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A FRAMEWORK FOR MODELING AND SIMULATION OF MULTI-DIMENSIONAL COUPLED SOCIO-ENVIRONMENTAL NETWORKED EXPERIMENTS

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ABSTRACT

Coupled Socio-Environmental Networked experiments have been used to represent and analyze complex social phenomena and environmental issues. There is a lack of theory on how to accurately model diverse entities and the connections between them across different spatial and temporal scales. This gap often leads to significant challenges in the modeling, simulating, and analysis of formal experiments. We propose a framework that facilitates software implementation of multi-dimensional coupled socio-environmental networked experiments. Our approach includes: (i) a formal data model paired with a computational model, together providing abstract representations, and (ii) a modeling cycle that maps socio-environmental interactions over time, allowing for multi-action, interactive experiments. The framework is flexible, allowing for a wide variety of network models, interactions, and action sets. We demonstrate its applicability through a case study on agroecological transitions, showing how the modeling cycle and data model can be used to explore socio-environmental phenomena.

1 INTRODUCTION

Coupled Socio–Environmental Systems (SESs) are complex adaptive systems, characterized by interactions within and among the environmental (e.g., natural, biological, physical) and human (e.g., economic, social, political) components (Berkes et al. 1998). These interconnected entities usually have different attributes and interact with each other, locally or via networks, on multiple spatial and temporal scales (Redman et al. 2004). Understanding SESs is critical to supporting sustainable resource management. SES modeling provides a science-informed platform where stakeholders can share and consolidate their knowledge, and test different scenarios for theory building and hypothesis testing (Elsawah et al. 2020; Lippe et al. 2019). An experimental environment provides spatial and temporal resource dynamics that allow a researcher to capture these two variables. SES experiments to study social behavior related to environmental issues have been used to explore phenomena such as punishment versus communication (Janssen et al. 2010), resource optimization (Gaba and Bretagnolle 2020), and collective action (Castillo and Saysel 2005; Waring and Bell 2013; Kimbrough and Wilson 2013). Given the intrinsic connection between social and environmental systems, Socio-Environmental Networks (SENs) have become a well-established approach to conceptualize and analyze their inter-dependencies within and across spatial and temporal scales (Janssen et al. 2006; Cumming et al. 2010; Bodin et al. 2019; Sayles et al. 2019; Felipe-Lucia et al. 2022).

SEN research studies produce patterns by socio-environmental entities/nodes and their relationships/edges. There is a lack of theory on how to accurately represent SEN diverse entities and define the connections between them across spatial and temporal scales. Temporal and spatial scale mismatches affect the ability to integrate, aggregate and disaggregate data (Virapongse et al. 2016). For example, temporal scale mismatches might occur when stakeholders have different timelines for the completion of a project. Also, location inconsistencies between stakeholders might produce spatial scale mismatches. To understand SENs across scales, it is also important to understand the roles of multiple stakeholders who may have direct or indirect influence and interest in decision making (Lippe et al. 2019).

To explore and analyze complex social phenomena and environmental issues, a combination of experiments, modeling, and simulations of SENs have been used to study resource management (Le Pira et al. 2017; Giordano et al. 2021; Matous and Bodin 2024; Zhou and Liu 2024) and explore social phenomena such as group dynamics and comparisons (Janssen et al. 2010; Gaba and Bretagnolle 2020). To understand and reason about socio-behavioral studies, computational modeling is useful (Fujimoto et al. 2017). Often, in SEN studies, there is emphasis on experiments (Janssen et al. 2010; Gaba and Bretagnolle 2020) or modeling (Le Pira et al. 2017; Giordano et al. 2021; Matous and Bodin 2024; Zhou and Liu 2024), with no iterations of experiments and modeling. Combining experiments with modeling, in a repeated and iterative process, enables each to inform and guide the other (Epstein 2007; Lazer et al. 2009). In research, each modeling approach assumes how the nodes and edges are related within and across different scales, using different network models (e.g. single layer, multiplex, multi-level or multi-dimensional) (Sayles et al. 2019). Multi-dimensional networks are appropriate to capture the complexities intrinsic in organizational life (Shumate and Contractor 2013), allowing different kinds and numbers of nodes in different layers and multiple edges within and among different node types.

This work presents a novel framework and modeling cycle for Modeling and Simulation (MAS) of multi-dimensional SEN experiments across scales. We design a data model and apply a computational model that together form abstract representations of SEN experiments and MAS so that we can determine whether an experiment or simulation can be introduced to our proposed modeling cycle, and ensure correspondence between experiments and MAS. Our framework and modeling cycle can be used as the base of a software platform for behavioral experiments on SENs. Figure 1 provides an overview of the proposed modeling cycle in which, SEN experimental data are transformed to conform to our Data Model, that is a combination of an Abstract Data Model and a Computational Model (see Section 2). The abstract data model and the computational model enable formal specification of SEN experiments and observations and MAS, allowing a generated Conceptual Model to be used in a Simulation Software Model. Any experiment whose data can be cast in terms of the model can be transformed into conceptual data models used in software development (i.e., ODL, UML, or data structure diagrams, among others). The implementation of model and simulation can be defined, as running software implementations of models (e.g. of agent-based models). Simulation results may provide insights through model validity. With controlled experiments we seek to specify the parameters for a next set of experiments (experiment specification).

