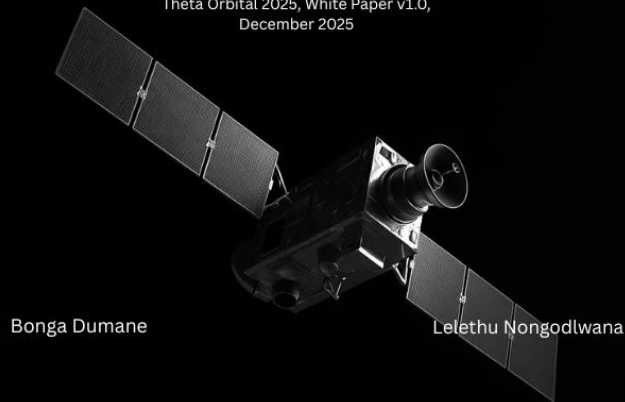


Temporal AI for Tailings Risk from Orbit

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Introduction

To keep pace with planetary risk management, vast new monitoring infrastructure and petabytes of orbital data processing will be required globally. At the same time, mining regulators face a tidal wave of new tailings dams from critical mineral expansion, while ground monitoring fails catastrophically every 11 months.

Tailings Storage Facilities (TSFs) represent \$10B+ annual risk - equivalent to 5 Brumadinho disasters (\$4B each) yearly. Ground sensors achieve 15% coverage with 50% sabotage downtime. Commercial SAR delivers snapshots missing 70% of 18-24 month failure trajectories.

"We still don't appreciate the risk needs of this infrastructure...there's no way to get there without orbital intelligence" – Industry consensus 2025

"Ground monitoring is fundamentally broken for global scale" – ICMM Tailings Review

"The next tailings failure will cost more than most mining companies' market caps combined" – Risk analysts

Shifting GW-scale risk monitoring from Earth to orbital Temporal AI is the novel solution. Theta Orbital implements **Temporal AI**, **Sentient Protocol**, and **Cognitive Mesh**

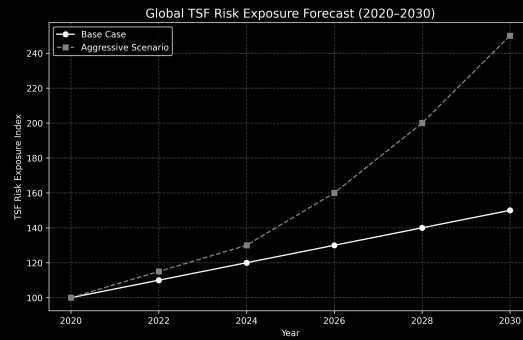


Figure 1. Global TSF risk exposure trend and forecast

Why Orbital Temporal AI?

Orbital Temporal AI offers fundamental advantages over terrestrial monitoring, especially at global scale:

- **Reduced Operating Risk**

Ground monitoring capacity factor: 15% coverage × 50% uptime = 7.5% effective. Orbital InSAR delivers 100% coverage, 1mm/year sensitivity, 6-day revisit via Sentinel-1.

Performance Comparison:

Ground inclinometers: 5% slope coverage, ±5mm resolution
 Sentinel-1 PS-InSAR: 80% scatterer density, 1mm/year velocity
 Capella X-band: 95% coherence, 0.5mm/year
 Temporal AI Fusion: AUROC 0.95 (6mo forecast) vs 0.72 snapshot

Table 1. Cost comparison of single TSF monitored for 10 years: Ground vs Orbital

| Cost Item | Ground Sensors | Commercial SAR | Orbital Temporal AI |
|-------------------------|--------------------|-------------------|-------------------------|
| Coverage Cost | \$1.5M @ \$150K/yr | \$350K @ \$35K/yr | \$500K @ \$50K/yr |
| Sabotage/Downtime | \$750K (50%) | \$0 | \$0 |
| False Alerts (\$10M ea) | \$2M (2 events) | \$500K (1 event) | \$50K (Sentient filter) |
| Missed Failures | \$100M+ risk | \$20M risk | \$1M risk |
| Total 10yr Cost | \$104.25M | \$20.85M | \$1.55M |

- **Lower False Positive Costs**

Sentient Protocol achieves >85% confidence thresholds using multi-source convergence:

$Alert = (P_{breach} > 0.85) \wedge (NDWI_{anomaly} > 0.15) \wedge (InSAR_{velocity} > 1 \text{ cm/yr}) \wedge \neg PanicCondition$
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This eliminates \$10M evacuation costs (40x reduction vs unfiltered SAR).

