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Opinion

Harmonizing nature's timescales in ecosystem models

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Modeling complex, nonlinear ecosystem processes across different timescales presents a significant challenge. We identify two key issues: selecting a representative timestep that captures interconnected processes across various timescales, and simulating these processes in an appropriate sequence. By synthesizing existing ecosystem frameworks, we find shared compromises between biological realism and computational performance. For the representative timestep, these include 'selective elimination of timescales', 'biting the bullet', 'each in their own time', and 'capture the unseen'. For processing order, we identify hierarchical, logical, iterative, and random approaches. Similar challenges exist in other disciplines, and we show how transferring methods from multiple fields, along with smarter computing, can improve timescale integration. Overcoming these challenges requires innovative transdisciplinary solutions, and we outline directions for future research.

Highlights

A central challenge in ecosystem modeling is accurately representing complex biotic and abiotic processes across different timescales, specifically finding a common model timestep and determining the computing sequence.

Existing ecosystem models either collapse or omit timescales, which can compromise biological accuracy, or include all timesteps, which reduces computational performance and increases uncertainty. These choices can lead to qualitative or quantitative errors and weaken predictive accuracy.

This temporal scaling problem pervades a diversity of disciplines – such as astrophysics, engineering, finance, meteorology, and artificial intelligence – generating the potential for knowledge transfer.

We argue that transdisciplinary solutions are key to harmonizing timescales. We illustrate one such approach, demonstrating concrete progress on multiple timesteps, and highlight opportunities for future research.

> 'How would you describe time?'. The Big Business Man smiled. 'Time' he said, 'is what keeps everything from happening at once.' 'Very clever' laughed the Chemist.
>
> [R. Cummings [1]]

Timing is key to accurately modeling complex ecosystems

Time is a central dimension in studying ecosystem dynamics, and many ecological questions can be understood only in the context of appropriate timescales [2–4]. This requirement makes selecting a representative timestep for ecosystem-scale modeling challenging because models must capture numerous interacting processes that operate nonlinearly across different timescales [5]. When processes cannot be represented with the same representative timestep, a sequence order must be decided, which is challenging given the nonlinear and simultaneous nature of complex systems [4,6]. These challenges persist despite recent advances in **ecosystem models** (see Glossary) [7]. We argue that a new approach to dealing with time in ecosystem models is necessary to meet these challenges.

Selecting a representative timestep for ecosystem-scale models requires balancing ecological complexity, uncertainty, and computational cost. Numerical integration methods efficiently approximate continuous time processes [6], but only when simulated processes operate at similar timescales. Linking processes at vastly different timescales (e.g., soil nitrogen fixation and tree growth) generally requires formulating them as separate sub-models, often represented by systems of differential equations. While these sub-models can operate at their own timestep, a representative timestep must still be chosen for exchanging information between them. Additionally, our conceptual understanding of processes at very short timescales is often limited [2,5,8], and including them might increase uncertainty and reduce confidence in the model output. For

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example, we cannot predict the exact behavior of an ant at the millisecond level, nor can we understand how this influences ecosystem productivity and resilience over decades.

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Modeling processes at such fine temporal resolution may be unnecessary at ecosystem level if we have robust mathematical formulations or observed relationships to approximate fast processes over longer timesteps. However, high-quality data for such **parameterization** are often unavailable. Further, if the model timestep is longer than the timescale of underlying processes, closely coupled processes become unsynchronized and compromise the model's predictive capacity. For example, insufficient synchronization frequency of gas exchange processes at the leaf–atmosphere interface (Box 1) can cause mismatches between plant productivity, soil moisture, and atmospheric conditions, disrupting the balance of energy, water, carbon, and nutrients in the model [9], and yielding erroneous predictions about ecosystem processes [10], especially under new conditions. The sign of such predicted errors can be altered by the order in which processes are computed.

Similar challenges in selecting representative timesteps and processing order arise in many fields, including physical sciences, life sciences, and social sciences [11]. Here we discuss limitations in how current models address these challenges and explore how insights from multiple disciplines and **smarter computing** can improve time representation in ecosystem models. We argue that **transdisciplinary research** is crucial for developing innovative solutions to handling the flow of time. While we focus on ecosystem models, these insights will likely have wider applications.

Current ecosystem models compromise on physical, functional, or computational level to achieve a common timestep

A number of **general ecosystem models** and **end-to-end models** have been developed for terrestrial and aquatic ecosystems [7]. Additionally, many models simulate ecosystem dynamics

Box 1. Timing sensitivity of leaf gas-exchange processes and potential ecosystem-wide implications of temporal mismatches

Simulating complex systems often requires breaking them down into smaller components based on physical, functional, or computational considerations. An ecosystem model could be divided by structure (atmosphere, soil, plants, animals) or function (C3 versus C4 plants, herbivore versus carnivore), with each component further subdivided for computation.

