Introduction to Agent-Based Modeling

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Overview

- Agent-based models are computer simulations used to study the interactions between people, things, places, and time.
- They are stochastic models built from the bottom up meaning individual agents (often people in epidemiology) are assigned certain attributes.
- The agents are programmed to behave and interact with other agents and the environment in certain ways. These interactions produce emergent effects that may differ from effects of individual agents.
- Agent-based modeling differs from traditional, regression-based methods in that, like systems dynamics modeling, it allows for the exploration of complex systems that display non-independence of individuals and feedback loops in causal mechanisms.

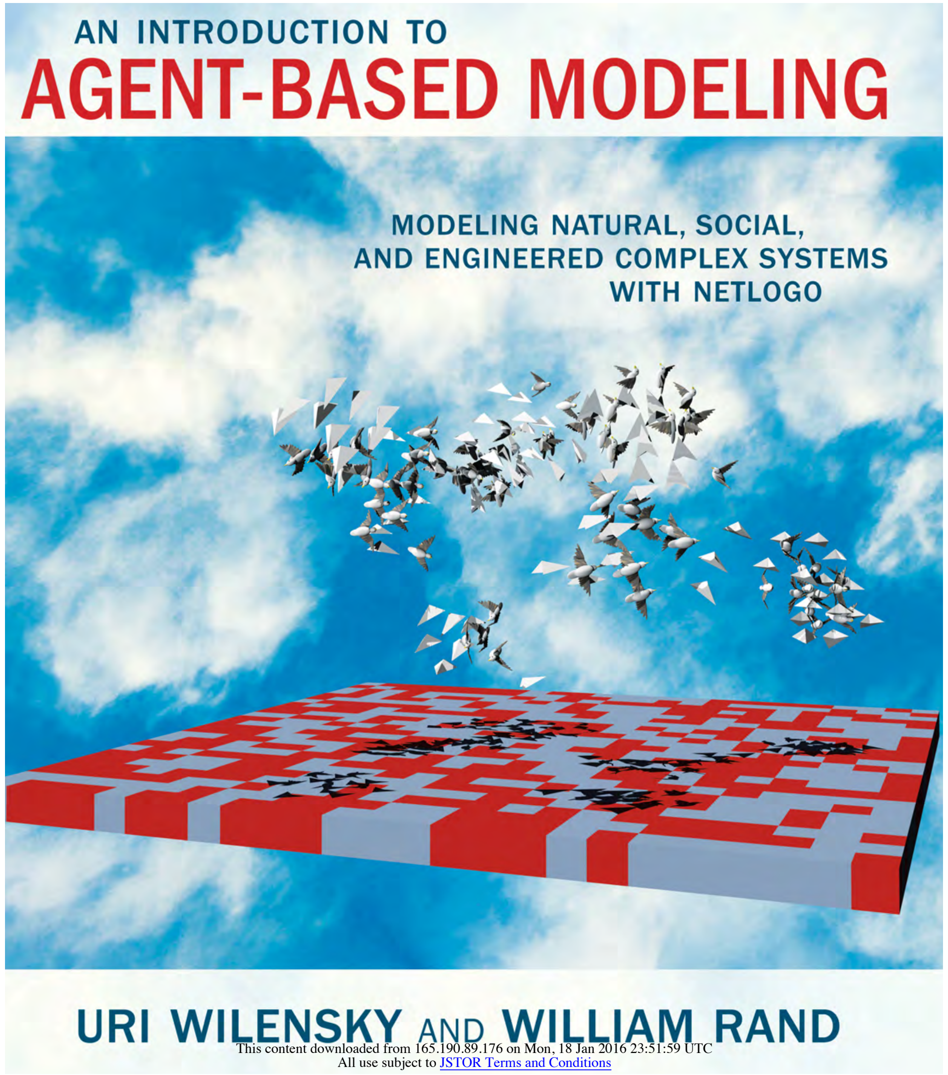
Overview

- It is not limited to observed data and can be used to model the counterfactual or experiments that may be impossible or unethical to conduct in the real world.
- The data parameters (such as the reproductive rate for infectious diseases) are often difficult to find in the literature. In addition, the validity of the model can be difficult to assess, particularly when modeling unobserved associations.
- Overall, agent-based models provide an additional tool for assessing the impacts of exposures on outcomes. It is particularly useful when interrelatedness, reciprocity, and feedback loops are known or suspected to exist or when real world experiments are not possible.

