Multi-level agent-based modelling of social-ecological systems: Bridging the gap between the micro and macro levels

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Abstract

Social-ecological systems (SESs) are complex adaptive systems that encompass multiple spatial, temporal, and organisational scales and levels. The dynamics of SESs are driven by interactions among processes occurring both within and across different levels. These multi-level interactions generate patterns of system behaviour that emerge at different spatial, temporal, and organisational levels. This has profound implications for managing SESs. Agent-based models (ABMs) are known for their ability to simulate emergent phenomena and are powerful tools for modelling SESs. However, most multi-level ABMs focus merely on individual/micro-level interactions and

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aggregated/macro-level interactions and rarely capture the true multi-level dynamics of SESs, which often include effects that cascade across multiple levels. We describe a conceptual framework for multi-level ABMs that couple processes occurring at intermediate levels with those occurring at micro and macro levels, and, more importantly, propose a mathematical construct that embodies the generic features of a truly multi-level ABM. We then discuss our proposed model within the context of past and potential future multi-level agent-based modelling efforts.

Keywords
human-environmental systems; multiscale modelling; social-ecological systems; cascading effects; cross-scale interactions

1. Introduction

Social-ecological systems (SESs) are complex, multiscale systems often characterised by hierarchical structures (McGinnis & Ostrom, 2014; Schlüter et al., 2019; Wu & David, 2002). Conceptually, SESs can be viewed as multi-tier structures with different levels of abstraction along various measurement scales (e.g., temporal, spatial, and organisational scales) (Iwanaga et al., 2022; Wang & Grant, 2021). This hierarchical structure has profound implications for modelling SESs. For example, deciding how the model should be constructed to effectively mimic the multi-tier structure of SESs.

Most SESs involve an extended range of human and natural processes operating and interacting within and across various spatial, temporal, and organisational levels (Ewert et al., 2011). SESs are often nested. That is, an element of a large-level SES is a smaller-level SES itself. Thus, the dynamics of a given SES are influenced by changes in larger and smaller-level SESs (Ostrom, 2007; Pelosi et al., 2010). As such, SESs can be described as multi-level complex adaptive systems with their dynamics driven by the behaviours of agents at multiple organisational and spatial levels (Gunderson & Holling, 2002; McGinnis & Ostrom, 2014; Ostrom, 2007).

Although the terms “scale”, “multiscale”, and “cross-scale” have been widely used in SESs research and other disciplines, their definitions and associated concepts often vary, leading to unnecessary confusion, as noted by Wang et al. (2023) and Vervoort et al. (2012). According to Gibson et al. (2000) and Cash et al. (2006), “scale” refers to the spatial, temporal, quantitative, or analytical dimensions used to measure and study any phenomenon, and “levels” refers to different positions or locations within a measurement scale/dimension. While this definition is clear, the understanding and usage of terms tend to be based on context and scientific discipline.

In the agent-based modelling and SESs research context, multiscale usually means multi-level on a particular scale. For example, An et al. (2005) used multiscale to refer to the individual, household, and landscape levels in an agent-based model of an SES. To avoid potential confusion, we mainly use levels and multi-level in this paper. On the spatial dimension, for example, we may perceive global, regional, landscape, and local levels of SESs. We define multi-level modelling as the practice of constructing models of processes, interactions, and dynamics across multiple levels along one or more scales. Organisational scales can be individuals, households, communities, and whole societies. Cross-scale interactions, in the SES modelling context, refer to the interactions, including feedback, among variables defined at different levels (Bialozyt et al., 2025; Iwanaga, Wang, Hamilton, et al., 2021; Iwanaga, Wang, Koralewski, et al., 2021). For example, a commodity price at the global level has implications for farmers' decision-making at the local level and vice versa (Barbrook-Johnson et al., 2024). We use cross-scale interaction, instead of cross-level interaction, mainly because this term has been widely accepted in SES modelling society. So, cross-scale interactions in this paper really mean cross-level interactions.

SESs are driven by cross-scale interactions, and the consequences of these interactions are difficult to account for and foresee. As a result, many problems in SESs can be viewed as “wicked problems” because the drivers, impacts, and solutions manifest themselves across different spatial, temporal, and organisational scales (DeFries & Nagendra, 2017; Macpherson et al., 2024). Much existing research describes cross-scale patterns without focusing on the underlying cross-scale interactions that shape the complex dynamics of SESs (Kleemann et al., 2020). When undetected, cross-scale interactions may cause errors in model predictions, which can mislead decision- and policy-makers (Soranno et al., 2014). For example, on the one hand, deforestation at the landscape scale results from the aggregated decision-making of land users at the individual scale. On the other hand, landscape deforestation is also influenced by agricultural and forestry policies at the national level and by world commodity trade at the global level. Multi-level modelling of SESs provides a unique opportunity to document, analyse, and understand these complex systems with the intention of identifying management trade-offs and avoiding unintended negative consequences (Smajgl, 2010).

Multilevel SES models can identify transitional processes of system change that are non-linear (e.g., tipping points), and, hence, provide early indicators of potential problems (e.g., regime shifts) that require adaptive management (Müller et al., 2014; Scheffer et al., 2009; Wang et al., 2025). However, understanding SES dynamics at multiple levels is challenging (Scholes et al., 2013; Verburg et al., 2016). Many SES phenomena involve cross-scale interactions whose effects “cascade” across levels. The COVID-19 pandemic demonstrated that a local-level virus outbreak could cascade onto regional, national, and global levels. Such cascades involve complex cross-scale interactions among interlinked SES sub-systems, and their management requires coordinated strategies implemented at different levels (Broomell & Kane, 2021; Paul et al., 2020; Perera, 2021; Ringsmuth et al., 2022). Local regime shifts in ecosystems can be triggered by regional climate change, which in turn results from gradual increases in global temperatures, illustrating the complexity of cascading effects driven by cross-scale feedbacks (Cumming et al., 2017; Rocha et al., 2018; Twidwell et al., 2019; White & Wulfing, 2024). Likewise, deterioration of local ecosystems can trigger regime shifts towards undesirable system states at a larger level, as has occurred in coastal ecosystems in China (Zhang, 2016). The deforestation of the Amazon is driven by interrelated multi-level drivers. Drivers at the global level include climate change, human population growth, and international commodity trade. Drivers at the regional scale include national conservation policies and land tenure systems. At the local level, farmers’ decision-making is a principal driver (Hertel et al., 2019; Malhi et al., 2008; Schielein & Börner, 2018). All these drivers are intertwined and shape the dynamics of SESs across all levels. In another example, coral reef ecosystems are governed by multi-level drivers and cross-scale interactions, wherein processes at cellular, organismal, population, community, ecosystem level, and even global level collectively shape patterns of resilience and ecological function (Donovan et al., 2023).

Agent-based models (ABMs) are powerful tools for modelling SESs because of their ability to represent the multi-scale, multi-level nature of the human decision-making processes supporting sustainable natural resource management (Filatova et al., 2013; Rounsevell et al., 2012; Thober et al., 2017). However, this ability is often underutilised so that interactions occurring outside the micro and macro focal levels are assumed to be exogenous or stationary in time and space. Under such assumptions, multi-level and cross-scale interactions, feedback, and cascading effects cannot be adequately represented (Verburg et al., 2016). The current challenge for the ABM community modelling SESs is to bridge the gap between the micro- and macro-levels via the representation of agents functioning at multiple levels and combine multi-level analysis in the same ABM (Filatova et al., 2013; Meyer et al., 2025; Müller et al., 2020; Rounsevell et al., 2012; Thober et al., 2017).

