Research Article **Open Acces**

Mining Reclamation Monitoring using Sentinel-2 Temporal Data: Case Study in PT Adaro Energy Indonesia Mining Area

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Abstract: Indonesia is one of the countries that has a wealth of energy and mineral resources. However, mining activities carried out to exploit these mineral resources have a negative impact on ecosystems, especially forest ecosystems, so there is a need for ecosystem rehabilitation which is realized in the form of post-mining land reclamation. Along with the development of science and technology, remote sensing is a technology that can be used in monitoring revegetated land so that it has the potential to be developed in monitoring post-mining land reclamation land. This research aims to study the spectral characteristics of post-mining land in PT Adaro Energi Indonesia, Calculate the revegetation area from 2016 to 2023 and Map the results of PT Adaro Energi Indonesia's post-mining land reclamation spatiotemporally from 2016 to 2023. This research involves several vegetation indices in analyzing the spectral characteristics of land and monitoring the results of revegetation spasiotemporally from 2016 to 2023. The results of the spectral characteristics analysis show that RVI and SLAVI have the ability to distinguish vegetation density. Meanwhile, the results of spatiotemporal analysis show that ARVI has a fairly fluctuating pattern of increase while NDVI shows the opposite pattern in response to the increase in vegetation. During the period 2016 to 2023, PT Adaro's reclamation area experienced high revegetation from an initial 342.53 ha revegetated area, in 2023 the vegetated area increased to 1,234.41 ha. The results of this research show that PT Adaro Energi has successfully revegetated the post-mining land area. In addition, the use of remote sensing technology has the potential to be used in monitoring reclamation areas using vegetation indices and certain algorithms.

Keyword: Mining**,** Reclamation, Vegetation Indices

INTRODUCTION

Indonesia is one of the countries that has a wealth of energy and mineral resources. This considerable potential causes mining activities to have an important role in supporting national development. Since the Dutch colonial era, mineral and coal mining has become an important commodity and strategy so that in its dynamics until now the regulation of utilization has been outlined in the form of legal regulations (Redi and marfungah 2021). According to the Central Bureau of Statistics, the export of Indonesian mining products has increased every year from 2012 to 2022. The high mining output in Indonesia has a positive impact due to the existence of the mining sector such as state revenue from mineral exports, inviting investors to invest, increasing community welfare due to job vacancies, infrastructure development in remote areas, and so on (Directorate General of Mineral and Coal 2015). Regulations regarding the utilization of forest areas for mining activities are regulated in Article 33 of Forestry Law No.41 of 1999 which regulates the regulation of the utilization of forest areas outside the forestry sector including mining through the granting of forest lease permits issued by the Minister of Environment and Forestry by considering the area limit, time period, and forest sustainability.

Mining activities in Indonesia have both positive and negative impacts. Although mining provides high state revenues, due to excavation, the natural ecosystems in the area can be disrupted. Due to the removal of vegetation and excavation of soil at the mining site, the role and function of the ecosystem can be disrupted such as increasing the rate of soil erosion and sedimentation (Yudhistira *et al.* 2011), increasing air and water pollution, and the emergence of marine pollution (Razi 2021). In addition, mining activities also cause social conflicts in communities around the mine (Siregar *et al.* 2021, Fitriyanti 2016). Globally, mining activities contribute greatly to the impacts of global warming, human health, and ecosystems so that these three factors become factors that must be considered in mining activities (Farjana *et al.* 2019).

Regarding the negative impacts that can be caused by mining activities, post-mining land reclamation efforts need to be carried out. Regulations on post-mining land reclamation are set out in the Minister of Energy and Mineral Resources Regulation No. 7/2014 and the Minister of Forestry Regulation No. 60/2009. Both regulations contain guidelines for post-mining land reclamation techniques and success assessment. The principles of post-mining land reclamation regulated in both regulations are based on the concept of restoration ecology by containing ecological indicators to restore the role and function of forests after mine clearing (Nugroho & Yasir 2017). Post-mining land reclamation activities require monitoring and evaluation to determine the level of success. The monitoring is carried out regularly, covering ecological, economic and social aspects (Rahmawati & Sartika 2023).

Currently, the development of science and technology in monitoring land, including post-mining

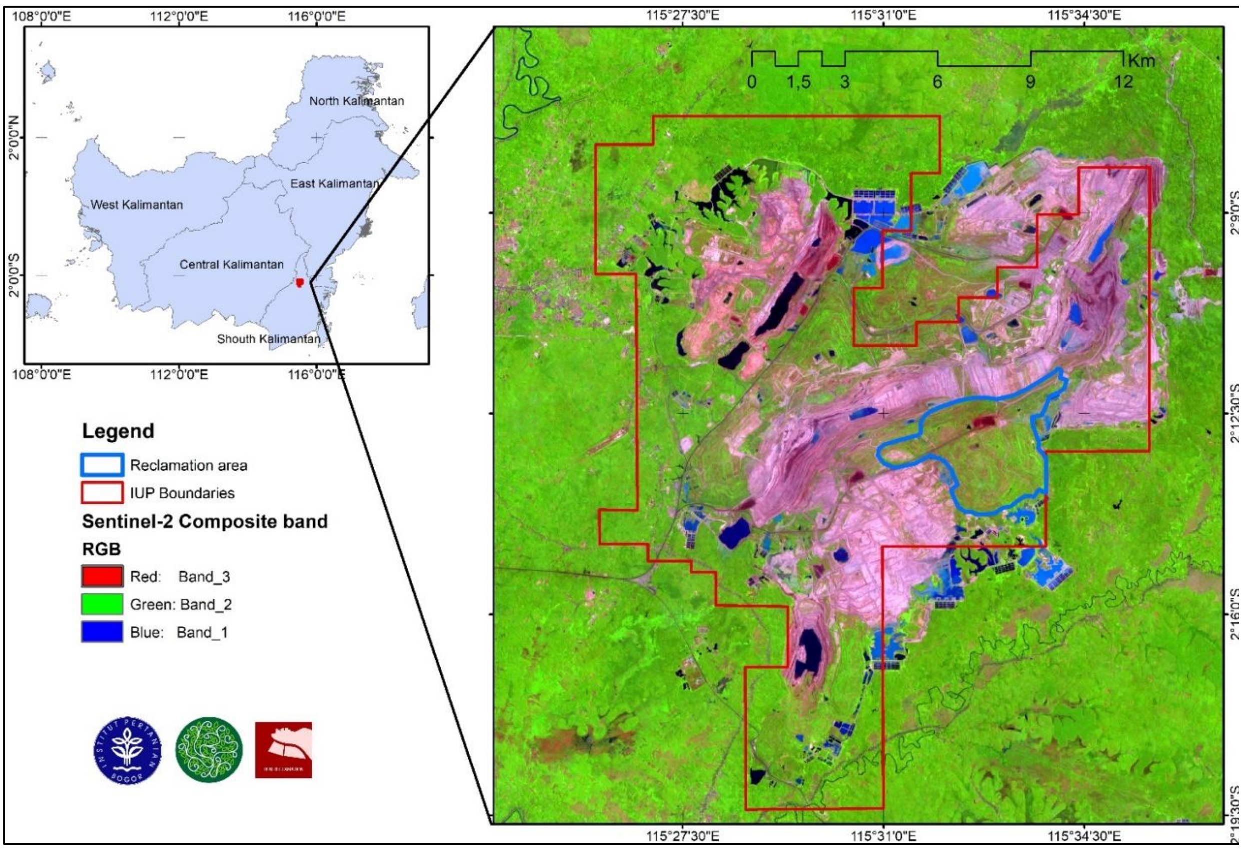

Figure 1. Google Earth Engine (GEE) platform

land, continues to grow. One of the technologies that can be done is the use of remote sensing. Remote sensing technology can be used to detect changes in land cover and spatial dynamics that occur spatiotemporally (Rogan & Chen 2004). Remote sensing technology uses multispectral sensors to capture reflectance data of the earth's surface so that with certain modeling using its spectral bands, the physical condition of the land can be interpreted (Radocaj *et al.* 2020). Based on the capabilities of remote sensing, monitoring of post-mining land reclamation can be done to assess its success or vegetation growth. The results of remote sensing modeling in post-mining land reclamation areas using vegetation indices can estimate ground surface biomass and standing volume with a fairly good level of accuracy (Pratama *et al.* 2022). In addition, the use of remote sensing involving vegetation indices can also estimate the health of vegetation every year so that the technique has the potential to be used as one of the post-mining land monitoring approaches (Karan *et al.* 2016). PT Energi Indonesia is a mining company in Indonesia that has successfully carried out post-mining land reclamation so that research on the potential of remote sensing in monitoring post-mining land can be carried out. Therefore, this research aims to study the spectral characteristics of post-mining land in PT Adaro Energi Indonesia, Calculate the revegetation area from 2016 to 2023 and Map the results of PT Adaro Energi Indonesia's post-mining land reclamation spatiotemporally from 2016 to 2023.

