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From Data to Meaning: Reframing Mediterranean and Northern European Computational Archaeology in a Post-Algorithmic Age

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Abstract

While computational archaeology has seen widespread adoption across regional and methodological contexts, its epistemological core remains unevenly developed. This paper reconceptualizes the comparative study of Mediterranean and Northern European computational archaeology by integrating three underrepresented dimensions: (1) post-algorithmic critique in digital humanities, (2) ethical reflexivity in AI-driven archaeology, and (3) integration of temporal modeling and uncertainty quantification. Through the reassessment of models such as the Habitation Model Trend Calculation (MTC) and advanced neural network applications in Scandinavian submerged landscapes, we advocate a paradigm shift from technical performance to knowledge generation. Case studies are used to explore how computation serves not only archaeological prediction but also theory formation, historical contingency modeling, and ethical mapping of cultural heritage futures.

Keywords: Computational Technologies, Prediction Models, GIS in Archaeology, AR/VR in Archaeology

1. Introduction: Beyond Performance - Toward Archaeological Epistemogenesis

The integration of digital technologies into archaeology has fundamentally altered how the past is interpreted (Forte, 2014; Malaperdas, 2019; Malaperdas, 2021; Alarmi, 2024). However, regional disparities in methodological application remain stark (Malaperdas & Panoskaltsis, 2021). In the Mediterranean, computational archaeology often centers around culturally dense contexts requiring theory-rich models (Malaperdas and Zacharias, 2019; Malaperdas et al, 2022) while in Northern Europe, practices, emphasize environmental modeling and large-scale geospatial analyses (Giatsiatsiou, 2024; Bailey, 2020).

This divergence is not merely technical—it is epistemological. Digital archaeology in the Mediterranean is shaped by traditions of critical theory and interpretive spatial logic, exemplified in the development of the Habitation Model Trend Calculation (MTC), which draws upon Karl Popper’s ontology of “three worlds” (Popper, 1979). In contrast, Northern European archaeology often operates within frameworks of environmental reconstruction, relying on big data, LiDAR, bathymetric mapping, and

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increasingly, machine learning (Kristiansen, 2019; Ståhl & Weimann, 2022).

This section proposes that digital archaeology be understood as an epistemogenetic system—a culturally contingent way of constructing and validating knowledge—rather than a neutral set of tools. It reflects how each region's academic traditions, institutional dynamics, and historical trajectories condition how data is produced, processed, and interpreted.

2. Methodological Reorientation: From Accuracy to Meaningfulness

Models such as MTC have been celebrated for predictive accuracy, correctly identifying 137 out of 140 Mycenaean sites in Messenia (Malaperdas & Zacharias, 2020). However, the exclusive focus on accuracy risks overlooking the interpretive value of such models. MTC is exemplary not merely for its statistical success (98% accuracy), but because it embeds archaeological theory directly into its computational logic using methods like AHP and WLC and integrating variables like solar exposure, terrain index, and slope categories (Malaperdas et al, 2022).

Northern European systems like the SASMAP predictive framework or CNN-driven cartographic analysis are highly effective in data extraction and geospatial prediction, but often lack philosophical or cultural interpretability. This methodological asymmetry calls for a rebalancing (Bailey, 2020).

Instead of solely optimizing for prediction, computational archaeology should prioritize meaningfulness—understood as interpretive depth, transparency of assumptions, and theoretical richness. Tools must support questions of human decision-making, symbolic landscapes, and socio-political structures—not just environmental suitability (Malaperdas, 2019).

3. Theoretical Reframing: Introducing Chronocomputational Archaeology

We introduce the concept of chronocomputational archaeology—an approach that embeds temporality within spatial models, acknowledging the uncertainty and fluidity of past human behavior. Temporal fuzzy modeling, Bayesian chronologies, and event-based simulations offer promising alternatives to static probability maps. MTC could, for example, integrate diachronic population shifts using adaptive temporospatial kernels, expanding its scope from site prediction to human-landscape co-evolution.

In Northern Europe, underwater predictive systems might gain from the introduction of ensemble learning models trained on chronostratigraphic sequences, not just bathymetry and topography. This would allow AI not just to locate sites, but to model their emergence, transformation, and abandonment over millennia.

One of the most underdeveloped aspects of computational archaeology is the integration of time not as a static variable but as an active dimension. We propose chronocomputational archaeology: the fusion of spatial analysis with temporal modeling. This includes:

- Temporal fuzzy logic models
- Bayesian time-series analysis
- Agent-based diachronic simulations

For instance, the MTC model could be enhanced to accommodate temporal layers by integrating population shifts, settlement duration, or trade intensities over time. Similarly, Northern European predictive frameworks could adopt diachronic modeling of sea-level change, Mesolithic settlement mobility, and vegetation regression using multi-scalar machine learning.

Such an approach aligns with recent advances in time-aware neural networks and adaptive geospatial systems (Chen et al, 2023). It allows archaeologists to move beyond "where" and ask "when" and "how long"—adding historical contingency to spatial prediction.

