Mineral Extraction sector: Mining and Quarrying Emissions Using InSAR Retrievals

Matthew Jolleys*and Paul Duddy
All authors affiliated with Hypervine and Climate TRACE
**Email- matthew@hypervine.io*

1. Introduction

This methodology provides an overview of a technique using InSAR retrievals from Sentinel-1A and 1-B satellites to derive estimates of mining activity over a period of 3 years. In short, the technique involves the development of a series of coherence image pairs as a means of identifying changes in ground surface properties, which are aggregated over periods of 12 months to provide a Normalised Difference Activity Index (NDAI). Variations in NDAI between years are represented using composite RGB images, which can be segmented into a series of colour bands to give an estimate of mining activity in each year. A conversion factor can then be applied to this value to infer the relationship between mined area and overall production. In future this could be based on analysis of the number of machines operating on a mine and typical performance values. However, given the ongoing development of this method, current assessments will be established using empirical relationships between known mine production statistics and observed active mining areas.

2. Satellite data

2.1 Satellite imagery

Satellite imagery resources, including PlanetScope and Google Earth, were used to identify mining sites and to verify geolocation of named assets where accurate coordinates were not provided. For some sites where reported locations were imprecise or poorly defined, additional resources were required to verify exact locations, including written reports and ground-level photographs. Optical satellite images were also used to develop detailed shapefiles of identified facilities, to provide high resolution demarcation of mining areas for use in image processing within mining area assessments.

2.2 Sentinel-1A/B SAR retrievals

As part of ongoing efforts to exploit direct remote sensing observations of mining activity, and move away from a dependency on limited or inconsistent third-party reporting, we have begun to develop techniques based on analysis of Interferometric Synthetic Aperture Radar (InSAR) coherence images. This imagery is generated using retrievals from ESA's Sentinel-1A and 1-B

SAR instruments. Sentinel-1A was launched on 3rd April 2014 and was deployed in a polar, sun-synchronous orbit at an altitude of 693 km, providing near-global coverage with a repeat interval of 12 days and capacity to observe the land surface day and night, without impact from clouds [1]. The launch of Sentinel-1B followed on 25th April 2016. Each satellite is equipped with a C-band SAR instrument operating at a frequency of 5.4 GHz providing a number of operational and polarisation modes. SAR retrievals over land mainly utilise interferometric wide-swath (IW) mode, which provides a swath width of 250 km with a spatial resolution of 5x20 m using the Terrain Observation with Progressive Scans SAR (TOPSAR) technique, whereby bursts from successive passes are synchronised to ensure alignment. These initial images are processed to generate a series of coherence images, which can then be used to develop indices of mining activity within an area of interest.

3. InSAR mining detection

InSAR Coherence provides a measure of the correlation between multiple SAR images, with values ranging between 0 (no coherence) and 1 (perfect correlation) [2]. Different land surfaces give rise to different characteristic coherence values, according to the stability of the surface (Figure 1). Stable surfaces, such as bare land, rocks, and buildings show very high coherence values because there is little change in land surface properties [3]. In contrast, highly dynamic surfaces such as vegetated areas or forests have low coherence values, due to both temporal decorrelation, whereby random movements over time cause changes to scattering properties, and volume decorrelation, which accounts for variations in the height of surface scatterers [1]. Coherence values for open-pit mines are quite high due to the removal of topsoil and absence of vegetation, which disturbs the land surface. However, mining activities such as blasting, excavation, and accumulation, can change the reflection characteristics over a short period of time, introducing decorrelation and decreasing coherence [3,4].

While coherence images provide a means of detecting mining activity, additional sources of decorrelation can introduce significant uncertainties. These sources include precipitation conditions, as rain or snow can contribute to observed temporal decorrelation between SAR retrievals, and the perpendicular baseline associated with image pairs, which is a function of the lateral offset in satellite position between orbits [5]. The impact of these effects can be reduced using a Normalised Difference Activity Index (NDAI) [3]. Stable points within the mining area are identified, selecting pixels where time-averaged coherence values are high and standard deviation is low. Subsequently omitting coherence images where the mean values for these points do not meet given thresholds (a minimum coherence of 0.8 and maximum standard deviation of 0.2) is expected to mitigate the effects of precipitation, as analysis of the temporal distribution of such points has shown a strong concentration during winter, which is expected to be a consequence of snowfall events [1,3]. As decorrelation effects from precipitation and perpendicular baseline are independent of surface properties, any impact on coherence values is expected to be broadly consistent across stable points and target sites. The NDAI can therefore be defined as follows in Eq.1:

$$NDAI = \frac{\rho^{stable} - \rho^{activity}}{\rho^{stable} + \rho^{activity}} \qquad [Eq.1]$$

