AURORA 2.0: Adaptive Mining Activity Monitoring

Beyond The Horizon – End-Term Technical Report

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January 2026

Abstract

AURORA 2.0 presents an intelligent, unsupervised learning system to monitor mining excavation activities through Sentinel-2 time-series imagery. The system can autonomously learn mine-specific excavation signatures without hard-coded thresholds, thus achieving adaptability across a range of mine types. The pipeline utilizes K-Means clustering on carefully crafted spatiotemporal features, uses metaclustering for identifying excavation, and deploys a confidence-based temporal validation mechanism for differentiating permanent excavation from seasonal changes. The system detects violations in no-go zones and generates detailed temporal analytics suitable for regulatory monitoring of mines. The significant achievements under this study include mine-agnostic adaptive learning from historical spectral signatures, robust differentiation of excavation against seasonal changes, a multilevel alerting framework for no-go zone violations, and a scalable architecture suitable for large mine inventories.

1 Introduction

Mining regulation agencies require continuous monitoring to ensure excavation remains within legal boundaries and avoids protected no-go zones. Traditional rule-based approaches fail across diverse mine types due to high spectral variability.Each mine type exhibits different characteristics, and fundamental differences make the universal spectral thresholds impractical.

This work presents AURORA 2.0, an intelligent system that automatically detects, quantifies, and monitors excavation activity using Sentinel-2 imagery. The system works across different mining commodities, handles diverse surrounding land cover, and remain resilient to seasonal vegetation changes, cloud contamination, and varying acquisition intervals. Key challenges include spectral diversity across mine types, temporal variability from seasonal changes that mimic excavation, scalability requiring generalization without reconfiguration, and false positive reduction. AURORA 2.0 addresses these by learning excavation signatures from data rather than relying on predefined thresholds.

2 System Architecture

The AURORA 2.0 pipeline consists of four distinct stages organized into training and monitoring phases. Training and monitoring are explicitly separated such that training learns the mine-specific excavation signature from historical data while monitoring applies the learned signature to unseen future data to continuously detect excavation and violations.

2.1 Training Phase

The training phase consists of two stages that take advantage of both cloud-based and local processing capabilities. Training Stage 1 utilizes Google Earth Engine for distributed processing of Sentinel-2 data acquisition, cloud masking using Scene Classification Layer, spatiotemporal feature engineering across the entire historical time series, and export to CSV format for local processing. Training Stage 2 performs local processing including feature scaling using RobustScaler with numerical stabilization, primary K-Means clustering into six clusters, meta-clustering to identify excavation versus non-excavation cluster groups, cluster pruning to eliminate false positives, and model persistence for deployment.

2.2 Monitoring Phase

The monitoring phase replicates the training architecture while applying the learned models to new data. Monitoring Stage 1 involves cloud-based processing: feature calculation on newly acquired imagery using the same feature engineering pipeline; application of the trained scaler and K-Means model within Earth Engine to optimize computational efficiency; morphological post-processing to refine binary masks; and export of binary excavation masks as multi-band GeoTIFF files. Monitoring Stage 2 is the local processing stage, which includes loading multiple files and their temporal merging, a confidence system for temporal validation, retroactive confirmation logic for detection latency, no-go zone violations detection with multi-level alerts, and full output generation that includes spatial maps and temporal analytics.

3 Methodology

3.1 Data Acquisition and Preprocessing

The system ingests Sentinel-2 Level-2A multispectral imagery at 10-meter spatial resolution accessed through Google Earth Engine Python API. Legal mine boundary polygons define the spatial extent of analysis while synthetic no-go zone polygons demonstrate violation detection capabilities. Cloud masking removes contaminated pixels by filtering Scene Classification Layer values corresponding to cloud shadows (SCL=3), medium probability clouds (SCL=8), high probability clouds (SCL=9), thin cirrus (SCL=10), and snow/ice (SCL=11). This preprocessing ensures that only high-quality surface observations contribute to the analysis.

