Use of Remote Sensing and In Situ Monitoring to Evaluate Turbidity in an Open-Pit Mining Lake

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Abstract

The formation of pit lakes in decommissioned open-pit mines has raised concerns regarding long-term water quality. Turbidity, a key indicator of suspended particulate matter, influences water clarity and aquatic ecological processes. This study estimates surface turbidity in the Águas Claras Mine (MAC) pit lake in Nova Lima, Brazil, using satellite imagery and in situ data to generate a continuous time series and assess compliance with thresholds established by current Brazilian environmental legislation. Landsat 5 and 8 imagery were used to derive a spectral turbidity index. Based on the temporal overlap between satellite and field data, a linear regression model ($R^2 = 0.77$) was developed and applied to extend the turbidity time series. The results indicate that turbidity values remained below the legal limits for Class 1 freshwater. Higher turbidity levels were observed during the initial filling phase, associated with exposed slopes, as well as episodic increases during the rainy season due to sediment runoff. Over time, progressive revegetation and minimal anthropogenic disturbance contributed to the stabilization of water quality conditions. The integration of in situ measurements and remote sensing proved to be an effective approach for monitoring water quality in post-mining environments, supporting both environmental liability assessment and closure management.

1. Introduction

Open-cut mining often creates large pits, which are environmental liabilities resulting from ore extraction and waste removal. After mining ceases, these pits may be backfilled with waste rock or tailings. Alternatively, they may become pit lakes filled with rainfall, catchment runoff, and groundwater (Castro and Moore, 2000; Lund and Blanchette, 2023).

Pit lakes can serve multiple purposes, including recreation - as in the case of the Ojamo mine (Finland) and Cenote “El Pit” (Mexico) (Lund and Blanchette, 2023) - irrigation, or even public water supply, as reported for the Klein Kopje Colliery (South Africa) and Wedge Pit (Australia), provided that water quality standards are met (Gonçalves, 2013). In Germany, pit lakes have been transformed into key sites for family leisure and environmental recovery (Weber, 2020). Pit lakes formed in gold or coal mines generally exhibit high concentrations of heavy metals, posing environmental risks. By contrast, lakes derived from iron ore mining tend to present low concentrations of dissolved metals, allowing the stored water to be allocated to higher-value uses (Gammons *et al*., 2009).

Since the 1990s, the accelerated exhaustion of large-scale mines (Sperling *et al*., 2004) has led to the increasing formation of pit lakes. Many of these remain abandoned due to company collapse and legal disputes, with responsibility subsequently transferred to the state (Lund and Blanchette, 2023). In Minnesota, United States, over 4,000 abandoned mine pits exist, most from iron ore extraction (Axler *et al*., 2003). Many of these have filled with water, forming lakes such as Cuyuna, Mesabi, and Vermilion (Axler *et al*., 2003).

Although their exact number remains uncertain due to the lack of a comprehensive global database, recent studies (Macklin *et al*., 2023; Tang and Werner, 2023) suggest that with advances in mining and the expansion of critical mineral production, the number of pit lakes is expected to increase in at least tens of thousands (Kemanga *et al*., 2024).

In Brazil, documentation on pit lake formation is scarce, though abandoned or exhausted mines have created several lakes that lack systematic long-term water quality monitoring (Gonçalves, 2013). More recently, new laws have required the rehabilitation and stabilization of degraded areas (ANM, 2021). Accordingly, a Mine Closure Plan and monitoring of environmental liabilities are required.

Turbidity is a key factor in assessing the quality of pit lake water. It represents the reduction in water clarity caused by the presence of fine suspended particles (organic, such as algae and microorganisms, or inorganic, such as sediment) (Lima *et al*., 2025). Turbidity is measured by the amount of light scattered by these particles, typically reported in Nephelometric Turbidity Units (NTU) (Trejo-Zúñiga *et al*., 2024). High turbidity reduces light penetration, thereby impacting ecological processes and overall aquatic ecosystem quality (Soni *et al*., 2014; Lima *et al*., 2025).