Where ρ^{stable} and ρ^{target} are the spatially-averaged coherence values for stable points and target sites, respectively [3]. Resulting NDAI values close to 1 are indicative of active mine areas (low coherence), while values close to zero correspond to stable points (high coherence).

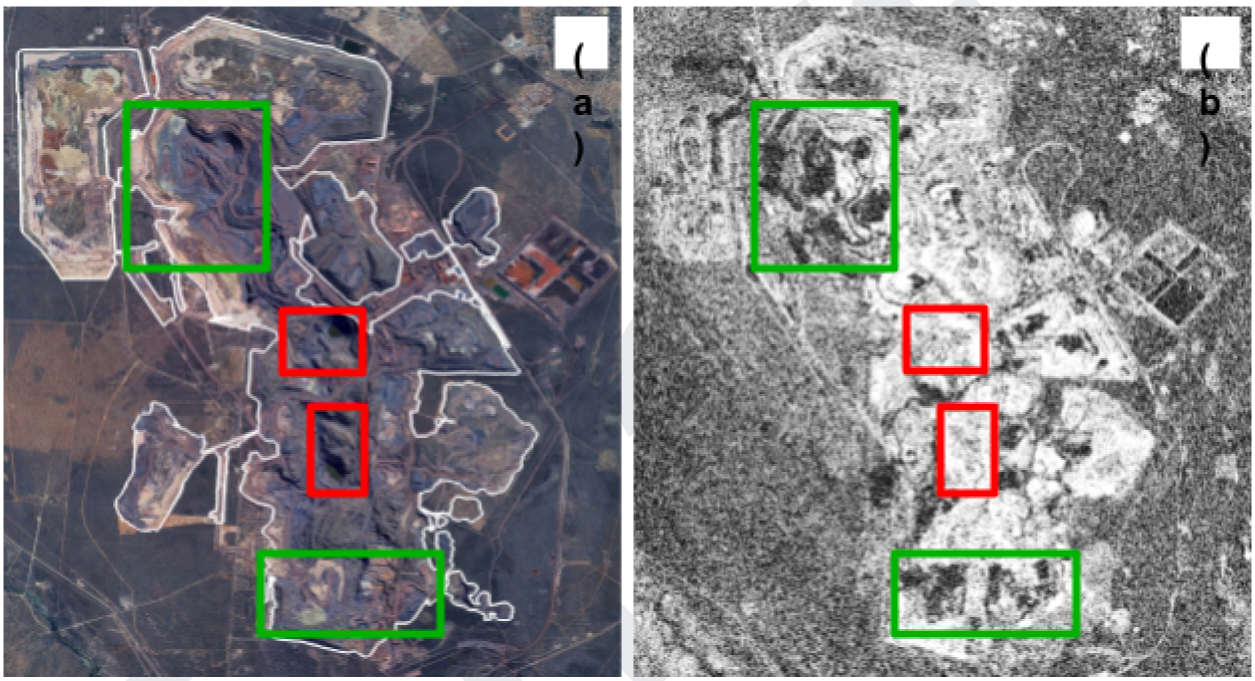


Figure 1 (a) *Google Earth imagery of the Anglo American Sishen Iron Mine, Northern Cape, South Africa.* **(b)** *InSAR coherence image of the Sishen Mine generated with ESA's SNAP toolkit using Sentinel-1A/B interferometric wide swath single-look complex imagery retrievals from 20/12/2019 and 01/01/2020. High coherence values within the mine area are clearly visible as expanses of white pixels, highlighted in the red boxes. Dark areas, in the green boxes, indicate low coherence.*