3.2 Feature Engineering

The success of unsupervised clustering depends critically on the quality of input features. The system employs eleven carefully designed spatiotemporal features that capture both instantaneous spectral state and temporal behavior patterns. The spectral indices include Normalized Difference Vegetation Index to capture vegetation removal, shortwave infrared bands to detect exposed rock and soil, Bare Soil Index calculated as to highlight bare soil exposure, Normalized Burn Ratio calculated as to detect surface disturbances, and Normalized Difference Moisture Index calculated as to track moisture reduction associated with excavation.In detail, the features we use are NDVI, B11 band, B12, NDVI median, B11 median, B12 median, BSI median, NDMI median, NDVI variance, NDMI variance, NBR slope.

Temporal features are computed using a 60-day rolling window and include median values of NDVI, B11, B12, BSI, and NDMI to provide robust central tendency estimates resistant to outliers, variance of NDVI and NDMI to capture temporal stability where stable values indicate permanent change.Mining activity produces a persistent negative trend in NBR values over time. To capture this pattern, NBR slope is computed using Earth Engine's `ee.Reducer.linearFit()` function which applies linear regression to NBR values within the 60-day rolling window. The slope parameter from this regression, expressed as change per day, serves as the temporal feature. A clamp of ± 0.1 is applied to prevent outliers from corrupting the feature space. The rolling window approach enables the system to distinguish between temporary seasonal fluctuations and permanent excavation-induced changes.

The rationale for the selection of features is to identify spectral-temporal patterns unique to excavation. Mining activities remove vegetation that causes NDVI to decrease persistently, expose bare soil and rock increasing SWIR reflectance and BSI, reduce surface moisture, decreasing NDMI, and create disturbances that manifest as negative NBR trends. Temporal features ensure that only sustained changes contribute to excavation detection while transient seasonal variations are filtered out.

3.3 Clustering Algorithm

The clustering approach employs a two-stage strategy beginning with primary clustering followed by metaclustering for excavation identification. Feature scaling uses RobustScaler with interquartile range(IQR) normalization to provide outlier resistance.

However, certain features exhibit extremely low variance across many pixels causing numerical instability when IQR becomes very small. To address this, numerical stabilization applies hard lower bounds on scale values. These constraints prevent scale explosion while maintaining relative feature importance which are chosen after inspecting data, so our scaled values don't explode. This is implemented for numerical stability and does not threshold the raw data.

Primary clustering applies K-Means with K equals six clusters. This value balances granularity and fragmentation by providing enough clusters to capture excavation diversity within mines while avoiding excessive fragmentation. Testing revealed that K equals six typically produces one to two excavation clusters per mine depending on operational diversity, which aligns with domain expectations.

Metaclustering addresses the challenge of identifying which of the six clusters represents excavation activity. A critical preprocessing step applies SWIR floor values to prevent water and shadow interference. Water bodies and shadows exhibit extremely low SWIR values in the negative range which would cause metaclustering to separate water versus non-water rather than excavation versus non-excavation. By applying a negative floor to SWIR-related features in cluster centroids during metaclustering, the algorithm focuses on the excavation-relevant spectral range.

The six cluster centroids are re-clustered into two metaclusters using K-Means with K equals two. One metacluster represents excavation-like clusters while the other represents non-excavation clusters. To identify which metacluster corresponds to excavation, an excavation score S for a cluster is defined as

$$S = 2\,\tilde{B}_{12} + \widetilde{\mathrm{BSI}} - 0.5\,\widetilde{\mathrm{NDVI}} - \widetilde{\mathrm{NDMI}}, \tag{1}$$

Here, $\tilde{B}_{12}$ and $\widetilde{\mathrm{BSI}}$ emphasize exposed soil and rock, while $\widetilde{\mathrm{NDVI}}$ and $\widetilde{\mathrm{NDMI}}$ penalize vegetated and moisture-rich surfaces. The NDVI term is down-weighted to avoid confusion between excavation and low-vegetation water bodies. The metacluster with higher mean excavation score is designated as the excavation metacluster.

3.4 Cluster Pruning System

Despite careful metaclustering, outliers and high mine diversity can cause misclassification of non-excavation clusters into the excavation metacluster. A multi-stage pruning process validates clusters before finalizing excavation labels. The primary mine identification step computes excavation scores for all clusters in the excavation metacluster and identifies the cluster with the highest score as the definitive primary mine signature. Secondary mine inclusion applies a relative threshold where clusters must achieve excavation scores of at least 0.6 times the primary mine score to be retained as secondary excavation signals. This accommodates mines with multiple excavation types or varying operational intensities.

