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Ecological change detection in PT. Semen Gresik Rembang, Indonesia (limestone mining) activities between 2016 to 2022

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Abstract. *Hanum U, Dianti, Safitri RN, Pratiwi VMR, Hermawan WG, Indrawan M, Setyawan AD. 2024. Ecological change detection in PT. Semen Gresik Rembang, Indonesia (limestone mining) activities between 2016 to 2022. Intl J Trop Drylands 8: 59-68.* Limestone mining, such as at the PT. Semen Gresik Rembang (Persero) Tbk in Rembang District, East Java Province, Indonesia, impacts long-term environmental changes. One way to minimize environmental impacts due to mining activities is through remote sensing and Geographic Information Systems (GIS) to determine the dynamics of landscape management. This study aims to assess ecological changes due to the cement industry or limestone mining activities in Rembang between 2016 to 2022, the assessment was carried out by considering the dynamics of land use-land cover (LULC), and measuring the emergence of water bodies and the dynamics of vegetation productivity. The data used includes Landsat 7 ETM+ satellite image data in 2016 and three Landsat 8 OLI/ TIRS satellite image data in 2018, 2020, and 2022 with a 30 m spatial resolution. Therefore, satellite image data is collected before image processing, including correction, band merging, and cropping. The maximum likelihood image classification technique was used to analyze the dynamics of land use, land cover, and the growth of water bodies. Changes in vegetation productivity were analyzed with NDVI. In the LULC analysis, an accuracy test has been conducted with satisfactory results of more than 0.81. In the occurrence of water bodies with LULC analysis, it is known that there is a possible occurrence of water bodies in the form of ex-mining ponds. During the vulnerable years of 2016 to 2022, it is known that the area of the water body increased by 5.26 hectares. The vegetation productivity results show that those area's productivity is improving; the increase in water body cover is associated with decreased vegetation land cover by 18.58 hectares and open land cover by 8.71 hectares. The increase in mining land coverage between 2016 and 2022 is 38.07 hectares; meanwhile, the increase in built-up land area from 2016 to 2022 also increased by 15.88 hectares. Thus, remote sensing and GIS can be used to determine the dynamics of landscape management in an area.

Keywords: Land cover change, maximum likelihood classification, NDVI, remote sensing, vegetation productivity

INTRODUCTION

Indonesia possesses abundant natural resources that are crucial for human existence. These resources can be classified into two categories: renewable and non-renewable natural resources (Astuti and Simandjuntak 2018). Renewable natural resources are resources that can be replenished at a relatively fast rate, either through natural processes or human-made technology. Non-renewables are natural resources that can be regenerated, but the process takes a significant amount of time (Pongtuluran 2015). Raw materials and minerals, including metals, coal, and karst rock, are examples of non-renewable natural resources (Risal et al. 2017).

Activities in the utilization of non-renewable natural resources are mining activities (As'ari et al. 2019). Mining is one of the natural resource utilization activities that support the country's economic development due to its role as a resource provider that is indispensable for the economic growth of a country (Ericsson and Löf et al. 2019). Along with the times, the demand for mining products in the future is increasing (Tabelin et al. 2021). This has led to the growth of mining companies in Indonesia because it has a huge attraction for investors (Sutomo et al. 2020).

One of the mining companies in Indonesia is PT. Semen Gresik Rembang (Persero) Tbk, a state-owned company that produces various types of cement and strongly desires to mine karst rocks as raw material for cement (Hidayatullah et al. 2016; Dharmawan et al. 2020). The increasing demand for cement raw materials has encouraged this company to build a new cement plant in Rembang District, Central Java (Wasito and Syaikhudin 2020). Mining activities pose a high risk to the environment, both the biological, physical and social environments (Mohsin et al. 2021; Haddaway et al. 2022). Mining activities impact environmental changes, such as geological changes, namely soil movement, collisions with mining cavities, aquifer deformation, and other negative impacts (Simion et al. 2021). Karst areas will be vulnerable to rocks collapsing due to natural conditions. Failure to exercise caution and disregard for the environmental fragility might result in the destabilization of karst rocks by the utilization of excessive vibrations in mining operations (Wei et al. 2023). Karst mining has the potential to diminish the amount of water and cause contamination of groundwater in karst water systems (Fang and Fu 2011). These alterations will have long-term repercussions on the ecosystem, including degradation of flora, creation of sinkholes, soil erosion, flooding, and contamination of soil and water. Even after restoration, if not done appropriately, these harmful impacts will persist (Agboola et al. 2020). According to the Law of the Republic of Indonesia Number 32 of 2009 Article 1 Number 16 (UU RI No. 32/2009; Wicaksono 2022), concerning Environmental Protection and Management described that "Environmental destruction is people's action who cause direct or indirect in the biological, physical, and/or chemical properties changes of the environment that exceeds the standard criteria for environmental damage."

Dynamic landscape management is a method that can be employed to reduce the environmental effects of mining activities (Saining et al. 2023). Landscape management is a comprehensive endeavor that involves organizing and utilizing the environment's upkeep, conservation, regulation, and enhancement to create a landscape that is advantageous to both humans and other organisms (Arroyo-Rodríguez et al. 2020). An effective method for monitoring short-term changes in the landscape involves evaluating the fluctuations in water bodies and vegetation over a period of time. These changes can yield significant data on enduring geological phenomena such as land subsidence, sinkhole development, and water table dynamics, as well as their environmental consequences (Padmanaban et al. 2017). Assessing the geological changes in active mining and reclamation regions is significantly influenced by changes in vegetation productivity (Vorovencii 2021).