Mining activity over several years can be represented visually by creating composite RGB images, whereby annually-averaged NDAI values for an area of interest are assigned to a specific colour channel (Figure 2). In this example, NDAI was calculated for the Sishen iron mine in Northern Cape, South Africa from 2020-2022, using a total of 92 coherence images generated over this period using InSAR imagery derived from C-band single-look complex retrievals in descending mode with dual polarisation (VV+VH). Image pairs with a typical interval of 12 days were used, although in some instances this increased to 24 days due to missing or unusable images. Scenes with an appropriate perpendicular baseline within the target area were identified, excluding scenes where the lateral offset exceeded 250m, and downloaded using the Alaska Satellite Facility Vertex (https://search.asf.alaska.edu). Coherence images were then generated using ESA's Sentinel Applications Platform (SNAP), applying the processing framework described by *Moon et al.* [3]. Each image in every InSAR pair was first split to select only the sub-swath of interest, before orbit information about the position of the satellite during acquisition was applied, in order for images to be back-geocoded to enable their coregistration and ensure alignment of paired images at sub-pixel accuracy. These coregistered images were then used to produce an interferogram, removing flat-earth and topographic phases using Shuttle Radar Topography Mission (SRTM) 1 arc-sec elevation data and applying a 7x2 (range by azimuth) averaging window. The separate bursts comprising each interferogram were then merged to remove seam lines, and Goldstein filtering applied to reduce noise before a terrain correction was performed, again using SRTM 1 arc-sec data. These final image stacks were then cropped to provide a subset for the area of interest, and exported as raster images.

Table 1 *RGB composite image values and meanings for the given study period*

Activity				
R (2019)	**G (2020)**	**B (2021)**	**Colour**	**Meaning**
High	Low	Low	Red	Active in 2020
Low	High	Low	Green	Active in 2021
Low	Low	High	Blue	Active in 2022
Low	High	High	Cyan	Active in 2021 + 2022
High	Low	High	Magenta	Active in 2020 + 2022
High	High	Low	Yellow	Active in 2020 + 2021
High	High	High	White	Active in all years
Low	Low	Low	Black	Stable in all years

Prior to the calculation of NDAI values for the Sishen mine, coherence images were masked using a high resolution shapefile plotted using Google Earth imagery. Annually-averaged NDAI were then converted to RGB values and combined to form a composite image, with data from 2020, 2021 and 2022 assigned to red, green and blue channels, representing mining areas which were active in each respective year. Composite colours of cyan, magenta and yellow subsequently formed by the combination of activities from multiple channels reflect sites that were active in more than one year, as described in Table 1 above. These colour bands can then be separated into individual images by converting to HSV (hue, saturation, value) colour space and segmenting values using intervals of the hue spectrum corresponding to each colour channel (Figure 3).