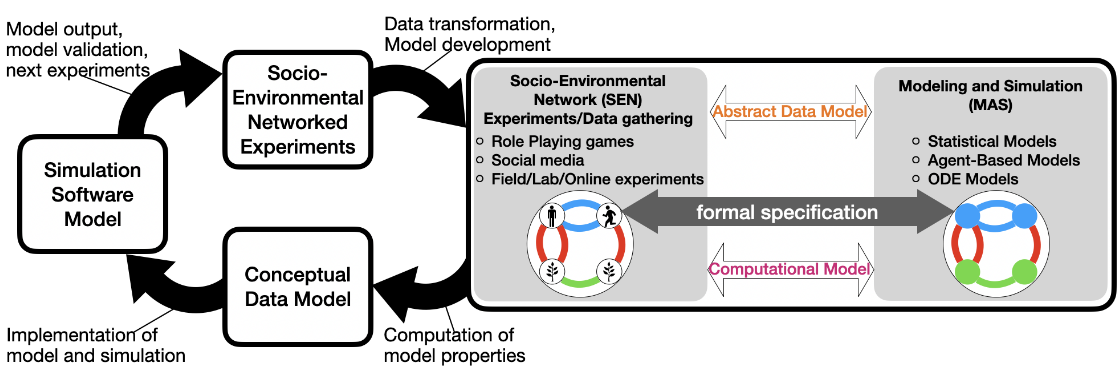

Figure 1: Proposed modeling cycle framework for implementing Socio-Environmental Networked experiments Modeling and Simulation (MAS).

Our contributions include:

A formal data model. We design a formal abstract data model for multidimensional SEN experiments. The data model proposed has the following seven characteristics, (1) an experiment may be composed of many phases (i.e., sub-experiments); (2) each phase may have a different finite duration; (3) each phase may be composed of many layers; (4) each phase may have a different interaction structure among layers; (5) each layer may have a different interaction structure among entities/agents (i.e., different networks); (6) each layer may have a different set of actions (and interactions) among entities/agents; and (7) these actions may be repeated by entities/agents any number of times within the duration of a phase (i.e., temporal interactions). The data model in 2.1, with our computational model in 2.2, provides a correspondence for experiments and models. Frameworks with different types of SEN modeling approaches and network models have been proposed to standardize the analysis of emerging phenomena in SENs (Ernstson et al. 2010; Ghandar et al. 2019; Felipe-Lucia et al. 2022; Man et al. 2023; Zhou and Liu 2024). In (Ernstson et al. 2010; Felipe-Lucia et al. 2022) purely conceptual network frameworks for modeling multi-dimensional SENs are described; but they don't employ a mathematical or computational model and they look for a theoretical understanding of specific research questions. (Ernstson et al. 2010) uses a narrative approach for a conceptual network model, that can be considered multi-dimensional, that describes how social network structure influences ecosystem governance. (Felipe-Lucia et al. 2022) provides a typology to represent ecosystem services using SENs, with the objective to improve research designs by aligning specific SEN conceptualizations and research questions. And, while they are frameworks that define MAS of SEN, (Ghandar et al. 2019; Man et al. 2023; Zhou and Liu 2024), they only focus on multi-level networks, allowing only one relationship between any two nodes and are oriented to a specific research domain. (Ghandar et al. 2019) proposes a framework for modeling urban agricultural systems. (Man et al. 2023) develops a multilevel social-ecological network analysis approach to identify the collaboration's effect on genetically connected coastal areas. (Zhou and Liu 2024) defines a SEN framework to quantify the supply-demand flow of grain ecosystem service, identifying supply and demand nodes and analyzing spatiotemporal patterns. None of these frameworks combines this approach of experiment-and-modeling iterations, to investigate multi-dimensional coupled SEN experiments and facilitate automatization. Our work is unique.

A modeling cycle. We provide a modeling cycle for SEN experiments that includes: (i) Gathering of data from SEN experiments, through observations, field/lab/online experiments, role playing games, social media, etc. (ii) Transforming the raw data into our abstract data model along a Computational Model. (iii) Computation of the model properties through a conceptual data model (i.e., ODL, UML, or data structure diagrams, among others). (iv) Implementing MAS of temporal, multi-action, interacting experiments to study behavioral experiments on SEN. We emphasize that our framework and modeling cycle in 2.3 can be used as the base of a software platform to run coupled socio-environmental behavioral experiments. There are experimental platforms available to conduct behavioral experiments on socio-environmental systems (Janssen et al. 2014), but their focus is distinct and they must be adapted for novel research questions. Depending on the phenomena being studied, our SEN experiments can vary widely because they are multi-phased, multisubject, and multi-action. In (Grimm et al. 2020), the Overview, Design concepts and Details (ODD) protocol describes individual and agent-based models in socio-ecological sciences but doesn't provide a computational model. In (Augusiak et al. 2014) a workflow for model design is presented, the objective is to help modelers and model users to organize model evaluation and its communication; but doesn't provide a formal data model. There is a need for a framework with systematic model analysis in combination with iterative model development for SESs (Thober et al. 2017).

