Agent-based modeling for sustainability

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Welcome!

These are the course notes and manual for the Agent-based Modeling for Sustainability, the second course in the Computational Social Science for Sustainability (CSS4S) series at the Stanford Doerr School of Sustainability.

The course and the `socmod` library are under active development. If you have suggestions, questions, want to report typos, etc., please help me out and open an issue on the repo's GitHub page.

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This online book is divided in two parts:

1. Notes on the theory and application of agent-based modeling to promoting the social diffusion of sustainable practices through social learning and social influence. Continue on to the Introduction to read the Notes.
2. Technical manual that reviews the skills and techniques needed to develop agent-based models for sustainability and present the results in a scientific article.

Please select a chapter from the list to the left or continue to the Introduction.

1 Introduction

Indigenous, local peoples of the South Pacific Islands and other coastal habitats have sustainably managed mangrove forests to dissipate storm surges and prevent erosion, mitigating potential costs of climate change since long before the anthropocene (Alongi 2002; Nalau et al. 2018; Pearson, McNamara, and Nunn 2020; McNamara et al. 2020). First peoples of western North America have similarly practiced prescribed burns to prevent destructive wildfires during times of drought for millennia (Eisenberg et al. 2019; Kolden 2019). Despite their long-known effectiveness, adaptive practices like these often fail to spread widely. Instead, international development agencies frequently advocate for the construction of seawalls, for example, even though seawalls can exacerbate flooding once breached and incur high maintenance costs (Piggott-McKellar et al. 2020). Inland forest management is beset by polarization among stakeholders (Swette, Huntsinger, and Lambin 2023), resulting in devastating wildfires burning a buildup of fuels or greenhouse gas-intensive clearcuts.

Here we introduce what we dub *the puzzle of diffusion*: why do some effective, sustainable practices like mangrove forest management fail to diffuse broadly, while other less effective or even maladaptive practices become widespread (Figure 1.1)? To answer this, we answer some more basic questions along the way. First, how do people decide what to do, i.e., how does learning work? Second, what is the effect of identity on how well or how likely we are to learn from people of the same or different identity? Third, what is the effect of social structure, i.e., who knows whom, represented as a social network? Agent-based models are useful because they provide a framework for creating rigorous, mechanistic, concrete models of social diffusion of adaptations. They help us deal with the complexity of causation in the real world through strategic selection of causal input variables and model details, which, over several model time steps, lead to social emergent phenomena like the diffusion of climate change adaptations.

The focus of this course is developing agent-based models that can help us simplify complex combinations of cognitive and social factors to represent only the most relevant ones, and observe the effect of these on simulated outcomes such as the proportion of people adopting adaptive behaviors, or opinion extremism and polarization.

1.1 Why agent-based models are useful

Agent-based models (ABMs) provide a structured way to explore complex systems by simulating interactions between autonomous *agents*, i.e., simulated people. In sustainability contexts,

Figure 1.1: Agent-based models can help us answer the puzzle of diffusion, i.e., why do certain adaptations widely diffuse socially and some do not, with maladaptations often taking their place?

ABMs offer a low-cost testbed for understanding how interventions might impact social dynamics and environmental outcomes. For example, Airoldi and Christakis (2024) demonstrated through regression analysis across that one method for selecting individuals targeted in a public health education campaign worked better than another. They studied over 20,000 individuals across Honduran villages of about 100 people each to reach their findings. Real-world verification of the efficacy of different intervention strategies is important. However, we can also use agent-based models to represent the diffusion of information in simulated populations where interactions are structured by model social networks. We can initialize thousands or millions of simulated villages in which this information could diffuse with different intervention strategies, and observe the distribution of the adoption of sustainable behaviors for each potential intervention strategy. We can then analyze which performed best *in silico*, which can be helpful if interventions will be taken to different contexts. In other worlds, we can use ABMs to deduce how different learning rules, group identities, and social structures shape sustainability outcomes generally, which can guide our selection of real-world intervention strategies.