Additional filters remove clearly invalid clusters including green cluster filtering which rejects clusters with NDVI median greater than 0.5 since active mines cannot be vegetated, and weak signal filtering which eliminates clusters with excavation scores below 0.5 indicating insufficient excavation characteristics. This elaborate pruning system limits false positives by removing water bodies, vegetation, and weak dust signatures caused by seasonal changes while preserving legitimate mining activity signatures.Further, it saves the scaler and KMeans model, and the cluster information in a JSON, which gives us detailed information on the clustering for debugging and for use during monitoring.

3.5 Confidence System for Temporal Validation

Due to overlapping Sentinel-2 tiles, multiple raster bands may correspond to the same acquisition date. To resolve this, all bands associated with the same date are grouped and stacked. For each pixel, if at least one valid (unmasked) observation exists for that date, the corresponding excavation label (0 or 1) is retained. Pixels that remain masked across all observations for a given date are assigned an unknown state (value 2). This strategy maximizes information usage while avoiding unnecessary assumptions.

After temporal stacking, the monitoring data is represented as a three-dimensional array of shape (T, H, W), where T is the number of unique acquisition dates and (H, W) define the spatial grid. Each pixel takes a value in $\{0, 1, 2\}$ corresponding to non-excavated, excavated, and unknown states respectively. The associated dates are sorted chronologically and used for subsequent temporal analysis. The confidence system addresses the fundamental challenge of distinguishing permanent excavation from temporary seasonal changes. The system operates on the principle that excavation produces persistent spectral change while seasonal variations are transient. Each pixel accumulates days of observed excavation where a pixel appearing in an excavation cluster at time t contributes the time delta since the previous observation to its accumulated days. If a pixel flips from excavated to non-excavated state before reaching the confidence threshold, the accumulated days reset to zero indicating the change was temporary.

The confidence threshold is set to 60 days meaning a pixel must appear excavated for at least 60 accumulated days to be confirmed. This duration effectively filters seasonal cycles while confirming true excavation. Masked pixels with value 2 pause the confidence accumulation rather than resetting it, avoiding erroneous conclusions from missing data. The confidence metric is computed as accumulated days divided by threshold, clamped to the range zero to one, providing a continuous measure of excavation certainty.

The system maintains three pixel classifications: candidate pixels currently appearing excavated but not yet confirmed, confirmed pixels that have accumulated sufficient days to pass the confidence threshold, and retroconfirmed pixels which are confirmed pixels backdated to their first detection. Retroactive confirmation reduces the latency involved in the confirmation process by taking into consideration the fact that a pixel, after being confirmed as excavated, has been excavated since the time of its initial detection. The system will then note the time of first detection and use retroactive excavation labels from that time onwards after confirmation.

3.6 Post-processing and Vectorization

Binary excavation masks undergo morphological cleaning before analysis. Opening operations implemented as focal minimum followed by focal maximum with one-pixel radius remove isolated false positive pixels. Closing operations implemented as focal maximum followed by focal minimum fill small holes within excavated regions creating coherent polygonal structures. These operations are performed within Earth Engine during monitoring stage one for computational efficiency.

Vectorization converts cleaned binary excavation masks into polygon geometries using the `shapes()` function from the `rasterio` library, which traces contiguous excavated regions. The resulting geometries are stored in a GeoDataFrame with a valid coordinate reference system. Excavation area is computed directly from the raster representation rather than polygon geometry. Pixel dimensions are derived from the raster affine transform, and total area is obtained by multiplying the number of excavated pixels by the corresponding pixel area. This approach ensures consistent and accurate area estimation independent of polygon complexity or projection choice.

For regulatory analysis, no-go zone polygons are rasterized using the same affine transform and spatial resolution as the excavation masks, ensuring perfect pixel-level alignment for intersection and alert generation.

4 Implementation Details

4.1 Technology Stack and Tools

Cloud processing leverages Google Earth Engine Python API for distributed Sentinel-2 data access and processing using the Sentinel-2 SR Harmonized Collection. Local processing employs Python 3.x with scikit-learn providing K-Means clustering and RobustScaler implementations, NumPy and Pandas for numerical operations and data manipulation, Rasterio for geospatial raster input/output and transform operations, GeoPandas for vector geometry operations and spatial joins, and Matplotlib for comprehensive visualization and plot generation.

