

The impact of nickel mining on vegetation index in Molawe Sub-district, North Konawe District, Southeast Sulawesi, Indonesia

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Abstract. Adidharma MA, Supriatna, Takarina ND. 2023. The impact of nickel mining on vegetation index in Molawe Sub-district, North Konawe District, Southeast Sulawesi, Indonesia. *Biodiversitas* 24: 4581-4588. Nickel mining activities in Molawe Sub-district, North Konawe District, Southeast Sulawesi, Indonesia have modified the land cover structure over time due to increased mining exploitation zones. This study intends to assess changes in land cover in the Molawe Sub-district, particularly around mining regions. The NDVI index was applied to Landsat 7 ETM+ satellite imagery data in 2001 to identify land cover conditions before mining activities, then to Landsat 8 OLI imagery data in 2015 and 2020 to identify land cover after mining activities. These data are then used to compute annual changes in the extent of each land cover. The NDVI classification produces four land cover types: non-vegetation, open soil, sparse vegetation, and moderate vegetation. The study shows that non-vegetation and open ground cover types experienced a significant increase in area from 2001 to 2015 and from 2015 to 2020. Meanwhile, sparse vegetation forest cover experienced a reduction in area from 2001 to 2015 and 2015 to 2020. In contrast to sparse vegetation, the moderate vegetation cover is experiencing a minor increase in area. Based on these results, relevant policymakers need to formulate policies to mitigate environmental impacts that may arise in the future.

Keywords: Molawe Sub-district, NDVI, nickel mining, vegetation

INTRODUCTION

The mining industry is an essential sector in the Indonesian economy, contributing 11% of Indonesia's GDP in 2020 (Laksana 2022). Based on data from the Indonesian Chamber of Commerce and Industry (2022), Indonesia's five largest types of mining products are nickel, gold and silver, bauxite, copper concentrate, copper ore, and tin. Nickel is the most produced mining product, amounting to 35.5 million metric tons. According to data from the Ministry of Energy and Mineral Resources for 2020, nickel mining activities in Indonesia are spread across several provinces, the largest in Southeast Sulawesi Province. Southeast Sulawesi has quite large nickel reserves. Based on data from the ESDM Office of Southeast Sulawesi Province, nickel reserves in Southeast Sulawesi reach 97 billion tons with a distribution area of 480 thousand hectares (Southeast Sulawesi Government 2021).

Because of the enormous nickel reserves in Southeast Sulawesi, nickel is the principal mining commodity in the province (Prasetyo et al. 2015), with production in 2018 totaling 16,926,763 tonnes and expected to reach 22,531,686 tonnes by 2020. The 143 nickel mining firms in Sulawesi Southeast contributed to the total nickel production. Based on data from the Central Bureau of Statistics for Southeast Sulawesi Province, in 2022, North Konawe District has the largest nickel mining activity in

Southeast Sulawesi, where as many as 70 nickel companies operate in this area. Its mining activities are spread over several sub-districts, where eight nickel mining companies operate in the Molawe Sub-district. The magnitude of mining activities in this area contributes to employment and local regional income (Kurakova and Ponomarenko 2021). However, on the other hand, it is a driving factor for deforestation (Mbaya 2013; Kramer et al. 2023) due to the expansion of the exploited area from time to time. These deforestation activities cause several negative impacts, such as increasing the average air temperature (Prevedello et al. 2019; Wolff et al. 2021) related to global warming (Lawrence et al. 2022), reducing the organic carbon content in the soil and significantly causing the soil more unstable (Amoakwah et al. 2022). In mining sites, especially those that use open-pit mining techniques, landslides are a calamity that is very likely to happen. Due to the easily destroyed and unstable rock and soil conditions in the mining area, open-pit mining locations will have a very high level of erosion susceptibility. The geographical position in steep mountains (Momon et al. 2021) and the presence of natural variables, such as rainfall (Chen et al. 2023), can worsen the instability of this soil structure. Based on these effects, land cover monitoring is required to gather data and serve as a resource when developing policies to safeguard and conserve coastal and forest areas (Romijn et al. 2015).

Normalized Difference Vegetation Index (NDVI) is an index commonly used to measure the level of greenness and density of vegetation to assess the temporal changes of vegetation (Gandhi et al. 2015; Huang et al. 2020). Besides providing an overview of the temporal dynamics of terrestrial ecosystems, NDVI can also provide information for ecosystem use and protection (Essaadia et al. 2022). According to Wang (2016) and Gao et al. (2022), human activity significantly impacts NDVI since different levels of human activity in land use might increase or decrease in NDVI. Studies have shown that using the NDVI to track land cover change yields accuracy ranging from 88% to 96%, according to research (Madasa et al. 2021). The spatial model's output from this study is anticipated to guide managing land and minimizing forest damage from nickel mining. According to the results, it is vital to use NDVI analysis to identify changes in land cover caused by mining activities. The study is anticipated to offer recommendations and feedback on forest regeneration techniques in nickel mining regions in the Molawe Sub-district

MATERIALS AND METHODS

Study area

The research area is the Molawe Sub-district, North Konawe District, Southeast Sulawesi Province, Indonesia (Figure 1). The Molawe Sub-district area stretches from north to south between 02°97' and 03°86' South and stretches from west to east between 121°49' and 122°49' East. Molawe Sub-district has an open nickel mining area in several village areas with mountainous, undulating, and hilly topography surrounding the lowlands (Central Bureau of Statistics for North Konawe Regency 2022). In addition, the Lasolo River Estuary is the largest river in North Konawe District. The Area of Interest (AOI) for observing

land cover is limited to four areas: Tapunggaya, Tapuemea, Mandiodo, and Mowundo Villages. AOI is limited by digitizing to form polygons in Google Earth Pro Software (Atiqah et al. 2020). The restricted area is a mining area in the Molawe Sub-district area. The created polygons are then exported in KML format. The KML file is then imported into the ArcMap 10.8 software and converted into layers. The AOI layer is then re-exported and saved in the Shapefile (SHP). The AOI SHP file will later be used further in image cropping.