Case study. We describe a case study in Section 3 to illustrate the use of the modeling cycle and data model as an analytical tool for SEN experiments. SEN experiments have been modeled and simulated, in research areas like mobility management (Le Pira et al. 2017), water management (Giordano et al. 2021), and soil nutrition management (Matous and Bodin 2024; Zhou and Liu 2024). SEN experiments have been implemented to explore behavioral phenomena in different experimental domains, including the laboratory (Janssen et al. 2010) and the field (Gaba and Bretagnolle 2020) In this case study, we describe SEN experiments to foster agroecological transition (i.e. reducing weed control intensity) (Gaba and Bretagnolle 2020), thus showing that we can evaluate such experiments and studies with our system.

The remainder of this paper is structured as follows. In Section 2 we present formalisms for the data model, and the computational model of discrete dynamical systems, and describe the implementation of the proposed modeling cycle for multi-dimensional SEN experiments and MAS. We provide a case study in Section 3, conclusions and future work in Section 4.

2 ABSTRACT DATA MODEL FOR MULTIDIMENSIONAL SEN EXPERIMENTS AND MAS

We present a formal abstract data model for Multidimensional SEN Experiments and Modeling and Simulation (MAS). The utility of this model is to determine whether a SEN experiment can be represented by the characteristics of our data model, then data from the experiment can be used in a modeling cycle to simulate the experiment, thus reducing time for implementation and analysis of modeling and simulation.

2.1 Formal Data Model

To model SESs adequately, interactions occur at multiple scales, and there is constant interaction not only within the same scale, but also across different scales. To overcome the static nature of SENs, the structure of our framework defines experiments with different phases and layers, capturing the continuous change and evolution that characterize SESs as complex adaptive systems. The data model can be used to formulate experiments and models for simulating experiments. Given a description of an experiment or model, and given a phenomenon to study, the number of phases and layers are defined. To overcome any temporal scale mismatch, each phase represents a system of agents as a (time-varying) graph, and has to define the unit of time of one time increment. To overcome any spatial scale mismatch, each layer defines a graph where nodes represent agents, and edges represent pairwise interactions. Entities/agents can be any combination of humans, animals, insects, plants, and inanimate objects, any object that can act or be acted on. Figure 2 shows an example of a multi-dimensional SEN experiment composed of n_p phases with a set of V entities where $n = |V|$, and a set of L layers where $n_l = |L|$.

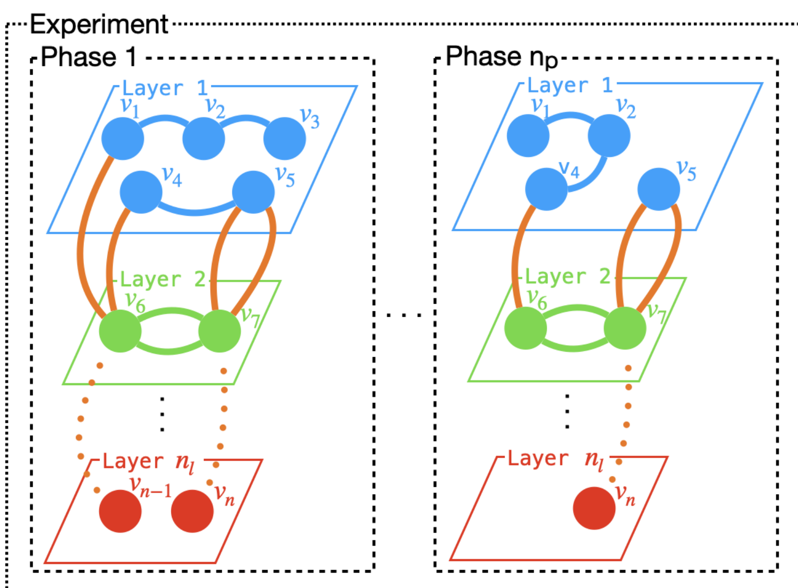

Figure 2: Representation of a SEN experiment composed of n_p phases with a set of V entities where $n = |V|$, and a set of L layers where $n_l = |L|$.

Table 1 shows part of the model with the computational model, to provide a formal representation for experiments and MAS.

Table 1: Partial definition of our abstract data model. The experiment schema describes the experiment parameters. The structure of the phase schema describes the parameter types for an experimental phase; an experiment can have any number n_p of phases. The structure of the layer schema describes the parameter types for a phase layer; a phase can have any number n_l of layers. Instance variables within the phase schema structure and layer schema structure can vary across phases.