Our lecture slides are based on the following textbook

An Introduction to Agent-Based Modeling

Modeling Natural, Social, and Engineered Complex Systems with NetLogo by **Uri Wilensky and William Rand (2015)**



The Center for Connected Learning and Computer-Based Modeling

Uri Wilensky – CCL Director

Uri Wilensky is the Lorraine H. Morton professor of Learning Sciences, Computer Science and Complex Systems at Northwestern University. He is the co-director of the joint PHD program in Computer Science and Learning Sciences (CSLS) . He is the founder and current director of the Center for Connected Learning and Computer-Based Modeling(CCL) and a co-founder of the Northwestern Institute on Complex Systems(NICO). He is also a faculty member in Cognitive Science, Philosophy, the program in Technology and Social Behavior, the Buffett center, the CIERA center and the Segal Design Center research council. He is the author of the NetLogo agent-based modeling software which his lab actively maintains and improves. It is the most widely used agent-based modeling software, and has hundreds of thousands of users worldwide using it for both research and education. Wilensky has published more than 300 scientific articles and more than 400 published agent-based models. Wilensky has received numerous awards including the 2016 ISDDE prize for excellence in design for his work on NetLogo

Quick navigation

Bio, Textbook, Current Research, Previous & Ongoing Research, Courses, Colleagues & Students, Contact Info, Personal Stuff

Textbook

Wilensky, U., & Rand, W. (2015). An introduction to agent-based modeling: Modeling natural, social and engineered complex systems with NetLogo. Cambridge, MA: MIT Press.

Current Main Endeavors

Research Overview
CCL Papers & Publications

Current Active Projects:

- NetLogo modeling tool.
- NIH NIDA. Center for Prevention Implementation Methodology for Drug Abuse and HIV

NSF-Funded Research Projects:

- NSF STEM+C.A Whole-School Model for Integrating Computational Thinking in High School Science and Mathematics.
- NSF ITEST. Group-Based Cloud Computing for STEM Education.
- NSF EAGER: MAKER: A Cultural Framework for Equity in Maker Practices
- NSF STEM+C. CT-ifying the high school science curriculum to broaden participation in computational science
- NSF STEM+C. Engaging students in building theories of scientific phenomena: A comparison of aggregate pattern-based and agent-based approaches

The history of ABM

- Many different fields have contributed ideas and methods to ABM. In this appendix, we will focus on the key antecedents of ABM technologies from computer science and associated computational fields. Besides the computational fields, we note that there have also been strong contributions from biology, physics, engineering, and social science.
- In biology, these contributions came largely from ecology and the independent development of Individual-Based Modeling alongside ABM (DeAngelis & Gross, 1992). Individual-based modeling foregrounds the role of individual animal or plant behavior in an ecosystem, as opposed to working with population-level variables (DeAngelis & Mooij, 2005).
- In physics, the Ising models were used to describe magnetics and showed that very simple models could produce phase transition. These models were also precursors of cellular automata. As described in chapter 3, physicist Per Bak created the classic Sandpile model, which Bak used to illustrate the concept of self-organizing criticality (SOC).
- In engineering, process engineering and cybernetics, among other areas of research, contributed to ABM's development. In process engineering, the goal is to design an optimal output given low-level behaviors, which can be thought of as a similar framework to ABM,
- In the last decade, we have witnessed tremendous growth in the field of network theory and the incorporation of support for networks as a core element of agent-based modeling. This work was pioneered by the mathematician Euler in the 1800s in solving the problem of the seven bridges of Konigsberg (see Newman, 2010).
- In the 1950s and early '60s, mathematicians Erdös and Rényi characterized random networks (1960), which was then followed by the Barabasi-Albert model on preferential attachment networks (1999). Work by psychologists such as Stanley Milgram suggested that the average path length in human networks is short (six degrees of separation) (1967), an idea later formalized in the Watts and Strogatz small-worlds network models (1998). These types of networks and their associated methods of analysis have become staples of agent-based modeling.

Contents

0. Why Agent-Based Modeling?

Complex Systems and Emergence

- What areas are widely thought to be difficult for people to comprehend and potentially ripe for restructuration? One such area is complex systems. Its very name suggests that it is a difficult area for comprehension.

- Complex systems theory develops principles and tools for making sense of the world's complexity and defines complex systems as systems that are composed of multiple individual elements that interact with each other yet whose aggregate properties or behavior is not predictable from the elements themselves.

- Through the interaction of the multiple distributed elements an "emergent phenomenon" arises. The phenomenon of *emergence* is characteristic of complex systems.

Complex Systems and Emergence

- The term “emergent” was coined by the British philosopher and psychologist G. H. Lewes, who wrote:
- *Every resultant is either a sum or a difference of the cooperant forces; their sum, when their directions are the same—their difference, when their directions are contrary. Further, every resultant is clearly traceable in its components, because these are homogeneous and commensurable. It is otherwise with emergents, when, instead of adding measurable motion to measurable motion, or things of one kind to other individuals of their kind, there is a cooperation of things of unlike kinds. The emergent is unlike its components insofar as these are incommensurable, and it cannot be reduced to their sum or their difference. (Lewes 1875)*

Understanding Complex Systems and Emergence

- We have said that understanding complex systems and emergence is hard for people. Emergence, in particular, presents two fundamental and distinct challenges.
- The first difficulty lies in trying to figure out the aggregate pattern when one knows how individual elements behave. We sometimes call this *integrative* understanding, as it parallels the cumulative integration of small differences in calculus.
- A second difficulty arises when the aggregate pattern is known and one is trying to find the behavior of the elements that could generate the pattern. We sometimes call this *differential* understanding (aka *compositional* understanding), as it parallels the search in calculus for the small elements that produce an aggregate graph when accumulated.