Multi-level simulation models present a computational challenge in many research domains (Chopard et al., 2014). ABMs are particularly suitable for the multi-level modelling of SESs because: 1) agents can be defined at different levels (e.g., as individuals, households or organisations) to model the human agency in various levels; 2) ABMs are intrinsically multi- and cross-scale with interactions of agents at lower levels leading to emergent phenomena at higher levels, which resembles the multi-level nature of real SESs; 3) the explicit inclusion of recognisable agents provides an intuitive perspective on cross-scale interactions that facilitates a participatory modelling approach (Voinov et al., 2018).

Nonetheless, few truly multi-level (more than two scales) ABMs have been developed for modelling SESs, except for a few multi-level cellular-automata models (Lahboub et al., 2018; Meyer et al., 2025; Wu & David, 2002). Most ABMs, however, stop at two levels of interaction—the interaction at the individual level leads to emergence at the upper level (Pike, 2019). Currently, there are several challenges to developing multi-level ABMs: 1) Real-world SESs often do not have clearly distinguishable levels and the multi-scale structure can be difficult to conceptualise and delineate; 2) The cross-scale interactions of agents operating at different scales (e.g., collective decision-making based on individual behavior) is challenging to represent; 3) Implementing multi-level ABMs can be technically difficult even though many ABM software platforms support multi-level modelling (e.g., RePast); 4) Modellers have to deal with scheduling algorithms among potential sub-models, and exchange data between agents on various levels (Brugière et al., 2022); 5) Multi-level modelling may require data from various levels for parametrisation, calibration or validation, which is often a limiting factor.

In this paper, we describe a conceptual framework for multi-level ABMs that explicitly connects processes functioning at intermediate levels with those functioning at micro and macro levels, and, more importantly, we propose a mathematical construct embodying the generic features of a truly multi-level ABM. We first introduce our general conceptual framework and define terminology (Section 2.1). Next, we review current modelling approaches for multi-level ABMs of SESs (Section 2.2) and present our stylised framework for multi-level ABMs of SESs (Section 2.3). Then, within our stylised conceptual framework, we describe our mathematical construct that embodies the generic features of a truly multi-level ABM of a SES (Section 3). Finally, we discuss our proposed modelling approach within the context of past and potential future multi-level ABM modelling efforts (Sections 4 & 5).

2. Multi-level and cross-scale modelling of Socio-Ecological Systems

2.1. General conceptual framework and basic terminology

According to hierarchy theory, SESs can be conceptually represented as nested multi-level sub-systems; at each level, SESs are coupled systems that operate at similar spatial and temporal levels. Sub-systems, including actors and components at a lower level, are nested within a higher level's actors and ecological components, as illustrated in Figure 1. SESs thus can include SESs at various levels, e.g., farm, landscape, regional, and all the way to the global level (Ewert et al., 2011).

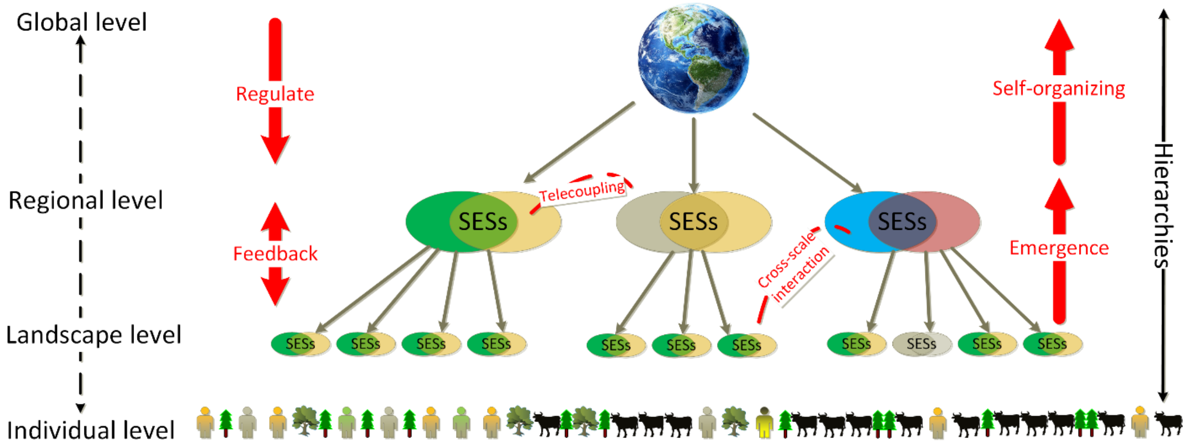

Figure 1: Conceptual representation of multi-level socio-ecological systems and cross-scale interactions.

On each level, agents interact with each other and their environment. The interactions can be competitive, cooperative, antagonistic, information sharing, mutual learning, etc. Lower-level interactions lead to the emergence of upper-level patterns and dynamics; groups of lower-level agents can also form superagents in one or more upper levels. For example, wolves organise as wolfpacks; rural residents form villages. Wolfpacks and villages, which both have mechanisms for collective cognition, could be regarded as superagents that might also interact with each other. Behaviours of lower-level agents are often regulated and constrained by upper-level environments or rules, e.g., an individual person's behaviours are influenced by community rules or social norms and regional or national policies. For example, Caillault et al. (2013) illustrated how a farmer's land-use behaviours are shaped by neighbours' actions at the local scale, social rules and norms at the community scale, and policies at regional, national, and international scales. As such, cross-scale interactions and resulting cascading effects can propagate across levels (e.g., cascading regime shifts across scales; Rocha et al., 2018). The conceptual framework introduced here is closely related to the system of systems approach, which models emergent system behaviours and patterns raised from interactions of heterogeneous sub-systems (Hadian & Madani, 2015; Hipel et al., 2008; Iwanaga, Wang, Hamilton, et al., 2021; Phillis et al., 2010). However, while the systems of systems approach describes nested systems in general, here we specifically focus on SESs, which can be conceptualised and studied with ABMs.

2.2. Modelling approaches of multi-level ABMs for SESs

Multi-level modelling has been applied in many scientific disciplines, such as biology (Dada & Mendes, 2011), biomedicine (Sloot & Hoekstra, 2010), physics (Engquist et al., 2007), engineering (Zeng & Qin, 2018), and land system science (Verburg et al., 2008). Various approaches and strategies have been proposed, which shed light on the multi-level nature of SESs. Zeng and Qin (2018) distinguished two categories of multi-level modelling strategies or approaches: sequential multi-level modelling approaches and concurrent multi-level modelling approaches. Sequential multi-level modelling establishes a macro-scale model with some details of the constitutive relations being precomputed from micro-scale models. Sequential modelling is also referred to as loose coupling (see Robinson et al., 2018). In sequential multi-level modelling, the macroscale model is determined first, except for some parameters or functions, which are then computed or tabulated using a micro-level model. Sequential multi-level modelling is mostly suitable for the case when only a few parameters are passed between the macro- and micro-level models. Thus, sequential multi-level modelling corresponds to the loosely coupled approach commonly used in multi-level modelling of SESs.

