High-Precision Rehabilitation - Maximizing Impact and Minimizing Costs

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Abstract

One of the main challenges in mining is ensuring the restoration of vegetation in post-mining areas, especially when satellite image analyses yield unexpected results. Field visits often reveal discrepancies between initial analyses and actual site conditions, highlighting the need for more accurate technologies to improve planning and data reliability. This study combines the Green Leaf Index (GLI) analysis and image binarization to enhance vegetation and environmental data monitoring. This approach offers a more efficient method for identifying vegetation patterns, assessing plant health, and mapping vegetation distribution across large areas. In this study, satellite images were replaced by drone-captured images, which were processed into orthomosaics using RGB (Red, Green, Blue) photos. These orthomosaics were aligned, corrected for distortions, and merged into continuous, georeferenced images. Vegetation indices were calculated to quantify plant reflectance, indicating photosynthetic rates and development stages.

The GLI, which focuses on chlorophyll, was used to assess vegetation health, identify live and dead plants, and detect exposed soil areas. Image binarization transformed colour or grayscale images into binary images, classifying pixels based on a set threshold. The combination of GLI analysis with image binarization resulted in more accurate results. Of the total 101 hectares, 76 hectares requiring maintenance were reduced compared to the previous method, saving 625 000 BRL (approximately 120 kUSD) in land preparation and 900 000 BRL (approximately 173 kUSD) in seedling production and planting, totalling 1 525 000 BRL (approximately 293 kUSD) in savings within a year. Additionally, this approach improved the reliability of the generated data. In conclusion, integrating GLI analysis and image binarization proves to be an effective tool for enhancing the monitoring and interpretation of environmental data in mining areas, leading to significant cost savings and improved environmental management.

Keywords: Rehabilitation of mined areas, Environmental monitoring, Spatial analysis, Geoprocessing, Cost reduction.

1. Introduction

Hydro Bauxite & Alumina is a global company operating in the aluminium and renewable energy sectors, with a significant presence in Brazil. Its operations cover the entire aluminium production chain, from bauxite mining to the production and extrusion of the metal. Committed to sustainability, the company adopts innovative environmental management practices, standing out in the rehabilitation of mined areas in Pará state (Figure 1).

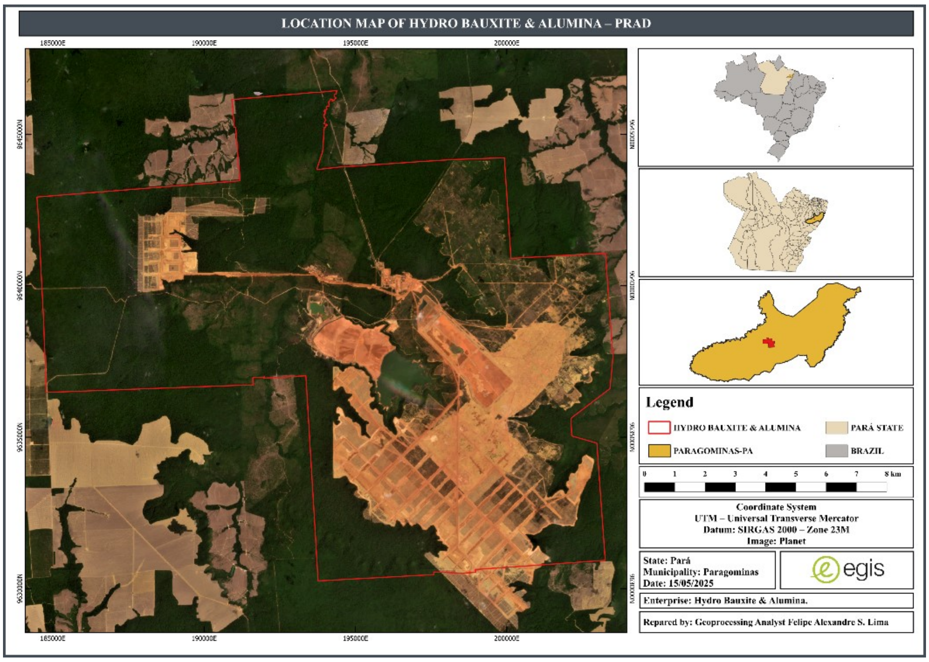


Figure 1. Location of Hydro Bauxite & Alumina.