Pit lakes often have high turbidity due to the rapid erosion of steep mine walls and wave action during storms. Another source is the oxidation of dissolved iron to hydrous ferric oxide, a fine, slow-settling, reddish-brown particulate (Soni *et al*., 2014).

Continuous monitoring is crucial to understanding turbidity dynamics in pit lakes. However, in situ data are scarce, and long-term monitoring faces logistical and financial challenges. Remote sensing provides a viable approach to expanding the spatial and temporal coverage of turbidity assessments in mining lakes. Satellite imagery enables monitoring of hard-to-access or decommissioned sites and provides consistent data at relatively low cost.

The pit lake at Águas Claras Mine (MAC) in Nova Lima, Minas Gerais, formed after iron ore mining stopped. It has gradually filled with groundwater, inflow from the Prata Creek, and precipitation. As one of the few Brazilian cases with a historical turbidity record, albeit only from 2001 to 2007, it serves as a timely case study to validate satellite-derived data and build an extended time series.

Therefore, this study aims to analyze the temporal dynamics of turbidity in the MAC pit lake using an integrated approach based on remote sensing and in situ data, as well as to assess compliance with thresholds established by current environmental legislation.

2. Study area

The MAC pit lake is located on the southeastern flank of the Serra do Curral, within the Quadrilátero Ferrífero (Iron Quadrangle), a geological province of approximately 7,000 km² in southeastern Brazil, rich in iron ore and roughly square in shape (Rezende, 2016). The Iron Quadrangle hosts large iron and gold mining operations, as well as other mining enterprises that exploit deposits of topaz, bauxite, and additional mineral resources (Rezende, 2016).

As shown in Figure 1, the pit lake lies in the municipality of Nova Lima, in the Belo Horizonte Metropolitan Region (RMBH), in the state of Minas Gerais (Grandchamp and Menegasse, 2004).

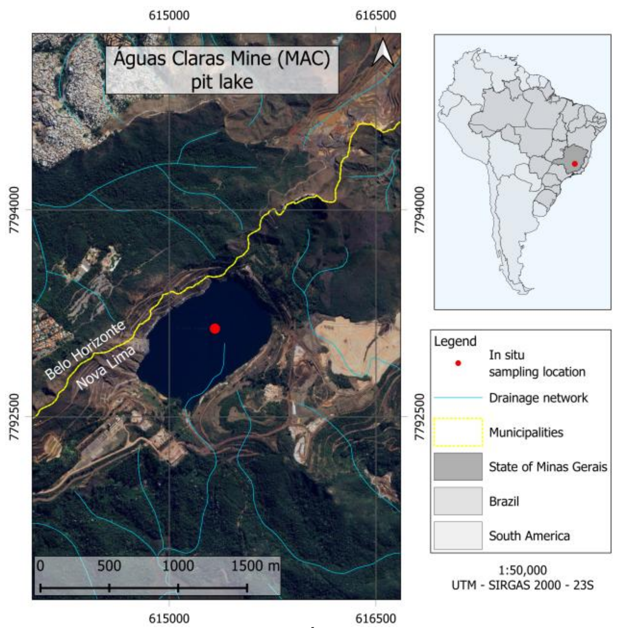

Figure 1. Location of the Águas Claras Mine pit lake.

Iron ore extraction at the Águas Claras Mine began in 1973, under the operation of MBR (Minerações Brasileiras Reunidas S/A), currently owned by Vale S.A. (Gonçalves, 2013).

In 1986, groundwater level drawdown was initiated, as the mining front had approached the elevation of the Águas Claras creek headwaters. Mining activities ceased in 2000, and complete resource exhaustion occurred in 2002. Subsequently, groundwater levels began to recover, and the pit started to fill, forming a lake.

By August 2022, the water level in the pit had reached 1,072.40 m, corresponding to a depth of 182 m. The lake is expected to reach a final depth of approximately 200 m and a surface area of 0.67 km² (Pereira, 2024).