Example 1: Integrative Understanding

- Figure 0.1 presents a system composed of a few identical elements following one rule. Each element is a small arrow.

- We imagine a clock ticking and at each tick of the clock the arrows follow their rule. We initialize the system so that each individual arrow starts on a circle (of radius 20 units).

- We start them all facing clockwise on the circle. Now, we give them one movement behavior (or rule).

- At every tick of the clock, they move forward 0.35 units then turn right one degree. As the clock ticks, they continue to move and turn, move and turn, moving clockwise along the circle.

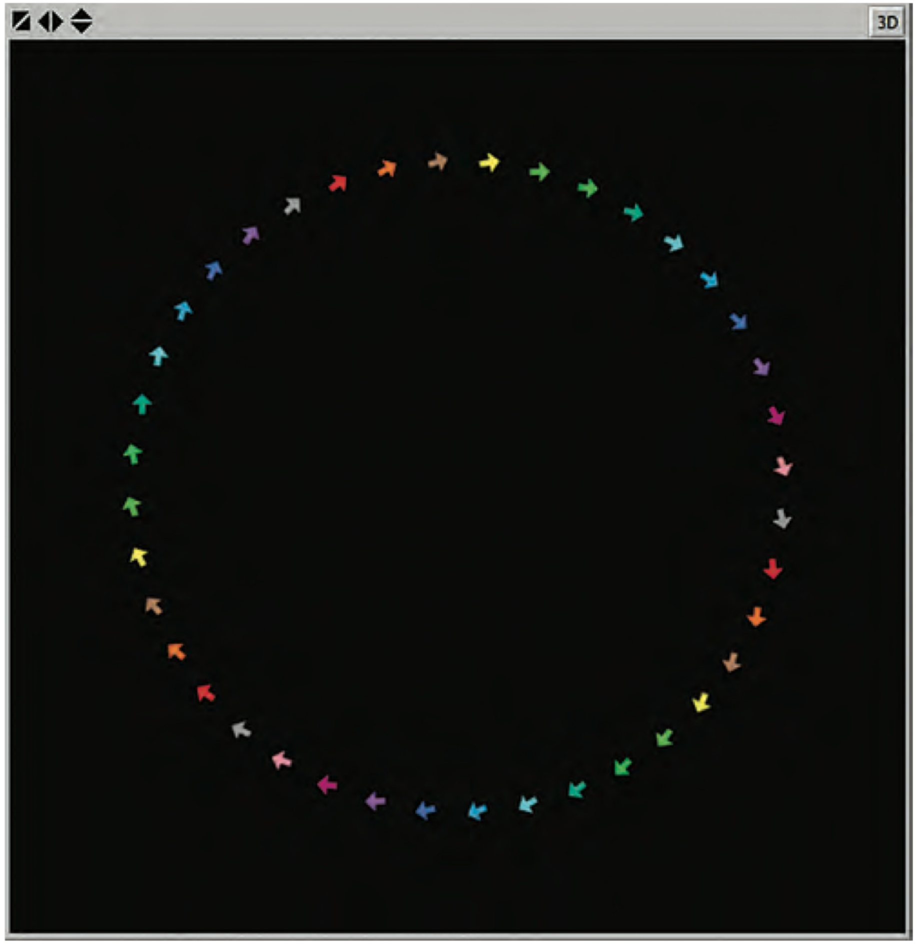


Figure 0.1
Some arrows moving clockwise around a circle of radius 20.

Outcome?