Hydro Bauxite & Alumina operations in Paragominas began in 2007 and currently involve the handling of approximately 16 million tonnes of ore per year, with an annual production of 11.4 million tonnes of bauxite. This material is transported via a 244-kilometer slurry pipeline to Barcarena, the first in the world designed for this purpose. By 2024, the company had rehabilitated a total of 3 467 hectares of mined land (HYDRO, 2025) (Figure 2).

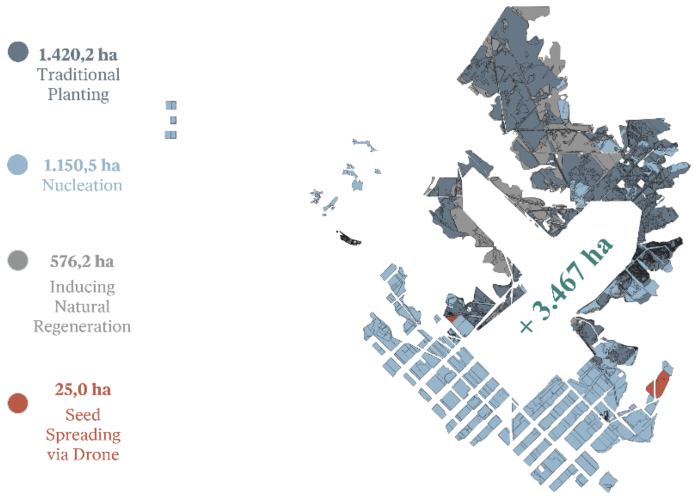


Figure 2. Areas under environmental rehabilitation (illustration).

The ore is mined using strip-mining method. As illustrated in Figure 3, the process starts with vegetation suppression (removal of trees, shrubs, and ground vegetation to access soil layers) and topsoil removal (horizon A and, occasionally, parts of subsequent horizons) to start rehabilitation in other areas. Subsurface soil removal (Overburden: horizons B and C) follows, varying from 10 to 12 meter deep, after which bauxite extraction occurs (average of 2 m). The landscape is then reshaped and levelled with residual soil, and normally, about 30 cm of topsoil is spread over the surface, as illustrated in Figure 3.

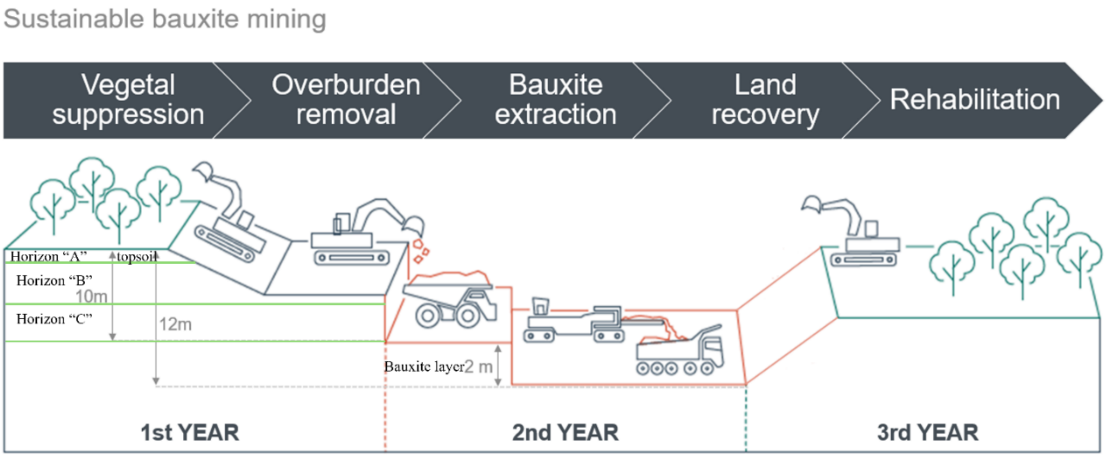
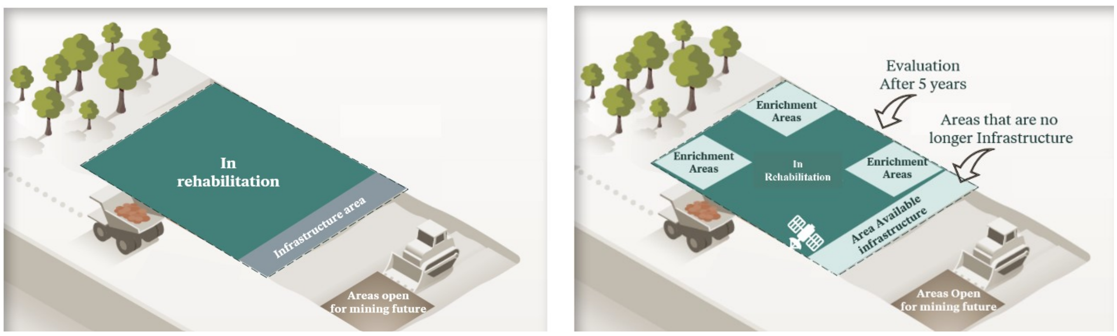


