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Time as event: bridging explicit and emergent temporal representations in computer-based social simulations

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Time is a fundamental yet conceptually undertheorized dimension in computational simulations of historical processes. This paper addresses the problem of temporal representation in these social models by distinguishing two types of *temporal information*—explicit and emergent—and suggests a formal definition of the temporal event as the primary unit of analysis in a unifying framework for both. In explicit-time models—such as reaction-diffusion systems calibrated against georeferenced calendar dates—time enters as an independent variable governed by differential equations, enabling rigorous testing of temporal sequences that in some circumstances may be consistent with causal hypotheses about the rate, direction, and intensity of social change. In emergent-time models—typically agent-based simulations governed by iterative cycles—temporality arises endogenously from local interactions, adaptive feedback, and cumulative system transformations, revealing how processes may have unfolded mechanistically without imposing predetermined chronological constraints. Our main point is that this difference has profound implications for determining what counts as an assumption and what counts as a result. It also determines the ability to compare computational models of social dynamics with historical empirical evidence. All along the paper, we use the origins of early farming communities in the Prehistoric Mediterranean as a case study for a comparative analysis to reveal critical differences in the way time and space are used as parameters or as emergent dynamics, and their methodological and epistemological consequences.

KEYWORDS
agent-based modeling (ABM), Neolithic farming dispersal, reaction-diffusion systems, spatio-temporal analysis, temporal representation

1 Introduction

Programming computers to reproduce historical processes helps amplify our understanding of social dynamics in the past. One of the most significant benefits of computer simulation of social dynamics lies in its ability to test historical hypotheses under controlled conditions. Simulations allow researchers to input known variables—such as population sizes, resource availability, social inequality, power relations, or technological capabilities—and observe how these factors interact over time and space. By adjusting parameters, historians can explore "what-if" scenarios on the computer, enriching our understanding of how events may be related, and how some occurrences trigger other occurrences. By integrating paleoclimatic, demographic, and socio-economic data, computer simulations of historical processes quantify uncertainty and equifinality, identifying factors like cultural shifts or peer networks invisible in static records. This contributes to the formalization of studies in spatial-temporal social change.

Fundamentally, what confers the "historic" character to a model of social dynamics is the inclusion of *time*. Without a temporal dimension, a model may describe structures, relationships, or states, but it cannot account for ordering and, change or transformation. It is the inclusion of temporal information that converts a static representation of social behavior into a historical one—allowing processes to unfold, events to be ordered, and trajectories to emerge. In this sense, it turns out that *time* is the defining axis that separates social modeling from historical one.

This paper is motivated by the need to make spatio-temporal modelling explicit, comparable, and critically examined in computational social historical simulations. First, we intend to define the very idea of temporal events rigorously as a basic unit of analysis for any historical process simulation. Second, we present contrasting approaches where the temporality of such events is encoded directly in their input or emerges from interactions as an output. In historical simulations, it is crucial to know whether "time" is a set of values or constrains you impose on the system (explicit time) or something that only appears when you look at how the system's own dynamics unfold (emergent time). We want to make the point that this choice has profound implications when determining what is an assumption, what is a result, and how you can compare the model's result to historical evidence.

In this paper, we will use this distinction between explicit and emergent time to analyze how three different forms of computer simulation of historical processes deal with time: equation-based, agent-based, and network-based. Each modality treats explicit and emergent time differently, yet they all aim to reconstruct how societies, ideas, or material systems evolved over time.

To illustrate the theoretical discussion, examples coming from the analysis of the early adoption of farming in prehistoric Mediterranean are provided. Most scholars consider this a complex, dynamic, expansive phenomenon combining demic movement and cultural transmission, from the Eastern to the Western Mediterranean (Ammerman and Cavalli-Forza, 1971; Ammerman and Cavalli-Sforza, 1984; García Puchol and Salazar-García, 2017; Borrell et al., 2022; Harris, 2024; Phillips, 2023; Castiello et al., 2025; Leppard, 2021). In this domain, *dynamics* refers to the processes through which farming practices emerge, spread, and transform across communities over time. It encompasses the interactions between groups, environmental conditions, technological innovations, and social decisions that shape the adoption, modification, or abandonment of agricultural strategies. In Mediterranean prehistoric contexts, *dynamics* captures how cultivation techniques, crop choices, settlement patterns, and resource management practices evolve through experimentation, transmission, and adaptation within and between populations across generations.

Mediterranean geographical heterogeneity, shaped by mountains, seas, and ecological gradients, generated uneven spread rates that challenge uniform temporal models: rapid coastal expansion stands out against slower inland diffusion. Across multiple temporal scales, from millennial to generational, the specific sequence of farming adoption can be explored and its dynamics reconstructed. Different modelling traditions—from the wave-of-advance model to reaction-diffusion and agent-based simulations—offers robust comparative frameworks, making the Mediterranean Neolithic a benchmark for evaluating how distinct temporal representations shape our understanding of prehistoric processes.

The Mediterranean Neolithic provides an exceptionally rich empirical record, with thousands of georeferenced radiocarbon dates from early farming sites between the Levant and the Iberian Peninsula forming a high-resolution chronological framework.

2 Questions regarding time and temporal information

In its most elemental sense, time is a parameter—a numerical measure that answers the "when" question, just as spatial coordinates answer "where?" In Newtonian mechanics, t enters as an independent variable in equations of motion, e.g., Newton's second law,

$$F(t) = m\,\frac{dv(t)}{dt}$$

where $F(t)$ is the force, m the (inertial) mass and v the velocity. It can be argued that time plays an analogous role in the description of historical processes. For example, in the case of a mathematical formulation of the expansion of early farming communities in prehistory: the net force $F(t)$ at time t may represent the sum of all factors pushing a population toward agriculture at that moment. These might include:

- *Demographic pressure*—population growth exceeding the carrying capacity of foraging
- *Climate change*—environmental shifts making wild resources less reliable
- *Contact with farming groups*—diffusion of knowledge, seeds, and techniques
- *Social incentives*—prestige, surplus accumulation, or emerging inequality

This sum also accounts for opposing factors—such as the reliability of existing wild resources or cultural resistance—which may act against adoption.

The inertial mass m represents the resistance of a society to change its subsistence strategy. A high "mass" means that a hunter-gatherer population is deeply adapted to its current way of life—through cultural traditions, ecological knowledge, established mobility patterns, or demographic stability—and therefore requires a greater force to alter its trajectory. Different populations may have different "inertial masses" depending on their social complexity, environmental context, or degree of sedentism.

The velocity $v(t)$ represents the rate at which agriculture is spreading at a given time t—for example, the number of new communities adopting farming per generation, or the kilometers of territorial expansion of the agricultural frontier per unit of time.

The term $dv(t)/dt$ captures whether the spread of agriculture is accelerating or decelerating at time t. A positive value means adoption is gaining momentum; a negative one means it is slowing down—perhaps due to geographical barriers, encounters with resistant populations, or diminishing returns in marginal environments.

Integration of the previous equation yields

$$v(t) = v(t_0) + (1/m) \cdot \int F(t')\,dt',$$

and we see that the current rate of agricultural spread is not determined solely by present conditions, but by the entire accumulated history of driving forces from the initial moment t_0 onward, filtered through the resistance of the population. This makes the model genuinely historical: the present state carries the imprint of all past forces acting through time.

In these equations, *time* appears as a continuous, external parameter—an independent axis along which the system evolves. It is not something the model measures, observes, or derives from the data. It is assumed: a uniform, abstract coordinate that structures the equations and enables the computation of derivatives and integrals. Time here is the container within which change happens, but it carries no information.

Temporal information is something fundamentally different. It includes not only the "when" but also the relational structure of the time-stamped occurrences—their ordering, spacing, clustering, acceleration, and sequential dependencies. Where parametric time asks "what is the state of the system at t = 3000 BP?", temporal information asks "what do we actually know about when this happened, and how confident are we?" The difference between a list of radiocarbon dates and a model of early farming dispersal in Prehistory lies precisely here: the list provides time-as-parameter; the model extracts temporal information by asking how those dates relate to one another across space, what patterns of proximity and sequence they form, and what processes could have generated the observed distribution.

The gap between time-as-parameter and temporal information cannot be bridged without defining a unit of analysis—the discrete, identifiable occurrence that anchors both measurement and explanation. In physics, this role may be played, for instance, by the "event" in relativistic spacetime: a point (x, y, z, t) at which something happens(ed). For social-historical simulation, we need an analogous concept, yet one that carries substantive content.

This is why we propose the *historical event* as the primary unit of analysis, simply defined as "things that happened" (Kim, 1976; Galton, 2012). It should become the basic unit of analysis for studying change and transformation: a bounded, identifiable occurrence that marks a discernible difference in the state of a system or entity before and after it takes place. It is *the* minimal episode of change or transformation that can be described in terms of its context, its actors or components, and its measurable consequences.

It can be formalized as

$$e_i = (agent_i, action_i, location_i, time_i),$$

Each event encodes who acted, what was done, where it occurred, and when—binding the parametric measure of time to the social content of change (Van Hage et al., 2011; Van Hagen and Ceolin, 2013; Piryani et al., 2023). Without a proper definition of *temporal events*, we are left with either raw dates (parameter without meaning) or narrative accounts (meaning without measure). The temporal event forces the analyst to specify what counts as a change, at what granularity, and under what criteria two changes are considered related—decisions that directly determine how time will function in the simulation.