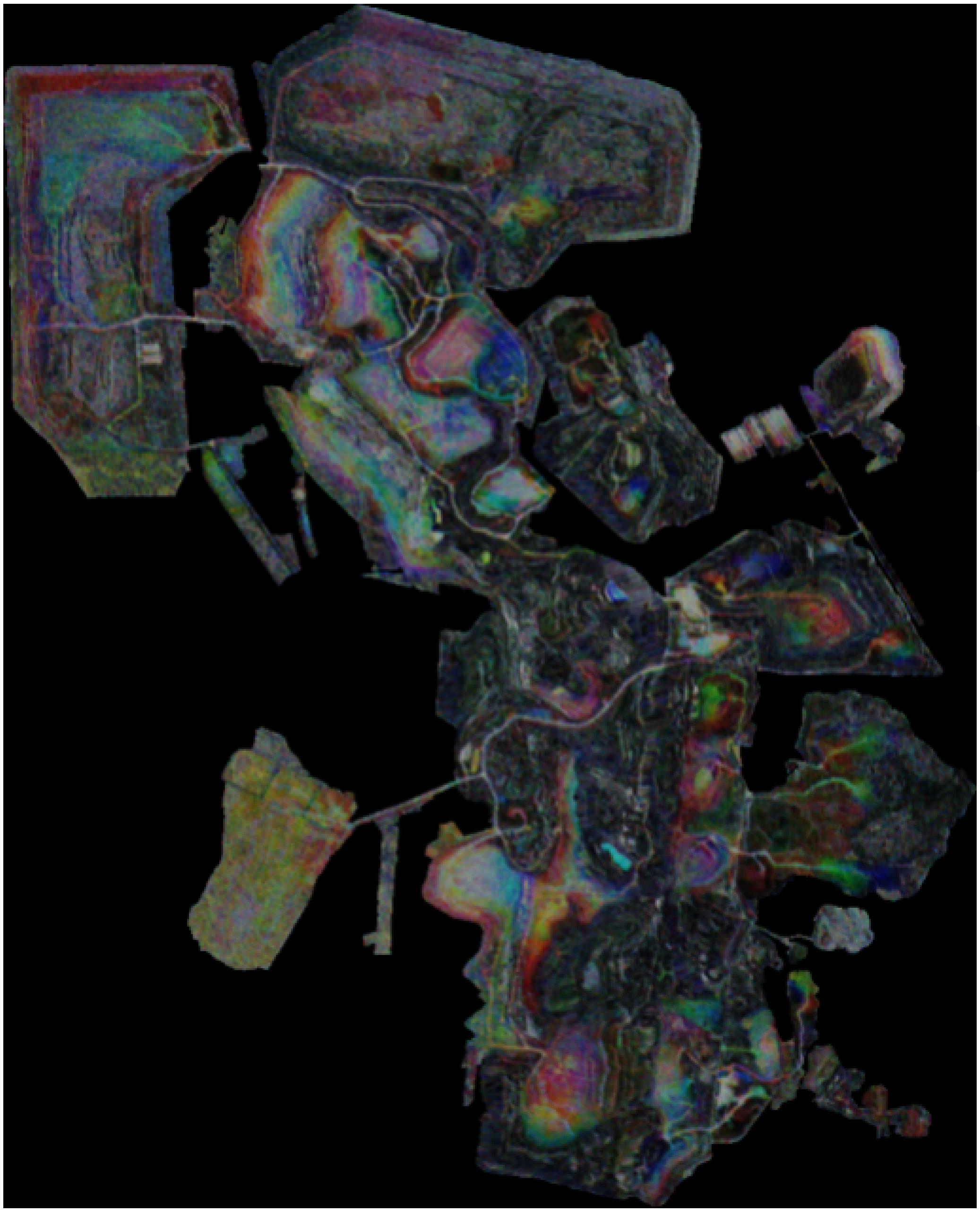
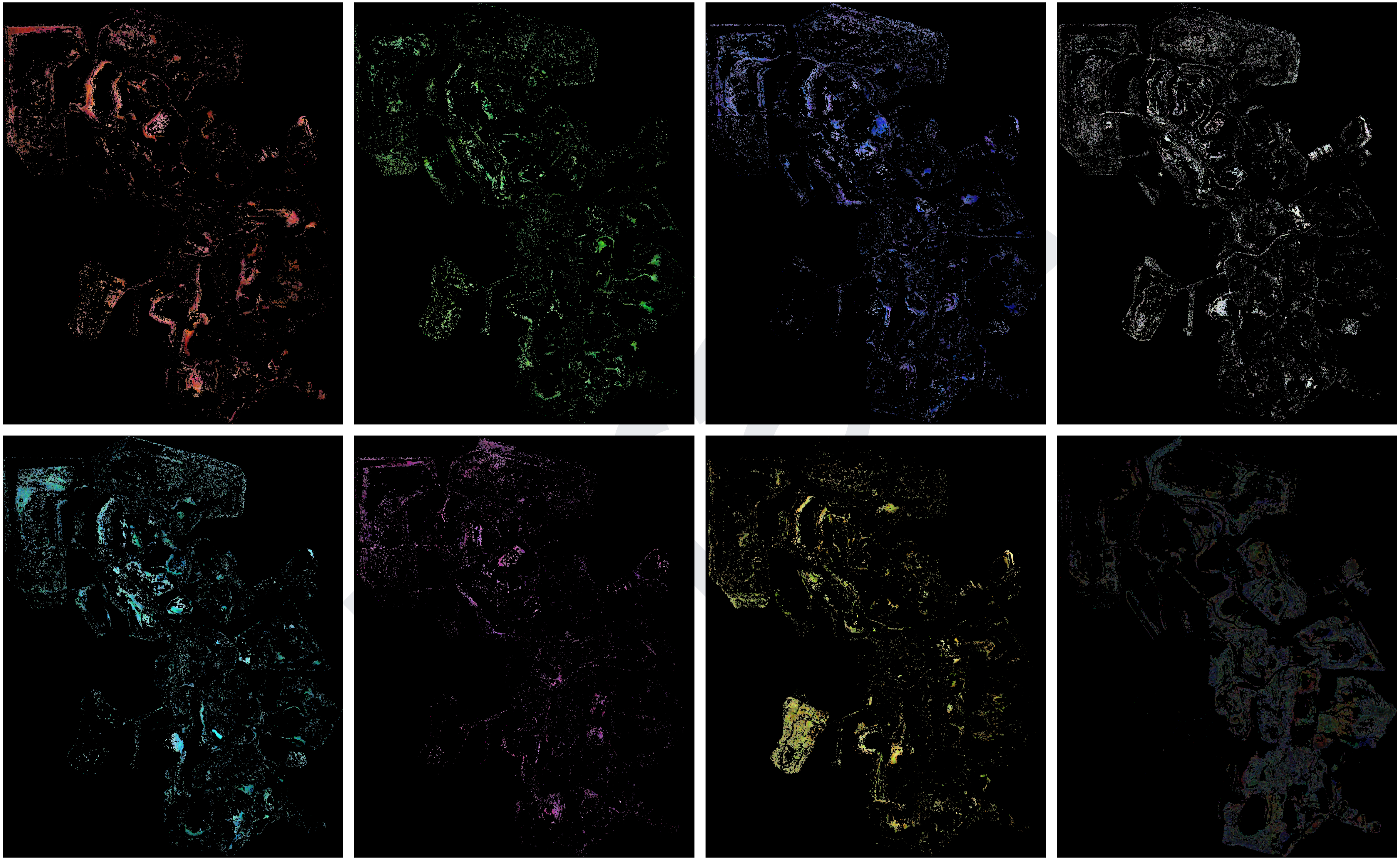