Procedures

Remote sensing data collection

The image data used in this study are level 2 Landsat 7 ETM+ and Landsat 8 OLI image data, which temporally represent periods prior to mining (2001) and following mining (2015 & 2020). Image data was downloaded from the website <https://earthexplorer.usgs.gov/>. Details of the remote sensing data used in this study are presented in Table 1. Landsat level 2 image data is selected based on the availability of image data that already contains surface reflectance data (Fawzi and Husna 2019; USGS 2022). Thus, there is no need for radiometric and atmospheric correction of the image. The image is selected based on the acquisition time criteria and cloud cover, which is a maximum of 20%.

Table 1. Satellite image data used in this research

Imagery File Name	Acquisition Date
LE07_L2SP_113062_20010121_20200917_02_T1	21 Jan 2001
LC08_L2SP_113062_20151120_20200908_02_T1	20 Nov 2015
LC08_L2SP_113062_20200829_20200906_02_T1	29 Aug 2020

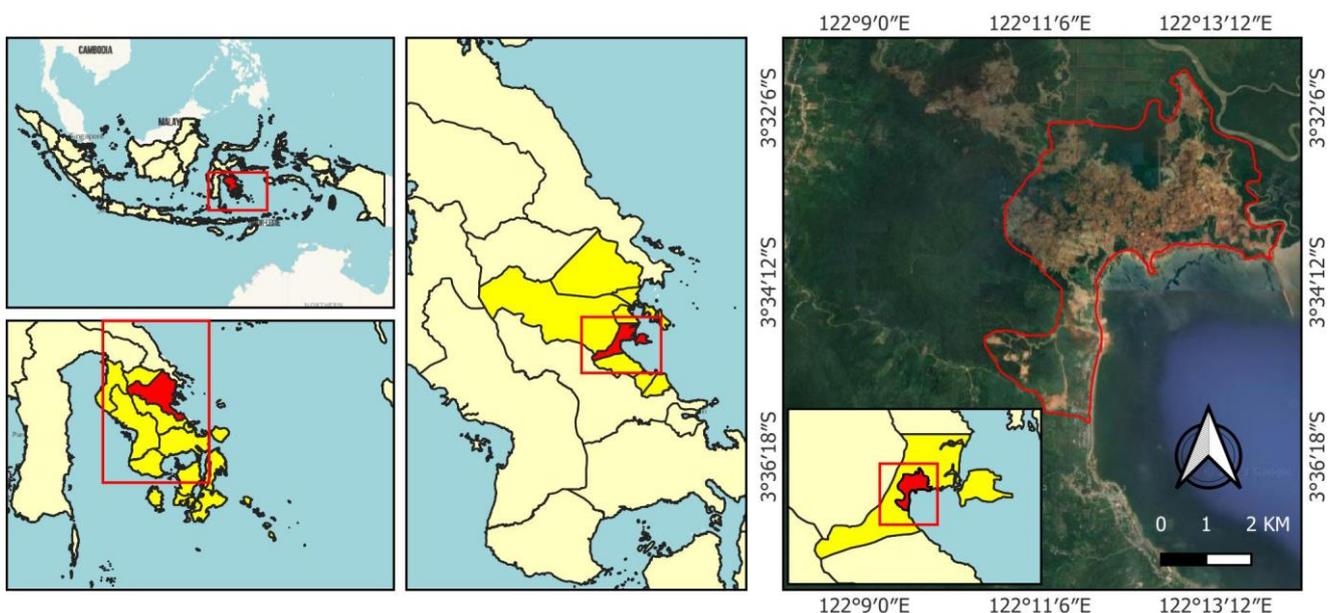


Figure 1. Location of AOI in Molawe Sub-district, North Konawe District, Southeast Sulawesi Province, Indonesia

NDVI classification

Land cover change analysis was conducted using Normalized Difference Vegetation Index (NDVI) analysis. A high NDVI index value will indicate forest, agricultural, and plantation areas, while a low value indicates vacant land or land without crops (Mohajane et al. 2017). NDVI classification is made by selecting well-defined class intervals with a specific color for each class (Essaadia et al. 2022). The NDVI formula is as follows:

$$NDVI = \frac{(NIR-Red)}{(NIR+Red)} \dots \dots \dots (1)$$

NDVI analysis can be performed using ArcMap 10.8 on the Raster Calculator tool. The bands used are bands 3 (red) and 4 (NIR) on Landsat 7 ETM+ and bands 4 (red) and 5 (NIR) on Landsat 8 OLI (Gessesse and Melesse 2019; Gutman et al. 2021). The results of the NDVI analysis of the images are then exported in TIFF format. The TIFF file is then imported into ArcMap 10.8 software for further analysis. The resulting NDVI image imported to ArcMap 10.8 is cropped according to the AOI area previously created using the Arc Toolbox > Data Management Tool > Raster > Raster Processing > Clip. After the image cropping process, the NDVI value is classified according to the NDVI range values (Kuzevic et al. 2022).