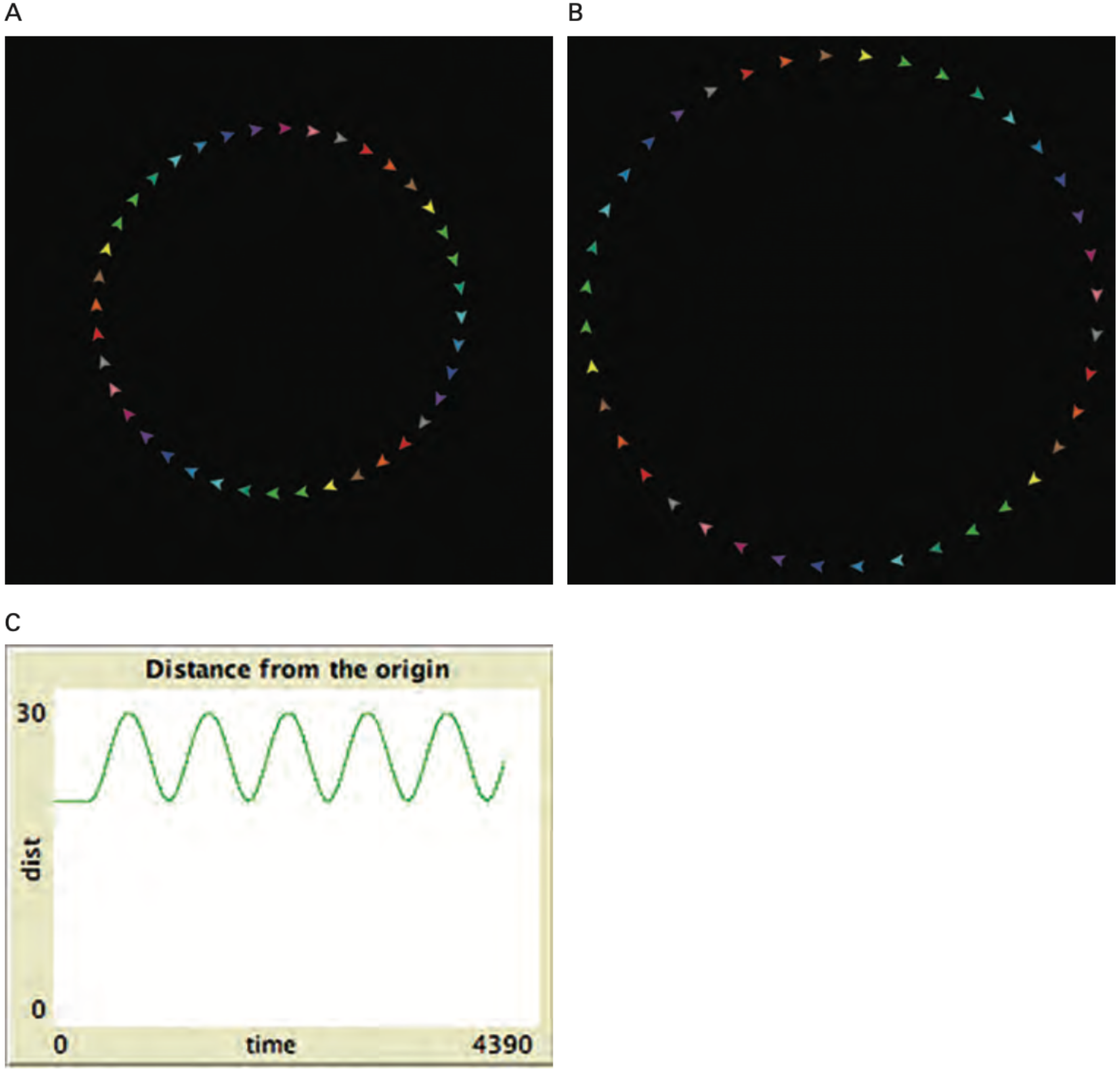


Figure 0.2
Pulsating circle, moving between large and small radius.

Example 2: Differential Understanding

- Now let's consider the flip side of these difficulties. There are many coherent, powerful, and beautiful patterns we observe in the world. What accounts for their prevalence? How do they originate?
- The secret to understanding the formation of these patterns is to understand that they are emergent, arising from the interactions of distributed individual elements.
- One such prevalent (and often beautiful) pattern is the flocking of birds. Birds fly together in many different formations, from the classic V formation of goose flocks to the large, very dense flocks of starlings that resemble insect swarms. How and why do these flocks emerge?

Figure 0.3
Flock of geese flying in a classic V formation.

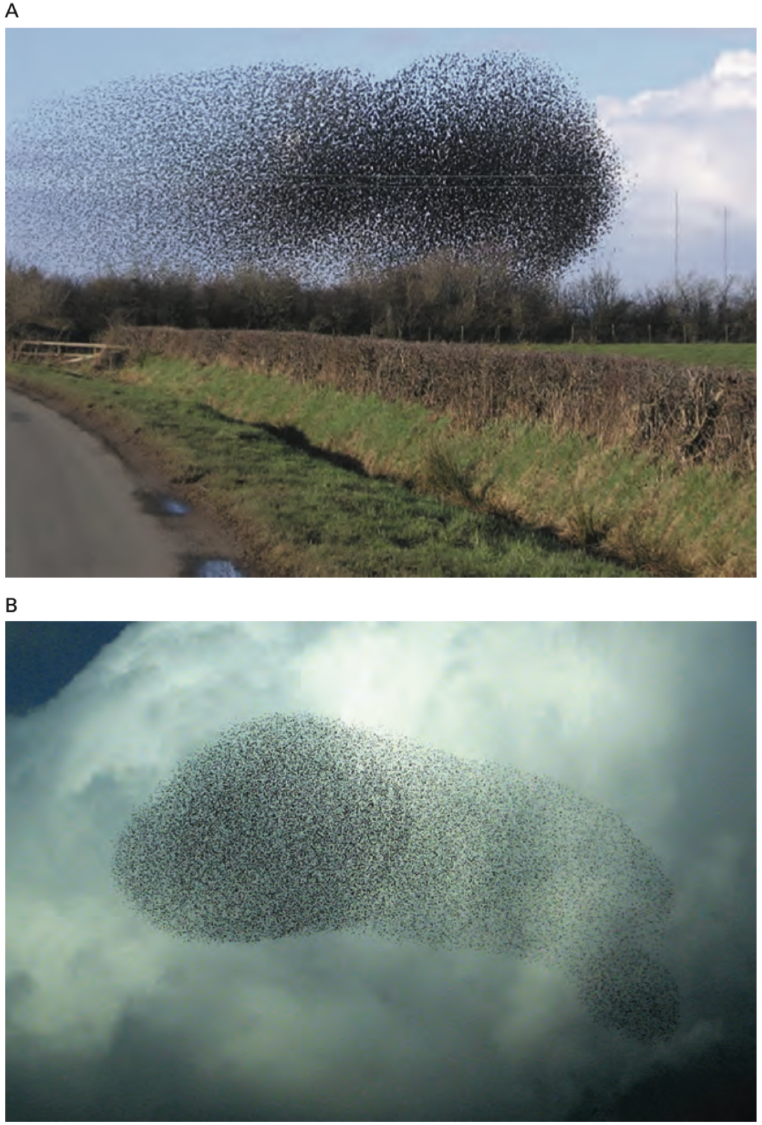


Figure 0.4
Flocks of starlings (thousands of birds) acting as a swarm.[2]