Compartmentalization can result in components operating at different timescales, decoupling processes that occur simultaneously in nature. For example, water and gas exchange at the leaf–atmosphere interface requires the timing of stomatal opening and closure to align closely with atmospheric dynamics and soil moisture [61]. Atmospheric turbulent dynamics and hydrological processes are best represented at timescales of seconds to hours [62], whereas plant growth can be approximated monthly based on average atmospheric conditions [63] or one representative day per month[ii]. A sub-daily model timestep requires plant acclimation to be computed explicitly at the cost of increasing parameter requirements and computational demand [64]. A longer model timestep risks mismatches between plants, soil moisture, and atmospheric conditions which can disrupt the balance of energy, water, carbon, and nutrients, leading to erroneous conclusions about ecosystem functioning and incorrect estimates of ecosystem performance [9].

Specifically, we might observe the following cascade of events: leaf area index and plant productivity are overestimated because available soil moisture is not depleted. Overestimated leaf area index affects the microclimate experienced by species [10], modifies the hydrological cycle [65], and allows excess herbivory. Overestimates in herbivore abundance cascade through the food web [66] and feed back onto plant biomass [67]. Overall higher trophic activity increases soil nutrient levels and alters spatial patterns of nutrient availability which mediates soil microbial community structures and enzyme activity [68]. Higher microbial activity provides more plant-available nutrients which positively feeds back on growth [69].

If such mismatches are systematic and can be quantified, we can adjust our expectations accordingly. However, mismatches may also lead to qualitative shifts in ecosystem dynamics over long timescales, driven by the order in which these processes are simulated. Focusing on one process as an example: for ecosystem primary productivity and the interaction of vegetation with regional climate, it matters whether plant growth is simulated before herbivory or afterwards. A shift of resources resulting from changing the order in which these processes are simulated could affect predictions about ecosystems such as the Amazon rainforest [70] or the North African Sahel region [71] that can potentially tip between different stable states.

based on a subset of ecosystem components (e.g., **hydro-ecological models** [12], **dynamic global vegetation models** [13], or **individual-based** forest gap models [14]). While these models have made notable progress in balancing biological realism with computational performance, they rely on compromises to address the challenges of multiple timesteps. Such compromises are typically guided by the model's intended purpose – whether to enhance understanding of ecosystem dynamics [15], predict ecosystem responses under alternative scenarios [13], or inform management decisions [16] – and the sensitivity of the system to timescale choices, which can vary depending on the processes being modeled [17,18]. Here we discuss the trade-offs and implications of four commonly used approaches to dealing with multiple timescales.

Selective elimination of timescales

The commonest approach to dealing with multiple timescales is to focus on one timescale in detail while ignoring slower or faster processes (Table 1, see section A). This **separation of timescales** approach, rooted in chemistry [19] and Michaelis–Menten enzyme kinetics [20], enhances computational performance while capturing the focal processes, but risks missing other important interactions and extreme events [21]. The absence or misrepresentation of such interactions might lead to misestimates of **ecosystem performance** and incorrect conclusions about ecosystem functioning (e.g., estimates of terrestrial primary productivity [9] or fish recruitment [22]).

Selective elimination of timescales is widely applied outside ecology, ranging from analyzing fast and slow spikes in brain activity of monkeys performing spatial attention tasks [23] to studying the temporal evolution of stars like the sun [24]. The approach's limitations remain here as well: many unresolved issues in stellar theory stem from the breakdown in these assumptions due to departures from a dynamical equilibrium [24,25].

Biting the bullet

The 'biting the bullet' approach simulates all processes at the timestep of the fastest component (Table 1, see section B). This approach enables close process coupling and biologically realistic representation of system dynamics (e.g., leaf gas-exchange) (Box 1) but is computationally expensive. Additionally, processes need to be well understood and accurately represented at the fast timescale, which is often not feasible. Ecosystem models often bite the bullet in short-term experiments to assess whether high temporal resolution improves quantitative predictions or impacts qualitative system behavior. For instance, daily fluctuations in marine biomass productivity can be represented on a monthly timescale [17], but daily plant–pollinator interactions significantly differ from seasonal networks [18].