When the occurrence of events is interdependent—where the probability of one event increases because another event has occurred nearby in time (Pearl 2009)—an ordering relationship emerges. This temporal coupling creates sequences that are not arbitrary but structured by conditional probabilities. Such ordering evokes the concept of time's arrow, the directional flow of time rooted in entropy: a settlement cannot be abandoned before it is found, crops cannot be harvested before they are planted. In social systems, entropy manifests as the proliferation of possible states and the diffusion of information, practices, and populations across space. As farming spread in prehistoric past, local adaptations multiplied, creating diverse regional variants from an initially more uniform practice. Settlements fragmented, populations dispersed, and knowledge diversified through imperfect transmission and innovation. Each branching event—a community splitting, a technology being reinterpreted, a migration to new terrain—increased the configurational possibilities of the system. This increasing diversity and irreversibility of social trajectories mirrors thermodynamic entropy: the system evolves toward states with more microstates, more heterogeneity, and less predictability. Historical contingency accumulates, making reversal to prior configurations increasingly improbable, thus establishing temporal directionality in the archaeological record.

Just as entropy generates temporal asymmetry in physical systems, the accumulation of historical contingencies and irreversible social transformations establishes a directional sequence in human history, giving prehistory its narrative structure and preventing reversibility (Mavrofides et al., 2011).

2.1 Historical and archaeological events as unit of analysis

In this paper we define *event* as the basic unit of analysis for studying change and transformation: a bounded, identifiable occurrence that marks a discernible difference in the state of a system or entity before and after it takes place. In other words, it is *the* minimal episode of change or transformation that can be described in terms of its context, its actors or components, and its measurable consequences. In formal terms, a *quantum*[1] refers to the smallest discrete unit of a phenomenon with specific properties allowing for its non-ambiguous definition, the *quantization* of any kind of historical process can be understood through the concept of discrete units or steps that allow the perception of change.

A historical event can then be defined as the specific occurrence of a *social action* or *singular activity*, in the precise sense of Cultural-Historical Activity Theory developed by Leontiev (1978) and Cong-Lem, (2022). In Leontiev's Cultural-Historical Activity Theory, the fundamental analytical hierarchy is *activity–motive, action–goal,* *operation–conditions.* A historical event, under this redefinition, is the occurrence of one bounded activity (or a specific action within it) at a determinate time and location, describable as: agent(s) + object/motive + goal +means/operations + conditions + spatio-temporal coordinates.

Its formal description would be:

> Agent A performed action/activity X, directed at object/motive O, by means of operations $\{op_1, op_2, \ldots\}$, at place p and time t, under conditions C.

A practical rule to distinguish events and phenomena follows: if the description of what may have happened can be fully indexed by one time–place coordinate pair, even if it involves many micro-actions within a short bounded episode, it qualifies as an event. Otherwise, if its description requires a time interval spanning many cycles and places, primarily denoting patterned repetition or an overarching narrative frame imposed retrospectively, it is a composite phenomenon, a process or a macro-event construct. The operational rule to distinguish historical events from complex phenomena or composite constructs is *singular indexability*: if the occurrence can be fully described by a single (agent, action, place, time) tuple—even if composed of brief subordinate operations—it is an historical event. This distinction preserves humanistic meaning (motives, goals, agents) while enabling formal modelling: events become the atomic units over which probabilities, spatio-temporal models, and stochastic processes are defined, while phenomena and macro-constructs emerge as statistical or narrative aggregations of event populations.

An *archaeological event* is a specific type of historical event. It can be defined as the minimum observable discretization of the formation process of an archaeological site (Brooks et al., 1982; Lucas, 2008; Barceló, 2010; Zubrow, 2010; Boissinot, 2015; Kolář, et al., 2016; Lucas, 2021). For instance, the deposition of sediment layers, the construction of structures, the accumulation of artifacts, and the erosion or alteration of the site should be seen as discrete events or processes that contribute to its formation. Each of these processes occurs in a quantized manner, with distinct stages or steps that incrementally shape the archaeological site. In some ways, this definition aligns with the idea of a sedimentary *depositional event*, defined as a single, finite episode during which sediment is accumulated continuously, forming a distinct, analyzable unit of deposition (Einsele et al., 1996). Because of post-depositional processes, single depositional events (excavating the foundations of a house, repairing the walls of that house, different episodes of refuse and cleaning within the house) cannot be distinguished by archaeologists excavating the site, and therefore the archaeological event may appear as a palimpsest formed by indistinguishable but probably related depositional events (Barceló, 2010; Barceló, 2020; Barceló and Bogdanovic, 2020; Andreaki and Barceló, 2024).

A *depositional event* in the strict stratigraphic sense is a minimal, temporally focused episode of sedimentation, whereas Harris's *units of stratification* (or *stratigraphic units*) are operational working units defined by the archaeologist's perception of "a single, coherent deposit" (Harris, 2024), and therefore they tend to be less temporally precise. Because Harris units are often based on visible changes in matrix, color, or structure alone, one Harris unit may lump together several distinct depositional events (e.g., successive occupation phases, multiple refuse dumps, or repeated floor-renewal episodes), just as a historical period may bundle heterogeneous processes under a single label. Moreover, Harris units can be delimited differently by archaeologists. Also, they can be inconsistent across contexts, and their boundaries are sometimes guided by convenience or visibility rather than by tight chronological or sedimentological criteria. In this sense, Harris units are "ambiguous" like traditional historical named time periods. Harris units of stratification may be useful for ordering and drawing Harris matrices, but they are too coarse and subjectively defined to function as discrete units of analysis in process-oriented or computational models of site formation and long-term change (May 2020).

A better way to decompose the site's biography into successive events would imply the identification of different *occupational floors*. This refers to the surface upon which human activities occurred, encompassing both visible structures like hearths and indirect features such as traces of former walls. This floor serves as a crucial element when recognizing "precise moments in past times" (LaMotta and Schiffer, 2013; Pingarrón, 2020), allowing for the identification not only of material remnants from past actions (Henry, 2012; May 2020; Reid et al., 2023; Andreaki and Barceló, 2024), but also of associated pedogenetic horizons (Zhurbin et al., 2022; Lisá et al., 2026). These horizons, along with distinguishable archaeological contexts, serve as reference points for defining the occurrence and temporal position of depositional events at a site. Identifying and comprehending the ground surface upon which a specific human activity occurred presents a complex challenge due to the multitude of factors and events that may have influenced the original deposition or subsequent modifications over time, a process integral to the study of taphonomy.

We consider that the tuple

$$e_i = (agent_i, action_i, location_i, time_i),$$

should remain formally identical across all domains. What changes is the nature of the evidence that fills each slot—and the degree of certainty, resolution, and directness with which each component can be known.

Historical textual documentary evidence provides the most direct and linguistically explicit instantiation of the tuple (Table 1). All four components are typically stated, and the event is narrated as such by a witness or recorder himself. The limitation is that textual sources are mediated by authorial intention: what was selected for recording, how it was framed, and what was omitted.

In the case of archaeological events, the tuple is never directly stated—it must be reconstructed inferentially from preserved material evidence (Table 2). The agent is almost always generic ("the potter," "the inhabitants"), the action is read from traces rather than described in words, and time is probabilistic rather than calendrical. The strengths are that the location is often known with great precision (to the centimeter), and evidence for actions is sound since it is materially grounded rather than subjectively selected by a personal narrative.

A depositional event is the most impoverished instantiation of the tuple (Table 3). The agent slot is frequently filled by a natural force rather than a person, which challenges the very concept of "agent" as intentional actor. *Action* is not always a human activity; it

TABLE 1 Historical events (textual data).

Component	Content	Data source
Agent	Named individuals, institutions, peoples — explicitly identified in documents	Chronicles, letters, administrative records, inscriptions
Action	Described in natural language: "Conquered," "signed," "declared," "traded" — verbs carrying intentionality	Narrative accounts, legal texts, diplomatic correspondence
Location	Named places, often with political or administrative meaning (a city, a kingdom, a court)	Toponyms in texts, itineraries, maps
Time	Dated explicitly: a year, a day, sometimes an hour — anchored to a calendar system	Dates in documents, regnal years, consular dates

TABLE 2 Archaeological events (objects and built structures).

Component	Content	Data source
Agent	Anonymous — inferred as "someone" or "a group" from the nature of the action; rarely identifiable as individuals	Artefact typology, craft traditions, activity signatures
Action	Inferred from material traces: Manufacture, use, deposition, breakage, construction, abandonment	Use-wear, refitting, spatial patterning, chaîne opératoire, feature morphology
Location	Precise spatial coordinates within a site or across a landscape; measured, not named	Excavation grid, GIS coordinates, stratigraphic position
Time	Relative (stratigraphic sequence) or absolute but imprecise (radiocarbon ranges, thermoluminescence)	Stratigraphy, radiometric dating, typological seriation

TABLE 3 Depositional events (sedimentary data).

Component	Content	Data source
Agent	Sometimes non-human: Gravity, water, wind, bioturbation, freeze-thaw cycles; or human agents acting unintentionally (trampling, dumping)	Sediment micromorphology, grain-size analysis, geochemistry
Action	Physical processes: Accumulation, erosion, flooding, collapse, compaction, burning — described in terms of physics and chemistry, not intentional	Depositional facies, soil horizons, microstratigraphy
Location	Defined by sedimentary unit boundaries; spatial but volumetric rather than point-based	Stratigraphic sections, micromorphological thin sections
Time	Often the least resolved: Duration of a deposit may span centuries; boundaries between events may be the only temporally sharp element	Sedimentation rates, interface dating, OSL, geochronology

may also be the result of natural processes without human intervention. Time is often a broad interval rather than a moment. And yet, depositional events are fundamental: they do produce the matrix within which archaeological and historical events are preserved, destroyed, or transformed.

