ADVANCING ABM IN ARCHAEOLOGY: A PROBABILISTIC AND EXPLAINABLE FRAMEWORK FOR INCOMPLETE DATA

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РАЗВИТИЕ АГЕНТНОГО МОДЕЛИРОВАНИЯ В АРХЕОЛОГИИ: ВЕРОЯТНОСТНАЯ И ОБЪЯСНИМАЯ МОДЕЛЬ ДЛЯ НЕПОЛНЫХ ДАННЫХ

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Abstract – Archaeological Agent-Based Models (ABMs) are increasingly used to study interactions between human populations and changing environments. However, archaeological evidence is often incomplete, making it difficult to evaluate competing explanations and assess uncertainty. This study presents an integrated modeling framework designed to explore multiple plausible scenarios rather than reconstruct a single version of the past. The framework combines forward modeling, probabilistic inference, parameter-space exploration, multi-scale validation, and Explainable Agent-Based Modeling (EABM) within a unified analytical structure. Its main innovation is the explicit inclusion of formation and taphonomic processes in the simulation workflow, allowing preservation bias to be treated as part of archaeological inference rather than as an external source of error. Simulated outcomes are compared probabilistically with archaeological observations across multiple analytical scales to address uncertainty and equifinality. The framework also supports systematic exploration of alternative parameter configurations, enabling broader investigation of complex model behavior. By integrating human behavior, material formation processes, and empirical evaluation within a single framework, the approach shifts archaeological analysis from deterministic reconstruction toward generative explanation and provides a transparent basis for comparing alternative interpretations.

Ամփոփում – Ագենտային մոդելավորումը (Agent-Based Models, ABMs) գնալով ավելի լայնորեն է կիրառվում հնագիտության մեջ՝ անցյալի հասարակությունների և փոփոխվող միջավայրի փոխազդեցությունները ուսումնասիրելու նպատակով: Հնագիտական տվյալները հաճախ ամբողջական չեն լինում, ինչը մեծացնում է անորոշության աստիճանը համապատասխան վերլուծություններում: Սույն հետազոտությունը ներկայացնում է ինտեգրված մոդելավորման առաջարկ, որը նախատեսված է ոչ թե անցյալի եզակի օրինակի, այլ բազմաթիվ հավանական օրինակների դիտարկման համար: Այն քննարկում է ագենտային մոդելավորումը մեկ միասնական համակարգում: Դրա հիմնական նորամուծությունը ձևավորման և տաֆոնոմիական փոխակերպման գործընթացների անմիջական ներառումն է մոդելավորման ընթացքի մեջ: Մոդելավորման արդյունքները համեմատվում են հնագիտական տվյալների հետ տարբեր վերլուծական մակարդակներում՝ անորոշությունն ու էկվիֆինալությունը գնահատելու համար: Այս մոտեցումը միավորում է մարդկային վարքագիծը, նյութական մշակույթի ձևավորման գործընթացները և էմպիրիկ գնահատումը մեկ շրջանակի մեջ՝ հիմք ապահովելով այլընտրանքային մեկնաբանությունների համար:

Аннотация – Агентно-ориентированные модели (Agent-Based Models, ABMs) всё шире используются в археологии для изучения взаимодействий популяции прошлого с изменяющейся окружающей средой. Однако археологические данные часто являются неполными, что затрудняет оценку конкурирующих объяснений и анализ неопределённости. В статье предлагается интегрированная модельная структура, предназначенная для исследования множества правдоподобных сценариев вместо реконструкции единственной версии прошлого. Подход объединяет forward-моделирование, вероятностный вывод, исследование пространства параметров, многомасштабную валидацию и Explainable Agent-Based Modeling (EABM) в единой аналитической системе. Основной инновацией является прямое включение процессов формирования и тафономической трансформации в моделирование, что позволяет рассматривать искажения сохранности как часть археологического вывода. Результаты моделирования вероятностно сопоставляются с археологическими данными на нескольких аналитических уровнях для учёта неопределённости и эквифинальности. Объединяя человеческое поведение, процессы формирования материальных остатков и эмпирическую оценку в рамках единой структуры, подход смещает акцент от детерминистической реконструкции к генеративному объяснению и создаёт более прозрачную основу для сравнения альтернативных интерпретаций.