METODOLOGI

Study Area

The study location is in the post-coal mine land reclamation area of PT Adaro Energi Indonesia. The coal mining area of PT Adaro is located in Tabalong and Balangan regencies of South Kalimantan Province. The study location map is shown in Figure 1. The land reclamation area is located at coordinates 2.22 S and 115.54 E. PT Adaro started commercial production in 1992. PT Adaro's mining location is in a forest area and quite close to residential areas. Currently PT Adaro has successfully carried out land reclamation as indicated by the reappearance of fauna species such as birds (Soendjoto *et al.* 2016) and a fairly high diversity index on ex-mining land (Ulfah *et al.* 2020).

Data Source and Research Flow

The data used in this research are Sentinel-2 Multispectral Instrument (MSI) satellite images, and IUP area maps taken from the official website of the Ministry of Energy and Mineral Resources, Minerba One Maps Indonesia (MOMI). Sentinel-2 imagery taken is shooting from 2016 to 2023 to see the dynamics of revegetation spatiotemporally. Sentinel-2 images were launched by ESA (European Space Agency) to monitor the state of the earth (Kushardono *et al.* 2017). Sentinel-2 image is a multispectral image that has 13 bands with a spatial resolution of 10 meters to 60 meters (Mandanicii & Biteli 2016). The bands contained in Sentinel-2 are shown in Table 1. Sentinel-2 is quite good

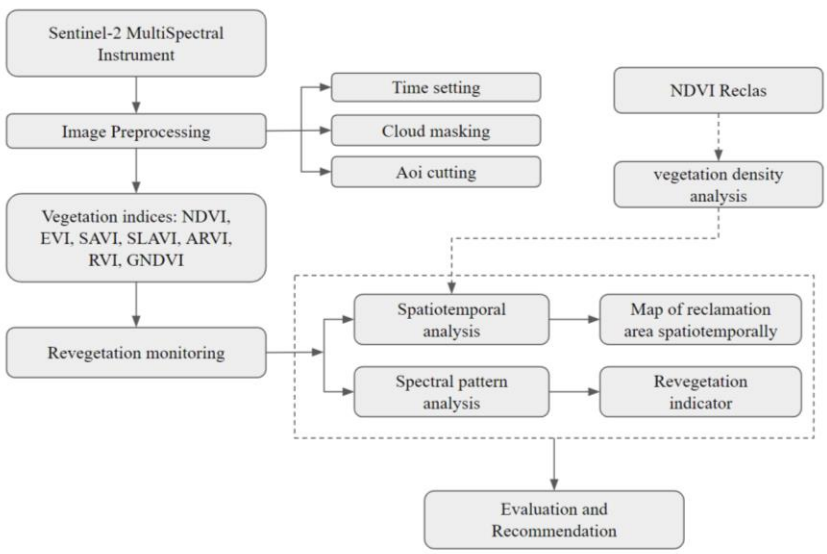

Figure 2. Research flow chart

Table 1. Multiple bands in Sentinel-2 Multispectral Instrument (MSI) imagery

Band Number	Band Description	Wavelength Range	Resolution
B1	Ultra Blue (Coastal aerosol)	443.9 nm - 442.3 nm	60 m
B2	Blue (B)	496.6 nm – 492.1 nm	10 m
B3	Green (G)	560 nm – 559 nm	10 m
B4	Red (R)	664.5 nm – 665 nm	
B5	Red-Edge 1 (Re1)	703.9 nm – 703.8 nm	10 m
B6	Red-Edge 2 (Re2)	740.2 nm – 739.1 nm	20 m
B7	Red-Edge	782.5 nm – 779.7 nm	20 m
B8	Near Infrared (NIR)	835.1 nm – 833 nm	10 m
B8A	Near Infrared narrow (NIRn)	864.8 nm – 943.2 nm	20 m
B9	Water vapor	945 nm – 943.2 nm	60 m
B11	Shortwave Infrared 1 (SWIR1	1613.7 nm – 1610.4 nm	20 m
B12	Shortwave Infrared 2 (SWIR2)	2202.4 nm – 2185.7 nm	20 m

at classifying land use and land cover, especially in monitoring agricultural areas, forests, built-up land, and water bodies with good accuracy reaching more than 80% (Phiri *et al.* 2020). In addition, by combining spectral bands into certain indices, Sentinel 2 can detect built-up areas, open land, vegetation, and can detect the effect of climate on vegetation (Fabre *et al.* 2020).

Monitoring of post-mining land reclamation areas was conducted involving vegetation indices in accordance with the research flow chart shown in figure 2. Spectral pattern analysis of vegetation indices was conducted from 2016 to 2023 to determine the dynamics of vegetation index values that represent vegetation density. The vegetation indices used include NDVI, GNDVI, ARVI, SAVI, SLAVI, EVI and RVI (Table 3). In addition, this research also reports the spectral characteristics of both the Sentinel-2 spectral bands and vegetation indices of several land covers in the mining area (bare land, forest, reclaimed area). By looking at the spectral pattern, it can be an indication of the success of the revegetation process. The research flow chart is shown in Figure 2

Spatiotemporal Analysis

Spatio temporal analysis is divided into two, namely analysis of vegetation index spectral patterns and analysis of the increase in vegetated area. Spatio temporal analysis was conducted from 2016 to 2023. Spectral pattern analysis was conducted on several vegetation indices to obtain the spectral pattern of vegetation on the post-mining land reclamation site. Meanwhile, the vegetated area was analyzed using the NDVI value class approach referenced in Marwoto & Ginting (2009). NDVI values can predict vegetation

Table 2. list of vegetation indices used

No	Method	Formulaj	References
1	Normalized Difference Vegetation Index (NDVI)	NDVI = (NIR - Red) / (NIR + Red)	Rouse jr et al. 1973
2	Green Normalized Difference Vegetation Index (GNDVI)	GNDVI = (NIR - Green) / (NIR + Green)	Dellinger et al. 2008
3	Enhanced Vegetation Index (EVI)	EVI = 2.5 x ((NIR – Red) / ((NIR) + (C1 x Red) – (C2 x Blue) + L))	Huete et al. 2002
4	Ratio Vegetation Indrx (RVI)	RVI = (Red/NIR)	Kogan 1995
5	Soil Adjusted Vegetation Index (SAVI)	SAVI = ((NIR – Red) / (NIR + Red + L)) x (1 + L) L = 0.5	Huete 1988
6	Specific Leaf Area Vegetation Index (SLAVI)	SLAVI = NIR / Red + MIR	Lymburner et al.2019
7	Atmospherically Resistant Vegetation Index (ARVI)	ARVI = (NIR – (2 Red) + Blue) / (NIR + (2 x Red) + Blue)	Kaufan et al. 1992

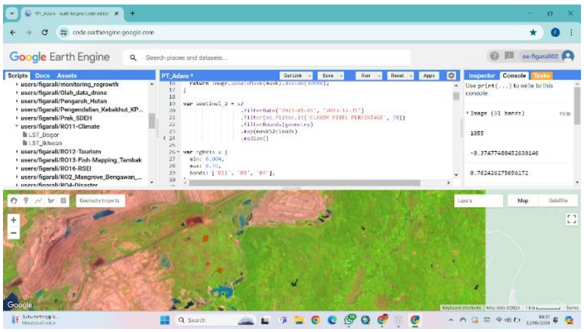

Figure 3. Google Earth Engine (GEE) platform

density. The NDVI value classes used in this analysis are presented in Table 2.

Vegetation Indices

A vegetation index is a combination of several bands that can be used to describe vegetation conditions. The vegetation index is designed using spectral bands from sensors (satellites) that are quite sensitive to vegetation. The vegetation information obtained by the sensor (satellite) is interpreted by the spectral characteristics of green leaves. The vegetation index algorithm is based on a mathematical algorithm that is compiled using light radiation, especially the NIR band, which is quite widely emitted by vegetation (Xue & Su 2017). Vegetation indices are sensitive to several factors such as plant productivity, vegetation density, plant health, and plant biomass (Bannari et al. 1995). Vegetation indices, especially NDVI, can be used to detect land cover and explain the annual cycle of plants (phenology) (Genovese *et al.* 2021). Erener (2011) reported that the use of remote sensing and vegetation indices has successfully provided data for monitoring the success of land rehabilitation including monitoring canopy cover and plant health. The vegetation indices used in this research are NDVI, GNDVI, SAVI, SLAVI, ARVI, EVI, and RVI. NDVI is an updated index of RVI that uses a normalized algorithm. NDVI has the ability to reduce sensitivity to radiometric effects (Bannari et al. 1995). However, NDVI is still sensitive to soil brightness and atmospheric effects. ARVI was developed to reduce atmospheric effects while SAVI was developed to reduce soil brightness effects (Xue and Su 2017). The index formulas used in reclamationmonitoring are presented in Table 3.