The formal invariance of the tuple e_i = *(agent, action, location, time)* across these domains makes visible a gradient of epistemic directness. As we move from historical to archaeological to depositional events:

1. Agency dissolves—from named persons to anonymous actors to impersonal forces
2. Action shifts register—from described intention to inferred behaviour to measured process
3. Location gains precision but loses meaning—from named places to coordinates to sedimentary volumes
4. Time loses resolution but gains depth—from calendar dates to radiocarbon ranges to geological durations

This is precisely where the distinction between *time as a parameter and temporal information* becomes critical: the tuple assumes parametric time, but the actual evidence delivers temporal information of vastly different quality and nature depending on the data source.

3 Explicit vs. implicit space-time coordinates

In computer simulations of historical processes, an important distinction can be made between *explicit* time and *emergent* time.

Time is *explicit* when the model directly incorporates empirical chronological information, so that the time variable is the same as that used in time-stamped observations at specific spatial coordinates. Even in the case the time measurement (calendar date, radiocarbon estimate) is uncertain, the time variable remains explicit when its precision is represented through calibrated ranges, confidence intervals, or posterior probability distributions. For example, approaches that analyze the spread of cultural or economic phenomena using georeferenced radiocarbon dates use time as a known variable measured in calendar years. In these frameworks, each data point already contains both spatial and temporal coordinates, and the modeling procedure seeks to detect patterns in this explicitly defined space–time structure. By comparing the spatial distribution of dated evidence with theoretical expectations—for instance, those derived from diffusion models, migration scenarios, or environmental constraints—researchers can evaluate whether a proposed mechanism is consistent with the observed chronological pattern.

In contrast, models based on *emergent* time operate differently. In these simulations, time is not initially tied to empirical data, but instead the occurrence of different events appears to be ordered as a consequence of from the repeated iteration of behavioral or demographic cycles. The computed simulation goes through many cycles in which agents reproduce, move, or interact according to specified rules, and the process gradually unfolds across the modeled landscape. The total number of iterations required for each simulated phenomenon to fully develop—such as the expansion of farming populations—defines the internal sequential order of the model. However, the computed model is agnostic and indifferent to the number of real-world years corresponding to each iteration. Only after the simulation is complete, we do assign a suitable time scale to the iteration steps to compare with explicitly dated archaeological events and thus link them to calendar years.

This distinction between *explicit* and *emergent* time is a free development of Troitzsch (1998), who stressed that *explicit* structures operate top-down, in which higher-level variables or constraints—such as time and space—directly dictate lower-level individual behaviors through mathematical formalisms such as coupled differential equations or state transitions. In contrast, *emergent* structures arise bottom-up. They are macro-level phenomena that arise from micro-level agent interactions and stochastic processes, often defying simple prediction. Troitzsch integrates these into hybrid simulations, for instance combining partial differential equations for explicit diffusion with individual rules yielding unpredictable emergence.

Arnold (2016) also distinguished *explicit mechanisms*, which involve symbolic, propositional representations maintained in working memory, updated via deliberate computation, from *emergent mechanisms* which arise implicitly from statistical regularities (frequency effects, repeated iteration) without dedicated representation. This structural duality parallels the distinction we suggest between explicit and emergent time: time correlations versus iterative process generation.

The distinction between *explicit time* and *emergent time* follows logically from the prior distinction between *time as a parameter* and *temporal information*. It is, in fact, its operational consequence—it is what happens when a model or a discipline must decide how time enters its representations.

On one hand, when time functions as a parameter, it should be declared in advance: a variable *t* that the modeler defines, controls, and assigns to the system from the outside. The system evolves *along* this axis, but the axis itself is not produced by the system. It is given. This is how time is used by chronology, or by simulation parameters, by radiocarbon databases, etc. It is computationally tractable and allows events to be ordered, compared, and synchronized. But it does so at a cost: it assumes that the temporal coordinate is known, or at least knowable, for every event—and that this coordinate is meaningful in isolation.

On the other hand, time may be only embedded in the running of the model. It must be *extracted* from actions that appear ordered in a certain way. *Emergent time* is what results when temporal order, duration, or rhythm is not declared but arises from the order relationships among entities and events. Time is not a pre-existing axis along which things are placed; it is the structure that *emerges* from the way things relate to each other.

The distinction is not merely terminological. It has consequences for how we build models reproducing historical social dynamics *in silico* and how we explain them.

3.1 Time in equation-based models

Equation-based models, such as reaction-diffusion systems, describe large-scale patterns through continuous variables governed by differential equations. These models allow tracking of a quantitative property that varies continuously across *space* and evolves over *time*. Two processes drive the model dynamics. First, *reaction terms* govern local changes at each spatial location. Second, diffusion spreads this quantity from areas of high concentration to low ones, mimicking movement. Together, they produce emergent patterns without any apparent global coordinator. Reaction–diffusion models use *partial differential equations* (PDE) because they must describe how a quantity changes both *in time* and *across continuous space*. PDEs naturally combine local "reaction" terms (growth, decay, interaction) with spatial "diffusion" terms (movement, dispersal), allowing the model to capture travelling waves and heterogeneous spread patterns in a mathematically coherent way (Fisher, 1937; Kolmogorov, 1937; Kolmogorov et al., 1937; Skellam, 1951; Petrovskii et al., 2020). Reaction-diffusion PDEs are an approximation that can be obtained from integro-difference equations, which provide more precise results in ecological and archeological applications such as the spread of the Neolithic (e.g., Fort et al., 2007).

Many efforts for modelling the adoption of early farming in prehistoric Europe as a wave of advance phenomenon following this approach have been published in the last 30 years (Fort and Méndez, 1999; Vlad and Ross, 2002; Fort et al., 2007; Isern and Fort, 2010; Baggaley et al., 2012; Fort, 2012; Isern et al., 2012; Fort et al., 2016; Kabir et al., 2018; Eliaš et al., 2018; Fort and Pareta 2020; Tsai et al., 2020; Barbujani, 2021; Elias et al., 2021; Fu et al., 2021; Xiao and Mori, 2024; Fort, 2022a; Fort, 2023; Aoki, 2024; Fort, 2025; LaPolice et al., 2025). In all those applications, some variation of a reaction-diffusion model combines demographic growth ("reaction") with the spread of a new economic practice across space ("diffusion"). The models treat early farmers as a population whose density increased locally through reproduction while simultaneously expanding outward through mobility or migration, and bringing with them the farming practices adopted earlier in the original location. By adjusting growth and diffusion parameters, researchers can test alternative hypotheses about how environmental constraints, seafaring routes, or cultural transmission dynamics shaped the pace and direction of farming adoption across the Mediterranean basin.

A reaction-diffusion model of population growth and spatial spread requires, at minimum, the following empirical inputs:

- An estimate of how fast the population reproduces—typically a net reproductive rate (R_0) meaning how many surviving offspring each individual produces per generation (or equivalently, the initial growth rate $a = \frac{ln R_0}{T}$). This is a demographic parameter, often derived from ethnographic analogy with pre-industrial farming populations.
- How far individuals move per generation (a characteristic dispersal distance or an histogram of distances and probabilities), and what fraction of the population actually moves rather than staying put (a persistence or migration probability). These are also typically drawn from ethnographic data on mobility patterns.
- A map—a grid of cells covering the geographic area of interest, where each cell is classified (land, coast, mountain, sea) so the model knows where populations can and cannot go.

Time enters the model in two distinct ways:

- As the independent variable of the differential equation. Population density is a function of space and time: *P(location$_i$, t_i).* The equation tells how *P* changes from one moment (or generation) to the next. In the discrete implementations used for Neolithic spread models, this means iterating the simulation in steps of one generation (e.g., T = 32 years), updating every cell at each step according to the rules of reproduction, cultural transmission, and dispersal.
- As the clock that sets the initial and boundary conditions. The simulation must be anchored to a calendar date—a value for t_0. From that origin, the model runs forward, and the simulated arrival time of the population wave at any given cell can be compared to the independently known archaeological dates at that location.

Time is imposed as a mathematical parameter that governs the rate of change. The model does not answer "this happened the year *y*", or "the cause of occurrence of y_2 is the occurrence of y_1. It says "given these rates of growth and movement, the spatial distribution may have one of these alternative appearances after *t* generations". The empirical dates (radiocarbon chronology of Neolithic sites) enter only at two moments: to set the start, and to validate the output. Between those two points, time is purely parametric—it is the axis along which the equations unfold, not information carried by the data itself. Boundaries are also probability intervals calculated from ^{14}C estimates, with an implicit Gaussian distribution and a significant central point.

When *time* is explicit and introduced into the model as part of the input, then it ceases to be the unknown output of the model and becomes a constraint on it. What you can then estimate are the kinetic parameters that govern the process (Fort et al., 2012; Fort and Méndez, 1999; Fort et al., 2007; Isern and Fort, 2010; Fort, 2012; Isern et al., 2012; Fort et al., 2016; Fort and Pareta 2020; Fort, 2022b; Fort, 2023; Fort, 2025):

- *The front speed.* This is the most direct inference. If you know the dates of arrival at multiple locations, you can calculate how fast the wave moved.
- *The combination of growth rate and dispersal.* The classical Fisher-Skellam result states that front speed depends on both the net reproductive rate and the diffusion coefficient (which encodes dispersal distance and the probability of mobility). Knowing the speed from dated sites, and fixing one parameter from ethnographic analogy (say, the dispersal distance), you can solve for the other (say, the net reproduction rate). Alternatively, if you trust your demographic estimate, you can infer the effective dispersal range.
- *The relative contribution of demic* vs. *cultural diffusion.* This is the more refined use. In demic-cultural models (Fort, 2012), the front speed depends (weakly) on the cultural transmission parameter η. If time is known well enough to determine the speed precisely, then η can be bounded, although the speed's weak dependence on η means that only a broad upper bound can be obtained from chronological data alone, namely, $\eta < 2.5$ (Fort, 2022a). Genetic clines were needed to pin it down to $\eta \approx 0.02$ (Isern et al., 2017a).