3. Methodology

3.1 In situ monitoring data and remote sensing data

The observed turbidity data for the pit lake were obtained from Gonçalves (2013), who reported that sampling was conducted in accordance with the analytical methods described in *Standard Methods for the Examination of Water and Wastewater* (APHA, 1998). The dataset comprised samples collected at a central, near-surface location in the lake (with no reported sampling depth), on a monthly basis from February 2001 to November 2007, excluding March 2001, January 2002, and June 2005. Although Vale S.A. continued to monitor water-quality parameters in the pit lake, only data from 2001 to 2007 were made available (Gonçalves, 2013).

To estimate turbidity from remote sensing, Landsat imagery was used, comprising Landsat 5 data from February 2001 to June 2013 and Landsat 8 data from June 2013 to June 2025. These images were obtained as atmospherically corrected products providing surface reflectance values.

Landsat 5, launched in 1984, operated for 28 years, using the Thematic Mapper (TM) sensor, which provides a spatial resolution of 30 m for six spectral bands and 120 m for the thermal band. The radiometric resolution is 8-bit, with a 16-day revisit cycle. Landsat 8, launched in 2013, offers a spatial resolution of 30 m for its eight multispectral bands, using the OLI sensor, and 15 m for its panchromatic band. Its radiometric resolution is 12-bit, resampled to 16-bit, with a 16-day revisit cycle (NASA, 2025).

The images were processed in Google Colab environment using the Google Earth Engine (GEE) Python API. Scenes with up to 20% cloud cover were selected and cropped to the study area centered on the lake. Given that the study area is restricted to the pit lake, a water mask derived from the Normalized Difference Water Index (NDWI) was applied to isolate pixels corresponding to the water surface. NDWI has been widely used across multiple sensor systems to delineate open water bodies (McFeeters, 2013).

Following Bande *et al*. (2018), an empirical band-ratio equation based on the relationship between red and blue reflectance (B3/B1 in Landsat 5 and B4/B2 in Landsat 8) was used to estimate apparent turbidity. The values obtained from the band ratio produced a turbidity index. A subset of images was randomly selected to perform an exploratory analysis of the spatial variation of index values across the lake surface. Only minor variation was observed, and, therefore, a mean index value was computed for the entire lake to be compared with the turbidity measurements collected in the central region.

Based on coincident data (2001–2007), a simple linear regression model was fitted between the calculated spectral index and turbidity values measured in NTU. The resulting equation was then applied to the remaining Landsat images (2008–2025), allowing extension of the turbidity time series to the present.

3.2 Time-series assessment

Measured turbidity values from in situ monitoring and estimated turbidity values derived from satellite imagery were analyzed as a time series, enabling the identification of seasonal patterns and the assessment of compliance with the limits established by the National Environment Council Resolution No. 357/2005 (CONAMA, 2005). This regulation, issued by the National Council for the Environment, defines the classification of water bodies and their corresponding environmental standards based on threshold values for water-quality parameters. Freshwater systems, such as the lake in the MAC mining pit, may be classified as:

1. Special Class: intended for human consumption after disinfection; preservation of the natural balance of aquatic communities; and protection of aquatic environments in fully protected conservation units;
2. Class I: intended for human consumption after simplified treatment; protection of aquatic communities, including those in Indigenous Lands; primary contact recreation (e.g., swimming, water skiing, and diving); and irrigation of vegetables consumed raw, as well as fruits that grow close to the ground and are consumed raw without peeling;
3. Class II: intended for human consumption after conventional treatment; protection of aquatic communities; primary contact recreation (e.g., swimming, water skiing, and diving); aquaculture and fishing activities; and irrigation of vegetables, fruit crops, and public areas (e.g., parks, gardens, and sports fields) with potential direct human contact;
4. Class III: intended for human consumption after conventional or advanced treatment; irrigation of arboreal, cereal, and forage crops; amateur fishing; secondary contact recreation; and livestock watering;
5. Class IV: intended for navigation and aesthetic landscape purposes.