Figure 2 *RGB composite image of the Sishen Iron Mine, Northern Cape, South Africa, created by assigning annually-averaged NDAI values for 2020, 2021 and 2022 to red, green and blue colour channels, respectively. Mine activity within a specific year, or combination of years, is represented by pixels of the colour associated with that year, or the composite colour derived from multiple years. White pixels represent locations active across all three years, while black pixels within the mining area reflect an absence of activity across the study period*



Emissions modelling by Hypervine.Version: Fall 2023

Figure 3 *Separate colour band images of the Sishen mine, Northern Cape, South Africa, for (top row, l-r) red, green, blue, white and (bottom row, l-r) cyan, magenta, yellow and black channels, based on colour assignment described in Table 1.*

4. Image processing and mining activity

Analysis of the distribution of pixel colour values across each year can provide a quantitative assessment of changes in mining activity throughout the site across the given time period (Figure 4). Given the location and setting of the Sishen mine and typical absence of vegetation cover, for the purpose of this analysis white pixels are considered to be areas of continuous mining activity, and as such are included in the pixel count for each year. However, this classification may require more rigorous parameterisation going forward, particularly for mines in more heavily vegetated regions. Vegetation cover could be quantified more accurately using the normalised difference vegetation index (NDVI), and compared with NDAI to give a more robust assessment of mining activity.

Table 2 *RGB colour band pixel counts for the Sishen Iron Mine, South Africa. Total area is determined by the total number of pixels present within the area delineated by the given shapefile*

<table>
<tr><th>Colour</th><th>Period</th><th>Pixel count</th><th>Year</th><th>Total count</th><th>Area (m^2)</th></tr>
<tr><td>Red</td><td>2020</td><td>43,398</td><td rowspan="2">2020</td><td rowspan="2">105,931</td><td rowspan="2">10,593,100</td></tr>
<tr><td>Green</td><td>2021</td><td>40,088</td></tr>
<tr><td>Blue</td><td>2022</td><td>47,177</td><td rowspan="2">2021</td><td rowspan="2">116,891</td><td rowspan="2">11,689,100</td></tr>
<tr><td>Cyan</td><td>2021/2022</td><td>28,779</td></tr>
<tr><td>Magenta</td><td>2020/2022</td><td>9,509</td><td rowspan="2">2022</td><td rowspan="2">110,392</td><td rowspan="2">11,039,200</td></tr>
<tr><td>Yellow</td><td>2020/2021</td><td>23,097</td></tr>
<tr><td>White</td><td>All</td><td>24,927</td><td>Total area</td><td>369,786</td><td>36,978,600</td></tr>
</table>

