AI-DRIVEN EARTH OBSERVATION FOR MONITORING ARCHAEOLOGICAL LOOTING: ADVANCES, OPPORTUNITIES, AND FUTURE DIRECTIONS

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ABSTRACT

Illicit excavations of archaeological sites constitute a major threat to cultural heritage, causing irreversible damage and information loss, an issue persisted for several years. However, at the beginning of the 21st century, advances in satellite Earth Observation (EO) and Artificial Intelligence (AI) are transforming how such activities can be detected, monitored, and understood. High-revisit optical constellations (e.g., PlanetScope, Sentinel-2) and synthetic aperture radar (SAR) missions (e.g., Sentinel-1) now provide dense, multi-temporal data for near-continuous surveillance. In parallel, AI-based methods - including deep change detection, temporal modeling, and multimodal fusion - enhance sensitivity to small, transient signals and enable scalable, reproducible monitoring. This paper synthesizes emerging approaches that integrate EO driven by AI for identifying and analyzing archaeological looting, discusses their technical implications, and highlights future directions for operational, transparent, and globally accessible heritage monitoring systems.

Index Terms- looting, illicit trafficking, remote sensing archaeology, cultural heritage, ANCHISE project

1. INTRODUCTION

Archaeological looting is a persistent and widely distributed form of cultural-heritage degradation. As [1] indicate “these antiquities are sold without provenance, so that their true nature is hard to discern”. Such actions often occur in remote or politically unstable regions, where field inspection is difficult or impossible. Satellite Earth Observation (EO) has therefore become a critical tool and method for understanding, documenting, and tracking the evolution of looted landscapes. Early work using very-high-resolution (VHR) imagery demonstrated that pit morphology, shadow geometry, and spectral signatures of freshly disturbed soil can be quantified over large areas [2-3]. The availability of historical archives further enabled reconstructions of how looting intensity varies with economic incentives, conflict, and accessibility [4].

During the last decade, the EO landscape has shifted decisively from occasional VHR snapshots to dense multi-sensor time-series monitoring [5]. PlanetScope provides daily 3–5m observations capable of capturing short-lived excavation episodes; Sentinel-2 delivers multispectral information, including red-edge and SWIR bands, that help separate anthropogenic disturbance from vegetation and moisture variability; Landsat-8/9 provides long-baseline continuity for contextual trend analysis. In parallel, C-band SAR from Sentinel-1 introduces cloud-independent measurements of roughness and micro-topography, ensuring observability during adverse weather conditions. Together, optical and SAR sensors form a complementary system for continuous monitoring of threatened archaeological landscapes.

At the preprocessing and further analytical levels, the field has undergone a rapid transformation driven by machine learning and AI [6]. Traditional photointerpretation is increasingly supplemented -or replaced - by deep learning models capable of learning spatial-temporal patterns associated with looting activity [7]. These innovations, coupled with cloud-native processing architectures, enable scalable, low-latency, and fully reproducible workflows for mapping cultural-heritage threats, leveraging high-bandwidth networks for real-time big complex data ingestion, processing, and dissemination.

2. THE ANCHISE PROJECT

The EU ANCHISE (GA 101094824) project (https://www.anchise.eu) is a Horizon Europe initiative focused on combating illicit trafficking of cultural goods through advanced digital technologies, interdisciplinary research, and strengthened cooperation between law enforcement agencies, heritage professionals, and researchers. Its mission is to enhance Europe's capacity to identify, monitor, and protect cultural heritage by integrating innovative technological tools with operational expertise from police, customs, and cultural institutions.

Central to the project's Earth Observation activities, ICONEM develops 3D digitisation and satellite imagery approaches for monitoring, detection and documentation of illicit activities at archaeological sites. By combining Very High-Resolution (VHR), high temporal resolution, multispectral and hyperspectral satellite imagery with photogrammetric and LiDAR technologies, these methods enable the detection of surface disturbances and changes indicative of looting activities. The resulting analytical visualization platform integrates archival documents, satellite imagery, successive 3D scans, and associated documentation, supporting trace detection and comparative analysis over time, as well as recording and inventorying tools ensuring consistent workflows. This multi-scale approach—from broad landscape monitoring to detailed site-level assessment—provides heritage authorities with actionable intelligence for prioritizing protective interventions.

