MineTracker: Visual Analytics for Spatiotemporal Analysis of Mining Areas in the Brazilian Amazon

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***Abstract*—Conserving tropical forests is a global imperative, yet accelerating deforestation — driven in part by industrial mining — demands timely, fine-grained monitoring. Most existing platforms provide only coarse regional summaries, obscuring the emergence and growth of individual mines. We introduce *MineTracker*, a novel visual analytics tool that delivers site-level spatiotemporal insights into mining across the Brazilian Amazon. The system overlays annual mining footprints on key territorial boundaries (Indigenous lands, municipal limits) and applies time-series clustering to surface characteristic growth trajectories. Applied to Roraima, *MineTracker* revealed a pronounced surge of mining within legally protected Yanomami territory, illustrating its capacity to expose actionable trends and support evidence-based forest conservation and land governance decisions.**

I. Introduction

Tropical forests are indispensable to global climate regulation and biodiversity conservation. Acting as vast carbon sinks, they help curb global warming while providing habitat for more than half of the planet's terrestrial species. Continued degradation releases large quantities of greenhouse gases and pushes countless species toward extinction, highlighting the urgency of safeguarding these ecosystems [1].

Industrial-scale mining now encroaches deeply into intact rainforest regions, such as the Amazon, producing both direct and indirect deforestation [2]. From 1985 to 2023, mining alone cleared roughly 0.31 million ha of Amazonian forest [3]. New access roads built to service mines open remote areas to additional settlement and logging, amplifying forest loss. Mining also threatens Indigenous communities through mercury contamination and other pollutants [4]. These impacts underscore the need for systematic, high-resolution monitoring of mining activities.

Satellite remote sensing has become the cornerstone of land-cover monitoring. Projects such as *Global Forest Watch*, *Amazon Mining Watch*, and *MapBiomas* combine satellite imagery with computer vision and machine-learning techniques to map forest change at increasingly fine resolution [5]–[7]. However, most products remain region-scale, limiting analyses of how individual mines emerge, expand, or decline over time.

We present ***MineTracker***, a visual analytics system that tracks mining at the *site* level, designed to help researchers, policymakers, and organizations monitor land use and environmental changes. Using the MapBiomas Mining Collection 9 dataset [8] on Google Earth Engine, we first extract annual mining polygons, merge them into coherent mining sites, and compute each site's area and yearly growth trajectory. We then cluster sites by their temporal signatures to reveal characteristic development patterns. Finally, linked interactive views allow analysts to examine spatiotemporal trends, compare clusters, and drill down to individual sites.

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Our main contributions are:

- A data-processing pipeline that delineates, aggregates, and clusters mining sites from annual polygon maps.
- *MineTracker*, an interactive visual analytics tool that supports site-level exploration of mining dynamics in the Brazilian Amazon.
- Two case studies illustrating how the system uncovers actionable patterns of mining expansion and decline.

II. Related Works

Land-use and land-cover (LULC) monitoring is a cornerstone of environmental data science. Large-scale initiatives such as *Global Forest Watch* [5] and the *MapBiomas* project [7], [9] exploit *Google Earth Engine* [10] to compile multidecadal statistics — *e.g.*, deforestation and urban expansion — at national, state, and municipal levels. The Dynamic World dataset [11] further extends these efforts by providing 10m, near-real-time land-cover classifications. Nevertheless, the sheer volume, spatial resolution, and temporal cadence of such data pose major analytical challenges.

Several visualization tools have emerged to help users explore spatiotemporal LULC change. *Global Forest Watch*, *MapBiomas*, and *Dynamic World* each provide interactive web portals featuring animated playback of annotated maps, giving an immediate sense of temporal evolution. *Esri's Land Cover Explorer* [12] enables side-by-side "swipe" comparisons of map layers across years, while Earth Map [13] offers a dashboard-style exploration of diverse geospatial datasets. Although these tools reveal macro-level trends, they treat entire administrative units as the fundamental entity of analysis, often masking site-specific or time-dependent behaviors.