A typical ABM simulation cycle includes (Figure 1.2):

- Initializing agent populations and environmental conditions
- Iterative steps where agents select partners, interact, and update behaviors based on outcomes and learning rules
- Repeating these steps until specific conditions or thresholds are met
- Generating output data for analysis

We will analyze and draw on several real-world empirical studies of interventions to develop our agent-based models that we in turn will use to simulate interventions in order to *deduce* which strategies are most effective for *social interventions* to promote sustainability, and why. A *social intervention* (or just *intervention*) for promoting sustainability is any concerted effort where those promoting a sustainable practice introduces information about how to perform that practice to a population. *Deductive* methods complement regression-based inferential or *inductive* strategies. Deductive strategies can explain which strategies are most effective and why in idealized, cost-free settings (cost-free at least compared to the cost of real-world social interventions at scale).

Low-cost experimentation with simulated social interventions to promote sustainability are critical. Unless progress is accelerated towards we can expect to "have 575 million people living in extreme poverty, 600 million people facing hunger, and 84 million children and young people out of school. Humanity will overshoot the Paris climate agreement's 1.5°C 'safe' guardrail on…temperature rise. And, at the current rate, it will take 300 years to attain gender equality" (Malekpour et al. 2023, 250). Accelerated transformations are required to reach goals necessary to avoid increasingly frequent and costly climate change disasters (United Nations 2023). It is not plausible to do real-world experiments at the global scale required to infer which strategies work best in which situations.

In this course we will focus on deducing how between different cognitive and social factors, or other initial conditions, affect simulated sustainability intervention outcomes. We will frame