Figure 3. Schematic of Hydro Bauxite & Alumina mining and environmental rehabilitation (illustration).

Five years after the start of environmental rehabilitation, Hydro Bauxite & Alumina's unit in Paragominas carries out technical assessments in the areas under rehabilitation process. The objective is to verify the effectiveness of the measures adopted, identify enrichment needs, and integrate available infrastructure areas (e.g., former roads no longer in use due to the advancement of mining) that have become available for environmental rehabilitation. These actions not only fulfill but go beyond the requirements of the Degraded Area Rehabilitation Program (DARP), exceeding the standards set by current Brazilian environmental legislation (HYDRO, 2024).

The assessment is conducted using remote sensing and geoprocessing tools, based on imagery from the Sentinel-2A satellite. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) are derived from these images, enabling both quantitative and qualitative monitoring of vegetation cover and tracking the progress of areas under rehabilitation. Remote sensing refers to the acquisition of objects or landscapes information without direct contact, by sensors capable of capturing data from a distance (Quartaroli et al., 2014).



Year of planting implementation (year 0) Year of planting assessment (year 5)

Figure 4. Schematic of DARP assessment five years after its implementation (illustration).

Despite advances in remote sensing monitoring, the spatial resolution of the satellite images used (10 meters) still imposes significant limitations on the precision of spatial analyses, especially during periods of high rainfall (cloud cover), in regions of great environmental heterogeneity, or in small areas. With recent technological advances, the use of drones for capturing high spatial resolution images has become viable, allowing for the application of more refined vegetation indices, such as the Green Leaf Index (GLI). According to Silva et al. (2022), the GLI provides more accurate vegetation analyses. França (2022) states that this index stands out for its sensitivity to chlorophyll presence, enabling a more precise distinction between live plants, those undergoing senescence (plant aging process, with decline in vitality and leaf loss), and areas with exposed soil. This sensitivity improves the assessment of vegetative vigor and contributes significantly to the environmental monitoring of ecologically complex areas. Thus, the adoption of drones and the GLI represents a significant advancement in vegetation analysis strategies for rehabilitation processes, allowing for more accurate diagnoses and better-informed decisions.

According to Zou et al. (2024), the application of automated and adaptive image classifications, combined with spatial vectorization through binarization, has increased efficiency in distinguishing between exposed soil and vegetation cover. Precisely defining the boundaries of vegetated areas allows for the accurate quantification of preserved zones, an essential aspect for effective land management, as highlighted by Mapscaping (2025). In addition, image binarization plays a central role in digital processing, especially in vegetation segmentation and analysis systems. According to Negri and Silva (2013), this technique has demonstrated high effectiveness in various contexts by allowing a clear separation between objects and background in images, thereby facilitating the application of indices such as the GLI.

2. Objective

2.1 General Objective

This study aimed to develop and apply a methodology that integrates the Green Leaf Index (GLI) with the image binarization technique using drone-captured images, focusing on the precise detection of active vegetation and a detailed assessment of vegetation cover. The proposal seeks to improve environmental management in mined areas under rehabilitation, offering greater precision in action planning and increased reliability of the information produced throughout the environmental rehabilitation process.