Keywords – modeling, archaeology, equifinality, validation, inference.
Հիմնաբառեր – մոդելավորում, հնագիտություն, էկվիֆինալություն, վալիդացում, եզրակացություն:
Ключевые слова – моделирование, археология, эквифинальность, валидация, вывод.

Introduction

Archaeological inference is fundamentally constrained by the nature of the available evidence. Material remains do not provide a direct record of past human behavior; rather, they represent the cumulative outcome of cultural and natural processes acting on archaeological deposits through time (Schiffer 1987, 13–16; Novoa et al. 2023). From the perspective of formation process theory, the archaeological record reflects the combined effects of depositional, postdepositional, and recovery processes more closely than the behaviors that originally produced it (Sobotkova, Hermankova 2022). Consequently, archaeological evidence is inherently fragmentary: only part of past activities survives, and only a fraction of that material is ultimately recovered through fieldwork (Binford 1981; Lyman et al. 2003; Renfrew, Bahn 2005, 10, 199). Taphonomic processes, including erosion, sedimentation, and biological or anthropogenic disturbance, further modify archaeological materials after deposition (Schiffer 1987, 20–25). The relationship between material traces and past behavior therefore remains indirect and requires interpretation rather than direct observation (Rogers, Cegielski 2017).

These conditions create a persistent problem of ambiguity in archaeological interpretation. Because archaeological data are incomplete and transformed, different explanatory pathways may remain consistent with the same material pattern, a phenomenon commonly described as equifinality (Premo 2010; Romanowska et al. 2021). Under such circumstances, conventional approaches-including qualitative interpretation, linear causal models, and analogical reasoning-face important limitations in addressing the nonlinear interactions, feedback mechanisms, and probabilistic variability that characterize past human systems (Lake 2014, 88–89; Romanowska et al. 2021). Although analogies have long been used to relate archaeological observations to ethnographic and experimental evidence (Binford 1967), their explanatory value depends on the identification of meaningful contextual similarities and often provides limited grounds for distinguishing among alternative causal processes when several mechanisms may generate comparable material outcomes (Bevan 2012; Romanowska 2015; Romanowska et al. 2021, 3, 88–89, 142–144; Shennan 2008). These challenges have encouraged the development of process-based and probabilistic approaches that address uncertainty directly through the explicit simulation of mechanisms responsible for observable patterns rather than through descriptive resemblance alone (Epstein 2006, 4–46; Romanowska 2015). Within this perspective, model outputs are interpreted as probability distributions rather than fixed predictions, allowing alternative explanations to be evaluated according to their consistency with the archaeological record (Beaumont 2010; Crema 2012).

Agent-Based Modeling (ABM) offers a means of addressing some of these challenges by simulating interactions among individual agents and examining how larger-scale patterns emerge from those interactions (Romanowska et al. 2021, 26–27). In archaeology, however, ABM has often been applied to a limited number of predefined scenarios designed to reproduce observed patterns or specific historical trajectories (Graham, Weingart 2015; Lake 2014). Although such applications have generated valuable insights, they may restrict exploration of the broader range of possible system behaviors (Crema 2014) and encourage deterministic interpretations of processes that are inherently stochastic (Kohler et al. 2012; Kohler, Varien 2012, 72–73). In addition, formal statistical evaluation of model outputs against archaeological evidence has frequently remained limited, complicating the assessment of model–data correspondence (Romanowska et al. 2021, 88–89, 142–144).

A more productive approach shifts attention from reconstructing discrete historical narratives toward simulating the processes that generate archaeological patterns and exploring the range of trajectories that may emerge from them. Within this perspective, ABM functions less as a tool for reproducing the past and more as a framework for generating ensembles of outcomes that can be compared with archaeological evidence (Crema 2014; Kohler et al. 2012). The analytical objective therefore moves from identifying a single preferred explanation to evaluating sets of outcomes and their relative consistency with the available data.