Complementing these monitoring capabilities, ANCHISE develops a toolkit addressing other stages of heritage protection: AI-powered image recognition for identifying stolen or looted artefacts (ARTE-FACT, PARCS), online marketplace monitoring (KIKu-Mon, Fraunhofer), semantic analysis and data visualization (ART-CH, ICCS), interoperability frameworks for cultural object descriptions (Guardian-CH, Cyprus Institute), and fluorescence spectroscopy for document authentication (INOV). The project also conducts social sciences research on practices such as metal detecting and the economic contexts driving heritage crime, and emphasizes awareness raising through international symposia, webinars, and policy forums.

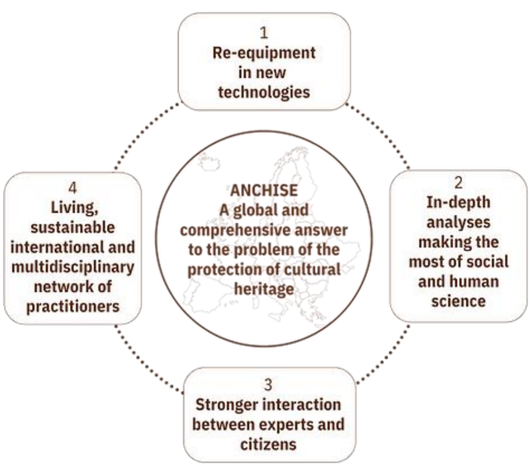

Figure 1. *ANCHISE overall methodology*

Looking ahead, the ANCHISE consortium advocates greater integration between Earth Observation and object identification technologies. At the EUSPA 2025 conference in Prague (December 2025), project representatives highlighted the complementarity between ICONEM's site monitoring capabilities and ARTE-FACT's image recognition system, arguing that the technological building blocks—EO, GNSS, image detection, web crawling—are now mature enough to be combined into a multimodal platform capable of providing daily alerts to law enforcement agencies. In this vision, EO-derived site monitoring would feed spatial risk indicators and activity alerts, while object-recognition systems would support downstream identification and tracking of artefacts circulating on digital platforms. Achieving this vision would benefit from a permanent institutional body serving as a bridge between ESA, EUSPA and the European Union on matters related to illicit trafficking of cultural goods. The overall methodology of the project is depicted in Figure 1.

3. EARTH OBSERVATION FOR LOOTING DETECTION

EO-based looting detection historically relied on photointerpretation of VHR optical imagery such as QuickBird, GeoEye, or WorldView (e.g. [8]). Analysts identified excavation pits through their circular geometry, high contrast, and texture (Figure 2). While effective, this approach is considered as labor-intensive and sensitive to interpreter variability.

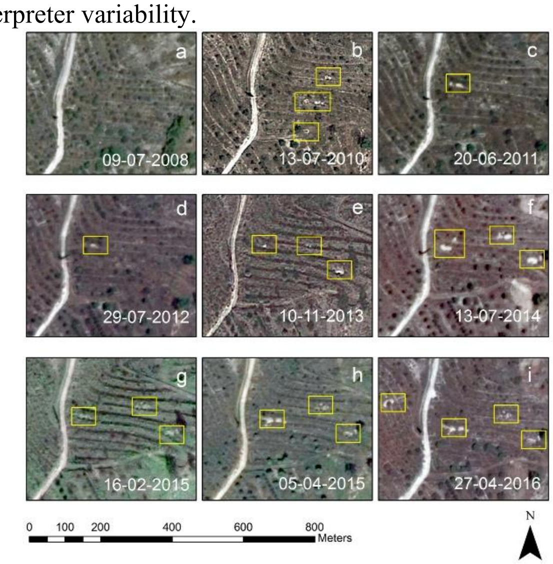

Figure 2. *RGB Google Earth© images over the area of interest between the years 2008 and 2016 as follows **(a)** 9 July 2008, **(b)** 13 July 2010, **(c)** 20 June 2011, **(d)** 29 July 2012, **(e)** 10 November 2013, **(f)** 13 July 2014, **(g)** 16 February 2015, **(h)** 5 April 2015, and **(i)** 27 of April 2016. Looted tombs are indicated by the yellow squares [4].*