The Geographic Information System (GIS) techniques and remote sensing are the monitoring tools to assess landscape dynamics, both long-term and short-term (Erener 2011; Ranjan et al. 2022; Li et al. 2024). This technique is highly efficient compared to other techniques because it does not require expensive equipment and shortens research time and data processing (Orimoloye and Ololade 2020). Landsat 8 images with 30 m resolution are excellent for monitoring the health of vegetation in mining areas (Erener 2011). Multispectral satellite imagery in this technique allows for detecting landscape changes over time (Wijaya 2015). This technique can also be used in monitoring and assessing mining impacts on the landscape and environment and associated geological changes and vegetation productivity dynamics. The Normalized Water Body Difference Index (MNDWI) and Normalized Difference Vegetation Indeks (NDVI) time series are used to identify and monitor rehabilitation progress and inform reclamation success (Erener 2011). The accuracy value in monitoring land use/land cover dynamics using this technique is overall above 91.55% (Owolabi 2020). This research aims to assess the dynamics of Land Use and Land Cover (LULC) in 2016, 2018, 2020, and 2022 in the mining activity and reclaimed area, measure the occurrence and growth of water bodies, and assess vegetation productivity dynamics of PT. Semen Gresik Rembang, Indonesia.

MATERIALS AND METHODS

Study area

The study area is Gunem and Bulu Sub-districts, Rembang District, Central Java, Indonesia, i.e. the limestone mining site of PT. Semen Gresik Rembang, Indonesia. The mine reclamation area is located between 6°51'49.64"S-111°27'59".33"E and 6°51'59.74"S-111°28'15.44"E with a total area of approximately 3.78 km^2 (Figure 1).

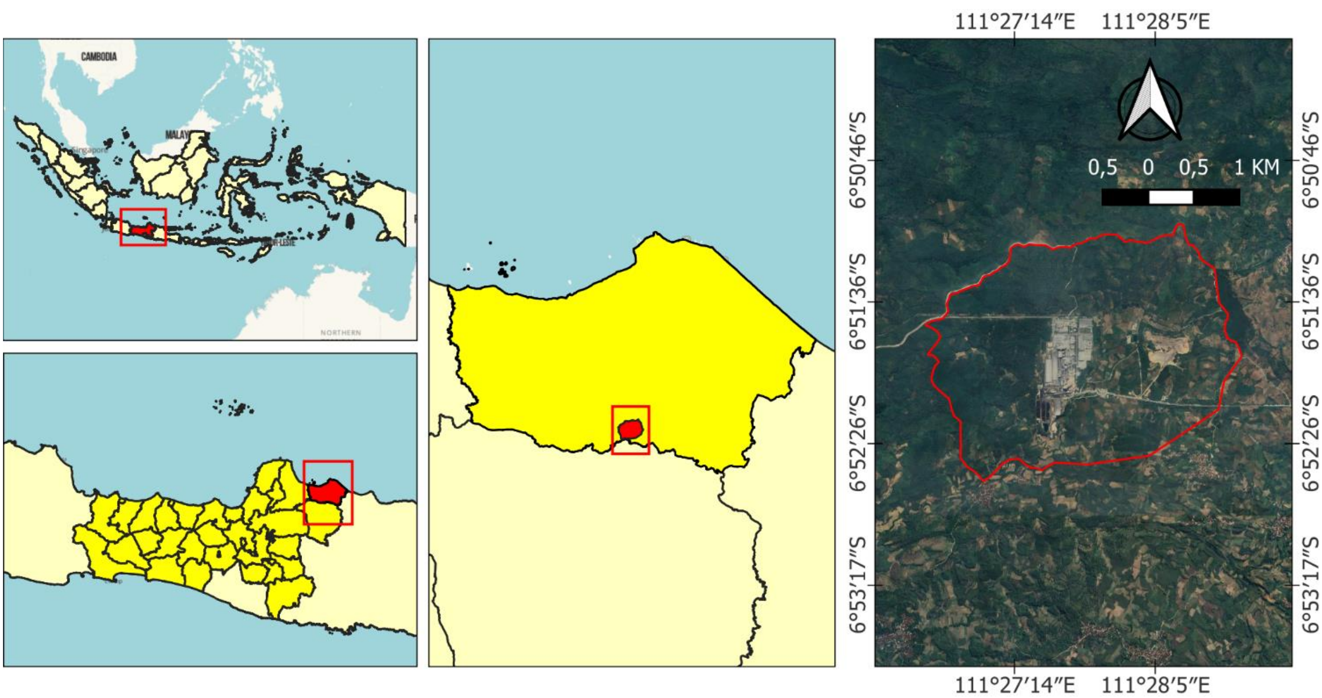

Figure 1. Site location of PT. Semen Gresik Rembang Factory in Rembang District, Central Java, Indonesia

This mining site was selected because the site carried out by PT. Semen Gresik Rembang was only opened in 2017. This can be seen in the satellite imagery on Google Earth, where land changes began to appear in 2017 and developed until 2022. Therefore, satellite data was collected from 2016 to 2022 to compare environmental conditions before and after the site's development. This research area includes the ownership area of the PT. Semen Gresik Rembang and the green belt areas located around the factory area. Therefore, from October to November 2023, data was processed using Landsat 8 and Landsat 7 images in 2016, 2018, 2020, and 2022. Figure 2 is a picture of the condition of the mining area at the study site, and the image is obtained from Google (Penamerahputih.com 2017; Nasional.tempo.co 2017).