The general principle is this: a reaction-diffusion model has three fundamental parameters: growth, dispersal, and speed. They are linked by an equation. In terms of our framework: when time is explicit—externally given, read from radiocarbon databases—it functions as temporal information that may be used to constrain the free parameters of the model. In other words, instead of allowing any mathematically possible wave of advance, the model must now reproduce the observed arrival of farming at specific locations by the recorded dates. This requirement filters out parameter values (e.g., growth and diffusion rates) that would make the front arrive too early or too late. As a result, the model's parameter space shrinks, and only those combinations that generate a spread consistent with the archaeological chronology remain admissible. In this way, the external temporal database turns a purely theoretical diffusion model into a data-constrained one, where both speed and pattern of spread are shaped by the empirical evidence.

This type of simulation requires a particular data structure (*x, y, t, archaeological information*) (Gkiasta et al., 2003; Manning, 2016; Manning et al., 2016; Martínez Grau et al., 2020; Huet et al., 2022; Castiello et al., 2025; Mazzuco et al., 2025). Researchers on the spread of the Neolithic (e.g., Pinhasi et al., 2005) present their data in this way because the reaction-diffusion model requires spatially and temporally indexed observations for calibration and validation. This format is not a departure from the event tuple e = (agent, action, location, time) — it is a specific encoding of it.

Location and *time* are explicit: *x, y* give the coordinates of the archaeological site, and *t* gives its radiocarbon date. Agent and action are implicit in the "archaeological information" field, since "Neolithic" already means: people who farmed, herded, made pottery, built settlements, reproduced, exchanged goods. The agent (inhabitants of a settlement) and the action (farming, reproducing, dispersing) are implicit in that field. What fills the "archaeological information" slot varies depending on the specific study: it might be the simple presence/absence of the archaeological evidence of farming (to check whether the simulated wave has arrived by that date at that location), or a haplogroup frequency (as in Isern et al., 2017b, to compare predicted vs. observed frequencies; see also Fort, 2022b; Fort and Pérez-Losada, 2024; LaPolice et al., 2025). The difference from the explicit tuple is a matter of resolution and directness, and not of ontological absence.

The reaction-diffusion model aggregates agents. The density $P(x, y, t)$ at a given grid cell corresponds to the quantity of agents, and this density is always generated by their actions—reproduction, farming, exchanging, etc. The grid cell itself circumscribes those agents: the population at cell (x_1, y_1) is distinguishable from the population at cell (x_2, y_2) precisely because the grid assigns them different locations.

When the spatial reference is enriched with a third coordinate z—elevation, drawn from a Digital Elevation Model—the grid gains topographic depth. Cells are no longer simple squares on a flat plane; they now carry information about altitude, slope, and rugged terrain. This enables the model to incorporate cost-surfaces: the diffusion coefficient need not be uniform across the grid but can vary according to the energetic or practical cost of traversing each cell. Mountain barriers slow or block dispersal; river valleys and coastal corridors channel it. The irregularities in the observed spread of farming—faster along the Mediterranean littoral, slower across the Alps, delayed into Scandinavia—become explicable not as anomalies but as consequences of a spatially heterogeneous diffusion landscape derived from the empirical topographical data. The model does not dissolve agents into nothingness; it dissolves individual agents into collective densities that are still located in a three-dimensional geographic space, still acting, still countable—just not individually named. And the richer the spatial information encoded in (x, y, z) is, the more finely the model can differentiate where and how those collective agents moved.

In some applications (Tsai et al., 2020; Eliaš et al., 2021; Fu et al., 2021), the intention is the equation itself, not the historical process. *Time* is not explicit in those papers because their goal is not to reconstruct what happened but to characterize what the equations can do. They ask: "given a system of partial differential equations describing two or three interacting populations, does a traveling wave solution exist? If so, what is its minimal speed? Under what parameter conditions does one wave profile appear rather than another?" In those models, *time* is implicit—present as the variable that makes the differential equation a differential equation, but carrying no date, no duration, no empirical content. *Time* is also *not emergent* in those models, because emergence requires that temporal information—however indirect—could be extracted from the results. Without identifiable locations and without calendar anchoring, no individual temporal event can be extracted. And if no event can be extracted, time cannot emerge. It remains what it was at the outset: the formal parameter of the equation, never converted into information about when anything occurred. These papers thus occupy a unique position in the spectrum: time is present as a variable, but it is neither explicit (given from outside) nor emergent (recoverable from the output). It is purely structural.

3.2 Time in agent-based models

Agent-based models (ABM) simulate autonomous agents following rules of interaction, adaptation, and decision-making. An agent represents an autonomous computational entity that simulates a decision-making unit, such as an individual prehistoric farmer, a household group, or even an entire settlement located on a gridded landscape. Different kinds of agents ("breeds": humans and animals, farmers and hunter-gatherers) can co-exist in the model, and their interaction is reproduced. These virtual agents operate independently within a shared virtual environment, constantly perceiving their surroundings—including neighboring agents, available resources, and local conditions—and then taking actions based on simple, predefined rules that mimic human-like decision processes- Natural processes and phenomena are included in the virtual environment as well.

These agents interact dynamically with their environment and other entities, producing emergent patterns like population growth or settlement nucleation that match archaeological data. Agents act as discrete expert systems receiving information (state of the environment at a particular moment) and behave according to specific plans (*if…then* rules), modifying the environment and themselves. Agents simulating households *decide* on actions such as planting crops, fallowing land, or relocating based on local carrying capacity and environmental feedback (e.g., cereal yield drops trigger fissioning). Survival hinges on utility maximization: agents balance energy intake against mortality risks via reproduction (age-structured), learning, and dispersal (Barceló and Del Castillo Bernal, 2016; Romanowska et al., 2021; Bernigaud, et al., 2022; Wunderlich et al., 2023; Grimm et al., 2025).

The goal of these simulations is to explore how agents simulating prehistoric individuals and their households may have taken decisions on migration, farming, gathering, hunting, fishing, and interact/exchange with other human agents (Wirtz and Lemmen, 2003; Van Hove, 2004; Drechsler and Tiede, 2007; Barton et al., 2010; Lemmen et al., 2011; Robb, 2013; Ortega et al., 2014; 2016; Bocquet-Appel et al., 2014; Saqalli et al., 2014; Bernabeu Aubán et al., 2015; Svizzero, 2015; Zanotti et al., 2015; Lane, 2023; Baum et al., 2016; Bergin, 2016; Vallée et al., 2016; Zhou, 2016; Dubouloz et al., 2017; Duering, 2017; Lemmen and Gronenborg, 2017; Pardo-Gordó et al., 2017; Lake, 2014; Bernabeu Aubán et al., 2018; Füzesi, 2019; Saqalli et al., 2019; Baum et al., 2020; Olives-Pons, 2020; Rudzinski, 2020; Bergin, 2022; Cummins and Morris, 2022; Pardo-Gordó, 2022; Pardo-Gordó and Bergin, 2021; Sikk, 2022; 2023; Lane, 2023; LaPolice et al., 2025). Differences among all these computer simulations of early farming societies and their territorial expansion concern primarily the geographical region under study -some are global world simulations, whereas others are restricted to some areas (Near East, Far East, Balkans, Iberia, etc.). Some of them simulate only the agricultural behavior cycle, others take emphasis on herding and the relationship between humans-animals, others investigate the consequences of social interaction, material exchange or genetic exchange.

In these simulations, each agent is defined by a set of attributes derived from real-world databases, producing a detailed profile that includes both fixed characteristics and dynamic states. For example, a settlement at a given phase can be represented as a single agent with a unique identifier, precise geographic coordinates (latitude and longitude) from GIS data, an initial timestamp indicating its founding date (such as a calibrated radiocarbon age like 9400 BP), population size at different moments, a farming adoption level ranging from 0 (pure foraging) to 1 (full agriculture), current resource stocks, knowledge or technology level, and a list of nearby neighbors based on spatial proximity. Static attributes, such as the terrain type at its location (e.g., alluvial plain or hilly slope), remain unchanged during the simulation, whereas dynamic variables are updated as the model runs.

Unlike equation-based simulations, artificial society models, based on the agent-based paradigm, use time primarily as an organizing framework for discrete interactions, where temporal and spatial patterns—cycles, delays, cascades—emerge from micro-level behaviors, decision rules, and network structures rather than being fixed in the equations. In these models, time arises from agent interactions rather than a fixed clock. The "historical tempo" the simulation run generates—pulses, pauses, leapfrogs—comes from feedbacks (resource depletion, density dependence, learning, competition), and not directly from the external database (Lake, 2020; Manson et al., 2020). Agents' actions are organized into behavioral cycles of fixed duration. In most cases, researchers implement relentless annual cycles that mirror the unyielding cadence of prehistoric farming life, from spring planting to winter dispersal decisions, (plow → grow → harvest → fallow or spring →summer→ autumn→ winter). Some other authors use alternative economic cycles (house repair, long-distance travels, generations) that imply longer time intervals that do not coincide with the seasonal rhythm of farming practices. Scheduling can be synchronous (all agents act simultaneously, with randomized order) or event-driven (agents self-schedule), thus modeling imperfect knowledge. Agents learn temporally by weighting recent vs. past events in memory, enabling studies of time-averaged archaeological records.