With the use of medium-resolution missions, multi-temporal detection has become more feasible. PlanetScope's daily and Landsat systematic acquisitions capture changes in looted clusters (e.g. Figure 3). Sentinel-2 provides multispectral data that improve soil-vegetation discrimination, enabling analysts to filter seasonal or agricultural disturbances that resemble looting scars. The red-edge and SWIR bands are particularly useful for identifying freshly exposed soil and compacted spoil.

Changes in the backscatter signal using Sentinel-1's synthetic aperture radar (SAR) can indicate soil disturbance, compaction, or sediment displacement. High-resolution spotlight SAR (e.g., TerraSAR-X) has demonstrated the ability to quantify monthly excavation rates in conflict zones through coherence loss and roughness changes [10]. When combined, optical and SAR datasets provide a multi-dimensional perspective on looting signatures, improving reliability in complex terrain.

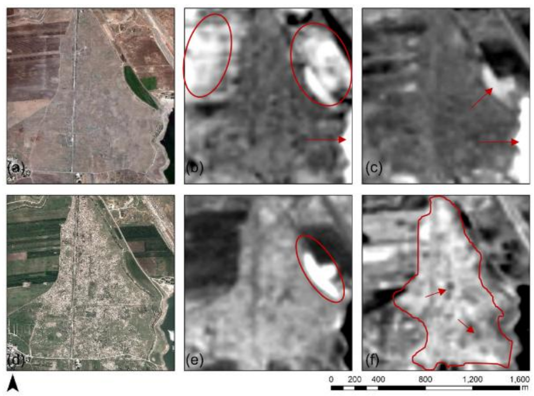

Figure 3. *High-resolution image from Google Earth of the area of Apamea before (a) and after the looting event (d). (b) first principal component – PC1; (c) second principal component – PC2; (e) third principal component – PC3 and (f) fourth principal component – PC4 using Landsat imageries [9].*

4. ARTIFICAL INTELLIGENCE ERA

Recent advances in AI have fundamentally reshaped how EO data can be used to detect and monitor archaeological looting. Deep-learning methods can address existing limitations by learning robust, context-aware representations of surface disturbance across multi-temporal satellite archives. In particular, temporal convolutional networks and recurrent architectures have demonstrated strong performance in capturing the temporal signatures associated with excavation sequences and suppressing background variability linked to phenology or climate-driven soil changes 11]. More recently, transformer-based architectures have emerged as highly effective models for multi-temporal EO analysis, owing to their self-attention mechanisms that can learn long-range temporal dependencies and integrate heterogeneous sensor inputs [12].

These models are especially advantageous for looting detection because excavation activity is often sporadic, subtle, and embedded within noisy environmental signals that evolve over time. In parallel, multimodal fusion strategies - combining optical and SAR data at either the feature level or the decision level -have proven crucial for increasing robustness, as SAR contributes structural and roughness-related information while optical data capture spectral and photometric cues linked to freshly disturbed soils. By integrating both modalities (see [13]), AI models can better distinguish real excavation features from other thematic classes.

A further challenge in the cultural-heritage domain is the scarcity of labeled training data, since providing ground truth for looted sites raises practical, ethical, and security concerns [14]. To address this constraint, pretrained models can then be fine-tuned on small, carefully curated training sets, significantly improving performance in rare-event detection tasks such as illicit excavation (see for instance [7]).