Total pixel counts for each colour band are shown in Table 2 above. Total mined areas for each year are calculated using a defined ground surface resolution for the Sentinel-1 IW mode of 5 x 20 m, and can then be compared to reported annual production statistics for the asset. Mining Data Online (http://www.miningdataonline.com) report production values of 36.2 Mt, 37.9 Mt and 35.0 Mt iron ore for 2020, 2021 and 2022 respectively. Total mined area as inferred by InSAR analysis increased by 10.4% between 2020 and 2022, with a corresponding increase in production of 4.7%. Production then decreased by 7.7% between 2021 and 2022, following a 5.6% reduction in mined area. The mass of ore produced per square metre of mined surface remained fairly constant across all years, ranging from 3.17 to 3.42 t/m^2.

InSAR analysis was typically not applied in estimations of emissions for mines with reported production statistics, but was instead used to develop an understanding of the relationship between detected activity and production. An exception to this occurred in instances where production data were not available for all years considered here, but were reported for at least one year. In such instances, the average production per square metre calculated for available years was used to estimate production from detected activity in additional years. For mines with no production data available in any years, the same approach was applied but using generalised average production values from a broader range of mines.

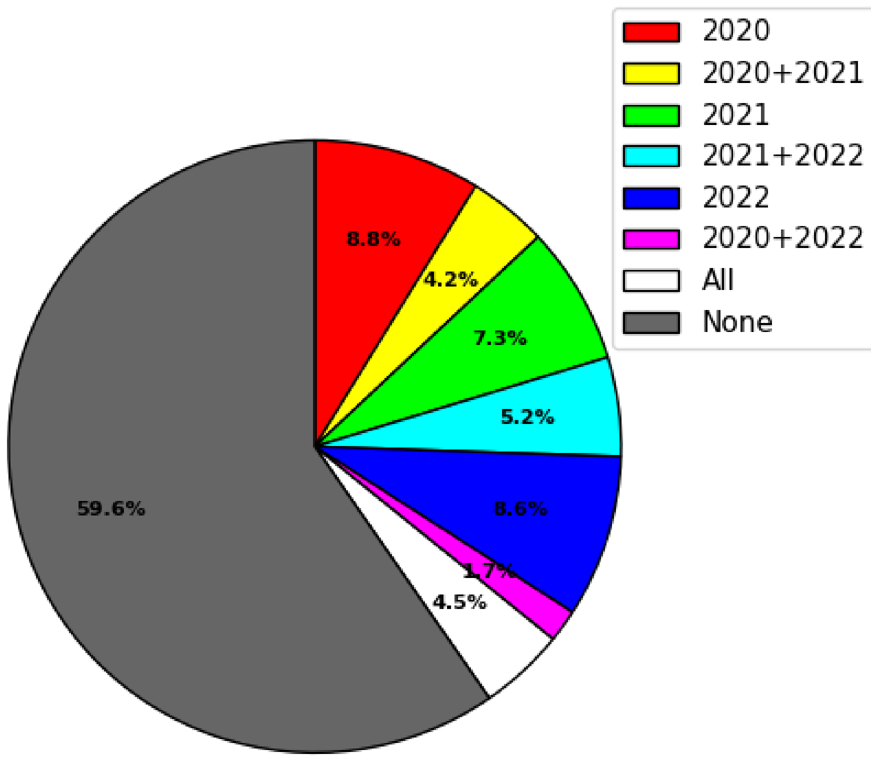


Figure 4 *Pixel colour analysis for an RGB composite image of Sishen Iron Mine, Para, South Africa based on annually-averaged NDAI values for 2020, 2021 and 2022.*

5. Production data and emissions estimates

As InSAR analysis was only performed for a limited number of mines within the full inventory comprising the dataset presented here, emissions estimates for a majority of mines were developed using only production statistics. These estimates were developed on the basis of the mass of ore extracted each year, as opposed to amounts of processed or finished products, in order to provide greater consistency across multiple mineral types. Furthermore, the total ore mass removed represents a better equivalence for detected activity, as the yield of processed or finished product will be affected by additional factors such as mineral grade, processing capacity and the stockpiling of raw material from previous years. Where production from a mine was only reported in terms of another product (for example, mass of copper cathode or iron pellets), a series of conversion factors were developed using data from mines where both extracted ore and other product masses were reported. These conversion factors were then averaged at a national or regional level in order to provide more representative values, and used to calculate estimated ore masses. Estimated ore production values, together with reported ore production data, comprise the activity values for the mining inventory presented here. Emission estimates were then calculated using a series of emission factors for mineral extraction. These emission factors were derived from annual emissions data reported by a range of mining companies operating worldwide. At the most accurate level, emissions were reported for an individual facility, and when combined with production data for that facility, give a specific asset-level emission factor. In other instances, emissions were reported on a division or company-wide basis, and as such were used to provide emissions factors for all assets within the given operation. Calculated emission factors were again averaged at a national or regional level to provide representative values for the full range of assets across all mineral types included within this inventory.