2.2 Specific Objectives

- ✓ Replace Sentinel-2A satellite images with drone-acquired images to improve spatial resolution and provide more detailed and accurate data for vegetation analysis;

- ✓ Generate georeferenced orthomosaics from RGB images captured by drones, applying geometric and radiometric corrections to ensure the accuracy and reliability of the data used in vegetation cover analysis;

- ✓ Calculate the Green Leaf Index (GLI) based on the reflectance of the red, green, and blue bands to identify areas of active vegetation and exposed soil;

- ✓ Use image binarization as a segmentation technique to automatically classify pixels into vegetated and non-vegetated areas, with a spectral threshold adjusted to the specific characteristics of the local vegetation.

3. Materials and Methods

The study was conducted in areas undergoing environmental rehabilitation at Hydro Bauxite & Alumina, Paragominas, focusing on areas planted in 2020. According to Hydro's internal procedure, areas under rehabilitation process must be assessed five years after their implementation, which was followed in the present analysis (Figure 5).

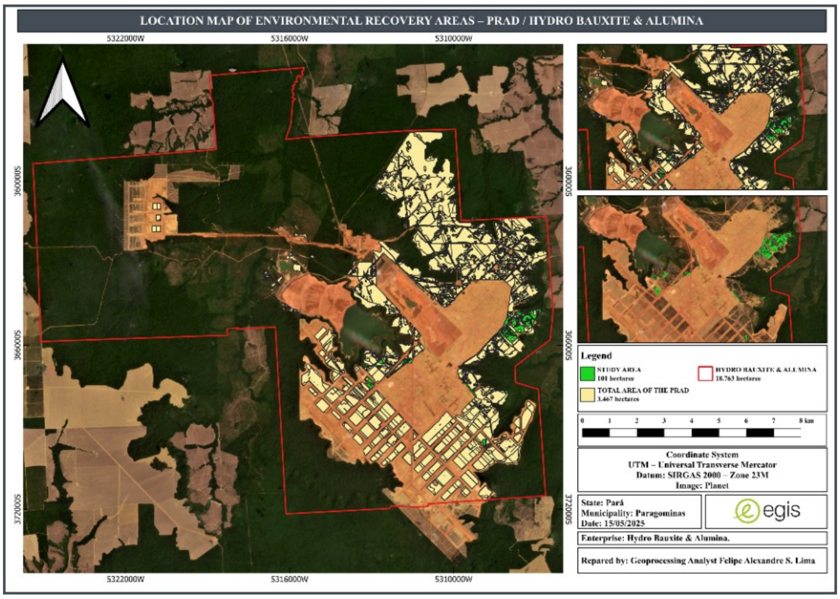


Figure 5. Study area's map.

The images used in this study are part of Hydro Bauxite & Alumina's Orthomosaic Database, captured in the visible spectrum bands (RGB – red, green, and blue), which enable spectral surface analysis (Gorelick et al., 2017; Drusch et al., 2012). These images presented spatial and temporal resolution suitable for the proposed analysis. The process steps are illustrated in Figure 6a.
For the analysis, the QGIS Desktop software, version 3.34.10, was used. The orthomosaic was initially loaded, and then the Green Leaf Index (GLI) was calculated using the "Raster Calculator" tool, based on the visible spectrum bands (RGB). The complete process is illustrated in Figure 6b. The GLI was calculated using the Equation 1.

$$GLI = (2G + R + B) / (2G - R - B) \tag{1}$$

where:
GLI Green leaf index,
G green band intensity,
R red band intensity,
B blue band intensity.

