed non-significant results for both the 4 km buffer (*CI* = 95%, p-value = 0.817, Figure 4.4A) and the 10 km buffer (CI = 95%, p-value = 0.164, Figure

4.4B). In the same light, the results for the deforestation plus forest degradation showed that iron-ore had caused 7,007 ha at the 4 km buffer and 50,695 ha at the 10 km buffer. The matched controls had a change of 12,635 ha and 94,502 ha at the 4 km and 10 km buffers, respectively. The statistical test showed that the influence of iron-ore mining on the changes recorded was statistically non-significant at 4 km buffer (CI = 95%, p-value = 0.203, Figure 4.4C) and the 10 km buffer (CI = 95%, p-value = 0.114, Figure 4.4D).

| Limestone

The limestone mines in SSA resulted in forest losses of 7,108 hectares (ha) and 38,255 ha within the 4 km and 10 km buffers, respectively, based on the GFC dataset. On average, each limestone mine contributed to a loss of 323 ha within the 4 km buffer and 1,738 ha within the 10 km buffer in the treatment areas. In comparison, the matched control areas experienced losses of 2,524 ha and 20,731 ha within the 4 km and 10 km buffers, respectively. The statistical analysis indicated a significant result at the 4 km buffer (p-value = 0.01322, 95% confidence interval), suggesting that the difference in forest loss between the limestone mining sites and the control areas was statistically significant (Figure 4.4A). However, at the 10 km buffer, the result was statistically non-significant (p-value = 0.08352, 95% confidence interval) (Figure 4.4B), indicating that the difference in forest loss between limestone mining sites and control areas was not statistically significant at this distance.

Considering the total deforestation plus forest degradation using the TMF dataset, the limestone mines caused a combined loss of 6,044 ha within the 4 km buffer and 34,042 ha within the 10 km buffer. In comparison, the control areas experienced losses of 2,743 ha and 16,041 ha within the 4 km and 10 km buffers, respectively. However, the statistical tests for deforestation plus forest degradation were not statistically significant at both the 4 km buffer (p-value = 0.297, 95% confidence interval) and the 10 km buffer (p-value = 0.195, 95% confidence interval) distances (Figures 4.4C and 4.4D).

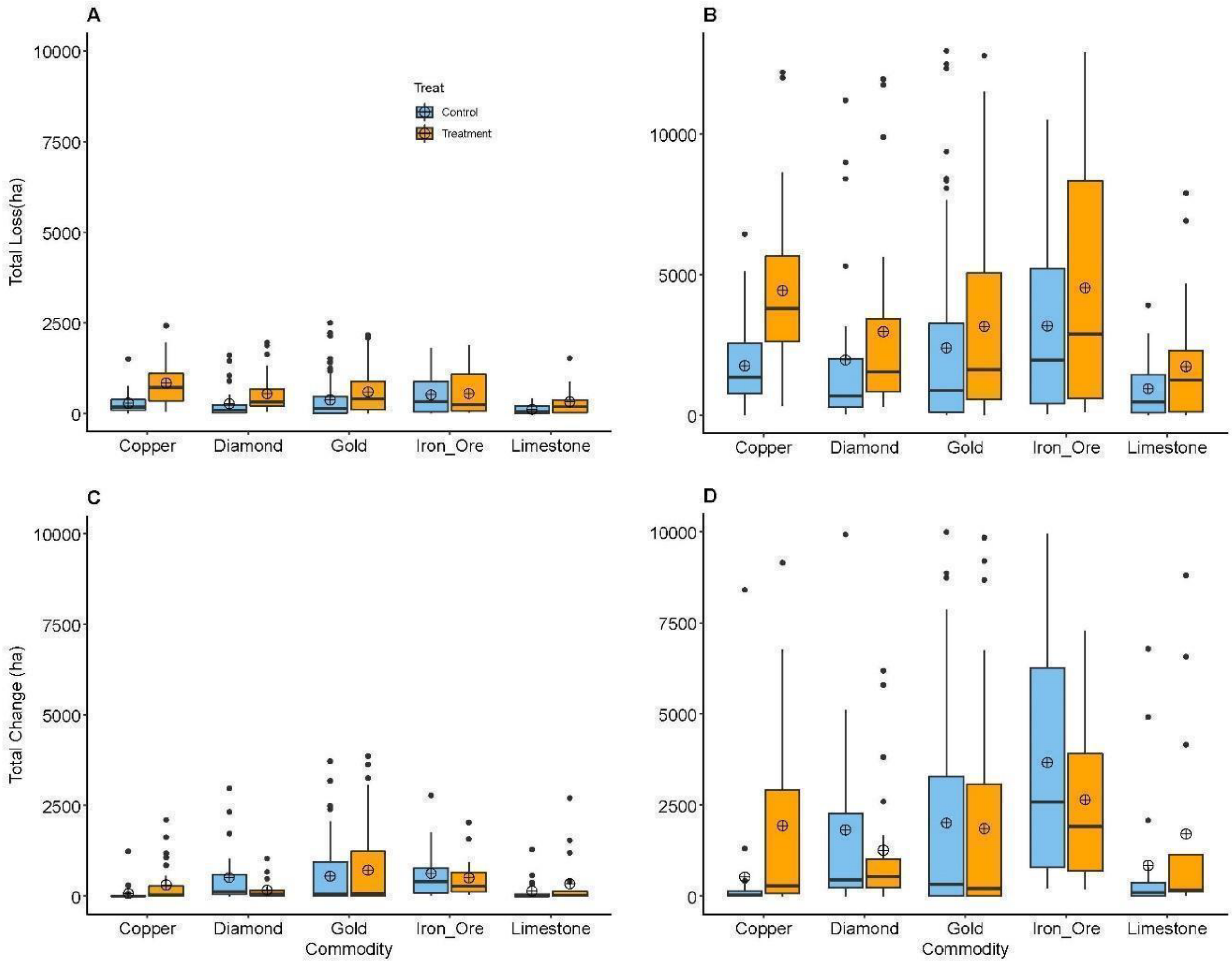

Figure 4. 4

Plots for paired test showing the mean deforestation between treatments and controls dataset for the 5 key commodities mapped using the GFC at **(A)** 4 km and **(B)** 10 km and the mean deforestation plus forest degradation using the TMF dataset at (**C**) 4 km and **(D)** 10 km. The black dots signify the outliers (observations with greater values than the majority), the circle cross are the mean values for the commodity (control and treatment) and the whiskers signify the variation in the group.

4.4.4 Difference between the amount of extra deforestation and forest degradation caused by individual key commodities (relative to control).

The difference in the mean of the extra deforestation caused by individual commodities mined from inception were calculated and compared to their respective matched controls. An analysis of variance (ANOVA) was conducted to determine the statistical significance of the mean differences. Within the 4 km buffer, analysing the Global Forest Change (GFC) dataset, it was found that copper had the highest mean difference in deforestation relative to the control group, amounting to 554 hectares. On the other hand, iron-ore had the smallest mean difference, with only 35.1 hectares of deforestation (p-value = 0.0105, Figure 4.5A). Moving to the 10 km buffer, copper again exhibited the highest mean difference, with 2668 hectares of additional deforestation, while gold had the lowest mean difference at 762 hectares (p-value = 0.0323 ha, Figure 4.5B). The result showed that these differences in means were statistically significant at both buffer distances.