6. Future developments

The potential for InSAR analysis to provide independent assessments of mining activity, and their subsequent application in the development of asset-level emissions estimates, has been demonstrated. However, several factors could contribute to inconsistencies in the relationship between mined area and production. Firstly, reported production values and emissions data are not directly observed, instead relying on self or third-party reporting. Secondly, such data is not available uniformly for all assets, and requires use of scaled or averaged values in some instances. Thirdly, there remains some uncertainty with regards to the influence of non-mining operations on detected activity. As discussed previously, the presence of vegetation can have a significant impact on InSAR retrievals, and needs to be accounted for more rigorously going forward. However, such effects are largely restricted to mines located within more heavily vegetated environments, such as the tropics, and are less prevalent in more arid settings. Measures can also be taken to limit any influence from vegetation, such as by excluding areas dominated by vegetation cover when plotting the shapefiles used in the InSAR analysis process. Digital elevation models could also be employed to gain further insights into vertical changes in mine morphology, and potentially provide a more accurate assessment of mining activity with regards to removal of material and the accumulation of tailings. Dependence on reported data in emission factor calculations could ultimately be removed by directly detecting the presence of emissions sources, such as plant machinery and other vehicles, through satellite imagery. Development within this area is ongoing, but is not yet at a stage where it can be reliably used for the purpose of developing emissions estimates.

To date this InSAR-based approach has only been used across a limited number of mines, but in future will be applied to the full range of mining assets identified for their global significance. This will provide the benefit of delivering accurate assessments of activity on mines for which production data of any sort was previously unavailable. Application of independent asset-specific emission factors to these coherence-derived assessments can ultimately provide more reliable, fully independent emissions estimates for the global mining sector, leading to greater transparency and increasing accountability amongst operators who represent a significant contribution to worldwide anthropogenic carbon emissions.

7. References

[1] Wang, L.; Yang, L.; Wang, W.; Chen, B.; Sun, X. Monitoring Mining Activities Using Sentinel-1A InSAR Coherence in Open-Pit Coal Mines. *Remote Sens.* 2021, *13*, 4485. https://doi.org/10.3390/rs13214485

[2] Tapete, D.; Cigna, F. COSMO-SkyMed SAR for Detection and Monitoring of Archaeological and Cultural Heritage Sites. *Remote Sens.* 2019, *11*, 1326. https://doi.org/10.3390/rs11111326

[3] Moon, J.; Lee, H. Analysis of Activity in an Open-Pit Mine by Using InSAR Coherence-Based Normalized Difference Activity Index. *RemoteSens.* 2021, *13*, 1861. https://doi.org/10.3390/rs13091861

[4] Wang, S.; Lu, X.; Chen, Z.; Zhang, G.; Ma, T.; Jia, P.; Li, B. Evaluating the Feasibility of Illegal Open-Pit Mining Identification Using Insar Coherence. *Remote Sens.* 2020, *12*, 367. https://doi.org/10.3390/rs12030367

[5] Canaslan Çomut, F. & Üstün, A. Impact of Perpendicular and Temporal Baseline Characteristics on InSAR Coherence Maps. *Proceedings of FIG Working Week, Rome, Italy, 6-10 May 2012*. 2012

Supplemental metadata section

Include a paragraph summarizing definitions and what is included in the country-level emissions or what is the asset/emitter included for this sector and what is not included. If a specific type of asset is missing, mention that (for e.g., we only estimate emissions for clinker producing cement plants).