Within the mining domain, *Amazon Mining Watch* [6] publishes annual maps that delineate mining patches derived from satellite imagery. While invaluable for locating mines and approximating their extent, the platform lacks quantitative tools for site-level area analysis or temporal trend detection. Consequently, users struggle to isolate anomalous activity in a single mine or to identify clusters of sites exhibiting similar growth trajectories.

Existing systems, therefore, share three main limitations: (i) weak support for outlier detection and correction of classification errors; (ii) limited facilities for discovering group-level temporal patterns; and (iii) insufficient detail for fine-grained cross-region comparisons.

In contrast, our proposal, *MineTracker*, is an interactive visual analytics system purpose-built for site-based mining analysis. By focusing on individual mines and enabling side-by-side comparisons, it offers a flexible framework for understanding mining dynamics across the Brazilian Amazon.

III. System Overview

This section outlines the design methodology underpinning *MineTracker*, including the system requirements, core analytical tasks, and high-level workflow that guided its development.

A. System Requirements

We conducted a literature review and drew on the experience of one author who had previously worked on multiple land-use monitoring projects. This process informed a set of requirements that build on the strengths — and address the shortcomings — of existing interactive visual analytics tools for LULC exploration (Sec. II), with a particular emphasis on fine-grained analysis of mining sites.

R1. Site-level spatiotemporal analysis. Analysts must inspect the evolving footprint of *individual* mines to determine whether activity is expanding, stabilising, or declining and to flag anomalous change that could signal misclassification. The fine-grained resolution also enables comparison across municipalities, protected areas, or Indigenous territories.

R2. Integrated satellite imagery for visual validation. Up-to-date, high-resolution imagery (*e.g.*, Sentinel-2, PlanetScope) provides essential context for confirming algorithmic classifications, gauging recent environmental impact, and spotting artifacts — particularly in small or fragmented sites where false positives are common.

R3. Scalable summarization of large site collections. The Brazilian Amazon is home to numerous mining sites. Clustering mines with similar temporal signatures and then offering aggregated views of those clusters reduces cognitive load, helping users focus on groups or outliers worthy of deeper investigation.

B. Analytical Tasks

Guided by the system requirements, we distilled five core analytical tasks that *MineTracker* must support:

T1. Track site-level area and growth. Allow users to monitor how each mine's footprint evolves in the absolute area (km^2) and year-over-year growth rate while flagging anomalous surges or contractions **(R1)**.

T2. Compare activity across regions and land categories. Enable side-by-side comparison of mining extent among municipalities and between Indigenous and non-Indigenous territories, exposing spatial inequalities and temporal shifts **(R1)**.

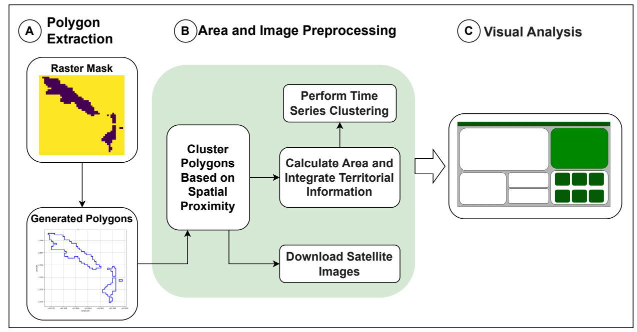

Fig. 1. ***MineTracker* workflow**. (A) Polygons are extracted from MapBiomas raster masks. (B) Polygons are clustered to create mining sites; territorial information is added, and area time series are computed and used to form mining-site clusters. Relevant satellite images are then downloaded. (C) The processed data is visualized through an interactive web-based tool.

T3. Map spatial context. Overlay mining sites on administrative boundaries, protected-area limits, road networks, and other reference layers so analysts can interpret patterns within their geographic setting **(R2)**.