Forward modeling extends this perspective by representing the sequence of processes through which archaeological data are generated. Instead of treating observed patterns as independent observations, it incorporates the interactions linking human behavior, environmental conditions, post-depositional transformation, and archaeological recovery (Kohler, Varien 2012, 4–6, 71–73). Preservation biases, sampling effects, and other sources of uncertainty are therefore integrated directly into the simulation, allowing archaeological patterns to be understood as emergent outcomes of interacting processes rather than isolated empirical observations.

Building on these developments, the present study proposes an integrated analytical framework that combines forward modeling, probabilistic inference, and process-oriented modeling. Rather than reconstructing a definitive historical sequence, the framework provides a structured approach for evaluating competing hypotheses under explicitly defined conditions. Its primary contribution is methodological: establishing a conceptual and computational foundation in which assumptions, parameter configurations, and inferential limitations are made explicit, thereby creating more transparent and testable conditions for comparing archaeological explanations.

A Forward Modeling Framework for Archaeological ABM

A recurring problem in archaeological analysis is the assumption that survey data provide a direct reflection of past human behavior. In reality, archaeological patterns emerge through a sequence of depositional, post-depositional, and observational processes that progressively alter the archaeological record (Schiffer 1987, 7–8, 10; Bevan 2012). Efforts to reconstruct behavior through retrospective correction of these transformations often introduce additional uncertainty, particularly in systems characterized by non-linear interactions and multiple causal pathways. Forward modeling offers an alternative by adopting a generative perspective in which behavioral processes are simulated directly and archaeological patterns emerge through the interaction of agents, environments, and material deposition over time (McLaughlin 2023). Consistent with the principles of generative social science, the objective is to explain how observable regularities arise from explicitly defined processes rather than treating those regularities as explanatory endpoints (Epstein 2006, 5, 7–8).

Within this framework, formation processes, taphonomic transformation, and agent behavior are treated as interconnected components of a single analytical system. Transformations such as erosion, burial, and differential visibility are modeled directly, allowing behavioral outputs to be converted into materially altered patterns comparable to empirical datasets (Schiffer 1983; Schiffer 1987, 7–10). Archaeological traces are therefore generated through behavioral dynamics and subsequently modified by the same processes that affect real-world evidence, integrating preservation bias and observational uncertainty into the simulation itself. Model evaluation is correspondingly grounded in Pattern-Oriented Modeling (POM), where validation depends on the simultaneous reproduction of multiple empirical regularities rather than a single pattern match (Grimm et al. 2005). Statistical approaches such as Approximate Bayesian Computation (ABC) and Monte Carlo simulation further support the probabilistic comparison of simulated and observed patterns.

The framework also adopts a socio-environmental perspective on human behavior. Early archaeological applications of Agent-Based Modeling (ABM) frequently emphasized environmental optimization, with agents responding primarily to resource availability or landscape conditions. While computationally efficient, such approaches capture only part of the processes underlying human action. Human behavior emerges through the interaction of environmental constraints, social relationships, and cognitive mechanisms (Kohler, Varien 2012, 6–8, 24–26, 70–71). Agents are therefore characterized by attributes such as memory, learning capacity, network position, and context-dependent decision rules. Social memory introduces path dependency by linking present choices to accumulated experience, while interaction networks structure the circulation of resources, information, and influence. These relational processes have been shown to shape both archaeological patterning and broader system trajectories (Romanowska 2015; Romanowska et al. 2021, 170, 301). Through their interaction with ecological conditions, macro-scale archaeological patterns emerge from micro-level processes in a manner consistent with generative social science (Epstein 2006, 5–6, 31, 37–38, 51–52).

Decision-making within the model is treated as inherently non-linear. Behavioral responses may remain stable for extended periods before relatively small changes in environmental or social conditions trigger substantial reorganization, a characteristic feature of complex adaptive systems (Grimm et al. 2005). Archaeological patterns are therefore understood as emergent outcomes of interactions among cognitive processes, social networks, and ecological conditions rather than direct reflections of environmental constraints alone. To address equifinality, the framework systematically explores probabilistic scenario space by varying key parameters across broad ranges rather than evaluating a limited set of predefined historical reconstructions (Romanowska et al. 2021, 333–334). Approximate Bayesian Computation (ABC) identifies regions of parameter space that remain statistically consistent with archaeological observations without requiring explicit likelihood functions, while Monte Carlo simulation helps distinguish persistent structural patterns from stochastic variation through repeated model execution (Beaumont 2010; Crema 2012; Grimm, Railsback 2006). The framework also supports the exploration of boundary conditions and critical transitions by exposing the model to a range of environmental and social perturbations (Grimm et al. 2005). Taken together, forward modeling, taphonomic representation, socio-environmental agent design, and probabilistic inference establish an integrated analytical framework in which data generation, transformation, and evaluation are treated as components of a single process, providing a more explicit basis for addressing uncertainty and equifinality in archaeological research.