Data collection procedures

Satellite data

The data used in this study includes Landsat 7 Enhanced Thematic Mapper plus (ETM+) satellite image data in 2016 and three Landsat 8 Operational Land Thermal Infrared Sensor (TIRS)/Operational Land Imager (OLI) satellite image data covering the years 2018, 2020, and 2022 with a spatial resolution of 30 m. The clipping of Landsat 8 OLI/TIRS satellite imagery should be consistent every year so that the landscape dynamics can be seen from the higher quality imagery compared to other Landsat satellites (Estoque and Murayama 2015). Furthermore, the satellite imagery utilized in this investigation was chosen based on the minimum proportion of pixel values within a single cloud cover that obscures the land surface in the Landsat data (referred to as Land Cloud Cover) (Zhu and Woodcock 2012). Nevertheless, in 2016, the Landsat 8 OLI/TIRS satellite imagery had the lowest proportion of pixel values affected by cloud cover. Thus, this study employed Landsat 7 ETM+ satellite image data from 2016. Hence, the chosen Landsat satellite photos spanned a duration of four years, allowing for the examination of short-term changes in the terrain. These images were acquired at no cost from the United States Geological Survey (USGS) gateway, as stated by Padmanaban (2012).

Image processing

Prior to analyzing satellite image data, preprocessing of the satellite image data is conducted. The pre-processing of satellite image data involves performing image correction, combining bands, and cropping the image based on the research region. In 2016, the Landsat 7 ETM+ satellite image data had scan line errors. To fix this, the Scan Line Corrector (SLC)-off Gap Landsat 7 tool was used to rectify the faults and create mosaics. Any residual gaps were then adjusted using histogram correction, as described by Chen et al. (2011). The image data utilized in this study underwent image correction by Top-of-Atmosphere (TOA) using QGIS. Furthermore, the process of radiometric correction was conducted to identify and quantify alterations in the landscape. This was achieved by utilizing the characteristics provided in the ETM+ metadata, specifically the Top-of-Atmosphere (TOA) radiance, as described by Chander et al. (2009). The rectified satellite image data was blended by amalgamating bands 1, 2, 3, 4, 5, and 7 to process the image using the highest likelihood approach. The subsequent step involves the segmentation of satellite image data using the Area of Interest (AOI) that has been established according to the specific geographical area of the research location.

Data analysis

Land use and land cover classification and accuracy assessment

Analyzed utilizing image classification techniques, the study examined four years of surface-level landscape processes. Subsequently, the photos from 2016, 2018, 2020, and 2022 were categorized into five distinct Land Use and Land Cover (LULC) classes, as shown in Table 1. The greatest likelihood classification technique was utilized to optimize the proximity of data points (Goslee 2011; Madasa et al. 2021). LULC classification was performed using the maximum likelihood method using ArcGIS software.

Table 1. Land Use and Land Cover (LULC) classification

LULC classes	Land uses involved in the class
Vegetation Land	Forests, gardens, and shrubs
Open Soil	Roads, unirrigated land, and dry land
Built-up Land	Factory building
Water Body	Open water
Mining Land	Mining

Figure 2. Location of PT. Semen Gresik Rembang in Rembang District, Central Java Province, Indonesia

The image classification accuracy was evaluated by comparing the classified LULC map with USGS EROS reference images from 2016 to 2022 of the study area obtained from the Google Earth platform. The accuracy assessment generated 100 randomly scattered points using the ArcGIS tool the Accuracy Assessment Point tool and extracted the values for four different study year periods (Assal et al. 2015). Subsequently, a set of arbitrary values was chosen, specifically obtained from Google Earth, and subsequently compared to the LULC map. In Stehman's (1996) study, the kappa coefficient was used to measure image accuracy. A kappa coefficient value greater than 0.8 implies that the categorized image is highly accurate and comparable to the reference data, as mentioned by Islami et al. (2022).

Vegetation productivity

NDVI analysis is used to determine the amount of vegetation productivity at PT. Semen Gresik Rembang during 2016-2022 every 2 years. According to Rouse et al. (1974), the following is the NDVI formula equation:

$$NDVI = \frac{(NIR - R)}{(NIR + R)}$$

Where: NIR: Near Infrared Band value; R: Red band value recorded by Landsat 8 imagery

The NDVI method utilizes the near-infrared band value and red band value to determine the relative density of green vegetation at PT. Semen Gresik Rembang. The NDVI value was categorized into different categories according to the density level. These ranges include non-vegetation (lowest value-0.1), open soil (0.1-0.2), sparse vegetation (0.2-0.4), moderate vegetation (0.4-0.6), and high vegetation (0.6-highest). The ranges are derived from the USGS website (USGS 2018) and have been adapted by the authors. The assessment of vegetation productivity change was conducted in 2016, 2018, 2020, and 2022 utilizing ArcGIS 10.8 software.