Complex models in other disciplines have well-established high-performance computing protocols to run long-term experiments at high temporal resolution which ecology could adopt, but this is inevitably a costly approach. For example, simulations in the Coupled Model Intercomparison Project phase 6 took several years – 21 **Earth system models**, 190 experiments, 40 000 years of simulation on sub-daily timesteps – producing a total of 40 PB of data and an estimated carbon footprint of 1692 t of CO_2 equivalent [26]. Simulating the evolution of the universe took over 50 million processor hours over 2 years [27].

Each in their own time

Models may simulate processes 'each in their own time' and exchange information at a common slow timestep (Table 1, see section C). Subcomponents can be simulated at appropriate timescales, which optimizes computational costs and biological realism of individual processes

Glossary

Big data: large, complex datasets generated at high frequency from various sources which require advanced tools and techniques for storage, processing, and analysis.
Dynamic global vegetation models: models that simulate vegetation dynamics and their responses to climate change and other environmental factors on a global scale.
Earth system model: model framework to simulate the interactions between the atmosphere, oceans, land, and biosphere to understand and predict climate and environmental changes.
Ecosystem model: here defined as a mathematical or computational representation of complex ecological systems, which can range from comprehensive models that simulate entire ecosystems to more focused models that examine specific subsystems or interacting processes.
Ecosystem performance: the capacity of an ecosystem to maintain functionality, productivity, and resilience while supporting biodiversity and ecosystem services.
End-to-end models: models that simulate the entire ecosystem from the base of the food web (e.g., primary producers such as plants or phytoplankton) to the top predators, covering all trophic levels in between. The aim is a comprehensive, detailed representation of specific species, their interactions, and how energy or matter flows through the system. End-to-end models are often used in fisheries or specific ecosystem studies where capturing the entire food web and its complexity is critical.
Game theory: a mathematical framework to analyze strategic interactions among individuals or groups, where the outcome for each participant depends on the decisions of others.
General ecosystem model: a model that simulates a wide range of ecological processes but often simplifies certain components to create a more abstract or generalized view of ecosystems. This approach provides broad insights into how ecosystems function by focusing on key dynamics like nutrient cycles, energy flows, and population interactions, but may not include all specific components or species in detail.

(e.g., daily hydrology/grazing and monthly vegetation dynamics) [28][i]. However, the slower communication interval can potentially miss short-term feedbacks and emergent properties such as resilience to rapid extreme events [21]. Multi-timestep approaches have a long history in engineering (e.g., [29]), where they are applied to practical problems such as predicting how a building with a shock-absorbing base will respond to an earthquake [30]. In finances, multi-timestep approaches are key to asset management [31] and financial crisis forecasting [32].

Capture the unseen

Models may 'capture the unseen' by approximating processes that are not directly accounted for, because they are faster than the model timestep or they are not well understood. This parameterization uses simplified equations or relationships derived from observations, experiments, or experts [33]. The opposite of biting the bullet, these models compromise on high temporal detail to enhance computational performance (Table 1, see section D). Examples include ignoring 'chemical reactors' in animal guts [34] or sub-daily hydrological processes in some general ecosystem models [35]. Because these approximations are not process-based, predictions are reliable only within the known observed limits and may not be transferrable between systems [36]. This is similar for numerical weather prediction where physical parameterizations are commonly used to approximate chemical processes, convection, and precipitation [37].

Decisions on process order can introduce errors

In some ecological dynamics the sequence of events is straightforward, such as the requirement that animals must be born before reproducing. However, the order is less clear when processes happen simultaneously in reality but are compartmentalized in a model with a timestep slower than the process. This problem is straightforward to solve only if all ecosystem processes of interest operate at a similar time scale, in which case a single set of differential equations can be simultaneously evaluated. In all other cases, erroneous choices of sequence may cause ecosystem models to yield inaccurate estimates – both qualitative and quantitative – of ecosystem performance, which could lead to flawed conclusions about the overall ecosystem functioning. For example, for ecosystem primary productivity and the interaction of vegetation with regional climate, it matters whether plant growth is simulated before herbivory or afterwards (Box 1). Most ecosystem models organize processes in hierarchically nested structures [2,38]. As illustrated in the following, the ordering could also be logical, iterative, or randomized.

Hierarchical process order

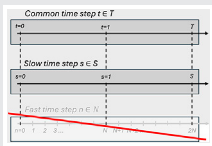
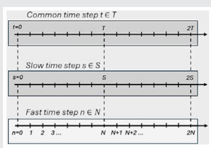
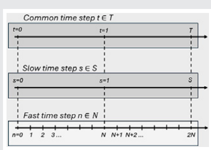
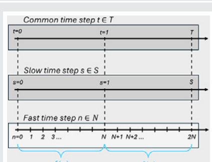
In hierarchical approaches, processes are executed in a consistent predefined sequence within each timestep (Table 2, see section A). In many ecosystem models, the physical environment is determined first, followed by reactive vegetation and animals [35]. Feedbacks from biota to the abiotic environment are usually not considered. While this approach simplifies model design and interpretation, it may introduce systematic biases. Hierarchical process order is also common in hydrodynamic simulations of star formation to manage the separation of timescales (turbulence > chemistry > radiative transfer [39]), and in dynamic supply chain management [40].