Google Earth Engine Platform

Image processing for land reclamation monitoring is done using the Google Earth Engine (GEE) platform. GEE is a cloud computing platform designed to store and process large amounts of data. GEE resources archive all data sets and connect to openly usable cloud computing engines. The data archive includes Geographic Information System (GIS)-based satellite data, demographics, weather, Digitas elevation Model (DEM), and climate data. GEE can be applied to vegetation mapping, land cover mapping, agriculture, and natural disasters (Mutanga and Kumar 2019).

RESULTS AND DISCUSSION

Land Cover Condition

The results of monitoring with remote sensing technology show that PT Adaro's IUP area has various land covers, including forests, open land, and reclamation areas. Open land refers to areas where coal mining activities are still taking place. The IUP area also includes forest areas that are still forested and have not been cleared for mining activities. Figure 4 is a composite band that shows land cover in the IUP area. Composite bands with a combination of SWIR-NIR-Red RGB bands can clearly show land cover, especially vegetation. This is due to the use of the NIR band which is quite sensitive to vegetation. The NIR band is a factor that can explain vegetation variations and predict canopy cover values (Yoshioka et al. 2000). As vegetation increases, NIR band values show an increasing trend (Gitelson et al. 2002). The presence of vegetation is indicated by green color.

The reclamation area shows almost the same hue and color as the forest land cover. This indicates the success of land reclamation carried out by PT Adaro. The results of research by Patiung *et al.* (2011). the implementation of PT Adaro's post-mining land reclamation has a good impact on the hydrological system, one of which is a decrease in erosion and an increase in infiltration rates. In addition, the success of post-mining land reclamation is also indicated by the presence of diverse bird species (Soendjoto *et al.* 2016). One of the indicators of successful land reclamation according to the Minister of Forestry Regulation P.60/Menhut-II/2009 is the revegetation aspect. This shows that land reclamation requires the presence of land cover plants. Monitoring results using remote sensing shown in Figure 4 show that the reclaimed land is well covered with vegetation.

Spectral Characteristic Assesment

The results of spectral analysis on several land covers show that each land cover (forest, reclaimed area, and open land) exhibits its own spectral characteristics. This research used several bands and indices for monitoring reclaimed fig. The spectral band characteristics of Sentinel-2 are visually displayed in Figure 5. The digital number value of a particular band is indicated by a color palette. High digital number values are marked in green while low digital number values are marked in red. The results of the spectral analysis show that band 2 - blue, band 3 - green, band 4 - red, and band 11 - SWIR show the same pattern for each land cover, namely the highest digital number value is found in open land cover followed by reclaimed areas and forests. Meanwhile, band8-NIR shows a different pattern. Band 8 tends to have a high value range in post-mining land reclamation areas. This shows that the land cover in the form of open land reflects quite a lot of the red, grees, blue, and SWIR wavelength ranges. The same results were also reported by Teffera *et al.* (2018) which states that open land has a fairly high reflectance for the red, green, and blue bands compared to vegetation but has almost the same reflectance in the NIR body. The digital number value of the NIR band tends to be high in vegetation land cover. This is because chlorophyll reflects quite a lot of NIR light waves which have a wavelength range of 720 nm to 1000 nm (Braga *et al.* 2021).

Each band on the Sentinel-2 satellite has a certain threshold value for each land cover. This shows that each band on Sentinel-2 can be a variable in detecting land cover. Mostly, visible light waves, namely red, green, blue (RGB) are less able to distinguish land cover, so it is necessary to use algorithms to improve the band's ability to detect land cover, especially vegetated land cover (Marcial-Pablo *et al.* 2019). The lack of ability of visible light waves in detecting land cover is due to the variation of reflectance values emitted by land cover higher than the wavelength range that can be captured by the sensor (Yang *et al.* 2015). The use of RGB bands in detecting land cover requires a suitable classification algorithm algorithm both guided and unguided. The use of a calcification algorithm using only RBG bands can produce a fairly high accuracy rate of up to 95% (Van *et al.* 2017).

Unlike the visible wavelengths, the infrared wavelength ranges of NIR and SWIR are quite good at describing land cover characteristics. The NIR band has the ability to interpret vegetation including describing biophysical conditions, health, and density of vegetation. Vegetation reflects a fairly high range of NIR wavelengths while water absorbs a fairly high range of SWIR wavelengths so the use of both bands is quite good in detecting land cover (Navin and Agilandeeswari 2020). The NIR band is also able to distinguish broadleaf and needle-leaf vegetation and distinguish vegetation based on the growing season (Nemani and Running 1997). Meanwhile, the SWIR band is quite sensitive to water so that the use of the band can predict soil moisture (Ishiyama 1996). The combination of both NIR and SWIR bands can determine the moisture

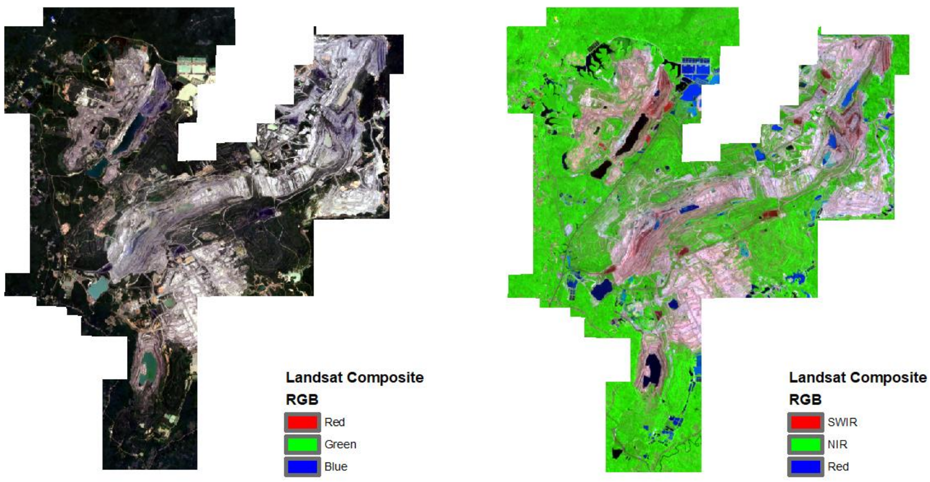

Figure 4. Map of composite band

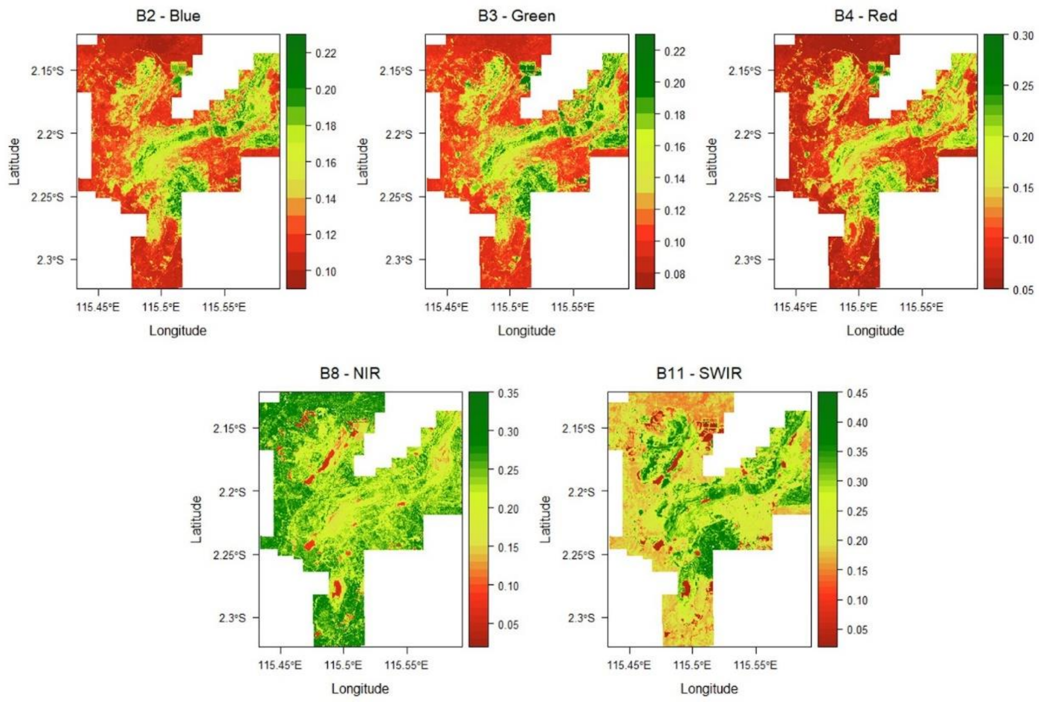

Figure 5. Band spectral characteristics

content in vegetation and provide information on plant health (Sato and Tateishi 2004).

