High-Precision Rehabilitation - Maximizing Impact and Minimizing Costs

Jonilton Paschoal[1], Alciene Santos[2], Vicente Sousa[3], Felipe Lima[4] and Dinei Farias[5]
1. Environment Manager
2. Environment Coordinator
3. Environmental Engineer
Hydro Bauxite & Alumina, Paragominas, Brazil
4. Environmental Analyst
5. Environmental Analyst
Egis – Engineering & Consulting, Paragominas, Brazil
Corresponding author: jonilton.paschoal@hydro.com
https://doi.org/10.71659/icsoba2025-bx020

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).

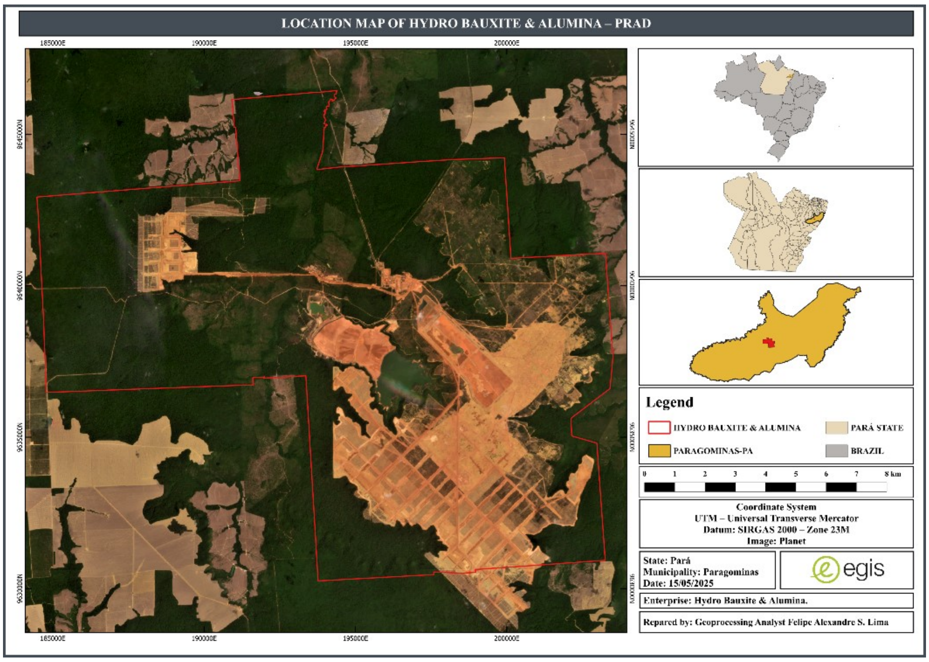

Figure 1. Location of Hydro Bauxite & Alumina.

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).

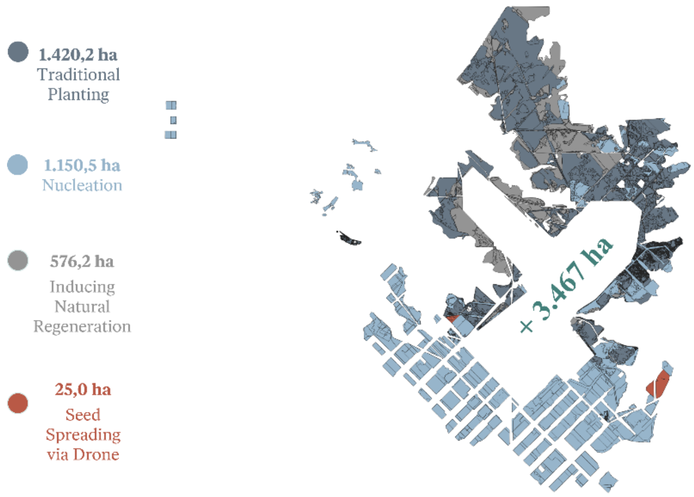

Figure 2. Areas under environmental rehabilitation (illustration).

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.

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.

