Terrestrial Carbon Sinks Project

For The Metals Company

Sustainability Team
Benchmark Mineral Intelligence

Report | London
August 2023

www.benchmarkminerals.com | info@benchmarkminerals.com

HQ: London, UK

Offices: Beijing, Edinburgh, Fort Lauderdale, Melbourne, New Delhi, Porto, San Francisco, Tokyo

Introduction

HQ: London, UK
Offices: Beijing, Edinburgh, Fort Lauderdale, Melbourne, New Delhi, Porto, San Francisco, Tokyo

The just energy transition

The energy transition regarding the replacement of ICE (internal combustion engines) to electric powered vehicles requires a fundamental shift on both the generation and use of energy. Whilst the transition to electric vehicles directly reduces carbon emissions, *how* the supply chain is structured can create significant differences on a range of impacts. Increasingly this means that the supply of critical minerals is under the spotlight.

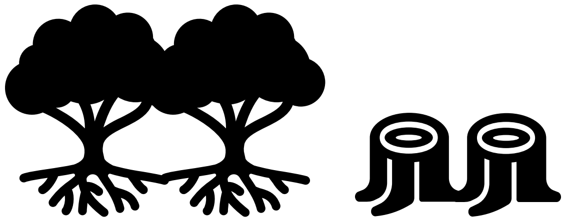
The terrestrial mining industry is increasingly being asked to demonstrate how it is managing wider impacts around its operation. One critical issue is gaining a clearer view of the wider carbon impacts of mining, and an understanding of how different means of extraction and processing will result in different levels of carbon emissions associated with operation and ultimately critical mineral supply.

A particular issue under the spotlight is how the sector measures and understands how land-use changes as a result of mining operations impact change carbon sinks. Effective action to mitigate against climate change depends not only on low carbon energy sources but also the protection and restoration of carbon sinks.

Forests are vital carbon sink ecosystems, with international attention focused on protection of these critical ecosystems. Forests are seen as the most critical of these terrestrial ecosystems in terms of their ability to capture and lock up carbon [1].

This dual role that forests play: sequestration of CO2 from atmosphere and carbon storage - is key to the carbon accumulation done by these forests.. Over time this sequestration builds up a store of carbon. Critical is the rate of carbon accumulation by these forests. The announcement at COP27 of a "rainforest OPEC" by Brazil, the DRC and Indonesia highlights the importance to such countries of protecting rainforests and gaining economic benefit from doing so.

Forest ecosystems are removed or/and degraded as a result of number of land-use changes. However, the terrestrial mining activity necessitates significant land-use, which may or may not be remediated after extraction[2]. Peer-reviewed research also points to the fact that once a mine establishes access infrastructure, it facilitates access for further deforestation for other industries like agriculture, palm oil, etc. Degradation of these forests will mean a reduction in carbon accumulation. Removal means not just a net loss of sequestration, but the release of CO_2 held in these carbon stocks [3].



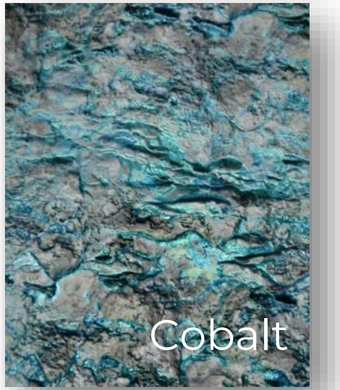
Terrestrial Carbon Sinks Project: Cobalt and Nickel

Quantification of carbon impact requires building up a clear picture of rates of carbon loss and accumulation allowing an understanding of how a carbon stock can change over time. This requires data on two issues:

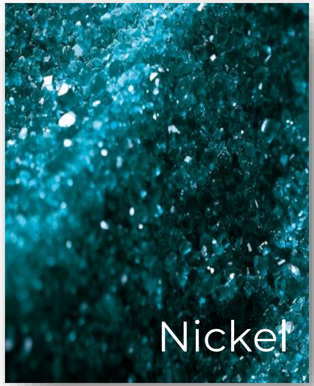
A. Estimation of carbon stocks (quantity of carbon stored in the forest ecosystems) before terrestrial mining sites and estimation of loss of carbon stock, and

B. Changes to carbon sequestration i.e., estimated changes to carbon flow – the removal of CO_2 from the atmosphere

This study is focused on the impact of land-use change on the forest carbon sinks in key cobalt and nickel mining: DRC and Indonesia for the Lithium-ion battery supply chain. To do this we have focused in areas essential to the mining of these critical minerals and sought to establish a clear picture of changes in carbon as a result of local mining and processing.



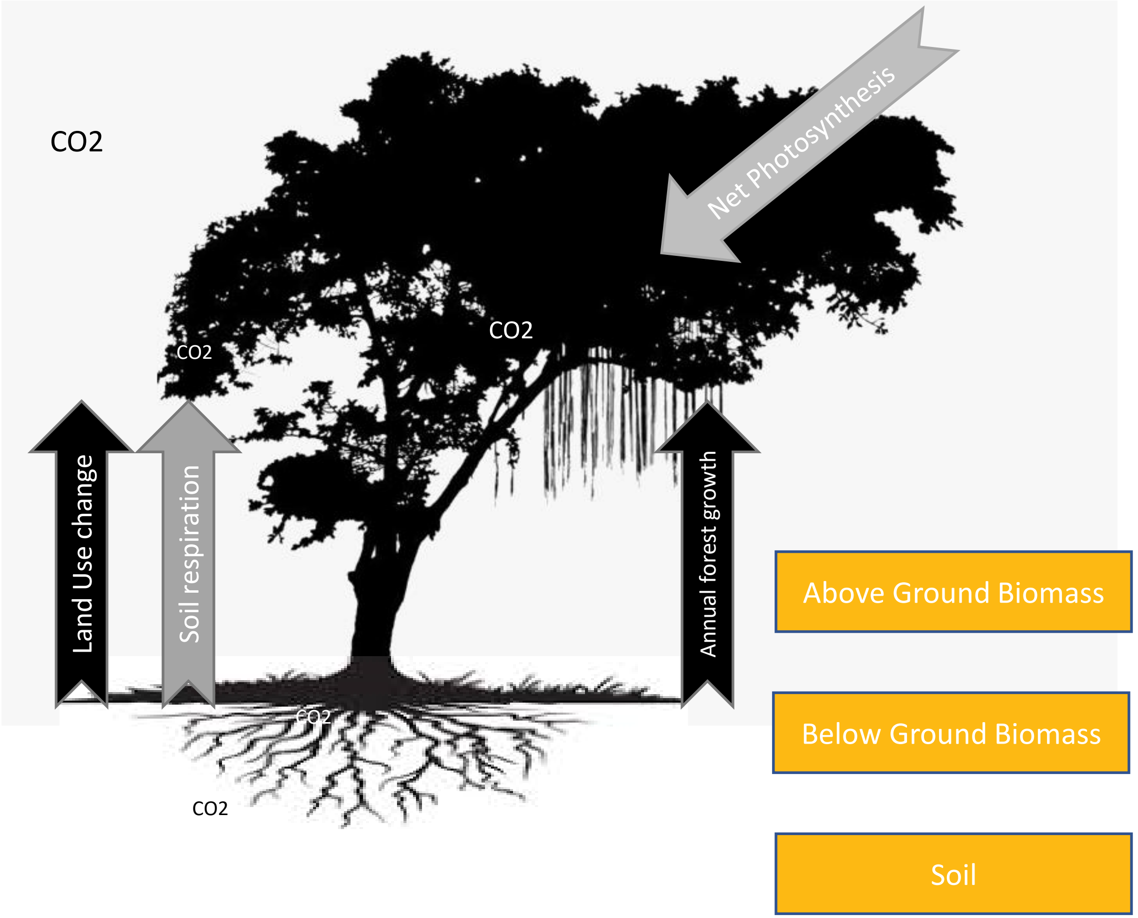
Cobalt is currently produced in the Democratic Republic of Congo (DRC) (75% of global production). Russia, Australia, Philippines Cuba, Madagascar Papua New Guinea, and Canada are also producers.



Nickel is currently produced in, Indonesia (50% of the global production). Philippines, Russia, New Caledonia, Australia, China, Brazil, US and Canada are also producers.

Carbon Sink Change – what to measure

Calculating carbon changes as a result of mining means understanding changes in land use, and also the different ways this impacts the carbon cycle as shown below.



This study measured:

Total ecosystem carbon stock (tonnes/hectare)
=
above ground biomass, below ground biomass, soil

Carbon emissions, due to land-use change
=
net photosynthesis to create biomass – i.e. the rate of biomass acquisition changes over time

Carbon sequestration
=
Soil respiration & decomposition (tonnes of carbon/per hectare/year)

Overview of main results

The carbon model is used to provide four main results relating to cobalt and nickel;

- The production of theses materials negatively changes forest/woodland carbon sinks negatively
- The increase in mine growth decreases carbon stock capacity overtime.
- Carbon flow capacity decreases and emissions increase overtime as mines grow.
- Carbon emissions for 5 mine sites have been compared to country REDD+ emissions. On average, these are the equivalent of 0.02% of DRC emissions and 6.5% of Indonesian emissions. Therefore, the impact as a proportion of country emissions is significant for Indonesia compared to DRC.

Differences between the two countries in terms of impact relate to relative carbon stocks due to different forest species mapped.

<u>CO_2e stock reduction:</u>

~39.5 kg per m^2 of mine developed

~3.6 kg per kg of cobalt produced

<u>CO_2e sequestration loss:</u>

~102 g/m^2

~9.4 g per kg of cobalt produced

<u>CO_2eq stock reduction:</u>

~168.25 kg per m^2 of mine developed

~6.96-9.39 kg per kg of nickel produced

<u>CO_2eq sequestration loss:</u>

~117 g/m^2

~4.8 - 6.5 g per kg of nickel produced

BENCHMARK

Cobalt Katanga Region, DRC Carbon Model

www.benchmarkminerals.com | info@benchmarkminerals.com

HQ: London, UK

Offices: Beijing, Edinburgh, Fort Lauderdale, Melbourne, New Delhi, Porto, San Francisco, Tokyo

Cobalt – Carbon model overview

This study focuses on the country and region with the most productive cobalt industrial mines. This is a desk-based study, utilizing Geographical Information System (GIS) analysis to measure the land-use change within contracted mining. The study was iterative in approach, however there were five main stages to the process;

1. Used Benchmark Intelligence data, to identify the Katanga region in the Democratic Republic Congo (DRC) as the biggest producer of cobalt. Selected five of the largest mines in this region as case study mines (csm) all within the Central Zambezian Miombo Woodland region.
2. Mapped the csm using a combination of Landsat & Sentinel 2 [4], the size & extent of each csm was determined by mining licensing maps. Habitat types are defined by the Land Cover Classification (LCCS). To track land-use change over time, three time points are mapped; 2008, 2014, 2022. The area (ha) of all the csm is the "pre-mine" time-point. It is assumed that this is undisturbed miombo woodland.
3. Sourced biomass data from peer reviewed literature for Miombo Woodland.
4. Selected appropriate biomass equations for habitat type and data availability to create biomass estimates.
5. Modelled carbon stock and carbon flow in the Katanga region and carbon flows due to land-use change observed in the study area.
6. To calculate the amount of carbon produced per unit of cobalt the ore grade and ore volume estimates for cobalt mines in the DRC were taken from the TMC Benchmark Life Cycle Assessment (LCA).

Image sourced D Johnson from Hollingsworth, L.T., D. Johnson, G. Sikaundi, S. Siame. 2015. Fire management assessment of Eastern Province, Zambia. Washington, D.C.: USDA Forest Service, International Programs

1. Cobalt – case study mine selection

The Democratic Republic of Congo (DRC) is the biggest producer of cobalt globally[5]. Located in central Africa with only 40km coastline on to the Atlantic Ocean it is essentially landlocked as the largest sub-Saharan African country it has a land area of ~2.345 km2[6]. Most cobalt reserves are in the south of the DRC in the Katanga region[7]. Industrial mines are interspersed with artisanal mines (see Figure 1).