The results of spectral analysis show that the vegetation index has a better ability to distinguish between vegetated and non-vegetated land. Figure 7 shows the visualization of the index response in representing the land cover in the IUP area. Based on Figure 7, it can be seen that NDVI, GNDVI, ARVI and SAVI have the same color or hue between forest and reclamation area. This shows that both land covers have the same range of index values. NDVI, GNDVI, ARVI and SAVI are normalized vegetation index types. They have a value range of -1 to 1 so that vegetated areas have almost the same range of values. Normalized indices have a characteristic logarithmic relationship with vegetation density so that in areas that have a high density the index tends to be biased in explaining the physical conditions (Gamon *et al.* 1995). Meanwhile, SLAVI, EVI and RVI have different colors indicating a different range of values between the two land covers. Figure 8 is a boxplot that provides information on the range of spectral values for each index. The figure shows that SLAVI and EVI have much lower spectral values in reclaimed land cover than forest. These values suggest that SLAVI and EVI are better able to distinguish vegetation density than other indices. These results correspond with the research of Aprilianti et al. 2021, which reported that the EVI spectral value has a high deviation between vegetation types and has a fairly different range of values between several vegetation types. In addition, Rahmawati *et al.* (2022) reported that EVI and SLAVI have significant interval differences in land cover.

Vegetation index is a remote sensing data algorithm used in evaluating vegetation cover, plant vigor, plant growth dynamics and so on. The remote sensing data used generally comes from the NIR and red bands (Xue and Su 2017). The vegetation indices used in this research are NDVI, GNDVI, ARVI, SAVI, SLAVI, EVI, and RVI. NDVI is a widely used index in detecting vegetation both globally and regionally (Grave *et al.* 2007). NDVI is widely used in predicting canopy structure and estimating canopy photosynthesis (Gamon *et al.* 1995). Mostly, NDVI can be used in estimating both biomass, density, health, phenology and yield. NDVI has a high correlation with forest stem biomass with an R-square of 0.82 (Gonzalen-Alonso *et al.* 2006). NDVI can also predict aboveground biomass with a fairly low RMSE although results are slightly better when using a combination of multiple indices (Zhu and Liu 2015). In addition, NDVI can also be used in estimating crop yields nationwide (Meng et al. 2013; Huang et al. 2014). NDVI also has the ability to evaluate land cover. Hu *et al.* (2023) reported that NDVI can predict land cover change with certain classification algorithms with an overall accuracy of 88% to 90%. Li *et al.* (2021) used NDVI to evaluate revegetation and found that NDVI can be used to evaluate revegetation success as well as the impact of human activities on vegetation by comparing theoretical NDVI (forest cover) and actual NDVI. NDVI shows significant changes in vegetation damage and recovery, so it has the potential to be developed for monitoring post-mining land reclamation (Bruck *et al.* 2017). Chao *et al.* (2011) developed a method to evaluate revegetation results of post-mining land by summing NDVI values and comparing them across multiple sites. The results showed that there was a relationship between the success rate of revegetation and the sum of NDVI over a year. Meanwhile, Kalabin (2011) reported that NDVI can analyze ecological responses due to human anthropological activities.

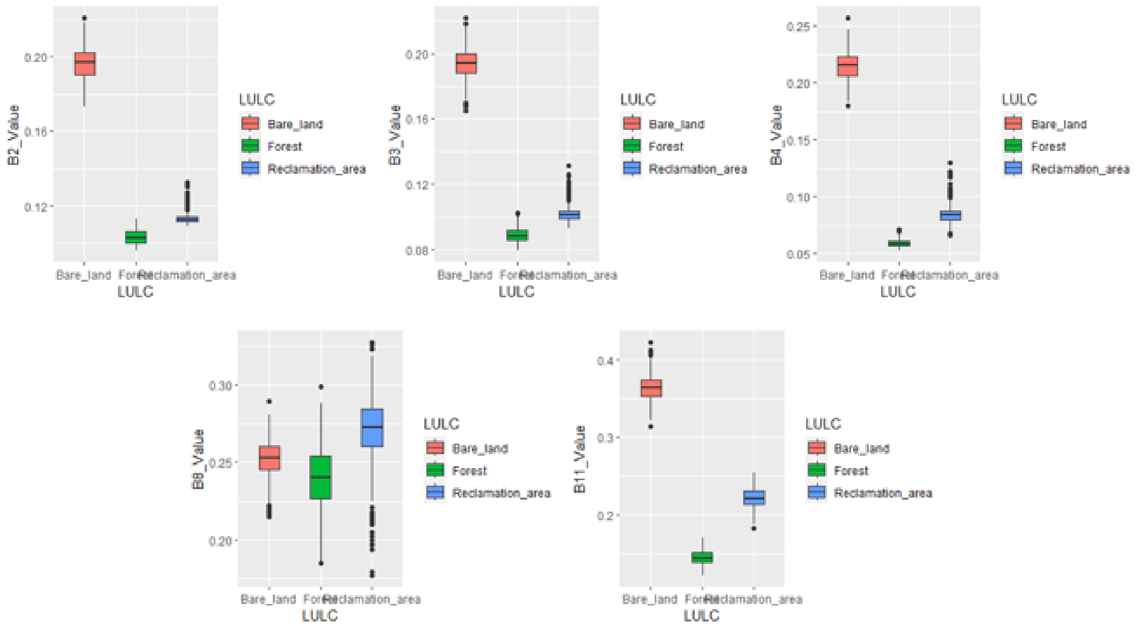

Figure 6. Threshold of spectral band on each LULC (forest, bare land, reclamation area)

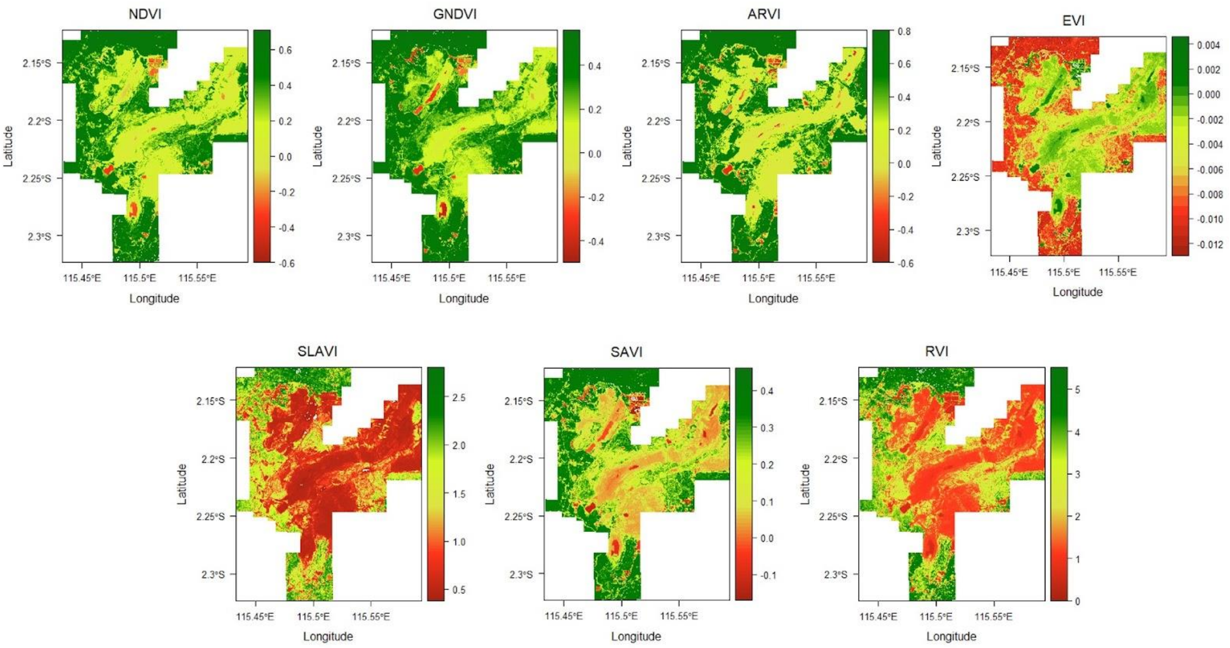

Figure 7. Spectral characteristics of vegetation indices

Meanwhile, ARVI, SAVI, and EVI were created to improve NDVI, namely reducing sensitivity to the atmosphere and ground brightness. the development of the ARVI index was aimed specifically at reducing sensitivity to atmospheric and ozone effects (Tanre *et al.* 1990; Ren *et al.* 1996). SAVI was developed from NDVI to reduce the effect of soil brightness by adding certain coefficients in the formula. The coefficient value is adjusted to the conditions and type of soil (Zhen *et al.* 2021). Meanwhile, EVI is an index developed to reduce sensitivity to the atmosphere and ground brightness by combining ARVI and SLAVI (Vijith *et al.* 2020). The research results of Shivangi et al. (2020) shows that ARVI has a fairly low deviation value from daily data because it has the ability to reduce atmospheric effects, making it suitable for monitoring areas that are polluted and have changing atmospheric conditions. ARVI also has quite good capabilities in estimating aboveground biomass in grassland ecosystems compared to NDVI, SAVI, EVI and other vegetation indices (Bayaraa *et al.* 2021). Meanwhile, SAVI has a smaller deviation from soil effects. The use of the coefficient value, namely "L" in SAVI has its own characteristics. An L value of 0.2 provides a fairly good model for red soil, while an L value of 0.4 provides a fairly good model for black soil in analyzing vegetation (Sashikkumar *et al.* 2021). EVI is