Multi-Pattern, Multi-Scale Validation

Validation in archaeological Agent-Based Modeling (ABM) is constrained by the nature of the archaeological record, which is fragmentary, shaped by taphonomic processes, and inherently non-repeatable. Under such conditions, evaluation based on a single output variable or isolated pattern provides only limited insight into model performance. Pattern-Oriented Modeling (POM) addresses this limitation by proposing that model credibility should be assessed through the simultaneous reproduction of multiple empirical patterns operating across different organizational scales (Wiegand et al. 2003; Grimm et al. 2005). This perspective is particularly important in archaeology, where equifinality often allows different mechanisms to produce similar observable outcomes. The validation framework proposed here therefore evaluates model performance through cumulative consistency across several independent dimensions rather than through correspondence with a single pattern, providing a stronger basis for assessing the plausibility of underlying mechanisms and causal explanations (Beven 2006; Romanowska et al. 2021, 142–145).

Validation is organized across three interconnected analytical levels. At the survey level, model outputs processed through the taphonomic component are compared directly with archaeological observations, including artefact densities, site distributions, and spatial patterns derived from survey data. At the macro level, assessment focuses on the model's ability to reproduce broader forms of spatial and socio-environmental organization, such as settlement clustering, regional settlement hierarchies, and landscape-scale structures associated with long-term system dynamics. At the micro level, evaluation concentrates on the plausibility of the behavioral mechanisms that generate model outcomes, including interaction networks, decision-making processes, and forms of social organization. Together, these levels provide a coherent framework for assessing both the empirical correspondence of model outputs and the credibility of the processes that produce them. Comparison at the survey level maintains direct relevance to the archaeological record (Romanowska et al. 2021, 85–87), while macro-scale patterns offer insight into regional socio-environmental dynamics (Kohler, Varien 2012, 52–54, 73–75). Micro-scale evaluation examines whether simulated behavioral processes remain theoretically plausible and consistent with available evidence concerning interaction, decision-making, and social organization (Romanowska et al. 2021, 25–26, 63, 66–67).

A central feature of the framework is the integration of multi-pattern validation with probabilistic parameter estimation. Parameter configurations are assessed according to their capacity to reproduce patterns across all analytical levels simultaneously rather than through agreement with a single output variable. This enables the elimination of parameter sets that fail under cross-scale comparison while retaining those that perform consistently across multiple empirical dimensions. By linking survey-level observations, macro-scale system organization, and micro-scale behavioral processes within a unified framework, the approach provides a stronger basis for interpreting archaeological system dynamics and evaluating alternative explanatory scenarios.