The five case study mines (csm) are all within the Katanga region and are all within the Central Zambezian Miombo woodland ecoregion which is one or two major ecoregions in the DRC[8]. The Congo basin to the north consists of tropical forests[9] ,(see Figure 2).

In the DRC, Miombo woodland covers an estimated 286,000 km^2, more than 70% of the Miombo woodland in the DRC are in Katanga region [10].

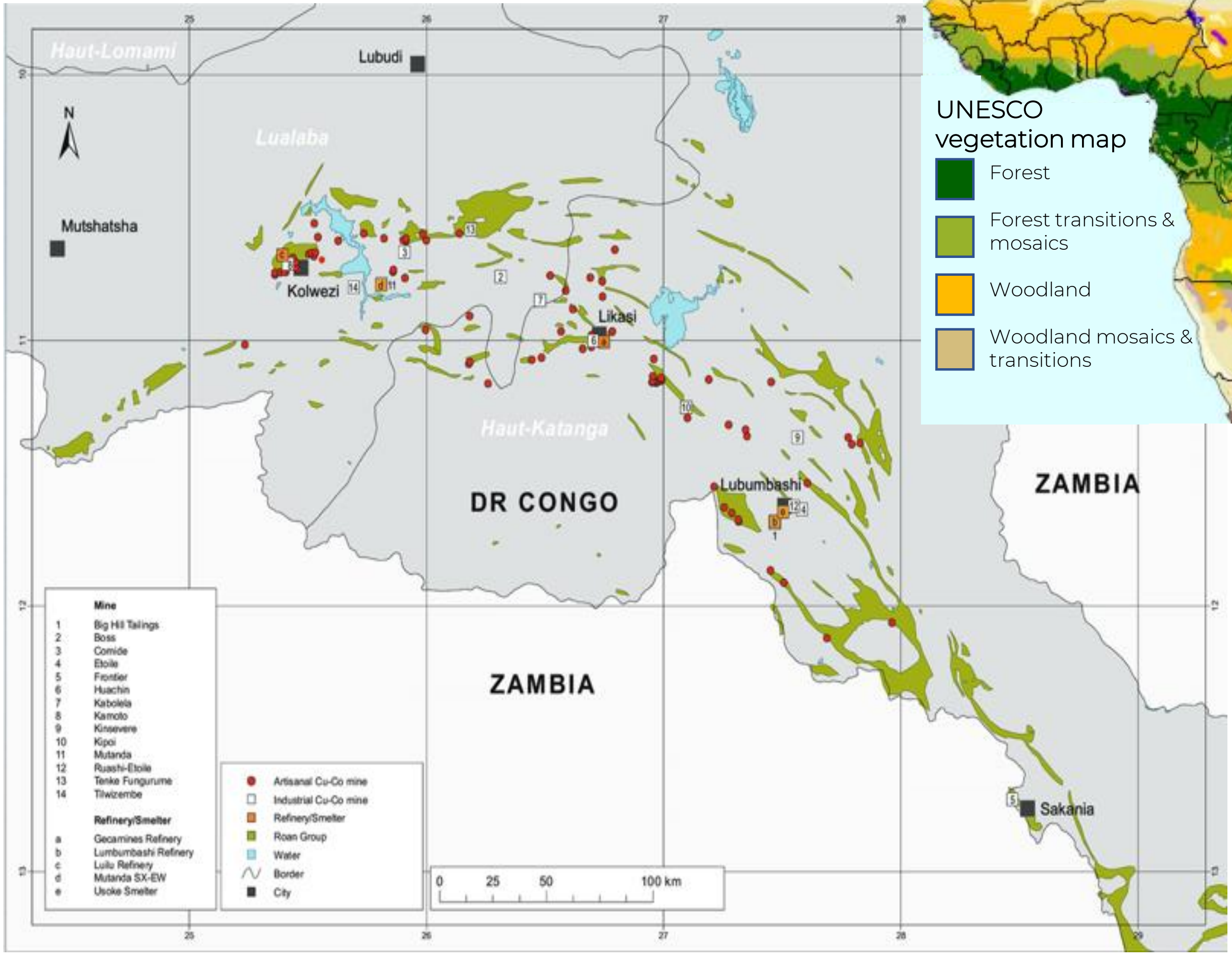


Figure 1 : map sourced from: Al Barazi et.al, 2017 [7] p.6 showing mines in Katanga region, DRC

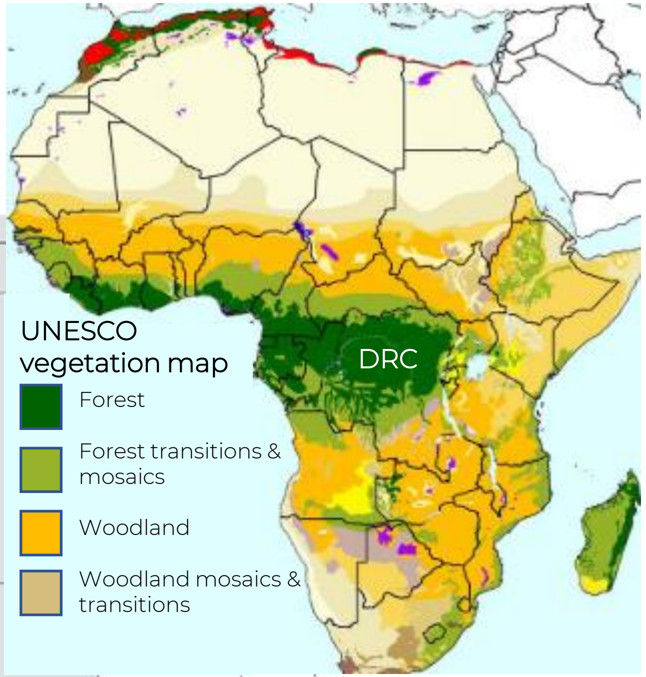


Figure 2: map sourced from Bouvet et al. 2018 [9], p 158 showing the main habitat types in the DRC – Woodland in this area is the Central Zambezian Miombo Woodland

2. Cobalt – Habitat composition

Miombo woodlands are defined both by their tree diversity and by their structure of a grassy herbaceous understorey with an often-sparse tree-canopy[11,12]. This ecosystem has been managed for ~55,000 years by frequent dry season fires, subsistence harvesting and cultivation[13]. Recently however, there has been increase in human activity including farming activity [14].

The Miombo Woodland, lends itself to a wide variation in natural cover[11] (see Figure 3). To understand the variation in habitat and the change over time, the Land Cover Classification system (LCC) [15] was used to map the different habitat types. In the case study mine (csm) areas it is assumed that the predominant habitat pre-mines is open broadleaved deciduous trees (LCC 2TOM28) and Woodland with sparse shrubs (LCC TVM28). Satellite imagery (see Figure 4) highlights the complexity of the study area[16]. Not all the habitats shown here are prevalent in the csm; however, the key components (woodland, shrubland and grassland) are.

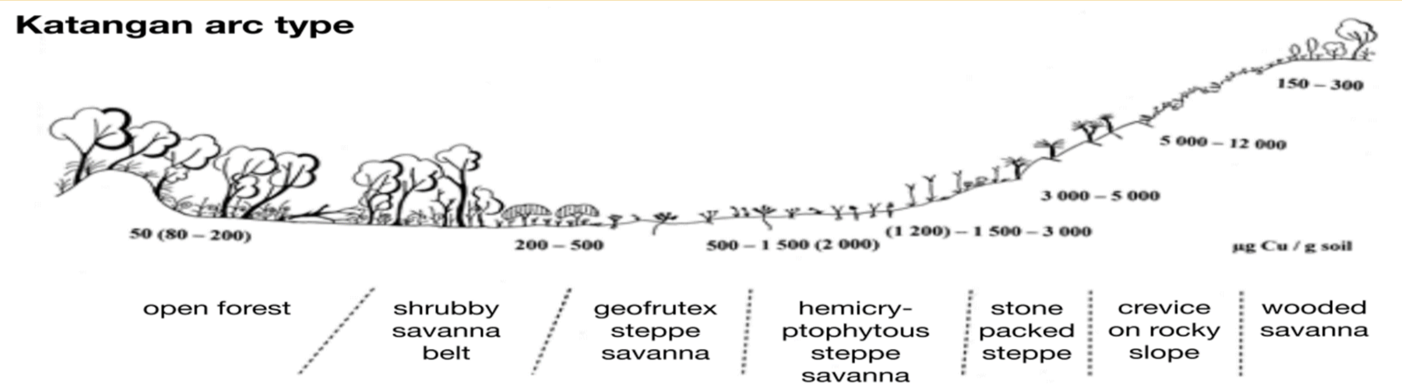


Figure 3: Malaisse et al. 2016 [11] p.21 field drawing of structure of the Miombo woodland in the Katanga region

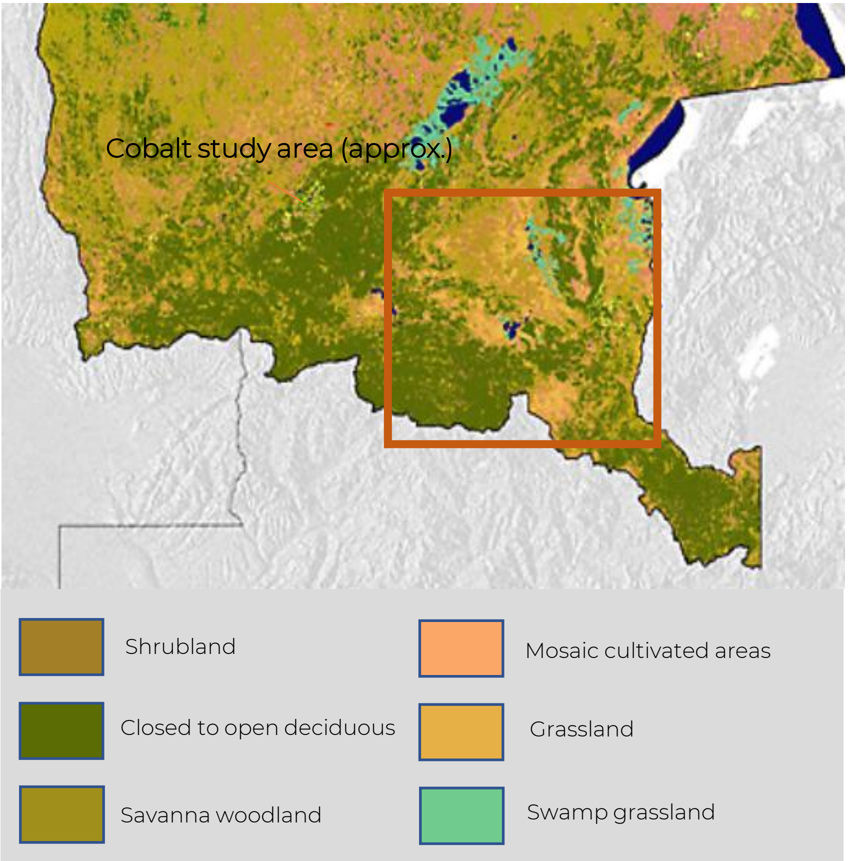


Figure 4: satellite image adapted from: Verhegghen et al 2012 [16], p.5068 shows the complex habitat coverage

3. Cobalt – Habitat species data

There has been only limited research in to the Miombo Woodland and adjacent Mopane biome, the majority of this has been focused on southern Tanzania, Mozambique, Malawi, Zimbabwe and Zambia [16-24]. In sub-Saharan Africa there are five different miombo ecoregions which extends over seven countries [17](see Figure 5). Broadly defined as dry or wet miombo [13] the case study mines area within the wet miombo (received >1000mm per annum). There is a lot of variation throughout the region which is influenced by several factors including differences in soil, climate and biogeography [16].

The miombo and adjacent mopane woodlands are dominated by Leguminosae which includes over 19,500 species [17]. The key tree species in the Miombo are from the *Brachystegia, Julbernardia* and/or Isoberlinia genrera which are all within the *Fabaceae* family *and Detaroideae* subfamily which generally hold the most biomass, forming a mostly open woodland canopy [24-26] Plant diversity in the Miombo is high with an estimated 8,500, tree, shrub, grass and herb species [12]. Miombo woodlands contain seven major soil groups [27], and most of the organic matter (SOM) is concentrated in the top 30cm of soil [19], (see Appendix).