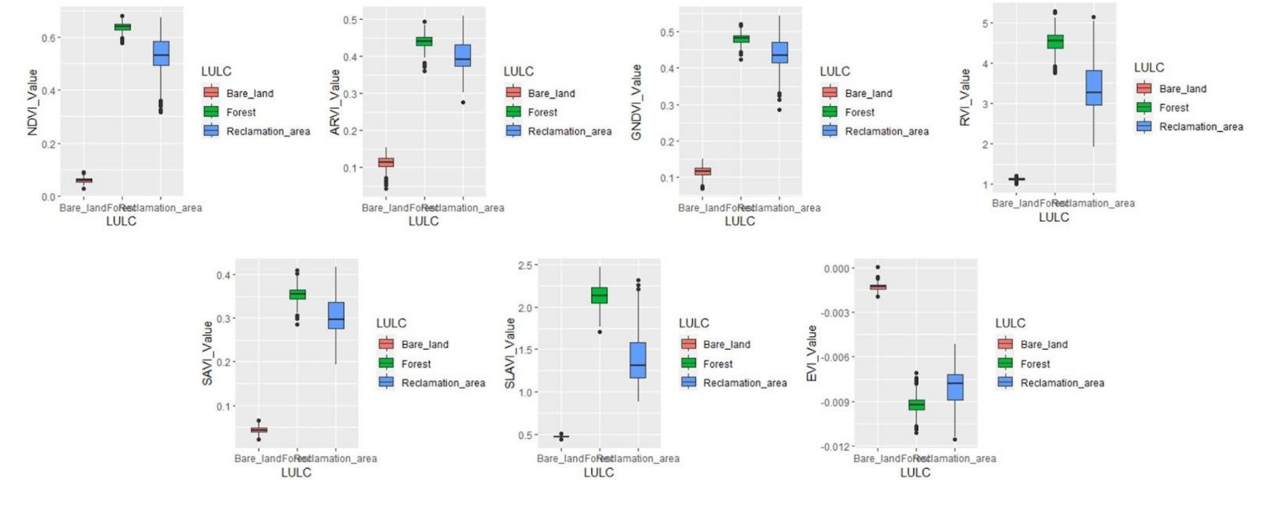

Figure 8 Threshold of vegetation indices on each LULC (forest, bare land, reclamation area)

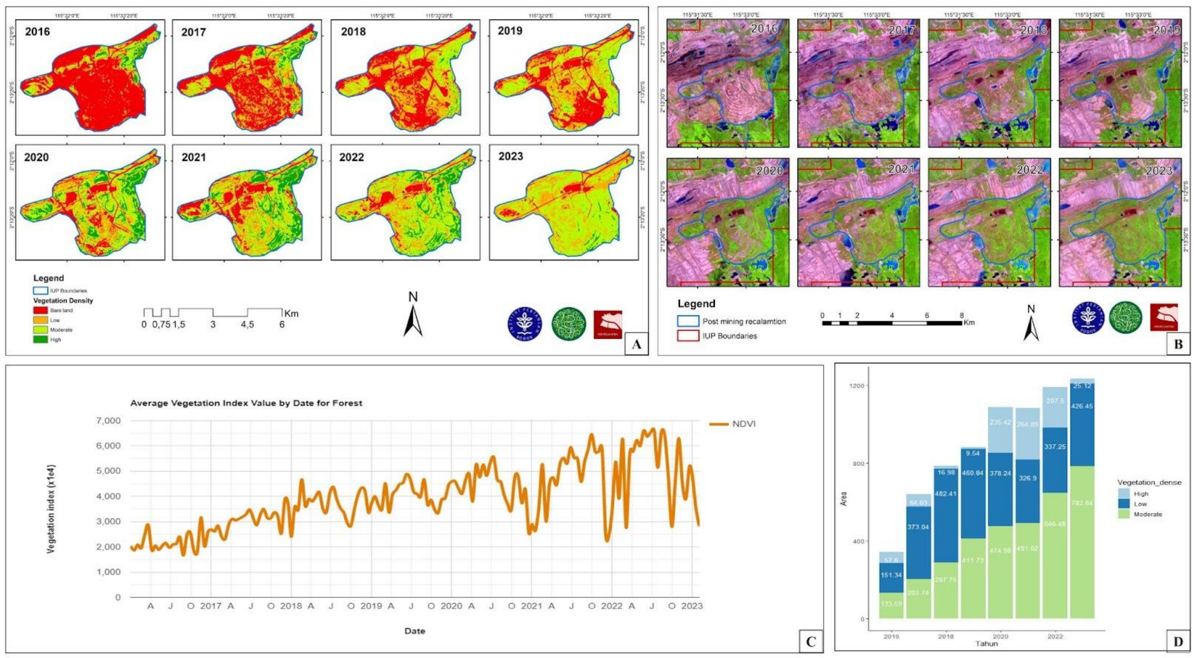

Figure 9. Increase in vegetated areas at post-mining land reclamation sites

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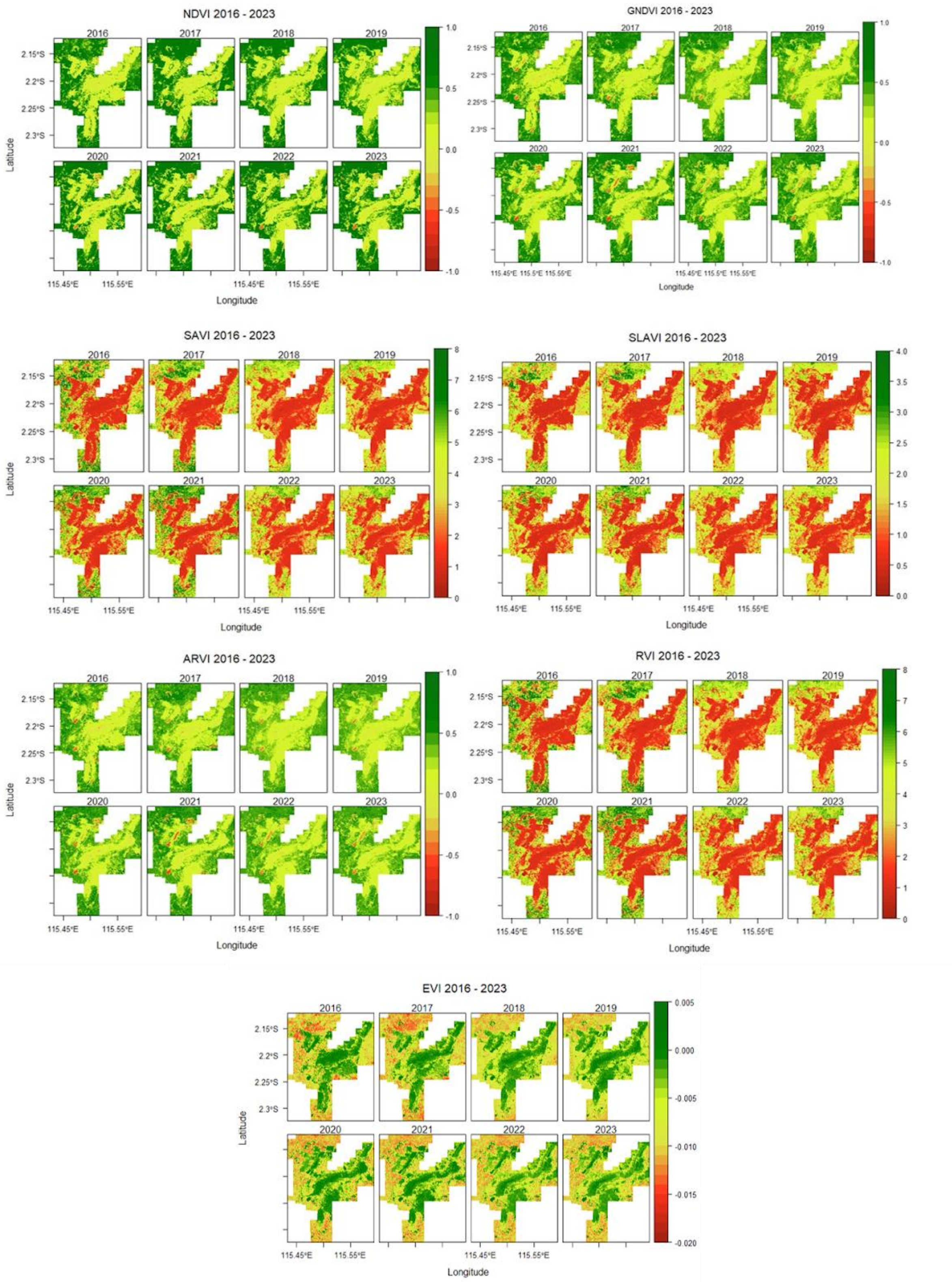