According to CONAMA (2005), class-specific turbidity limits for freshwater are presented in Table 1.

Class	Turbidity (NTU)
Special Class	Not specified
Class I	40
Class II	100
Class III	100
Class IV	Not specified

Table 1. Class-specific turbidity limits for freshwater.

For Special Class waters, no turbidity limit is defined, as the regulation requires preservation of the water body's natural conditions. For Class IV waters, no limit is established due to their less restrictive intended uses, provided that turbidity does not impair these uses.

Figure 2 summarizes the methodological steps followed in this study.

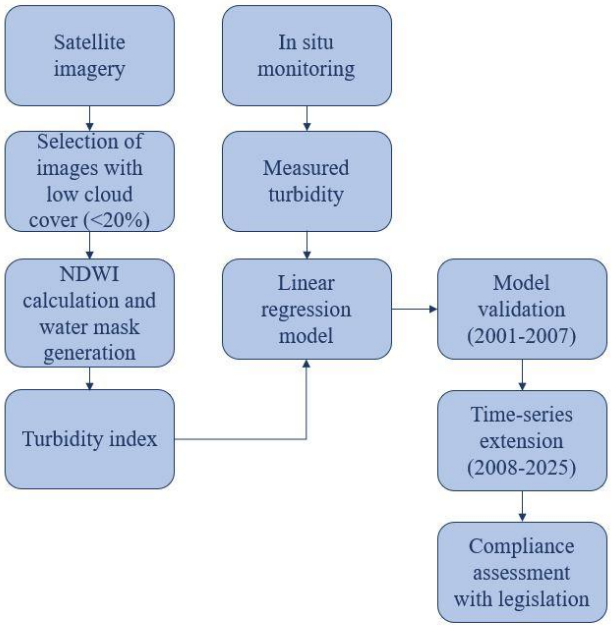

Figure 2. Methodological steps.

4. Results and discussion

4.1 Remote sensing data processing and regression model

Between February 2001 and November 2007 (the period for which in situ data are available), 36 Landsat 5 images with low cloud interference were identified and selected. For each image, NDWI was computed.

The distribution of NDWI revealed a predominance of negative values, indicating that most of the selected area corresponds to exposed soil, vegetation, or surfaces with low moisture content. A smaller group of pixels with positive values was initially associated with surface water. Visual inspection of selected images indicated that NDWI values ranging from -0.005 to 0.5 correspond to water surfaces. Based on this assessment, a threshold of NDWI > -0.005 was adopted to delineate water pixels. Figure 3 illustrates the application of this mask to isolate the lake area.

In the earliest images (2001-2002), the water-covered area within the pit is limited, as this period corresponds to the end of pit exploitation and the onset of lake filling. From August 2003 onwards, a substantially larger water surface is observed inside the pit.

For each water pixel selected within the pit, the turbidity index was calculated (the ratio of red to blue reflectance – B3/B1 for Landsat 5). The mean turbidity index for each image was then computed (Figure 4).

In the early years, the turbidity index exhibited higher values. This is consistent with the initial filling stage, when shallow water conditions facilitated sediment resuspension. At that stage, vegetation had not yet developed on the pit walls, increasing sediment detachment by the action of wind, water, and vehicle traffic associated with the demobilization of mining operations.

The turbidity indices were compared with the in situ turbidity measurements using a simple linear regression model. Initially, the correlation between the two datasets was weak, with a coefficient of determination R^2 of 0.41.