After calculating the GLI, the binarization of the generated raster was performed using QGIS's "Raster Calculator" tool. To distinguish vegetation areas from exposed soil, a threshold of 0.05 was adopted based on the GLI value distribution. Values greater than 0.05 were classified as vegetation (1), while lower values were assigned as exposed soil (0). This threshold was chosen to efficiently highlight vegetated areas, considering that the GLI ranges from -1 to 1, with vegetation generally presenting higher positive values. The use of this threshold is common in vegetation segmentation studies as it contributes to classification accuracy (Oliveira et al., 2022). The process steps are illustrated in Figure 6c. The formula used for binarization was the Equation 2.

$$((GLI < 0.05) \times 0) + ((GLI \geq 0.05) \times 1) \tag{2}$$

where:
GLI Green Leaf Index,
0.05 Adopted digital value of the pixel in the image,
0 values below threshold classified as exposed soil,

1 values above threshold classified as vegetation.

The next step consisted of transforming the binary raster into a vector using the QGIS "Polygonize" tool. This process converted the binarized pixels into polygon shapefiles, representing areas classified as vegetation (1) and exposed soil (0) as vector objects (QGIS Documentation, 2023). The conversion to vector format enabled more detailed spatial analysis and allowed precise area calculations and the integration of data with other spatial datasets for a more comprehensive assessment. From the shapefiles generated in the "polygonization" step, it was possible to extract areas corresponding to vegetation and exposed soil. For this, the concept of total area was adopted, with the extraction of vegetation area considered as complementary. The remaining area, composed of exposed soil, was designated for planting planning. The QGIS "Difference" tool was used for this analysis, allowing the exclusive extraction of the vegetated area from the total area. The differentiation operation was essential to accurately isolate vegetated areas, allowing more detailed calculations and comparison between vegetated and exposed soil areas (Silva et al., 2020). The process steps are illustrated in Figure 6d. With the quantification of vegetation and exposed soil areas, it was possible to conduct a quantitative assessment of changes in vegetation cover, providing essential information for planning enrichment activities and monitoring environmental sustainability (Tian et al., 2020). The complete process steps are illustrated in Figure 6.

Image collection by drone	Green Leaf Index (GLI)	Image binarization	Binary raster to vector

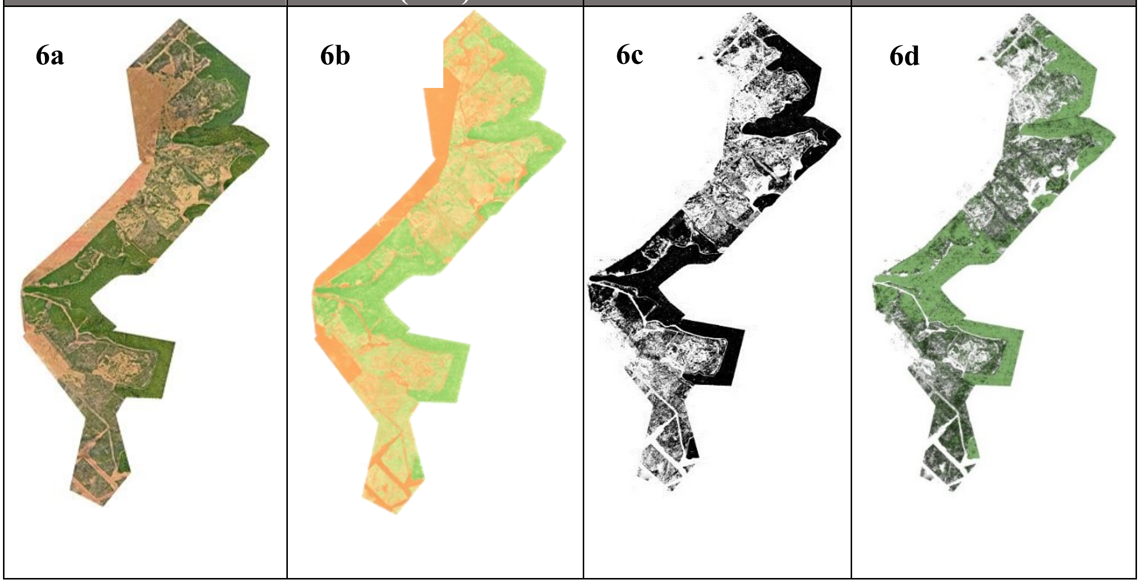


Figure 6. Image processing schematic (illustration).