Example 2: Differential Understanding

- Another more common (though less beautiful) pattern—this time, from the social rather than the natural world—is the traffic jam.
- We tend to think of traffic jams as being composed of thousands of individual cars, but seen from a bird's-eye view, traffic jams appear as a single object moving backward against the flow of traffic.
- What causes these jams to form?

Figure 0.5
Traffic Jam by Osvaldo Gago, 2005.

Example 3. Predator-Prey model

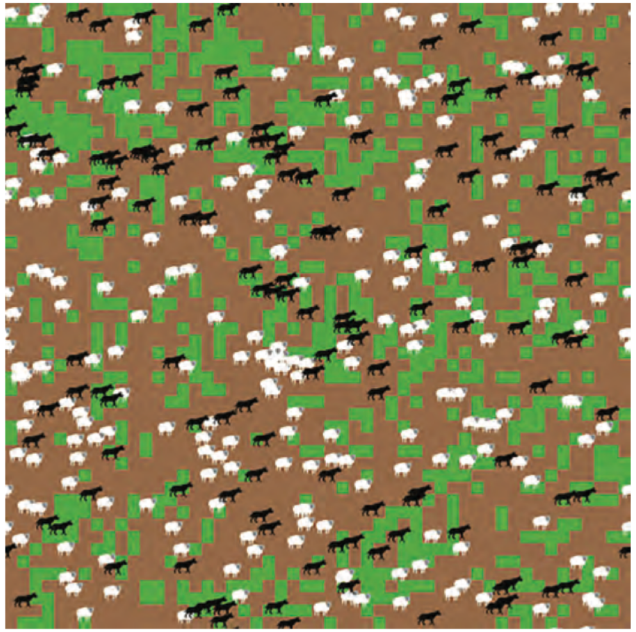
Example: Predator-Prey Interactions

Let us start with the study of predator-prey interactions. This domain is often first introduced qualitatively in high school, then quantitatively at the university level. In its quantitative form, the population dynamics of a single predator and prey are introduced by the classic Lotka-Volterra differential equations, a pair of coupled differential equations that proceed as follows:

$$\frac{dPred}{dt} = K_1 * Pred * Prey - M * Pred$$

$$\frac{dPrey}{dt} = B * Prey - K_2 * Pred * Prey$$

The first equation says that the number of predators increases as predators interact with prey (by fixed constant K_1) and decreases by a constant mortality rate (M). The second equation says that the number of prey increase by a constant birthrate (B) and decreases in interaction with predators (by a fixed constant K_2). The solution to these equations resembles the classic sinusoidal curves that show a cycling of the predator populations with one ascendant when the other is at a trough.



Example 4: Forest Fires

Example: Forest Fires

Our second example is about the spread of a forest fire. This domain is not usually present in the K-12 or university curriculum, but when taught, it typically falls under the subject matter of physics, described in terms of two classic partial differential equations. The first is the classic heat equation, which describes the distribution of heat in a given region over time, where theta represents the thermal diffusivity of the material through which the heat is traveling.

$$\frac{dH(x,t)}{dt} = \theta \frac{d^2 H(x,t)}{dx^2}$$

The second equation physicists use to describe the spread of a forest fire treats the fire as if it were a potentially turbulent fluid, thus using the Reynolds equation of fluid flow.

$$\frac{dU_i}{dt} + U_j \frac{dU_i}{dx_j} = -\frac{1}{\rho}\frac{dP}{dx_i} + \nu \frac{d^2 U_i}{dx_j dx_j} - \frac{d}{dx_j}\overline{u_i^t u_j^t}$$