T4. Inspect multi-temporal imagery. Present co-registered satellite scenes from different years in a single view, permitting rapid visual assessment of land cover change and verification of automated classifications **(R2)**.

T5. Explore behaviour-based clusters. Group sites with similar temporal signatures, summarise each cluster's characteristic trajectory, and let users drill down from overview to individual mines **(R3)**.

C. Workflow

Fig. 1 shows a three-stage pipeline. **Stage A, Polygon Extraction:** Annual raster masks of mining pixels are converted to clean vector polygons that outline each detected mining scar. **Stage B, Area, and Image Preprocessing :** Polygons that lie within proximity are first merged to form coherent mining sites; up-to-date satellite images (*e.g.*, Sentinel-2) are then retrieved for each site's bounding box; annual area, growth rate, and contextual attributes such as municipality and Indigenous-territory status are computed; finally, the resulting time-series signatures are clustered to reveal groups of mines with similar expansion or contraction trajectories. **Stage C, Visual Analysis:** The curated set of site polygons, temporal metrics, satellite thumbnails, and behavioral clusters is loaded into coordinated interactive views, allowing analysts to filter, compare, and validate mining dynamics.

IV. Mining-Site Delineation and Clustering

This section details the preprocessing pipeline that converts raw raster masks into coherent mining-site objects, enriches them with spatial context and imagery, and finally groups sites based on their temporal behavior.

A. Polygon Extraction

We begin by downloading the annual mining classifications from the MapBiomas Collection 9 using the Google Earth