Consequently, *emergent time* is produced by the model's own scheduling: each timestep (or event) is one iteration of an economic cycle in which agents perceive, decide, act, and update state (stores, fertility, settlement choice, exchange ties). Whenever an agent performs some activity, the values of its relevant attributes change, reflecting the outcome of its decisions and interactions. This may even change the values of some parameters in the model, including the generation time each agent carries a state vector such as (x_i,y_i, t_i, $traits_i$). The model advances by applying rules that map the state from tick one to the next. Because the rules are applied repeatedly, every agent automatically produces a time-ordered log of x_t,y_t, t_t, $traits_t$, which is the raw material for building "temporal trajectories."

These successive updates of the agent's initial state have ripple effects: one agent's adoption might influence its neighbors in the next step, leading to cascading transformations across the population. In so doing, agents update state vectors at each time-step, according to their decisions and their participation in different activities that modify their landscape, and hence their activity over time. Successive states are written out as time-stamped GIS layers and exported as tables (CSV/GeoJSON) with agent identity, temporal position in a calendar scale, geographical coordinates and attributes at that temporal position. They can be queried as spatio-temporal databases, animated in GIS, or summarized into macro-observables like front position through time, residence-time distributions, or branching (fission) rates.

We can use the general data structure suggested throughout this paper as a logging format that captures every adoption-related change produced by the agent-based model's internal clock.

$$e_i = (agent_i, action_i, location_i, time_i)$$

Here, the event represents the typical actions that the model simulates ("first farming", "intensification", "abandonment", "reversion to foraging", etc). The agents can be a series of settlements, households, regions, or even individuals, depending on the model scale. Whenever an agent's farming state crosses a defined threshold (e.g., adoption level goes from <0.5 to ≥0.5), the program will append one record

$$e_i = (agent_A, \text{"first farming"}, x, y, time_1),$$

We can proceed in the same way for other transitions (e.g., "abandonment" when adoption drops below a threshold).

After the simulation run, we get a dataset of emergent adoption events: each row ties a *who* (agent), *what* (action), *where* (coordinates or cell ID), and *when* (model time step or simulated calendar year).

ABMs may also use *temporal information* as a hybrid construct. The start-up scenario may be pinned to a known date, with all parameters and values (even the agents' geographical location, the number of agents, technology, resource availability, environmental and soil features, etc.) sourced from external datasets. Endogenous execution generates a fine-grained sequence of economic actions (plant–harvest–store–consume–move) that reproduces history in the model.

Explicit time at start-up means the environment is altered over the run and it can be checked whether it follows an external time series (e.g., rainfall, temperature, productivity), so agents experience a dated sequence of constraints that they did not create. In so doing, climate fluctuations may act as stimuli that may trigger migration or population decline, effectively providing external perturbations that synchronize regional dynamics to known Holocene variability (Wirtz and Lemmen, 2003).

3.3 Spatio-temporal network models

Network-based models represent history as temporal event graphs, where nodes are events, agents, or entities and edges encode dependencies or associative relations. By studying the topology and dynamics of these graphs, we can identify central actors, key turning points, and structural dependencies behind complex sequences such as demic movements, cultural interaction, routes, and/or communication networks. Social network models handle time in two ways: explicit time via timestamped events, or emergent time through iterative network evolution (Ibañez et al., 2015; Claßen, 2004; Claßen et al., 2009; Coward, 2010; Coward, 2022; Bernabeu-Auban et al., 2013; Goring-Morris and Cohen, 2022; Mithen et al., 2023; Scharl, 2023; Bagheri-Jebelli 2024; Barrera-Cruz et al., 2024; Gürçal et al., 2026).

Nodes in a network model are more than static dots in a map. They usually represent a set of social agents at a particular location, performing some activity that had, in the past, a material consequence still observable in the present (archaeological excavation) (Knappett, 2013; Mills, 2017; Brughmans and Peeples, 2023; Brughmans et al., 2024). Therefore, nodes in archaeological social networks can be conceptualized as spatial-temporal events within a historical process by treating each node not merely as a static site or community, but as a localized, bounded episode of social activity—a point in spacetime where human interactions, decisions, and material practices unfold (Claßen, 2004; Claßen and Zimmermann, 2004; Brughmans, 2010; Peeples, 2019; Coward and Knappett, 2013). We can also distinguish strong *ties* (frequent, emotionally intense, reciprocal, trust-based relations) from *weak ties* (sporadic contacts that bridge otherwise separate clusters). Strong ties are particularly important for diffusing complex or high-risk innovations because they provide credibility, social reinforcement, and repeated exposure; weak ties act as brokers across structural holes, injecting novelty between clusters (Collar, 2022). Alternatively, other authors (Scharl, 2023) differentiate edges representing small-scale mobility (exogamy, seasonal herding, exchange) from edges representing longer-distance movements (knowledge transfer, specialist travel) since these brought innovations like pottery, metallurgy, or new tool technologies.

Spatially, the node is anchored to precise geographic coordinates (longitude/latitude) derived from excavation data, representing the physical locus where social relations manifested through artefact deposition, architecture, or subsistence remains, enabling the computation of Euclidean distances between nodes and the mapping of network structure onto the landscape. This allows us to analyze how settlement density, territorial organization, and regional clustering influence connectivity patterns.

Regarding time, a duration or interval can be assigned to each node, marking when those activities occurred. This transforms a timeless point into an event with meaningful duration in time. Since relationships between nodes may strengthen or decay over time, new topologies cascade through configurations of strong and weak tie clusters, producing identifiable phase transitions when connectivity thresholds enable rapid diffusion. These can be further investigated to discover whether they produced temporal waves of social/cultural/economic interaction, or instead bursts of connectivity that pulsed through the network at specific moments of time rather than flowing continuously. We see here that the network does not have a fixed architecture but a dynamically reconstituted system of relationships that were built again and again through social practice.

In this setting, we can consider each tuple e_i= ($agent_i$, $action_i$, $location_i$, $time_i$) as a timestamped interaction event and this, we can "grow" a time-ordered network whose nodes are people, and the places, and edges encode their farming-related relations. Each event e_i then defines one or more edges, depending on how social ties are referred to. For instance, if $action_i$ = "migration to farming village", then we will connect the origin and destination locations. We may as well connect the migrating agent to the households at the destination. And we should always explicitly attach $time_i$ to the edge as a birthdate, optionally adding a decay or death time too so that the same pair of nodes can be linked at multiple different moments.

To represent expansion through time, we need to maintain a sequence of network "snapshots" $G_{t_1}, G_{t_2}, \ldots$ or else a fully time-stamped dynamic network (De Nooy, 2011)

- Spatial layer: locations (sites, regions) become nodes in a spatial network; events at a site alter their attributes (e.g., proportion of farmers, crop repertoire).
- Temporal layer: edges from events with $time_i$ within a chosen interval (e.g., 200-year bin) belong to that snapshot; overlapping intervals give a moving-window diachronic network.
- Diachronic change: by comparing the network's values between successive G_t (density, centrality, modularity, component structure), it becomes clear how farming-related connectivity strengthens, fragments, or shifts geographically.

Time in this spatio-temporal network models becomes visible as a sequence of changing patterns, rather than in a single static map. At the start of the simulation, a sparse network of communities linked by a limited set of contacts is observed. As the model advances, each time step adds a new "frame" in which node attributes and ties are updated: some communities may cross the threshold into farming, their symbols changing colour or shape to signal adoption, while new links appear, strengthen, or disappear as interaction patterns evolve.

If we animate these frames, time is then experienced as movement: waves of farmer communities spread across the map, corridors of connectivity light up and then fade, and clusters emerge where dense ties accelerate adoption. The network's timeline can also be unfolded into event sequences, where each logged event (a community adopting farming, a tie forming, an alliance breaking) is placed on a common temporal axis. In this way, time is both a continuous animation of the network's changing geometry and a discrete series of time-stamped events, in this way allowing us to see not only where farming spread, but in what order, through which connections, and at what pace.

Besides diachronic networks as the one just described, spatially embedded social networks without timestamps can be defined to generate emergent temporal information as output. The basis for such an alternative network is the implementation of distance-weighted diffusion processes on static graphs (Fritz, 2018). Nodes do still represent georeferenced archaeological sites (e.g., Neolithic settlements across the Mediterranean basin, positioned via latitude/longitude in a GIS lattice). Edges then encode potential interactions (exchange, direct or indirect interaction, imitation) including weights representing Euclidean or least-cost geographic distance. No time parameters are needed as input.

In this new type of network, temporal emergence arises from iterative *message-passing* or *heat diffusion* on this static structure. Each event appears as a tuple, where (sender), (receiver) are nodes, plus locations (e.g., settlements), actions (e.g., "cultivate wheat", "herd sheep"), and the emergent timestamp (cycle count or hazard-derived). The network acts as an event history, annotating changes of state in the spatial nodes. There is no global clock here, and nodes activate stochastically based on local history.

In this way, time steps may be calculated from interactions—rather than being introduced as external input. "Time" emerges as the *step count until activation thresholds* are met—e.g., farming adoption, yielding per-node timestamps—. This results in a stream of *relational events* with internally generated timestamps. This data can be exported as an output file with emergent time *k*. The adoption threshold step can be exported for each node, geographically fixed at a particular location.

4 Discussion

4.1 Newton vs. Einstein

Some readers may consider that this paper is centered around a Newtonian conceptualization of *time* thus neglecting modern accounts (Einstein's relative time). Whereas time (explicit or emergent) can be considered as a measure, as exposed in this paper, Einstein's Theory of Relativity reveals that time is non-homogeneous and observer-dependent: each frame of observation generates its own rate of change, and therefore simultaneity is not a given principle.