RESULTS AND DISCUSSION

Landscape dynamics at the PT. Semen Gresik Rembang in 2016-2022

Figure 3 shows the LULC map of the PT. Semen Gresik Rembang plant area obtained in 2016, 2018, 2020, and 2022 using Maximum Likelihood classification. The area of interest includes land outside their ownership because it is easier to classify landscape dynamics on land around PT. Semen Gresik Rembang Factory. Based on the accuracy test results, an overall accuracy value of more than 80% was obtained for the classified LULC maps for all years with a kappa coefficient average value is 0.84 (Table 2). These values indicate the classified LULC maps have satisfactory accuracy.

The maximum likelihood method in ArcGIS software is used to assess land changes based on spatial analysis after analyzing changes in land size in the PT. Semen Gresik Rembang area. The spatial maps acquired are displayed in Figure 3, while the land class areas are presented in Table 3, providing a comparison of land use and land cover. The land classes examined in this study include vegetative land, open soil, built-up land, water bodies, and mining land. Figure 3 illustrates the comparison of land classes between 2016 and 2022, revealing a noticeable rise in land coverage in built-up areas, aquatic bodies, and mining sites. Table 3 reveals that the land area difference between 2016 and 2022, namely in the built-up land category, exhibits a 15.88 ha rise. The water body classes from 2016 to 2022 indicate a land expansion of 5.26 hectares, while the mining land classes during the same period demonstrate a land expansion of 38.07 hectares. Upon closer examination, it can be noticed that the water body area in the form of ponds increased in 2018 (14.72 hectares) and 2020 (23.98 hectares), but dropped in 2020 (5.26 hectares). Millán et al. (2014) found that as water bodies expand, it leads to a fall in groundwater levels and also causes changes in them. Decreasing groundwater levels can result in collisions with exposed mining structures, infiltration of groundwater, and floods on the surface (Liu and Zhang 2023).

The expansion in land area in the water body and mining land class categories appears to be substantial during the transition from 2016 to 2018, given there were no water bodies or mining land present in these areas in 2016. Subsequently, there was a reduction in land area within the vegetated land and open soil categories. Table 3 reveals that the land area difference between 2016 and 2022 indicates a drop of -18.58 ha in the vegetation land class and a loss of -8.71 ha in the open soil class. The vegetated land underwent substantial changes throughout the years.

Table 2. The image classification accuracy by test matrix value 2016-2022

Years	Accuracy test matrix value	
	User accuracy	Kappa
2016	0.92	0.80
2018	0.92	0.84
2020	0.90	0.81
2022	0.95	0.89

Table 3. Comparison of Land Use and Land Cover (LULC) types during 2016-2022

Classes LULC	Land area (Ha)				Difference (Ha) 2016-2022
	2016	2018	2020	2022	
Vegetation land	495.55	459.50	456.79	476.97	-18.58
Open soil	120.48	142.96	142.19	111.77	-8.71
Built-up Land	48.37	48.93	49.56	64.25	15.88
Water body	-	14.72	23.98	5.26	5.26
Mining land	-	5.36	16.85	38.07	38.07