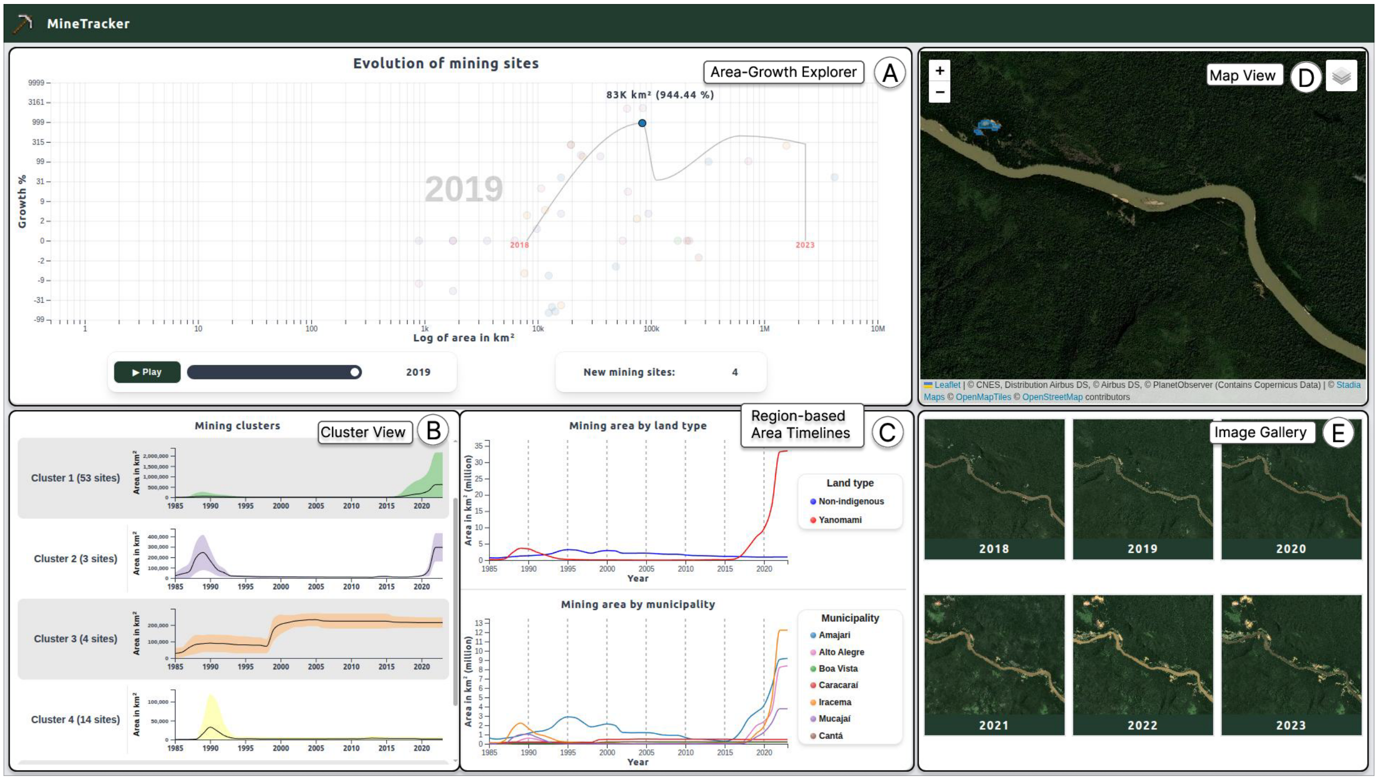

Fig. 2. ***MineTracker* interface.** (A) Area-Growth Explorer – displays the distribution and evolution of mining sites over time, allowing users to interact through temporal sliders. (B) Cluster View – presents the average time series of identified clusters, illustrating temporal mining patterns. (C) Region-based Area Timelines – shows two line charts tracking mining area expansion over time, segmented by land category (e.g., Indigenous vs. non-Indigenous) and municipality. (D) Map View – displays spatial polygons of mining sites overlaid on satellite imagery. (E) Image Gallery – provides yearly satellite images (2018–2023).

Engine API. Focusing on the state of Roraima (administrative level 2), we export one `.tif` mask per year (1985–2023) at a 30 m spatial resolution. Each mask is transformed into vector geometry with `rasterio.features.shapes`, producing one polygon in the World Geodetic System (WGS-84, used in cartography, geodesy, and satellite navigation, including GPS) for every contiguous patch of non-zero pixels.

B. Area and Image Processing

Because a single mine often appears as multiple disjoint fragments, we cluster polygons by spatial proximity. Pairwise distances, computed with `GeoPandas.distance`, feed a `DBSCAN` [14] model whose density-based logic requires no prior knowledge of site count or shape. Polygons assigned to the same cluster are merged with `GeoPandas.dissolve`, yielding a single `MultiPolygon` per mining site.

For each site and year, we calculate area $A_s(t)$ (km^2) with `GeoPandas.area` and derive the year-over-year growth rate. Gaps where $A_s(t) = 0$ (no data) are bridged by linear interpolation limited to internal runs of missing years; growth is then recomputed from the interpolated series.

To provide up-to-date visual context, we download images provided by Norway's International Climate and Forest Initiative (NICFI) PlanetScope base maps (5m) for the buffered bounding box of each site. Images are compressed to minimize latency, then enhanced by (i) brightening vegetation in HSV color space and (ii) applying a 1.3× global stretch plus CLAHE (Contrast Limited Adaptive Histogram Equalization, an image process algorithm for enhancing local contrast) in Lab space to sharpen local contrast. The resulting thumbnails reveal mine pits, access roads, and vegetation loss more clearly in the user interface.

Territorial attributes are attached through spatial overlay with official municipal and Indigenous-territory boundaries, enabling subsequent analyses.

C. Time-Series Clustering

Roraima alone contains more than 80 distinct sites — too many for effortless manual exploration. We, therefore, cluster sites by the shape of their area trajectories. Dynamic Time Warping (DTW) distances, which accommodate temporal shifts and unequal expansion rates, are computed pairwise between all $A_s(t)$ series. A second `DBSCAN` run on the DTW distance matrix groups mines into patterns such as sustained growth, steady decline, or intermittent activity. These clusters serve as high-level entry points for analysts, allowing them to drill down to individual cases.