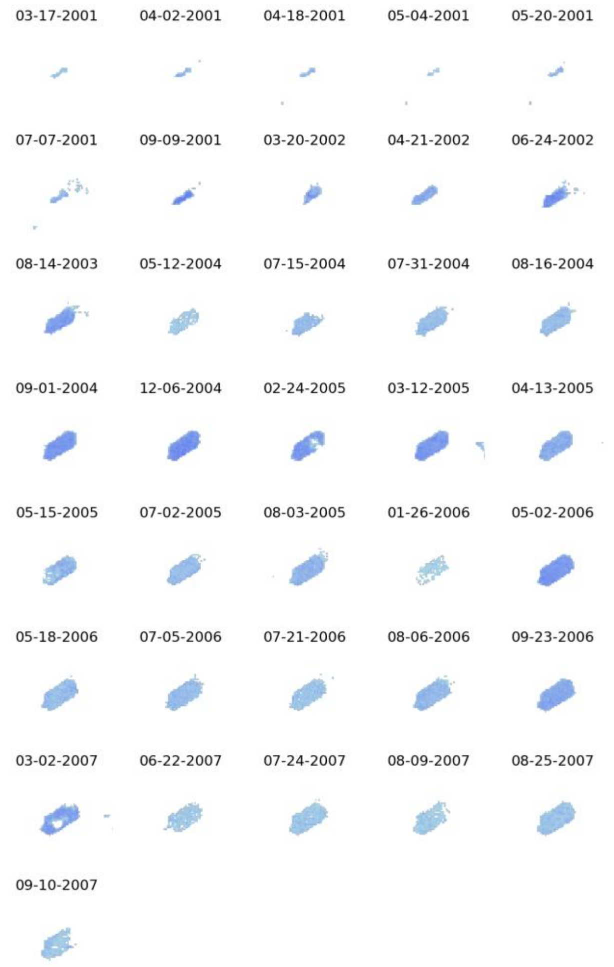

Figure 3. Water mask applied to isolate the lake area.

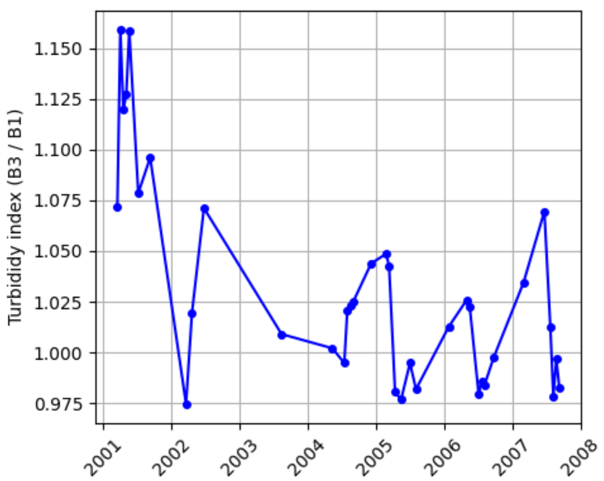

Figure 4. Mean turbidity index in the MAC pit lake.

A closer analysis revealed that three turbidity index values significantly affected the correlation. Two of these values, obtained on September 9, 2001, and March 20, 2002, corresponded to the pit-filling period, when the lake was still small and shoreline pixels were likely influenced by surrounding land surfaces (mixed pixels). The third value, obtained on June 22, 2007, was influenced by cloud shadow.

After removing these outliers, the model produced a substantial improvement, with the regression fit yielding a good correlation (R^2 = 0.77), as illustrated in Figure 5. This result demonstrates the improved reliability of satellite-derived turbidity estimates following data refinement and is consistent with findings reported elsewhere (Potes *et al*., 2012; Shahzad et al., 2018; Assunção *et al*., 2024; Kong *et al*., 2025).

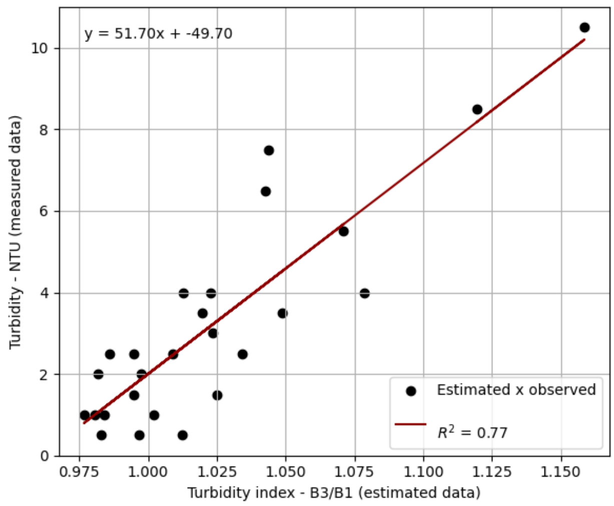

Figure 5. Regression model for turbidity estimation.