The main species inventory used in this study is from the Mikembo Natural Reserve in the Katanga region[28]. However, due to availability, biomass data is from a peer reviewed fieldwork research, from different countries outside of DRC (see Table 1). The biomass data for the herbaceous/grass understorey is taken from Mozambique [19].

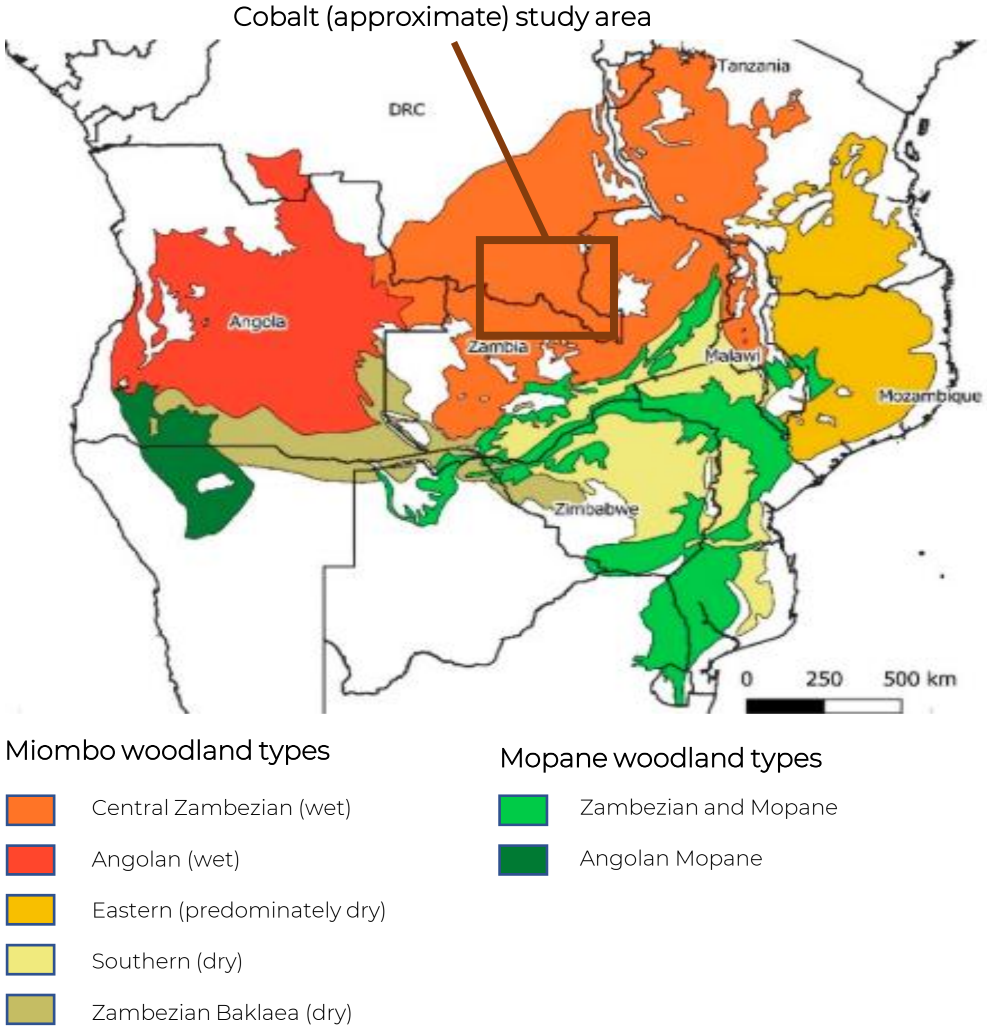


Figure 5: map adapted from: Maquia et. al. 2019 [17], p3 & Pelletier et. al. 2018 [13], p2 to show the different miombo ecosystem types

4. Cobalt - Biomass

Biomass has been calculated based on the predominant miombo woodland, with herbaceous grassy understorey also accounted for. Table 1 details the key data points for biomass and their sources.

To calculate carbon stock, it is necessary to use and develop equations to calculate the different components that make up Total Living Biomass (TLB) which include Above Ground Biomass (AGB) and Below Ground Biomass (BGB) and soil. Allometric equations are commonly used to estimate aboveground biomass (AGB) in forests. Chave et al. (2015)[29] allometric equation for moist forest (at a 0.25 ha scale), achieves a 90% accuracy [30,31].

$$\mathbf{AGB} = \boldsymbol{\rho\ x\ esp\ \{-0.667 + 1.784\ x\ ln\ (dbh) + 0.207\ x\ [ln\ (dbh)]^2\ - 0.0281\ x\ [ln(dbh)]^3\}}$$

The BGB is calculated from the equation from Cairns et al. (1997)[32] to estimate root biomass calculated from the AGB.

$$\mathbf{BGB} = \boldsymbol{exp\ \{-1.057 + 0.8836\ x\ 1n\ (AGB)\}}$$

Soil was taken as ratio based on seven different soil types (see Appendix).

	Miombo Woodland		
Unit	Source	Location	Data point
(ρ) Average bone dry -wood Density	Global Wood Density Database	Generic database	0.61715
(dbh) Average Diameter Breast Height (cm)	Kapinga et al. (2018) Chiteculo, et al. (2018) Chamshama Augustine et al. (2008)	Mwekera National Forest Reserve Zambia Huambo Province, Angola. Urumwa Forest Reserve, Tanzania	29.469 cm
Grassland/hebraous Biomass	Mercader et. al, (2009)	Niassa National Reserve (NNR) in northern Mozambique	4.5 mg(ha)
Average tC/ha in Soil	Batjes, N. H. (2008)	(SOTER) database for Central Africa	61.68 tC/ha
Relative density (average) (per key tree species)	Ilunga Muledi et. al.(2017)	Mikembo Forest Reserve, Upper Katanga DRC	See Appendix 2
Average (n) of trees (per ha	Ilunga Muledi et. al. (2017)	Mikembo Forest Reserve, Upper Katanga DRC	459.7

Table 1: Key data points and sources for cobalt study area

5. Cobalt – Carbon Models

Carbon stock is the calculation of the Total Living Biomass per hectare of measured case study mine (csm) area. This is multiplied by the proportion of carbon in bone-dry wood density (per hectare per year). Table 2 shows tree coverage ratio per miombo woodland. The average (n) of trees per hectare is variable dependent and there is a big variation per habitat type. Cropland is the csm traditionally include natural tree type and some understory.

Carbon flow is the estimation of the intake of carbon through respiration annually, using the annual forest growth.

LCC CODE	Description	Tree Coverage (Tc)	Number of Trees (Fct)	Understorey
HR47	Rainfed Herbaceous crop, Small Fields	3%	16	30%
2SPJ67	Open General Shrubs With closed to open Herbaceous and sparse Trees	10%	53	60%
HR247	Rainfed Herbaceous crop, Isolated Small Fields	5%	27	30%
2TVM28	Woodland with sparse shrubs	100%	531	40%
4SPJF6	Open general medium to high shrubs with closed to open herbaceous on temporarily flooded land - fresh water	10%	53	100%
HR2Y	Post Flooding Herbaceous Crop, Isolated Small Fields	5%	27	10%
2H(CP)8	Closed To Very Open Herbaceous with Sparse Shrubs	20%	106	70%
2TOM28	Open broadleaved deciduous trees with open shrubs	90%	478	90%
TL47PL	Forest Plantation - Large Fields	5%	27	0%
Deforested area	Deforested area	0%	0	0%
Herbaceous	Herbaceous	1%	5	10%
2SJ67	Herbaceous with sparse trees	10%	53	40%

Table 2: Relevant Land Cover Classification (LCC) codes and observed prevalence

Carbon stock

$$\text{Carbon stock}\left(\frac{\frac{tC}{ha}}{yr}\right) = TLB\left(\frac{\frac{t}{ha}}{yr}\right) \times c + SCS\left(\frac{\frac{tC}{ha}}{yr}\right)$$

tC/ha/yr = carbon stock tonnes per hectare (tC/ ha / yr)

TLB = total living biomass tonnes per hectare (t / ha / yr)

c = proportion of carbon in bone-dry wood (unitless or kg / kg) x (i.e. IPPC data 0.5)

SCS = Soil carbon stock tonnes of carbon per hectare (tC / ha / yr)

Carbon flow (per year)

$$CO_2 \text{ sequestrated per annum}\left(\frac{\frac{kgCO2}{ha}}{yr}\right) = a\left(\frac{\frac{m^3}{ha}}{yr}\right) \times b\left(\frac{kg}{m^3}\right) \times c\left(\frac{kg}{kg}\right) \times d$$

a = annual forest growth (m^3 / ha / yr)

b = bone-dry wood density (kg / m^3)

c = proportion of carbon in bone-dry wood (IPPC data: 0.57)

d = ratio of molecular mass of CO_2 to C (44/12)

BENCHMARK

Cobalt Key Findings

HQ: London, UK

Offices: Beijing, Edinburgh, Fort Lauderdale, Melbourne, New Delhi, Porto, San Francisco, Tokyo

1. The production of Cobalt in DRC changes the carbon sink negatively

Impact on carbon stock is a reduction of 3.61 kg CO_2 eq/kg of cobalt

Impact on carbon sequestration is reduction of 9.32 g CO_2 eq/kg of cobalt

This change to the carbon sink in the Katanga region due to cobalt mining at area (per square metre) is estimated by calculating the following four factors:

1. The **estimated** cobalt produced per annum per average mine – **15,750 tonnes** (ore grade – 0.35% & 90% global recovery)

2. The **average area** of vegetation change per case study mine over 14 years assessed via GIS:

   Total area change: 20,159,034 m2
   Yearly: **1,439,931 m2**

3. The **land use intensity:**

   0.091 m2 / kg of Cobalt

4. The carbon impact on land-use change (i.e. deforestation) – **formulas on pages 12 & 13**

   Carbon Stock – **39.5 kgCO2eq / m2**
   Carbon Flow – **102 grams CO2eq / m2**

1. LCA ore grades and Benchmark expert opinion on global recovery.
2. GIS data collection.
3. Calculated.
4. Calculated.

Mining impact on Carbon Stocks and Flows in Katanga, DRC

1,439,931	average annual land change per mine (m^2)
56,855	carbon stock loss, average per mine (tCO_2eq/pa)
146.7	Carbon sequestration loss per mine (tCO_2eq/pa)
39.5	loss of carbon stock of mine area developed (kgCO2eq/m2)
102	loss of carbon sequestration of mine area developed (gCO2eq/m2)

On average, 1,439,931 m^2 of vegetation land is transformed in mining area per year (mine plus infrastructure).

Based on estimated forest loss, an average cobalt from DRC mine causes the loss of 56,855 tonnes of CO_2eq stock per year.

Based on estimated forest loss, an average DRC cobalt mine causes the loss of 146.7 tonnes of CO_2eq sequestration activity per year.

For every kilogram of cobalt produced, there is an average, carbon stock loss of 39.5 CO_2eq per m^2 or 10.8 kgC/m2

For every kilogram of cobalt produced, there is an average, carbon sequestration loss of 102 gCO2 eq / m^2

Cobalt impact on Carbon: Katanga, DRC

1:317	ratio of cobalt to ore extracted*
15,750	average mine annual cobalt production (tonnes)
11	kg of cobalt per m^2 per mine (land intensity)
1 : 3.6	Cobalt/ CO_2eq Stock ratio
1 : 0.009	Cobalt/ CO_2eq Sequestration ratio

*On average, for every 317 tonnes of ore extracted, 1 tonne of cobalt is produced. *Excludes stripping ratio (overburden) Ore grade 0.35%*

An average mine has a production yield of 15,750 tonnes of cobalt per year, assuming 90% global recovery rate.

For every square meter of mine area (i.e. mine plus infrastructure), on average an additional 11 kg of cobalt are produced (0.091 m^2 / kg of cobalt).