Different types of models running at various levels can readily be linked to model SESs at various levels. In many cases, the sequential approach only accommodates one-way feedback or parameter exchange. For example, Schaldach et al. (2012) simulated future European land and water use with a multi-level and multi-model approach where climate simulations, global population dynamics, and partial equilibrium models calculate large-scale changes, which in turn feed into the spatially explicit land use model (LandSHIFT) and then passes updated land use data to a spatially explicit freshwater model (WaterGAP) to calculate water requirements for Europe under climate and socio-economic change scenarios. In this case, parameters from the macro-level model are passed down as inputs to a micro-level model, which generates output parameters to be passed back up again. However, due to the models' loose coupling, no cross-scale dynamics or temporal feedback are modelled. Multi-level modelling does not always include cross-scale interactions because some models may have more than one level without mechanisms that couple the dynamics at these levels. For example, land use models such as CLUMondo (Van Asselen & Verburg, 2013), LandSHIFT (Schaldach et al., 2011), and Metronamica SL (Van Delden & Vanhout, 2017) are multi-level by incorporating regional policies and implementing them at the level of pixels, but not providing bottom-up feedback that could change the policies.

Verburg et al. (2008) simulated future European land use with a multi-level and multi-model approach where a global trade model (GTAP) and an integrated assessment model are first used to calculate the changes in agricultural land use areas, which in turn feed into the spatially explicit land use model (CLUE-s) to spatially allocate the land use areas on the local level. In this case, parameters from the macro-level model are passed down to the micro-level model as inputs; there are no bottom-up feedbacks modelled. Land use models such as Metronamica ML allow for feedback processes between regional and local levels, and integrated models such as LUMOCAP, WISE, and ISE include interaction from (inter) national and regional economics to local land use and back, and hence these models incorporate cross-scale interactions (Rutledge et al., 2008; Van Delden et al., 2010; Van Delden et al., 2005).

In concurrent multi-level modelling, the variable values in macro-level models and micro-level models are computed on the fly as the computation proceeds (also referred to as tight coupling; see Robinson et al., 2018). Thus, the macro- and micro-level models are closely integrated and run concurrently, as the degree of coupling is considered a guiding factor for a model's ability to represent feedback and cross-scale interaction (Robinson et al., 2018). As multi-level ABMs of SESs may consider both at-scale and cross-scale interactions, the concurrent modelling approach is clearly the most suitable strategy because it allows two-way, bottom-up and top-down, feedback and (quasi)-simultaneous simulation of dynamics at multiple levels in an endogenous manner.

In the context of multi-level SESs, Verburg et al. (2016) summarise multi-level modelling strategies into three categories: 1) model coupling, 2) model outscaling, and 3) model upscaling or nesting. These strategies are not explicitly addressed to agent-based modelling. Nevertheless, we can borrow and adapt accordingly in multi-level ABMs for SESs. In model coupling strategies, ABMs are often coupled with other types of models at larger or smaller levels. For example, Jager et al. (2000) coupled an ABM, simulating human decision behaviours with the Consumat approach, with an ecological model of a lake at the macro-level. The agents decided whether to go fishing or mining; these micro-level decisions had implications on the macro-level environment, as mining would pollute the lake and thus impact fishing. In another example, the ILUMASS model coupled an ABM simulating households' behaviours in shaping micro-level land use and a meso-level transportation model that runs on district levels to simulate the complex dynamics between macro-level land-use and transportation patterns (Strauch et al., 2005; Wagner & Wegener, 2007). Following similar coupling strategies, Berger et al. (2019) coupled a land-use ABM at the farm level with multidisciplinary models from leaf level to landscape level, to support climate-relevant ecosystem management in South Africa. The ENVISION framework application for Central Oregon coupled an ABM representing forest managers and fire managers from the plot level to landscape level with spatially explicit simulation models for the wildland-urban interface, vegetation succession, and wildfires, i.e., ecological components operating on different spatial levels (Spies et al., 2017; Spies et al., 2014).

In model outscaling strategies, ABMs are often first developed, calibrated, and tested for small regions, and the models are then outscaled to a much larger geographic area by modelling behaviours of tens of thousands or even millions of agents across multiple levels. For example, Valbuena et al. (2010) modelled more than 2000 farm agents in the Eastern Netherlands by outscaling the 333 surveyed farms through farm typology analysis. Brown et al. (2019) developed and applied CRAFTY-EU, an ABM of the European land system, to the continental level to investigate the effects of aspects of human behaviour on land management. Due to computational limitations, most agents in such models have relatively simple decision rules; levels of the system and cross-scale interactions are also kept minimal. Thus, such models are large in terms of the area covered but not complex in terms of representing multi-level and cross-scale interactions and feedback.

2.3. Stylised conceptual framework of multi-level ABMs for SESs

Based on the previously discussed conceptual frameworks of multi-level SESs and the system of systems approach, we constructed a stylised multi-level agent-based modelling framework, as illustrated in Figure 2. Intended as a conceptual modelling framework, we keep it as parsimonious as possible by including only three levels: micro-scale, meso-scale, and macro-scale. In reality, there could be more than three levels, as illustrated in Figure 1. Agents are situated at different scales; upper-level agents can be, but do not have to be, superagents composed of multiple lower-level agents. The properties and behaviours of superagents are at least partially determined by their constituent agents. Lower-level agents' behaviours are influenced and constrained by the properties and rules of upper-level agents and environments. Micro-level agents can interact with each other, potentially leading to learning or changes in their behaviour. Meso-level (super)agents also interact with each other and have the potential for learning from these interactions, as do macro-level (super)agents. Given the focus on SESs, it is especially important to acknowledge that the "ecological" system component is not considered exogenous or external to the system. Rather, important environmental components are also represented at the micro-, meso-, and macro-scale, interacting and "learning" (or adapting) based on these interactions. Our conceptual framework additionally emphasises interactions across levels, allowing for feedback (Figure 2), which can shape SESs' dynamic behaviour across levels.

An example helps to describe the potential applications for multi-level ABMs for studying and analysing SESs. An ABM could represent farmers in a semi-arid area that heavily depends on irrigation for crop production. Individual farmers and their production systems would constitute the micro level. Farmers at this level would interact with social and ecological system components through communicating or working with other farmers, through farming their land, and also adjust their behaviours, e.g., through learning experience or from communicating with other farmers. As such, multi-level ABMs can, for example, simulate water resource management at basin and sub-basin levels, where agents (water users, water use organisations, policymakers, and water management agencies) at different levels interact with each other while also interacting with the stocks and flows of water in the water systems at various levels.

3. From stylised framework to multi-level agent-based metamodel

In this section, we elaborate the concepts from Figure 2 into a metamodel that is intended to capture generic features of multilevel SES ABMs, responding to recent reviews (Brugière et al., 2022; Dressler et al., 2022) that have highlighted the need for a formal bridge between micro-level ABMs and higher-level representations. Here, a metamodel is "a model of a model", which defines the core structure and rules for creating specific models. The metamodel describes what can be modelled, how elements connect, and ensures consistency, acting as a schema or framework for model development. We do not attempt to be comprehensive but rather sketch how