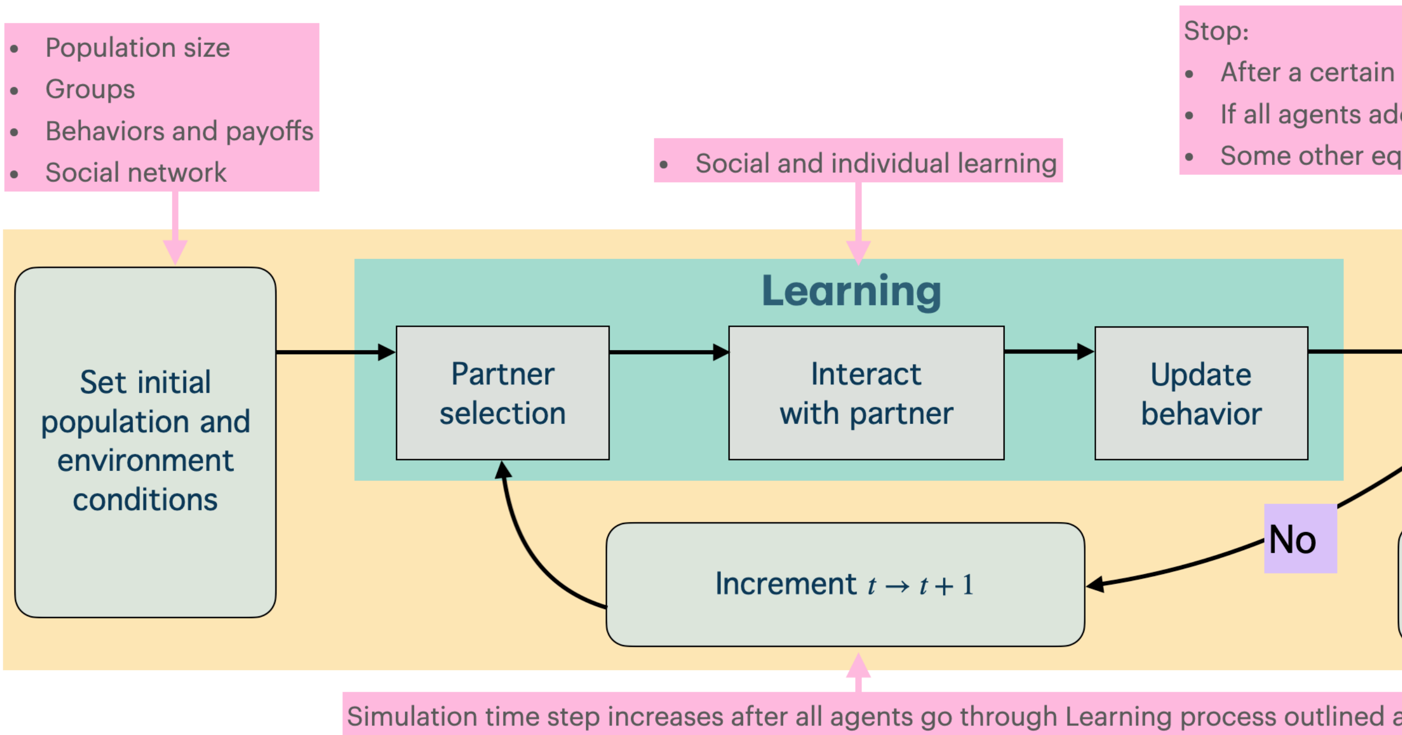

Figure 1.2: Agent-based modeling simulation cycle.

our studies in terms of sustainable development goals, but we will never fit our models to observations. Nonetheless, we will strive to develop models that are amenable to real-world interventions against which the models could be fit and predictions could be compared. It seems this is not done too much in practice yet in sustainability. However, some of our colleagues focused on studying basic processes that underlie cultural transmission do exactly this to explain experimental data and archaeological observations (Deffner et al. 2024), which thereby improves their theory, models, and understanding of cultural evolution in a theory-model-observation cycle. With more time and research effort, this cycle may become commonplace in sustainability.

The urgent need to understand how sustainable behaviors spread in order to develop effective interventions pressures social scientists to make social science more rigorous, reliable, and digestible by non-social scientists. In the rest of this Introduction we review cognitive and social theories of social learning, identity and influence, homophily and core-periphery network structures, and preview the remainder of the course material. For an overview of the course feel free to skip ahead to the Plan in table format.

1.2 Social learning strategies

Human kind is set apart by powerful learning and reasoning capabilities (Witt et al. 2024) that enable cultural transmission and accumulation of technologies and practices no other species matches (Henrich 2015). For our sustainability models, we only need simple models of cognition and learning. It would never be practical to do psychological or cognitive tests in the context of sustainability interventions that targets large populations, for one thing, so we could never compare detailed cognitive assumptions or predictions with reality. For our purposes we will consider three general classes of learning strategy:

1. **Contagion**: Individuals copy behaviors simply by observing others performing them.
2. **Frequency-biased learning**: Individuals adopt behaviors because others are already doing them, creating a conformity effect.
3. **Success-biased learning**: Individuals are more likely to adopt behaviors perceived to be successful or beneficial.

In the mangrove versus seawall example, success-biased learning might favor seawalls if influential external actors, who seem successful or wealthy, advocate for them, even if seawalls are ultimately less effective. Mangrove forests might become widely adopted if, on the other hand, frequency-biased learning predominates and many communities have adopted that method.

1.2.1 Formal social learning models with example

To make this more concrete, we *formalize* (i.e., *give formulas for*) these three learning strategies as follows using the example in Figure 1.3. In the example, there is one *focal agent* who is the one doing the observing/learning, labelled with the ID *1*, and three social network neighbors with IDs *2, 3,* and *4*. The focal agent is deciding whether or not to install residential solar. One of his neighbors has installed it, 2. Based on 1's perception, 2 is the wealthiest, represented by four dollar symbols. 3 is perceived to have one dollar and 4 has two dollars.