For every kilogram of cobalt produced, there is an average carbon stock loss of 3.6 kgCO2eq/kgCo or 0.98 kgC/kgCo

For every kilogram of cobalt produced, there is an average carbon sequestration loss of 9.3 gramsCO2/kgCo

2. As cobalt mines increase in size, in the Katanga region, there is a reduction of carbon stock

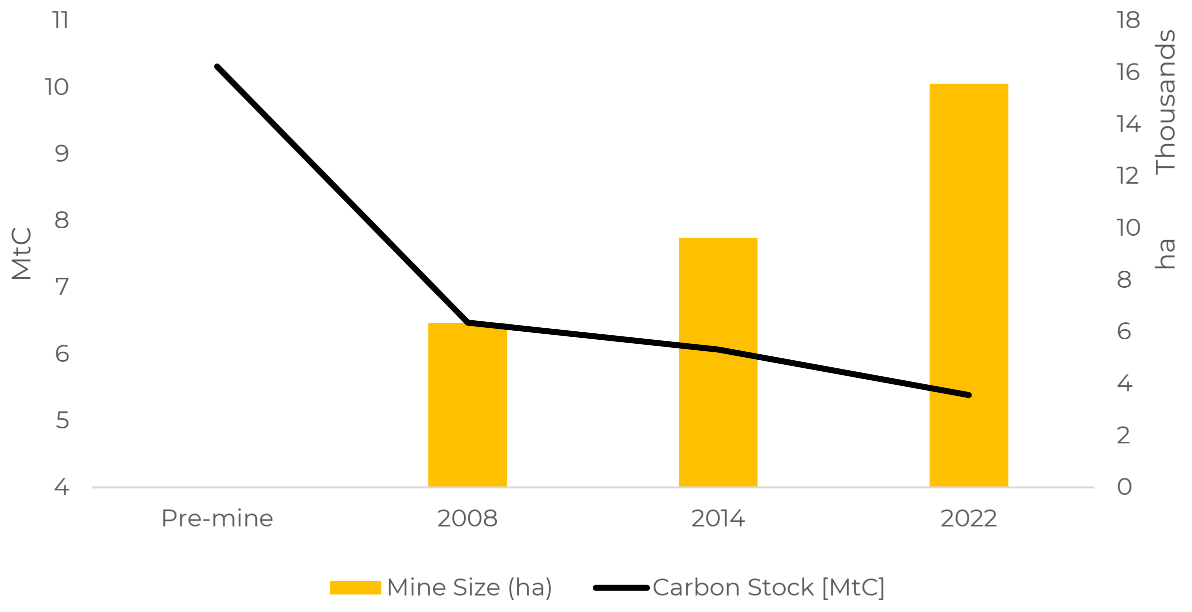


Figure 6: Katanga region carbon emissions compared to carbon flow

-1.1 MtC (4 $MtCO_2eq$)	Carbon stocks reduces from 6.5 MtC in 2008 to 5.4 MtC by 2022
-4.9 MtC (18 $MtCO_2$ eq	Carbon stocks reduces from 10.3 MtC **pre-mine** to 5.4 MtC by 2022

Cobalt mine growth in the Katanga region has led to a reduction of carbon stock (shown in mega tonnes carbon (MtC)) in the Central Zambezian Miombo Woodlands. The size of the mines and corresponding carbon stock changes are shown at three intervals over the 14 years assessed (2008-2022).

Carbon stocks reduce from 6.5 MtC (24 $MtCO_2eq$) in 2008 to 5.4 MtC (20 $MtCO_2eq$) by 2022.

Note, the methodology means that habitat and site changes across 2008-2014 exclude changes that pre-date this study period. To account for this, an estimation of habitat "pre-mine" has been made, to allow for a comparator of change in carbon stock from this pre-mine state to the years 2008, 2014 & 2022. A date allocation of this "pre-mine" state is not given and will in any case vary by mine site.

Carbon stocks pre-mine in this study area are estimated at 10.3 MtC (37.8 $MtCO_2eq$).

3. As cobalt mines increase in size, in the Katanga Region, carbon flow capacity decreases and emissions increase

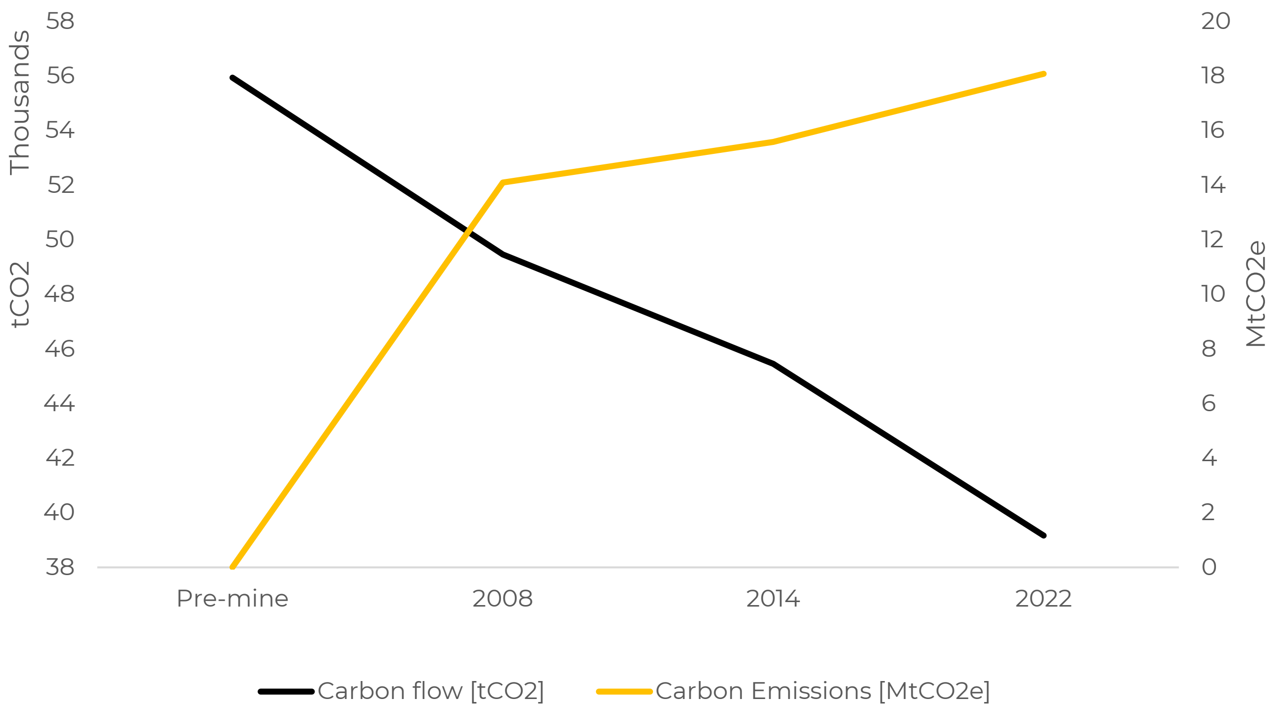


Figure 7: Carbon emissions compared to carbon flow as nickel mines grow in the Katanga region, the DRC.

As expected, as the cobalt mines in Katanga region grow and the forest is deforested and/or degraded the carbon flow (tC) decreases and the carbon emissions increase significantly.

It has been assumed that pre-mine the mapped areas were forest, allowing an estimation of pre-mine carbon stocks and carbon flow. Note pre-mine is not defined by time and in any case, this will vary by mine site.

As carbon flow (i.e. capture of carbon) reduces over time, so carbon emissions from the mine sites increase from 0 to 4.9 MtC (18 $MtCO_2$ eq).

4. Cobalt emissions - Comparison to REDD+ for the DRC

CO_2eq Emissions/year (REDD+, DRC		CO2eq stock change/ year (5-Mines)	(%) of DRC emissions (Case study mines)	(%) of DRC emissions (Whole of)
Year	Mt/year	Mt/year		
2008	483.740	-0.184	0.038%	2691.0%
2009	483.740	-0.184	0.038%	2691.0%
2010	830.530	-0.184	0.022%	1567.3%
2011	830.530	-0.184	0.022%	1567.3%
2012	830.530	-0.184	0.022%	1567.3%
2013	830.530	-0.184	0.022%	1567.3%
2014	830.530	-0.199	0.024%	1697.6%
2015	979.151	-0.199	0.020%	1439.9%
2016	1028.693	-0.199	0.019%	1370.6%
2017	1078.235	-0.199	0.018%	1307.6%
2018	1127.777	-0.199	0.018%	1250.1%
2019	1177.318	-0.199	0.017%	1197.5%
2020	1232.838	-0.199	0.016%	1143.6%
2021	1290.976	-0.199	0.015%	1092.1%
2022	1351.856	-0.199	0.015%	1042.9%

Figure 8: Carbon changes in the case study areas (csm) compared to REDD+ result for the DRC

Figure 8 shows the carbon changes due to cobalt extraction in the case study areas (csm) compared to REDD+ result for the DRC.

CO2eq Stock change/year (5-Mines)
the converted carbon stock loss result to show per year, compared to REDD+ figures in the DRC.

(%) of DRC emissions (Case Study mines)
Compares the carbon stock loss (%) per year to the REDD+ results [33]. Results are then converted into CO_2eq.

$tCO_2eq/ha/yr/$ x REDD+

(%) of DRC emission (Whole DRC)
This is multiplied by the difference in total area. This shows how much more intense emissions would be if the all the areas that REDD+ looked at are were also mined areas.

However, the study area is miombo forest and disturbed forests **only.** So, if the same intensity of mines per land were developed for the forests that REDD+ includes, then the emissions would be much greater. This is because there would be a greater percentage of Total Living Biomass (TLB) per hectare.

BENCHMARK

Nickel Sulawesi, Indonesia Carbon Model

www.benchmarkminerals.com | info@benchmarkminerals.com

HQ: London, UK

Offices: Beijing, Edinburgh, Fort Lauderdale, Melbourne, New Delhi, Porto, San Francisco, Tokyo

Nickel – Carbon model overview

This study focuses on the country and region with the most productive nickel industrial mines. This is a desk-based study, utilizing Geographical Information System (GIS) analysis to measure the land-use change within contracted mining areas as specified by the mining licences. The study was iterative in approach, however there were five main stages to the process;

1. Used Benchmark Intelligence data, to identify Sulawesi in Indonesia as the biggest producer of nickel. Selected five of the largest mines in this region as case study mines (csm).
2. Mapped the csm using a combination of Landsat & Sentinel 2 GIS [34], the size & extent of each csm was determined by mining licensing maps where appropriate. Habitat types are defined by two natural ecosystems; rainforest mangrove and by various agricultural practices. Three time points are estimated; 2008, 2014, 2022 to track land-use change over time. The area (ha) of all the csm is the "pre-mine" time-point. It is assumed that this is undisturbed natural habitats; rainforest and mangroves.
3. Sourced biomass data from peer reviewed literature for Sulawesi woodland.
4. Selected appropriate biomass equations for habitat type and data availability to create biomass estimates.
5. Modelled carbon stock and carbon flow in the Sulawesi region and carbon flows due to land-use change observed in the study area.
6. To calculate the amount of carbon produced per unit of nickel, ore grade and ore volume estimates for laterite nickel mines in Indonesia were taken from the TMC Benchmark Life Cycle Assessment (LCA).

Image sourced from: Makassar.Tribunnews.com

1. Nickel – case study mine selection

Indonesia is one of the biggest producers of nickel globally[35]. Located between the Indian Ocean and Pacific Ocean in South-East Asia, Indonesia is the largest archipelagic country in the world, with a land area of 1.91 million km^2, spread across 17,504 islands[36]. The five main islands include Sulawesi, which is the largest island in the Wallacean island chain and is ~180,681 km^2 [37,38] (see Figure 9). Sulawesi is the biggest region for laterite nickel mines as it includes some of the largest areas of ultramafic bedrock in the world[38]. These are mainly large industrial mines with concessions allocated adjacent to each other [39,40].