Calculating land cover area/vegetation density

Calculation of land cover area using the reclassify tool. Reclassification can be used to reclassify the variable's value on the raster gained value basis (Jebur et al. 2015). The NDVI results are in raster format on ArcMap, then were reclassified using ArcToolbox > Spatial Analyst Tools > Reclass. In reclassifying the raster, manual classification was according to the range of NDVI values, as presented in Table 2. After reclassifying, we convert the reclassified raster into polygons using the Conversion Tools > From Raster > Raster to Polygon tool. The converted polygon file will then limit the cover area according to the classification value in Table 2. Using the Start Editing command button, We merge all the polygons according to their respective grid codes in the data attribute table. After all the polygons are put together according to their respective grid codes, we create a new column (add field) in the data attribute table with Double type. Then, do Calculate Geometry on that column and determine the area unit to be used. Calculate Geometry is a tool that can calculate a polygon's coordinates, length, and area (Sobatnu et al. 2017). The area calculation results will appear in the column.

Relationship between distance from mine and vegetation density

The distance from the mine area and the vegetation density were correlated using a simple linear regression analysis in Microsoft Excel 2019. The distance is measured every 200 meters from the mine, especially on the west and north sides of the mining region. The analysis results are then given graphically in the form of a scatter plot, along with the coefficient of determination (R^2) value, which indicates the level of the relationship.

RESULTS AND DISCUSSION

Land cover in 2001, 2015 and 2020

The analysis results show that four land cover types are produced, i.e., non-vegetation, open soil, sparse vegetation, and moderate vegetation. Sparse vegetation is the widest land cover type, i.e., 19.893 km² in 2001, 13.650 km² in 2015, and 11.358 km² in 2020. Non-vegetation and open soil types have an area of 0.003 and 0.155 km² in 2001, 2.892 and 2.590 km² in 2015, and 4.910 and 2.620 km² in 2020. Moderate vegetation cover type had an area of 0.287 km² in 2001, 1.206 km² in 2015, and 1.450 km² in 2020. The distribution pattern of land cover, area, and percentage in 2001, 2015, and 2020 has been presented in Figures 2 and 3, Tables 3 and 4.

Land cover area changes

The non-vegetation and open soil cover increased 2.889 and 2.435 km² from 2001 to 2015 and 2.018 and 0.030 km² from 2015 to 2020. Sparse and moderate vegetation cover experienced different things, where sparse vegetation decreased by 6.243 in the 2001 period to 2015 and 2.292 km² in the period 2015 to 2020, while moderate vegetation increased by 0.919 km² in the period 2001 to 2015 and 0.244 km² in the period 2015 to 2020. Data on changes in the land cover area have been presented in Table 5 and Figure 4.

Table 2. NDVI value class

No.	Cover Type	NDVI Value
1	Non-Vegetation	NDVI<0.1
2	Open Soil	0.1<NDVI<0.2
3	Sparse Vegetation	0.2<NDVI<0.4
4	Moderate Vegetation	0.4<NDVI<0.6
5	Dense Vegetation	0.6<NDVI<1

Table 3. The area of each land cover

Cover Type	Cover Area (km ²)		
	2001	2015	2020
Non-vegetation	0.003	2.892	4.910
Open soil	0.155	2.590	2.620
Sparse vegetation	19.893	13.650	11.358
Moderate vegetation	0.287	1.206	1.450
Dense vegetation	0	0	0
Total		20.338	

Table 4. Percentage of each land cover area

Cover Type	Cover Percentage (%)		
	2001	2015	2020
Non-vegetation	0.01	14.22	24.14
Open soil	0.76	12.73	12.88
Sparse vegetation	97.81	67.12	55.85
Moderate vegetation	1.41	5.93	7.13
Dense vegetation	0	0	0