Logical process order

A similar, more reasoning-based approach is temporal logic (Table 2, see section B). This framework uses conditional dependencies and operators like 'always' and 'next', with a verification step ensuring that processes occur dynamically based on earlier outcomes (e.g., thresholds or triggers) [41] (Table 2, see section B). Hierarchical order, by contrast, is structured around a fixed priority or scale, with processes arranged according to their perceived importance or temporal scale. While temporal logic provides a clear and mathematically rigorous way to describe the order and duration of events over time, the computational cost of the verification process

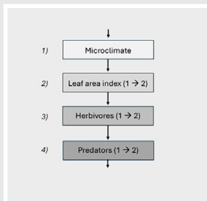
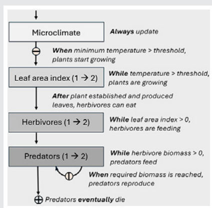
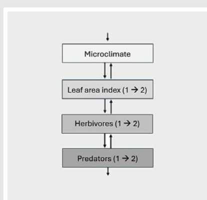
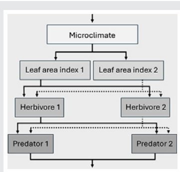
Hydro-ecological models: models that focus on the interactions between water cycles and ecological processes, often used to study the effects of hydrological changes on ecosystems.
Individual-based models: models that simulate the behavior and interactions of individual organisms within an ecosystem; often used to study population dynamics and community structure.
Parameterization: a method used to approximate processes that occur faster than the model's timestep by using simplified equations or relationships based on observations. Instead of explicitly simulating these processes, parameterizations summarize their effects on the system. The approach assumes that fast processes reach equilibrium quicker than slower ones, allowing their behavior to be captured through parameters describing the equilibrium state.
Separation of timescales: a concept that assumes that certain parts of a system operate so much faster than others that they can be treated as if they have reached a steady state, allowing the faster components to be eliminated for a simplified system description. Parameterizations are achieved through separation of timescales.
Smarter computing: the application of new mathematics and algorithms, advanced computing methods, efficient programming languages, high-performance computing infrastructure, and collaboration with software engineers to enhance model simulations.
Transdisciplinary research: research that integrates knowledge across academic disciplines ('interdisciplinary research') and involves non-academic stakeholders to address societal challenges, aiming for solutions that are practical and beneficial to society.

Table 1. Common approaches to dealing with multiple timescales in complex models, underlying mechanisms, strengths, and limitations, and examples from ecology and other fields[a]

Approach	Mechanism	Strengths (+) and limitations (–)	Examples from ecology ( ) and other fields ( )
(A) Selective elimination of timescales		+ High computational performance + Appropriate timescale and level of detail for processes of interest + Faster or slower less-well-understood processes can be treated implicitly – Risks for decoupling important interactions and feedbacks	Terrestrial ecosystem models use average climate conditions to simulate animal and vegetation dynamics [9] Many marine ecosystem models of intermediate [16] and high [72] complexity focus on economically important species Enzyme kinetics separate timescales to simplify the analysis of complex biochemical reactions [20] Astrophysical simulations separate timescales to model the of temporal evolution of stars [24] Neuroscience models separate timescales to analyze fast and slow spikes in brain activity of monkeys performing spatial attention tasks [23]
(B) Biting the bullet		+ Close process coupling + High level of temporal detail for all processes – Computationally expensive – All processes need to be well understood and accurately represented at the fast timescale	General ecosystem models test different timesteps to identify qualitative or quantitative biases, e.g., daily versus monthly fluctuations in marine biomass productivity [17], daily versus seasonal dynamics in plant–pollinator networks [18] Earth system models simulate climate dynamics over centuries on a sub-daily timestep (e.g., CMIP6) [51] Cosmology models simulate the complete evolution of the universe over millions of years [27]
(C) Each in their own time		+ Optimized computational costs + Appropriate timestep and level of detail for all processes + Implicit representation of not so well-understood processes – Slower communication interval risks decoupling – short-term interactions and feedbacks	Systems dynamics models run with multiple process- and objective-relevant timescales, for example monthly vegetation and daily hydrology [28] or daily grazing[i] Engineering uses multiple timestep models to predict how a building with a shock-absorbing base will respond to an earthquake [23] Finance models apply multi-timestep methods in forecasting and asset management [31], and for financial crisis forecasting [32]
(D) Capture the unseen		+ High computational performance + Implicit representation of not so well-understood processes – Risks for decoupling important interactions and feedbacks – Low representations of detail for fast processes	Terrestrial ecosystem models implicitly consider how chemical reactions in animal guts drive foraging behavior in the context of whole ecosystem dynamics [34] General ecosystem models ignore hydrological processes faster than 1 day because the longer-term dynamics in a small landscape can be effectively captured with a daily timestep [35] Numerical weather forecasting parameterizes many fast or not well-understood processes like radiation and chemical processes, convection, cloud physics, and precipitation [37]