Examining the TMF dataset, within the 4 km buffer, the mean differences in extra deforestation plus forest degradation caused by the mined commodities demonstrated interesting patterns. Copper, gold, and limestone exhibited negative mean differences, indicating lower levels of deforestation compared to the control group (-180 ha, -106 ha, and -150 ha respectively). Conversely, diamond and iron-ore showed positive mean differences, with 337 ha and 281 ha respectively (p-value = 0.0268, Figure 4.5C). Shifting to the 10 km buffer, the deforestation and forest degradation patterns did not significantly differ from those observed within the 4 km buffer for most commodities in comparison to their respective control groups (p-value = 0.0039,Figure 4.5D).

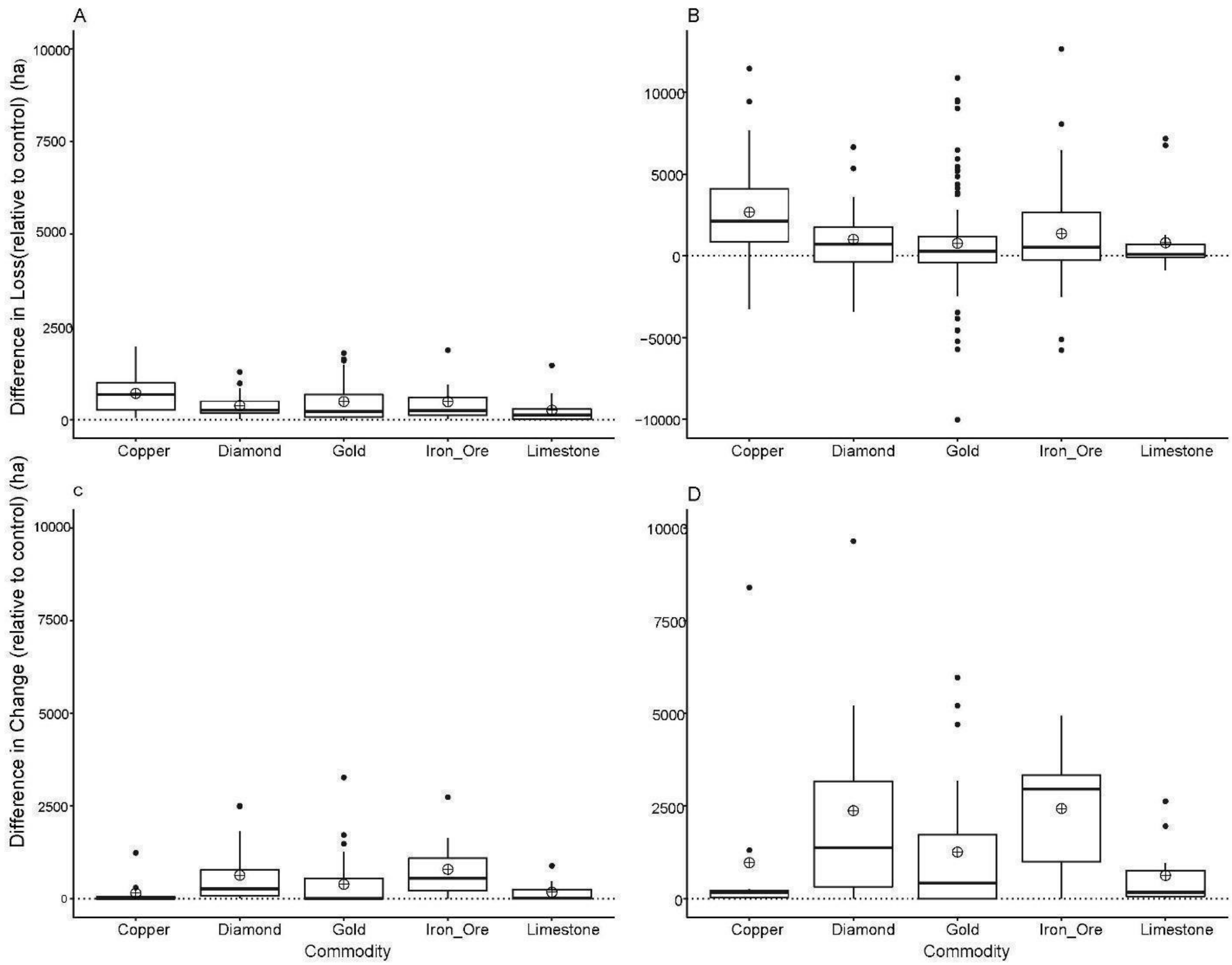

Figure 4. 5

The mean of the difference in extra deforestation relative to control at 4 km and 10 km buffers GFC dataset (**A, B**), and deforestation plus forest degradation at 4 km and 10km buffers TMF dataset (**C, D**). The black dots signify the outliers (observations with greater values than the majority), the circle cross are the mean points for the commodity and the whiskers signify the variation in the group.

4.4.5 Changes in commodity caused deforestation and forest degradation pre-mine and post-mine creation with distance from mine.

Using the Global Forest Change (GFC) dataset, the study analysed the proportion of forest area deforested pre-mine and post mine creation. Specifically, the focus was on the relationship between distance from the mine and the extent of deforestation and forest degradation. For the

4 km buffer, the analysis revealed that copper mining resulted in losses ranging from -0.1% to 0.18% during the 10 years leading up to mine creation (Figure 4.6A). Similarly, at the 10 km buffer, the proportion of forest loss caused by copper mining ranged from -0.08% to 0.11%. Turning to diamond mines, some losses were observed at both buffer distances, with proportions ranging from 0.1 to 0.5 prior to mine creation. Following mine establishment, the proportions increased to -0.08 to 0.2 at both buffers between 1 and 17 years after mine creation (Figures 4.6B & 4.6G).

Regarding gold mines, the proportion of loss within the 4 km and 10 km buffers ranged from -0.1 to 0.1 before mine creation. However, this trend shifted post-mine creation, with most mines exhibiting losses between 0.02% and 0.35%. It is worth noting that not all gold mines experienced significant losses, as some locations even showed an increase (gain) in forest cover at a proportion greater than 0.2% within the 4 km and 10 km buffers after mine creation (Figures 4.6C & 4.6H). In the case of iron-ore mines, a mix of gains and losses was observed within both buffer distances in the 1 to 8 years preceding mine creation. After mine establishment, the trend continued, with proportions ranging from -0.18 to 0.39, indicating both gains and losses (Figures 4.6D & 4.6I). As for limestone mines, there were relatively few losses before mine creation at both buffer distances. However, post-mine creation, the proportion of loss increased, ranging from 0.01 to 0.3 within the 4 km buffer, and a gain of approximately 0.04 with losses up to 0.2 within the 10 km buffer at 1 and 10 years after mine creation (Figures 4.6E & 4.6J).