V. The *MineTracker* System

MineTracker is an interactive visual analytics environment that lets users explore how individual mining sites in the

Brazilian Amazon grow, shrink, or remain stable over time. The interface (Fig. 2) is organized into five coordinated views. The remainder of this section provides a detailed description of these views.

A. Area–Growth Explorer

Borrowing the "temporal scatter" paradigm of DimpVis [15], the *Area–Growth Explorer* plots every mining site as a dot whose position evolves frame by frame **(T1)**. The horizontal axis shows the site area on a logarithmic scale, while the vertical axis encodes year-to-year percentage change. Color denotes the municipality in which the site originated (useful when a large complex straddles multiple jurisdictions).

A timeline slider and *Play* button control the animation, allowing analysts to either watch a continuous movie of expansion and contraction or step through individual years for closer inspection. Hovering over a dot traces its full trajectory, with dashed red segments marking values that were linearly interpolated. Clicking a dot pins that trajectory for comparison and simultaneously updates the *Site Map* and *Image Gallery*, giving immediate spatial and photographic context for the chosen mine. This component directly supports task **T1**, while task **T2** is addressed through interactive legends in the *Region-based Area Timelines* (Fig. 2C), which enable filtering of the displayed sites by municipality or land category.

B. Mining-Group Overview

Following the time-series clustering step (Sec. IV), the resulting groups are summarised in the *Mining-Group Overview* (Fig. 2B). Adapting the design of CriPAV [16], the panel renders, for each cluster, the mean area trajectory as a solid black curve surrounded by a colored ± 1 SD ribbon **(T5)**. A sidebar lists the cluster label and its site count. Clicking a cluster acts as a filter across the interface — most notably in the *Area–Growth Explorer*, where only the selected group's dots remain highlighted — so analysts can quickly compare archetypal growth patterns. This component supports task **T5**.

C. Region-based Area Timelines

Spatial trends are conveyed through two coordinated line charts (Fig. 2C). The lower chart traces, for every year since 1985, the cumulative footprint of mining sites within each municipality. The lines are color-coded by the municipality, and the y-axis reports the area in square kilometers. The upper chart aggregates the same data into two policy-critical categories — sites inside Indigenous territories versus those outside — thereby exposing trajectories of (il)legal extraction. Both charts include interactive legends: clicking a legend item isolates the corresponding municipality or land category across all views, enabling analysts to focus on targeted regions while preserving the broader temporal context. This component directly addresses task **T2**.

D. Site Map

The *Site Map* (Fig. 2D) overlays all mining polygons on an interactive Leaflet map, coloring each site by its municipality of origin. When the user clicks a dot in the *Area–Growth Explorer*, the map pans and zooms to the corresponding site, immediately drawing attention to its spatial context. Toggle switches allow analysts to show or hide auxiliary layers, including municipal boundaries, Indigenous-territory limits, the Amajari Mining Reserve outline [17], and two alternative base maps: a detailed satellite view and a soft-toned cartographic style that minimizes clutter and emphasizes selected mines. This module aligns with the goals of task **T3**.

E. Image Gallery

The *Image Gallery* (Fig. 2E) presents a six-frame strip of annual PlanetScope thumbnails (2018–2023) centered on the chosen site and buffered to ensure full coverage. These thumbnails are the contrast-enhanced images described in Sec. IV.B, which allow users to visually track pit enlargement, road construction, and vegetation loss. The gallery updates instantly whenever a different site is selected in the *Area–Growth Explorer* or *Site Map*. Support for task **T4** is provided by this component.