#	Parameters	Symbols	Description
Experiment Schema			
1	Set of layers IDs	L	$L = \{l_1,\ldots,l_{n_l}\}$. Set of layers over all phases; $l_i \in L$.
2	Set of entities IDs	V	$V = \{v_1,\ldots,v_n\}$. Set of entities over all phases; $v_i \in V$.
Layer Schema			
1	Entity attributes	Ω	$\Omega = \cup_{j=1}^{n_e} \Omega_j$. $\Omega_j = (\omega_{j1}, \omega_{j2}, \ldots, \omega_{j,n_{sa}})$ is the sequence of n_{sa} attributes for $v_j \in V$.
2	Network definition	$H(V_i,E_i)$	Node set $V_i = \{v_1,...,v_\eta\}$ and edge set $E_i = \{e_1,\ldots,e_m\}$, where $V_i \subseteq V$ may not be all nodes (entities) in the system, and $e_k = \{v_j, v_\ell\}$ with $v_j, v_\ell \in V_i$. E_i may be empty and $i = i_{n_l}$.
3	Edge meaning	Λ	Set Λ of string representations $\lambda \in \Lambda$ stating the meaning(s) of an edge (e.g., $\lambda =$ "communication channel" or "influence").
4	Action set	A_i	$A_i = \{a_1, a_2, ..., a_{n_a}\}$. Set of n_a actions an entity can execute, over time, any number of times, during a phase, $n_a \geq 0$ and $A_i \subseteq A$.
Phase Schema			
3	Phase begin	*t_ph_begin*	Timestamp of phase beginning.
4	Phase duration	t_p	Number of time increments in the phase.
5	Unit of time	u_p	Time unit of one time increment (e.g., seconds, days).
6	Phase Network definition	$G(V',E')$	Node set $V' = \{v_1,\ldots,v_\eta\}$, edge set $E' = \{e_1,\ldots,e_m\}$, where $V' \subseteq V$ may not be all nodes (entities) in the system, $e_i = \{v_j, v_\ell\}$ with $v_j, v_\ell \in V'$. E' may represent across layer edges, and empty.
7	Node attributes for a phase	Γ	$\Gamma = \cup_{t=0}^{t_p} \big(\cup_{j=1}^{\eta} \Gamma_j(t)\big)$. $\Gamma_j(t) = (\gamma_{j1}(t), \gamma_{j2}(t), \ldots, \gamma_{j,\eta_v}(t))$ is the sequence of η_v attributes for $v_j \in V'$ in the phase i_{n_p} at time t. Γ is a triple nested sequence in attributes, entity ID, and time.
8	Edge attributes for a phase	Ψ	$\Psi = \cup_{t=0}^{t_p} \big(\cup_{j=1}^{m} \Psi_j(t)\big)$. $\Psi_j(t) = (\psi_{j1}(t), \psi_{j2}(t), \ldots, \psi_{j,\eta_e}(t))$ is the sequence of η_e attributes for $e_j \in E'$ in the phase i_{n_p} at time t. Ψ is a triple nested sequence in attributes, entity ID, and time.
9	Action set	A	Set of actions executed, over time, any number of times.
10	Action sequence	T	$T = \cup_{t=0}^{t_p} \big(\cup_{k=1}^{\eta} T_k\big)$. $T_k = (\sigma_i, a_j, v_{\ell_1}, v_{\ell_2}, t_o, py_q)$ is the schema for an *action tuple*. σ_i is a string that is a unique identifier for an action sequence. Action $a_j \in A'$ is initiated by node $v_{\ell_1} \in V'$, and v_{ℓ_2} is the target node of the action, with edge $e = \{v_{\ell_1}, v_{\ell_2}\} \in E'$. $t_o \in \mathbb{R}$ is the time of the action ($0 \leq t_o \leq t_p$); py_q is the payload represented as a JSON schema.

Experiment Schema. Each experiment has the following elements: a unique id *exp_id*, a number n_p of phases, a number n_l of layers, a number n of entities, a *t_begin* timestamp for the beginning of the experiment, and a *t_end* timestamp for the end of the experiment. Each layer has a unique id l_i for identification and each entity has a unique id v_i for identification. A set of layers in an experiment is defined by $L = l_1,...,l_{n_l}$. A set of entities in an experiment is defined by $V = v_1,...,v_n$.

Layer Schema. Each layer has the following elements: a unique id *l_id*, a number n_e of entities. A layer has n_{sa} entity attributes defined for each entity. Entity attributes Ω are invariant across phases. Each layer represents the interaction structure among entities as a network $H(V_i, E_i)$ with meanings of edges Λ. Entities and edges may have initial conditions B^v and B^e, respectively. A is the set of available actions.

Phase Schema. Each phase schema has the following elements: a unique id *ph_sch_id*, the number i_{np} of the phase in the sequence of phases, a *t_ph_begin* timestamp at the beginning of the phase, number t_p of time increments in the phase, and the unit of time u_p of one time increment. Each phase represents the interaction structure among entities as a network $G(V', E')$ with meanings of edges Λ'. Over all nodes and edges, node attributes Γ and edge attributes Ψ capture attribute changes in time. Edges may have initial conditions δ^e. A is the set of permissible entity actions. An action tuple Ti that captures pair-wise interactions between entities, from the attribute sequences Γ and Ψ of a phase when action tuples, may cause or be caused by changes in node and edge attributes. In essence, Γ and Ψ can be viewed as sequences of node and edge states. There are several sequences of values for a particular node or edge j. Each entry in these sequences can be scalars, sequences, sets, maps, and other structures. Then, these entries are sequenced over time through the union of entries over time, from time 0 to time t_p. The exceptions are the initial conditions B^v_j, B^e_j and δ^e_j, specified only at time 0.