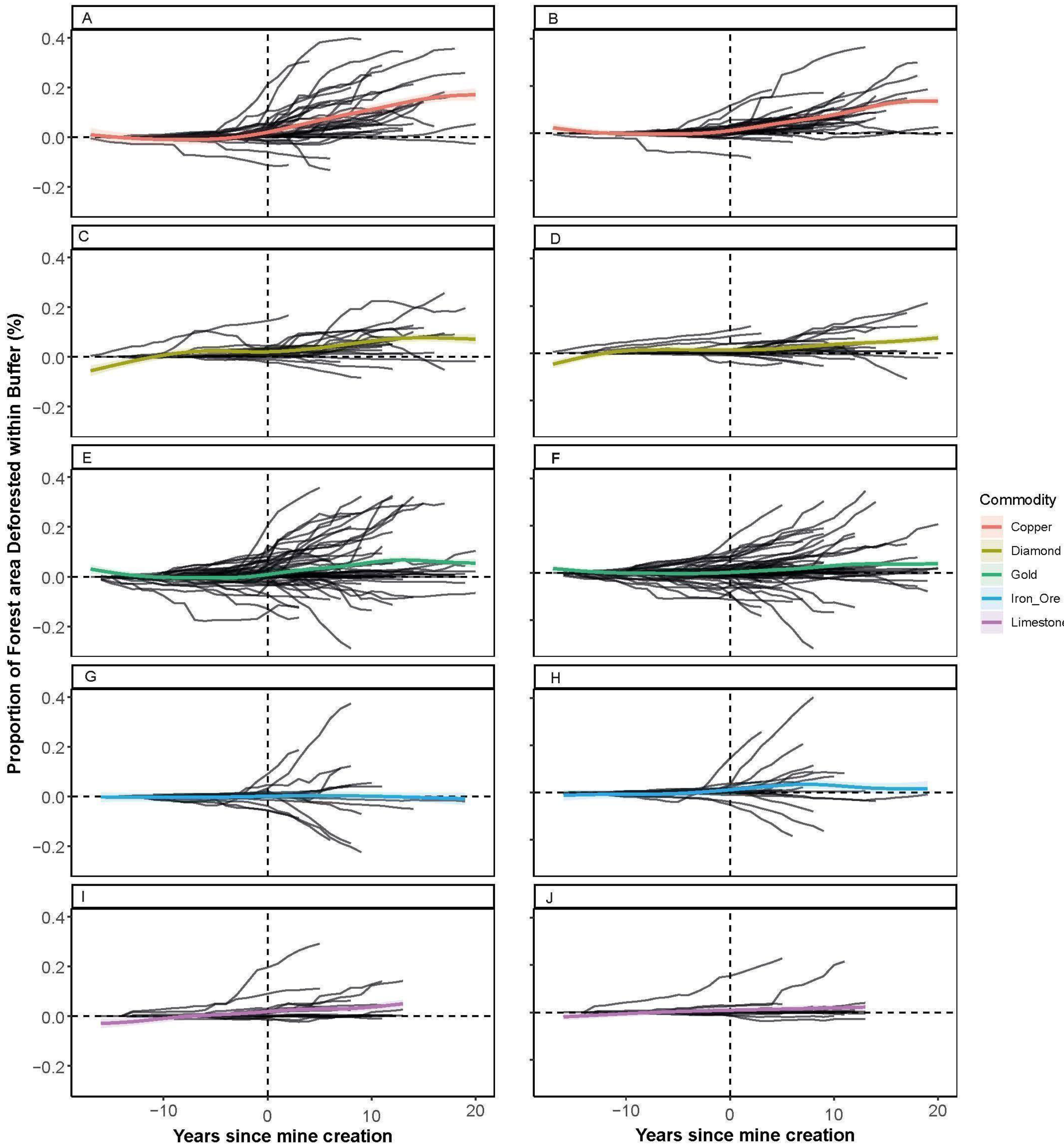

Figure 4. 6

Proportion of forested are deforested within the 4 km (**A, B, C, D, E**) and 10 km **(F, G, H, I, J)** buffers in SSA by commodities (GFC dataset), The black lines refer to the number of mines for each commodity and the thick coloured horizontal lines represents the fitted GAMs at the confidence intervals for each commodity.

The proportion of deforestation plus forest degradation of forest cover pre-mine and post-mine creation by commodity within the 4 km and 10 km buffers. Using the TMF dataset,

Within the 4 km buffer of copper mines, the proportion of change ranged from -0.05 to 0.13 during the 1 to 8 years leading up to mine creation. Following mine establishment, the proportion of change increased to -0.25 to 0.5 at 5 to 15 years post-mine creation (Figure 4.7A). At the diamond mines within the 4 km buffer, the proportion of change ranged from -0.5 to 0.2 before mine creation, and from -0.45 to 0.02 after mine creation at 1 to 15 years post-mine (Figure 4.7B). Gold mines exhibited a consistent increase in the proportion of change, both pre-mine and post-mine creation, ranging from -0.5 to 0.6. This trend was observed approximately 10 years before mine creation and up to about 14 years after mine creation (Figure 4.7C). Within the 4 km buffer of iron-ore mines, the proportion of change ranged from -0.1 to -0.3 in the 1 to 10 years preceding mine creation. However, post-mine creation, the proportion shifted to a range of 0.2 to -0.5, with more mines showing gains rather than losses (Figure 4.7D). The proportion of change at limestone mines was initially low, ranging from -0.05 to 0.2 before mine creation. However, post-mine creation, the proportion increased to a range of -0.2 to 0.5 (Figure 4.7E).

Interestingly, the analysis revealed that within the 10 km buffer, there was no significant difference in the proportion of deforestation plus forest degradation compared to the values observed within the 4 km buffers for all five key commodities (Figures 4.7F, 4.7G, 4.7H, 4.7I, and 4.7J).