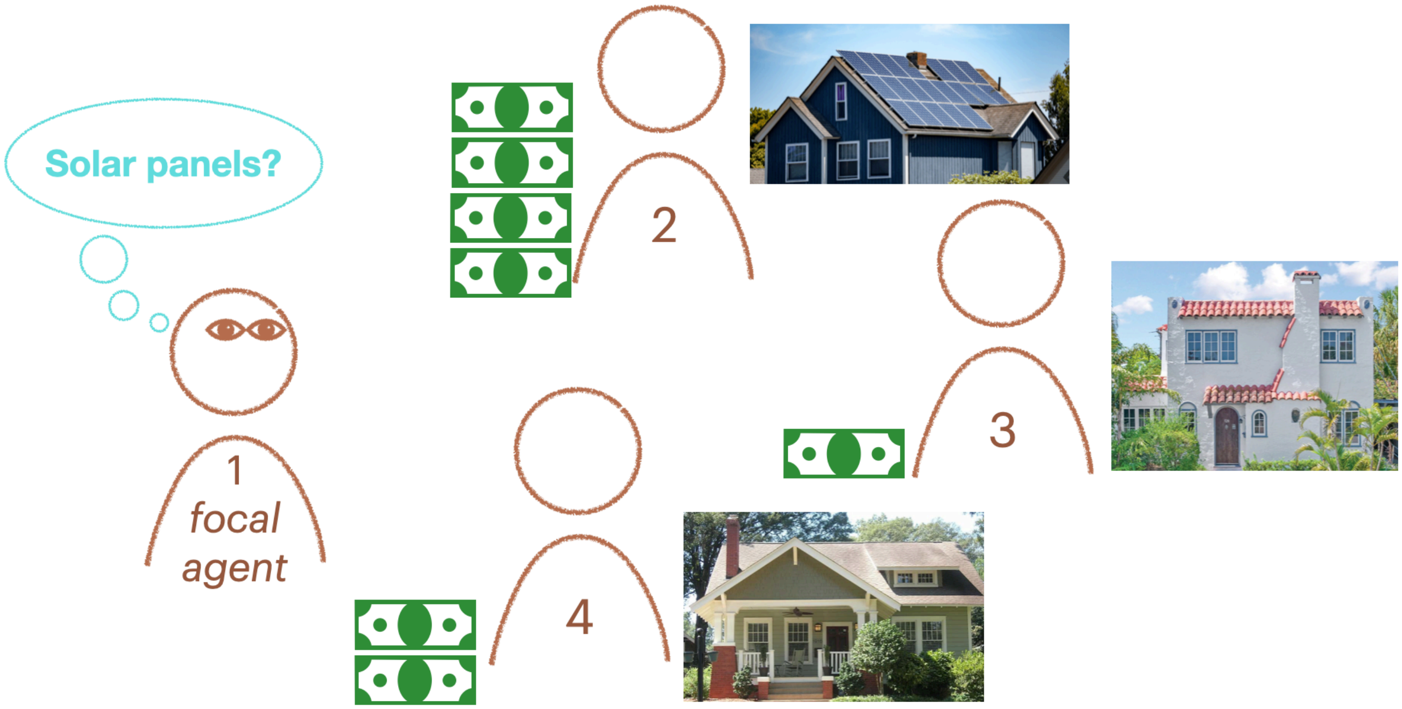

Figure 1.3: Agent 1, the focal agent, is considering whether to install residential solar. The probability agent 1 installs residential solar depends on its social learning strategy.

1.2.1.1 Contagion learning

In the contagion learning model, the focal agent's (i.e., the *learner*'s) *teacher* (i.e., interaction partner) is chosen at random. Then, the learner adopts the teacher's behavior with probability α, the adoption rate. In this case, then, the probability that 1 adopts residential solar is

$$\Pr(1 \text{ adopts solar}) = \alpha \Pr(1 \text{ selects 2 as teacher}) = \alpha \frac{1}{3}.$$

More generally, for focal agent i with the set of neighbors n_i ($n_1 = \{2, 3, 4\}$ in the example), where m_i is the set of neighbors who have adopted the adaptive behavior ($m_i = \{2\}$ in the example). We call the adaptive behavior A. The general probability of adoption in contagion learning is therefore

$$\Pr(i \text{ adopts } A) = \frac{\alpha |m_i|}{|n_i|},$$

where the $|\cdot|$ operator counts the number of elements in a set.