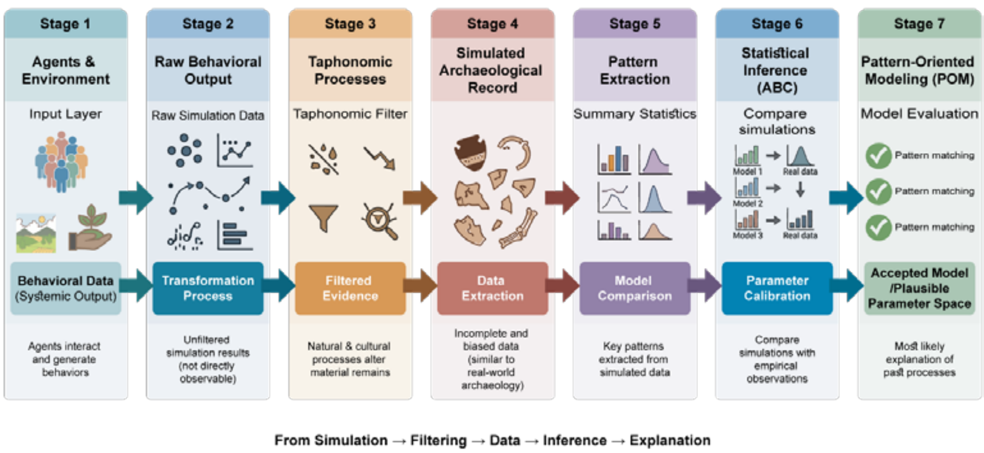

Fig. 1. Integrated probabilistic workflow for archaeological ABM. Behavioral simulations are transformed through taphonomic processes into synthetic archaeological records and evaluated using Pattern-Oriented Modeling (POM) and Approximate Bayesian Computation (ABC) to identify plausible explanatory scenarios.

Methodological Innovations

Scenario Stress Testing and System Fragility

Scenario stress testing addresses a central challenge in computational archaeology: understanding how socio-environmental systems respond under conditions of disruption as well as stability. Models focused primarily on equilibrium states often provide only a partial view of system behavior, particularly where non-linear dynamics and abrupt change are important. Recent research has therefore emphasized exposing models to extreme but plausible conditions in order to identify vulnerabilities, critical thresholds, and pathways of transformation (Kohler, Varien 2012, 73; Romanowska et al. 2021, 25–26, 63, 142–144). The objective is not to reconstruct a particular historical sequence but to examine the conditions under which resilience is maintained or weakened.

In complex adaptive systems, pressures may accumulate gradually before crossing thresholds that trigger rapid reorganization (Kohler, Varien 2012, 8–11; Scheffer et al. 2001). Archaeologically, such dynamics may appear in changes in settlement organization, subsistence practices, demographic trajectories, or patterns of social interaction (Kohler, Varien 2012, 245–248). Stress testing investigates these processes by exposing models to a range of pressures, including resource shortages, disruptions to exchange networks, and demographic or institutional decline (Kohler, Varien 2012, 58–62, 165–171, 202–205, 245–249). Rather than focusing on individual simulations, analysis compares distributions of outcomes across multiple scenarios, allowing recurring patterns of adaptation, reorganization, and instability to be identified despite stochastic variation.

This perspective shifts attention from reconstructing specific outcomes toward evaluating the conditions under which systems become susceptible to transformation. Consistent with probabilistic approaches in archaeology, stress testing supports the construction of comparative fragility landscapes in which alternative configurations can be assessed according to their capacity to absorb disturbance and maintain stability (Premo 2010). At the same time, understanding why particular outcomes emerge requires examination of the mechanisms that generate them, highlighting the importance of combining stress testing with process-oriented modeling approaches.

Explainable ABM (EABM) as State-Space Analysis

State-space analysis extends this perspective by focusing on the trajectories through which systems evolve. In many complex systems, gradual pressures can accumulate until critical thresholds are crossed, producing rapid reorganization. Such transitions are often preceded by early warning indicators, including increasing variance and critical slowing down, both of which suggest declining resilience (Scheffer et al. 2001; Scheffer et al. 2009). Monitoring these indicators within simulations provides insight into the processes that precede transformation rather than focusing exclusively on final outcomes.

A complementary perspective is provided by network analysis. Agent behavior is embedded within structures through which resources, information, and social influence circulate. Network properties such as connectivity, density, and centrality influence how local interactions scale into broader system outcomes (Romanowska et al. 2021, 179–182). Different network configurations may therefore contribute to resilience, vulnerability, or reorganization in distinct ways. Together, state-space and network analysis reposition ABM as a tool for process tracing as well as pattern generation, making internal model dynamics accessible to systematic examination and strengthening explanations of causation, resilience, and social change.

Parameter Space Exploration and Bayesian Approximation

Applying Agent-Based Modeling (ABM) to archaeological research requires methods capable of identifying parameter configurations consistent with observed material patterns. Because archaeological evidence is incomplete and often compatible with multiple interpretations, focusing on a narrow parameter range or a single optimal solution can unnecessarily restrict inference. Recent work has therefore emphasized systematic exploration of parameter space, in which model behavior is examined across broad combinations of environmental and behavioral variables (Crema 2012; Premo 2010).