[a]Models often use more than one approach to coordinate the processes on a slow timestep $s \in S$ and a fast timestep $n \in N$ into a common model timestep $t \in T$. (A) The 'selective elimination of timescales' approach simulates processes occurring on one timescale in great detail while ignoring slower or faster processes. In this example, fast processes are omitted and $S = T$. (B) The 'biting the bullet' approach means that all processes are simulated at the fastest timestep with potentially high computational costs and $N = S = T$. (C) The 'each in their own time' approach allows submodules to run with their respective timestep and communicate at a common timestep. Models maintain their respective timestep s and n, and communicate at frequency of t, thus $S = T = 2N$. (D) The 'capture the unseen' approach uses parameterizations to represent fast processes during slower timesteps without explicitly simulating them. This approach assumes that processes on faster timescales are at equilibrium on the slower timescale and use parameters to describe the steady state conditions. In this example, the processes happening on the fast timescale are described with a function $f(n)$ over the interval t and the returned proxy variables communicate with the slow model on common timestep t, thus $S = T = f(n)$. More details on the examples are given in the supplemental information online.

Table 2. Common approaches to dealing with processing order of simultaneous processes in complex models, underlying mechanisms, strengths and limitations, and examples from ecology and other fields[a]

Processing order	Mechanism	Strengths (+) and limitations (–)	Examples from ecology ( ) and other fields ( )
(A) Hierarchical		+ Simple model design and easy interpretation – Systematic advantage for some components	Terrestrial ecosystem models simulate abiotic environment first, followed by reactive vegetation, and finally animals [35] Hydrodynamic simulations of star formation simulate turbulence first, followed by chemistry, and finally radiative transfer [39] Dynamic supply chain management often uses hierarchical approaches to coordinate procurement, production, and distribution across organizations [40]
(B) Logical		+ Clear and mathematically rigorous way to describe the order and duration of events over time – Computationally expensive	NatureTime presents a temporal logic reasoning framework specifically adapted for ecological modeling [42] Computer sciences use temporal logic to schedule the execution of programs in operating systems, synchronize real-time processes and systems, manage databases with multiple users, and model dynamic behaviors in artificial intelligence, agent-based systems and robotics [41,43]
(C) Iterative		+ Minimizes risk for desynchronization of processes and pools – Computationally expensive – Risk for overfitting to historical data	Microclimate model uses iterative approach to derive ground and canopy heat exchange surface temperatures[ii] Iterative near-term ecological forecasting cycles between analyzing data and updating predictions with new observations to continuously refine models, improve ecological forecasts, and support adaptive decision-making and basic science [44] Iterative supply chain models continuously refine strategies across multiple planning periods to respond to disruptions, improve efficiency, and align operations with evolving market dynamics [40,45]
(D) Random		+ Stochasticity can offer more balanced and realistic representation of ecosystem dynamics + Prevent systematic bias from linear process order – Computationally expensive – Difficult to interpret results	Terrestrial ecosystem models randomize feeding order of functional groups to remove artificial competitive advantage [17] The Gillespie algorithm is used in systems where discrete events happen randomly at different rates [6] Delivery companies employ stochastic optimization techniques to find reliable routes among varying conditions such as shipping volume, time constraints, vehicle availability, and road closures [46]

[a]For clarity, a subset of processes is selected for each graph. (A) The 'hierarchical process order' approach implies that processes are executed in a consistent predefined sequence for each timestep. Here the microclimate is calculated first, plants second, then herbivore 1, herbivore 2, predator 1, and predator 2. (B) In the 'logical process order' approach, processes are also executed in a predefined order; however, the arguments are based on reasoning in the form of '*x* has to come first' or 'threshold *y* has to be crossed before *z* can start'.(C) The 'iterative process order' approach iteratively cycles through closely linked processes, gradually refining the outcomes at each step. Here, the resulting process order is also identical to the hierarchical approach, but the prediction error is likely reduced.(D) The random process order approach introduces a degree of stochasticity which can offer a more balanced and realistic representation of system dynamics. Here, the order in which leaf area index 1 and 2, herbivores 1 and 2, and predators 1 and 2 are simulated is randomly chosen at each timestep. More details on the examples are given in the supplemental information online.