3.1. Ethical Reflexivity and Algorithmic Transparency

As algorithmic mediation becomes central to heritage assessment and resource allocation, ethical considerations become critical. Who designs the models? Whose pasts do they prioritize? Tools like the MTC or neural classifiers for cartographic analysis must be accompanied by transparent documentation, open datasets, and participatory modeling with descendant communities. We propose an "Archaeological Algorithmic Ethics" (AAE) framework, building upon recent efforts in AI governance (Chen et al, 2023) and heritage justice (Smith, 2006).

As digital tools increasingly determine what is excavated, preserved, or funded, ethical reflexivity becomes urgent. Algorithmic decisions often go unchallenged in archaeological practice, masking biases in data collection, training sets, or cultural assumptions (Smith, 2006; Hugget, 2020).

We propose the framework of Archaeological Algorithmic Ethics (AAE), built upon four pillars:

- Transparency: Documenting assumptions, parameters, and training datasets.
- Participation: Engaging local and descendant communities in model co-design.
- Accountability: Tracking the socio-cultural consequences of predictions.
- Inclusivity: Modeling underrepresented groups, practices, and ecologies.

Without such considerations, tools like CNN classifiers or AI-based historical reconstructions risk reinforcing present-day exclusions. Conversely, when ethically designed, digital tools can become means of decolonizing archaeology, giving voice to communities previously marginalized in both analog and digital heritage (Forte, 2014; Reich, 2018).

3.2. Cross-Regional Reassessment: Toward a Post-Regional Model

While regional distinctions remain useful, a strict Mediterranean vs. Northern European dichotomy risks essentialism. We instead advocate for a post-regional lens based on shared methodological typologies:

Typology	Example (Mediterranean)	Example (Northern Europe)
Theory-Embedded Modeling	MTC (Malaperdas & Zacharias, 2019)	"Decentralized Complexity" (Kristiansen, 2014)
Sensor-Fusion GIS	Virtual Pompeii (Forte, 2015; Allentoft, et al, 2015)	SASMAP sonar-LiDAR integration (Bailey et al, 2020; Giatsiatsiou, 2024)
AI-Augmented Mapping	AR in Mycenaean sites (Malaperdas &	CNN cartographic classifiers (Ståhl &

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	Sarris, 2023)	Weimann, 2022)
Bio-Cultural Data Integration	aDNA + GIS in Messenia (Haak et al, 2015).	Steppe migration models (Allentoft et al, 2015).

4. Conclusions: Toward a Reflexive, Open, and Plural Digital Archaeology

This article has reconceptualized computational archaeology not as a toolset but as a mode of knowledge production (Sarris, 2024). The MTC model, AI-driven mapping, and geospatial network theory can only realize their full potential within interpretive and ethically grounded frameworks. The post-algorithmic age in archaeology will require interdisciplinary teams that combine historical depth, computational literacy, ethical clarity, and reflexive practice. The field must move beyond performance metrics and toward inclusive, accountable, and meaningful digital heritage science.

This comparative study has demonstrated that computational archaeology should no longer be perceived as a neutral technological tool, but rather as an active framework for the production of knowledge—an interpretive and analytical domain where science, theory, and ethics intersect.

Specifically, the study leads to four main conclusions:

1. Technological accuracy is insufficient without theoretical depth: The MTC model proves that statistical accuracy gains real meaning when it integrates philosophical concepts such as Karl Popper's triadic ontology. The inclusion of interpretive parameters and the rejection of environmental determinism allow archaeologists to shift from static spatial modeling to dynamic historical scenario-building.
2. Time must become a functional component in archaeological modeling: The proposed concept of chronocomputational archaeology offers a new way to align spatial data with historical timelines, demographic movements, and landscape transformations. Future applications could incorporate variables such as duration of occupation, seasonality, or environmental degradation rates to simulate long-term historical patterns.
3. Digital archaeology must be ethically transparent and socially accountable: The proposed Archaeological Algorithmic Ethics (AAE) framework introduces essential standards for how computational models are constructed, applied, and evaluated. The absence of ethical oversight in data and algorithm design risks reproducing exclusions in both digital environments and heritage interpretation (Smith, 2006; Huggett, 2020).
4. Comparative approaches must advance toward post-regional methodological innovation: The methodological typology presented in this article (e.g., theory-embedded modeling, sensor fusion, biocultural integration) offers a novel framework that avoids rigid geographic divisions. Instead, it promotes the transfer of tools and ideas across different contexts while respecting cultural specificity.

The next generation of computational archaeology must integrate:

1. Computational complexity (AI, machine learning, deep learning),
2. Philosophical awareness (critical theory, epistemology),
3. Ethical empathy (open data, transparency, reflexivity),
4. Interdisciplinary integration (genomics, topography, cultural narratives).

The success of digital archaeology will not depend on the speed or sophistication of its algorithms, but on its capacity to foster meaningful dialogue between disciplines, theoretical frameworks, and communities. Tools such as MTC or CNNs are no longer mere prediction mechanisms—they represent turning points in how we think about, represent, and debate the past.

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