Parameter space exploration generates large ensembles of simulations in which variables such as resource regeneration, demographic thresholds, mobility strategies, and interaction dynamics are varied systematically. The objective is not to identify a uniquely correct configuration but to determine which regions of parameter space produce outcomes compatible with empirical observations (Romanowska et al. 2021, 145–146, 321–323, 334–336). Calibration therefore shifts from optimization toward evaluating plausible parameter combinations and examining how alternative assumptions influence model behavior.

Approximate Bayesian Computation (ABC) provides a practical framework for this process. Parameter values are sampled from prior distributions, simulations are compared with archaeological observations, and configurations that generate sufficiently similar outcomes are retained (Beaumont 2010). Repeated sampling produces posterior distributions that characterize the relative plausibility of alternative parameter combinations without requiring explicit likelihood functions. Because direct comparison of raw simulation outputs is rarely feasible, evaluation commonly relies on summary measures such as settlement-size distributions, spatial clustering patterns, and network characteristics.

A complementary component is Global Sensitivity Analysis (GSA), which evaluates how variation across multiple parameters contributes to variation in model outputs. Unlike local approaches that examine parameters individually, GSA considers their combined effects across the full parameter space, making it possible to identify influential parameters and interactions more systematically (Saltelli et al. 2008, 160–164, 184). Together, these methods support probabilistic evaluation, clarify the importance of model assumptions, and provide a stronger basis for assessing archaeological interpretations under alternative conditions.

Computational Tractability and Model Emulation

Although large-scale simulation and probabilistic evaluation are increasingly important in archaeological ABM, their application is often constrained by computational cost. Exploring extensive parameter spaces, particularly in spatially explicit models integrated with GIS data, may require very large numbers of simulation runs, making exhaustive analysis difficult in practice.

One response has been the use of surrogate modeling, or model emulation, in which an approximate statistical representation of model behavior is constructed in place of repeated execution of the full simulation (Kennedy, O'Hagan 2001). Trained on a subset of simulation results, emulators can estimate outputs across untested configurations while substantially reducing computational demand (Williams, Rasmussen 2006, 7–8, 16–18, 30, 193; Beaumont 2010). Parallel computing provides a complementary solution by distributing independent simulation runs across multiple processors, making large simulation ensembles more feasible and reducing runtime considerably (Romanowska et al. 2021, 342; Railsback, Grimm 2019, 106–109).

Further efficiency can be achieved through guided sampling strategies that concentrate computational effort on parameter regions more likely to generate outputs consistent with empirical patterns. Often combined with iterative search procedures, these approaches reduce redundant evaluations and improve exploration of informative areas of parameter space (Beaumont 2010). Together, model emulation, parallel computation, and guided sampling provide a scalable framework that supports more systematic exploration of complex archaeological models.

Moving Beyond Case Studies: Stylized Generative Modeling

A recurring issue in archaeological ABM is the emphasis on highly detailed, case-specific reconstructions in which model outcomes become closely tied to local data limitations and contextual uncertainties. In response, computational social science has increasingly adopted stylized generative models designed not to reproduce particular empirical settings but to isolate mechanisms capable of generating observable patterns (Epstein 2006, 8–13; Kohler, Varien 2012, 10–11).

This approach relies on synthetic environments that retain selected structural characteristics while minimizing unnecessary contextual complexity. Topography may be represented through abstract elevation surfaces or grid-based landscapes that capture the effects of movement constraints and accessibility without reproducing empirical detail (Lake 2014; Verhagen et al. 2019, 109–127, 217–249). Resources such as water, arable land, and raw materials are modeled as heterogeneous spatial variables, allowing systematic examination of scarcity, competition, and environmental gradients (Crema 2015; Kohler, Gumerman 2000, 179; Kowarik et al. 2015). Mobility and interaction are similarly represented through simplified rules, often incorporating least-cost path approaches to approximate movement across constrained landscapes (Romanowska et al. 2021, 108–110).