However, this relationship must be interpreted in light of certain limitations. As previously mentioned, turbidity as well as other water-quality parameters were obtained from a single, centrally located, near-surface sampling point.

Although pit lakes often exhibit vertical heterogeneity due to stratification, the epilimnion is typically well mixed and tends to display relatively homogeneous conditions over short spatial scales (Wells and Troy, 2022; Wilson *et al*., 2020). Nevertheless, spatial variability may still occur, particularly in response to localized inputs or wind-driven processes.

In this context, a single monitoring point may not adequately represent the horizontal variability of turbidity across the lake surface. In contrast, the mean index calculation inherently integrates spatial variability, partially accounting for it. This discrepancy may partly explain the remaining dispersion observed in the regression results. A stronger correlation could likely be achieved using multiple, spatially distributed sampling points that better capture surface conditions.

Studies conducted in open water environments (Thouvenin-Masson *et al*., 2022; Yu *et al*., 2026) have reported uncertainties between satellite-derived and in situ water-quality parameters associated with the limited number of sampling points.

4.2 Validation of turbidity values

Based on the regression equation, turbidity values in NTU were obtained for the 2001–2007 period. The turbidity values estimated from satellite imagery and those measured in situ were plotted as a time series (Figure 6) and are also presented in Table 2.

Overall, the model successfully reproduced the fluctuations in turbidity over the study period, particularly between 2001 and

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2004. Table 2 shows that, over the analyzed period, the model exhibited balanced under- and overestimation errors. During the rainy season (October to March), absolute bias values frequently exceeded 1 NTU, which may be attributed to increased inputs of suspended material from the surrounding area, as well as enhanced water surface agitation caused by direct precipitation. Similar results were observed by Kong *et al*. (2025) when assessing coastal water turbidity in Los Angeles.

Although the measured and satellite-derived datasets share coincident dates, the timing of in situ sampling was not reported, which may introduce uncertainties in the retrieval results. Furthermore, it cannot be guaranteed that in situ measurements and satellite observations correspond to the same sampling depth. In optically clearer waters, increased light penetration allows satellite sensors to integrate signals from deeper layers, potentially differing from near-surface measurements. The sampling depth was not specified, although the referenced standard typically recommends measurements between 0.2 and 0.5 m. Similar uncertainties associated with spatial and temporal mismatches between point-based samples and satellite overpasses have been reported by Yu *et al*. (2026) in the analysis of water-quality parameters in Wenzhou Bay, China, and by Thouvenin-Masson *et al*. (2022) when assessing sea surface salinity.