F. Implementation Details

MineTracker's backend is written in Python with Flask. The front end combines HTML, JavaScript, and D3.js. The leaflet enables the map view. All code, including reproducible processing notebooks, is available on GitHub.[1] [2]

VI. Usage Scenarios

We present two author-conducted usage scenarios from the state of Roraima, aiming to showcase the system's utility. The first provides a macroscopic view of mining dynamics; the second delves into the relationship between policy decisions and site expansion. The state of Roraima was chosen due to its manageable and well-characterized mining footprint, along with documented impacts on Indigenous communities.

A. State-wide Mining Dynamics in Roraima

Dynamic-time-warping clustering (Sec. IV) partitioned Roraima's 80+ mining sites into six temporal patterns, plus a small "noise" group (`-1`). The clusters capture markedly different life-cycle trajectories:

Cluster 0. *Sustained decline* (3 sites). Sites shrink steadily from 1995 to 2023 (Fig. 3A). All lie inside the Amajari municipality and overlap the Amajari Mining Reserve, established by Ministerial Ordinance 143 of 3 Feb 1984 [17]. Reserve regulations appear to have curtailed further expansion (Fig. 3B–C).

Cluster 1. *Late-onset surge* (53 sites). Minimal change occurred before 2010, followed by rapid growth, often on or near Indigenous land. The political drivers behind this boom are explored in Case Study 2.

Cluster 2. *Reactivation after dormancy* (3 sites). A peak in the early 1990s is followed by quiescence and renewed expansion

[1] https://github.com/visual-ds/minetracker

[2] https://visualdslab.com/papers/MineTracker/

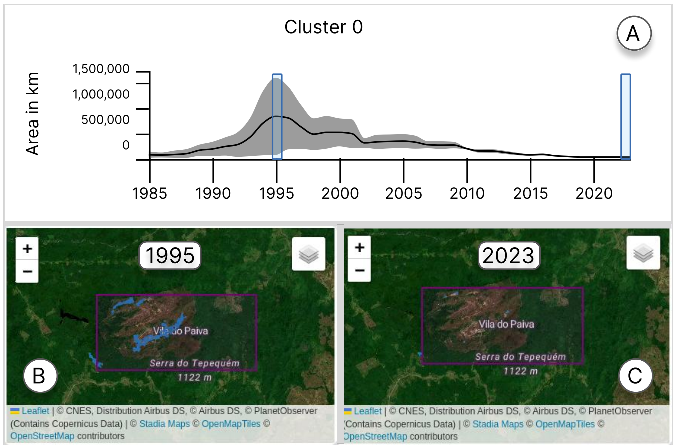

Fig. 3. **Temporal dynamics and spatial footprint of Cluster 0 sites.** (A) Mean-area time series (1985–2023) for the three Cluster 0 polygons. (B–C) Spatial extents of those same polygons in (B) 1995 (their maximum recorded area) and (C) 2023. Blue polygons denote mining sites; the purple rectangle delineates the Amajari Mining Reserve boundary (Portaria 143/1984).

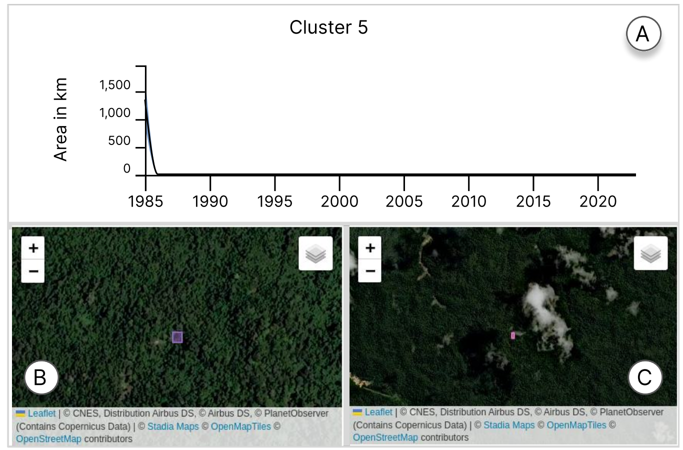

Fig. 4. **Cluster 5 transient sites in 1985.** (A) Mean-area time series showing two sites that only appear in 1985. (B–C) Corresponding spatial footprints of each site in that year.

after 2015, hinting at abandoned pits being brought back into production.