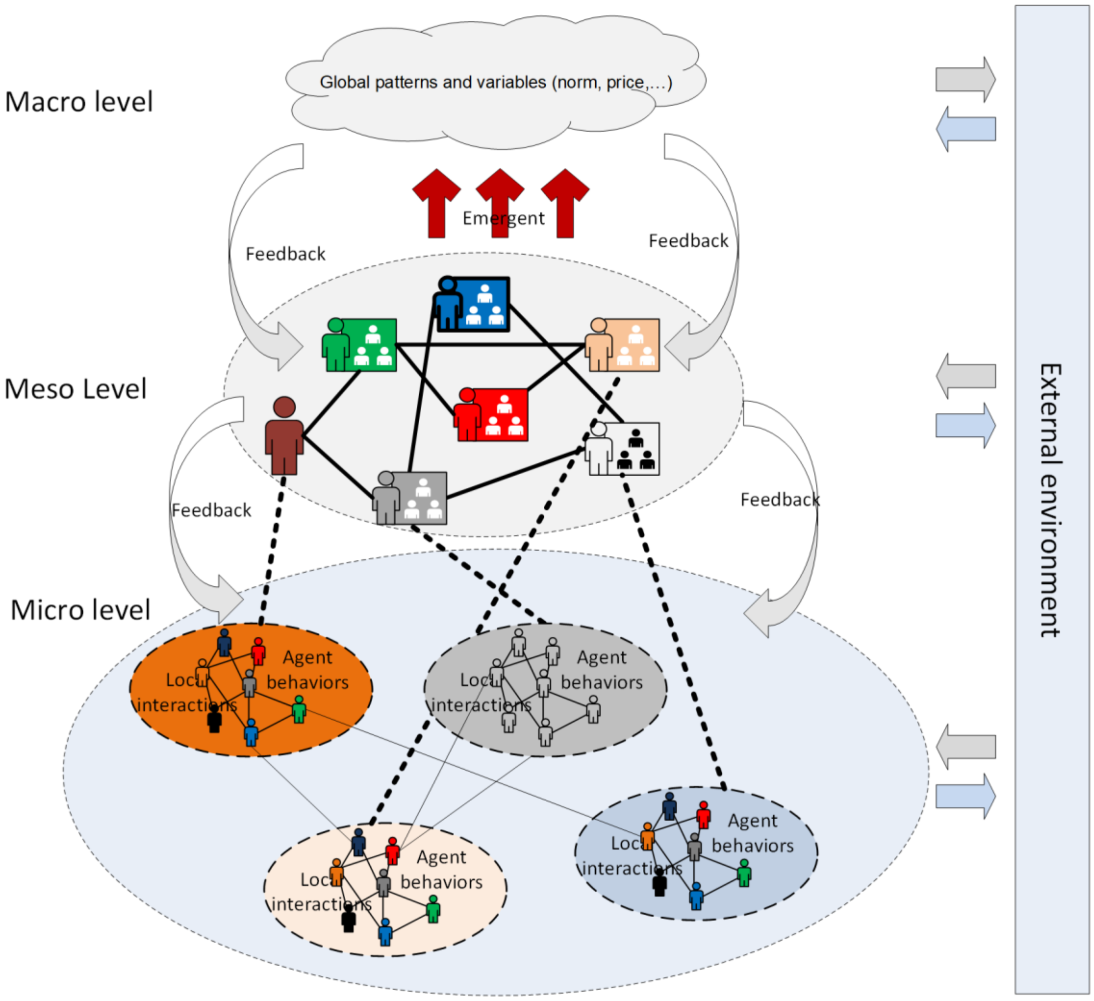

Figure 2: A stylised modelling framework of multi-/cross-scale ABM for SESs.

a range of established methods might be adapted and combined into a coherent modelling methodology that enables the development of models for specific systems. We acknowledge that this includes some speculation. Our proposed approach will need to be tested and refined through application to establish its effectiveness. The methods that we draw on include the renormalisation group (RG) (Orioli & Faccioli, 2016; Scoppola, 1993; Wilson, 1975), equation-free modelling (Gear et al., 2003; Kevrekidis et al., 2004), and Markov chain aggregation (Banisch, 2016).

Our approach is distinct from that used in most existing multilevel SES models, in which independent, phenomenological models predefined at different levels are linked post hoc through variable and/or parameter maps. For example, the Atlantis end-to-end marine ecosystem model links independently specified ecological, physical, fleet, and socio-economic sub-models through post-hoc information and parameter exchanges (Audzijonyte et al., 2019). In such models, cross-scale dependencies are imposed exogenously, and higher-level equations are assumed rather than derived. By contrast, our approach derives each coarser model directly from the structure and dynamics of the finer one at the level below, through recursive coarse-graining (Figure 3). Higher-level patterns and feedbacks therefore emerge endogenously from lower-level interactions, ensuring that each level remains formally consistent with the one beneath it even when stochasticity, nonlinearities, and feedbacks are present.

Although the base-level ABM contains the full system description, building an ordered set of progressively coarsened models provides insights and capabilities that cannot be obtained from the fine model alone. Each

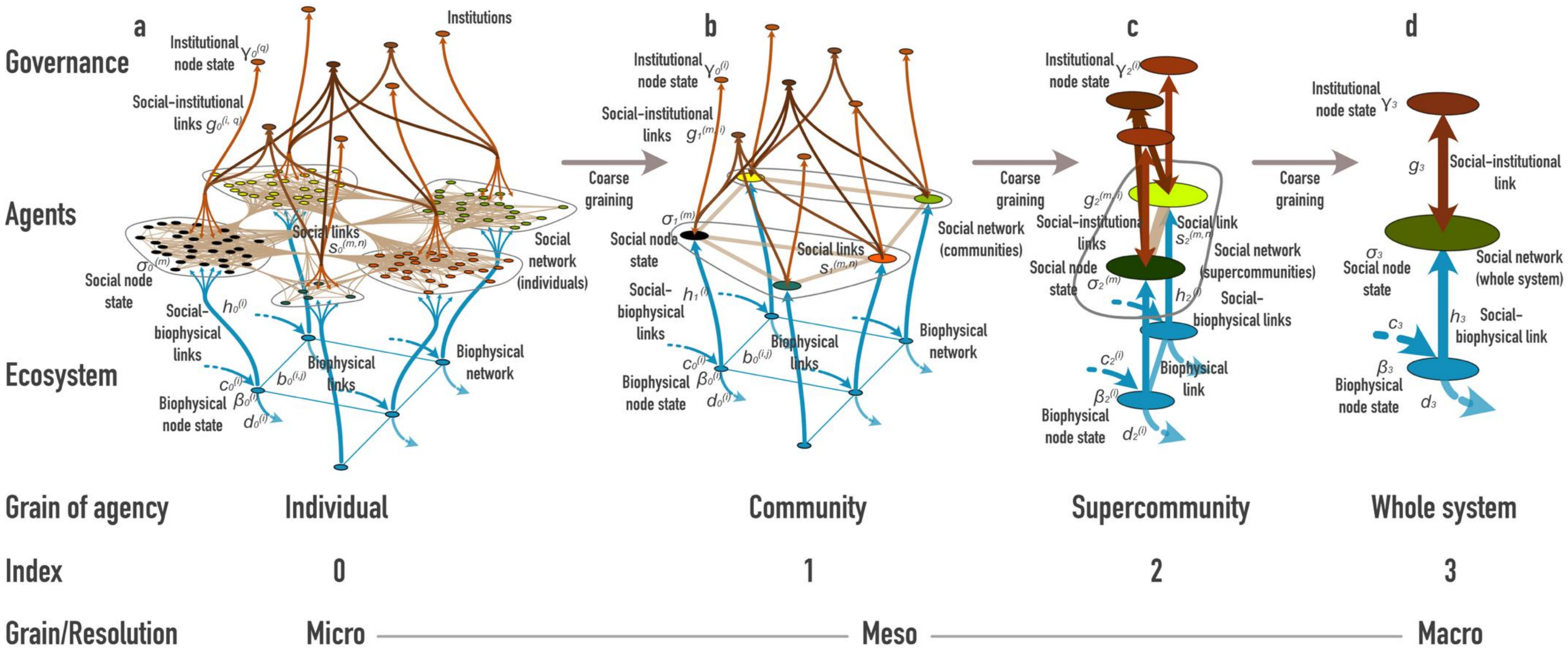

Figure 3: Ordered set of progressively coarsened multilayer social-ecological network metamodels.

successive level compresses the micro-dynamics into a smaller set of effective variables that capture slower collective modes; that is, dynamics at another level, such as changes in community norms or regional resources. The resulting set of interacting ABMs is not merely a collection of coupled models but a mutually consistent family of dynamical representations, each capturing dynamics at one of the system's characteristic levels and each linked to the next by explicit projection and disaggregation operators (Figure 3).