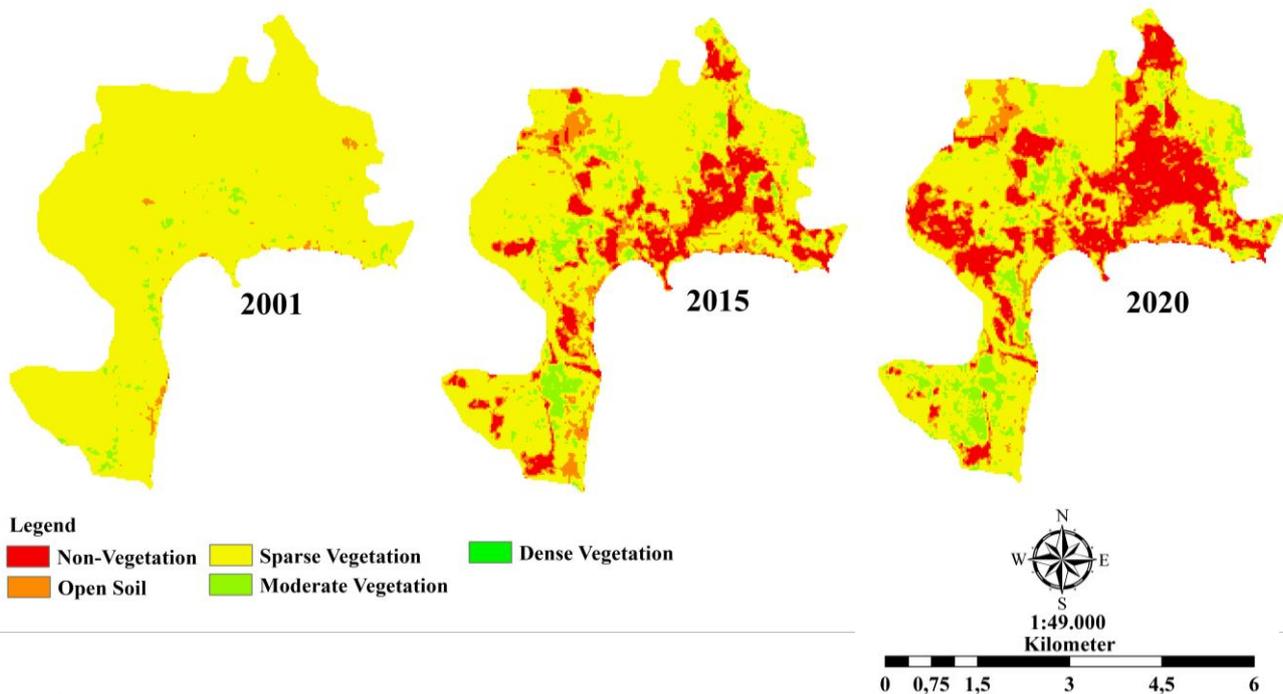


Figure 2. Map of land cover patterns in 2001, 2015 and 2020

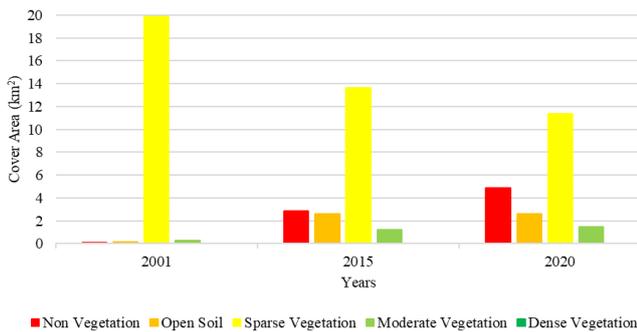


Figure 3. Comparison of land cover areas in 2001, 2015 and 2020

Table 5. Changes in the land cover area in the 2001-2015 and 2015-2020 periods

Cover Type	Period	
	2001-2015 (km ²)	2015-2020 (km ²)
Non-vegetation	2.889	2.018
Open soil	2.435	0.030
Sparse vegetation	-6.243	-2.292
Moderate vegetation	0.919	0.244
Dense vegetation	0	0

Discussion

The land cover classification produces four types: non-vegetation, open soil, sparse vegetation, and moderate vegetation. The results of measuring the area of land cover types in 2001, 2015, and 2020 produce different variations each year (Figure 4). In 2001, the land cover was dominated by sparse vegetation (97.81%) with an area of

19.893 km². Non-vegetation land cover types (0.01%), open soil (0.76%), and moderate vegetation (1.41%) have an area of 0.003, 0.155, and 0.287 km², respectively. In 2015, all land cover categories experienced changes in the area, where sparse vegetation (67.12%) was still dominant with an area of 13.650 km², non-vegetation (14.22%) covering 2.888 km², open soil (12.73%) covering 2.590 km² and moderate vegetation (5.93%) covering an area of 1.206 km². In 2020, sparse vegetation (55.85%) and non-vegetation (24.14%) dominated with an area of 11.358 and 4.910 km², respectively. While another cover, such as open soil (12.88%), covers an area of 2.620 km² and moderate vegetation (7.13%) covers an area of 1.450 km².

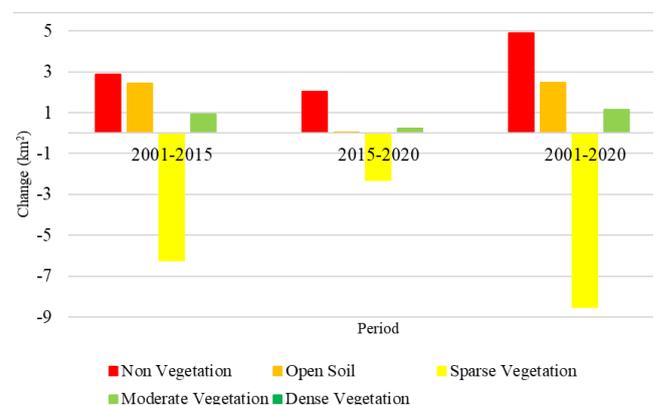


Figure 4. Changes in the land cover area in the 2001-2015 and 2015-2020 periods

The land cover change analysis shows, in general, there has been an increase in the area of the mining area, which is assumed to be a non-vegetation area increasing. Meanwhile, sparsely vegetated areas continued to experience a significant decrease from 2001 to 2020. Sparsely vegetated areas decreased by 6.243 km² from 2001 to 2015 and 2.292 km² from 2015 to 2020. Vegetation is experiencing a slight increase in area, namely 0.919 km² from 2001 to 2015 and 0.244 km² from 2015 to 2020. Meanwhile, 2.889 km² of non-vegetation increased from 2001 to 2015, and an additional 2.018 km² from 2015 to 2020 due to the opening of mining land. The open soil area assumed to be a non-vegetated area also increased by 2.435 km² from 2001 to 2015 and a minor 0.030 km² from 2015 to 2020. This decrease in vegetation cover was due to the open-pit mining method applied in this area. The open-pit mining method damages the landscape and forests at the mining site because trees, plants, and topsoil are cleared from the area to be mined (Stracher, 2019). Reducing vegetation due to mining activities also occurs in the Sungun mine area in Iran, the Athabasca mine in Canada, and the Hambach mine in Germany. The Sungun mining area in Iran experienced a forest reduction of 4.05 km² during the period 1989-2019, the Athabasca mine in Canada experienced a forest reduction of 9.05 km² from 1999-2019, and the forest at the Hambach mine in Germany decreased by 46.39 km² during 1989-2017 (Firozjahi et al. 2021).

Based on the land cover map, mining areas are developing in the coastal areas of Tapunggaya and Tapuemea Villages. This development in the coastal area is thought to be caused by the influence of the availability of transportation infrastructure because the connecting road to the locations of Tapunggaya and Tapuemea Villages is along the coast. In addition, the availability of land roads greatly supports the development of the mining industry because it will be vital for logistics distribution (Zhang and Wu 2022; Zhang and Cheng 2023).