This discrepancy between absolute and relative time could structurally be considered analogous to the shift in social theory from an external, measured clock-time to an internally *experienced* time. The intention is to keep a clear separation between (a) a common analytical time scale for measurement and comparison, and (b) diverse, situated temporal experiences (context-dependent), rather than collapsing the latter into a relativistic metaphor that undermines the former. Time used by historians is not the same as time experimented by social agents participating in the analysed historical phenomena.

In this paper, we emphasize the need for comparability across observers and the perceived (formally described and measured) historical events by them; this requires shared reference scales and traceability, instead of a fully observer-dependent time. The comparative and analytical study of social change assumes a particular ordering that can be expressed in terms of a common temporal axis (e.g., calendar years, standardized periods) so that different groups' trajectories can be aligned, correlated, and modelled.

In anthropology, *emic* refers to insider meanings and categories; *etic* denotes an external, comparative analytical framework. In that sense, we can distinguish an *emic time*—how actors named, structured, and felt time—from *etic time*: standardized metrics and typologies used to compare societies and identify regularities in processes of change. The latter must be as homogeneous and invariant as possible. The use of an *etic time* scale in the social sciences is a *convention* designed precisely to override subjective differences in pacing, allowing aggregation and explanatory inference. From this perspective, an epistemological approach that would use a sweeping Einsteinian "relativity" of time could be criticized as too broad epistemology: the relative, emic times may be the *object of study*, yet homogeneous, objectively measurable etic time is the requirement for their systematic analysis, and it is not something to be "dissolved" for the sake of relativity.

The conceptualization of etic time as a parameter that indexes the unfolding, successive historical events has profound implications for computing simulations of social processes, and in the emerging field of computational history too. When time is understood primarily as a measure of the rate and sequence of change, it functions as a tool, rather than as a container. Several profound methodological implications emerge for the explanation of model results and the ensuing construction of historical narratives. This perspective shifts the focus from time as an absolute, neutral backdrop to time as a dynamic, relational framework—one that is inseparable from the processes it measures.

4.2 Dealing with extension, duration and uncertainty

The data structure e_i= (*agent*$_i$, *action*$_i$, *location*$_i$, *time*$_i$) appear to be too *point-like* for many historical and archaeological phenomena. It looks as if it forces each event to a single location and a precise time scalar measurement, with no room for spatial footprint, temporal interval, or probability distribution over possible dates.

Certainly, historical and archaeological events cannot be considered unidimensional points in space–time because they are not instantaneous nor perfectly located (in space and time). A "site foundation", a "phase of occupation", or a "transition to farming" and other similar events unfold over a time interval, often involving multiple actions, actors, and places. Spatial extension is the fact that something occupies a portion of space with non-zero size, rather than being a point with no length, width, or height. In human terms, it is the *area* (or volume) within which actions actually occur, not just where they are theoretically possible. Historical and archaeological events have *duration* because their occurrence go on for days, years, centuries, rather than a single exact date. Moreover, both their spatial footprint and timing are known with *uncertainty*, constrained by dating errors, incomplete stratigraphy, and interpretive choices. Representing such events as simple points collapses their extension, duration, and uncertainty into a fictional perfect precision, which is analytically misleading, and distorts computer simulations hiding the extension, duration, and uncertainty of the events. Equation-based, agent-based, and network models might then be calibrated against an artificial precision, overfitting to single coordinates and dates that are, after all, only a rough approximation of the original event properties. This bias then impacts the calculation of spread rates, interaction strengths, and event sequences. Also, it makes it difficult to propagate dating uncertainty through the simulation.

Computer simulations should combine spatial *extension* ("where it was") with temporal *duration* ("when it lasted", "how long it took"). Spatial extension is typically encoded using polygons: each feature (e.g., a settlement, a land-use patch, or a flood extent) is stored as a vector polygon whose geometry can evolve over time. Temporal duration is encoded as time intervals attached to those polygons, specifying a start and end time values during which the feature exists or is valid.

Using this approach, *buffer zones* can be defined as spatial-temporal regions that extend both into geographical space and along the temporal axis. For an event E_i, the spatial extension of the buffer is the set of all locations whose distance from E_i is less than or equal to a fixed radius:

$$B_{\text{space}}(E_i, r) = \{q \in \mathbb{R}^2 \mid \text{dist}(E_i, q) \leq r\},$$

which forms a circular area (or polygonal approximation) centered on E_i. Similarly, the duration of the buffer is an extended time interval during which this spatial region is considered valid or relevant. The *spatio-temporal buffer zone* included all such spatio-temporal coordinates and results in a a cylindrical region in spacetime: a circular disk in space "persists" over a defined temporal interval, rather than being a mere circle on a static map.

In this way, the *spatio-temporal buffer* defines a 4D "cloud" of possible locations and times where an event (a battle, a settlement phase, a ritual activity) may have occurred. Instead of insisting on a single point in space and a single year, the historian uses the buffer to explore correlations—such as whether two events fall within the same spatio-temporal zone—while explicitly acknowledging the uncertainty in the sources.

An additional and probably more significant problem is that calendar dates and geographical locations are usually uncertain, given the ambiguity of historical sources. As a result, spatio-temporal coordinates may be given in terms of probability distributions, not points, reported with 95% confidence intervals (2σ). That means that the true location of the event lies somewhere inside, possibly multimodal (Ramsey, 2008). Yet the mean of the interval may be pulled in skewed distributions by outliers, which is common in older dates, thus violating the uniform prior assumption of simple calibration. The event might even be found *outside* the 95% HPD range. Therefore, it neither represents the mode or the maximum likelihood date, which should better approximates the most probable true date, but still misses the uncertainty span (Ramsey, 1997; Weninger et al., 2011; Carleton et al., 2018).

A possible solution would be to aggregate homogeneous series of radiocarbon dates—those from the same occupational layer that share similar formation contexts—into a "phase" model, assuming uniform temporal sampling within a "start" and "end" boundaries. Bayesian statistics allow pooling these calibrated probability density functions (PDFs) under a prior (a uniform distribution over the phase span), using Markov Chain Monte Carlo (MCMC) to sample joint posteriors. The model infers boundaries as hypothetical events that delimit each phase: all dates must lie between Start and End, tightening individual uncertainties through stratigraphic or prior constraints. The posterior marginals for each boundary emerge as PDFs, often approximately Gaussian (normal) due to MCMC convergence and central limit effects, especially with sufficient dates (>5–10). From this Gaussian-like PDF, a representative mean (highest posterior density mode or expectation) is extracted with ±1σ/2σ intervals, providing point summaries for further analysis while retaining probabilistic rigor (Ramsey, 2009; Molak et al., 2015; Price et al., 2021).

An alternative temporal aggregation method is *Binning*. It groups calibrated radiocarbon dates into discrete time blocks (bins) to create a robust scalar proxy for population trends via summed probability distributions (SPDs), while mitigating calibration noise, over-sampling bias, and multimodality. This procedure first thins out redundant dates within sites/phases, keeping one that is representative per "event". Then, it aggregates dates into fixed-width bins (e.g., 100–200 years), normalizing each bin's SPD to unity before global sum. The midpoint of the assigned bin (e.g., 5950 BC for 6000–5900 BC bin) becomes the scalar, robust to interval shape since normalization discards absolute probabilities (Ramsey, 1995; Scott et al., 2007; Crema et al., 2017; Castiello et al., 2025).

Several alternatives to standard fixed-width binning exist for handling radiocarbon intervals in archaeology, focusing on bias reduction, changepoint detection, and model-based aggregation rather than simple time slices (e.g., Crema and Bevan, 2021; Crema and Shoda, 2021; Castiello et al., 2025; de Navascués et al., 2025; Heaton et al., 2025; Roe et al., 2025; Rotunno and Crema, 2025).

Once properly estimated the start and end boundaries of the *duration* of an historical or archaeological event, we can conclude that they should be expressed, formally, as a 6D construct: $E = (x_c, y_c, z_c, r, t_s, t_e)$, where (x_c, y_c, z_c) is the spatial centroid (mean coordinates), $r > 0$ the isotropic extension radius (an spatial buffer in meters/km), and $t_s < t_e$ the start/end calendar dates. The spatial domain is the filled region $B_r(x_c) = \{x\colon \ \|x - (x_c, y_c, z_c)\| \le r\}$; temporally, the interval $[t_s, t_e]$.

4.3 Visualizing time

We finish this paper suggesting different ways to *see* time, after measuring it. Time can also be treated as an uncertain variable, represented through probabilities or probability intervals rather than as a single fixed point in time. Instead of treating time as an invisible parameter on a mathematical or formal model, we can picture it as an axis on a diagram, alongside space, so that every event in history becomes a point in a space–time picture, and every person, village, or institution traces a continuous line through that diagram.

The most common visualization is the map sequence: a series of spatial snapshots, each showing the system's state at a fixed moment. *Time* is represented as the succession of frames. An alternative is the space-time transect: a single spatial axis plotted against time, producing a two-dimensional diagram where the wave front appears as a diagonal line whose slope encodes the speed of advance. A third option would be the arrival-time map, where each cell may be colored not by its current density but by the date at which the wave reached it. Here, time is folded back into space as a chromatic gradient.

When we try to visualize historical occurrences, we see them as structured spatio-temporal events. Each event participates in a time-ordered sequence: founding a settlement, clearing land, harvesting, exchanging goods, migrating to a new location. Plotting these successive events on a diagram where the horizontal axes represent geographic space and the vertical axis represents time produces a curve—the complete record of that agent's passage through space and time. When the temporal placement of events is uncertain, the diagram should no longer be drawn as a single line, but as a probabilistic envelope that expresses likely positions on the calendar scale. Each event can be represented by a temporal interval with a degree of confidence, so its duration and ordering appear as overlapping bands rather than fixed points. In this way, the spatio-temporal trajectory becomes a field of possible paths, where uncertainty is visible and historical inference is shown as a distribution instead of a certainty.