This structure provides quantitative tools for assessing the dynamical closure of each level (the degree to which the level's dynamics depend on other levels), and for diagnosing emergence and cross-scale feedbacks as measurable departures from perfect closure. Under certain assumptions that are explored below, coarser models can also be simulated independently to explore long timescales or large scenario spaces that are computationally prohibitive for the base ABM. The set of coarsened models, therefore, acts as both an analytical and computational tool, revealing how each level's characteristic dynamics emerge from and feed back to other levels within a single coherent dynamical framework. This moves beyond descriptive frameworks to provide SES modellers with a practical procedure for constructing, testing, and adapting multilevel ABMs.

3.1. Full-resolution metamodel

At the base level (0; Figure 3a), the SES is represented as a multilayer network with a social layer of agents, an ecological layer of biophysical nodes, and a governance layer of institutional nodes. Within-layer adjacency matrices $S_0 = \left[S_0^{(m,n)}\right], B_0 = \left[b_0^{(i,j)}\right]$ describe social and biophysical couplings, while cross-layer incidence matrices $H_0 = \left[h_0^{(m,i)}\right]$ (social-biophysical), $G_0 = \left[g_0^{(i,q)}\right]$ (social–institutional), and $V_0 = \left[v_0^{(i,q)}\right]$ (biophysical–institutional) capture inter-layer couplings. Note that V_0 is omitted from Figure 3 for visual clarity, and for simplicity, we have assumed that institutions interact only via the social layer and not directly.

Each node has a state variable — $\sigma_0^{(m)}(t)$ for agents, $\beta_0^{(i)}(t)$ for biophysical resources, and $\gamma_0^{(q)}(t)$ for institutions—so that the full system state is the concatenated vector $X_0(t) = (\sigma_0(t), \beta_0(t), \gamma_0(t))$. The coupled dynamics are generically :

$$\begin{aligned}
\sigma_0(t+\Delta t) &= F_S(\sigma_0(t), S_0, \beta_0(t), H_0, \gamma_0(t), G_0), \\
\beta_0(t+\Delta t) &= F_B(\beta_0(t), B_0, \sigma_0(t), H_0, \gamma_0(t), V_0), \\
\gamma_0(t+\Delta t) &= F_G(\gamma_0(t), G_0, \sigma_0(t), \beta_0(t), V_0),
\end{aligned}$$

where F_S, F_B, and F_G may contain stochastic and/or deterministic components. Together, these maps define a propagator $\mathrm{P}_0^{\Delta t}$ that advances the probability distribution of system states forward in time by Δt, such that:

$$\mathrm{p}\big(\mathrm{X}_0(\mathrm{t}+\Delta\mathrm{t})\big) = \mathrm{P}_0^{\Delta\mathrm{t}}\, \mathrm{p}\big(\mathrm{X}_0(\mathrm{t})\big)$$

When all relevant influences are included, this level-0 process is usually assumed to be Markovian, meaning that the propagator depends only on the current state $X_0(t)$ and not on its earlier history. This Markovian closure—whereby the present state contains all information needed to predict the next—is an idealisation that holds only approximately for complex, path-dependent systems like SESs, but remains standard practice for ABMs (Banisch, 2016).

3.2. Coarse-graining the state variables and network structure

A coarser representation at level 1 (Figure 3b) is obtained by applying a projection operator Π_1, which maps the fine-grained variables of level 0 onto a smaller set of coarser variables at level 1 that represent functional modules of 0th-level components:

$$X_1(t) = \Pi_1 X_0(t).$$

As a simple example, consider a social community i whose individual members have a scalar state variable $\sigma_0^{(m)}(t)$ (e.g., binary opinions or continuous resource harvesting rates). The community's coarse state might then be represented by a weighted average of its members' states:

$$\sigma_1^{(i)}(t) = \mathit{\Pi}_1^{(i)}\,\sigma_0(t) = \frac{1}{W_1^{(i)}}\sum_{m=1}^{N_1^{(i)}} w_0^{(m)}\sigma_0^{(m)}(t),$$

where $N_1^{(i)}$ is the number of community members, $w_0^{(m)}$ is each member's weight based on, for instance, status, income, or land share and $W_1^{(i)} = \sum_{m=1}^{N_1^{(i)}} w_0^{(m)}$ normalises the total. In matrix form, the row vector $\mathit{\Pi}_1^{(i)} = \frac{1}{W_1^{(i)}}\, w_0^{\top}$ is the projection operator for community i, and stacking such rows for all communities yields the full coarse-graining matrix Π_1. This weighted-average projection is linear, but nonlinear projections can also be used, such as a thresholding function that evaluates to 1 for the community's collective opinion when any majority of its agents hold opinion 1, and 0 otherwise. Although only the social layer is coarsened between panels a and b in Figure 3, the other layers are also included in the coarsening to panels c and d, which will be reflected in the forms of Π_2 and Π_3.

The precise form of the coarse-graining projection operator at a given level will depend on the system under study and the observables of interest, and should be formulated so that the resulting coarsened dynamics are consistent with the full-resolution dynamics as closely as possible (see discussion of commutation error, below). There is no general algorithm for *a priori* identification of the best coarse-graining procedure for any given system or level. Rather, how to best partition components for the coarse-graining projection, the form of the projection operator, and how the network topology should be concomitantly simplified are all questions to be answered through informed trial and error. The modeller must start with an informed hypothesis about which substructures act semi-autonomously at a slower timescale. Structural patterns—such as communities in the social network S_0, spatial clusters in the biophysical network B_0, or existing jurisdictions in the governance network G_0—provide natural candidates, but are only a guide. Dynamical evidence is also important: candidate groups can be tested through short simulations or empirical time series to assess whether their members evolve coherently over the timescale of interest. Suitable indicators of coherence include correlated trajectories, similar responses to perturbation, or shared participation in slower collective modes. More formal diagnostics, such as minimising the commutation error at the coarse level, can be used when data permits. Because coherence between SES components is often transient and context-dependent, overlapping or dynamic partitions may be necessary to capture heterarchical structures (Cumming, 2016). If C_S, C_B, and C_G are the chosen partitioning matrices that map level 0 nodes (indexed by the matrix rows) to level 1 nodes (matrix columns), within- and between-layer networks contract as:

$$\begin{aligned} S_1 &= C_S S_0 C_S^{\top}, \quad B_1 = C_B B_0 C_B^{\top}, \quad G_1 = C_G G_0 C_G^{\top}, \\ H_1 &= C_S H_0 C_B^{\top}, \quad V_1 = C_B V_0 C_G^{\top}. \end{aligned}$$

3.3. Coarse graining the dynamics

How can the dynamics at a given level be faithfully represented by a coarser model at the next level above? The Disaggregate–Evolve–Aggregate (DEA) cycle, adapted from equation-free multilevel modelling (Gear et al., 2003; Kevrekidis et al., 2004), is a practical method for constructing and testing coarse-grained models without mathematically deriving their governing equations from those of the level below, which may be very difficult or impossible in highly complex systems like SESs. The central idea is to relate the fine- and coarse-level propagators through a series of short simulations.