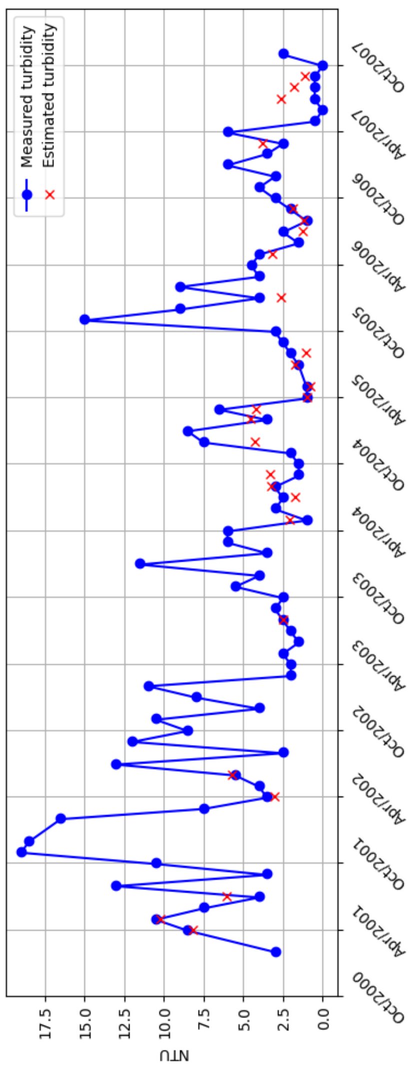

Figure 6. Time series of estimated and measured turbidity.

Date	Measured turbidity (NTU)	Estimated turbidity (NTU)	Bias
Apr-01	8.50	8.18	-0.32
May-01	10.50	10.20	-0.30
Jul-01	4.00	6.06	2.06
Apr-02	3.50	3.01	-0.49
Jun-02	5.50	5.68	0.18
Aug-03	2.50	2.47	-0.03
May-04	1.00	2.11	1.11
Jul-04	2.50	1.73	-0.77
Aug-04	3.00	3.21	0.21
Sep-04	1.50	3.29	1.79
Dec-04	**7.50**	**4.27**	**-3.23**
Feb-05	**3.50**	**4.51**	**1.01**
Mar-05	**6.50**	**4.21**	**-2.29**
Apr-05	1.00	0.99	-0.01
May-05	1.00	0.79	-0.21
Jul-05	1.50	1.73	0.23
Aug-05	2.00	1.06	-0.94
Jan-06	**4.00**	**2.66**	**-1.34**
May-06	4.00	3.17	-0.83
Jul-06	2.50	1.28	-1.22
Aug-06	1.00	1.18	0.18
Sep-06	2.00	1.86	-0.14
Mar-07	**2.50**	**3.77**	**1.27**
Jul-07	0.50	2.65	2.15
Aug-07	0.50	1.83	1.33
Sep-07	0.50	1.11	0.61
Sum	83.00000	83.00027	0.00027

Table 2. Measured and estimated turbidity.

4.3 Turbidity time series in the MAC pit lake

All the procedures described above were applied to Landsat 5 images from 2008 to 2013 and Landsat 8 images from 2013 to 2025. These steps included the selection of images with low cloud cover, calculation of NDWI, application of a water mask to isolate water pixels, and computation of the turbidity index and its mean value.

Based on the regression equation validated for the 2001–2007 period, the model was applied to Landsat 5 (2008–2013) and Landsat 8 (2013–2025) images. This enabled the construction of a surface turbidity time series for the MAC pit lake spanning the period from 2001 to 2025 (Figure 7).

Overall, surface turbidity values in the pit lake remained low, staying below 40 NTU, which corresponds to the threshold established by CONAMA (2005) for Class 1 freshwater bodies. Class I waters are intended for human consumption after simplified treatment, as well as for primary-contact recreation and the protection of aquatic communities.

Between 2001 and 2005, Batista (2006) studied the MAC pit lake and concluded that it tends to exhibit low concentrations of nutrients, conductivity, and suspended solids, indicating typical oligotrophic conditions.

Despite the low turbidity observed during the analyzed period, higher values were recorded in the early years of lake filling, which can be attributed to the fact that the pit walls were still exposed and lacked vegetation cover (Figure 8a). The surroundings of the forming lake were revegetated by the mining company and are not subject to direct external interference, given that the lake is located within a privately owned area with restricted access. Over the years, the expansion of vegetation cover (Figures 8b, 8c, and 8d) and the area's isolation likely contributed to the reduction in turbidity values.

According to Gammons *et al*. (2009), mining lakes often exhibit high concentrations of total dissolved solids, which are influenced by interactions with the pit walls. During the filling phase, material from the pit slopes is transferred to the lake, increasing total suspended solids concentrations and, consequently, turbidity.