2.2 Graph Dynamical System Model

The relationships between diverse entities in SESs make these systems nonlinear and complex. To model the interaction structure of a time varying SEN, a mathematical formalism can capture the diversity and interactions of the entities. To describe a formal framework for Multidimensional SEN experiments and MAS, we use a mathematical and computational framework known as a discrete Graph Dynamical System (GDS) (Adiga et al. 2018; Mortveit and Reidys 2007). GDS provides a modeling framework for bio-social systems. To formalize experiments and MAS, this model explicitly represents individual components of a system, capturing the interactions among them via a network. For example, there may be a set of entities representing farmers in a social network defined by a set of n nodes, where each node i has a state s_i from a set K that is $\{0,1\}$. $s_i = 1$ could encode that farmer i has executed landscape management, while $s_i = 0$ could encode a non-management state. A set of local transition functions $\mathscr{F} = \{f_1, \ldots, f_n\}$ governs the local dynamics by using f_i to determine how the state of node i evolves from time t to $t+1$. An update scheme $\mathscr{U}$ determines how the functions $\mathscr{F}$ assemble to a map $F : K^n \to K^n$ with the form $F = (F_1, F_2, F_n)$. The update scheme $\mathscr{U}$ applies the functions f_i in parallel. The set $\mathscr{F}$ has an associated graph G with nodes $\{1, 2, \cdots, n\}$ that captures the dependency between variables, and there is a directed edge $\{i, j\}$ whenever a function f_i depends on the state of node j.

Formally, a GDS $\mathscr{S}$, is a triple $(G, \mathscr{F}, \mathscr{U})$, where (i) $G(V,E)$ is an undirected graph with node set V and edge set E where $\mid V \mid = n$ and $1 \leq i \leq n$, (ii) $\mathscr{F} = \{f_1, f_2, \ldots, f_n\}$ is a collection of local transition functions where f_i is used to determine how the state of node v_i evolves from time t to $t+1$ for some suitable time scale, (iii) $\mathscr{U}$ is the state space representing the union of the nodes state space $\mathscr{U}^v$ with the edges state space $\mathscr{U}^e$, $\mathscr{U} = \mathscr{U}^v \cup \mathscr{U}^e$. An undirected edge $\{v_i, v_j\} \in E$ can be represented by two directed edges: (v_i, v_j) and (v_j, v_i). To each node v_i, a G-local transition function f_i is assigned. This function depends only on the state of node i and those of the neighbors of v_i in G. The inputs to function f_i are the state of v_i, the states of the neighbors of v_i, and the states of the edges outgoing from v_i in G. Function f_i maps each combination of inputs to $s'_i \in \mathscr{U}^v$ for v_i and to $s'_{ij} \in \mathscr{U}^e$ for each directed edge e_{ij}. s'_i is the next state of node v_i and s'_{ij} is the next state of edge e_{ij}. These functions are executed synchronously in parallel at each time step t. The GDS model is equivalent to the data model in Subsection 2.1.

Connections between the data model and GDS. The abstract data model described in Section 2.1 and partially defined in the Table 1 is consistent with a GDS. In each phase, the graph $G(V', E')$ is equivalent to the graph $G(V,E)$ of the GDS. In the model, the nodes state space $\mathscr{U}^v$ and the edges state space $\mathscr{U}^e$ are subsets of the node attributes Γ and the edge attributes Ψ. Attributes may have additional parameters that are not part of the node or edge state (i.e., name and description). Action tuples T_k may be part of the state. Entity/agent actions, the network, and many other parameters are well defined.

2.3 Implementation of Modeling Cycle

We describe the modeling cycle detailed in Figure 1 to implement SEN experiments. To make scientific modeling of SESs efficient, researchers use various heuristics at different hierarchical levels of a modeling project (e.g. rephrasing the problem, drawing a system diagram, imaging themselves in the system, identifying essential variables and small problems) (Grimm and Railsback 2005). Heuristics can be powerful, but do not include the full cycle of tasks performed in developing and using models. Our modeling cycle is based on formal models, and theoretical models while taking the semantics of social experiments into account and largely focusing on providing a generic data schema. In a typical modeling cycle, modeling is an iterative process. The cycle includes the different elements of model development, model implementation, model evaluation, verification, and validation into a coherent framework. The idea of iterative experiments and modeling can be operationalized in various ways. For example, in our cycle, an abductive analysis will perform experiments first, then identify patterns in the experimental data, and this information will be used to construct, validate, and modify models.

SEN experiments. SEN experiments are defined. These types of experiments offer researchers the potential to understand coupled socio-environmental systems by allowing the testing of different hypotheses related to socio-environmental behavior.