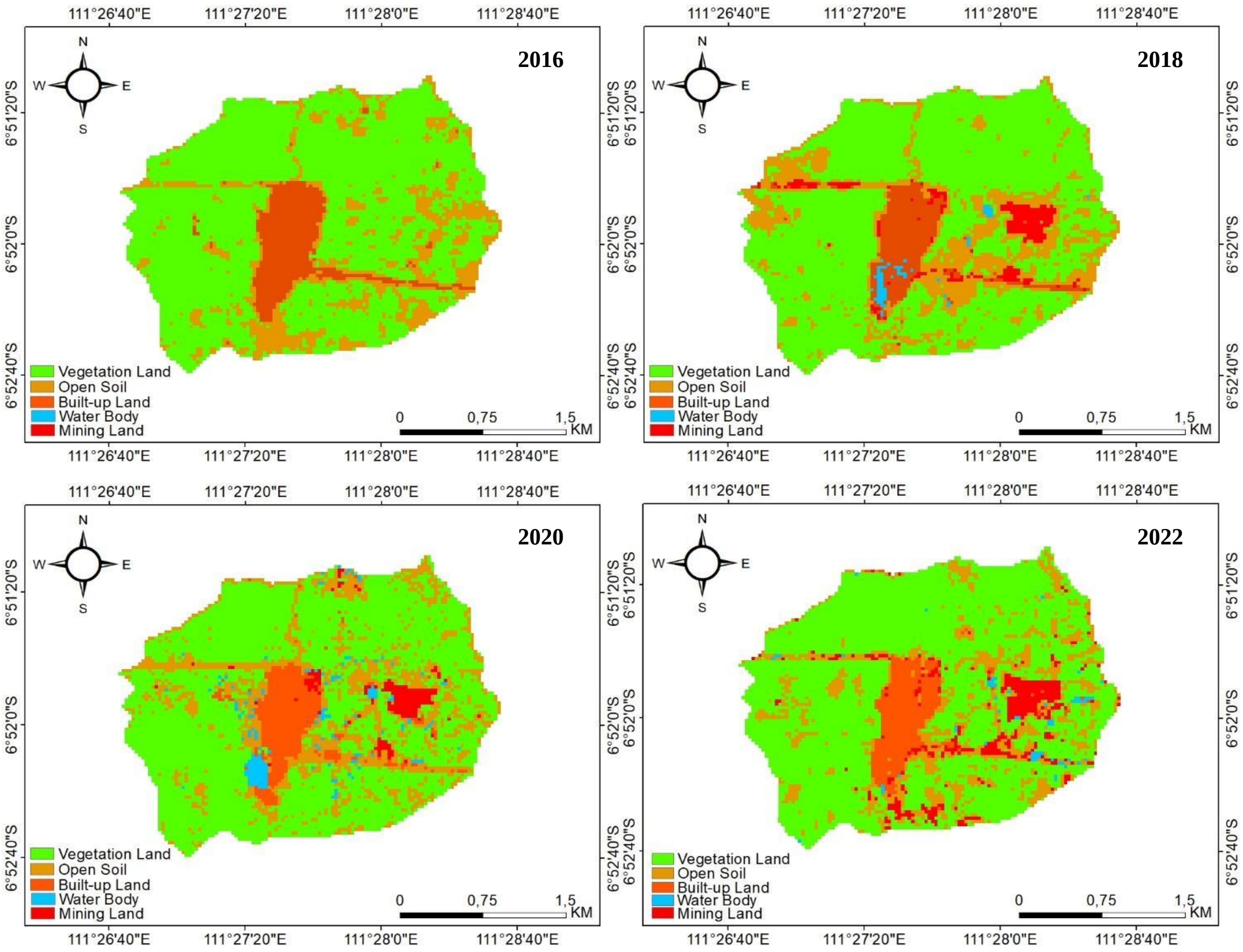

Figure 3. Map of Land Use and Land Cover (LULC) at PT. Semen Gresik Rembang, Indonesia in 2016, 2018, 2020, and 2022

In 2016, the area measured 495.55 ha, which declined to 459.50 ha in 2018 and further to 456.79 ha in 2020. However, in 2022, there was a notable increase to 476.97 ha. Despite this increase, the vegetated land in 2022 is still smaller than the vegetated land in 2016. Within the open soil class, the land area had a growth of 142.96 hectares from 2016 to 2018, followed by a reduction to 142.19 hectares in 2020 and further down to 111.77 hectares in 2022. The conversion of open space to built-up land has led to a significant decline in vegetative land, plantations, and agricultural land mostly because of the fall in groundwater levels (Besser and Hamed 2021).

Occurrence and growth of water bodies

Through the LULC classification that has been carried out, the land use area for water bodies at the study site has been identified (Figure 4). The water body will likely be an ex-mining pond filled with rainwater (Gautama 1994). Water puddles that fill the mine pits are also called voids, which become a storage area for runoff and rainwater in a topography lower than the surrounding area with compacted soil conditions (Sahu et al. 2016). Voids are categorized as dangerous because their depth reaches an average of 4 meters, especially if there are no warning signals. In addition, mine pits are dangerous because they contain residual excavated materials such as acid mine drainage, which is unsuitable for the growth and development of flora and fauna and is at risk of fatalities if contaminated (Yunanto et al. 2021).

Moreover, from 2016 to 2022 (Figure 4), water bodies began to appear in 2018 because the mining process at this location had not yet been carried out in 2016. In 2020, the area of the water body was the largest, with a land coverage of 23.98 ha; this indicates that mining activities have been carried out, but ex-mining pits have not been managed. The area of the water body continued to decrease in the following years by -5.26 ha in 2022. The decrease in area of water bodies suspected to be void has decreased from 2018 to 2022 due to the possibility that the ex-mining pit reclamation has begun by the PT. Semen Gresik Rembang. One of the reclamation management activities that has been carried out by its group companies, PT. Semen Gresik Tuban is the reclamation of limestone mining land into Bukit Daun Park, which is located in Tuban District, East Java, built as a conservation and tourist destination in 2018. In addition, a form of post-mining land reclamation is usually carried out before becoming a tourist attraction through replanting teak (*Tectona grandis*) and trembesi (*Samanea saman*) trees covering an area of 6.8 hectares in 2019 (Siregar et al. 2020).

Vegetation land cover dynamics

Figure 5 shows the NDVI map of PT. Semen Gresik Rembang in 2016, 2018, 2019, and 2020, respectively. The map shows the productivity of improving vegetation areas yearly, with the high vegetation area expanding in 2022 compared to 2016. The map also illustrates the decreasing area of non-vegetation; in 2016, the area of non-vegetation was larger than in 2022. Sparse and moderate vegetation areas dominated the PT. Semen Gresik Rembang area in 2020 prediction (Padmanaban et al. 2017).