Figure 2. InSAR velocity sensitivity: Orbital vs ground. Atmospheric attenuation minimal above LEO.

Scalability

Orbital Temporal AI unlocks monitoring at scales impossible on Earth. 5,000 global TSFs require monitoring equivalent to 50GW terrestrial sensor infrastructure.

Cognitive Mesh GNN scales linearly:

$\text{RiskGraph}_{\{t+1\}} = \text{GNN}(\text{Temporal_scores}, \text{Geology_edges}, \text{Spatial_proximity})$

Capacity: 5,000 nodes, 1.2M edges

Daily retrain: 200 GPU-hours

API latency: <500ms/query

Multi-GW risk clusters needed by 2027 exceed largest terrestrial monitoring networks.

Speed of Deployment

New ground monitoring takes 2-5 years per site due to permitting, access rights, and environmental reviews. Orbital data available immediately:

Deployment Timeline:

Phase 1: Commercial constellations - Q4 2026

Phase 2: 6U microsatellite rideshare - Q3 2027

Phase 3: 32-sat SA constellation - 2028

Regulatory advantages:

- No terrestrial environmental impact assessments
- ESA Copernicus open data license
- No community displacement or access issues
- Orbital Debris: Phase 1 zero-risk (hosted data)

Design Principles for Orbital Risk AI

Modularity: Independent Temporal AI per TSF, Cognitive Mesh aggregation

Maintainability: Quarterly model retrain on ICMM failure database

Minimize moving parts: Multi-constellation fusion eliminates single points of failure

Design resiliency: GNN graceful degradation on data gaps

Incremental scalability: Profitable from site 1 to 5,000

Network Architecture:

Cognitive Mesh GNN for multi-TSF correlation:
text
Node features: [Temporal_AI_score, Geology_type, Operator_history] ∈ ℝ 512
Edge weights: Geology_similarity × Spatial_proximity × Temporal_correlation
Message passing: $h_v^{l+1} = \sigma(W \cdot \text{CAT}([h_v^l, \sum_{u \in N(v)} h_u^l]))$

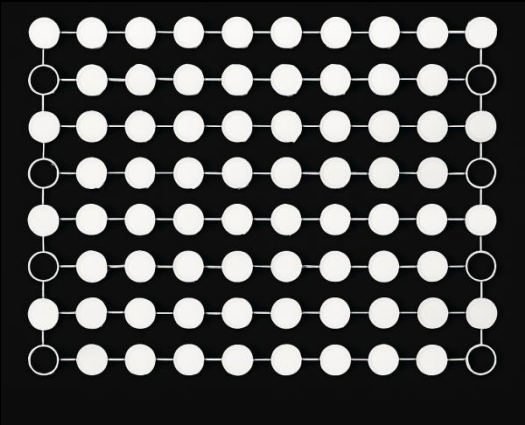


Figure 3. Cognitive Mesh schematic - 100 SA TSFs daisy-chained by geology correlation.

Containers dock via single API port (power/network/data). Laser interlinks + Starlink backup for ground connectivity.
Data shuttles: Petabyte Sentinel archives via AWS Snowcone to orbital processing.