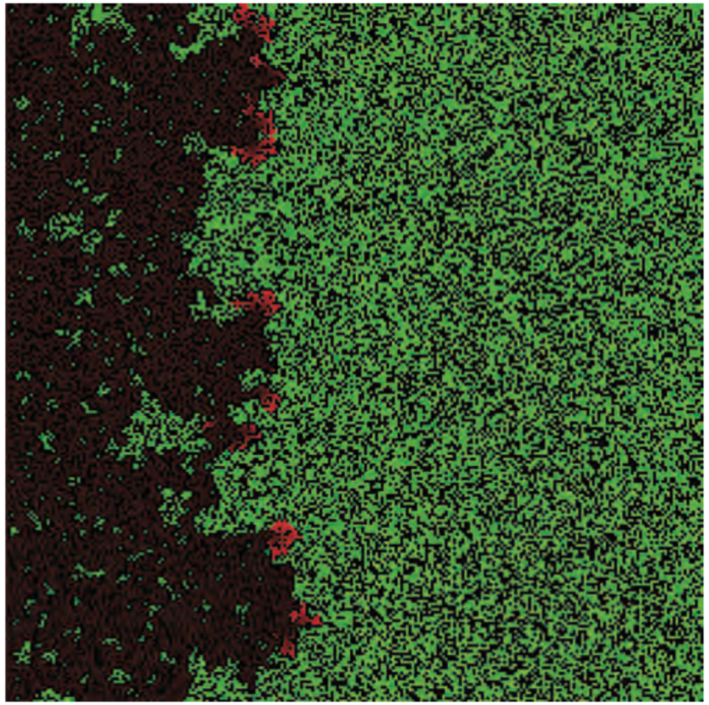


Figure 0.7
An agent-based model of a forest fire. (See *Wilensky, 1997b*)

NetLogo program

- http://www.netlogoweb.org/
- https://ccl.northwestern.edu/netlogo/docs/
- Examples: Flocking, traffic basic, 2 lanes, grid, etc

1. What Is Agent-Based Modeling?

- The ant opens her eyes and looks around. There are many of her siblings nearby, but there is no food. The ant is hungry, so she heads out from the ant colony and starts to wander around.
- She sniffs a little to the left and a little to the right, and still she cannot smell any food. So she keeps wandering. She passes by several of her sisters, but they do not interest her right now; she has food on her mind.
- She keeps wandering. Sniff! Sniff! Mmmm ... good! She gets a whiff of some of that delightful pheromone stuff. She heads in the direction of the strongest pheromone scent;
- As the ant proceeds along the trail, she arrives at some delicious food. She grabs some food and heads back to the colony, making sure to drop some pheromone along the way.
- On the way back, she runs into many of her sisters, each sniffing her way along pheromone trails, repeating the same process they will carry out all day.

Creating the Ant Foraging Model

Many biologists and entomologists have observed ants in the wild (Hölldobler & Wilson, 1998; Wilson, 1974) and have described how ants seemed to form trails to and from food sources and their nest. Some hypotheses about how the ants accomplish this behavior and what mechanisms are at work that enable ants to find food in this way.

http://www.netlogoweb.org/launch#http://www.netlogoweb.org/assets/modelslib/Sample%20Models/Biology/Ants.nlogo

A B

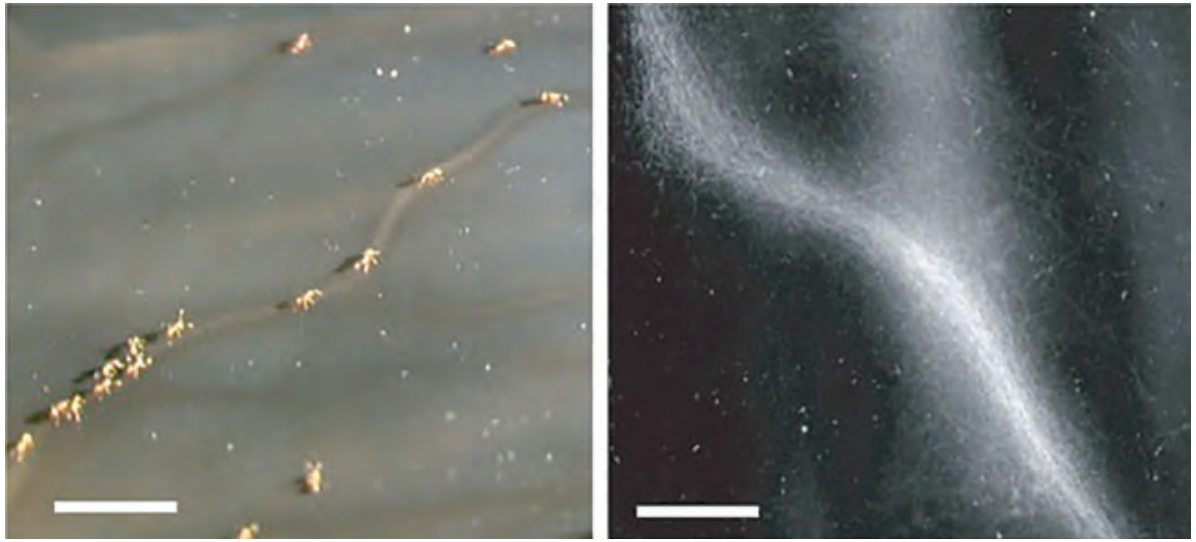


Figure 1.1
Ant trails. Pheromone trail networks of pharaoh ants on a smoked glass surface. (A) Part of a network showing bifurcations to smaller trails (scale bar: 1 cm). (B) Close-up of a single bifurcation (scale bar: 0.5 cm).[4]