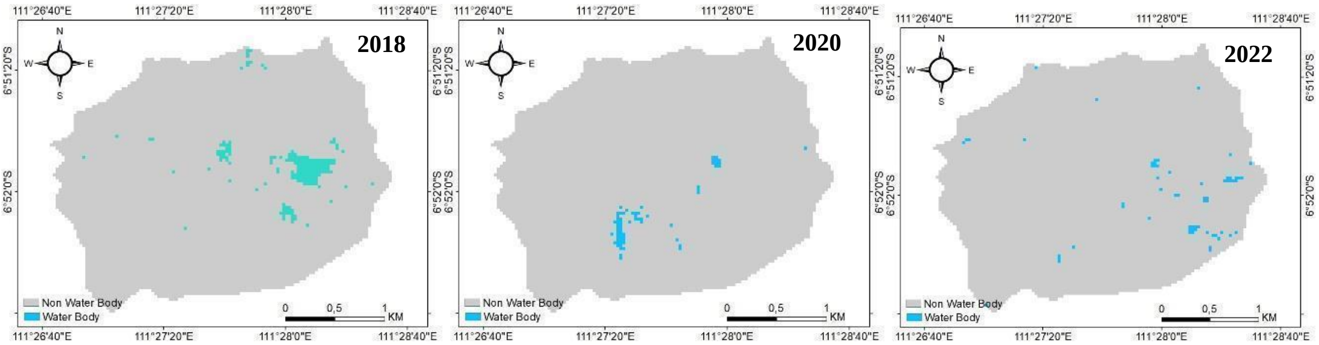

Figure 4. Changes in the location of water body occurrence and growth in 2018, 2020, and 2022 at the PT. Semen Gresik Rembang, Indonesia

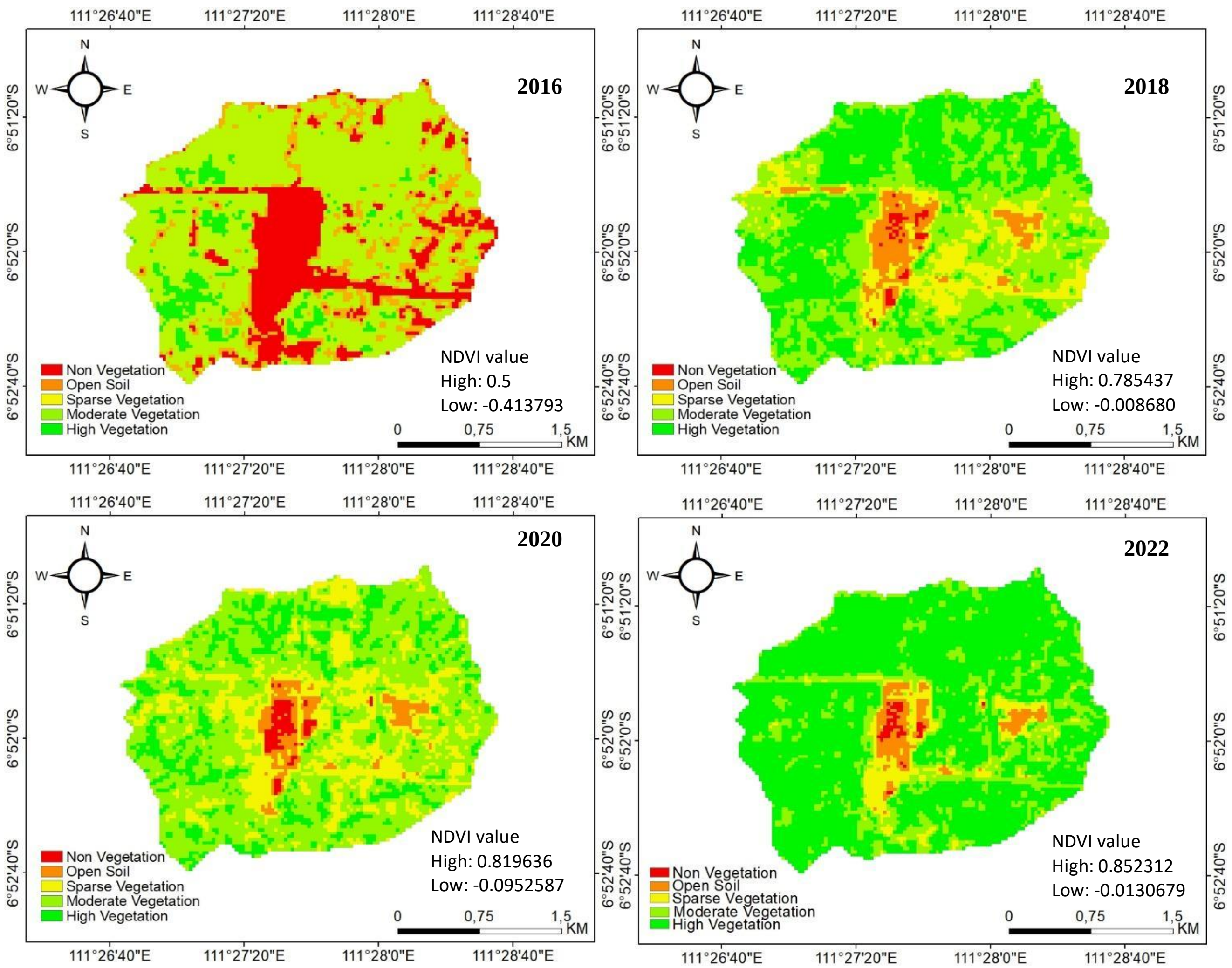

Figure 5. Map of vegetation productivity at PT. Semen Gresik Rembang, Indonesia, in 2016, 2018, 2020 and 2022