limits its feasibility for large complex systems. Other limitations arise when model components operate at different temporal resolutions or involve cyclical processes, as is common in ecological models [42]. Computer science uses temporal logic extensively for scheduling the execution of programs in operating systems, synchronizing real-time processes and systems, managing databases with multiple users, and modeling dynamic behaviors in artificial intelligence (e.g., agent-based systems and robotics [41,43]).

Iterative process order

Iterative cycling through closely linked processes while gradually refining the outcomes at each step can enhance communication between system components (Table 2, see section C). Some microclimate models use iterative approaches to derive equilibrium ground/canopy/air temperatures[ii], and near-term ecological forecasting uses the approach to continuously integrate new data, improve ecological forecasts, and support adaptive decision-making [44]. While iterative cycling minimizes the risk of pools becoming desynchronized and consequent mis-estimations of state variables and overall ecosystem performance, it can be computationally expensive. Like iterative ecological forecasting, iterative supply chain planning involves continuously refining decisions and strategies across multiple planning periods to respond to disruptions, improve efficiency, and align operations with evolving market dynamics [45].

Random process order

Randomizing processes within biological constraints adds an element of stochasticity that can prevent systemic biases arising from a fixed process order and offers a more balanced and realistic representation of system dynamics (Table 2, see section D). Models randomize the ordering in which functional groups feed to prevent any one group gaining an artificial competitive advantage in the model [17], or apply the Gillespie algorithm in systems where discrete events happen randomly at different rates [6]. Similarly, delivery companies employ stochastic optimization techniques to find reliable routes given variables such as shipping volume, time constraints, vehicle availability, and road closures [46]. However, randomizing process order can complicate the interpretation of model outcomes, requiring additional simulations to disentangle deterministic patterns from stochastic behaviors, thus increasing computational complexity.

Leveraging insights from different fields could benefit ecological modeling

Some of the remaining challenges in dealing with multiple timesteps and processing order could be mitigated by faster computing that utilizes new hardware or algorithms (e.g., biting the bullet, iterative processing order). Other approaches require collaborative innovations and out-of-the-box thinking (e.g., selective elimination of timescales, temporal logic). We propose three complementary research directions to address the remaining numerical challenges, gaps in conceptual understanding, and lack of data: methods transfer, smarter computing, and transdisciplinary research for collaborative innovation (see Box 2 for a hypothetical example).

Methods transfer

Approaches constrained by the numerical complexity of ecosystem processes could employ methods developed in other fields to avoid the computational cost of high temporal resolution and allow for flexible process complexity. A partial solution for addressing 'biting the bullet' could be variable timestep models for energy systems [47] which reduce the timestep during highly fluctuating conditions (e.g., storms) and increase it during stable periods (e.g., at night). This temporal 'zoom-in' technique is itself inspired by spatial adaptive mesh refinement methods used to simulate climate [48] or galaxy formation [49]. The method could capture the effects of short-term extreme weather events or human intervention (e.g., burning, species introduction) on long-term ecosystem dynamics. Similarly, multi-adaptive timestep numerical integration methods can choose a separate optimal timestep for each subsystem of a more complex model [50] but are under-utilized in ecology.

Smarter computing

Modeling approaches limited by computational capacity (e.g., biting the bullet, iterative approaches) could benefit from recent advances in computing and mathematics. New algorithms provide efficient numerical methods for solving physiologically structured population models [51]. Cloud-based computing has accelerated iterative ecological forecasting, advancing research and providing decision-relevant information to stakeholders [52]. High-performance computing, including graphic processing units, has revealed complex system properties such as social inequalities in access to ecological public goods [53]. Collaborating with software engineers to optimize performance through efficient programming and unit testing promises novel insights into tropical rainforest resilience [15]. Ultimately, smarter computing allows simulation of ecological processes at increasingly finer spatiotemporal resolutions, aligning more closely with the scales at which organisms and ecosystem operate [54]. The example workflow in Box 2 illustrates how adaptive time algorithms exemplify this potential for 'smart' computing.