Figure 10. Spatiotemporal of post mining reclamation in each indices

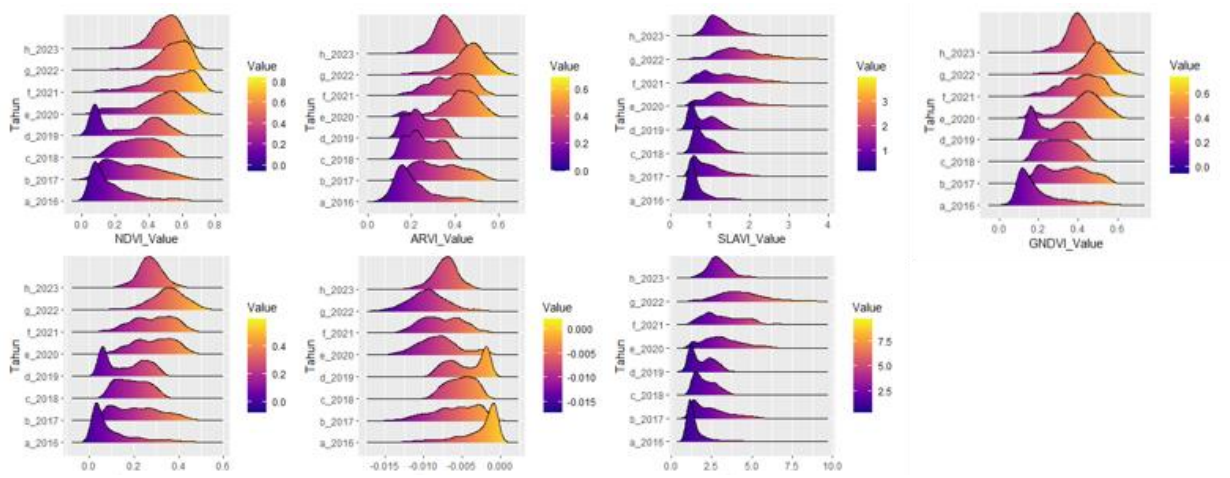
brightness so that the EVI value has a low deviation for each land cover. According to Liao *et al.* (2015), EVI is able to properly reduce topographic effects in monitoring vegetation. Apart from that, EVI is also able to analyze climatic effects on vegetation including rainfall and temperature. EVI has a fairly strong correlation with rainfall and temperature (Zhong *et al.* 2021; Zoungrana *et al.* 2015).

Figure 7 shows that SLAVI and RVI have different hues between forest land cover and reclamation areas. This is also shown in Figure 8 which provides information that the range of SLAVI and RVI values for forest land cover and reclamation areas has greater differences than other vegetation indices. According to Dobrowski *et al.* (2002) RVI has a higher ability to explain canopy density because it has a higher linear relationship than NDVI which has a more logarithmic relationship so that at fairlyhigh canopy cover NDVI has a fairly high bias. Broge and Mortensen (2002) also stated that RVI has a more linear relationship to biophysical characteristics than the normalized vegetation index. RVI has a higher ability than NDVI in detecting vegetation. RVI can detect low density forests (Yaghobi *et al.* 2019). Similar to RVI, SLAVI has a fairly wide range of values between forest land cover and reclamation areas. SLAVI is able to detect the Leaf Area Index (LAI) on land cover. According to Balzarolo *et al.* (2009), SLAVI has a good correlation with daily CO2 flux.

Spatiotemporal for Reclamation Area

The results of the spatiotemporal analysis show an increase in vegetation between 2016 and 2023 (Figure 9). The results of vegetation density analysis using the NDVI class approach show that in 2016 the revegetation area was 432.53 ha, in 2023 the vegetated area increased to 1234.41 ha in the reclamation area (Figure 9). Every year the vegetated area continues to increase. The increase in vegetation is also proven by the NDVI time series analysis shown in Figure 9c. This image shows the trend of increasing NDVI values in the period 2016 to 2023, indicating an increase in vegetation elements. The results of spatio temporal monitoring at post-mining land reclamation sites are also displayed in the form of RGB composite bands (SWIR-NIR-Blue) as shown in Figure 9b. The increasing vegetation elements found on reclaimed land indicate the success of post-mining land reclamation. The research results of Sari and Pangkung (2020) show that PT Adaro Energi Indosnesia has succeeded in reclaiming its post-mining land with a success rate of 92%. PT Adaro Energi Indonesia's post-mining land reclamation activities include land arrangement, seeding, revegetation and final settlement. Implementation of the revegetation stage consists of planting cover crops, making planting holes, improving soil quality by fertilizing, planting trees with a composition of 40% fast growing species and 60% slow growing species, monitoring and evaluation. PT Adaro Energi Indonesia has also succeeded in processing its acid mine waste water into water suitable for consumption using artificial swamp forest techniques. Water that comes out of mining activities is channeled into the artificial swamp forest to raise the pH and neutralize other pollutants (Adaro.com 2015).

As the vegetation element increases (vegetation growth), the vegetation index involved indicates a certain pota. The index spectral pattern caused by revegetation is shown in figures 10 and 11. Figure 10 shows it visually in the form of a spatio-temporal map



Figur 11. Spectral patterns in post-mining land reclamation areas spatiotemporally

for each index, while figure 11 shows a density graph which shows the spectral pattern of the vegetation index as revegetation progresses. These two images show that all vegetation indices except EVI experience an increasing trend in the spectral value range. Each index has a different pattern in detecting an increase in vegetation. ARVI, SAVI, and EVI show quite high fluctuations compared to other vegetation indices, while NDVI shows quite low fluctuations among the others. These results are in accordance with Erener's (2011) report that NDVI shows quite high differences in areas experiencing revegetation. EVI values are strongly influenced by climate variability such as temperature, humidity and rainfall. Apart from that, EVI is also able to analyze plant stress due to climatic elements such as temperature and water stress so that the EVI value fluctuates quite a bit every year (Fan *et al.* 2021). Meanwhile, the SAVI value is greatly influenced by rainfall. The SAVI value is quite sensitive to biophysical land conditions such as fluctuations in the dry season and wet season (Bezerra *et al.* 2022). Fluctuations in vegetation index values are thought to be caused by the influence of climate on vegetation, thereby affecting the reflectance received by the sensor. This is indicated by the range of vegetation index values which tends to decrease in 2019 and 2023 because that year the El-Nino phenomenon occurred.

CONCLUSIONS

Several vegetation bands and indices involved in monitoring PT Adaro Energi Indonesia's post-mining land reclamation areas have different spectral characteristics. Band 2 (blue), band 3 (green), band 4 (red) and band 11 (SWIR) show almost the same spectral pattern in each land cover, namely (open land), forest and reclamation areas, while band 8 - NIR shows a different pattern. Similar to band characteristics, several vegetation indices, namely NDVI, GNDVI, SAVI, and ARVI show the same pattern for each land cover. These four indices have almost the same range of values between land cover in the form of forests and reclamation areas. However, SLAVI, EVI, and RVI show quite different ranges of values compared to the other indices so that these three indices are quite good at differentiating between the two land covers (forest and reclamation area. These three indices also have the potential to be used to assess the success of reclamation because they have the ability to estimate density The results of the spatio temporal analysis show that during the period 2016 to 2023, the reclamation area of PT Adaro Energi Indonesia experienced an increase in the area of vegetation from 342.53 ha in 2016 to 1234.41 ha in 2023. The spectral pattern of vegetation shows the presence of vegetation. increasing trend in the range of vegetation index values except EVI. Several vegetation indices experienced fluctuations in values thought to be due to the El-Nino phenomenon from 2019 to 2023

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REFERENCES

Aprilianti HS, Ari RA, Ranti A, Aslam MF. **2021**. Identification and classification of cloud computing-based vegetation index values on several lands used in Bogor Regency, Indonesia. In IOP Conference Series: *Earth and Environmental Science*. 918(1): 012011. doi:10.1088/1755-1315/918/1/012011.