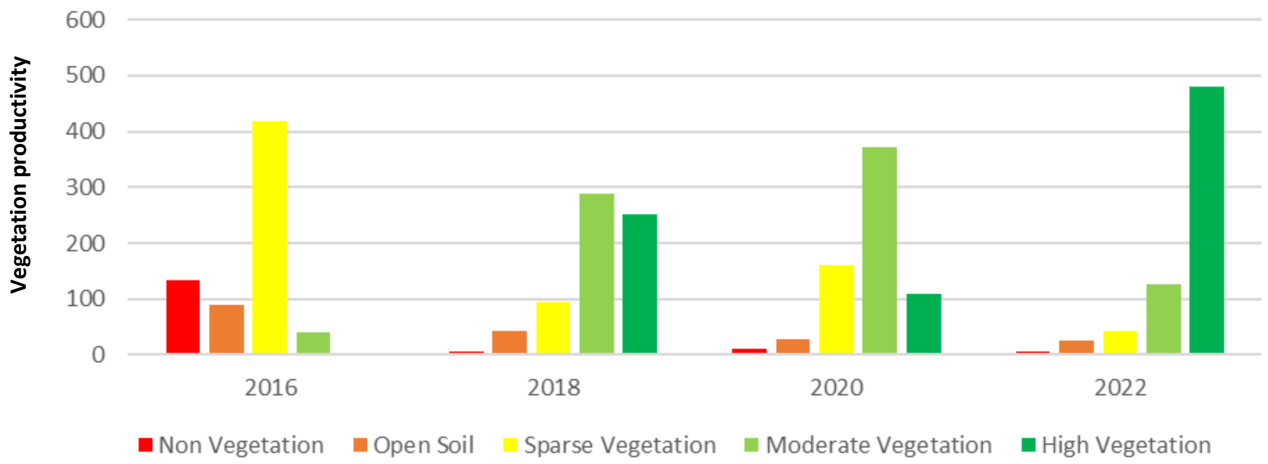

Figure 6. Vegetation productivity at PT. Semen Gresik Rembang, Indonesia in 2016, 2018, 2020, and 2022

Table 4. Vegetation change in the PT. Semen Gresik Rembang, Indonesia coverage area in 2016, 2018, 2020, and 2022

Vegetation productivity class	NDVI value	Change in area coverage (Ha)				Difference (Ha)
		2016	2018	2020	2022	2016-2022
Non vegetation	lowest value-0.1	133.51 (19.63%)	5.61 (0.82%)	10.98 (1.61%)	5.10 (0.75%)	-128.41
Open soil	0.1-0.2	88.44 (13.00%)	41.32 (6.08)%	27.88 (4.10%)	25.09 (3.69%)	-63,35
Sparse vegetation	0.2-0.4	417.94 (61.44%)	94.58 (13.91%)	161.30 (23.71%)	43.49 (6.40%)	-374,45
Moderate vegetation	0.4-0.6	40.38 (5.94%)	288.07 (42.36%)	372.26 (54.72%)	126.76 (18.64%)	86,38
High vegetation	0.6-highest value	-	250.45 (38.83%)	107.85 (15.85%)	479.65 (70.53%)	479.65

Moreover, Table 4 and Figure 6 show a significant change in vegetation productivity at PT. Semen Gresik Rembang, which is associated with an increase and decrease in the area. The non-vegetation area in 2016 was the highest at 133.51 ha and about 19.63% of the total area at 680.26 ha; Figure 6 shows a decrease to -5.61 ha in 2018 and briefly increased to 10.98 ha in 2020 and then fell back to -5.10 ha in 2022. The decrease in the non-vegetation area is good for the ecosystem because the area is covered with a high vegetation area again. The PT. Semen Gresik Rembang vegetation area has increased productivity due to the company's concern for the surrounding vegetation by promoting reforestation activities. PT. Semen Gresik Rembang developed a green belt area to change the limestone mining areas, once barren, to greener environments (Dewi 2016). These greening areas are evidenced by the value of vegetation productivity for the classification of high vegetation areas, which was worth 0 ha in 2016 and can increase rapidly to 479.65 ha or about 70.53% in 2022. The open soil area continues to decline from 2016 at 88.44 ha to about 25.09 ha in 2022. The decline is insignificant because it is dominated by the increase and decrease in sparse, moderate, and high vegetation areas. The sparse vegetation class experienced a decreased area in 2018 to 94.58 ha, increased in 2020 to 161.30 ha, and decreased in 2022 to 43.49 ha. Moderate vegetation from 2016 to 2020 increased from 40.38 ha to 372.26 ha but decreased in 2022 to 126.76 ha. The decrease in moderate vegetation is due to the change of vegetation to high vegetation (Padmanaban et al. 2017).

Discussion

According to Table 3, the LULC data, the total area of vegetative land in 2016 was 495.55 hectares. Table 4 presents the NDVI findings, indicating that no vegetation was observed in the sparse and moderate classes under the high vegetation category. The extent of vegetation classified as sparse has both reduced and increased. However, in 2022, it reached 43.49 hectares, indicating a fall in the sparse vegetation category. The moderate vegetation class experienced significant growth in area between 2018 and 2020, growing from 40.38 hectares to 288.07 hectares and further to 372.26 hectares. Nevertheless, the vegetation class categorised as moderate experienced a reduction to a value of 126.76. The levels of vegetation had both increases and decreases, but in 2022, there was a significant addition of 479.65 hectares. In 2016, according to Table 3, the land class with the highest vegetation was seen, despite the fact that the vegetation was higher compared to the subsequent year. The environmental circumstances in 2022 had improved characteristics, as seen by the heightened productivity of plants, which was bolstered by elevated NDVI values. Ultimately, the current vegetation was characterized by a scarcity of plant life and a moderate amount of vegetation. This is consistent with the study conducted by Johansen and Tømmervik (2014). They found a strong association between NDVI derived from vegetation communities and recorded phytomass, indicating a close relationship.