Most mining areas in the study area are in the Mandiodo, Tapuemea, and Tapunggaya Village Molawe Sub-districts. This is thought to be caused by the distribution of nickel laterite deposits, which are more abundant in all three villages. Nickel laterite deposits in the Molawe Sub-district have different thicknesses at each point or area, with the highest thickness being in the central to eastern sides, namely 5-13 meters, while in the western sides, they only have a relatively lowest, namely 1-2 meters (Raivel and Hasrianto 2023).

The effect of decreasing vegetation cover due to mining activities usually occurs around mined areas, while areas outside mining areas have relatively better vegetation cover. According to Pour et al. (2021), the direct and indirect effects of mining activities on the growth and health of plant vegetation generally decrease linearly, followed by increasing the distance of vegetation from the mine to at least 600 m. Research Fakhimi (2020) also suggests that increasing the distance of vegetation from the mining area can significantly increase the cover percentage for several plant species, including Asteraceae, Fabaceae, Poaceae, Chenopodiaceae, and Lamiaceae. The difference

in vegetation cover affected by the distance of vegetation to the mine site is due to the relatively better soil quality in areas far from the mine. The soil near mining sites generally contains more contaminants due to the heavy metal residues released into the soil (Fashola et al. 2016).

The correlation analysis results between the distance from the mine and the vegetation cover (Figure 5) at the study site show an R² value of 0.052. This value indicates no linear relationship between the distance from the mine and the vegetation cover. This is due to the increasingly widespread conversion of forest functions around mines to other uses, such as residential areas and agriculture development. Based on Figures 6 and 7, the north side of AOI has been converted into plantation and agricultural development, while the east side is a mangrove forest that is starting to turn into an aquaculture area, and the west side is a forest area that has uneven coverage. Uneven forest cover on the western side of the AOI is caused by several factors, including the effects of mining, which reduces fertility will further inhibit vegetation growth (Prematuri et al. 2020) and differences between vegetation types, vegetation ages, and environmental conditions (Fang et al. 2014).

The area on the north side of AOI, which is in the administrative area of Andowia sub-district, has mostly been converted into oil palm plantation land owned by PT. Sultra Prima Lestari (SPL) and community agricultural land. Agricultural development in rural areas is strongly tied to most rural communities that work as farmers (Moomen and Dewan 2015) and will heavily rely on the agricultural industry (Waddington et al. 2014). Aside from the agricultural sector, settlement is expanding around mining locations. The increasing need for residential areas for local communities and migrant workers from outside the area to support ease of access and proximity to workplaces is a driving force for residential development. According to Pratama et al. (2019), settlements that emerge in mining areas tend to develop relatively quickly due to the strong demand for residential areas and suitable services and infrastructure availability. Moreover, several mining companies in North Konawe have allocated their Corporate Social Responsibility (CSR) funds to develop several village infrastructures, educational and religious infrastructure (Kasmudin et al. 2018; Masri et al. 2019).