To begin, the modeller disaggregates a coarse state $X_1(t)$ into a statistically consistent ensemble of microstates X_0 using a disaggregation operator $\mathcal{D}_1$, which samples from the conditional distribution $p(X_0 \mid \Pi_1 X_0 = X_1)$ and satisfies $\Pi_1\mathcal{D}_1 = I_1$. The fine model is then evolved for one coarse time step Δt using the level-0 propagator $P_0^{\Delta t}$, after which the results are aggregated back to the coarse level with Π_1. Together, these define the effective coarse propagator:

$$P_1^{eff} = \Pi_1 P_0^{\Delta t}\mathcal{D}_1, \qquad X_1(t+\Delta t) = P_1^{eff} X_1(t).$$

The operator $\mathrm{P}_1^{\mathrm{eff}}$ is not yet a closed model but an empirical mapping that reproduces the coarse-level evolution implied by the fine dynamics. A self-contained coarse model $\mathrm{P}_1^{\Delta\mathrm{t}}$ can then be estimated or learned so that it approximates $\mathrm{P}_1^{\mathrm{eff}}$ while acting only within the coarse state space. In practice, this involves fitting a parametric or nonparametric representation of $\mathrm{P}_1^{\Delta\mathrm{t}}$ to the state pairs $\{X_1(t), X_1(t+\Delta t)\}$ generated by the DEA cycle. These pairs serve as input–output examples of the effective coarse dynamics implied by the fine model at the level below. Depending on the complexity of the system and data availability, $\mathrm{P}_1^{\Delta t}$ may be represented in various ways, from a parametric transition matrix fitted by maximum-likelihood or Bayesian estimation (Brugière et al., 2022; Hooten & Hefley, 2019), to a nonparametric surrogate such as locally weighted regression (Cleveland & Devlin, 1988), Gaussian-process regression (Rasmussen & Williams, 2005), or neural-network emulators (Champion et al., 2019; Lusch et al., 2018). In all cases, the objective is to obtain a form of $\mathrm{P}_1^{\Delta t}$ that, when applied iteratively, generates trajectories of the coarse-level variables whose statistical properties match those of the fine-level trajectories after projection by Π_1. This ensures that the coarse model captures not only the mean tendencies but also the stochastic variability present in the fine-level dynamics when viewed through the projection, Π_1.

The modeller must choose or specify the functional form (e.g., linear transition matrix or neural mapping) before fitting. The resulting fitted model then defines both the structure of the coarse propagator and its parameters, which may be interpretable (e.g., effective interaction strengths, growth or decay rates, etc.) or purely statistical. Empirical data, such as time series of aggregate social indicators, resource stocks, or governance metrics, can be utilised at this stage to constrain or validate the fitted parameters, ensuring that the coarse model reproduces not only the simulated fine dynamics but also the observed macrodynamics of the real system (E et al., 2003).

The difference, $\mathcal{E}_1 = \left\| \Pi_1 \mathrm{P}_0^{\Delta t} - \mathrm{P}_1^{\Delta t} \Pi_1 \right\|$, quantifies the commutation error, which measures how closely the coarse model reproduces the dynamics implied by the fine model (Banisch, 2016; Orioli & Faccioli, 2016). Here, the norm applied to the difference may be chosen according to context (e.g., operator or Frobenius norm; for distributions, a statistical divergence such as the Kullback-Leibler distance (Banisch, 2016)). If the operators commute ($\mathcal{E}_1 \approx 0$), evolving the fine system first and then coarse-graining yields the same result as coarse-graining first and then evolving the coarse model. In that case, the coarse model is said to be Markovian (memoryless) and closed at its level; its variables together, at a given point in time, contain all the information needed to predict their own evolution. When $\mathcal{E}_1$ is large, the coarse variables lose predictive sufficiency, revealing hidden dependencies on their past values (path-dependence) and/or variables at other levels (cross-scale interactions). This loss of closure can be reduced by adding memory terms (which encode dependence on past states) or cross-scale couplings (which explicitly link dynamics across levels).

How frequently the DEA procedure must be applied to enforce consistency between levels will depend on system stability and the presence or absence of cross-scale interactions. In quasi-stationary regimes, the cycle can be run once to calibrate a stable coarse model $\mathrm{P}_1^{\Delta t}$. If exogenous conditions drift, it should be re-run periodically to update the model set. Near tipping points or under strong cross-scale feedbacks, the DEA cycle should be executed at every coarse time step (or at a fixed multiple of fine time steps) to maintain trajectory consistency between levels. In general, trajectory-by-trajectory consistency between levels is required only when path dependence or cross-scale interactions break Markovian closure. That is, when different realisations of a particular state at a given level evolve differently depending on their underlying micro-realisations at the level below, or when top-down feedbacks from higher levels alter their dynamics in ways not captured by their current propagator. In more stable regimes, statistical consistency suffices: it is enough that the ensemble distribution projected from the fine model, $\Pi_1 \mathrm{p}_0(\mathrm{t})$, closely matches the distribution generated by the coarse model, $\mathrm{p}_1(\mathrm{t})$. This ensemble-level closure allows each model to be simulated independently while preserving the correct large-scale statistics of the system. The DEA cycle thus provides a statistical bridge between levels, allowing the modeller to validate whether the coarse dynamics inferred from fine-scale simulations remain consistent over time, and to update them adaptively as the system evolves.

3.4. Model closure, commutation error, and emergence

A model is *closed* at level k when the coarse variables are sufficient to predict their own evolution without input from other levels. Formally, closure implies that coarse-graining and time evolution approximately commute: $\mathcal{E}_\mathrm{k} \approx 0$. Local interactions continuously generate and erode correlations among agents, resources, and institutions. These correlations determine which aggregates evolve slowly enough to be meaningful coarse variables. As correlations shift, a fixed projection Π_k can lose adequacy, producing a rise in $\mathcal{E}_k$ – a signature of emergence in progress as new collective patterns begin to form (Banisch, 2016). Once a new correlation structure stabilises, a revised projection Π_{k+1} can recover closure ($\mathcal{E}_{k+1} \to 0$), marking the consolidation of an emergent pattern. Because SESs, and the levels of organisation within them, are open and adaptive, this cycle of loss and recovery of closure repeats as new forms of organisation arise within and across levels.

When non-closure is moderate, predictive power at the coarse level can often be restored by expanding its state space. Short-term dependence on recent states introduces finite memory, which by definition makes the process non-Markovian on the standard state space. However, the process can still be Markovian in the augmented space that includes the extended set of variables required to capture the relevant memory or hidden dependencies that were omitted from the original coarse description (Banisch, 2016). Longer-lived dependencies often require explicit representation of slow variables or feedback across levels, rather than being treated as short-term memory effects (E et al., 2003). For instance, the update rule for an agent m within community i may depend on the community's mean state:

$$\sigma_0^{(m)}(t+\Delta t)=F_S\big(\sigma_0^{(m)}(t),S_0,\beta_0(t),\gamma_0(t),\sigma_1^{(i)}(t)\big)$$

so that micro-level decisions respond to macro-level context. These extensions keep the overall micro–macro system Markovian, even if the coarse variables alone are not.

3.5. Heterarchy, tipping, and adaptive renormalisation

Because social, ecological, and institutional processes rarely align perfectly, 'hierarchies' in SESs are best conceived as *heterarchical* networks of partially overlapping modules (Cumming, 2016). By unifying hierarchy theory (top-down/bottom-up) and network analysis (lateral/peer-to-peer), heterarchy describes a framework in which elements of social–ecological systems can occupy multiple, context-dependent positions along a continuum, and interact vertically (across scales/levels) and horizontally (at the same level) simultaneously. This provides a more realistic and integrative way to conceptualise complex systems than relying on either hierarchical or network perspectives alone. Projection operators Π_k can therefore encode multiple memberships across levels of aggregation, allowing a single fine-level component to contribute to several coarser-level components. The degree of model closure, quantified by $\mathcal{E}_k$, remains the criterion for whether a given representation adequately captures the relevant dependencies.