4.2 Computational Optimizations

Earth Engine integration provides significant computational advantages by implementing scaler and K-Means inference directly within the Earth Engine environment avoiding expensive data downloads, utilizing the toBands method to efficiently export multi-temporal data as multi-band images reducing file counts, and performing focal operations for morphological processing at scale leveraging distributed computing. Data handling optimizations include multi-file support for large temporal datasets exceeding export limits, smart band stacking for overlapping tiles that maximizes information while minimizing assumptions, and memory-efficient streaming for raster operations avoiding full array loading.

4.3 Pipeline Functions

The training pipeline begins with trainingStart which filters Sentinel-2 data by mine boundaries and time range, applies cloud masking, performs comprehensive feature engineering, and exports pixel-level features to CSV via Earth Engine. The trainingComplete function loads exported features, applies RobustScaler with numerical stabilization, performs K-Means clustering with K equals six, executes metaclustering and pruning, and persists models and metadata using joblib and JSON.

The monitoring pipeline begins with monitoringStart which loads trained scaler and K-Means models, implements scaling and clustering within Earth Engine for efficiency, applies morphological post-processing, and exports multi-temporal binary masks as GeoTIFF files. The monitoringComplete function loads and merges multi-file exports, implements the confidence system with retroactive confirmation, generates comprehensive outputs including spatial maps and temporal plots, performs no-go zone violation detection, and produces multi-level alert logs.

5 Outputs and Deliverables

5.1 Temporal Analytics

The system generates comprehensive time-series visualizations providing regulatory insights. Retroconfirmed excavated area plots show cumulative excavation within legal mine boundaries from 2018 to 2025 with yearly major ticks and six-month minor ticks for temporal resolution. Candidate excavated area plots display early excavation signals before confirmation useful for understanding detection sensitivity and seasonal noise levels. Excavation growth rate plots show daily area change in square meters per day with zero baseline highlighting periods of active versus dormant excavation. Comparison plots overlay candidate and retroconfirmed areas on the same axes illustrating the relationship between early detection and final confirmation. Normalized excavation plots display excavation as a fraction of total mine area enabling intensity comparison across mines of different sizes.

5.2 Spatial Visualizations

Spatial maps provide georeferenced visual context for excavation patterns. RGB Sentinel-2 composites show natural color imagery with excavation polygon overlays in cyan for clear visual identification. Legal mine boundaries appear in black while no-go zones appear in yellow dashed lines establishing regulatory context. Confidence heatmaps display per-pixel confidence values from zero to one using red-yellow-green colormaps where red indicates low confidence, yellow moderate confidence, and green high confidence. First detection date maps show when each pixel was first identified as excavated using viridis colormap scaled in days since monitoring start, revealing spatial progression patterns.

Temporal coverage includes maps at 0, 25, 50, 75, and 100 percentiles of the monitoring period providing representative snapshots. An excavation progress panel displays twelve subplots at 10 percent intervals from 0 to 100 percent showing complete temporal evolution on a single figure useful for presentations and reports.

5.3 Alert System for No-Go Zones

The three-level alert structure provides graduated warnings for regulatory action. Level 1 candidate intrusion alerts trigger when candidate pixels first appear inside no-go zones providing early warning of suspected excavation with affected area in square meters. Level 2 confirmed violation alerts trigger when pixels inside no-go zones reach confirmation threshold indicating sustained excavation activity with affected area quantification. Level 3 violation expansion alerts trigger when confirmed excavation area inside no-go zones increases by more than the expansion threshold indicating ongoing violation growth with newly added area reported.

All alerts are timestamped and logged to persistent files with structured format including date, mine identifier, alert level, violation type, and affected area. No-go zone temporal plots show candidate and confirmed excavation areas within no-go zones over time enabling trend analysis. Debug visualizations at six temporal snapshots show raw cluster assignments overlaid on RGB imagery for validation and quality assurance.