1.2.1.2 Frequency-biased learning

In frequency-biased learning there is no interaction partner or teacher chosen. The probability of adoption is only given by the relative frequency of each behavior. The general expression is

$$\Pr(i \text{ adopts } A) = \frac{|m_i|}{|n_i|}.$$

In our example, then, the probability of installing residential solar under frequency-biased learning is $\frac{1}{3}$.

1.2.1.3 Success-biased learning

In success-biased learning, learners first choose an interaction partner/teacher randomly weighted by observed fitness of their neighbors, which is a generic term for wealth, power, status, etc. In general for this case, the probability that learner i chooses teacher j is

$$\Pr(i \text{ chooses } j) = \frac{f_j}{\sum_{k \in n_i} f_k}.$$

The probability that i adopts A is then the sum of the probabilities of choosing each neighbor performing A (contained in the set m_i),

$$\Pr(i \text{ adopts } A) = \frac{\sum_{j \in m_i} f_j}{\sum_{k \in n_i} f_k}.$$

In our example, only one neighbor installed residential solar with a fitness (i.e. *wealth* in this example) of 4, while the others have finess 1 and 2. Therefore, $\Pr(1 \text{ adopts } A) = \frac{4}{7}$.

1.2.1.4 Combinations of learning models

There is no reason different learning models cannot be combined. The software we will use in this class, `socmod`, provides flexibility to the user to define their own learning models. The simplest combination of the three learning models above is to add an adoption rate to either frequency- or success-biased learning. In this approach, one could call the behavior selected by the models above could be considered *prospective* or *candidate* behavior to learn, then is actually learned with probability α.

For another potentially useful modification, α could be defined at the individual level, say α_i, or for *dyads* (i.e., a pair of interacting individuals) , α_{ij}, where i is still the focal agent learner, but we have added j, representing the selected teacher.

1.3 Identity and Influence

Group identity critically influences social learning. Neuroscience research demonstrates that our brains distinctly respond to individuals identified as part of our group (Cikara and Van Bavel 2014), as revealed through fMRI neural imaging (Figure 1.4). This ability likely evolved because when humans first emerged about two million years ago, it was much more important for survival to be able to rapidly identify whether someone was a friend or foe based on group markers. Although group membership can affect how we respond to information learned from others, group membership itself is quite plastic, meaning who belongs to which group can be rapidly reconfigured. For example, neural signals of race-based group perception was observed to be suppressed and overridden when individuals were in mixed-race groups created by experimenters that competed against other mixed-race groups in an psychological experimental task (Van Bavel, Packer, and Cunningham 2008).

Studies further show that group identity can strongly influence behavioral choices. For instance, experimental evidence reveals people resist adopting beneficial behaviors if associated with opposing political identities (Ehret et al. 2022), emphasizing how identity can create substantial barriers to sustainability. This general effect of group membership interfering with learning is called *outgroup aversion* (Paul E. Smaldino et al. 2017).

1.4 Social networks, homophily, and core-periphery structure

Social structure can significantly impact behavioral diffusion, especially in core-periphery configurations. Core-periphery networks emerge as a response to risk and uncertainty, e.g., in food sharing networks (Ready and Power 2018), so they are hypothesized to also be important in climate change adaptation transmission networks (Jones, Ready, and Pisor 2021). Core-periphery networks can be created by setting appropriate group sizes and *homophily* levels