Abstract Data Model + Computational Model. The purpose of the data model for multi-dimensional SENs, provided partially in Table 1, together with the computational model of GDS, is to provide formal representations for experiments and MAS, and their iterative interactions.

Conceptual Data Model. The data model can be transformed into an entity-relationship diagram that is a more typical representation for reasoning about software, for implementation purposes. The abstract data model can be translated to customary forms of data models (e.g., UML) for software development. A UML representation of an entity-relationship diagram for our abstract data model is presented in Figure 3.

Simulation Software Model. To progress from a conceptual data model to a software model, specification, building, and execution of experiments and simulators of experiments must be programmed. The ideal outcome after developing a GDS is that the complete dynamical behavior of the system is computed. For dynamical systems of hundreds, thousands or billions of nodes, computationally intractable problems might be addressed by computing forward trajectories (Adiga et al. 2018). The technical challenges of building software systems to analyze SEN experiments include (i) the definition of abstractions that capture data analytics and computation; (ii) identifying appropriate levels of abstraction for tasks, pipelines, and systems. Our SEN experiments are complex, defined as multi-phased, multisubject, and multi-action. Because SEN experiments can vary widely, depending on the phenomena being studied; they require more sophisticated software, and a greater range in modeling functionality. Our formal model, with high-level abstractions, provides a system more understandable and reusable helping to solve these abstraction problems. In a software implementation, these custom analyses can be addressed at a task level within a pipeline, or at a pipeline level with the addition of new pipelines. The case study in Section 3 provides a full theoretical modeling cycle execution, for reducing weed control intensity experiments.

3 CASE STUDY

In this Section we demonstrate the versatility and wide applicability of the modeling cycle framework. We present a full theoretical modeling and simulation cycle execution for experiments in real-field conditions to foster agroecological transition.

A socio-environmental experiment to reduce the intensity of weed control: In Gaba and Bretagnolle (2020), an experimental socio-environmental approach is presented, identifying management practices that optimize multiple objectives in adaptive governance. The experiment highlights the interactions between

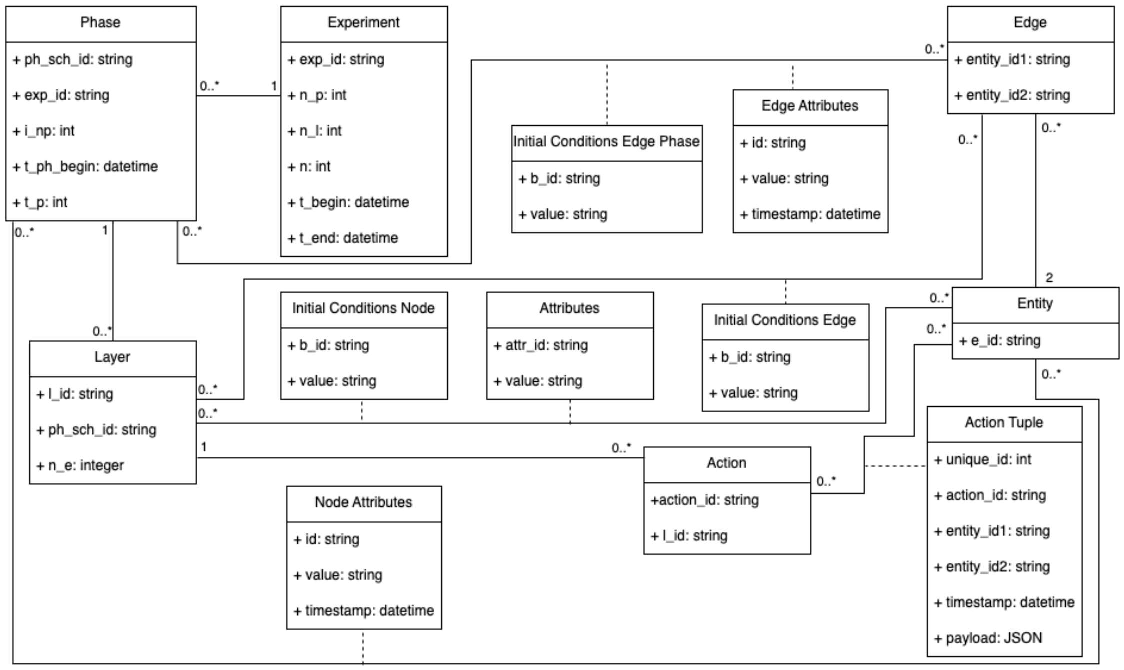

Figure 3: The data model from Table 1 can be transformed into data models used in software development, like this entity-relationship diagram in Unified Modeling Language (UML) notation.

environmental and social processes. A socio–environmental experiment is defined to investigate how to reduce weed control in winter cereal fields. SEN dynamics are driven by human actions, in this case through farming practices and landscape management. No two farmers cultivate their fields exactly the same way, making these human actions diverse, resulting in a wide range of management strategies that may interact differently with environmental processes. To transform data from these experiments and model them, our framework provides a clear path. In this case, experiments are used to establish causal links between patterns and processes. Each field or farm is an experimental unit interacting with a social network. The management practices may be sowing a crop or reducing pesticides or nitrogen. Different levels of changes in management practices are implemented in several plots from a unit, while the rest of the plots use their standard practices as a control. Variables include biodiversity indicators (e.g. plants, pollinators, and pest enemies), long-term and short-term crop yields, economic returns (e.g. fixed and variable costs), ecological functions (e.g. soil properties), the farm infrastructure and the farmers' practices, and the benefits to different stakeholders (e.g. yields and other economic and cultural goods).