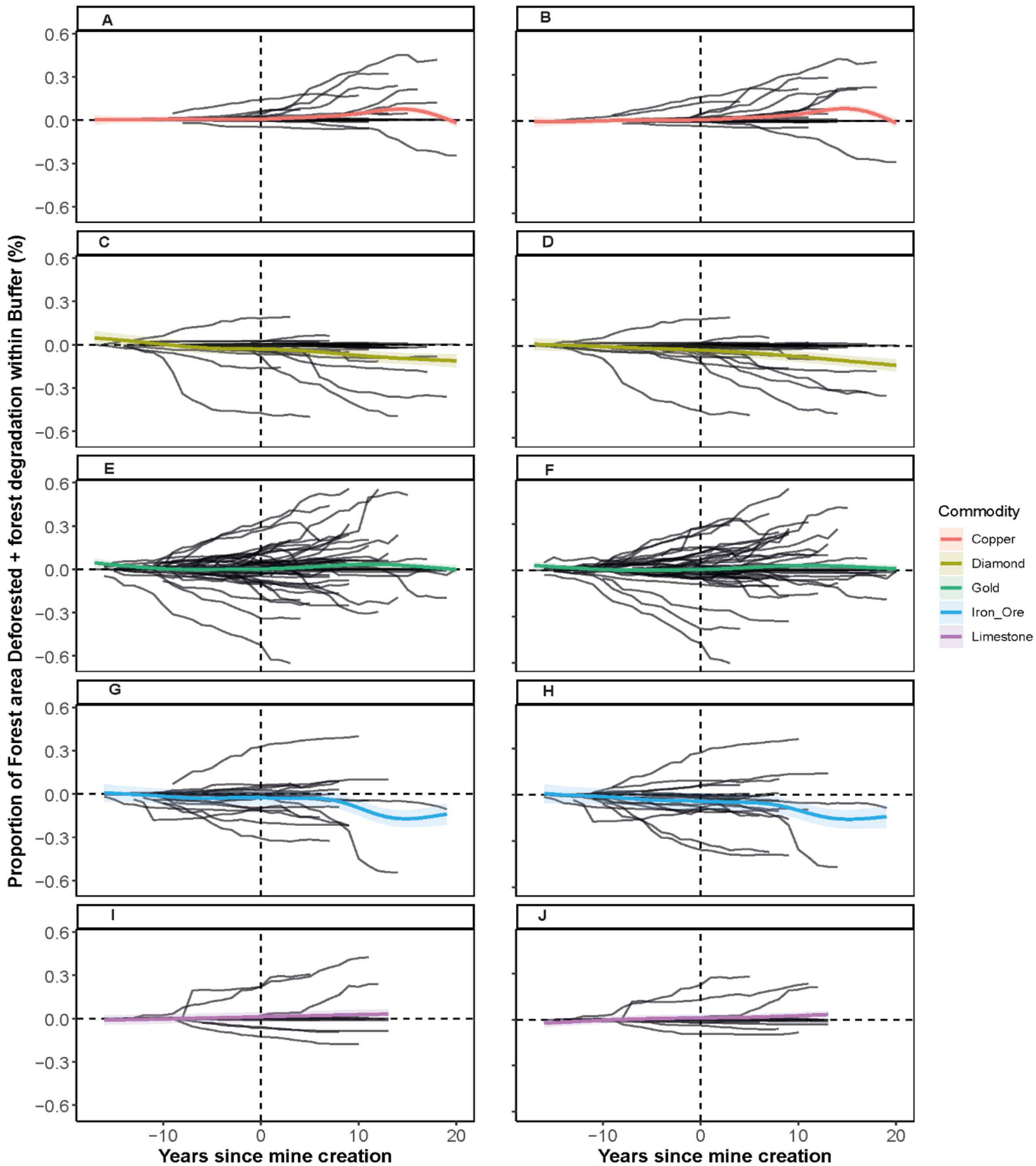

Figure 4. 7

The proportion of forested area that was deforested plus degraded within the 4 km (A, B, C, D, E) and 10 km (F, G, H, I, J) buffers in SSA by commodities (TMF dataset). The black lines refer to the number of mines for each commodity and the thick coloured horizontal lines represent the fitted GAMs at the confidence intervals for each commodity.

4.4.6 Deforestation and forest degradation of initial forest area caused by commodity mining within various buffer distances at 10 years post-mine creation relative to controls.

Estimating the proportion of initial forest area deforested (GFC dataset). For each of the 5 key commodities, the proportion of initial forest area that was deforested after 10 years of mine creation within each of the 1 to 10 km buffers was modelled, the result showed a loss of 40% of forest area within the 0-1 km buffer ring around the copper mines relative to control (Figure 4.8A), this drastically dropped to 11 % at the 1-2 buffer ring and continued declining further away from the mines to 7% at the 9-10 km buffer ring. The mines for diamond and gold had 15% and 18% initial forest areas losses respectively, relative to control within the 0-1 km buffer ring; they both recorded a similar pattern of decline, from 10% within the 1-2 km buffer ring to < 5% at the 9-10 km buffer ring (Figures 4.8C & 4.8E). The iron-ore mines had initial forest area losses of 3% within the 0-1 km buffer ring and -1% at the 3-4 km buffer ring relative to control, the loss increased to 5% at the 8-9 km buffer ring (Figure 4.8G). The limestone mines had lost 8% of its initial forest relative to control at the 0-1 km buffer ring and this declined steadily to 2% further away within the 9-10 km buffer ring (Figure 4.8I).

Estimating the proportion of initial forest area deforested plus degraded (TMF dataset). The TMF dataset and the GAM, were used to estimate the proportion of initial forest cover that has changed within the various buffer rings at 10 years post mine creation relative to controls. The result showed that the copper mines had an average of 5% change in their initial forest cover relative to control within all the buffer rings (Figure 4.8B), the diamond mines had an average change of -5% relative to control within the 0-1 km,, up to the 9-10 km buffer rings (Figure 4.8D). The gold mines had changes of 2% at the 0-1 km buffer ring and 5% at the 3-4 km buffer ring, the rest of the buffer rings had changes of < 4% of their initial forest cover relative to control (Figure 4.8F). The iron-ore had a change of -5% at the 0-1 km buffer ring relative to control and this declined steadily by distance to -12% at the 9-10 km buffer ring (Figure 4.8H), the mines for limestone had changes in their initial forest area of between 5% and 3% within the 0-1 km up to the 9-10 km buffer rings (Figure 4.8J).