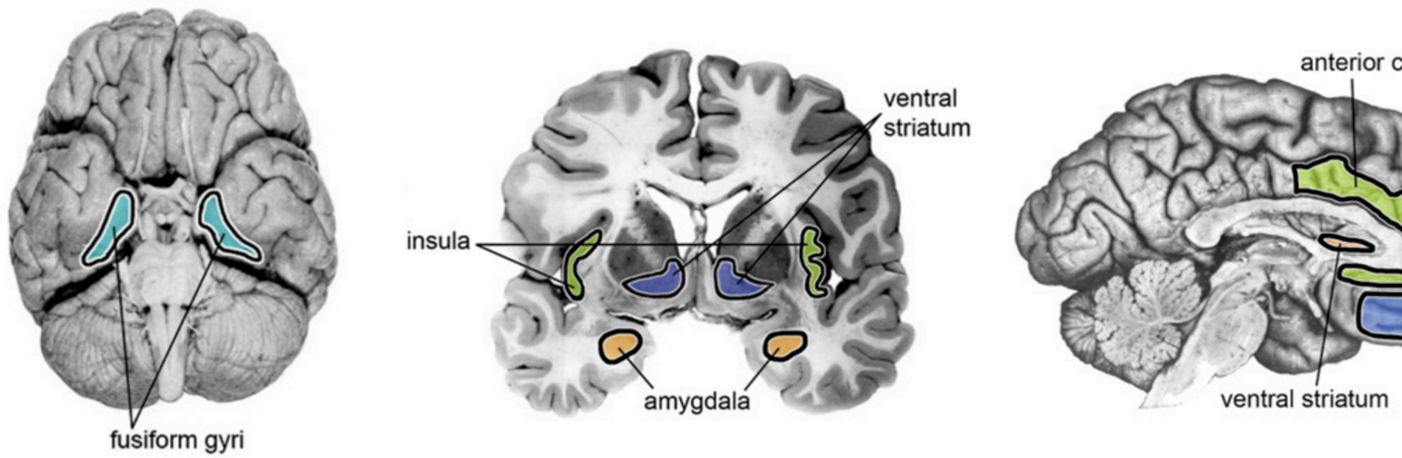

Fig. 1. Anatomical images of several key brain regions associated with group categorization and evaluation, functional relations between groups, empathy, and prosocial and antisocial behavior. As such, this figure is meant to serve as a guide to the location of various regions we reference frequently (not to represent a neural circuit supporting one process in particular). mPFC = medial prefrontal cortex; OFC = orbitofrontal cortex.

Figure 1.4: Figure 1 reorganized with original caption from Cikara and Van Bavel (2014)

in homophily network models (Turner, Singleton, et al. 2023) or specifying certain connectivity probabilities to the *stochastic block matrix* algorithm for creating structured random graphs (Rombach et al. 2014; Milzman and Moser 2023). Homophily is the measure of how much more likely an individual is to socially connect within their own group versus with a member of a different group. Homophily can range from -1 to +1, where -1 represents no within-group connections and only between-group connections (i.e., *anti-homophily*); 0 represents an equal probability of within- and between-group connections, and +1 represents only within-group connections. We will define homophily as either a global or group-level variable, though homophily could vary individually as well. There are two types of homophily:

- **Choice Homophily**: Individuals actively prefer interacting with similar others.
- **Induced Homophily**: Social interactions limited by historical or external conditions like geography, profession, birthplace, etc.

These structural elements can significantly limit the diffusion of sustainable practices from peripheries, like the mangrove management on smaller islands, to central cores. However, as colleagues and I have showed, this core-periphery structure, defined by moderately high majority-group homophily can actually *promote* the diffusion of adaptations, provided the adaptation is practiced by the minority group (Turner, Singleton, et al. 2023), as is the case for mangrove forest management or prescribed burns. Formal definitions of homophily and core-peripheriness will be given in the networks chapter.

1.5 Course outline in the context of sustainable development

The agent-based modeling approach developed in this course provides a structured way to test the effectiveness of social interventions aimed at promoting sustainable behavior. By formalizing and testing our assumptions about social dynamics, agent-based modeling supports better design and evaluation of policies and programs aimed at driving real-world change. This deductive, experimental approach allows us to explore how cooperation, coordination, identity, homophily, and influence affect the likelihood that beneficial behaviors will spread. In the coming chapters and associated problem sets we will analyze social learning of behaviors and social influence of opinions in various contexts.