Beyond accuracy, recent work has emphasized the need for trustworthy AI outputs [14]. Equally important are interpretability tools, including saliency maps, attention rollouts, and attribution methods, which provide insight into which temporal or spatial features the model relies on when identifying potential looting activity. These tools are vital for responsible stakeholders where false positives may lead to unnecessary resources and false negatives may leave vulnerable sites unprotected. Taken together, modern AI approaches offer a path toward scalable, interpretable, and operational monitoring systems, enabling proactive detection of illicit excavations across large territories while providing transparent, auditable outputs suitable for expert review.

5. EMERGING OPPORTUNITIES

The next generation of EO sensors is expected to significantly expand the capabilities of AI-driven looting detection, both by improving the spectral and spatial richness of observations and by increasing the temporal density at which excavation activity can be monitored.

Spaceborne imaging spectrometers such as EnMAP (https://www.enmap.org) and PRISMA (http://www.prisma-i.it/index.php/en/) introduce hundreds of narrow spectral bands that offer fundamentally new opportunities for identifying subtle material changes associated with soil disturbance. In parallel, emerging radar missions promise improved revisit frequency, increased polarization diversity, and enhanced coherence stability. Systems such as NISAR (NASA–ISRO) (https://science.nasa.gov/mission/nisar/) and the proposed ROSE-L mission (www.eoportal.org/satellite-missions/rose-l) are expected to generate higher-resolution C- and L-band observations, enabling detection of micro-topographic changes and disturbance morphology under more diverse environmental conditions, particularly in regions with persistent cloud cover. Commercial VHR constellations are also evolving rapidly, with sub-50-cm sensors providing increasingly detailed mappings of pit geometry features that serve as strong visual indicators of organized excavation activity.

These sensor innovations align closely with advances in AI, particularly the emergence of EO foundation models trained on multi-petabyte archives. Such models offer transferable, general-purpose representations capable of integrating heterogeneous data streams including multispectral, hyperspectral, SAR, and thermal imagery. Their ability to process irregular time series, attend to long-range temporal dependencies, and fuse disparate sensor modalities positions them to tackle the inherent variability of looting patterns across climates, seasons, and land-use regimes. Furthermore, next-generation AI workflows increasingly incorporate active learning, enabling models to request human feedback on ambiguous detections, and privacy-preserving training frameworks such as federated learning, which allow multiple institutions to contribute annotated examples without sharing sensitive coordinates [15]. Combined with cloud-native infrastructures and the rising availability of global analysis-ready data, these developments point toward a future in which looting detection is not only more accurate and timelier but also more scalable, secure, and ethically grounded. Together, emerging sensors and advanced AI models are redefining the operational horizon for heritage monitoring, transforming EO from a documentation tool into a proactive system capable of supporting early intervention and informed management decisions.

6. DISCUSSION

The integration of AI with increasingly diverse and temporally dense EO datasets is opening new possibilities for the systematic monitoring of archaeological looting, yet significant scientific, operational, and ethical challenges remain. Although modern deep-learning models can extract subtle spatial–temporal signatures of excavation, their performance is often constrained by the scarcity, imbalance, and regional specificity of labeled training data (see more in [14]). Many looted areas lack ground verification and publicly releasing annotations (labels), limiting the availability of open training samples. As a result, future research must prioritize responsible data-curation frameworks, including redacted or spatially generalized annotations, synthetic data if necessary, and labeling environments governed by controlled-access protocols. Another key challenge is the transferability of models across soil types, and cultural landscapes; models trained in semi-arid regions frequently degrade when applied to agricultural environments. Addressing this will require the wider adoption of foundation models, domain adaptation techniques, and cross-region benchmarking datasets that explicitly include several land-use types. Operational deployment also depends on building trustworthy and interpretable workflows, where model outputs are accompanied by calibrated uncertainty estimates, spatial confidence layers, and visual explanations that facilitate expert review and reduce false-alarm fatigue among heritage practitioners. As automated systems scale to national or continental monitoring programs, the emphasis must shift toward human–AI collaboration, in which analysts remain central to validating alerts, refining training sets, and guiding model retraining cycles.