Abstract Data Model + Computational Model: Each experiment, *exp_id*, consists of three phases $n_p = 3$ and two layers $n_l = 2$. The number of unique nodes V over all phases in the experiment is n, where $V = \{v_1, ..., v_n\}$. Layer 1 is composed of experimental plots, each one of 200 m^2. Layer 2 defines the farmers/cooperatives social networks. $G(V', E')$ is the network that defines the connections within and between the layers. The meaning of an edge is Λ = influence channel between pairs of nodes. Γ_i contains variables for v_i initial node attributes like costs. Each layer i has a set of actions A_i. The action set A_1 in Phase 1 surveys, the weeds (a_{11}), and harvested weeds (a_{12}) and crop plants (a_{13}) to estimate weed biomass, crop yield and quality. The action set A_2 in Phase 2 is related to decision-making by farmers and defines pesticide (a_{21}) and fertilizer use (a_{22}), crop plating (a_{23}), ploughing (a_{24}), and weed control (a_{25}). Each agent can execute any action from the action set A_2, such as herbicide use in a plot. The surveys' action set A_1 in Phase 3, allows comparing yields and gross margins between experimental treatments. Figure 4 provides an illustrative example of data model elements, showing many of these variables, and examples of action tuples in each phase.

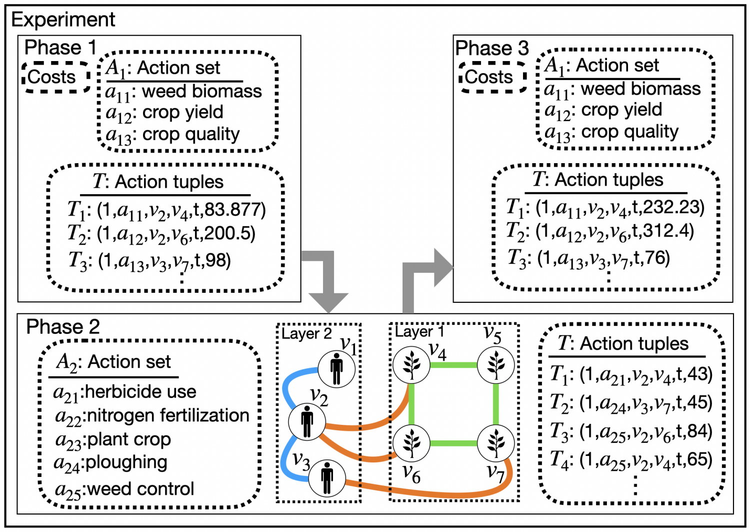

Figure 4: Elements of a partial data model on Table 1 developed for the experiment conducted in Gaba and Bretagnolle (2020).

Conceptual Data Model: Table 2 partially details the experiments in (Gaba and Bretagnolle 2020) with our data model. Schema definitions for the experiment, layer 1 and phase 1 are presented. Schema definitions for Layer 2, Phase 2 and Phase 3 are not shown, but they follow the definition of our abstract data model. We define one experiment with three independent phases. In the first phase, values are gathered through a survey to farmers associated with specific plots (scientists measure parameters). In the second phase, management practices are defined between the farmers and plots. In the third phase, values are gathered again through a survey to farmers associated with specific plots to assess the effect of management actions. This data model instance, coupled with a GDS formulation (section 2.2), allows the experiment to be transformed into data models used in software development to automatize procedures. Our abstract mathematical data model is more abstract in its use, it corresponds much more closely to the information required for software design capabilities, and enables compact representations of simulation models. The data model can be translated into a entity-relationship diagram in unified modeling language (UML) form. Figure 3 illustrates that the abstract data model can be translated to customary forms of data models (e.g., UML) that are more amenable for software development.

Simulation Software Model: The objective of the experiment is to analyze the data using statistical models to compare the results, and the conceptual data model allows this. Our model also allows the definition of a simulation environment for the experiments. For example, for phase 2, we can define the implementation of modeling and simulation, where there are 5 actions, and i and j represent the actions a_i and $a_j \in A$. The experiment, layer and phase schemas in Table 2 show data structures that can be translated into standard forms of data model, like an entity-relationship diagram in unified modeling language (UML). Experimental data can be transformed, into a data common specification that conforms to our data model. After this, with any programming language, we can define an Agent Based Model with a transition probability matrix from one action $a(t) = a_i$ at time t to the next action $a(t+1) = a_j$ for each node v_i and $a(t) \in A$, where the probability π_{ij} is given by $P_r(a(t+1) = j|a(t) = i)$ with $\sum_{j=1}^{5} \pi_{ij} = 1$. The experiment can be defined in increments of days, weeks, or months, depending on the frequency of the interviews to the participants, or data collection. Figure 5 shows the experiment in phase 2 modeled with agents and a transition probability matrix for one action to the next action for each agent from actions set A. An agent v_i can execute an stochastic process driven by transition probability matrix P. The specification of models, software and pipelines represents the Software Design, that our model facilitates. At the end of the execution of a simulation software model, and with model outputs, a new set of experiments may

Table 2: Experiments in Gaba and Bretagnolle (2020) defined partially with our data model.