Markov processes help by describing how that distribution evolves step by step over time, with each transition depending only on the current state, and not on the full sequence of past states. This formally satisfies the Markov (memoryless) property: the conditional probability of the future depends only on the given present conditions. This makes it possible to propagate uncertainty forward, estimate likely future states, and express results as ranges of probabilities instead of deterministic outcomes.

Within this approach, a *worldline* is the path of temporally ordered states of an entity experiencing some kind of transformation through space and time: where it was, what state was in, and at each moment (Arthur, 2006; Dominges, 1995; Raskin, 2008). Such a worldline appears as a complete curve in the joint space-time manifold—the unbroken record of an agent's spatial position as a function of time. This simultaneously answers: "where was this agent, and when?". Each point on the worldline corresponds to an event e_i; the slope of the worldline at any segment encodes the velocity of movement, the spatial displacement per unit time, and changes in slope reveal acceleration, deceleration, pauses, or sudden leaps. In this setting, historical change appears as bends, forks and crossings of these worldlines—moments when a community migrates, adopts a new economic practice, or transforms its social structure. The worldline of a farming household would encode the full diachronic biography of that agent in spacetime. A steep, nearly vertical segment would mean the household stayed in place for a long time (slow spatial change, fast temporal passage). A shallow, nearly horizontal segment would mean rapid migration over large distances in a short time—as we observe in the "leapfrog" colonization along the western Mediterranean coast (Zilhao, 2001; Isern et al., 2017a; Fort, 2022b), where farming spreaded at rates approaching ~8–10 km/year rather than the continental hinterland average of ~1 km/year. When multiple agents' worldlines are drawn on the same spacetime diagram, the result is a bundle of curves whose collective geometry encodes the macroscopic dynamics of the historical process under analysis:

- Parallel, closely spaced worldlines indicate a coherent population moving together at similar velocities—this is, a wave of advance.
- Diverging worldlines signal fragmentation, with subgroups pursuing different routes or settling at different times.
- Worldline intersections mark encounters: moments when two agents (or communities) occupy the same location at the same time, enabling interaction, exchange, conflict, or cultural transmission.
- Gaps between worldline bundles reveal barriers—mountains, seas, hostile territories—that delay or redirect movement.

Markov processes give us a simple rule for how worldlines change: the next step's state depends only on the current position in state space, not on the entire past worldline trajectory. This makes modelling complex historic processes mathematically tractable.

This problem is not unique to computational archaeology. It is the same problem that Minkowski addressed in 1908 when he proposed the geometrical unification of space and time in special relativity. A process that unfolds in space and time cannot be shown in its totality on a flat surface. Every visualisation is a projection, and every projection implies a theory of what matters—whether the observer privileges spatial pattern at a moment, temporal trajectory at a place, or the geometry of the wavefront itself. In Minkowski spacetime, events are points in a four-dimensional manifold, and the physicist's task is to slice this manifold into intelligible lower-dimensional representations—simultaneity planes, worldlines, light cones—each of which makes certain relationships visible at the cost of obscuring others. This analogy is structural, not physical. No relativistic effects operate in the spread of farming. But the representational challenge is identical: we embed social, cultural, and economic events in a unified geometric framework, where each possible change is a point, and influence can travel only within "historical light-cones" defined by contact, communication, or trade. This allows us to model social and cultural evolution as a network of probabilistic worldlines evolving in a shared spacetime, capturing both the constraints of temporal order ("what can affect what, and when") and the stochastic character of historical transformation (Figure 1).

In Physics, Minkowski spacetime defines dependence relationships through the light-cone: event A can influence event B only if B lies within A's future light-cone, bounded by the invariant interval $\Delta s^2 = c^2\Delta t^2 - \Delta x^2 - \Delta y^2 - \Delta z^2 \geq 0$. In social spacetime, no universal speed limit exists. Information and influence travel at very different speeds depending on technology, terrain, and social organisation—face-to-face contact spreads slowly and locally, while traded goods, symbolic practices, or transmitted knowledge can propagate across hundreds of kilometres within a single generation.

A complete representation of an historical event requires six dimensions: three spatial coordinates (x, y, z), one time coordinate t, and two uncertainty dimensions (σ_s, σ_t) capturing how precisely we know the location and date of the event. The spatial uncertainty σ_s reflects imprecise site mapping or surface survey error; the temporal uncertainty σ_t reflects chronological error, typically expressed as a calibrated radiocarbon posterior or Bayesian phase estimate. Each event is therefore not a point but a region—a blob—in this 6D space. The boundary of what is temporally related from a given event within one time step can be formalized as a dispersal kernel $K(x, t)$: a probability density function over displacement vectors that encodes how likely it is for a cultural practice or population to move from one location to another in a given time interval. Here, the kernel $K(x,t)$ is a probability density over displacements: for any possible movement from one place to another in a given time interval, it tells you how likely that movement is. Instead of assuming a sharp, circular frontier of influence (like a perfect light-cone), the dispersal kernel is estimated from real constraints such as terrain cost (how hard it is to move across the landscape), known mobility patterns, and the structure of routes or networks. The result is not a hard edge between "affected" and "unaffected" areas, but a smooth probability field showing which locations are more or less likely to be reached by a cultural practice or population in that time step.

Implementing this 6D representation introduces non-trivial computational challenges. Standard spatial indexing structures such as R-trees index d-dimensional data by grouping objects within nested minimum bounding hyperrectangles (MBHs). An R-tree index works by grouping data points into nested bounding boxes, allowing fast spatial queries (Dong and Wang, 2017; Leutenegger and Lopez, 2018). This works well in two or three dimensions, but as the number of dimensions grows, the bounding boxes increasingly overlap with one another. Once overlap becomes pervasive, the index loses its ability to eliminate irrelevant regions, and every query must scan nearly

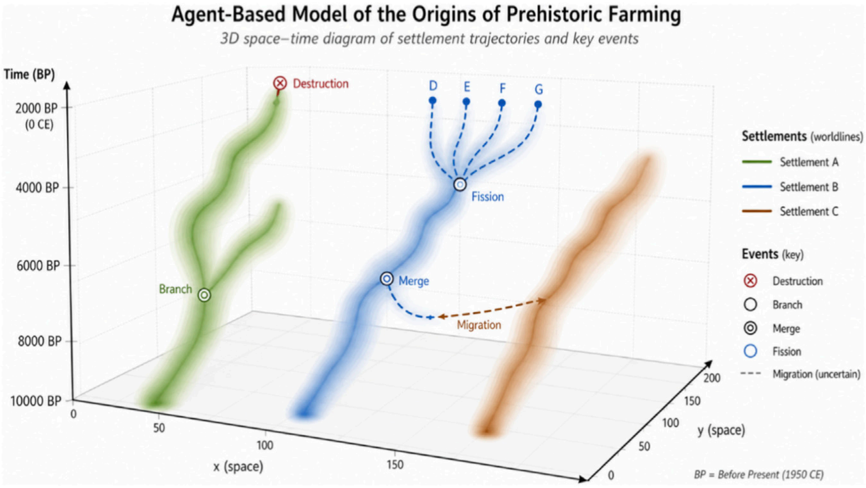

FIGURE 1
This 3D spacetime diagram represents the evolution of settlements through time and space in an agent-based model of prehistoric farming. Each trajectory traces one settlement's history, showing continuity, migration, branching, merging, fission, and destruction. Bands of different intensity express the probabilistic nature of some of the worldlines. Discontinuous segments mark migration, where a settlement relocates but remains the same agent. Branching and fission create new settlements, while merging shows aggregation. Together, the graph visualizes how local settlement dynamics generate broader patterns of expansion and reorganization.