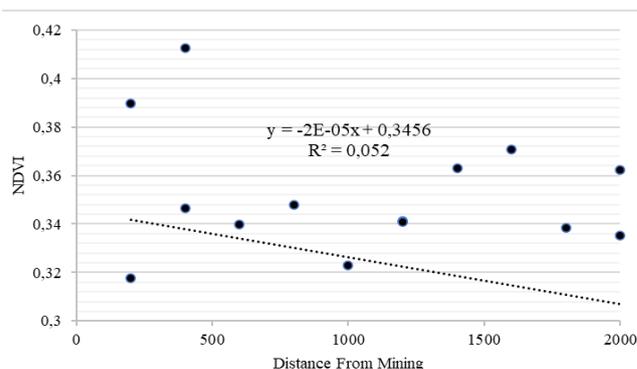


Figure 5. The relationship between distance from the mine and image reflectance

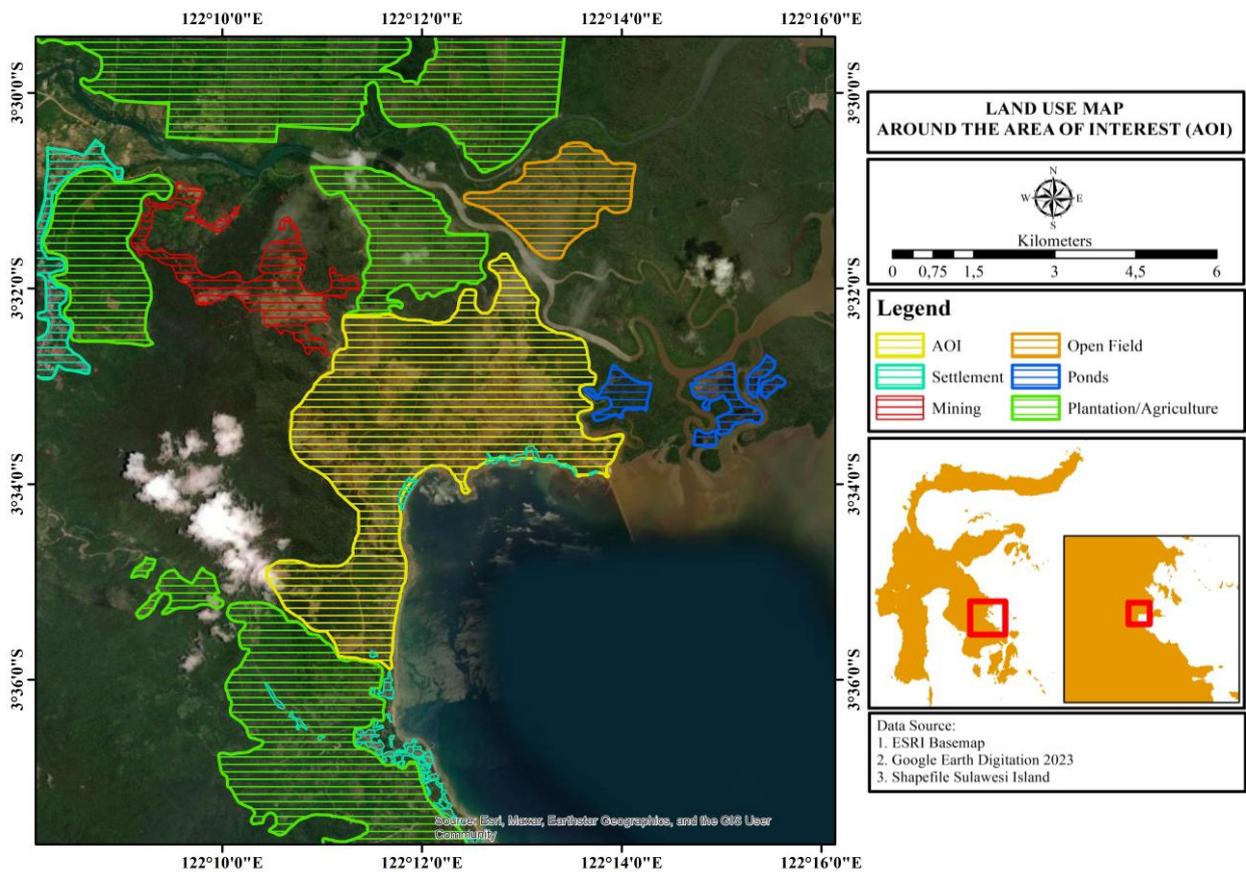


Figure 6. Map of land cover around the area of interest (AOI)

0.318	0.347	0.340	0.348	0.323	0.341	0.363	0.371	0.339	0.335	North
0.390	0.413	0.285	0.264	0.271	0.341	0.227	0.277	0.231	0.362	West
200	400	600	800	1000	1200	1400	1600	1800	2000	Distance (m)

Figure 7. NDVI pattern based on distance from north and west mine side

Forest degradation caused by mining activities in the Molawe Sub-district requires the Central and Regional Governments' attention to mitigate the significant impact in the future. Consider that the mining area in the Molawe Sub-district is mountainous, close to settlements, and borders Lasolo Bay. Landslides are a disaster that can be produced by mining in this area (Mu et al. 2021) because the soil is more unstable after extra mining activities in various North Konawe's nickel mining locations (Barus et al. 2022). The presence of mines on the mainland directly impacts Lasolo Bay. In addition to water, mining can also pollute groundwater sources. Research by Ullah et al. (2022) reveals that groundwater sources in areas close to mining experience heavy metal contamination in the groundwater. This can impact the health of the people who live around it. Based on several examples of impacts that can occur as a result of mining, all stakeholders need to

carry out management that is conserving and realizing environmental sustainability because preserving the environment of settlements in mining areas must be given attention to social, economic, environmental and policy (Sushanti et al. 2020).