The five case study mines (csm) of nickel laterite ores are all within the Southeast arm of Sulawesi. This is where most of the nickel mining concessions are allocated on the island (see Figure 10).

Sulawesi is mainly tropical moist lowland rainforest and is considered a globally significant ecoregion. [41,It currently has approximately 95,000 km2 of forest area[42] and has fourteen different forest ecosystems. This wide diversity of forests is part of the reason for the islands high rate of endemism and biodiversity [43].

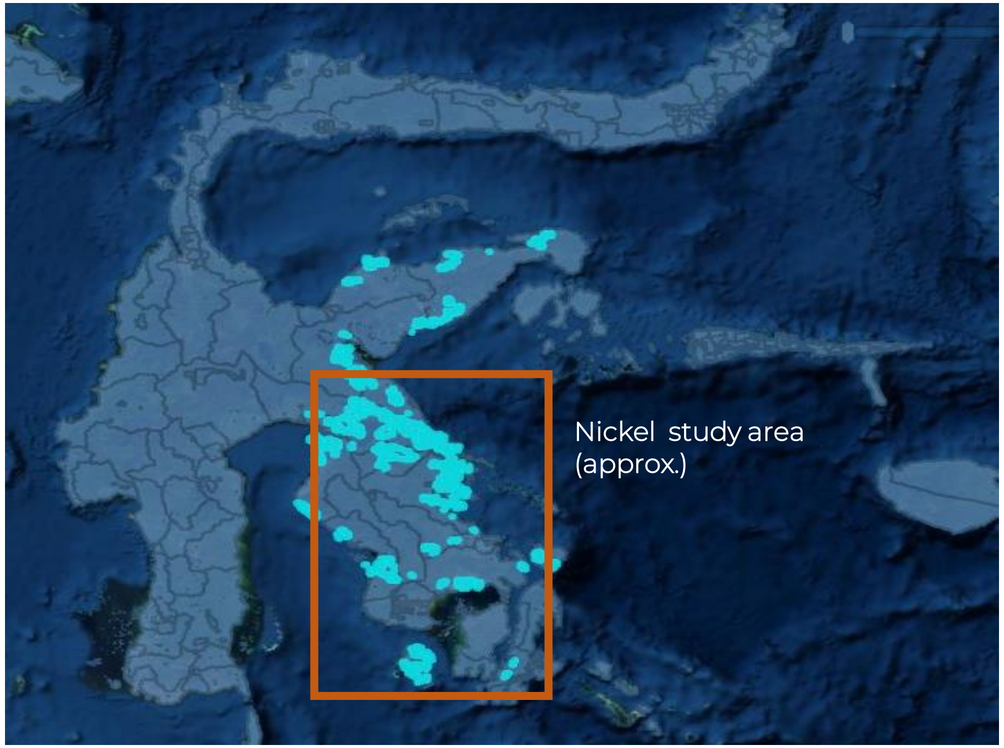


Figure 9: Map; BP-REDD+, (2015) [38] *p23*
Figure 10 Map of Nickel Contracts in Sulawesi highlighted in blue ArcGIS Pro (2022)

2. Nickel – Habitat composition

Across Indonesia the main forest types are Evergreen Needleleaf Forest (ENF), Evergreen Broadleaved Forest (EBF) and Remnant Forest (IFL), in the southeast arm of Sulawesi this is mainly EBF, and IFL [44] (see Figure 11). Sulawesi forests are globally important with high degrees of biodiversity and endemism due to a complex geology[45]. However, Sulawesi like much of Indonesia has experienced high rates of deforestation and degradation due to several factors including mining operations and plantations [43,46]. This has changed the forest composition and structure on the island. Pitopang (2012)[46] profile diagrams (Figure 12) show the structure of undisturbed and moderately disturbed rainforest in Lore Lindu National Park. Undisturbed forests contain larger, taller trees with a dense understorey. However, as the forest is degraded the taller species are removed and the understorey becomes less dense and less uniform[46]. With case study mine area (csm), forest has been removed and replaced with plantations such as oil palm.

Coastal mangrove forests were prominent around most Sulawesi, but have been in decline because of mining, aquaculture and coastal tourism [47,48]. They are among the most carbon-rich forests in the tropics [49], and they have also been modelled. Two csm contained mangrove forest before the mining operations began, however, this habitat was lost when the mining activity commenced.

Southeast Sulawesi Vegetation Cover

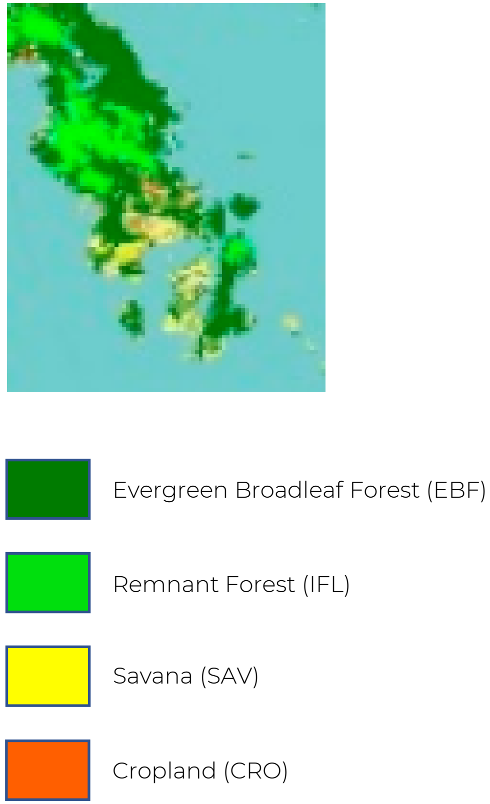


Figure 11: map adapted from Arjasakusuma et al, 2018 [44], p 3 – to show extent of main forest type in the case study area

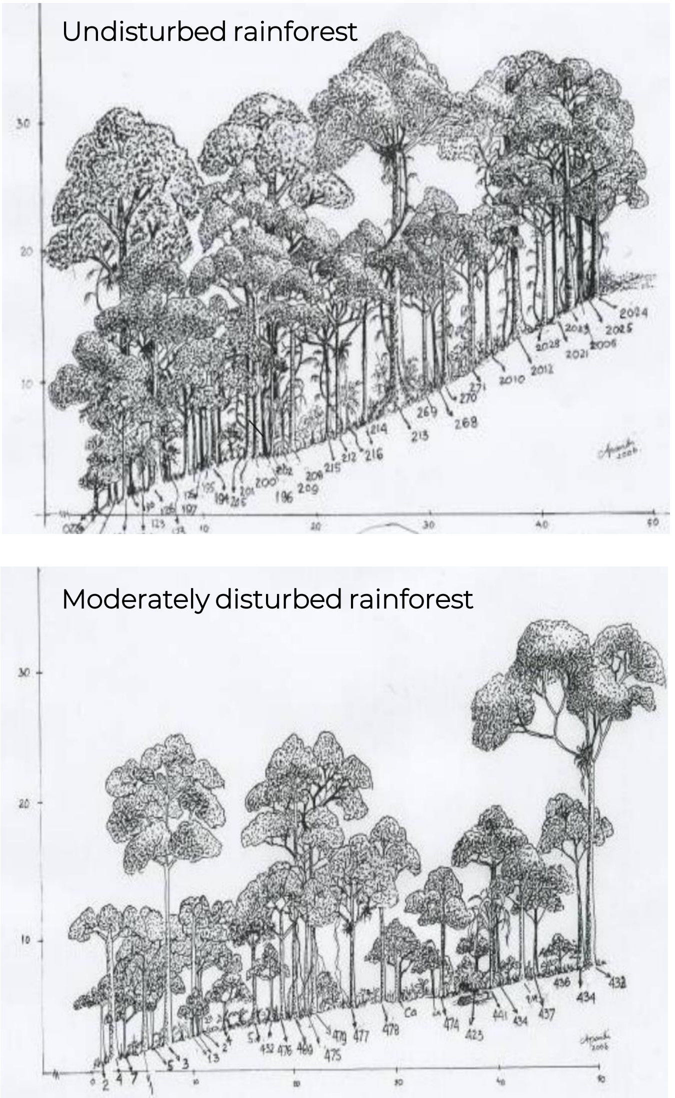


Figure 12: profile diagrams from Pitopang, (2012) [46], p.183 to show change in forest structure

3. Nickel – Biomass data

Despite being a conservation hotspot [50]. plant collection rates in Sulawesi have been some of the lowest in Indonesia [51]. The distribution of known taxa, and the extent of diversity of taxa is poorly understood [52,53]. Primary dryland and secondary forest in studies in Sulawesi, are often classified as a single forest cover differentiated by elevation range[43]. Figure 13 shows the variation in elevation change corresponding to soil type [45].The csm are mostly within lowland areas. Most biomass studies in Sulawesi have been conducted in a UNESCO Biosphere Reserve; Lore Lindu National Park, which at its highest point is within upper montane (~>1800 m), however it does range down to submontane (~<1000 m)[54-56].

Although Lore Lindu is at a higher altitude than most of csm, it is it still the most appropriate data to use. Especially the data points used are from submontane level. There is a higher family diversity at submontane level compared to higher altitudes. Forest cover is rich in trees from the *Fagaceae, Myrtaceae, Icacinaceae*, and *Escalloniaceae*, families[52]. Culmsee et al. 2010[52] found that the presence of Fagaceae provided a higher Above Ground Biomass (AGB) to tree stands. Carbon estimates from soil have been calculated as a mean from nine soil types[57] (see Appendix).

Biomass data for *Rhizophora stylosa* mangrove forest[49] was used to estimate loss of carbon stock pre-mine.

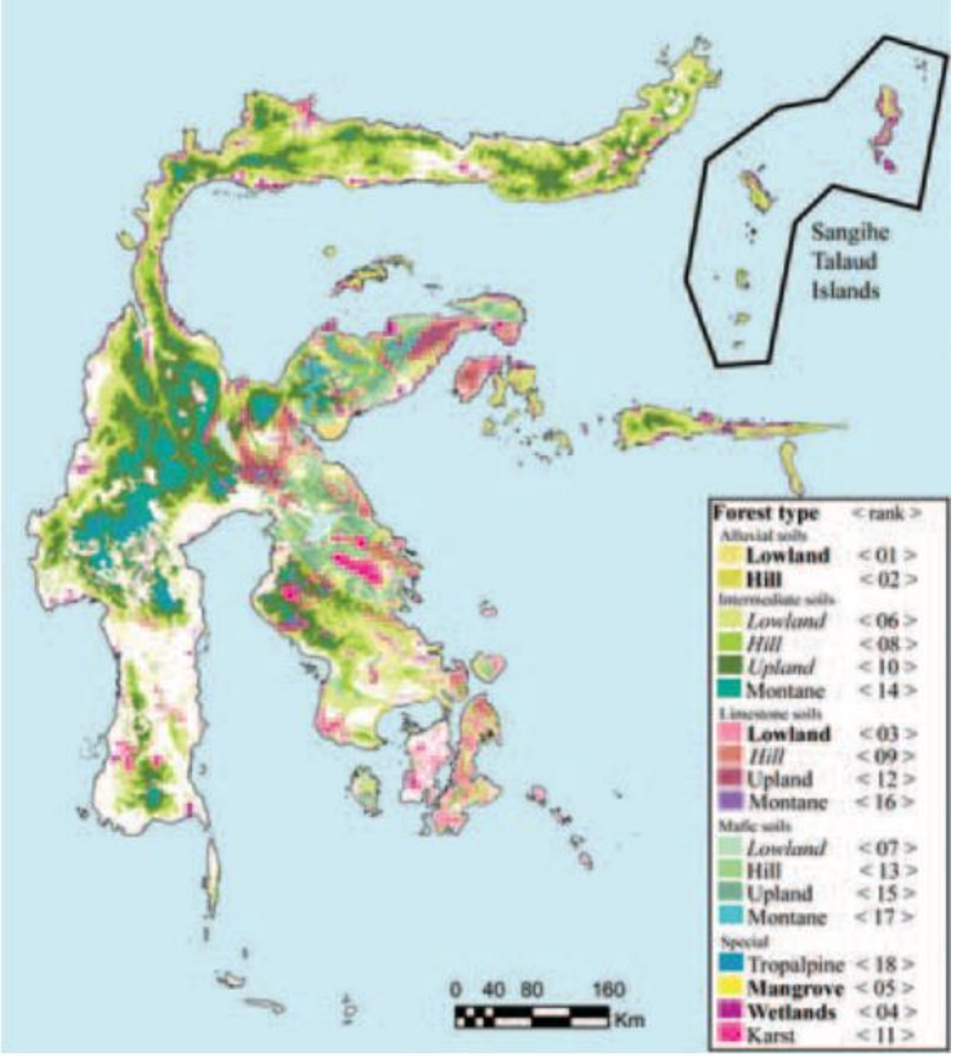


Figure 13: the map of Sulawesi Cannon, (2007) [45] *, p.752 to shows the major forest types categorised by topography, soil and type.*

4. Nickel - Equations

Biomass has been calculated based on the two predominant habitat types rainforest and mangroves. The same equations have been used and Table 3 details data sources.