The goal is to build up a repertoire of agent-based modeling techniques for incorporating different assumptions about how social learning or influence work, whether group structure is important to these processes, and for modeling social network structure. This repertoire can then be applied to sustainability contexts of interest to understand how different sustainability intervention strategies, such as who should learn about sustainable adaptations first in an educational intervention or how best to assist stakeholder deliberations to reduce opinion polarization that can derail collective adaptation. To choose model components wisely requires an understanding of elements of sustainability, cognitive and social science, network science, and software engineering.

The UN Sustainable Development Goals help us focus and organize our work by providing concrete goals for evaluating progress towards sustainable development for all Figure 1.5. These goals include targets for institutional development that promotes basic conditions for human thriving (justice, equality, education, public health, and no poverty) so as to assemble and enable a critical mass of people to participate bringing about sustainable development. People cannot participate in sustainability if they suffer in poverty, from illness, or subjugation by authoritarians–all but the most zealous environmental defenders will fight on when these basic needs are unmet. Since progress has been slower than necessary.

Sustainability, then, has several different dimensions, all of which contribute to climate action and environmental protection. I have organized these goals into a coding system called the vIBE system: ***v**ibrant* ***I**nstitutions* support ***B**asic* human needs of people who protect the ***E**nvironment*. All 17 goals and the organization system are illustrated in Figure 1.5. Organizing and connecting our work to has two benefits. First, it helps us identify which cognitive and social factors are at work in different sustainability foci. Second, it expands the corpus of existing research on which we draw to consolidate our social and cognitive theories of behavior change that we will apply to sustainability interventions.

1.5.1 Plan

In the rest of the course, we will develop our knowledge of computational social science and agent-based modeling techniques to enable you to pursue independent projects designing sus-

Figure 1.5: The 17 United Nations Sustainable Development Goals (SDGs) can be organized into groups for vibrant Institutions (Group I) that provide Basic needs (Group B) required for people to actively work towards Environmental and Ecological protection (Group E)–we dub this the vIBE coding of the sustainable development goals.

tainability interventions or more general studies of how different cognitive and social factors affect the diffusion of adaptations.

Here is a plan for the following chapters (and the remaining ten-week course):

Topic	Real-world sustainability application	Cognitive or social science background and theory	vIBE code sustainable development goals	Associated problem set
Diffusion of adaptations in toy network models	• Sustainable agricultural practices (Dwyer, Ibe, and Rhee 2022; Kling et al. 2024) • Health education in rural Honduras (Airoldi and Christakis 2024) • Preventative health behaviors such as vaccinations and masking (Fast et al. 2015; Paul E. Smaldino and Jones 2021). • Preventing female genital cutting (Vogt et al. 2016; Efferson, McKay, and Fehr 2020)	• Introduction to programming contagion models of social learning (Paul E. Smaldino 2023b). • Introduction to basic social network models: fully connected networks, regular lattices; Erdős-Reyni, small-world, and preferential attachment networks (Paul E. Smaldino 2023d).	• E-13,15: Climate action, life on land • B-3,5: Public health, gender equality • I-9,16: Infrastructure, institutions	1

Topic	Real-world sustainability application	Cognitive or social science background and theory	vIBE code sustainable development goals	Associated problem set
Diffusion of adaptations in homophily and core-periphery networks	• Mangrove forest management, ecosystem-friendly farming, and other climate change adaptations in South Pacific islands (McNamara et al. 2020). • Social justice movements like the Arab Spring that tend to start in socially peripheral communities (Barberá et al. 2015; Steinert-Threlkeld 2017).	• Introduction to frequency-biased (aka conformist) and success-biased learning (Kendal et al. 2018). • Minority-majority diffusion dynamics in homophily networks (Turner, Singleton, et al. 2023). • Stochastic block model of core-periphery networks (Milzman and Moser 2023).	• E-13,15: Climate action, life on land • B-3,5: Public health, gender equality • I-9,16: Infrastructure, institutions • IBE-7: Affordable clean energy	2