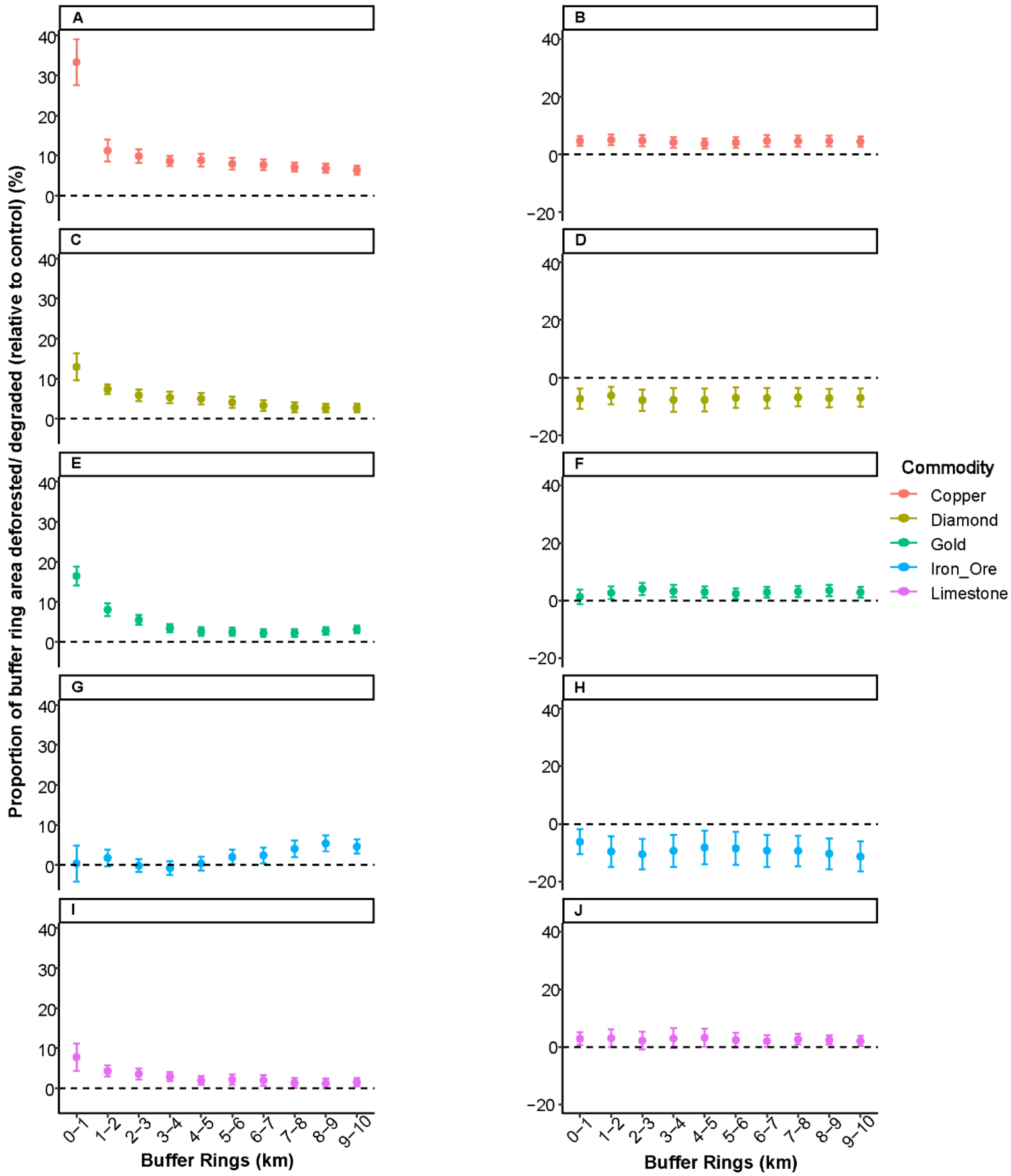

Figure 4. 8

The proportion of buffer area that was deforested at 10 years post mine creation within a distance of 0 to 10 km from the mines GFC, (**A, B, C, D, E**) and deforested plus degraded TMF (**F, G, H, I, J**) buffers in SSA by commodities (TMF dataset). The error bars represent the 95% confidence intervals of the estimated proportion of initial forest cover loss/changed (derived from the upper and lower CIs of the buffer rings), the dotted line marks the reference points and the values below zero indicate a negative forest cover loss/ change (i.e., forest gain).

4.5 | Discussion

4.5.1 |Mining locations and their density (mining hotspots).

This study assessed the variation of total deforestation and forest degradation based on the commodity mined. One of the aspects analysed was the density of mines within a 100 km radius, identifying locations with a high concentration of mines within this defined distance. These locations are referred to as mining hotspots in sub-Saharan Africa. The presence of a greater number of mines in these hotspots suggests they are more susceptible to disruption compared to areas with fewer mines, irrespective of the specific commodity being extracted. However, it should be noted that some areas with fewer mines may coincide with biodiversity hotspots, which are crucial for conservation priorities according to Myers et al. (2000). These biodiversity hotspots harbour numerous important plant and animal species (IUCN, 2012). The density of mines and their proximity to regions of high biodiversity richness pose significant threats to biodiversity conservation, as highlighted by Cabernard and Pfister (2022) and Sonter et al. (2020).

For example, the high density of artisanal small-scale mining (ASM) and large-scale mining (LSM) operations in Ghana has resulted in substantial deforestation and forest degradation in mining areas. Between 2000 and 2019, this led to a loss of 21,300 hectares of forest (Giljum et al., 2022). Another notable mining hotspot is the Central African Copperbelt (CAC), which contains over 25 mines within a 100 km radius. In the Democratic Republic of Congo (DRC) and Zambia, industrial mining in the CAC caused the loss of 9,900 hectares and 9,500 hectares of forest, respectively from 2000 to 2019 (Giljum et al., 2022). These findings indicate that a significant proportion of mines in the CAC are located within 1-10 km of protected areas and biodiversity habitats. This observation aligns with Durán et al. (2013), who reported that 27% of mines globally are situated within a 10 km radius of protected areas. It underscores the potential threats posed by mineral extraction to areas of high biodiversity value and emphasizes the need for regulated mining practices to prevent the expansion of mining activities into intact habitats, thereby mitigating the risk of extensive deforestation in sub-Saharan Africa.

4.5.2 Variation in habitat changes by commodity.

The findings of this study indicate that the extent of deforestation and forest degradation varied significantly depending on the specific commodity being mined. Copper mining within the 10 km buffer led to 251 % more deforestation compared to the matched controls. Similarly, gold and diamond mining resulted in 130 % and 150 % more deforestation respectively compared to their controls. A similar trend was recorded for iron-ore and limestone too.

Certain key commodities exhibited a tendency to expand into areas of high biodiversity value. For example, gold mining often involves open-cast artisanal small-scale mining (ASM) practices, the use of mercury, and the continuing exploration and prospecting of new frontiers driven by its increasing market value. Copper (and associated Cobalt) is anticipated to be in high demand in the near future due to its applications in technology and electricity generation (Ali et al., 2017).This demand will likely lead to the expansion of existing mines and the establishment of new ones at the expense of the forest. Although this research focussed on five different commodities, this approach is similar to Sonter et al. (2014b) who investigated land-use change from the increased demand for steel.

In summary, the findings indicate that the type of commodity being mined plays a crucial role in determining the extent of deforestation and forest degradation. Some commodities, such as copper, gold, diamond, iron-ore, and limestone, exhibit higher impacts on forest cover, raising concerns about their encroachment into biodiverse regions. Additionally, the increasing demand for certain commodities and their associated market value may drive further expansion of mining activities, contributing to ongoing forest loss.

4.5.3 Habitat changes over time and distance from mine.

Results from the GAM model showed that the rates of biodiversity loss increased significantly at 10 years post mine creation with increasing distance from the mines. Gold and diamond mines were particularly responsible for substantial deforestation within a 10 km buffer zone. For example, in 2010, the average annual deforestation caused by gold mining was 62 hectares, while for diamond mining it was 40 hectares. By 2020, these numbers had risen to 291 hectares and 173 hectares, respectively. These losses were most prominent in countries such as Ghana, Tanzania, Zambia, and the Democratic Republic of Congo (DRC). This was also evidenced in the neotropics where gold mining was responsible for the loss of 1,915 ha of forest per year in the Peruvian Amazon between 2006-2009 (Swenson at al., 2011), and in recent years in Guiana shield in the Amazon basin (Kalamandeen et. al., 2020). When comparing these findings with the work of Alvarez-Berríos and Mitchell Aide (2015), it becomes evident that gold mining has significantly increased from 2001 to 2020, indicating a steady expansion of gold mines and a surge in mining activities overall (e.g., Luckeneder et al., 2021). This finding suggests that gold is a major driver of deforestation beyond the immediate extent of the mines in SSA.