To calculate carbon stock, it is necessary to use and develop equations to calculate the different components that make up Total Living Biomass (TLB) which include Above Ground Biomass (AGB) and Below Ground Biomass (BGB) and soil. Allometric equations are commonly used to estimate aboveground biomass (AGB) in forests. Chave et al. (2015)[29].

$$\text{AGB} = \rho\ x\ esp\ \{-0.667 + 1.784\ x\ ln\ (dbh) + 0.207\ x\ [ln\ (dbh)]^2\ - 0.0281\ x\ [ln(dbh)]^3\}$$

The BGB is calculated from the equation from Cairns et al. 199 [32] to estimate root biomass calculated from the AGB.

$$\text{BGB} = exp\ \{-1.057 + 0.8836\ x\ 1n\ (AGB)\}$$

Soil was taken as ratio of nine different soil types (see Appendix).

	Rainforest			Mangrove		
Unit	Source	Location	Result	Source	Location	Result
(ρ) Average bone dry - wood Density	Global Wood Density Database	-	0.549	Global Wood Density Database	-	0.549
(dbh) Average Diameter Breast Height	Dietz et al. (2006)	Lore Lindu National Park, Sulawesi	31.7	Analuddin et.al (2020)	Rawa Aopa Watumo ha National Park, Sulawesi	10.3
Average tC/ha in Soil	Shofiyati et al. (2010)	Indonesian wide database	109.6 tC/ha	Shofiyati et al. (2010)	Indonesia n wide database	109.6 tC/ha
Tree density (average) (per key species)	Hertel et. al (2006)	Lore Lindu National Park, Sulawesi	(see Appen-dix)	Analuddin et.al (2020)	Rawa Aopa Watumo ha National Park, Sulawesi	(see Appendix)
Average (n) of trees (per ha)	Dietz et al (2009)	Lore Lindu National Park, Sulawesi	2511	Analuddin et.al (2020)	Rawa Aopa Watumo ha National Park, Sulawesi	3,500

Table 3: Key data points and sources for nickel study area

5. Nickel – Carbon Models

Carbon stock is the calculation of the Total Living Biomass per hectare of measured case study mine (csm) area. This is multiplied by the proportion of carbon in bone-dry wood density (per hectare per year).

Table 4 shows tree coverage ratio per habitat type (i.e. rainforest or mangrove forest). As expected, the average (n) of trees per hectare is variable dependent and there is a big variation per habitat type. Plantations have been accounted as having nominal natural tree cover. It should be noted that the carbon stock of plantation trees is not included in biomass calculations.

Carbon flow is the estimation of the intake of carbon through respiration annually, using the annual forest growth rate (for both rainforest, and mangrove).

Description	Tree Coverage ratio	Number of Trees (Fct)
Crops	0.01	25.11
Degragaded RF	0.5	1255.5
Rainforest	1	2511
Mangrove Forest	1	3500
Degraded Mangrove	0.5	1750
Herbaceous	0.01	25.11
Plantation	0.01	25.11

Table 4: Relevant habitat types and observed prevalence

Carbon stock

$$\text{Carbon stock}\left(\frac{\frac{tC}{ha}}{yr}\right) = TLB\left(\frac{\frac{t}{ha}}{yr}\right) \times c + SCS\left(\frac{\frac{tC}{ha}}{yr}\right)$$

tC/ha/yr = carbon stock tonnes per hectare (tC / ha / yr)

TLB = total living biomass tonnes per hectare (t / ha / yr)

c = proportion of carbon in bone-dry wood (unitless or kg / kg) x (i.e. IPPC data 0.5)

SCS = Soil carbon stock tonnes of carbon per hectare (tC / ha / yr)

Carbon Flow (per year)

$$CO_2\ \text{sequestrated per annum}\left(\frac{\frac{kgCO2}{ha}}{yr}\right) = a\left(\frac{\frac{m^3}{ha}}{yr}\right) \times b\left(\frac{kg}{m^3}\right) \times c\left(\frac{kg}{kg}\right) \times d$$

a = annual forest growth (m^3 / ha / yr)

b = bone-dry wood density (kg / m^3)

c = proportion of carbon in bone-dry wood (IPPC data: 0.57)

d = ratio of molecular mass of CO_2 to C

BENCHMARK

Nickel Key Findings

www.benchmarkminerals.com | info@benchmarkminerals.com

HQ: London, UK

Offices: Beijing, Edinburgh, Fort Lauderdale, Melbourne, New Delhi, Porto, San Francisco, Tokyo

1. The production of Nickel in Indonesia changes the carbon sink negatively

Units	Limonite - HPAL	Saprolite - RKEF
Carbon stock loss [kgCO2eq/kgNi]	9.4	7.0
Carbon sequestration loss [grams CO2/kgNi]	6.5	4.8

This change to the carbon sink in the Sulawesi from the production of nickel is estimated by calculating the following four factors:

1. LCA ore grades and Benchmark expert opinion on global recovery.
2. GIS data collection.
3. Calculated.
4. Calculated.

1. The estimated nickel produced per annum per mine:

Limonite – **47,250 tonnes** (ore grade – 1.35 % & 70 % global recovery)
Saprolite - **63,750 tonnes** (ore grade – 1.50 % & 85 % global recovery)

2. The average area of vegetation change per case study mine over 14 years assessed via GIS:

Total area change : 36,910,496 m^2
Yearly: **2,636,464 m2**

3. Land use intensity per operation process:

Limonite – **0.056 m2 / kg of Nickel**
Saprolite – **0.041 m2 / kg of Nickel**

4. The carbon impact on land-use change (i.e. deforestation) – formulas on pages 26 & 27

Carbon Stock – **168.25 kgCO2eq / m2**
Carbon Flow – **117 grams CO2 / m2**

Mining impact on Carbon Stocks and Flows in Sulawesi

2,636,464	average annual land change per mine (m^2)
443,598	carbon stock loss, average per mine (tCO_2eq/pa)
309	Carbon sequestration loss per mine (tCO_2eq/pa)
168.3	loss of carbon stock of mine area developed (kgCO2eq/m2)
117	loss of carbon sequestration of mine area developed (gCO2/m2)

On average, 2,636,464 m^2 of vegetation land is transformed in mining area per year (mine plus infrastructure).

Based on estimated forest loss, an average Indonesian nickel mine causes the loss of 443,498 tonnes of CO_2eq stock per year.

Based on estimated forest loss, an average Indonesian nickel mine causes the loss of 309 tonnes of CO_2eq sequestration activity per year.

For every kilogram of nickel produced, there is an average, carbon stock loss of 168.3 CO_2eq per m^2 or 45.85 kgC/m2

For every kilogram of nickel produced, there is an average, carbon sequestration loss of 117 gCO2 / m^2

Nickel impact on Carbon: Limonite - HPAL scenario

1:106	ratio of nickel to ore extracted*
47,250	average annual nickel production (tonnes)
17.92	kg of nickel per m^2 per mine (land intensity)
1 : 9.4	Nickel/ CO_2eq Stock ratio
1 : 0.006	nickel/ CO_2 Sequestration ratio

*On average, in a HPAL operation, for every 106 tonnes of ore extracted, 1 tonne of nickel is produced. *Excludes stripping ratio (overburden) Ore grade 1.35%*

An average HPAL production yields 47,250 tonnes of nickel per year, assuming 70% global recovery rate.

For every square meter of mine area (i.e. mine plus infrastructure), on average an additional 17.92 kg of nickel are produced (0.056 m^2 / kg of nickel).

For every kilogram of nickel produced, there is an average carbon stock loss of 9.4 kgCO2eq/kg Ni or 2.6 kgC/kg Ni

For every kilogram of nickel produced, there is an average carbon sequestration loss of 6.5 gramsCO2/kg Ni

Nickel impact on Carbon: Saprolite - RKEF scenario

1:78	ratio of nickel to ore extracted*
63,750	average annual nickel production (tonnes)
24.18	kg of nickel per m^2 per mine (land intensity)
1 : 7	Nickel/ CO_2eq Stock ratio
1 : 0.005	nickel/ CO_2 Sequestration ratio

*On average, in a RKEF operation, for every 78 tonnes of ore extracted, 1 tonne of nickel is produced. *Excludes stripping ratio (overburden) Ore grade 1.5%*

An average RKEF production yields 63,750 tonnes of nickel per year, assuming 85% global recovery rate.

For every square meter of mine area (i.e. mine plus infrastructure), on average an additional 24.18 kg of nickel are produced (0.041 m^2 / kg of nickel).

For every kilogram of nickel produced, there is an average carbon stock loss of 7 kgCO2eq/kg Ni or 1.9 kgC/kg Ni

For every kilogram of nickel produced, there is an average carbon sequestration loss of 4.8 gramsCO2/kg Ni

2. As nickel mines increase in size, in Sulawesi, there is a reduction of carbon stock

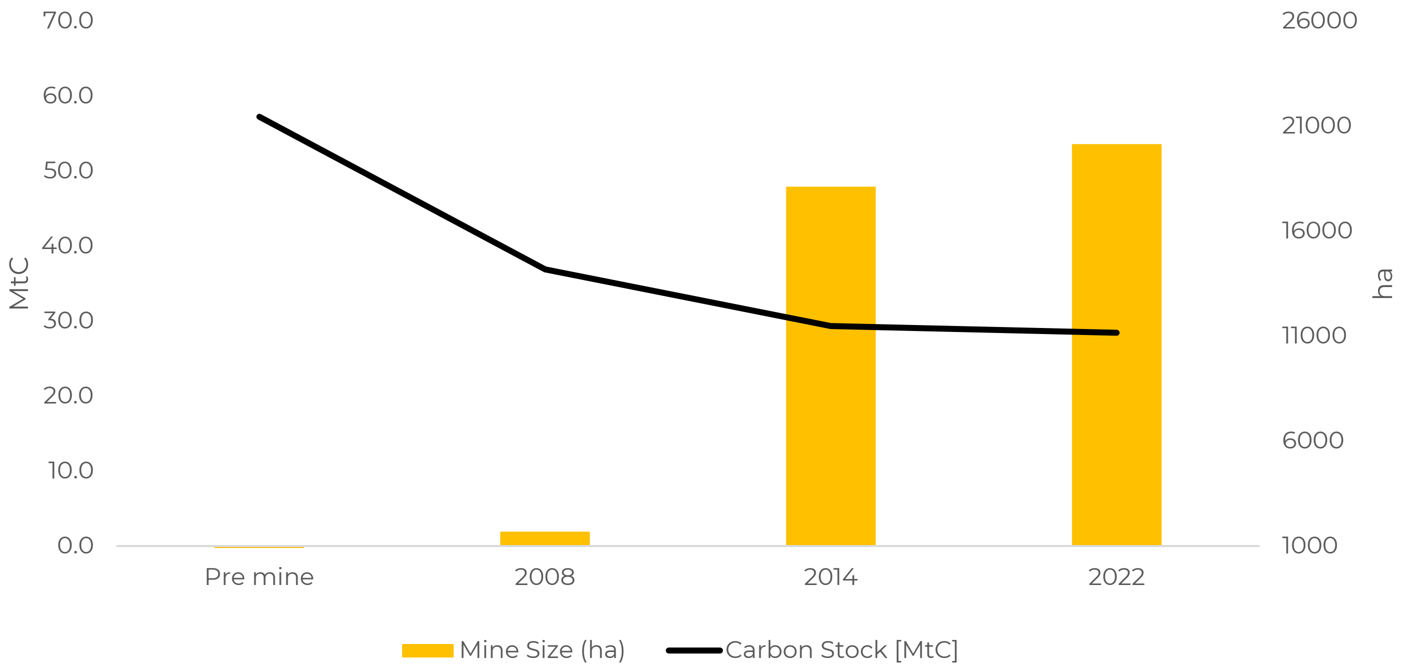


Figure 14: Sulawesi nickel mine growth compared to carbon stock loss

-8.5 MtC (-31 MtCO2eq)	Carbon stocks reduces from 36.9 MtC in 2008 to 28.4 MtC by 2022
-28.8MtC (-105 MtCO2eq)	Carbon stocks reduces from 57.3 MtC pre-mine to 28.4 MtC by 2022

Nickel mine growth in Sulawesi has led to a reduction of carbon stock (shown in mega tonnes carbon (MtC) in rainforest and mangroves. The size of the mines and corresponding carbon stock changes are shown at three intervals over the 14 years assessed (2008-2022).