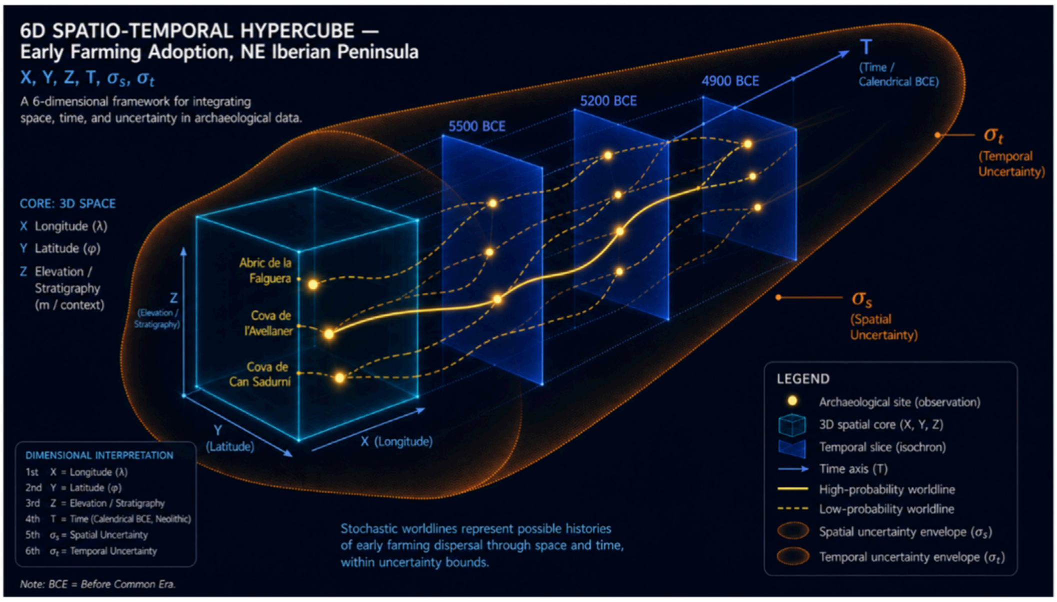

FIGURE 2
Six-dimensional spatio-temporal hypercube representing early farming adoption at three Neolithic cave and rock-shelter sites in the northeastern Iberian Peninsula (Abric de la Falguera, Cova de l'Avellaner, Cova de Sant Sadurní), ca. 5500–4900 BCE. The three spatial axes (X: Longitude, Y: Latitude, Z: Elevation/Stratigraphy) define the core 3D spatial volume (cyan wireframe cube). Vertical indigo planes mark isochronous time slices along the T axis (Calendrical BCE), discretizing the Early Neolithic sequence into three intervals. Each golden dot represents an archaeological observation—a site with associated material culture indicative of farming adoption. Solid yellow tubes are high-probability worldlines: the most likely trajectories of farming practices or human communities through spatio-temporal space, connecting site occupations across successive time slices. Dashed tubes are low-probability worldlines: alternative, less likely dispersal routes, reflecting the stochastic nature of cultural transmission and population movement. The width of each tube encodes local uncertainty—wider sections indicate intervals where chronological or locational evidence is poorly constrained, narrower sections indicate tighter, better-dated occupations. The outer orange glowing envelope along the σ_s axis represents the spatial uncertainty region: the probabilistic area within which the true geographic location of each event falls, derived from survey precision and site boundary estimates. The outer orange envelope along the σ_t axis represents the temporal uncertainty distribution: the calibrated radiocarbon posterior or Bayesian phase estimate associated with each occupation event, whose breadth reflects the inherent imprecision of radiocarbon dating at this chronological range. Note that the coordinates (X,Y,Z) of a site (e.g., Abric de la Falguera) are mean values over those of the recovered archaeological remains, and moreover each original value has a measurement error. Thus the values (X,Y,Z) of a site may change in time in general but for sites that did not rellocate (X,Y,Z) will be (approximately) constant.

all the data—no better than searching through the entire dataset point by point. This degradation is known as *dimensionality collapse*. In a 6D space with dimensions (x, y, z, t, σ_s, σ_t), the problem is particularly acute. The uncertainty extents σ_s and σ_t produce large, irregularly shaped volumes that differ enormously in size from one event to another. Bounding boxes around such volumes overlap almost everywhere, and the index becomes effectively useless.

Extensions of the R-tree designed for moving objects—known as TPR-trees—partially address the time dimension by tracking how bounding boxes shift over time. However, these were built for 2D geographic data with a time component and have not been successfully generalised to six dimensions. That generalisation remains an unsolved engineering challenge.

Beyond indexing, the fundamental obstacle is the curse of dimensionality. Uniform coverage of a d-dimensional unit hypercube requires data points that grow exponentially as $N \sim r^{-d}$, where r is the desired resolution per axis. For $d = 6$ and a modest resolution of 10 bins per axis, this implies 10^6 cells—but real archaeological datasets rarely exceed a few thousand spatially located events, so the occupancy of the 6D space is extremely sparse (Figure 2). Nearest-neighbour and kernel-density operations, which underlie dispersal modelling and worldline inference, become unreliable because in high-dimensional spaces the ratio of the nearest to the farthest neighbour distance converges to 1, making distance-based similarity measures effectively uninformative. Sparse-grid approximation schemes and tensor-train (TT) decompositions have been proposed to break this curse by decomposing high-dimensional integrals into sequences of lower-dimensional summations (Bigoni et al., 2016; Eigel et al., 2023), but their application to irregularly sampled, heterogeneous archaeological data remains methodologically underdeveloped.

Further complexity arises in uncertainty propagation through worldline inference. A worldline in this framework is not a curve in 4D but a stochastic process defined over the 6D manifold: a tube whose cross-section at each time slice is a 5D joint distribution over (x, y, z, t, σ_s, σ_t). Practical implementation requires either Monte Carlo approximation (particle filters or sequential importance sampling), variational Bayes methods that factorise the joint distribution into lower-dimensional marginals, or sparse tensor representations.

To adapt historical and archaeological data to a Minkowski-like spacetime, we must abandon the ideal of sharp point-events and work instead with probabilistic extended regions in space and time. Rather than points, each event becomes a subset of the 6D manifold: a spatial region (polygon, buffer, or kernel-smoothed probability field) and a temporal distribution (such as a calibrated radiocarbon posterior or a Bayesian phase estimate derived from stratigraphic constraints). Worldlines then become uncertain trajectories: not thin curves but tubes or bands of plausible paths of communities or cultural practices through spacetime, whose width reflects the compounded uncertainty on location and date. Processes like diffusion or Markov dynamics should be defined on latent *true* spacetime coordinates $(x_{\text{true}}, t_{\text{true}})$, while observation models integrate over the fuzzy 6D regions that we may infer from the empirical record. This preserves a Minkowskian spatio-temporal structure—events ordered by what can influence what—while acknowledging that the precise timing and location of many historical events remain indeterminate within error margins, so spatiotemporal order is sometimes only probabilistically or partially known.

5 Conclusions

In this paper we have developed an original distinction between "time-as-parameter" (explicit in equations) and "time-as-emergent-order" (arising from agent interactions). We show how each differently encodes assumptions about spatiotemporal dependence, inertia, and historical contingency. If a model uses *time* as input (e.g., calendar dates, radiocarbon estimates), it implies an explicit approach. Instead, if the model allows extracting time as output, it implies an emergent view of temporal information. This is an aspect that must be clarified when reconstructing timelines from computer-based simulations.

Emergent-time models have the advantage of helping reconstruct how a process may have unfolded dynamically in the past, because they explicitly represent the mechanisms that generated social/economic change over successive behavioral cycles. By focusing on local interactions between agents, institutions, and environments, such simulations enable us to trace how higher-level patterns of settlement, exchange, or social differentiation arise from repeated micro-level decisions rather than from imposed trajectories. This iterative perspective emphasizes contingency, feedback, and path dependence, showing how small differences in initial conditions or changing behavioral rules may lead to divergent historical outcomes, thereby enriching our understanding of "what if"under different assumptions.

Explicit-time analyses, on the other hand, excel at confronting hypotheses with empirical chronological evidence without the need to use many parameter values that would increase the uncertainty of the results. When models are anchored in time-stamped observations—such as georeferenced radiocarbon series—they provide a statistically robust means of evaluating whether proposed drivers of change (e,g., climate pulses, demographic pressure, or technological innovation) are temporally consistent with observed transformations in the archaeological record. This explicit spatial-temporal frame not only sharpens inferences about sequencing and duration but also constrains equifinality by ruling out scenarios that fail basic chronological tests.

Together, these approaches provide complementary perspectives: *emergent*-time simulations illuminate the possible dynamics of historical processes, while *explicit* space–time analyses offer a rigorous framework for testing explanations involving time sequences against the chrono-referenced archaeological record. Their combined use encourages a cyclical research strategy in which exploratory *emergent*-time models generate hypotheses about mechanisms and trajectories, *explicit*-time analyses evaluate these hypotheses against empirical evidence using a few parameters, and discrepancies between the two-prompt model refinement, new data collection, or theoretical revision. In this sense, integrating *emergent* and *explicit* temporality does not merely add methodological diversity; it is a necessary condition for a mature computational archaeology capable of linking formal processual narratives to the heterogeneous, incomplete, and traces of past lives.

Our effort in this paper has been directed at showing that *explicit* and *emergent* temporal information can be expressed as variations of a general data structure e_i= (*agent*$_i$, *action*$_i$, *location*$_i$, *time*$_i$). In emergent time scenarios, this tuple is the output of the investigation. In explicit time scenarios it is used as input and therefore it can be used to test the likelihood of emergent time simulations.

Using a unified spatio-temporal data structure with this shape provides a rigorous common ground for integrating otherwise heterogeneous simulation approaches. In explicit-time models, like in equation-based or reaction–diffusion formulations, spatial and temporal coordinates naturally serve as inputs. Observed archaeological states—e.g. the onset and termination of a cultural phase—can be encoded as time-stamped events attached to specific locations and then used to parameterize, calibrate, or validate the governing equations. For instance, front speeds or local growth rates can be fitted so that simulated trajectories reproduce the empirical start–end intervals associated with each site.

This shared representation enables systematic cross-analysis across modelling paradigms. Event sets derived from equation-based, agent-based, and network-based simulations can be merged into a shared spatio-temporal domain, supporting joint visualization, statistical comparison, and hypothesis testing. Crucially, emergent temporal patterns—for example, simulated adoption windows at each site—can be quantitatively checked against explicit-time archaeological evidence encoded in the same format, thereby strengthening model validation and genuinely facilitating integrative interpretations of past processes.

In conclusion, the complementary strengths of emergent-time and explicit-time approaches constitute a powerful synthesis for advancing the computer simulation of historical processes beyond isolated methodologies of mere technical interest.

Author contributions

JB: Funding acquisition, Software, Supervision, Project administration, Writing – review and editing, Conceptualization, Methodology, Writing – original draft, Formal Analysis, Visualization, Investigation, Data curation, Resources, Validation. JF: Project administration, Methodology, Funding acquisition, Writing – review and editing, Conceptualization, Investigation, Resources. AP: Formal Analysis, Methodology, Writing – review and editing, Conceptualization. OP: Conceptualization, Investigation, Formal Analysis, Methodology, Writing – review and editing. RB: Writing – review and editing, Data curation, Investigation. JN: Writing – review and editing, Formal Analysis, Conceptualization, Investigation.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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