Mines that extract low-value, high-bulk commodities such as iron ore and limestone are typically large in size, and necessitate supporting infrastructure (i.e., electricity, roads, and rails) which often extends to several kilometres away from the mine (Chatham House, 2020); thereby instigating secondary deforestation beyond the mining footprint. Extraction of other commodity types also caused notable levels of deforestation in SSA post-mine creation when compared to their controls. The findings indicate that the rates of deforestation are higher within the 0 to 4 km buffer rings than beyond (5 to 10 km buffer rings) for all commodities. Forest loss around iron-ore mines differed from other commodities at these distances, as it showed higher losses beyond the 5 km buffer. This could be because iron-ore is wholly exported as a bulk product for processing at industries unlike other commodities that are processed at source, and so iron-ore mines are unlikely to require supporting infrastructure and cause secondary deforestation. Diamond and limestone mines do not pose significant threats to biodiversity beyond the 5 km buffer zone. Additionally, limestone mining has the lowest proportion of mines located within forests, and it is processed at source.

Overall, these findings highlight variation in habitat change over time and distance from mines, with gold mining being a major driver of deforestation beyond the immediate mine sites in sub-Saharan Africa. Mines extracting low-value, high-bulk commodities can lead to secondary deforestation due to the infrastructure development required. Deforestation rates are generally higher within the 0 to 4 km buffer zones compared to the 5 to 10 km buffer zones for all commodities, except for iron ore mines, which show higher losses beyond the 5 km buffer. Diamond and limestone mines have less impact on biodiversity beyond the 5 km buffer zone, with limestone mining having the lowest proportion of mines located within forests and processing occurring at the source.

4.5.4 Caveats

There are important caveats to consider in this study regarding the approach used and the data utilized. Firstly, the TMF dataset was utilized for assessing deforestation plus forest degradation. To create a simplified classification, the *Undisturbedforest* and *ForestRegrowth* layers were aggregated into a single category called "forest," while the *DeforestedLand* and *DegradedForest* layers were grouped as "deforested plus degraded forest." This aggregation technique may introduce some discrepancies in the data and should be considered when interpreting the results. Secondly, the analysis did not include certain commodities, such as bauxite, coal, and cobalt, which have growing demand. This exclusion was due to the limited number of mines associated with these commodities in the database used for the study. Consequently, modelling the past, present, and future forest disruptions related to these commodities was not feasible. Their absence from the analysis should be considered when assessing the overall impact of mining activities on deforestation and forest degradation.

These caveats highlight the need for further research and data collection to improve the accuracy and comprehensiveness of studies examining the environmental effects of mining activities.

4.6 | Management Implications and Conclusions

The hotspots of mining are in close proximity to the areas of biodiversity richness, indicating the vulnerability of these habitats to further deforestation and forest degradation. The increasing demand for key commodities globally may lead to the rapid increase of mining activities across the SSA in the near future, leading to extensive deforestation and forest degradation, and the loss of biodiversity richness. It is crucial for mine operators to take responsibility for both onsite and offsite effects triggered by mineral extraction, especially the mines for commodities whose method of extraction requires heavy forest clearing and movement of earth, such as copper and gold. Deforestation caused by mining should be followed by habitat restoration efforts, including soil recovery and tree planting initiatives. Additionally, measures should be taken to offset any biodiversity loss by protecting nearby forests.

Poor mining operation can be curtailed by the regulatory agencies of government, by making it mandatory for operators to commit to implementing the regulations spelt out in the environmental impact assessment (EIA) before the commencement of exploration. Mineral producing countries and those with prospects of mineral exploration, need robust mining regulations that prioritize forest protection, biodiversity conservation, and the mitigation of deforestation and forest degradation caused by mining activities in SSA. Compliance can be achieved through the enactment of stringent mining laws and binding them to monetary bonds. These laws should be regularly reviewed to align with current circumstances, as penalties and fines may become outdated over time.

Regulations prohibiting mining-related deforestation should also extend to industrialised nations where these commodities are used. This approach aims to minimise the use of resources that were obtained through extensive deforestation. Habitat fragmentation caused by mining leads to atmospheric carbon dioxide (CO_2) emissions, therefore, mining EIAs should include assessments of carbon emissions and plans for carbon uptake. This is particularly important in SSA, where numerous large-scale mineral excavations are being proposed in areas of high biodiversity richness of pan tropical regions (ELAW, 2010). It is established that mineral exploration is driven by increased demand and high commodity prices (Lobo et. al., 2016; Asner et. al., 2013; Swenson et al., 2011), therefore, sustainable mining practices should be promoted and the use of alternative commodities with lesser environmental impact should be encouraged. In turn, the recycling and reusing of metal products should be highly emphasised by all stakeholders, and governments can introduce incentives such as tax waivers or reductions to encourage industries to use recycled metals, thereby moving towards a circular economy (Ali et al., 2017). In addition, the rollbacks by some governments on environmental and social safeguards in order to allow large-scale mining in areas of biodiversity richness (Dil et al., 2021) is counterproductive, and it undermines the earlier efforts on conservation (e.g., the Democratic Republic of Congo) Furthermore, policies should be developed to incorporate and register artisanal and small-scale mining (ASM) operators as part of the formal mining stakeholders, as this would make them take responsibility for their own share of habitat disruptions.

Overall, the analysis highlighted the substantial contribution of the key commodities to deforestation and forest degradation in SSA. Gold mining emerged as the leading driver of deforestation, while copper mining also had a notable impact. The findings underscore the need for effective management of mining activities in SSA. This requires a comprehensive approach that includes strong regulations, enforcement of environmental impact assessments, habitat restoration measures, carbon emission considerations, promotion of sustainable practices, recycling of metals, and the inclusion of ASM operators. These measures will help mitigate the negative impacts of mining-induced deforestation and forest degradation, protect biodiversity, and move towards a more environmentally responsible mining industry.

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Chapter 5: General discussion

5.1 Summary

Understanding the intricate dynamics between natural resource abundance, mining activities, deforestation and forest degradation, and socio-economic challenges in the sub-Saharan Africa region is crucial for formulating effective strategies to promote sustainable development, and poverty alleviation. By delving into the complexities of this multifaceted issue, policymakers and stakeholders can work towards addressing the root causes of conflict and implementing inclusive and equitable policies that prioritize the well-being and prosperity of the region's population. The growing demand for commodities globally, will give rise to the expansion and creation of new mines. Given that such development will cause negative impact on the environment (Luckeneder et al., 2021) and considering the need to reduce the socio-ecological impacts of mining into intact areas of conservation interest. It is imperative to adopt sustainable methods that would minimise the impact of mining on forest and biodiversity conservation, because most mineral deposits occur within or near the forests.

Numerous comprehensive studies have thoroughly addressed and shed light upon the prevailing uncertainties surrounding mining as a key driver of deforestation, employing robust empirical indicators to ascertain its ecological ramifications (Geist & Lambin, 2002; Sonter et al., 2017; Sonter et al., 2014a). These scholarly endeavours have significantly contributed to our understanding of the multifaceted impacts of mining on forest ecosystems, particularly in the vast expanse of pantropical regions that encompass diverse geographical locations and ecosystems teeming with invaluable biodiversity (Chakravarty, Ghosh, & Suresh, 2011). However, it is crucial to acknowledge that the magnitude of such impacts attributed to mining operations exhibits considerable variability contingent upon the distinctive contexts of individual countries as well as the specific commodities being extracted, thereby necessitating nuanced assessments and analyses (Luckeneder et al., 2021; Chuhan-Pole et al., 2017).