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REFERENCES

- Amoakwah E, Lucas ST, Didenko NA, Rahman MA, Islam KR. 2022. Impact of deforestation and temporal land-use change on soil organic carbon storage, quality and lability. *PLoS One* 17 (8): e0263205. DOI: 10.1371/journal.pone.0263205.
- Atiqah AH, Rhyma PP, Jamhuri J, Zulfa AW, Samsinar MS, Norizah K. 2020. Using google earth imagery to detect distribution of forest cover change-is the technique practical for Malaysian forests? *Malays For* 83 (1): 1-15.
- Barus B, Tarigan SD, Tejo RK, Stanny YA. 2022. Development of a land stability index for land damage assessment: The case of a nickel mine, North Konawe, Indonesia. *J Degrad Min Land Manag* 9 (4): 3695-3702. DOI: 10.15243/jdmlm.2022.094.3695.
- Central Bureau of Statistics for North Konawe Regency. 2022. Molawe Sub-district in figures 2022. Central Bureau of Statistics for North Konawe Regency, Wanggudu. [Indonesian]
- Central Bureau of Statistics for Southeast Sulawesi Province. 2022. Directory of Mining Companies in Southeast Sulawesi Province 2022. Central Bureau of Statistics for Southeast Sulawesi Province, Kendari. [Indonesian]
- Chen T, Shu J, Han L, Tovele GSV, Li B. 2023. Landslide mechanism and stability of an open-pit slope: The manglai open-pit coal mine. *Front Earth Sci* 10: 1038499. DOI: 10.3389/feart.2022.1038499.
- Essaadia A, Abdellah A, Ahmed A, Abdelouahed F, Kamal E. 2022. The Normalized Difference Vegetation Index (NDVI) of the Zat Valley, Marrakech: Comparison and dynamics. *Heliyon* 8: e12204. DOI: 10.1016/j.heliyon.2022.e12204.
- Fakhimi E. 2020. Impact of mining on variation of species diversity, richness and structure of vegetation cover (case study copper mine in Dareh Zereshk, Yazd Province, Iran). *Iran J Rangel Desert Res* 27 (4): 772-781. DOI: 10.22092/ijrdr.2020.123152.
- Fang J, Kato T, Guo Z, Houghton RA. 2014. Evidence for environmentally enhanced forest growth. *Proc Natl Acad Sci* 111 (26): 9527-9532. DOI: 10.1073/pnas.1402333111.
- Fashola MO, Ngole-Jeme VM, Babalola OO. 2016. Heavy metal pollution from gold mines: Environmental effects and bacterial strategies for resistance. *Intl J Environ Res Public Health* 13 (11): 1047. DOI: 10.3390/ijerph13111047.
- Fawzi NI, Husna VN. 2019. Landsat 8-A Basic Level of Theory and Processing Techniques. El Markazi, Bengkulu. [Indonesian]
- Firozjaei MK, Sedighi A, Firozjaei HK, Kiavarz M, Homae M, Arsanjani JJ, Makki M, Naimi B, Alavipanah SK. 2021. A historical and future impact assessment of mining activities on surface biophysical characteristics change: A remote sensing-based approach. *Ecol Indic* 122: 107264. DOI: 10.1016/j.ecolind.2020.107264.
- Gandhi MG, Parthiban S, Thummalu N, Christy A. 2015. NDVI: Vegetation change detection using remote sensing and GIS-A case study of Vellore District. *Procedia Comput Sci* 57: 1199-1210. DOI: 10.1016/j.procs.2015.07.415.
- Gao W, Zheng C, Liu X, Lu Y, Chen Y, Wei Y, Ma Y. 2022. NDVI-based vegetation dynamics and their responses to climate change and human activities from 1982 to 2020: A case study in the Mu Us Sandy Land, China. *Ecol Indic* 137: 108745. DOI: 10.1016/j.ecolind.2022.108745.
- Gessesse AA, Melesse AM. 2019. Chapter 8 - Temporal relationships between time series CHIRPS-Rainfall estimation and eMODIS-NDVI satellite images in Amhara Region, Ethiopia. In: Melesse AM, Abtew W, Senay G (eds.). *Extreme Hydrology and Climate Variability: Monitoring, Modelling, Adaptation and Mitigation*. Elsevier, Amsterdam. DOI: 10.1016/B978-0-12-815998-9.00008-7.
- Gutman G, Skakun S, Gitelson A. 2021. Revisiting the use of red and near-infrared reflectances in vegetation studies and numerical climate models. *Sci Remote Sens* 4: 100025. DOI: 10.1016/j.srs.2021.100025.
- Huang S, Tang L, Hupy JP, Wang Y, Shao G. 2020. A commentary review on the use of Normalized Difference Vegetation Index (NDVI) in the era of popular remote sensing. *J For Res* 32: 1-6. DOI: 10.1007/s11676-020-01155-1.
- Indonesian Chamber of Commerce and Industry. 2022. Indonesia's mining sector in brief. <https://bsd-kadin.id/2022/06/22/indonesias-mining-sector-in-brief/>
- Jebur MN, Pradhan B, Shafri HZM, Yusoff ZM, Tehrani MS. 2015. An integrated user-friendly arcmap tool for bivariate statistical modelling in geoscience applications. *Geosci Model Dev* 8: 881-891. DOI: 10.5194/gmd-8-881-2015.
- Kasmudin, Hamuni, Safar M. 2018. Implementasi tanggungjawab sosial perusahaan (corporate social responsibility) terhadap masyarakat kawasan pertambangan (studi di Kecamatan Motui Kabupaten Konawe Utara). *Selami IPS* 4 (48): 383-394. DOI: 10.36709/selami.v4i48.8513. [Indonesian]
- Kramer M, Kind-Rieper T, Munayer R, Giljum S, Masselink R, Ackern PV, Maus V, Luckeneder S, Kuschnig N, Costa F, Rüttinger L. 2023. Extracted Forests: Unearthing the Role of Mining-Related Deforestation as a Driver of Global Deforestation. WWF, Deutschland.
- Kurakova KN, Ponomarenko TV. 2021. Impact of mining industry growth on sustainable development indicators. *E3S Web Conf* 266: 06007. DOI: 10.1051/e3sconf/202126606007.
- Kuzevic S, Bobikova D, Kuzevicova Z. 2022. Land cover and vegetation coverage changes in the mining area - a case study from Slovakia. *Sustainability* 14: 1180. DOI: 10.3390/su14031180.
- Laksana MPA. 2022. Export taxes and trade pattern: Case from the Indonesian mineral industry. *Indones J Dev Plan* 6 (2): 37-53. DOI: 10.36574/jpp.v6i1.243.
- Lawrence D, Coe M, Walker W, Verchot L, Vandecar K. 2022. The unseen effects of deforestation: Biophysical effects on climate. *Front For Glob Change* 5: 756115. DOI: 10.3389/ffgc.2022.756115.
- Madasa A, Orimoloye IR, Ololade OO. 2021. Application of geospatial indices for mapping land cover/use change detection in a mining area. *J Afr Earth Sci* 175: 104108. DOI: 10.1016/j.jafrearsci.2021.104108.
- Masri M, Isalman, Putera A. 2019. Implementasi dan dampak Corporate Social Responsibility (CSR) pada perusahaan pertambangan di Kabupaten Konawe Utara. *Seminar Nasional INOBALI 2019 Inovasi Baru dalam Penelitian Sains, Teknologi dan Humaniora*: 1154-1162. Bali, Indonesia. [Indonesian]
- Mbaya RP. 2013. Land degradation due to mining: The gunda scenario. *Intl J Geogr Geol* 2 (12): 144-158. DOI: 10.18488/journal.10/2013.2.12/10.12.144.158.
- Ministry of Energy and Mineral Resources. 2020. Indonesian Nickel Investment Opportunities. Ministry of Energy and Mineral Resources, Jakarta.
- Mohajane M, Essahlaoui A, Oudija F, Hafyani ME, Teodoro AC. 2017. Mapping forest species in the central middle atlas of Morocco (Azrou Forest) through remote sensing techniques. *ISPRS Intl J Geoinf* 6 (9): 275. DOI: 10.3390/ijgi6090275.
- Momon, Adji BM, Kusuma DW, Yolarita E, Ukhwatu V, Masbiran K, Dodi A. 2021. Study analysis of landslide vulnerability of mining area in the Sub-District Lembah Gumanti, Solok Regency (Lubuk Selasih Street-Surian). *E3S Web Conf* 331:06007. DOI: 10.1051/e3sconf/202133106007.
- Moomen AW, Dewan A. 2015. Mining, agricultural space and land use conflicts: The role of local government. 2015 Fourth International Conference on Agro-Geoinformatics (Agro-Geoinformatics). Istanbul, Turkey, July 2015. DOI: 10.1109/Agro-Geoinformatics.2015.7248103.
- Mu C, Yu X, Zhao B, Zhang D, Mao X, Zhu J. 2021. The formation mechanism of surface landslide disasters in the mining area under different slope angles. *Adv Civ Eng* 2021: 6697790. DOI: 10.1155/2021/6697790.
- Pour SI, Zadeh ARK, Taghizadeh-Mehrjardi R, Boeck HJD, Gul A. 2021. Dust-related impacts of mining operations on rangeland vegetation and soil: A case study in Yazd Province, Iran. *Environ Earth Sci* 80: 467. DOI: 10.1007/s12665-021-09758-5.
- Prasetyo BE, Supriadi A, Darmawan A, Kurniasih TN, Kurniawan F, Oktaviani K, Isra A, Aprilia R, Rabbani Q, Anggreani D, Setiadi I. 2015. The Impact of Smelter Construction in the Special Economic Zone of Southeast Sulawesi Province. Center for Data and Information Technology of the Ministry of Energy and Mineral Resources, Jakarta.
- Pratama Y, Wunas S, Arifin M. 2019. Perkembangan permukiman sekitar wilayah pertambangan nikel Sorowako Kabupaten Luwu Timur. *J Reg Marit City Stud* 7: 274-280. DOI: 10.20956/jwkm.v7i0.1237. [Indonesian]
- Prematuri R, Turjaman M, Sato T, Tawaraya K. 2020. The impact of nickel mining on soil properties and growth of two fast-growing tropical trees species. *Intl J For Res* 2020: 8837590. DOI: 10.1155/2020/8837590.
- Prevedello JA, Winck GR, Weber MM, Nichols E, Sinervo E. 2019. Impacts of forestation and deforestation on local temperature across the globe. *PLoS One* 14 (3): e0213368. DOI: 10.1371/journal.pone.0213368.