Therefore, comparing the results between LULC and NDVI may not be accurate, and this is because the two methods have different analytical (da Silva et al. 2020); the different analytical methods comparison are not appropriate. However, in this study, the NDVI results can be used to determine the vegetation level, including low-class, medium-class, and high-class vegetation. Therefore, we can at least know whether the vegetation areas detected using the LULC method have good productivity of land cover by vegetation. Higher NDVI values indicate more vegetation on the land cover than lower NDVI values (Akbar et al. 2020). Based on this, the NDVI value can be used to determine the level of health and productivity of existing vegetation in this research. Even though the vegetation area in 2022 will not be as much as in 2016 (Table 3), at least the reclamation and revegetation efforts of mining land operated by the former mining pit of the PT. Gresik Semen Rembang is showing quite good results. Environmental improvement efforts can be maintained to achieve maximum results in the return to normal conditions; if possible, increasing the reclamation and revegetation of mining land is necessary. Revegetation of tailing dumps improves soil quality through aesthetic improvement, stabilization, pollution control, and soil fertility (Buta et al. 2019). This study also demonstrated how revegetating abandoned mine lands restored their ecological integrity and self-sustainability, leading to significant improvements in soil quality.

Moreover, PT. Semen Gresik Rembang land clearing for mining has changed the open or vegetation land into built-up and mining land. Furthermore, this research begins in 2016 to 2022 because land clearing and built-up development began in 2017 and shows an increase in mining and built-up land areas. The most significant increase occurred between 2020 and 2022 because the mining land area doubled. Research conducted by Shen and Zeng (2022) shows that land clearing for mining sites has also increased rapidly in certain years, changing groundwater levels. A continuous increase in built-up and mining lands in mining areas can cause collisions with unburied mine workings, groundwater intrusion, and surface flooding (Liu and Zhang 2023). However, reclamation has been conducted at this research location, hopefully avoiding possible environmental risks.

The results of this study are similar to previous research conducted by Firozjaei et al. (2021), which indicated that forest cover and green open space decreased from 9,950 hectares in 1989 to 5,900 hectares in 2019 for Sungun mine in Iran; from 42.14 hectares in 1999 to 33.09 hectares in 2019 for Athabasca oil sands in Canada; from 231.46 hectares in 1996 to 263.95 hectares in 2016 for Singrauli coalfield in Indian; and from 180.38 hectares in 1989 to 133.99 hectares in 2017 for Hambach mine, as a result of the expansion and development of mineral activities. The results in Sungun indicate that in the future, by 2039, there is likely to be a decrease in forest cover and green open space by 15% of the total study area, resulting in a decrease in mean NDVI of almost 0.06 and an increase in standardized mean Land Surface Temperature (LST) from 0.52 in 2019 to 0.61 in 2039. The study in Sungun shows that in the future, by 2039, there will most likely be a decrease in forest and green open space cover by 15% of the total study area, resulting in a decrease in mean NDVI of almost 0.06 and an increase in mean standardized Land Surface Temperature (LST) from 0.52 in 2019 to 0.61 in 2039. Research conducted by Firozjaei et al. (2021) showed that for the Athabasca oil sands (Singrauli coalfield, Hambach mine), the average standardized LST and NDVI values will change from 0.5 (0.44 and 0.4) and 0.38 (0.38; 0.35) in 2019 (2016; 2017) to 0.57 (0.5; 0.47) and 0.33 (0.32; 0.28) in 2039 (2036; 2035). This is mainly due to increased past and future mining activity (Firozjaei et al. 2021). Therefore, the potential for mining land degradation is higher if mining activities are carried out continuously without adequate environmental conservation efforts.

In conclusion, the difference in land area of PT. Semen Gresik Rembang in 2016-2022, i.e., the built-up land class, shows an increase in the amount of land of 15.88 hectares. The water body classes 2016-2022 show a land increase of 5.26 hectares, and the mining land classes 2016-2022 show a land increase of 38.07 hectares. The difference in land area in 2016-2022, i.e.: the vegetation land class showed a decrease in land area of -18.58 hectares, while the open soil class experienced a decrease of -8.71 hectares. Vegetated land has changed significantly; where in 2016, an area of 495.55 hectares decreased in 2018 (459.50 hectares) and 2020 (456.79 hectares) and increased quite high in 2022 to 476.97 hectares, but the area of vegetated land in 2022 is still not as large as the vegetated land in 2016. In the open soil class, there was an increase in land area from 2016 to 2018, which was 142.96 hectares, and then decreased in 2020 and 2022 to 142.19 hectares and 111.77 hectares, respectively. The results of the LULC analysis of water bodies show that there is a possibility that water bodies are formed from former mining ponds, and in the prone years 2016 to 2022, it is known that the area of water bodies will decrease because of the PT. Semen Gresik Rembang manages those areas. The addition of vegetated land is accompanied by an increase in NDVI values, where the highest NDVI values in 2016, 2018, 2020, and 2022 are 0.5, 0.79, 0.82, and 0.85, respectively. This indicates that the study area has vegetation with better productivity from year to year. Better vegetation productivity indicates that PT. Semen Gresik Rembang has care and concern for the environment.

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