Topic	Real-world sustainability application	Cognitive or social science background and theory	vIBE code sustainable development goals	Associated problem set
Cooperation	• Groundwater management (Castilla-Rho et al. 2017) • Forest management (Andrews and Borgerhoff Mulder 2018), including prescribed burns, an ancient Indigenous adaptation (Kolden 2019; Eisenberg et al. 2019)	• Behavioral payoffs become dependent on the behavior of both people in an interacting dyad (Paul E. Smaldino 2023a)	• E-15: Life on land • IB-6: Clean water and sanitation	2
Coordination	• Gender equality in general and in household bargaining (O'Connor 2019). • Minority disadvantage (Mohseni, O'Connor, and Rubin 2019).	• Social norms affect behavior and payoffs, in combination with frequency-dependence as in simple cooperation (Paul E. Smaldino 2023c, Ch. 7)	• B-5,10: Gender equality, reduced inequality	2
Polarization	• Forest management is more difficult when stakeholders are polarized (Swette, Huntsinger, and Lambin 2023)	• Opinion dynamics in social networks (Turner and Smaldino 2018)	• E-15: Life on land	2

Topic	Real-world sustainability application	Cognitive or social science background and theory	vIBE code sustainable development goals	Associated problem set
How uncertainty affects social learning	• Resilience to climate uncertainty (Pisor and Jones 2021; Jones, Ready, and Pisor 2021)	• The form of uncertainty affects selection for social learning (Turner, Moya, et al. 2023)	• E13: Climate action	3
Reinforcement learning agents	• Social learning for climate action (Ensor and Harvey 2015; Nicolletti, Maschietto, and Moreno 2020)	• Complex integration of socially-learned and personally-experienced information streams (Witt et al. 2024)		3

2 Introduction to R programming for agent-based modeling

3 Social networks

igraph

3.1 Regular networks

3.2 Random networks

3.3 Homophily

3.4 Core-periphery networks

Part I

Social science for sustainability modeling

With whom we interact and how we learn are essential components in explaining the puzzles of diffusion and belief change that underlie the transition to more sustainable practices. In this section we will review relevant topics in cognitive and social science and demonstrate their use in agent-based models to promote sustainability.

4 Diffusion

Coming soon!

5 Cooperation

Coming soon!

6 Coordination

Coming soon!

7 Polarization

Coming soon!

8 Uncertainty

Coming soon!

9 Reinforcement learning

Coming soon!

Part II

Manual

Techniques for doing ABM for sustainability.

10 Agent-based models

Coming soon!

11 Writing

One of the most overwhelming challenges for me as a researcher is writing research papers. I've been lucky to learn from excellent teachers and currently have a network of mentors I can turn to for help. Still, writing is an inherently solitary endeavor that is in many ways an exploration, the building of a map of information. When we present our scientific work, much of the information already exists in the form of previous work on which we build. In terms of information volume, the work we present in scientific papers is relatively miniscule compared to the vast wealth of science amassed up to today. However, our work we want to write is new to the world, including ourselves even though we created it. This means that we need to take special care to explain

Good scientific writing (1) reviews previous work in the context of our project goals; (2) notes the location of some dark, foggy corners of our current understanding to motivate new work we intend to present to the reader; (3) presents the model in sufficient detail so the reader can re-produce the model and analysis; (4) presents results by contextualizing them in terms of our research questions and explains *why* the model outcomes emerged as they did; and finally, (5) reviews the findings, the model that produced them, the research questions that motivated the model, the impact of the findings for the research questions and more broadly for social behavior/sustainability, for social behavioral sciences, and even for our general understanding of the universe, as appropriate.

Scientific papers share a structure that we will use as a template so one need not start from scratch. The structure is known as either the IMAD or IMRaD structure, which stands for the major section headings of the papers indicating the major logical divisions of the presentation of social behavior modeling studies: either the Introduction, Model, Analysis, Discussion structure or the Introduction, Methods, Results, and Discussion structure.

Each of these major divisions contain standard types of information about the study. The Introduction…

12 High-performance computing

Coming soon!

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