Cluster 3. *Stepwise regulated growth* (4 sites). Two modest growth spurts — one just after 1985, the other around 2000 — are separated by long, stable periods, suggesting controlled, permit-driven expansion.

Cluster 4. *Boom–and–bust* (14 sites). A pronounced early-1990s peak collapses to decades of near-zero activity, possibly reflecting the exhaustion of easily accessible deposits or stricter enforcement.

Cluster 5. *Ephemeral artifacts* (2 sites). Tiny polygons appear only in the 1985 snapshot and never again (Fig. 4A–C), indicating likely classification errors rather than real mines.

Taken together, these patterns underscore the need for tailored monitoring strategies, including continuous enforcement within protected reserves (Cluster 0), real-time surveillance of post-2010 expansion fronts (Cluster 1), and periodic quality control to eliminate spurious detections (Cluster 5).

B. Rise of Illegal Mining Inside Indigenous Lands

We focus here on the sites belonging to **Cluster 1**. Selecting the *Indigenous land* category in the *Region-based Area Timelines* highlights 51 of the 53 Cluster 1 sites in the *Area–Growth Explorer*, confirming that nearly all are located within Yanomami territory.

Two clear phases emerge (Fig. 5A). **Phase 1 – Deregulated boom (2016–2022).** Total mined area and site count (orange area) rise steeply, coinciding with deregulatory decrees issued under Presidents Michel Temer (Decree 9.142/2017) [18] and Jair Bolsonaro (Decree 10.966/2022) [19]. **Phase 2 – Enforcement slowdown (2023).** After President Luiz Inácio Lula da Silva reinstated stricter environmental controls (Decree 11.369/2023) [20], expansion stalls almost everywhere (green area). By December 2023, only five sites — clustered around Alto Alegre — continue to grow (Fig. 5B3).

Fig. 5B2 spotlights the largest of these mines. Its trajectory in the *Area–Growth Explorer* (Fig. 5B2) shows a four-fold area increase between 2019 and 2023. Corresponding map insets (Fig. 5C1–C3) visualize the expanding pit and access roads at those same time points.

The sharp contrast between the boom years and the post-2022 slowdown highlights how policy enforcement (or its absence) directly influences mining pressure within protected Indigenous lands. Without rigorous oversight, illicit extraction can surge within a few seasons, bringing severe social and environmental impacts.

VII. Discussion

The case studies demonstrate that *MineTracker* makes spatiotemporal mining dynamics both visible and interpretable. By combining coordinated filters with linked maps, timelines, and imagery, the tool surfaces trends that would be difficult to spot in raw tabular data.

Results suggest a clear spatial realignment of mining pressure. In non-Indigenous areas, the overall footprint and growth rate decline, while Yanomami territory shows dramatic expansion during periods of pro-mining policy and an equally sharp slowdown once stricter enforcement resumes. Such contrasts underscore the pivotal role of regulatory action.

MineTracker also aids data-quality control. Ephemeral "mines" that appear in only a single year quickly stand out as potential misclassifications and can be flagged for further verification.

Although developed for mining, the workflow generalizes to any LULC layer where tracking site-level extent and growth matters — for example, mapping urban sprawl, monitoring agricultural conversion, or assessing wetland loss. By simply substituting the input masks and adjusting clustering parameters, analysts can repurpose the system for new domains.