Collaborative innovation

While technological advances can address the computational constraints on the timestep issue, solving the conceptual problem of representing complexity across different timescales in a meaningful order requires innovative ideas (e.g., selective elimination of timescales). Transdisciplinary research can spark innovative solutions through cocreation of knowledge [55] and by offering new perspectives on time [3]. For example, indigenous groups and artists can challenge conventional ways of thinking and help codevelop new ecological theory and modeling concepts [56].

The Sustainable and Healthy Food Systems project is a successful example of transdisciplinary research that contributed substantially to policy in the UK, South Africa, and India, resulting in

Box 2. Example workflow for managing flood risk in tropical ecosystems through 'harmonized' ecosystem modeling

Managing flood risk in tropical rainforests requires balancing biodiversity conservation, sustainable land use, and local needs. Achieving this balance depends on understanding ecological processes, environmental change, and human decision-making, each operating on different timescales, from rapid hydrological flows and vegetation responses to long-term recovery of natural ecosystems and policy implementation. A transdisciplinary modeling approach can help to integrate these factors to minimize qualitative and quantitative prediction errors, and support effective flood management.

Step 1: define stakeholder contributions, priorities, and model strategy

Managing flood risk requires input from diverse stakeholders. Ecologists, hydrologists, and climate scientists provide insights into natural processes. Software engineers develop and optimize modeling tools. Local communities and land managers offer contextual knowledge and practical constraints (e.g., funding, community values). Policymakers and conservation organizations need evidence-based strategies that balance ecological health with economic and social demands.

The team identifies key processes, priorities, and critical timescales; local communities may prioritize immediate flood control, conservationists may focus on long-term biodiversity, and policymakers may consider medium-term resource allocation (e.g., flood defenses) and regulations (e.g., deforestation limits). Together, they establish measurable indicators (e.g., rainfall intensity) and agree on either threshold-based or continuous strategies (Figure IA,C) to guide the model's timestep dynamics.

Step 2: implement adaptive timestep model with agreed indicators

A self-optimizing adaptive timestep model (temporal zoom-in) adjusts the temporal resolution dynamically based on selected strategy:

- Threshold-based strategy: when an indicator crosses a predefined threshold, the model switches to finer timesteps and adjusts process implementation (Figure IC,D). This threshold detection could be informed and iteratively refined by AI training on satellite and sensor data prior to the simulation. Agents make short-term decisions informed by classic economic theories such as the **game theory**. After the event, the model recalibrates ecosystem states before resuming coarser timesteps. Agents learn and adjust long-term strategies.
- Continuous strategy: the model continuously adjusts the timestep based on predefined parameterization (Figure IA,B). This approach improves computational efficiency but limits flexibility in switching process implementations. Additional assumptions about the agents' behavior need to be agreed.

Step 3: review and feedback

After the simulation, the group evaluates the accuracy of predictions, effectiveness of decision-making processes, and alignment with stakeholder priorities. Researchers and software engineers refine model parameters, improve data integration, and adjust strategies based on feedback. This iterative process ensures that the model remains responsive to new data, evolving needs, and changing environmental conditions.