Ethical stewardship will be equally important in shaping the next decade of development. Automated systems capable of detecting looting at high spatial and temporal resolution raise concerns about inadvertent disclosure of site locations, potential misuse of alerts, and inequalities in access to advanced EO–AI infrastructure. To ensure this, future monitoring frameworks should incorporate standards and policies, as well as governance mechanisms involving local heritage authorities. Simultaneously, capacity building must become an integral component of AI-enabled monitoring, ensuring that heritage institutions - particularly in regions most affected by illicit excavation- can access training, computation, and data resources necessary to adopt EO technologies sustainably. Looking forward, the convergence of hyperspectral imaging, next-generation SAR, and global foundation models has the potential to move looting detection from reactive documentation to proactive early warning, enabling rapid response, resource prioritization, and long-term monitoring of risk evolution. Achieving this vision will require coordinated international efforts, transparent methodological standards, and interdisciplinary collaboration between archaeologists, remote-sensing specialists, AI researchers, and policy makers. With these elements in place, AI-driven EO systems can become powerful, ethically grounded tools for safeguarding cultural heritage at scale. Indeed, the integration of AI with increasingly diverse and temporally dense Earth Observation (EO) datasets is opening new possibilities for the systematic, large-scale monitoring of archaeological looting. However, substantial scientific, operational, and ethical challenges persist, and addressing them forms a key component of the recent research activities of the MNHMOSYNE Research Center.

7. CONCLUSIONS

The combined evolution of EO on and AI is reshaping how archaeological looting can be detected, analyzed, and monitored at regional to global scales. Multimodal remote sensing datasets, including satellite imagery, optical, radar, and emerging hyperspectral missions, now provides the observational depth necessary to capture small, and spatially dispersed excavation activity. At the same time, modern AI methods are enabling more robust interpretation of these complex big data, multi-temporal datasets (satellite, low altitude, ground data) even under severe label scarcity and environmental variability. Together, these developments signal a transition from retrospective, imagery-based documentation toward proactive, scalable early-warning systems capable of supporting evidence-based cultural-heritage management (Figure 4).

Nevertheless, operational deployment must address ongoing challenges related to generalization across landscapes, uncertainty quantification, ethical management of sensitive site information, and equitable access to data and computational resources. Continued collaboration between the multidisciplinary users in this domain such as archaeologists, remote-sensing scientists, AI researchers, and policy makers will be essential to ensure that technological progress translates into meaningful, responsible, and sustainable protection of the world's archaeological heritage.

A global 3D atlas and geo-database of cultural-heritage sites and monuments could be established to support continuous monitoring and timely alerting of national authorities. Achieving this vision requires urgent pan-European cooperation to ensure interoperability and seamless exchange of information and data. Furthermore, a cloud-based online repository could document all relevant activities and maintain spatiotemporal records of ground degradation, structural modifications, and other changes, enabling authorities to track the evolution of each site over time. At the same time the training of the responsible authorities for the use of these technologies and their feedback is essential.

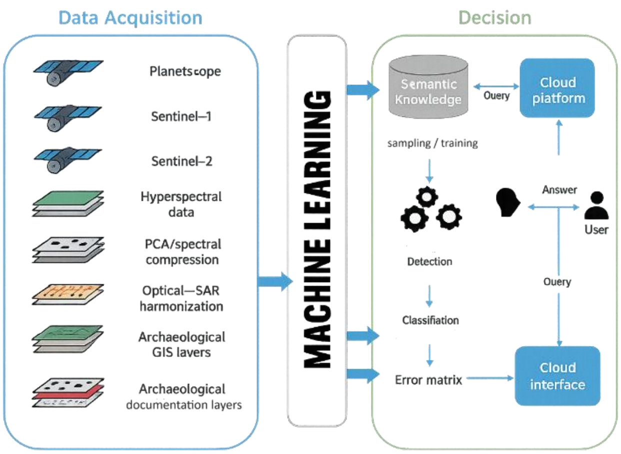

Figure 4. *AI and EO technologies synergies in the near future for monitoring archaeological sites and looted areas.*

8. AKNOWLEDGEMENTS

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