#	Parameters	Description
Experiment Schema		
1	L	$L = \{l_1, l_2\}$, set of layers over all phases.
2	V	$V = \{v_1, \ldots, v_n\}$, set of entities over all phases.
Layer Schema		
1	$l\_id = 1$	Unique id for layer.
2	n_e	Number of entities in the layer.
3	Ω	$\Omega_j = (\omega_{j1}, \omega_{j2}, \ldots, \omega_{j,n_{sa}})$, sequence of n_{sa} attributes for $v_j \in V$.
4	$H(V_1, E_1)$	Node set $V_i = \{v_1, ..., v_\eta\}$ and edge set $E_i = \{e_1, \ldots, e_m\}$.
5	λ	$\lambda =$ influence channel between entities.
6	B^v	$B^v_j = (plant_{j1}, cost_{j2}, property_{j3}, ...)$, initial conditions for nodes.
7	A_1	$A_1 = \{weed\_biomass, crop\_yield, crop\_quality\}$.
Phase Schema		
1	$ph\_sch\_id = 1$	Id for phase schema.
2	$i_{n_p} = 1$	Element of the sequence of phases of the experiment.
3	t_ph_begin	Timestamp of phase beginning.
4	t_p	Number of time increments in the phase.
5	$u_p = days$	Time unit of one time increment.
6	$G(V', E')$	Node set $V' = \{v_1, \ldots, v_\eta\}$, and edge set $E' = \{e_1, \ldots, e_m\}$.
7	λ'	$\lambda' =$ influence channel.
8	Γ	$\Gamma_j(t) = (\gamma_{j1}(t), \gamma_{j2}(t), \ldots, \gamma_{j,\eta_v}(t))$ is the sequence of η_v attributes for $v_j \in V'$.
9	δ^e	$\delta^e_j = (yield, value, ...)$ initial conditions for edges between layers.
10	$A = A_1$	$A_1 = \{weed\_biomass, crop\_yield, crop\_quality\}$.
11	T	$T_1 = (1, a_{11}, v_2, v_4, t, value)$. v_2 measures v_4 plot. $T_2 = (1, a_{12}, v_2, v_6, t, value)$. v_2 measures v_6 plot. ...

be defined and executed over many loops in a study. Figure 5 shows an example of a software pipeline execution to transform raw experimental data from a mathematical model to a software model; here we show this output in json files that represent the input files for any system in an specific programming language (where models and simulations are defined), after simulations are performed, model results are obtained through output files.

4 CONCLUSIONS AND FUTURE WORK

SENs have become a widely recognized approach to conceptualize and analyze the inter-dependencies within the natural connection between social and environmental systems. However, the variety in how SENs are conceptualized poses challenges for their application to different problems and research questions. This

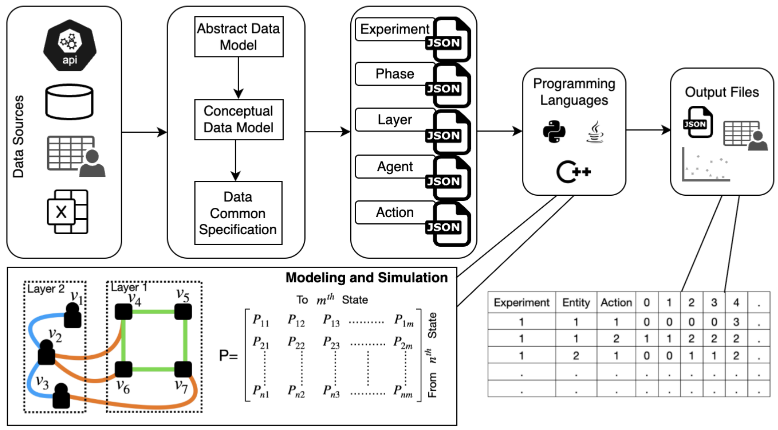

Figure 5: Example of a software pipeline execution to transform raw experimental data from different data sources, into a data common specification.

work aims to develop a framework, supported by iterative experiments and modeling, for MAS in multi-dimensional SENs. A formal abstract data model is provided to ensure an agreement between experiments, modeling, and simulation. We introduce a modeling cycle for SEN experiments, highlighting how our framework and cycle can serve as the foundation for a software platform to run coupled socio-environmental behavioral experiments. A case study on fostering agroecological transitions demonstrates the practical application of the modeling cycle and data model. Future work will focus on implementing a distributed experimental platform for the design of MAS of SEN experiments using our cycle and framework.

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