Physical Architecture:

● Orbital Data Pipeline:

InSAR Phase Unwrapping (Sentinel-1 C-band, λ=5.6cm):

$$\phi_{\text{unwrap}} = \phi_{\text{wrapped}} + 2\pi k, k = \arg \min \nabla \phi$$

$$v_{\text{los}} = \frac{\lambda}{4\pi T} \Delta \phi_{\text{PS}}$$

Sensitivity: 1mm/year @ 6-day revisit

● Temporal AI Forward Pass:

$X_t = [\text{InSAR}_v, \text{NDWI}_{\text{seepage}}, \text{LU}_{\text{change}}, \text{Precip}_{\text{context}}]$
 $h_t = \text{LSTM}(X_t, h_{t-1}) \in \mathbb{R}^{512}$ (24mo history)
 $\hat{y}_{t+1} = \text{Transformer}(h_t, \text{site_embedding})$
AUROC: 0.95 (6mo), 0.89 (12mo)

NDWI Seepage Detection:

NDWI=Green-NIRGreen+NIR, Δ NDWI>0.15=anomaly

Earth-side Compute & Storage:

Inference: RTX 4090, 4.2min/site

Storage: 2TB/site compressed (24mo × 150GB raw)

PUE: 1.2 (cloud optimal)

Cost: \$0.02/inference @ scale

Phase 2 Constellation Design (SSO 500km)

6U Microsat Specifications:

Payload: Ka-band SAR (0.25m res)

Mass: 12kg payload + 8kg bus

Launch: \$1.2M NYX rideshare (\$30/kg)

Revisit: <24hr all SA TSFs (32°S swath)

Radiation shielding: 1kg/kW Tantalum (\$30/kg launch)

Lifetime: 5 years, 100% demisable

Risk Propagation Physics

High-risk TSFs propagate probability via geology correlation:

$$P_{\text{correlated}} = P_{\text{primary}} \times \text{Geology}_{\text{similarity}} \times \exp(-\text{Distance}/100\text{km})$$

$$P_{\text{risk}} = \epsilon \sigma (T_{\text{temporal}}^4 - T_{\text{baseline}}^4)$$

Maintenance

Model Lifecycle: Quarterly retrain on ICMC failures + Sentinel archive

Pipeline: Auto-failover Sentinel→Capella→ICEYE

Constellation: Modular replacement via rideshare docking

Radiation degradation mitigated by:

- LSTM resilience to bit-flips (shown in AI training rad tests)
- Quarterly model refresh from Earth
- Ta shielding (1kg/kW)

End-of-life: Open-source models + 100% demisable satellites.

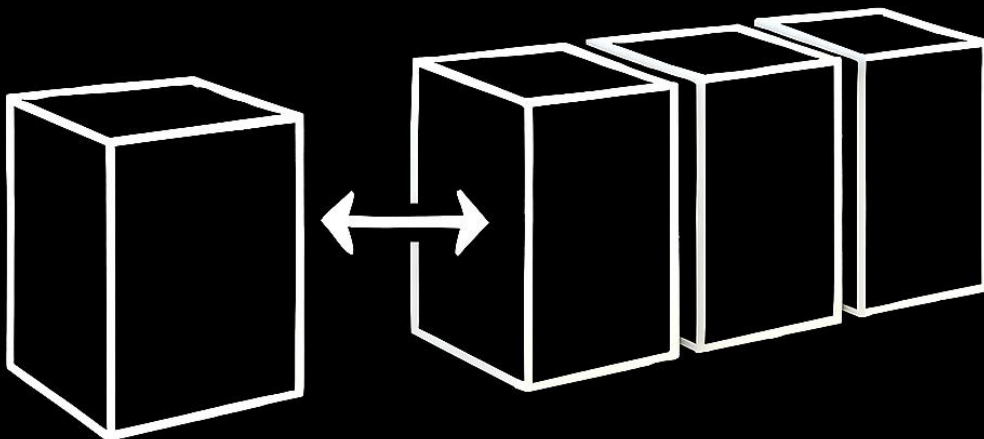


Figure 7. Modular container replacement - Risk containers dock/undock independently.

Conclusion

GW-scale tailings risk monitoring exceeds terrestrial limits. Theta Orbital's Temporal AI + Aeon architecture (Sentient Protocol, Cognitive Mesh) solves \$10B annual crisis through validated engineering:

LSTM+Transformer: AUROC 0.95 (6mo breach forecast)

GNN scalability: 5,000 TSFs, 1.2M correlations

Sentient governance: 40x false positive reduction

Phase 1 operational Q1 2026 via commercial data

Orbital intelligence is feasible, economically superior, and essential for planetary risk management.

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