6. References

1. Drusch, M., et al. (2012). Sentinel-2: ESA’s optical high-resolution mission for GMES operational services. Remote Sensing of Environment, 120, 25–36. https://doi.org/10.1016/j.rse.2011.11.026
2. França, L. (2022). Índices de vegetação com RGB de ortomosaicos de drone. GeoOne, 7 maio 2022. Disponível em: https://geoone.com.br/indices-de-vegetacao-com-rgb/. Accessed on: May 14, 2025
3. Gorelick, N., et al. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031
4. Hydro. (2025). Mineração Paragominas. Accessed on: May 10, 2025. Disponível em: https://www.hydro.com/br/global/sobre-a-hydro/a-hydro-no-mundo/americas/brasil/paragominas/mineracao-paragominas/. Accessed on: May 15, 2025.
5. Hydro. (2025). Operação. Accessed on: May 10, 2025. Disponível em: https://www.hydro.com/br/global/sobre-a-hydro/a-hydro-no-mundo/americas/brasil/paragominas/mineracao-paragominas/operacoes/. Accessed on: Mar 11, 2025.
6. Hydro. (2025). Relatório de Recuperação de Áreas Mineradas. Atualizado em 5 de abril de 2025. Hydro’s internal report.
7. Hydro. (2024). Relatório de Avaliação de Áreas Mineradas / Nota Técnica. Atualizado em 24 de dezembro de 2024. Hydro’s internal report.
8. Negri, R. G., & Silva, M. F. S. (2013). Um novo método de segmentação de imagem com abordagem baseada em bordas e regiões. Revista Brasileira de Cartografia, 65(3), 1–13. D https://seer.ufu.br/index.php/revistabrasileiracartografia/article/view/44797. Acesso em: 14 maio 2025.
9. Oliveira, E. D., Pereira, J. R., & Lima, G. M. (2022). Binalização de imagens em sensoriamento remoto para análise de uso de cobertura de solo. Revista Brasileira de Sensoriamento Remoto, 44(1), 32–47. https://doi.org/10.1590/1809-4554.202250145.
10. QGIS Documentation. (2025). QGIS 3.28 - Raster to vector Conversion. Disponível em: https://qgis.org/en/docs/. Acesso em: 15 maio 2025.
11. Quartaroli, C. F., Vicente, L. E., & Araújo, L. S. de. (2014). Sensoriamento remoto. In: EMPRESA BRASILEIRA DE PESQUISA AGROPECUÁRIA. Geotecnologias e geoinformação. Brasília: EMBRAPA, 2014. p. 61–79.

12. Silva, C. A., Santos, A. F., & Lima, R. A. (2020). Utilização do software QGIS como ferramenta de apoio à análise ambiental em áreas de expansão urbana. Jornal de Engenharia e Aplicação em Pesquisa, 5(2), 45–58. Disponível em: https://www.jornals.ufrpe.br/index.php/JEAP/article/view/1839. Acesso em: 15 maio 2025.
13. Silva, M. H., Elias, A. R., & Rosário, L. L. (2022). Análise da cultura da soja a partir de índices de vegetação (ExG – TGI – GLI - VEG) advindos de imagens RGB obtidas com ARP. Revista Brasileira de Geomática, 10(2), 140–154.
14. Tian, Y., et al. (2020). Temporal dynamics of vegetation cover and soil moisture using remote sensing data: A case study from the arid region of Northwest China. Science of the Total Environment, 724, 138374. https://doi.org/10.1016/j.scitotenv.2020.138374.
15. Zou, G., et al. (2024). RemoteTrimmer: Adaptive Structural Pruning for Remote Sensing Image Classification.
16. ALCOA. Huntly Bauxite Mine Fact Sheet. [S.l.]: Alcoa of Australia, 2024. Disponível em: https://www.alcoa.com/australia/en/pdf/mining-huntly-fact-sheet.pdf . Acesso em: 23 maio 2025.
17. MINERAÇÃO RIO DO NORTE – MRN. Relatório de Sustentabilidade 2023. Porto Trombetas: MRN, 2024. Disponível em: https://mrn.com.br/images/relatorioadm/MRN_Sustainability_Report_2023.pdf. Acesso em: 23 maio 2025.
18. ICMM – International Council on Mining and Metals. (2025). Integrated Mine Closure: Good Practice Guide (3rd ed., updated). London: ICMM. Retrieved from https://www.icmm.com/website/publications/pdfs/environmental-stewardship/2025/guidance_mine-closure_update.pdf?cb=95109 .