The advent of cutting-edge geospatial and remote sensing technologies has revolutionized our ability to precisely pinpoint the spatial distribution of mining sites nestled within intricate forest landscapes, thereby facilitating rigorous empirical evaluations of their ecological footprints and subsequent impacts on habitats (Ferretti-Gallon & Busch, 2014). These advancements have empowered researchers to delve deeper into the intricate dynamics between mining activities and forest ecosystems, enabling a more comprehensive understanding of their interconnectedness.

This research focused on the identification of mines and their proximity to areas of biodiversity richness, and the quantification of forest disruptions caused by mining from 2001 to 2020. The results in this study have shown that a substantial number of mines are quite close to protected areas of biodiversity richness in SSA, and how much relative deforestation and forest degradation they have caused post creation. The distance of mines to areas of biodiversity conservation and the type of commodity mined are important factors in studying the impact of mining on the forest.

5.2 Mining activities in forested landscape in sub-Saharan Africa.

The comprehensive database of the spatial location of mines and their dynamics in sub-Saharan Africa (SSA) was very scarce in the public domain, as it was difficult to distinguish between a mine and a bare surface using satellite images. However, data was collected from various repositories, and through the utilization of remote sensing techniques, 469 mining locations were identified. In addition to the geo-location of the mines, the data on the year of establishment, commodity mined, active or abandoned and the operators of the mines were also added to the database, although ownership changes over time could make it challenging to provide up-to-date information on current ownership status. A notable finding was that over 58% of the mapped mines in SSA were established between 2000 and 2020, indicating a significant expansion of existing mines to meet the growing demand for certain commodities. Artisanal and small-scale mining (ASM) occurs more rampantly in SSA than any other region of the globe because of its high poverty rate.

In many cases the ASM operates in very inaccessible locations within the forest (Durán, Rauch, & Gaston, 2013). Consequently, mapping the precise locations of these ASM mines can be challenging due to their size and the transient nature of their operations, they move rapidly to different locations without a specific pattern, it is difficult to ascertain their ownership (Heemskerk et al 2004). To effectively monitor and mitigate the impacts of mining on deforestation and forest degradation in the Afrotropic region, the use of geospatial techniques and remote sensing becomes imperative. Continuous monitoring of mining activities using these tools can contribute to reducing the negative environmental consequences associated with mining-induced deforestation and forest degradation in the region. By establishing a robust database of mining activities and utilizing remote sensing technologies for ongoing monitoring, it becomes possible to enhance our understanding of the spatial distribution and dynamics of mining in SSA. This knowledge can inform policy and management strategies aimed at promoting sustainable mining practices, mitigating environmental impacts, and preserving the valuable forested landscapes of sub-Saharan Africa.

5.3 Mining as driver of deforestation and forest degradation

Mining is one driver of deforestation and forest degradation that is overlooked globally, attention is mostly given to the impacts caused at the immediate extent of the mines. Despite the economic role of mining as a key source of employment and income for governments of most countries, it has some negative consequences on the environment when not responsibly managed. The findings of this study indicate that a substantial portion of the mapped mines, approximately 68%, are located within ecologically important zones characterized by high biodiversity richness. These zones primarily include tropical rainforests and tropical moist deciduous forests (FAO, 2010). The proximity of these mines to forested areas has resulted in negative consequences over time, as mining operations have expanded into conservation areas, causing secondary impacts on forests located several kilometres away. In fact, the number of mines mapped within the red zone (mines situated within 0 to 10 km of protected areas) increased by 250% during the study period, with their physical footprints more than doubling in size between 2000 and 2020.

This clear illustration demonstrates the gradual but significant expansion of mining activities into forested lands, even though the rates of expansion may not have been readily noticeable. The depletion or degradation of forests due to mining activities has far-reaching implications. Forests play a crucial role in providing ecosystem services and maintaining carbon balance. When forests are depleted or degraded, their capacity to provide these services is compromised. Furthermore, the process of deforestation and forest degradation releases substantial amounts of carbon into the atmosphere, contributing significantly to greenhouse gas emissions (Bebbington et al., 2018; Briber et al., 2015; Gibbs et al., 2007). It is therefore imperative to address all drivers of deforestation seriously and take measures to mitigate their effects, regardless of the proportion of deforestation they may cause. Considering the substantial impact of mining on forested landscapes and its associated environmental consequences, there is a pressing need for responsible and sustainable mining practices. Effective management strategies should be implemented to minimize the negative impacts of mining on forests and ensure the preservation of vital ecosystem services. This includes considering the ecological sensitivity of mining locations, implementing comprehensive environmental impact assessments, and enforcing stringent regulations to promote responsible mining practices. Additionally, efforts to restore and rehabilitate degraded mining sites and offset biodiversity loss should be prioritized to mitigate the long-term impacts on forest ecosystems. By adopting a holistic approach and integrating conservation priorities into mining activities, it is possible to strike a balance between economic development and environmental sustainability.

5.4 Key commodities driving forest loss.

The extraction of key commodities in SSA, such as bauxite, copper, diamond, gold, and iron-ore, has resulted in significant loss of forest cover. However, there are variations in the volume of loss caused by the mining for each commodity, for instance it was discovered that mines for gold and copper were the leading causes of forest disruptions in the Afrotropic. Looking ahead, there is a projected rapid increase in the demand for these key commodities in the near future. This surge in demand can be attributed to their vital role in the manufacturing of technological equipment and gadgets (Signé & Johnson, 2021; Phadke, 2018). Consequently, this increase in demand is expected to drive the expansion of existing mines and potentially lead to the establishment of new mining operations. Unfortunately, this expansion and creation of mines will come at the expense of the region's forests and areas of intact biodiversity. The impacts of mining on forest loss are especially concerning given the ecological significance of the affected areas. Forests are vital ecosystems that provide numerous benefits, including habitat for biodiversity, carbon sequestration, and regulation of water cycles. The loss of forest cover due to mining not only disrupts these ecosystem services but also contributes to greenhouse gas emissions and the loss of valuable biodiversity.

Addressing the environmental consequences of mining-induced deforestation and forest degradation requires a multi-faceted approach. It is crucial to promote sustainable mining practices that prioritize environmental protection and minimize the ecological footprint of mining operations. This includes implementing rigorous environmental impact assessments, adhering to robust regulatory frameworks, and adopting responsible land reclamation and restoration practices. Furthermore, efforts should be made to encourage the use of alternative commodities and promote the recycling and reuse of metals to reduce the reliance on resource-intensive mining activities. Collaboration between governments, mining companies, and other stakeholders is essential in addressing the negative impacts of mining on forest ecosystems. Sustainable mining practices should be prioritized and integrating conservation considerations into decision-making processes, it is possible to strike a balance between economic development and the preservation of valuable forest resources in sub-Saharan Africa.