Balzarolo M., Papale D, Richardson AD. **2009**. Relationships between canopy greenness and CO2 dynamics of a Mediterranean deciduous forest assessed with webcam imagery and MODIS vegetation indices. *Geophysical Research*. 11: 1-2

Braga P, Crusiol LGT, Nanni MR, Caranhato ALH, Fuhrmann MB, Nepomuceno AL, Mertz-Henning LM. **2021**. Vegetation indices and NIR-SWIR spectral bands as a phenotyping tool for water status determination in soybean. *Precision Agriculture*. 22: 249-266. doi:10.1007/s11119-020-09740-4.

Broge NH., Mortensen JV. **2002**. Deriving green crop area index and canopy chlorophyll density of winter wheat from spectral reflectance data. *Remote sensing of environment*. 81(1): 45-57. doi: https://doi.org/10.1016/S0034-4257(01)00332-7.

Bayaraa B, Hirano A., Purevtseren M, Vandansambuu B, Damdin B, Natsagdorj E. **2022**. Applicability of different vegetation indices for pasture biomass estimation in the north-central region of Mongolia. *Geocarto International*. 37(25): 7415-7430. doi: https://doi.org/10.1080/10106049.2021.1974956.

Bezerra AC, da Silva JLB, de Albuquerque Moura GB, Lopes PMO, Nascimento CR., Ribeiro EP, da Silva MV. **2022**. Dynamics of land cover and land use in Pernambuco (Brazil): Spatio-temporal variability and temporal trends of biophysical parameters. *Remote Sensing Applications: Society and Environment*. 25: 100-677. doi: https://doi.org/10.1016/j.rsase.2021.100677.

Brück Y, Overberg P, Pohle I, Hinz C. **2017**. NDVI (Normalized Difference Vegetation Index) signatures of transient ecohydrological systems: The case of post-mining landscapes. *Proceedings of the EGU General Assembly*. 5353.

Chao MA, Guo ZZ, Zhang XK., HAN RM. 2011. Annual integral changes of time serial NDVI in mining subsidence area. *Transactions of Nonferrous Metals Society of China*. 21: 583-588. doi: https://doi.org/10.1016/S1003-6326(12)61644-6.

Dellinger AE, JP Schmidt, DB Beegle. 2008. Developing nitrogen fertilizer recommendations for corn using an active sensor. *Agron*. 100: 1546–1552. doi:https://doi.org/10.2134/agronj2007.0386.

Dobrowski SZ, Ustin SL, Wolpert JA. 2002. Remote estimation of vine canopy density in vertically shoot-positioned vineyards: determining optimal vegetation indices. *Australian Journal of Grape and Wine Research*. 8(2), 117-125. doi: https://doi.org/10.1111/j.1755-0238.2002.tb00220.x.

Erener A. 2011. Remote sensing of vegetation health for reclaimed areas of Seyitömer open cast coal mine. *International Journal of Coal Geology*. 86(1): 20-26. doi: 10.1016/j.coal.2010.12.009

Fabre S, Elger A, Riviere T. 2020. Exploitation of Sentinel-2 images for long-term vegetation monitoring at a former ore processing site. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. 43: 1533-1537. doi: 10.5194/isprs-archives-XLIII-B3-2020-1533-2020.

Fan J, Chen T, Lu S. 2017. Unsupervised feature learning for land-use scene recognition. IEEE transactions on geoscience and remote sensing. 55(4): 2250-2261. doi: 10.1109/TGRS.2016.2640186.

Fan X., Song Y, Zhu C, Balzter H, Bai Z. 2021. Estimating ecological responses to climatic variability on reclaimed and unmined lands using enhanced vegetation index. *Remote Sensing*. 13(6): 1-21. https://doi.org/10.3390/rs13061100.

Farjana SH, Huda N, Mahmud MP, Saidur R. 2019. A review on the impact of mining and mineral processing industries through life cycle assessment. *Journal of Cleaner Production*. 231: 1200-1217. doi: 10.1016/j.jclepro.2019.05.264.

Fitriyanti R. 2016. Pertambangan batubara: dampak lingkungan, sosial dan ekonomi. *Jurnal Redoks*. 1(1). doi: doi.org/10.31851/redoks.v1i1.2017.

Gitelson AA, Kaufman YJ, Stark R, Rundquist D. 2002. Novel algorithms for remote estimation of vegetation fraction. Remote sensing of Environment. 80(1): 76-87. doi: https://doi.org/10.1016/S0034-4257(01)00289-9.

Genovese G, Vignolles C, Nègre T, Passera G. 2001. A methodology for a combined use of normalised difference vegetation index and CORINE land cover data for crop yield monitoring and forecasting (a case study on Spain). *Agronomie*. 21(1): 91-111. doi: 10.1051/agro:2001111.

Gamon JA, Field CB, Goulden ML, Griffin KL, Hartley AE, Joel G., Valentini, R. (1995). Relationships between NDVI, canopy structure, and photosynthesis in three Californian vegetation types. *Ecological Applications*. 5(1): 28-41. doi: https://doi.org/10.2307/1942049.

Gamon JA, Field CB, Goulden M.L, Griffin K.L, Hartley AE, Joel G, Valentini R. 1995. Relationships between NDVI, canopy structure, and photosynthesis in three Californian vegetation types. *Ecological applications*. 5(1), 28-41. doi: doi.org/10.2307/1942049.

Grace J, Nichol C, Disney M, Lewis P, Quaife T, Bowyer P. 2007. Can we measure terrestrial photosynthesis from space directly, using spectral reflectance and fluorescence?. *Global Change Biology*. 13(7), 1484-1497. Doi: https://doi.org/10.2307/1942049.

Hu Y, Raza A, Syed NR., Acharki S, Ray RL, Hussain S, Elbeltagi A. 2023. Land use/land cover change detection and NDVI estimation in Pakistan's Southern Punjab Province. *Sustainability*. 15(4): 35-72. doi: https://doi.org/10.3390/su15043572.

Huang J, Wang H, Dai Q, Han D. 2014. Analysis of NDVI data for crop identification and yield estimation. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. 7(11), 4374-4384. doi: https://doi.org/10.1109/JSTARS.2014.2334332.

Ishiyama T. 1996. Vegetation index algorithm for vegetation monitoring in arid and semi arid land. J. Arid Land Studies, 6, 35-47.

Karan SK, Samadder SR, Maiti SK. 2016. Assessment of the capability of remote sensing and GIS techniques for monitoring reclamation success in coal mine degraded lands. Journal of environmental management. 182: 272-283. Doi: https://doi.org/10.1016/j.jenvman.2016.07.070.

Liao Z, He B, Quan X. 2015. Modified enhanced vegetation index for reducing topographic effects. Journal of Applied Remote Sensing. 9(1), 1-21. doi: https://doi.org/10.1117/1.JRS.9.096068.

Li B, Wang Y, Wang W, Wang C, Lin A. 2022. Satellite remote sensing analysis to monitor revegetation in the Yangtze River basin, China. *Land Degradation & Development*. 33(1), 68-78. doi: https://doi.org/10.1002/ldr.4129.

Mandanici E. Bitelli G. 2016. Preliminary comparison of Sentinel-2 and Landsat 8 imagery for a combined use. Remote Sensing. 8: 10-14. doi: doi.org/10.3390/rs8121014.

Meng J, Du X. Wu B. 2013. Generation of high spatial and temporal resolution NDVI and its application in crop biomass estimation. *International Journal of Digital Earth*. 6(3): 203-218. doi: http://dx.doi.org/10.1080/17538947.2011.623189.

Mutanga O, Kumar L. 2019. Google earth engine applications. *Remote Sensing*. 11(5): 1-4. doi: doi.org/10.3390/rs11050591.

Navin MS, Agilandeeswari L. 2020. Comprehensive review on land use/land cover change classification in remote sensing. *J. Spectr. Imaging*. 9(8):1-21. Doi:10.1255/jsi.2020.a8.

Nemani R, Running S. 1997. Land cover characterization using multitemporal red, near-IR, and thermal-IR data from NOAA/AVHRR. *Ecological applications*. 7(1): 79-90. doi: doi.org/10.1890/10510761(1997)007[0079:LCCUMR]2.0.CO;2.