6 Results and Validation

6.1 Adaptive Learning Performance

The system demonstrates successful adaptation across diverse mine types without requiring mine-specific parameter tuning. Open-cast coal mines with dark surfaces and high moisture content are correctly identified through low NDVI, moderate SWIR, and high NDMI variance. Limestone quarries with bright reflective surfaces are detected through very high B12 values and high BSI. Bauxite mines with reddish-brown oxidized materials are identified through moderate SWIR and specific BSI patterns. Sand mining operations with light granular surfaces are detected through high B11 and B12 values with low NDMI.

6.2 Temporal Consistency and Robustness

The confidence system effectively filters seasonal variations as demonstrated by candidate area plots showing higher variability during monsoon and winter seasons while retroconfirmed area plots show smooth monotonic growth indicating successful filtering of temporary changes. The 60-day threshold proves sufficient to distinguish permanent excavation from seasonal vegetation cycles, agricultural activities, and weather-related spectral variations. The retroactive confirmation mechanism eliminates the systematic 60-day lag in excavation dating providing accurate onset times for regulatory compliance assessment.

6.3 False Positive Control

The cluster pruning system significantly reduces false positives as evidenced by the removal of water body clusters exhibiting very low NDVI and extremely negative SWIR values, vegetation clusters with high NDVI median above 0.5, and weak dust signatures from seasonal wind patterns with low excavation scores. The morphological post-processing removes isolated pixel noise and fills small data gaps creating clean coherent polygons suitable for area calculation and regulatory reporting.

6.4 Scalability Demonstration

The scanForActivity function demonstrates batch processing capabilities by applying a reference mine's trained model to multiple target mines, computing excavation areas for 2022 and 2024, calculating growth metrics in both absolute area and percentage terms, and classifying mines as active or inactive based on growth thresholds. This functionality enables rapid assessment of large mine inventories for regulatory prioritization.

7 Technical Innovations

7.1 Mine-Specific Signature Learning

Unlike static threshold approaches that fail across diverse mine types, AURORA 2.0 learns excavation signatures directly from each mine's historical data. This adaptation occurs automatically through the clustering process which identifies the specific spectral-temporal patterns associated with excavation for that particular mine type, geological composition, surrounding land cover, and operational practice. The system requires no manual threshold tuning or expert knowledge encoding making it truly adaptive and scalable.

7.2 Hybrid Temporal-Spectral Features

The combination of instantaneous spectral indices with rolling statistics and temporal slopes enables robust differentiation between excavation characterized by permanent change with low temporal variance and persistent negative trends in NBR, and seasonal changes characterized by temporary fluctuations with high temporal variance and cyclical rather than monotonic patterns. This hybrid approach leverages both the what of spectral state and the how of temporal behavior to achieve high accuracy.

7.3 Metaclustering Strategy

The two-stage clustering approach provides flexibility to capture multiple excavation types within a single mine such as active digging areas versus older exposed surfaces while maintaining unified excavation identification across diverse pixel clusters. The SWIR floor preprocessing prevents water and shadow interference enabling the metaclustering to focus on excavation-relevant spectral variations. The pruning system adds robustness by removing obvious misclassifications through both absolute and relative thresholds.

7.4 Confidence-Based Temporal Validation

The temporal validation system with retroactive confirmation provides multiple advantages including elimination of confirmation latency bias through backdating, accurate excavation onset dates for compliance assessment, quantified detection uncertainty through continuous confidence metric, and distinction between early candidate signals useful for monitoring and final confirmed excavation suitable for regulatory action. The handling of masked pixels through pausing rather than resetting prevents erroneous conclusions from data gaps.

8 Research and Background

8.1 Sentinel-2 Multispectral Data

Sentinel-2's twin satellites (2A and 2B) provide 5-day revisit multispectral imagery through ESA's Copernicus program. We used Level-2A atmospherically corrected surface reflectance data, leveraging 10m visible/NIR bands (B2, B3, B4, B8) and 20m SWIR bands (B11, B12) for mining detection. The Scene Classification Layer (SCL) enabled effective cloud masking by filtering values 3, 8, 9, 10, and 11, ensuring temporal consistency.