5.5 Mitigating the impact of mining on biodiversity loss.

Addressing the detrimental effects of mining-induced deforestation and forest degradation in sub-Saharan Africa (SSA) requires effective measures to mitigate biodiversity loss. One approach that shows promise is the adoption of modalities for offsetting forest loss through the implementation of a no net loss (NNL) policy, as exemplified in countries like Madagascar (Devenish, 2022). However, it is important to recognize that governments in the global South may face challenges in allocating sufficient resources for conservation due to the growing economic hardship in the region. Therefore, new sources of funding and partnerships are highly required for biodiversity conservation (IUCN & ICMM, 2004). The concept of NNL would ensure that the amount of forest loss caused by mining would be compensated for in other locations in greater amounts, even though this initiative is not new. The implementation of NNL is not widely practised in SSA (Johnson & Howell, 2019), as the cost of attaining the NNL is a burden to the poor communities around the offsets (Devenish, 2022).

The success of this mitigation process requires active monitoring by governments civil conservation groups and the mine operators (Chakravarty, Ghosh, & Suresh, 2011), even though the strategies for achieving success may vary from country to country, it is most important to have effective implementation. It is worth emphasizing that if greenhouse gas emissions resulting from mining-induced deforestation and forest degradation continues at the current rates, it will contribute to increased temperatures and exacerbate climate change which would be devastating to most species (Achard et al., 2014). Therefore, it is important for stakeholders worldwide to support the initiatives aimed at the reduction of carbon emissions such as the United Nations Reducing Emissions from Deforestation and Forest Degradation (REDD+) program (Hund et al., 2017). This approach can be particularly effective in curbing emissions in the tropical regions and safeguarding forests (Silva Junior et al., 2021). By promoting the preservation and sustainable management of forests, REDD+ not only helps mitigate climate change but also protects biodiversity and the valuable ecosystem services provided by forests.

5.6 Conclusion and Recommendations

In conclusion, this study has provided evidence that mining activities contribute significantly to deforestation and forest degradation, highlighting the urgent need for conservation efforts in mining regions. The application of geospatial techniques, as demonstrated in this study, allows for the quantification, monitoring, and mitigation of mining-related deforestation and forest degradation. The availability of free satellite data and other ancillary data required, has made it possible to observe forest in near real-time to ensure that the excesses of mining operators are curtailed. Both the primary and secondary effects of mining can be monitored spatially explicitly at various distances from the mines. The strengthening of Environmental regulations on mining should be strengthened in developing countries of the global south, this would help in curbing habitat fragmentation and loss of biodiversity in the region. Efforts on projects to restore the disrupted forestlands need to be increased by all stakeholders, especially the governments and mine operators who need to synergize to monitor and minimise forest losses in SSA.

Mine operators should take responsibility for both onsite and offsite forest disruptions caused by mineral extraction, particularly in cases where heavy forest clearing and earth movement are involved, such as in copper and gold mining. Deforesting mines should prioritize habitat restoration immediately after mine closure, including initiatives for soil recovery and tree planting. Furthermore, these mines should consider offsetting any biodiversity loss by protecting nearby forests. By actively engaging in habitat restoration and biodiversity conservation, mine operators can contribute to mitigating the environmental impacts of their activities. Informal mining operations that contribute to forest fragmentation can be reduced and formalised through the involvement of regulatory agencies of government. By integrating artisanal miners as part of the formal mining stakeholders, this would make them responsible for their own share of forest loss. This approach encourages responsible mining practices among artisanal miners and helps reduce their negative impact on forests.

In light of these findings, it is recommended that all stakeholders, including governments, mine operators, and regulatory bodies, increase their efforts to restore disrupted forestlands. Collaborative projects should be initiated to restore the ecological integrity of mined areas through soil recovery, reforestation, and the protection of nearby forests. Moreover, ongoing monitoring and evaluation of mining activities and their environmental impacts should be prioritized to ensure compliance with environmental regulations and to guide future conservation efforts. In summary, addressing the environmental consequences of mining in SSA requires a multifaceted approach that involves strengthened regulations, responsible mining practices, habitat restoration, and the involvement of all relevant stakeholders. By implementing these recommendations, it is possible to mitigate the impact of mining on forest loss and protect the valuable biodiversity of sub-Saharan Africa for future generations.

5.6.1 Future research

Future research on mining-induced deforestation and forest degradation should prioritize several key areas to enhance our understanding of this critical issue. Firstly, there is a need for comprehensive studies that delve into the long-term ecological impacts of mining activities on forest ecosystems. These studies should take into account the need to always identify a matched control location at the beginning of any mining exploration in the future, these would serve as a baseline for comparing the effect of the mining on the environment over time. This would enhance the monitoring of forest loss in near real-time as the mine develops. Future studies should also encompass a broader temporal scope, tracking the changes in forest cover and biodiversity over extended periods following mine creation and closure. By examining the post-mining landscape, researchers can assess the effectiveness of restoration and reclamation efforts, identify any lingering ecological vulnerabilities, and determine the long-term resilience of forest ecosystems.

Secondly, further investigations should focus on understanding the underlying drivers and mechanisms that contribute to varying levels of deforestation and degradation associated with different mining commodities. By examining the unique characteristics of various commodities and their extraction processes, researchers can unravel the specific factors that exacerbate environmental impacts. This knowledge will enable the development of targeted mitigation strategies tailored to different mining sectors, ensuring more effective environmental management practices. Thirdly, future research should explore the socio-economic dimensions of mining-induced deforestation and degradation. This includes assessing the socio-economic factors driving mining activities in forested areas, studying the impacts on local communities and indigenous populations, and analysing the trade-offs between economic development and environmental conservation. By adopting an interdisciplinary approach, researchers can generate valuable insights into the complex interplay between mining, livelihoods, and sustainable development, informing more holistic and inclusive policies and practices.

Furthermore, advancements in remote sensing and geospatial technologies offer promising avenues for future research. Leveraging high-resolution satellite imagery, LiDAR data, and other cutting-edge tools can provide more accurate and detailed assessments of mining footprints, allowing for precise mapping of deforestation and forest degradation. Integrating these remote sensing techniques with field observations and on-the-ground data collection will enhance the accuracy of impact assessments, enable the monitoring of environmental changes in near real-time, and support evidence-based decision-making for sustainable mining practices. Lastly, it is crucial to examine the potential role of innovative solutions and alternative approaches to mining that minimize environmental impacts. This includes investigating the feasibility and effectiveness of green mining technologies, such as eco-friendly extraction methods and efficient waste management systems.

Finally, exploring the potential for circular economy practices within the mining industry, such as recycling and reusing mineral resources, can contribute to reducing the overall demand for new extraction and alleviate pressure on forest ecosystems. In conclusion, future research on mining-induced deforestation and forest degradation should encompass long-term ecological assessments, explore the drivers, and impacts of different mining commodities, incorporate socio-economic perspectives, leverage remote sensing technologies, and investigate innovative approaches for sustainable mining. By addressing these research gaps, we can develop a more comprehensive understanding of the complex interactions between mining and forests, ultimately informing more effective conservation strategies and promoting sustainable development in mining regions.

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