The principal value of stylized generative modeling lies in the analytical control it provides. Because initial conditions are explicitly defined, model behavior can be evaluated systematically before methods are applied to more uncertain archaeological datasets (Epstein 2006, 4–6, 15–16). Such environments are particularly useful for testing forward-modeling strategies, probabilistic inference methods, and extreme scenarios that may be only partially visible in the archaeological record (Miller, Page

2007, 65–67). More broadly, these models support mechanism-based explanation by examining how macro-scale patterns emerge from micro-level rules rather than relying solely on descriptive correspondence (Epstein 2006, 7–9). In doing so, they complement empirical research and contribute to the development of more transferable and theoretically grounded explanations in archaeology.

Implications for Archaeological Theory

The integration of forward modeling, probabilistic inference, explainable simulation, and computational optimization has important implications for archaeological theory. Rather than treating Agent-Based Modeling (ABM) primarily as a tool for reproducing observed patterns, this framework positions simulation as a means of investigating the processes through which archaeological evidence is generated. As a result, attention shifts from descriptive correspondence toward the evaluation of alternative mechanisms and their capacity to account for observed material patterns under conditions of incomplete evidence (Romanowska et al. 2021, 25; Smaldino 2023, 9–13, 301–304).

This perspective encourages a different understanding of archaeological explanation. Traditional approaches have often sought a dominant causal account, whereas process-oriented simulation highlights the coexistence of multiple plausible pathways. Interpretation becomes less concerned with reconstructing a single historical sequence and more focused on evaluating the conditions under which different outcomes become probable. Archaeological inference is therefore reframed as the assessment of alternative trajectories rather than the selection of a single explanatory narrative.

Theoretical significance also lies in the capacity of ABM to connect individual action with broader social and environmental dynamics. Archaeological phenomena such as settlement hierarchies, exchange systems, social inequality, and political integration emerge through interactions operating across multiple scales. By representing these interactions explicitly, ABM provides a framework for examining how large-scale patterns develop from localized processes and how feedbacks between levels of organization shape long-term system behavior (Epstein 2006, 4–6, 15–16; Kohler, Varien 2012, 7–9, 14).

More broadly, this approach supports a shift from deterministic reconstruction toward generative explanation. Uncertainty is treated not as a methodological obstacle but as an inherent feature of archaeological inference that can be examined explicitly through simulation and probabilistic evaluation. Theoretical interpretation consequently becomes less focused on identifying singular causes and more concerned with understanding the range of mechanisms and conditions capable of producing the archaeological record. In this way, ABM serves as a bridge between empirical evidence and broader debates concerning social change, adaptation, resilience, and the dynamics of complex human systems.

Conclusion

The framework developed here proposes a shift from reductive forms of archaeological inference toward a generative modeling perspective in which the production, transformation, and evaluation of archaeological data are treated within a single analytical process. By explicitly integrating agent behavior with taphonomic processes, the approach establishes a closer connection between socio-environmental dynamics and the material traces observed in the archaeological record (Sobotkova, Hermankova 2022, 6–7, 232–235; Epstein 2006, 4–6, 15–16). Its principal innovation lies in treating uncertainty, formation processes, and behavioral mechanisms as integral components of explanation rather than as external complications to be addressed after analysis.

Methodologically, the framework combines forward modeling, probabilistic evaluation, multi-scale validation, explainable simulation, and systematic exploration of parameter space within a common structure. This integration provides a more transparent basis for assessing alternative scenarios, evaluating competing explanations, and examining the mechanisms through which archaeological patterns emerge. Rather than seeking a single best reconstruction, analysis focuses on identifying plausible regions of explanation and assessing their consistency with empirical observations (Premo 2010; Romanowska et al. 2021, 228–232). The result is a more flexible and theoretically informed approach to archaeological inference.

Future research can extend this framework through the development of richer behavioral representations, improved methods for linking simulation outputs with archaeological datasets, and greater use of scalable computational techniques. Continued integration of probabilistic inference, explainable modeling, and large-scale simulation offers opportunities to investigate increasingly complex archaeological questions while maintaining analytical transparency. In this sense, the framework is intended not as a fixed methodological solution but as a foundation for a broader computational archaeology capable of addressing causation, uncertainty, and social change within a formally specified and empirically grounded analytical environment.

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