Tipping phenomena—abrupt shifts between metastable system regimes—manifest as transient breakdowns of closure. As correlations reorganise during tipping, $\mathcal{E}_k$ increases. Once the system stabilises around the new state, closure is restored with updated projections and propagators. In *static-rule* ABMs (e.g., Schelling segregation, voter, or Ising-type opinion models), the microscopic rules are fixed and networks are static. A single, unchanging set of coarse-grained models can describe the entire trajectory. In this case, peaks in $\mathcal{E}_k$ indicate the onset of criticality because higher-level dynamics become sensitive to micro-fluctuations (Scheffer et al., 2009), while the same projection and propagation operators remain valid before and after the transition.

In contrast, *adaptive* SES ABMs allow micro-rules and/or network topologies to evolve. When this occurs, the base-level propagator $P_0^{\Delta t}$ becomes time-dependent, reflecting changes in the microscopic interaction structure. Because the coarse-graining operator Π_1 is calibrated to the correlation patterns and slow modes of a particular microdynamics; these structural changes gradually invalidate its assumptions. Rising $\mathcal{E}_k$ in this case indicates not merely the strong cross-scale couplings of a critical state near a tipping point but a transformation of the underlying interaction architecture—the emergence of new effective "laws" for the model dynamics. Capturing such change requires *adaptive renormalisation*, in which the set of coarsened models itself evolves: projection operators and propagators are re-estimated through renewed DEA cycles as the system reorganises. The resulting framework tracks the dynamics of both system states and system structure.

3.6. Practical workflow for model construction

Model development proceeds iteratively. Candidate groupings of level-0 components are proposed from structural or spatial cues and tested for dynamical coherence. Coarse variables are defined by interpretable summaries such as means, majorities, or diversity measures, and network topologies are contracted accordingly. The DEA cycle is then used to estimate effective propagators P_k^{eff} and to compute the commutation error $\mathcal{E}_k$. If the error is small, the coarse-graining advances to the next level; if it is large, the grouping or projection is revised, or additional memory and/or CSI terms are introduced.

The time evolution of $\mathcal{E}_k(\mathrm{t})$ should be interpreted relative to the assumptions of the base-level model (fixed or adaptive) and the system's current dynamical regime (stable or unstable). A rising trend can signal either genuine structural change within the system—such as the build-up of new correlations, self-organisation, or approach to a critical transition—or a gradual loss of adequacy in the current coarse-graining as exogenous conditions or internal system structure drift. Conversely, a declining $\mathcal{E}_k$ indicates that closure is being restored, either because the system itself has stabilised into a new metastable regime or because the modeller has adaptively updated the set of coarsened models (revised Π_{k+1} and/or $P_{k+1}^{\Delta t}$) to reflect the changed structure.

When closure is strong and stable, each level can be simulated independently using its calibrated propagator. In this case, the trajectories of individual model runs will diverge between levels due to stochasticity and/or nonlinearity, but their ensemble statistics will agree. When $\mathcal{E}_k(\mathrm{t})$ grows—indicating either intrinsic transformation or model drift—the DEA cycle should be reapplied periodically or at every time step to maintain cross-level consistency. In this way, the modeller balances computational efficiency with the need to represent evolving multilevel dynamics faithfully.

3.7. Illustrative mock example: a three-level common-pool resource system

To illustrate how the framework can be applied in practice, consider a stylised common-pool resource (CPR) system with three characteristic levels of organisation. At the base level (0), individual agents harvest from resource patches that regenerate biologically and are influenced by local institutions. Each agent's harvesting effort $\sigma_0^{(m)}(t)$ affects the patch resource stock $\beta_0^{(i)}(t)$, while local institutions $\gamma_0^{(q)}(t)$ impose social or regulatory constraints. The social, ecological, and institutional layers are connected through adjacency matrices S_0, B_0, and G_0, and the full system evolves under the propagator $P_0^{\Delta t}$.

To model the community level (1), the modeller groups socially clustered agents and resource patches into functional modules, such as fishing or pastoralist communities, that display partially coherent dynamics. A projection operator Π_1 maps the fine-level state $X_0(t)$ onto the coarser state:

$$X_1(t) = \Pi_1 X_0(t)$$

with components $\sigma_1^{(i)}(t)$, $\beta_1^{(i)}(t)$, and $\gamma_1^{(i)}(t)$, respectively (for example) a community's total effort, aggregate resource stock, and institutional enforcement effectiveness. Using the DEA procedure, the modeller samples microstates consistent with each community state, runs the fine ABM for a short time window, and aggregates the results to fit an empirical community-level propagator $P_1^{\Delta t}$. This provides an effective model of collective resource use and local adaptation dynamics.

At the regional level (2), communities are further grouped into regional supercommunities that share ecological and governance linkages. For example, a coastal management district or pastoral district. A second projection operator Π_2 maps from communities to regional supercommunities,

$$X_2(t) = \Pi_2 X_1(t)$$

producing regional variables such as total harvest, mean institutional compliance, or cross-community inequality in resource access. The regional-level dynamics $P_2^{\Delta t}$ are then learned by repeating the DEA cycle, using short runs of the community-level model rather than the full level-0 simulation.

The modeller evaluates commutation errors $\mathcal{E}_1 = \| \Pi_1 P_0^{\Delta t} - P_1^{\Delta t} \Pi_1 \|$ and $\mathcal{E}_2 = \| \Pi_2 P_1^{\Delta t} - P_2^{\Delta t} \Pi_2 \|$ to assess how well each level reproduces the dynamics implied by the finer one below. When both errors remain small, the coarse propagators provide an adequate autonomous description of the system, and each level can be simulated independently to explore long-term or large-scale scenarios. If the system is in a stable regime but the errors are large, this indicates that the coarse models are missing dependencies; the modeller should refine the model set by revising the coarse-graining maps, re-estimating the propagators, or adding memory or/and cross-scale feedback terms until closure is restored. In contrast, if a rise in $\mathcal{E}_k$ accompanies clear signs of structural reorganisation, such as the collapse of cooperation or a rapid shift in resource-use patterns, it signals an unfolding regime shift rather than model misspecification. In this case, continuous fine-tuning of the coarse propagators can help track the transition, but the coarse-graining structure itself should only be revised once the system stabilises around a new regime, to avoid capturing transient correlations during the transition rather than stable organisation. During a regime shift—such as the collapse of a regional fishery—$\mathcal{E}_1$ may rise first as local cooperation patterns destabilise, followed by an increase in $\mathcal{E}_2$ as regional coordination erodes. Restoring closure at level 1 may require incorporating memory of past enforcement outcomes or strengthening the dependence of individual decisions on evolving community norms, while closure at level 2 may require introducing cross-scale feedback from regional policy to community governance.

This simplified example illustrates how our framework links micro-level interactions, community dynamics, and regional outcomes within a single consistent formalism. It allows the modeller to trace how local overharvesting can scale up to regional collapse, how governance adaptation at intermediate levels can stabilise the system, and how changes in correlations between agents and communities, reflected in the evolution of $\mathcal{E}_k(t)$, quantify the formation and decay of collective organisation across scales.