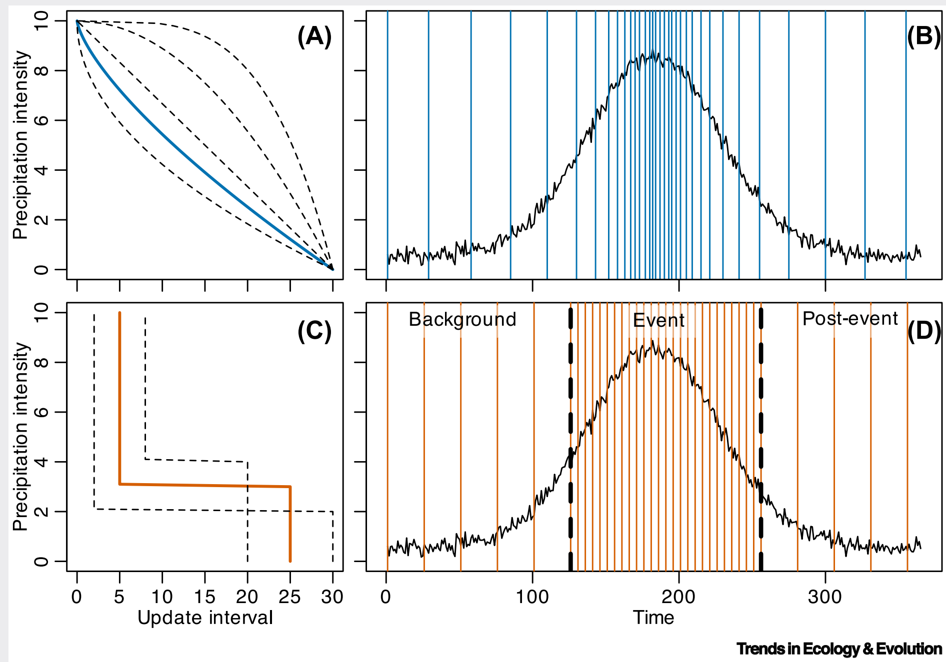


Figure I. Dynamic workflow for managing flood risks in tropical ecosystems through 'harmonized' ecosystem modeling. Left: proposed (dashed) and agreed (solid) parameterization of update intervals as a function of precipitation intensity for a continuous (A) or threshold-based (C) strategy following initial stakeholder conversation. Right: model time intervals (blue and orange vertical lines) over the course of a single rainfall event (black timeseries). In the continuous strategy (B) the time interval changes dynamically. In the threshold-based strategy (D) the model switches between two timesteps, and three distinct phases can be defined (from left to right) as follows. (i) Background: simplified processes at slower timesteps reduce computational costs. Ecosystem model runs at a monthly timestep, local communities extract resources at a constant rate, policymakers make no decisions or long-term ones. (ii) Event: upon detecting a threshold (left black dashed line), the system refines its temporal resolution and incorporates detailed environmental process representations. Agents make fast decisions. (iii) Post-event: after the event, when precipitation has fallen below the threshold (right black dashed line), the model recalibrates ecosystem states before resuming coarser timesteps. Agents learn and adjust long-term strategies.

measurable benefits to society [57]. This impact was achieved by connecting ecological processes, short- and long-term societal needs, and political constraints. Even here, full integration of timescales was not achieved, due largely to challenges outlined in this paper: computational cost of running models at high temporal resolution to inform long-term strategies (biting the bullet), uncertainty in fast processes such as climate variability, land use change, and species response over such timescales, and the need to approximate (capture the unseen) or ignore (selective elimination of timescales) these processes [58].

Concluding remarks

Dealing with time in complex system modeling remains a challenge in ecology and beyond (see Outstanding questions). Yet pushing the boundaries to overcome these challenges is critical because such models are essential for understanding, reproducing, and predicting ecological patterns, processes, and the impacts of environmental changes across temporal scales. The perspective we present here is particularly timely given the current momentum in ecosystem model development and the shared challenges across disciplines. Furthermore, the scientific and political landscape is well aligned to support this progress, with growing support for transdisciplinary research and the integration of ecosystem models into systematic assessments

Outstanding questions

Knowledge gaps and uncertainty:

- How do nonlinear dynamics at smaller temporal scales, such as diurnal temperature variation, scale up to larger temporal scales, like seasonal or annual population dynamics or long-term ecosystem stability? And how can this be captured in one modeling framework?
- How sensitive are model inferences to the application of competing approaches for dealing with multiple timescales and processing order? When should ecosystem modelers use or not use which approach?
- How can uncertainty in timescale selection or processing order propagate through ecosystem models, and how should it be addressed?
- What criteria should guide the balance between computational complexity and ecological realism?

Methods transfer and innovation:

- The temporal zoom-in method is a successful example of methods transfer from spatial scaling challenges across disciplines. How can methods such as adaptive mesh refinement or multi-adaptive timesteps be adapted to ecological systems? What more can we learn from spatial scaling approaches across disciplines to improve handling of multiple timescales in ecosystem models?
- As ecology moves towards '**Big data**' approaches (e.g., machine learning), the physical meaning of the dimension becomes less significant. How could multiple timescales be represented differently, for example as a spectrum or wave function?
- Can viewing time as a consumable resource, rather than a linear axis, help resolve challenges in modeling multiple timescales and processing orders?

Overcoming barriers in transdisciplinary collaboration:

- What strategies can overcome disciplinary silos to promote knowledge exchange and foster the integration of new methods into ecological modeling?
- What funding models and collaborative frameworks can support the time-intensive process of adapting and

such as the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) report [59] and the sustainable development goals [60]. We should seize this momentum to foster new, maybe unconventional collaborations that drive truly innovative solutions to the challenge of time in complex models, helping solve future challenges in ecology and beyond.

testing methods from other fields in ecological research?

- What institutional structures or funding mechanisms are needed to support sustained transdisciplinary collaborations for ecological modeling?

Declaration of interests

The authors declare no competing interests.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used OpenAI's ChatGPT (version 2) to improve language and conciseness of the text. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Resources

[i] www.simulistics.com/index.htm

[ii] https://rdrr.io/github/ilyamaclean/microclimf/

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