Carbon stocks reduce from 36.9 MtC (136 $MtCO_2eq$) in 2008 to 28.4MtC (104 $MtCO_2eq$) by 2022.

Note, the methodology means that habitat and site changes across 2008-2014 exclude changes that pre-date this study period. To account for this, an estimation of habitat "pre-mine" has been made, to allow for a comparator of change in carbon stock from this pre-mine state to the years 2008, 2014 & 2022. A date allocation of this "pre-mine" state is not given and will in any case vary by mine site. Mangroves is included in the pre-mine calculation. However, in the case study mines this habitat was removed by 2008 so is not therefore, included after that point in the carbon stock calculations.

Carbon stocks pre-mine in this study area are estimated at 57.3 MtC (210 $MtCO_2eq$).

3. As nickel mines increase in size, in Sulawesi, carbon flow capacity decreases and emissions increase

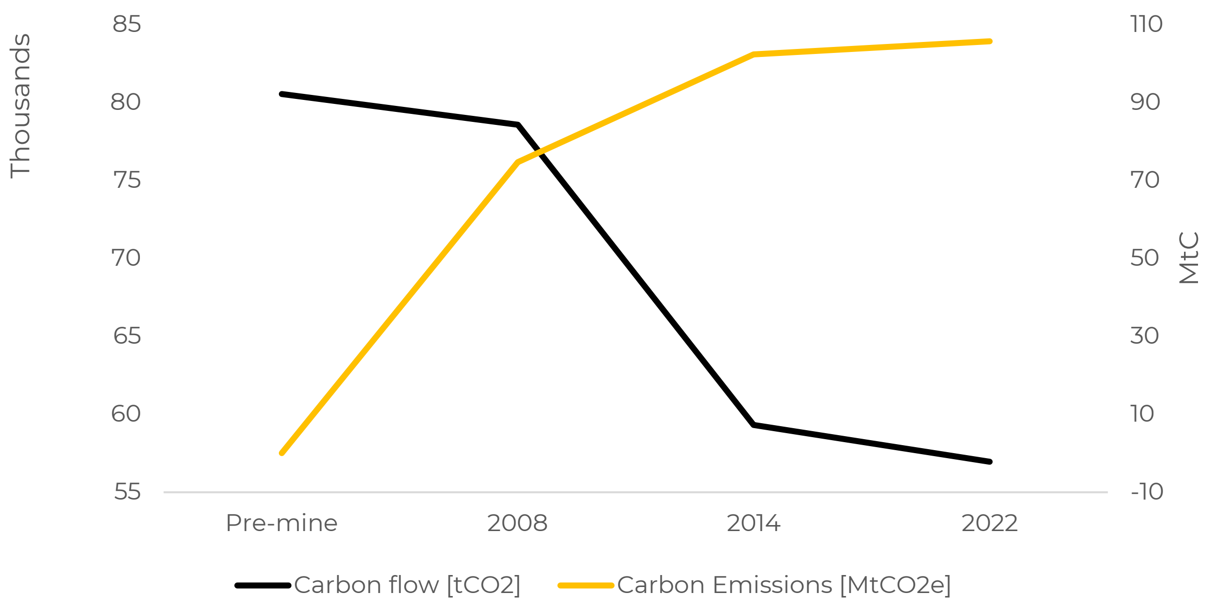


Figure 15: Carbon emissions compared to carbon flow as nickel mines grow in Sulawesi, Indonesia

As expected, as the nickel mines in Sulawesi grow and the forest is deforested or degraded the carbon flow (tC) decreases and the carbon emissions increase significantly.

It has been assumed that pre-mine the mapped areas were forest, allowing an estimation of pre-mine carbon stocks and carbon flow. Note pre-mine is not defined by time and in any case, this will vary by mine site.

As carbon flow (i.e., capture of carbon) reduces over time, so carbon emissions from the mine site increase from 0 to 28.8 MtC (106 $MtCO_2eq$).

4. Nickel emissions - compared to REDD+ in Indonesia

CO_2eq Emissions/year (REDD+, Indonesia		CO_2eq change/ year (5-Mines)	(%) of Indonesian emissions (Case study mines)	(%) of Indonesian emissions (Whole of)
Year	Mt/year	Mt/year		
2014	48.98	-3.181	6.5%	10691.6%
2015	48.98	-3.181	6.5%	10691.6%
2016	48.98	-3.181	6.5%	10691.6%
2017	48.98	-3.181	6.5%	10691.6%
2018	48.98	-3.181	6.5%	10691.6%
2019	48.98	-3.181	6.5%	10691.6%
2020	48.98	-3.181	6.5%	10691.6%
2021	48.98	-3.181	6.5%	10691.6%
2022	48.98	-3.181	6.5%	10691.6%

Figure 16: Carbon changes in the case study areas (csm) compared to REDD+ result for Indonesia

Figure 16 shows the carbon changes due to nickel extraction in the case study areas (csm) compared to REDD+ result for Indonesia.

Carbon Stock change a year (5-Mines)
The converted carbon stock loss result to show per year, compared to REDD+ figures in Indonesia.

.

(%) of Indonesian emissions (Case study mine)
Compares the carbon stock loss (%) per year to the REDD+ results [58]. Results are then converted into CO_2eq.

$tCO_2eq/ha/yr/ \times$ REDD+

(%) of Indonesian emission (Whole of)
This is multiplied by the difference in total area. This shows how much more intense emissions would be if the all the areas that REDD+ looked at were also mined areas.

However, the study area is tropical forest in Sulawesi, and disturbed forests **only**. So, if the same intensity of mines per land were developed for the forests that REDD+ includes, then the emissions would be much greater. This is because there would be a greater percentage of Total Living Biomass (TLB) per hectare.

BENCHMARK

References

www.benchmarkminerals.com | info@benchmarkminerals.com

HQ: London, UK

Offices: Beijing, Edinburgh, Fort Lauderdale, Melbourne, New Delhi, Porto, San Francisco, Tokyo

Report references 1

1. Bonan, G. B. (2008). Forests and climate change: forcings, feedbacks, and the climate benefits of forests. science, 320(5882), 1444-1449.
2. Giljum, S., Maus, V., Kuschnig, N., Luckeneder, S., Tost, M., Sonter, L. J., & Bebbington, A. J. (2022). A pantropical assessment of deforestation caused by industrial mining. *Proceedings of the National Academy of Sciences*, *119*(38), e2118273119.
3. Malhi, Y., & Grace, J. (2000). Tropical forests and atmospheric carbon dioxide. Trends in Ecology & Evolution, 15(8), 332-337
4. Li, Q., Qiu, C., Ma, L., Schmitt, M., & Zhu, X. X. (2020). Mapping the land cover of Africa at 10 m resolution from multi-source remote sensing data with Google Earth Engine. Remote Sensing, 12(4), 602
5. Benchmark Minerals Intelligence – cobalt intelligence
6. World bank data country data on Democratic Republic of Congo
7. Al Barazi, S., Schutte, P., & Naeher, U. (2017). Cobalt frim the DRC - potential risks and significance for the global cobalt market (Issue July).
8. Gumbo, D., Clendenning, J., Martius, C., Moombe, K., Grundy, I., Nasi, R., Mumba, K. Y., Ribeiro, N., Kabwe, G., & Petrokofsky, G. (2018). H have carbon stocks in central and southern Africa's miombo woodlands changed over the last 50 years? A systematic map of the evidence. *Environmental Evidence*, *7*(1), 1–19. https://doi.org/10.1186/s13750-018-0128-0
9. Bouvet, A., Mermoz, S., Le Toan, T., Villard, L., Mathieu, R., Naidoo, L., & Asner, G. P. (2018). An above-ground biomass map of African savannahs and woodlands at 25 m resolution derived from ALOS PALSAR. *Remote Sensing of Environment*, *206*(December 2017), 156–173. https://doi.org/10.1016/j.rse.2017.12.030
10. Sikuzani, Y. U., Muteya, H. K., & Bogaert, J. (2020). Miombo woodland, an ecosystem at risk of disappearance in the Lufira Biosphere Reserve (Upper Katanga, DR Congo)? A 39-years analysis based on Landsat images. *Global Ecology and Conservation*, *24*. https://doi.org/10.1016/j.gecco.2020.e01333
11. Malaisse, F., Schaijes, M., & D'Outreligne, C. (2016). Copper-Cobalt Flora of Upper Katanga and Copperbelt: Field Guide. In *Les Pressess Agronomiques de Gembloux* (Vol. 150, Issue 2). https://doi.org/10.5091/plecevo.2017.1273
12. Mercader, J., Bennett, T., Esselmont, C., Simpson, S., & Walde, D. (2009). Phytoliths in woody plants from the Miombo woodlands of Mozambique. *Annals of Botany*, *104*(1), 91–113. https://doi.org/10.1093/aob/mcp097
13. Pelletier, J., Paquette, A., Mbindo, K., Zimba, N., Siampale, A., Chendauka, B., Siangulube, F., & Roberts, J. W. (2018). Carbon sink despite large deforestation in African tropical dry forests (miombo woodlands). *Environmental Research Letters*, *13*(9). https://doi.org/10.1088/1748-9326/aadc9a
14. Molinario, G., Hansen, M. C., Potapov, P. V., Tyukavina, A., Stehman, S., Barker, B., & Humber, M. (2017). Quantification of land cover and land use within the rural complex of the Democratic Republic of Congo. Environmental Research Letters, 12(10). https://doi.org/10.1088/1748-9326/aa8680
15. Di Gregorio, A., and Jansen, L. J. M. (2000). Land Cover Classification System (LCCS): Classification Concepts and User Manual. Fao, 53(January), 179.
16. Verhegghen, A., Mayaux, P., De Wasseige, C., & Defourny, P. (2012). Mapping Congo Basin vegetation types from 300 m and 1 km multi-sensor time series for carbon stocks and forest areas estimation. *Biogeosciences*, *9*(12), 5061–5079. https://doi.org/10.5194/bg-9-5061-2012