Kalabin GV. 2011. Qualitative assessment of vegetation in disturbed mining-and-metallurgical areas by the remote and surface monitoring. *Journal of Mining Science*. 47: 538-546. doi: https://doi.org/10.1134/S1062739147040174.

Kogan FN. 1995. Application of vegetation index and brightnesstemperature for drought detection. *Advances in Space Research*. 15(11): 91–100. Doi: https://doi.org/10.1016/0273-1177(95)00079-T.

Marcial-Pablo MDJ, Gonzalez-Sanchez A, Jimenez-Jimenez SI, Ontiveros-Capurata RE, Ojeda-Bustamante W. 2019. Estimation of vegetation fraction using RGB and multispectral images from UAV. *International journal of remote sensing*. 40(2): 420-438. Doi: https://doi.org/10.1080/01431161.2018.1528017.

Nugroho AW, Yassir I. 2017. Kebijakan penilaian keberhasilan reklamasi lahan pasca-tambang batubara di Indonesia. *Jurnal analisis kebijakan kehutanan*. 14(2): 121-136. Doi: https://doi.org/10.1080/01431161.2018.1528017.

Patiung O, Sinukaban N, Tarigan SD, Darusman D. 2011. Pengaruh umur reklamasi lahan bekas tambang batubara terhadap fungsi hidrologis. *Jurnal Hidrolitan*. 2(2):60-73.

Priatama AR, Setiawan Y, Mansur I, Masyhuri M. 2022. Regression models for estimating aboveground biomass and stand volume using landsat-based indices in post-mining area. *Jurnal Manajemen Hutan Tropika*. 28(1): 1-14. Doi: https://doi.org/10.7226/jtfm.28.1.1.

Rahmawati AD, Asy'Ari R., Fathonah MA., Zamani NP, Pramulya R., Setiawan Y. 2022. Vegetation-Water-Built Up Index Combined: Algorithm Indices Combination for Characterization and distribution of Mangrove Forest through Google Earth Engine: The spatial characteristics of Jakarta's urban mangroves. CELEBES Agricultural, 3(1), 20-42. Doi: 10.52045/jca.v3i1.298.

Razi MF. 2021. Dampak Aktivitas Pertambangan Batubara Terhadap Lingkungan dan Masyarakat Kalimantan Timur.

Rachmawati A, Sartika A. 2023. Implementasi proses reklamasi melalui monitoring dan penilaian lingkungan lahan bekas tambang PT X, Kalimantan Timur tahun 2022. *Ruwa Jurai: Jurnal Kesehatan Lingkungan*. 17(2): 91-99. doi: http://dx.doi.org/10.26630/rj.v17i2.3924.

Radočaj D, Obhođaš J, Jurišić M, Gašparović M. 2020. Global open data remote sensing satellite missions for land monitoring and conservation: a review. *Land*. 9(11): 1-23. Doi: https://doi.org/10.3390/land9110402.

Redi A, Marfungah L. 2021. Perkembangan kebijakan hukum pertambangan mineral dan batubara di Indonesia. Undang: Jurnal Hukum. 4(2): 473-506. Doi: https://doi.org/10.22437/ujh.4.2.473-506.

Ren-hua, Z., Rao, N. X., & Liao, K. N. (1996). Approach for a vegetation index resistant to atmospheric effect. Journal of Integrative Plant Biology, 38(1). doi:

Rogan J, Chen D. 2004. Remote sensing technology for mapping and monitoring land-cover and land-use change. Progress in planning. 61(4): 301-325.

Sashikkumar MC, Selvam S, Karthikeyan N, Ramanamurthy J, Venkatramanan S, Singaraja C. 2017. Remote sensing for recognition and monitoring of vegetation affected by soil properties. *Journal of the Geological Society of India*. 90: 609-615. https://doi.org/10.1007/s12594-017-0759-8.

Sato HP, Tateishi R. 2004. Land cover classification in SE Asia using near and short wave infrared bands. International Journal of Remote Sensing. 25(14): 2821-2832. doi: 0.1080/01431160310001618400.

Sari R, Pangkung,YG. 2020. Assesment of reclamation succes of ex-mining land in Paringin high wall 2 area block PT Adaro Indonesia South Kalimantan. *INTAN Jurnal Penelitian Tambang*. 3(2): 145-153. Doi: https://doi.org/10.56139/intan.v3i2.69.

Somvanshi SS, Kumari M. 2020. Comparative analysis of different vegetation indices with respect to atmospheric particulate pollution using sentinel data. *Applied Computing and Geosciences*. 7: 1-10. doi: https://doi.org/10.1016/j.acags.2020.100032.

Siregar ES, Adawiyah R, Putriani N. 2021. Dampak aktivitas pertambangan emas terhadap kondisi ekonomi dan lingkungan masyarakat muara soma kecamatan batang natal. Jurnal Education and development. 9(2): 556-567. doi: https://doi.org/10.29244/jskpm.1.3.317-338.

Soendjoto MA, Riefani MK, Triwibowo D, Wahyudi F. 2016. Jenis burung di area reklamasi PT Adaro Indonesia yang direvegetasi tahun 1996/1997. In Proceeding Biology Education Conference: *Biology, Science, Enviromental, and Learning*. 13(1): 723-729.

Tanré D, Deroo C, Duhaut P, Herman M, Morcrette JJ, Perbos J, Deschamps PY. 1990. Technical note Description of a computer code to simulate the satellite signal in the solar spectrum: the 5S code. *International Journal of Remote Sensing*. 11(4): 659-668. doi: https://doi.org/10.1080/01431169008955048.

Teffera ZL, Li J, Debsu TM, Menegesha BY. 2018. Assessing land use and land cover dynamics using composites of spectral indices and principal component analysis: a case study in middle Awash subbasin, Ethiopia. *Applied Geography*. 96: 109-129. Doi: https://doi.org/10.1016/j.apgeog.2018.05.015.

Ulfah AN, Soendjoto MA, Peran SB, Wahyudi F. 2020. Keragaman spesies herba-liana dan kemiripan komunitasnya di area reklamasi PT Adaro Indonesia, Provinsi Kalimantan Selatan, Indonesia. *Jurnal Sylva Scienteae*. 3(3): 432-439. Doi: https://doi.org/10.20527/jss.v3i3.2176.

Vijith H, Dodge-Wan D. 2020. Applicability of MODIS land cover and Enhanced Vegetation Index (EVI) for the assessment of spatial and temporal changes in strength of vegetation in tropical rainforest region of Borneo. Remote Sensing Applications: *Society and Environment*. 18: 100-311. Doi: https://doi.org/10.1016/j.rsase.2020.100311.

Yang W, Wang S, Zhao X, Zhang J, Feng J. 2015. Greenness identification based on HSV decision tree. *Information Processing in Agriculture*. 2(3-4): 149-160. Doi: https://doi.org/10.1016/j.inpa.2015.07.003.

Yoshioka H, Miura T, Huete AR, Ganapol BD. 2000. Analysis of vegetation isolines in red-NIR reflectance space. *Remote Sensing of Environment*. 74(2): 313-326. https://doi.org/10.1016/S0034-4257(00)00130-9.

Yudhistira Y, Hidayat WK, Hadiyarto A. 2011. Kajian dampak kerusakan lingkungan akibat kegiatan penambangan pasir di Desa Keningar daerah kawasan Gunung Merapi. *Jurnal Ilmu Lingkungan Undip*. 9(2): 76-84.

Zhen Z, Chen S, Yin T, Chavanon,E, Lauret N, Guilleux J, Gastellu-Etchegorry, JP. 2021. Using the negative soil adjustment factor of soil adjusted vegetation index (SAVI) to resist saturation effects and estimate leaf area index (LAI) in dense vegetation areas. Sensors, 21(6): 1-14. doi: 10.3390/s21062115.

Zhong R, Wang P, Mao G, Chen A, Liu J. 2021. Spatiotemporal variation of enhanced vegetation index in the Amazon Basin and its response to climate change. *Physics and Chemistry of the Earth, Parts A/B/C*. 123: 103024. doi: 10.1016/j.pce.2021.103024.

Zoungrana BJB, Conrad C, Amekudzi LK, Thiel M, Da ED. 2014. Land use/cover response to rainfall variability: A comparing analysis between NDVI and EVI in the Southwest of Burkina Faso. *Climate*. 3(1), 63-77. doi:https://doi.org/10.3390/cli3010063.

Zhu X, Liu D. 2015. Improving forest aboveground biomass estimation using seasonal Landsat NDVI time-series. ISPRS Journal of Photogrammetry and Remote Sensing, 102, 222-231. doi: https://doi.org/10.1016/j.isprsjprs.2014.08.014.