4. Results and Discussion

The results of this study revealed that the area previously designated for vegetation enrichment actually presented a denser vegetation cover than initially estimated based on satellite images. Detailed analysis of the orthomosaics indicated a significant presence of active vegetation in much of the study area, allowing the reassessment of intervention zones and promoting the preservation of existing vegetation. This avoided unnecessary soil scarification and preparation actions, which would otherwise lead to the loss of already established vegetation.

This finding corroborates recent studies that demonstrate the effectiveness of spectral indices and digital image processing techniques in the precise delineation of vegetation cover. Qin et al.

(2024) emphasize that the use of indices such as the GLI enables highly accurate identification of areas with active vegetation, supporting more sustainable decisions in land-use planning. Additionally, Zou et al. (2024) highlighted that the combination of automated image classification and spatial vectorization enhances the precision in distinguishing between vegetation and exposed soil. The results obtained in this study are fully consistent with these conclusions, demonstrating that the integrated application of GLI and binarization promoted a more accurate segmentation of different land cover classes.

The vectorization of binarized images also significantly contributed to the spatial accuracy of the analysis. The clear definition of vegetated area boundaries enabled a more rigorous quantification of preserved zones—an element considered essential for continuous monitoring and strategic land management, as highlighted by Mapscaping (2025).

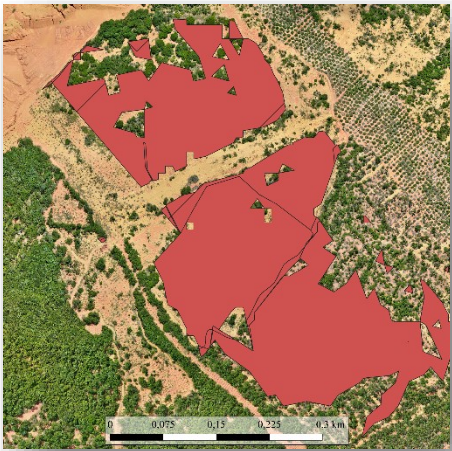
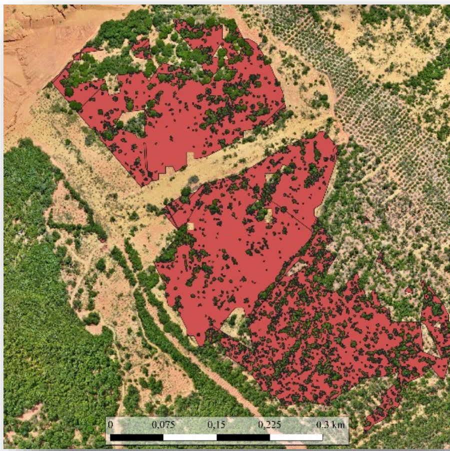
Assessment with satellite imagery	Assessment with drone imagery – GLI
	

Figure 7. Comparative analysis.

From a practical standpoint, the integration of the Green Leaf Index (GLI) with image binarization techniques led to the exclusion of 25 hectares from the originally designated 101-hectare area planned for vegetation enrichment. This optimization resulted in direct cost savings of 625 000 BRL (approximately 120 kUSD) in land preparation and 900 000 BRL (approximately 173 kUSD), in seedling production and planting, totalling 1 525 000 BRL (approximately 293 kUSD) in a single annual cycle. In addition to the economic benefits, the methodology enhanced the reliability of spatial information and reduced the risk of unnecessary environmental interventions (HYDRO, 2025).

Table 1. Cost of the stages for environmental rehabilitation.

Number of hectares	Land Preparation / ha	Planting / ha	Results
1 ha	25 000 BRL (4 800 USD)	36 000 BRL (6 900 USD)	61 000 BRL (11 700 USD)
25 ha	625 000 BRL (120 200 USD)	900 000 BRL (173 100 USD)	1 525 000 BRL (293 300 USD)

The results demonstrate the robustness and applicability of remote sensing technologies and digital image processing as effective tools to support decision-making in environmental rehabilitation projects. The integration of spectral data, vectorization, and binary analysis constitutes a promising strategy for rational, technically grounded, and environmentally responsible management of mined areas undergoing rehabilitation.