Table S1 *General dataset information*

General Description	Definition
Sector definition	*Emissions from extraction of copper, iron and bauxite ores (asset-level/country-level), sand/gravel and rock/stone quarrying*
UNFCCC sector equivalent	*1.A.2.g.iii. Mining (Excluding Fuels) and Quarrying*
Temporal Coverage	*2015 – 2022*
Temporal Resolution	*Annual*
Data format(s)	*CSV*
Coordinate Reference System	*EPSG:4326, decimal degrees*
Number of assets/countries available for download and percent of global emissions (as of 2022)	*1,266 assets (555 copper, 536 iron and 175 bauxite)*
Total emissions for 2022	*166,739,605 tonnes CO_2e*
Ownership	*We used permit data and research to identify ownership information*
What emission factors were used?	*Industry emission factors*
What is the difference between a "NULL / none / nan" versus "0" data field?	*"0" values are for true non-existent emissions. If we know that the sector has emissions for that specific gas, but the gas was not modelled, this is represented by "NULL/none/nan"*
total_CO2e_100yrGWP and total_CO2e_20yrGWP conversions	Climate TRACE uses IPCC AR6 CO_2e GWPs. CO_2e conversion guidelines are here:https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_Full Report_small.pdf

Table S2: *Asset level metadata description confidence and uncertainty*

Data attribute	Confidence Definition	Uncertainty Definition
type		N/A
capacity_description	N/A	N/A
capacity_factor_description	N/A	N/A
capacity_factor_units	N/A	N/A
activity_description	Ore mass reported for current year (high), ore mass scaled from reported non-ore mass for current year/ore mass from previous year or InSAR-derived value (medium), ore mass scaled from reported non-ore mass from previous year (low)	± std dev of scaling factors used in activity calculation
CO2_emissions_factor	Emissions factor calculated from reported asset-specific emissions data (medium), emissions factor averaged at national level (low), emissions factor averaged at regional level (very low)	± std dev of emission factors used in national/regional level calculations

CH4_emissions_factor	N/A	N/A
N2O_emissions_factor	N/A	N/A
other_gas_emissions_factor	N/A	N/A
CO2_emissions	Taken as the lower confidence level from 'Activity' and 'CO_2 emissions factor'	Product of uncertainty from 'Activity' and 'CO_2 emissions factor'
CH4_emissions	N/A	N/A
N2O_emissions	N/A	N/A
other_gas_emissions	N/A	N/A
total_CO2e_100yrGWP	Taken as the lower confidence level from 'Activity' and 'CO_2 emissions factor'	Product of uncertainty from 'Activity' and 'CO_2 emissions factor'
total_CO2e_20yrGWP	Taken as the lower confidence level from 'Activity' and 'CO_2 emissions factor'	Product of uncertainty from 'Activity' and 'CO_2 emissions factor'

Data citation format: Jolleys, M. and Duddy, P. (2023). *Mining and Quarrying Emissions Methodology.* Hypervine, UK, Climate TRACE Emissions Inventory. https://climatetrace.org [Accessed date]

Geographic boundaries and names (iso3_country data attribute): The depiction and use of boundaries, geographic names and related data shown on maps and included in lists, tables, documents, and databases on Climate TRACE are generated from the Global Administrative Areas (GADM) project (Version 4.1 released on 16 July 2022) along with their corresponding ISO3 codes, and with the following adaptations:

- HKG (China, Hong Kong Special Administrative Region) and MAC (China, Macao Special Administrative Region) are reported at GADM level 0 (country/national);
- Kosovo has been assigned the ISO3 code 'XKX';
- XCA (Caspian Sea) has been removed from GADM level 0 and the area assigned to countries based on the extent of their territorial waters;
- XAD (Akrotiri and Dhekelia), XCL (Clipperton Island), XPI (Paracel Islands) and XSP (Spratly Islands) are not included in the Climate TRACE dataset;
- ZNC name changed to 'Turkish Republic of Northern Cyprus' at GADM level 0;
- The borders between India, Pakistan and China have been assigned to these countries based on GADM codes Z01 to Z09.

The above usage is not warranted to be error free and does not imply the expression of any opinion whatsoever on the part of Climate TRACE Coalition and its partners concerning the legal status of any country, area or territory or of its authorities, or concerning the delimitation of its borders.

Disclaimer: The emissions provided for this sector are our current best estimates of emissions, and we are committed to continually increasing the accuracy of the models on all levels. Please review our terms of use and the sector-specific methodology documentation before using the data. If you identify an error or would like to participate in our data validation process, please contact us.