Report references 2

17. Maquia, I., Catarino, S., Pena, A. R., Brito, D. R. A., Ribeiro, N. S., Romeiras, M. M., & Ribeiro-Barros, A. I. (2019). Diversification of African tree legumes in Miombo–Mopane woodlands. *Plants*, *8*(6). https://doi.org/10.3390/plants8060182
18. Augustino, S., & Hall, J. B. (2008). Population status of Pterocarpus tinctorius: A medicinal plant species in Urumwa forest reserve, Tanzania. Tanzania Journal of Forestry and Nature Conservation, 78(1).
19. Ribeiro, N. S., Matos, C. N., Moura, I. R., Washington-Allen, R. A., & Ribeiro, A. I. (2013). Monitoring vegetation dynamics and carbon stock density in miombo woodlands. *Carbon Balance and Management*, *8*(1), 1–9. https://doi.org/10.1186/1750-0680-8-11
20. Kuyah, S., Sileshi, G. W., Njoloma, J., Mng'omba, S., & Neufeldt, H. (2014). Estimating aboveground tree biomass in three different miombo woodlands and associated land use systems in Malawi. *Biomass and Bioenergy*, *66*, 214–222. https://doi.org/10.1016/j.biombioe.2014.02.005
21. Missanjo, E., & Kamanga-Thole, G. (2015). Estimation of Biomass and Carbon stock for Miombo Woodland in Dzalanyama Forest Reserve, Malawi. *Research Journal of Agriculture and Forestry Sciences*, *3*(3), 7–12.
22. Chamshama, S. A. O., Mugasha, A. G., & Zahabu, E. (2004). Stand biomass and volume estimation for miombo woodlands at kitulangalo, morogoro, tanzania. *Southern African Forestry Journal*, *200*(1), 59–70. https://doi.org/10.1080/20702620.2004.10431761
23. Chidumayo, E. N. (2002). Changes in miombo woodland structure under different land tenure and use systems in central Zambia. Journal of Biogeography, 29(12), 1619–1626. https://doi.org/10.1046/j.1365-2699.2002.00794.x
24. Kapinga, K., Syampungani, S., Kasubika, R., Yambayamba, A. M., & Shamaoma, H. (2018). Species-specific allometric models for estimation of the above-ground carbon stock in miombo woodlands of Copperbelt Province of Zambia. Forest Ecology and Management, 417(February), 184–196. https://doi.org/10.1016/j.foreco.2018.02.044
25. Godlee, J. L., Gonçalves, F. M., Tchamba, J. J., Chisingui, A. V., Muledi, J. I., Shutcha, M. N., Ryan, C. M., Brade, T. K., & Dexter, K. G. (2020). Diversity and structure of an arid woodland in Southwest Angola, with comparison to the wider miombo ecoregion. *Diversity*, *12*(4). https://doi.org/10.3390/D12040140
26. Sikuzani, Y. U., Muteya, H. K., & Bogaert, J. (2020). Miombo woodland, an ecosystem at risk of disappearance in the Lufira Biosphere Reserve (Upper Katanga, DR Congo)? A 39-years analysis based on Landsat images. Global Ecology and Conservation, 24. https://doi.org/10.1016/j.gecco.2020.e01333
27. Batjes, N. H. (2008). Mapping soil carbon stocks of Central Africa using SOTER. Geoderma, 146(1–2), 58–65. https://doi.org/10.1016/j.geoderma.2008.05.006
28. Ilunga Muledi, J., Bauman, D., Drouet, T., Vleminckx, J., Jacobs, A., Lejoly, J., Meerts, P., & Shutcha, M. N. (2016). Fine-scale habitats influence tree species assemblage in a miombo forest. Journal of Plant Ecology, 10(6), rtw104. https://doi.org/10.1093/jpe/rtw104

Report references 3

29. Chave, J., Réjou-Méchain, M., Búrquez, A., Chidumayo, E., Colgan, M. S., Delitti, W. B., ... & Vieilledent, G. (2015). Improved allometric models to estimate the aboveground biomass of tropical trees. Global change biology, 20(10), 3177-3190
30. Mpoyi, A., Nyamwoga, F., Kabamba, F., & Assembe-Mvondo, S. (2013). The context of REDD+ in the Democratic Republic of Congo: Drivers, agents and institutions. In *The context of REDD+ in the Democratic Republic of Congo: Drivers, agents and institutions* (Issue October). https://doi.org/10.17528/cifor/004267
31. Kengoum, F., Pham, T. T., Moeliono, M., Dwisatrio, B., & Sonwa, D. J. (2020). The context of REDD+ in the Democratic Republic of Congo: Drivers, agents and institutions (Vol. 207). CIFOR.
32. Cairns M.A., Brown S., Helmer E.H. and Baumgardner G.A., Root biomass allocation in the world's upland forests, Oecologia, 111, 1–11 (1997)
33. UNFCCC (2018) Report of the technical assessment of the proposed forest reference emission level of the Democratic Republic of the Congo https://unfccc.int/sites/default/files/resource/tar2018_COD.pdf
34. Chen, N., Tsendbazar, N. E., Hamunyela, E., Verbesselt, J., & Herold, M. (2021). Sub-annual tropical forest disturbance monitoring using harmonized Landsat and Sentinel-2 data. *International Journal of Applied Earth Observation and Geoinformation*, *102*, 102386.
35. Benchmark Minerals Intelligence nickel intelligence
36. Dwiyahreni, A. A., Fuad, H. A., Soesilo, T. E. B., Margules, C., & Supriatna, J. (2021). Forest cover changes in Indonesia's terrestrial national parks between 2012 and 2017. *Biodiversitas*, *22*, 1235-1242.
37. Stelbrink, B., Albrecht, C., Hall, R., & von Rintelen, T. (2012). The biogeography of Sulawesi revisited: is there evidence for a vicariant origin of taxa on Wallace's "anomalous island"?. Evolution: International Journal of Organic Evolution, 66(7), 2252-2271.
38. BP-REDD+. (2015). *National Forest Reference Emission Level for Deforestation and Forest Degradation in the Context of the Activities Referred to in Decision 1 / CP . 16 , Paragraph 70 (REDD +) Under the UNFCCC : A Reference for Decision Makers*. *70*, 74. www.reddplus.go.id
39. Van der Ent, A. J. M. M. J., Baker, A. J. M., Van Balgooy, M. M. J., & Tjoa, A. (2013). Ultramafic nickel laterites in Indonesia (Sulawesi, Halmahera): mining, nickel hyperaccumulators and opportunities for phytomining. Journal of Geochemical Exploration, 128, 72-79.
40. Camba, A. (2021). The unintended consequences of national regulations: Large-scale-small-scale relations in Philippine and Indonesian nickel mining. Resources Policy, 74, 102213

Report references 4

41. Olson, D. M., & Dinerstein, E. (1998). The Global 200: a representation approach to conserving the Earth's most biologically valuable ecoregions. Conservation biology, 12(3), 502-515.
42. Voigt, M., Supriatna, J., Deere, N. J., Kastanya, A., Mitchell, S. L., Rosa, I. M. D., Santika, T., Siregar, R., Tasirin, J. S., Widyanto, A., Winarni, N. L., Zakaria, Z., Mumbunan, S., Davies, Z. G., & Struebig, M. J. (2021). Emerging threats from deforestation and forest fragmentation in the Wallacea centre of endemism. Environmental Research Letters, 16(9). https://doi.org/10.1088/1748-9326/ac15cd
43. Pusparini, W., Cahyana, A., Grantham, H. S., Maxwell, S., Soto-Navarro, C., & Macdonald, D. W. (2023). A bolder conservation future for Indonesia by prioritising biodiversity, carbon and unique ecosystems in Sulawesi. Scientific Reports, 13(1), 1–13. https://doi.org/10.1038/s41598-022-21536-2
44. Arjasakusuma, S., Yamaguchi, Y., Hirano, Y., & Zhou, X. (2018). ENSO-and rainfall-sensitive vegetation regions in Indonesia as identified from multi-sensor remote sensing data. *ISPRS International Journal of Geo-Information*, *7*(3). https://doi.org/10.3390/ijgi7030103
45. Cannon, C. H., Summers, M., Harting, J. R., & Kessler, P. J. A. (2007). Developing conservation priorities based on forest type, condition, and threats in a poorly known ecoregion: Sulawesi, Indonesia. Biotropica, 39(6), 747–759. https://doi.org/10.1111/j.1744-7429.2007.00323.x
46. Pitopang, R. (2012). Impact of forest disturbance on the structure and composition of vegetation in tropical rainforest of Central Sulawesi , Indonesia. 13(4), 178–189. https://doi.org/10.13057/biodiv/d130403
47. Kusmana, C. (2014). Distrubution and current status of mangrove forest in Indonesia. In Mangrove Ecosystems of Asia: Status, Challenges and Management Strategies (Issue April 2014, pp. 1–471). https://doi.org/10.1007/978-1-4614-8582-7
48. Malik, A., Rahim, A., Sideng, U., Rasyid, A., & Jumaddin, J. (2019). Biodiversity assessment of mangrove vegetation for the sustainability of ecotourism in West Sulawesi, Indonesia. AACL Bioflux, 12(4), 1458–1466.
49. Analuddin, K., Kadidae, L. O., Yasir Haya, L. O. M., Septiana, A., Sahidin, I., Syahrir, L., Rahim, S., Fajar, L. O. A., & Nadaoka, K. (2020). Aboveground biomass, productivity and carbon sequestration in rhizophora stylosa mangrove forest of southeast sulawesi, indonesia. *Biodiversitas*, *21*(4), 1316–1325. https://doi.org/10.13057/biodiv/d210407
50. Myers, N., Mittermeier, R. A., Mittermeier, C. G., Da Fonseca, G. A., & Kent, J. (2000). Biodiversity hotspots for conservation priorities. Nature, 403(6772), 853-858Ref a
51. Culmsee, H., Pitopang, R., Mangopo, H., & Sabir, S. (2011). Tree diversity and phytogeographical patterns of tropical high mountain rain forests in Central Sulawesi, Indonesia. Biodiversity and Conservation, 20(5), 1103–1123. https://doi.org/10.1007/s10531-011-0019-y

Report references 5

52. Propastin, P. (2013). Large-scale mapping of aboveground biomass of tropical rainforest in Sulawesi, Indonesia, using Landsat ETM+ and MODIS data. *GIScience and Remote Sensing*, *50*(6), 633–651. https://doi.org/10.1080/15481603.2013.850305
53. Supriatna, J., Shekelle, M., Fuad, H. A. H., Winarni, N. L., Dwiyahreni, A. A., Farid, M., Mariati, S., Margules, C., Prakoso, B., & Zakaria, Z. (2020). Deforestation on the Indonesian island of Sulawesi and the loss of primate habitat. *Global Ecology and Conservation*, *24*, e01205. https://doi.org/10.1016/j.gecco.2020.e01205
54. Culmsee, H., Leuschner, C., Moser, G., & Pitopang, R. (2010). Forest aboveground biomass along an elevational transect in Sulawesi, Indonesia, and the role of Fagaceae in tropical montane rain forests. Journal of Biogeography, 37(5), 960–974. https://doi.org/10.1111/j.1365-2699.2009.02269.x
55. Hertel, D., Moser, G., Culmsee, H., Erasmi, S., Horna, V., Schuldt, B., & Leuschner, C. (2009). Below- and above-ground biomass and net primary production in a paleotropical natural forest (Sulawesi, Indonesia) as compared to neotropical forests. Forest Ecology and Management, 258(9), 1904–1912. https://doi.org/10.1016/j.foreco.2009.07.019
56. Dietz, J., Hölscher, D., Leuschner, C., & Hendrayanto. (2006). Rainfall partitioning in relation to forest structure in differently managed montane forest stands in Central Sulawesi, Indonesia. Forest Ecology and Management, 237(1–3), 170–178. https://doi.org/10.1016/j.foreco.2006.09.044
57. Shofiyati, R., Las, I., & Agus, F. (2010, September). Indonesian soil database and predicted stock of soil carbon. In Proceedings of international workshop on evaluation and sustainable management of soil carbon sequestration in Asian countries Bogor, Indonesia Sept (pp. 28-29).
58. Budiharto, Krisnawati, H., Manuri, S., Purwanto, J., Asaad, I., Nurhayati, & Gunawan, W. (2022). NATIONAL FOREST REFERENCE EMISSION LEVEL FOR DEFORESTATION AND FOREST DEGRADATION In the Context of Decision 12/CP.17 para 12 UNFCCC.

FOR ANY QUERIES, CONTACT US :

sustainability@benchmarkminerals.com
info@benchmarkminerals.com

www.benchmarkminerals.com

@benchmarkmin

BENCHMARK

Scan to find out more about **Benchmark Mineral Intelligence**