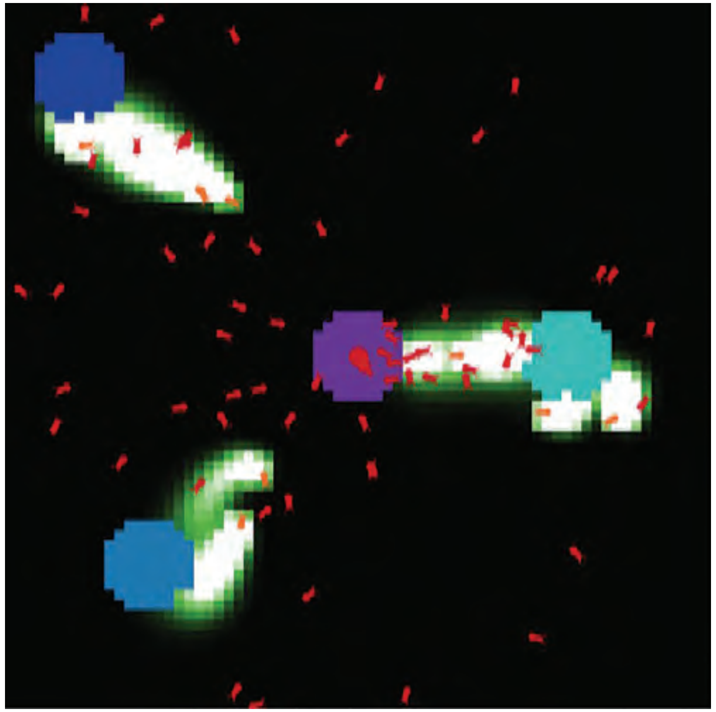


Figure 1.2
NetLogo "Ants" model of foraging behavior.[8]

- The ants as a group appear to exploit food sources in an optimal manner. That is, they first gather food from the nearest food source, then the second nearest, and so on.
- This optimal exploitation of food sources could be placed within a larger context. In many ways, the colony of ants seems to balance exploration and exploitation (Dubins & Savage, 1976).
- In any situation in which an entity is operating in an unknown environment, the entity must spend some time exploring the environment to understand how its actions affect its rewards, and some time exploiting the environment, that is taking actions that it knows have produced the best rewards in the past.
- By allocating a large number of ants to exploit the current nearest food source while other ants continue to explore, the ant colony as a whole successfully balances exploration and exploitation.

- However, these "trails" that the ants build to the food source, the "optimal" behavior that they exhibit, and the "balance" between exploration and exploitation are not coded into any one ant.
- There is nothing that tells the ant to build a trail; there is nothing that tells the ant to go to the nearest food source first; there is nothing that tells some ants to explore while others exploit.
- The "trails," "optimal," and "balance" behavior of the ants is not coded into any of the ants but is instead an *emergent* phenomenon of the model (Holland, 1998; Anderson, 1972; Wilensky & Resnick, 1999).
- Having run and used the model, it may seem obvious that these low-level rules can create these rich and optimal global patterns.
- But the history of science is full of wrong turns in which scientists believed that a complex phenomenon needed a complex organizational structure and a leader (Resnick, 1994; Wilensky & Reisman, 2006; Wilensky & Resnick, 1999).
- In contrast, through ABM we understand that this complexity can self-organize without a leader.

Agent-Based Models vs. Other Modeling Forms

- What makes agent-based models distinct from other models? The most common form of scientific models is the equation form.
- Parunak, Wilensky, and colleagues (Parunak et al., 1998; Wilensky, 1999b; Wilensky & Reisman, 2006) discuss the many differences between ABM and equation-based modeling (EBM).
- One distinction is that because ABM models individuals it can model a heterogeneous population, whereas equational models typically must make assumptions of homogeneity.
- In many models, most notably in social science models, heterogeneity plays a key role. Furthermore, when you model individuals, the interactions and results are typically discrete and not continuous.
- Continuous models do not always map well onto real-world situations. For instance, equation-based models of population dynamics treat populations as if they are continuous quantities when in fact they are populations of discrete individuals.
- When simulating population dynamics it is very important to know if you have a sustainable population. After all, a wolf population cannot continue if there are fewer than two wolves left; in reality, a millionth of a wolf cannot exist and certainly cannot reproduce, but it can result in increased wolf population in EBMs

Agent-Based Models vs. Other Modeling Forms

- One does not need to know what global pattern results from the individual behavior. When modeling an outcome variable with EBM, you need to have a good understanding of the aggregate behavior and then test out your hypothesis against the aggregate output.
- For example, in the wolf-sheep (predator-prey) example, to build the EBM, you need to have an understanding of the relationship between (aggregate) wolf populations and sheep populations.
- To encode this aggregate knowledge such as in the classic Lotka-Volterra equations (Lotka, 1925; Volterra, 1926), you must have knowledge of differential equations. In contrast, ABM enables you to write simple rules for simple entities, requiring knowledge only of commonsense behaviors of individual wolves and sheep and yet still observe the aggregate result by running the model.
- Thus, even if you have no hypothesis as to how the aggregate variables will interact, you can still build a model and generate results.