- Raivel, Hasrianto. 2023. Model of laterite nickel deposit in the Molawe area North Konawe Sub-district Southeast Sulawesi Province. *Min Sci Technol J* 2 (1): 70-81. DOI: 10.2021/minetech%20journal.v2i1.447.
- Romijn E, Lantican CB, Herold M, Lindquist E, Ochieng R, Wijaya A, Murdiyarto D, Verchot L. 2015. Assessing change in national forest monitoring capacities of 99 tropical countries. *For Ecol Manag* 352 (7): 109-123. DOI: 10.1016/j.foreco.2015.06.003.
- Sobatnu F, Irawan FA, Salim A. 2017. Identifikasi dan pemetaan morfometri daerah aliran Sungai Martapura menggunakan teknologi GIS. *Jurnal Gradasi Teknik Sipil* 1 (2): 45-52. DOI: 10.31961/gradasi.v1i2.432. [Indonesian]
- Southeast Sulawesi Government. 2021. Changes of the Southeast Sulawesi Provincial Medium Term Development Plan 2018-2023. Southeast Sulawesi Province Government, Kendari. [Indonesian]
- Stracher GB. 2019. Environmental monitoring in the Jharia Coalfield, India: Vegetation indices and surface temperature measurements. In: GB Stracher (ed.). *Coal and Peat Fires: A global Perspective*, volume 5: Case Studies - Advances in Field and Laboratory Research. Elsevier, Netherlands. DOI: 10.1016/B978-0-12-849885-9.00017-2.
- Sushanti IR, Jauhari L, Abednego IA. 2020. Settlement's feasibility parameters in the village outer mining area. *IOP Conf Ser Earth Environ Sci* 413: 012019. DOI: 10.1088/1755-1315/413/1/012019.
- Ullah Z, Rashid A, Ghani J, Nawab J, Zeng XC, Shah M, Alrefaei AF, Kamel M, Aleya L, Abdel-Daim MM, Iqbal J. 2022. Groundwater contamination through potentially harmful metals and its implications in groundwater management. *Front Environ Sci* 10: 1021596. DOI: 10.3389/fenvs.2022.1021596.
- United States Geological Survey (USGS). 2022. Landsat 8-9 Collection 2 (C2) Level 2 Science Product (L2SP) Guide, Version 4.0. Department of the Interior U.S. Geological Survey, South Dakota.
- Waddington H, Snilstveit B, Hombrados J, Vojtkova M, Phillips D, Davies P, White H. 2014. Farmer field schools for improving farming practices and farmer outcomes: A systematic review. *Campbell Syst Rev* 6: 335. DOI: 10.4073/csr.2014.6.
- Wang T. 2016. Vegetation NDVI change and its relationship with climate change and human activities in Yulin, Shaanxi Province of China. *J Geosci Environ Prot* 4 (10): 28-40. DOI: 10.4236/gep.2016.410002.
- Wolff NH, Zeppetello LRV, Parsons LA, Aggraeni I, Battisti DS, Ebi KL, Game ET, Kroeger T, Masuda YJ, Spector JT. 2021. The effect of deforestation and climate change on all-cause mortality and unsafe work conditions due to heat exposure in Berau, Indonesia: A modelling study. *Lancet Planet Health* 5 (12): e882-e892. DOI: 10.1016/S2542-5196(21)00279-5.
- Zhang H, Wu D. 2022. The impact of transport infrastructure on rural industrial integration: Spatial spillover effects and spatio-temporal heterogeneity. *Land* 11 (7): 1116. DOI: 10.3390/land11071116.
- Zhang Y, Cheng L. 2023. The role of transport infrastructure in economic growth: Empirical evidence in the UK. *Transp Policy* 133: 223-233. DOI:10.1016/j.tranpol.2023.01.017.