4. Discussion

We increasingly recognise that the world functions as a complex system. Addressing the societal challenges that arise during the transition toward sustainability requires coordinated actions across multiple levels, each directed at different but interconnected subsystems. The growing interconnectedness of places and regions demands coherent and adaptive policy design and interventions that span across levels and decision-making processes, acknowledging the multi-level complexity of social-ecological systems and their interactions (Bialozyt et al., 2025; Ewert et al., 2011). Often, policies and events focused on one system at one scale may cause unanticipated and even harmful effects in other systems, which could be at another level (Macpherson et al., 2024). To improve our understanding of the cross-scale interactions and emergent behaviours and patterns at various levels in social-ecological systems (SESs), we need to construct multi-level modelling accordingly (Preston et al., 2015).

Explicitly modelling feedback and interaction across multiple levels can reveal the complex dynamics of SESs, and is increasingly demanded for tackling the complex and interlinked societal challenges stated in the 17 Sustainable Development Goals (SDGs) (Moallemi et al., 2022; Sachs et al., 2019). Solutions to achieve the SDGs need to be implemented at various levels and need to take into consideration heterogeneous social, cultural, and environmental contexts; global impacts and effects are not simple aggregations of the actions at lower levels (Moallemi et al., 2022; Ringsmuth et al., 2022). Furthermore, nonlinearities intrinsic to complex systems mean that the past may not always serve as a reliable predictor for the future. Therefore, it is crucial not only to understand patterns but also to focus on the processes and mechanisms at various levels that shape these patterns (Wang et al., 2024).

The growing cross-scale interactions and tele-coupling of social-ecological systems (SESs) can lead to sudden social, economic, and ecological changes, as well as increased and novel risks (Reyers et al., 2018). Actions at local levels are regulated, constrained, and shaped by large-level or even global goals and policies—and these should not be merely regarded as exogenous. Modelling the linkages and feedback across multiple dimensions and levels is crucial to understanding and predicting the dynamics of complex SESs, albeit extremely challenging. Dealing with scales, levels, and scalings was regarded as one of eight grand challenges in SES modelling (Elsawah et al., 2020). Nevertheless, multi-level modelling has proven useful for a range of complex systems in different scientific fields and bears the potential to help policymakers and actors address the “wicked problems” in managing and shaping SESs (Soranno et al., 2014; Willemen et al., 2012).

A key contribution of multi-level ABMs is that they support interdisciplinary collaboration between different disciplines. Having mathematics as a formal language, it has now become possible to explore and discuss the causal mechanisms that connect the different systems, e.g., the dynamics of consumer behaviour in relation to farmer investments and ecological dynamics. This constitutes an important development in formal integration in the interdisciplinary study of complex societal issues that overarch the traditional sciences.

There are various approaches to developing multi-level agent-based models of SESs (Brugière et al., 2022). While the nested hierarchical framework is a promising strategy, as demonstrated in our meta-model, alternative approaches are feasible, for example, by linking, coupling, or tightly integrating multiple quasi-independent agent-based models at different levels or places, as demonstrated by Dou et al. (2019). Both approaches can achieve multi-level modelling and effectively capture cross-scale interactions within these intricate systems. The upscaling of SES models, including ABMs, could achieve multi-level modelling, indirectly, although research on the model upscaling aspect has received less attention (Dressler et al., 2022).

For an interdisciplinary approach to be successful, it is, however, critical that scientists and practitioners from different fields have a common understanding of concepts and terminology (Vervoort et al., 2012). This paper makes an attempt to clarify some of the key concepts around scale and level in the context of agent-based modelling of SESs. However, we acknowledge that researchers in different fields may still have different conventions in using these terminologies. It is very difficult, if possible at all, to define the terminology consistently across all fields. Authors of this paper, from various fields, struggled to reach a consensus during the writing process.

A potential limitation of complex multi-level SES models concerns their interpretability (Jakeman et al., 2024; Wang et al., 2024). Whereas it is possible to build very complex multi-level models, a key issue of their usability resides in our capacity to understand the dynamics these models show (Amorocho-Daza et al., 2025). If the model is too complex, users may find it hard or impossible to understand what is happening in the model, turning it more into a crystal ball than a tool that helps us to understand complex dynamics on a deeper level than is possible without such models. The balancing of realism with simplicity thus requires careful reflection on who will use such models and for what purposes (Sun et al., 2016). Furthermore, the multi-level aspects of ABMs are not explicitly addressed in modelling protocols, such as ODD (Grimm et al., 2010). Here, we advocate for a clear and detailed description of ABMs' approach to representing multiple levels and their interactions.

While we mentioned that the implementation of the multi-level ABM can be technically difficult, a few ABM platforms have enhanced their capacity to support multi-level agent-based modelling. While NetLogo (Tisue & Wilensky, 2004) does not support inheritance (subclasses or sub-breeds) in defining agents, the LevelSpace extension allows modellers to connect multiple models hierarchically to achieve multi-level agent-based modelling (Hjorth et al., 2020). Note that LevelSpace is not included in the standard installation and needs to be installed manually. Multi-level Mesa was designed to extend the capacity of Mesa, making it possible to simulate multi-layered networks (Pike, 2019). Other library-based platforms, RePast, MASON, and GAMA, can also support multi-level agent-based modelling with Java or Python, although the learning curve can be steep. Rapidly emerging AI technologies, especially large-language models, can help modellers overcome some technical limitations and develop more sophisticated and realistic models, accelerate the coding process and analyse outputs.

The increasing availability of fine-resolution data, at various levels, coupled with advances in computing power and analytical techniques, is revolutionising the field of agent-based modelling. Researchers can potentially access vast datasets from individual levels to global levels to calibrate and validate their models, leading to more accurate and realistic simulations—essentially creating a "digital twin" of the studied system by incorporating real-world data into agent-based models (Mrosla et al., 2025). This allows researchers to explore complex social and ecological phenomena with greater precision under various scenarios. This data-driven approach, now often coupled with machine learning, can empower scientists and policymakers to make more informed decisions and develop effective strategies for addressing pressing global challenges (Kavak et al., 2018; Ravaioli et al., 2023).

5. Conclusion

While numerical and statistical models have been widely used in studying the properties and patterns of SESs at various levels, agent-based modelling offers particular advantages, such as intuitiveness, intrinsic multi-level structure, dynamic nature, and flexibility. Moreover, they provide a way to analyse and help understand the processes and interactions at various levels that shape society and the environment. In this paper, we first constructed a conceptual framework to illustrate the concepts and structures in multi-level modelling of SESs, and presented a nested agent-based metamodel in the context of natural resource utilisation and management. Furthermore, we outlined a practical workflow for model construction, and followed with a mock model of a three-level common-pool resource system to illustrate how the metamodel can potentially be applied in modelling practice. With that, it shows how we can advance beyond existing conceptual treatments and schematic architectures of multilevel SES modelling. We also illustrate the importance of multi-level modelling of SESs and demonstrate that ABMs could be highly effective and useful tools in modelling the cross-scale dynamics of SESs. Multi-level ABMs of SESs provide enormous potential for understanding the highly complex dynamics of SESs, such as cascading regime shifts and the emergence of social movements across scales. They can also help policymakers to foresee possible future trajectories of SESs, identify the best intervention level and time points, and make holistic policy measurements to shape the sustainable development of SESs.

As multi-level agent-based modelling of SESs is still in its infancy (Brugière et al., 2022), many challenges remain. This paper lays out a blueprint for multi-level agent-based models of socio-ecological systems (SES) by building on conceptual frameworks and modelling strategies, and presenting a conceptual modelling framework and a metamodel. We aim to spotlight multi-level modelling as a promising avenue for future research, inspiring both theoretical exploration and practical applications. Our goal is to foster the development of more sophisticated multi-level ABMs for SES, thereby enhancing our ability to comprehend and address the complexities and uncertainties inherent in managing social-ecological systems.

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