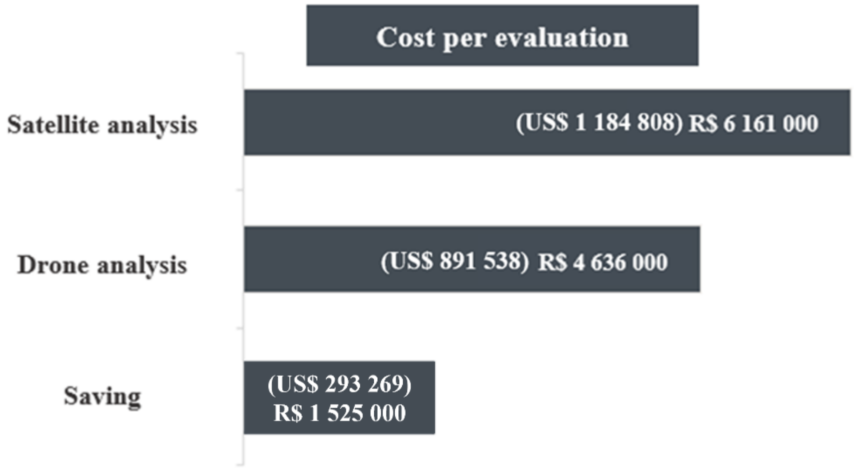


Figure 8. Graph showing cost savings resulting from the analysis

5. Conclusions

The combination of Green Leaf Index (GLI) analysis with image binarization has proven to be an effective tool to enhance the assessment and interpretation of environmental data in post-mining areas undergoing rehabilitation. This approach not only yields more precise and reliable results but also significantly contributes to reducing operational costs by optimizing planning and interventions in recovering areas.

The adoption of new technologies in the preparation and restoration of degraded areas – including geotechnologies and intelligent planning – has demonstrated substantial operational and economic efficiency. The reduction of the restoration target from 101 to 76 hectares, while maintaining environmental outcomes, resulted in an approximate 25 % cost saving.

International benchmarking of environmental rehabilitation practices in bauxite mining reveals a growing trend toward progressive rehabilitation strategies and analytical precision among industry leaders. Hydro Bauxite & Alumina, through its Paragominas operation, has rehabilitated a cumulative 3 467 hectares since 2009, averaging 300 to 400 hectares per year. This performance positions the company among global references, alongside initiatives such as Alcoa in Australia (500–700 ha/year) and South32 in Worsley (416 ha in 2024).

The integration of drones, spectral indices such as the Green Leaf Index (GLI) and image binarization not only improves the traceability and accuracy of environmental data, but also contributes to significant cost reductions in the restoration process. Hydro's operations, but also in the global aluminium and mining industries — including major players such as Alcoa, South32, EGA, as well as others operating in diverse ecological contexts that need to adopt progressive closure practices while balancing cost optimization. According to the *Integrated Mine Closure: Good Practice Guide, 3rd Edition*, published by the International Council on Mining and Metals (ICMM, 2019), progressive closure is one of the most effective strategies to reduce the uncertainties associated with mine closure costs. The guide highlights that actual closure costs have often deviated significantly from initial estimates, representing a financial and regulatory risk for companies. By implementing progressive closure, mining operations gain direct experience with rehabilitation activities, allowing them to more accurately characterize true costs and integrate these insights into future planning and budgeting.

The methodology presented in this study, based on remote sensing tools such as the Green Leaf Index (GLI) and image binarization, enhances the traceability, accuracy, and cost-effectiveness of environmental rehabilitation. This contributes not only to technical innovation but also to more responsible and financially robust mine closure practices across the global industry. By enabling real-time feedback on the effectiveness and true costs of rehabilitation activities, methodologies like the one presented in this study support more precise planning, cost control, and liability management. As such, this approach offers not only technical innovation, but also strategic value to companies committed to responsible and financially sound mine closure practices. In a global context where progressive mine closure is increasingly demanded by regulators and financiers, technologies that enhance the reliability of rehabilitation metrics will be crucial to ensure the issuance of compliance certificates, future licensing, and closure plan approvals. Thus, the case of Hydro Bauxite & Alumina in Paragominas becomes a reference for balancing productivity, innovation, and socio-environmental responsibility, pointing the way forward for the global aluminium industry.

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