VIII. Limitations and Future Work

Linear interpolation for missing years may oversimplify temporal dynamics; advanced modeling could better capture

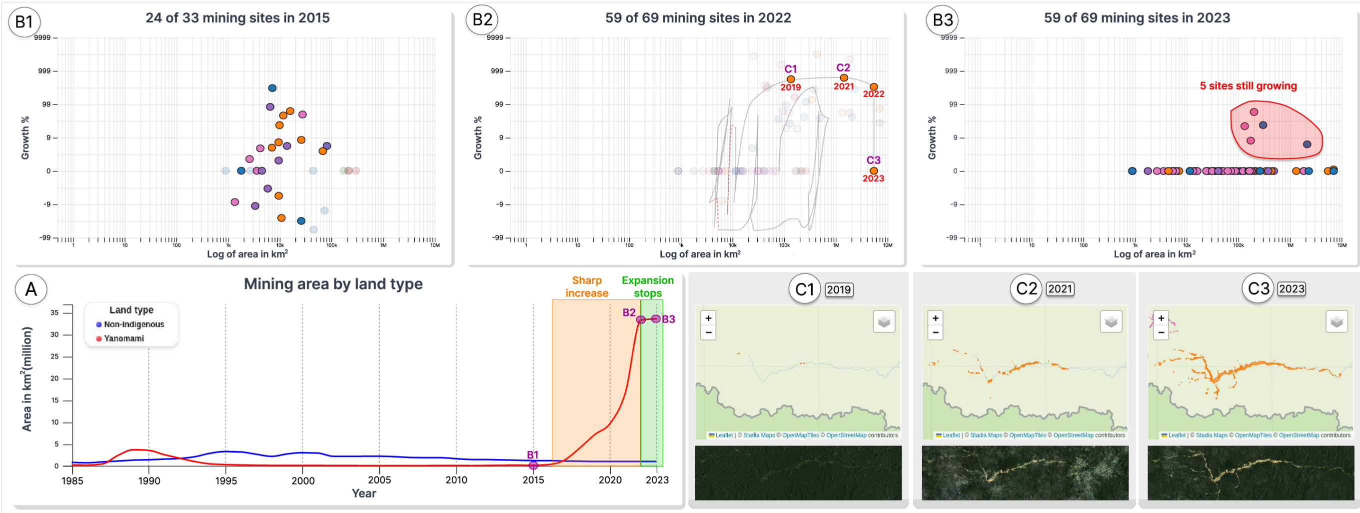

Fig. 5. **Proliferation of mining activities on Indigenous lands.** (A) Total mining area on Indigenous lands (million km²) from 1985 to 2023, split between Yanomami territory (red) and other non-indigenous areas (blue). Two distinct growth phases are identified: a period of sharp increase (orange), starting in 2016, followed by a halt in site expansion (green). (B1–B3) Snapshots of the *Area–Growth Explorer* for 2015, 2022, and 2023, filtered to display sites located on Indigenous lands. (B2) Highlights the trajectory of a specific site, showing rapid expansion between 2019 and 2023. (B3) Shows sites that continued to grow in 2023, despite most others halting. (C1–C3) Vectorized mining-polygon footprints overlaid on a street map baselayer for the site highlighted in (B2), alongside corresponding satellite images, illustrating the progressive enlargement of the excavation over time.

variability. Although connected scatterplots with logarithmic scales may be less intuitive for non-experts, they remain suitable for policymakers and environmental organizations, the system's target users. Future versions will incorporate data from the remaining states to enable a more complete analysis.

IX. Conclusion

We have introduced *MineTracker*, an interactive visual analytics environment that reveals the spatiotemporal dynamics of mining in Roraima, Brazil. By fusing annual MapBiomas masks, satellite imagery, site-level clustering, and coordinated visualizations, the system turns otherwise opaque raster stacks into actionable insight. Analysts can now pinpoint periods of rapid expansion, verify trends against ground truth imagery, compare trajectories across administrative and Indigenous lands, and flag potential classification errors — all within a single interface. Although demonstrated in mining, the processing pipeline and interface design generalize to any land-use class where the site-level extent and change over time are key analytical targets.

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