Additionally, turbidity peaks are typically associated with the rainy season and are related to the transport of suspended material from the surrounding areas and pit slopes via surface runoff that does not infiltrate into the soil.

5. Conclusions

The results demonstrate the feasibility of integrating in situ monitoring and remote sensing to estimate surface turbidity in pit lakes. The validated linear regression model ($R^2 = 0.77$) enabled the extension of the turbidity time series for the MAC pit lake up to 2025.

Throughout the study period, turbidity values remained below the 40 NTU threshold established by CONAMA (2005) for Class 1 freshwater bodies, indicating favorable water quality conditions. Higher turbidity values observed during the early filling stage were likely associated with exposed pit slopes and the absence of vegetation cover. Over time, slope revegetation and the isolation of the area appear to have contributed to system stabilization and a reduction in turbidity. Turbidity peaks were primarily associated with the rainy season, reflecting increased sediment transport by surface runoff.

The proposed methodology proved to be effective for long-term monitoring of environmental parameters in post-mining pit lakes, particularly in areas with difficult access or scarce in situ data. Satellite imagery thus represents a complementary tool for environmental management in the context of mine closure and the rehabilitation of degraded areas.

Figure 8. General view of the pit at different stages of lake filling (Source: Pereira, 2024).

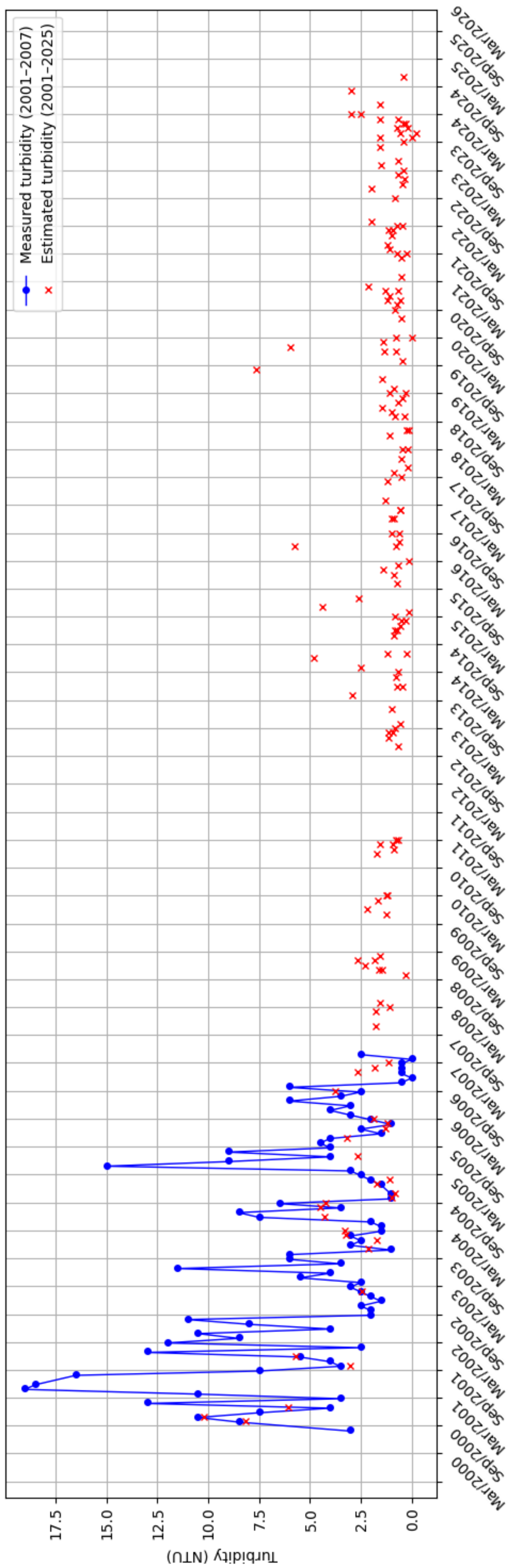

Figure 7. Time series of surface turbidity in the MAC pit lake.

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