8.2 Spectral Indices for Mining Detection

Literature review guided index selection:

- **NDVI** [(NIR - Red)/(NIR + Red)]: Detects vegetation loss from mining

- **SWIR bands** (B11, B12): Respond to exposed rock and bare soil, with B12 excelling at differentiating excavated surfaces
- **BSI** [((SWIR + Red) - (NIR + Blue))/((SWIR + Red) + (NIR + Blue))]: Identifies exposed soil
- **NBR**: Surface disturbances create spectral patterns similar to burned areas
- **NDMI** [(NIR - SWIR1)/(NIR + SWIR1)]: Captures vegetation water content and soil moisture changes

8.3 Google Earth Engine Platform

GEE's cloud-based architecture enables petabyte-scale analysis without local downloads. Key advantages include continuous Sentinel-2 archive access, distributed computing for multi-year time series, and built-in geospatial functions. We used Python API for machine learning integration, implementing critical functions like `linearFit()` for temporal slopes and `Reducer.median()` for statistics. A technical challenge was replicating scikit-learn K-Means within GEE using native band math and centroid distance calculations.

8.4 Unsupervised Learning Approach

Supervised methods require expensive labeled training data across diverse mine types. K-Means clustering groups spectrally similar pixels without labels. Our novel **metaclustering** approach first clusters pixels into groups capturing spectral diversity, then clusters these centroids into excavation versus non-excavation categories. Temporal statistics (variance, slopes) distinguish permanent changes from seasonal fluctuations, informed by agricultural monitoring research.

8.5 Addressing Existing Gaps

Current mining monitoring relies on supervised classification with extensive training data, hard-coded thresholds failing across mine types, or labor-intensive manual interpretation. Recent ML approaches lack continuous temporal monitoring and require mine-specific training. **AURORA 2.0** addresses these gaps through unsupervised clustering learning from each mine's historical data, spatiotemporal features capturing spectral and temporal behavior, and confidence-based validation distinguishing permanent excavation from temporary changes.

9 Conclusion

AURORA 2.0 successfully addresses the challenge of adaptive mining activity monitoring through a data-driven, unsupervised learning approach. The system demonstrates adaptability by learning mine-specific signatures without manual tuning, robustness in distinguishing excavation from seasonal variations through temporal validation, scalability to diverse mine types and new sites without reconfiguration, and actionability through comprehensive temporal analytics and violation alerts.

The impact potential for regulatory agencies is significant as the system provides an automated, reliable tool for continuous mining compliance monitoring. By eliminating the need for mine-specific configuration and hard-coded thresholds, AURORA 2.0 enables scalable deployment across large mine inventories. The distinction between candidate and confirmed excavation provides both early warning capability and high-confidence regulatory evidence.

Future work will focus on validation with ground truth data to establish quantitative accuracy metrics, integration into the VEDAS platform for operational deployment, and extension to multi-sensor fusion combining Sentinel-1 and Sentinel-2 for enhanced robustness. The adaptive learning paradigm demonstrated by AURORA 2.0 has broader applicability to other land cover change detection problems where spectral signatures vary across sites and temporal persistence distinguishes real change from noise.

Acknowledgments

We thank VEDAS at SAC-ISRO for providing the problem statement and domain expertise, IIT Dharwad for hosting PARSEC 6.0, and the Copernicus program for open access to Sentinel-2 data.

A Feature Formulas

The spectral indices are computed using the following formulas:

$$\mathrm{NDVI} = \frac{B8 - B4}{B8 + B4} \tag{2}$$

$$\mathrm{NBR} = \frac{B8 - B12}{B8 + B12} \tag{3}$$

$$\mathrm{BSI} = \frac{(B11 + B4) - (B8 + B2)}{(B11 + B4) + (B8 + B2)} \tag{4}$$

$$\mathrm{NDMI} = \frac{B8 - B11}{B8 + B11} \tag{5}$$

$$\text{Excavation Score} = 2 \times B12_{\text{median}} + BSI_{\text{median}} - 0.5 \times NDVI_{\text{median}} - NDMI_{\text{median}} \tag{6}$$

B System Parameters

Parameter	Value	Rationale
K (Primary Clustering)	6	Balances granularity and fragmentation
Rolling Window	60 days	Filters seasonal cycles
Confidence Threshold	60 days	Ensures persistence validation
NBR Slope Clamp	± 0.1	Prevents contamination effects
Scale Floor (variance)	0.5	Numerical stability
Scale Floor (NBR slope)	0.05	Numerical stability
Pruning Threshold	0.6	Relative to primary mine score

Table 1: Key system parameters and their rationale