Agent-Based Models vs. Other Modeling Forms

- Because agent-based models describe individuals, not aggregates, the relationship between agent-based modeling and the real world is more closely matched.
- It is therefore much easier to explain what a model is doing to someone who does not have training in the particular modeling paradigm.
- This is beneficial because it means that no special training is required to understand an agent-based model.
- It can be understood by all of the stakeholders in a modeling process. Moreover, with some ABM languages like NetLogo, the syntax is so readable that stakeholders without knowledge of how to build a model can often read the model code and understand what is going on.
- This helps improve the verifiability of the model. This “glass box” approach to modeling (Tisue & Wilensky, 2004) enables all interested parties to talk about the model all the way down to its most basic components.

Agent-Based Models vs. Other Modeling Forms

- Finally, the results generated by ABMs are more detailed than those generated by EBMs. ABMs can provide both individual and aggregate level detail at the same time.
- Since ABMs operate by modeling each individual and their decisions, it is possible to examine the history and life of any one individual in the model, or aggregate individuals and observe the overall results.
- This "bottom-up" approach of ABMs is often in contrast with the "top-down" approach of many EBMs, which tell you only how the aggregate system is behaving and do not tell you anything about individuals.
- Many EBMs assume that one aspect of the model directly influences, or causes, another aspect of the model, while ABMs allow indirect causation via emergence to have a larger effect on the model outcomes.

Randomness vs. Determinism

- One important feature of agent-based modeling, and of computational modeling in general, is that it is easy to incorporate randomness into your models.
- Many equation- based models and other modeling forms require that each decision in the model be made deterministically.
- In agent-based models this is not the case; instead, the decisions can be made based on a probability.
- For instance, in the Ants model, as the ants move around the landscape, their decisions are not completely determined; instead, at each time step they change their heading a small amount based on a random number. As a result, each ant follows a unique, irregular path.
- In reality, ants might be affected by small changes in elevation, the presence or absence of twigs and stones, and even the light of the sun. There is no guarantee that a more deterministic model will provide us with a better answer to this question.
- Thus, using the random number serves as an approximation that may turn out to be just as correct in answering our driving question.

When Is ABM Most Beneficial?

- Agent-based modeling has some benefits over other modeling techniques, but, as with any tool, there are contexts in which it is more useful than others.
- Agent-based models are more useful when the agents are not homogenous. Even in the Ants model, while the ants all had the same rules of behavior, they were not homogenous in location, heading, food-carrying state, and so on.
- ABM is very useful when agents are heterogeneous and the heterogeneity of the agents affects the overall performance of the system.
- Since ABM enables each individual to be tracked and described at the individual level, it is much more powerful than techniques such as systems dynamics modeling (Forrester, 1968; Sterman, 2000; *Richmond & Peterson, 1990*).

When Is ABM Most Beneficial?

- In the same way that ABM is useful when the interaction between agents is complex, it is also useful when the agents' interaction with the environment is complex.
- The environment in an ABM is often itself composed of stationary agents, and thus modeling agent-environment interactions has all of the power of modeling any agent-to-agent interaction.
- Another way that ABM provides more detailed information than equation-based or many other modeling approaches is through its rich conception of time.
- In ABM, one models agents and their interactions with each other. These interactions occur temporally; that is, some interactions occur before or after others.
- ABM thus enables you to move beyond a static snapshot of the system and toward a dynamic understanding of the system's behavior.

Trade-offs of ABM

- Agent-based modeling provides some benefits over other methods of modeling, but, in any particular situation, choosing a modeling methodology is a case of choosing the appropriate tool at the appropriate time, and sometimes agent-based modeling is not the right tool for the job.
- For example, ABM can be computationally intensive. Simulating thousands or millions of individuals can require great computing power. Equation-based models, by contrast, are often very simple to run and essentially just require repetitive mathematical calculations. This is true only for simple equation-based models; numerically solving complicated equation-based models may take as much computational time as agent-based models.
- The computational expense of running an ABM is a price one pays for having the benefits of rich individual-level data. The additional computational power needed for running ABMs is the same power that allows the tracking and development of rich histories of individuals.

Trade-offs of ABM

- The more detail there is in a model, the more modeling decisions have to be made by the modeler. In the equation-based modeling (EBM) literature, variables whose values are determined by the modeler are referred to as “free parameters.”
- For example, in the Ants model, the rate at which the pheromone evaporates can be modified. This creates an additional free parameter in the system. In contrast to EBM, in ABM, there are typically more free parameters for control of the additional levels of detail.
- Calibrating these free parameters and making sure that they are set correctly can be a time-intensive process. Some critics of agent-based models have argued that, since ABM uses so many free parameters, it can be used to generate any result desired.
- We disagree. In our view, EBMs and other aggregate models and simulations simply “hide” these free parameters by making implicit assumptions about the way the system works. Often, the mathematical equations hide the implicit free parameters, since it is not possible to incorporate them within the equation.
- In ABM, free parameters such as the evaporation rate are exposed. One can initially set up a model to use an idealized value for evaporation rates, but the rates can also be tuned to match true biological evaporation rates. ABM generally uses more free parameters than other types of modeling because these free parameters control assumptions of the model, and ABM explicitly exposes those assumptions at more levels of action.

2. Creating Simple Agent-Based Models

Life

- In 1970, the British mathematician John Horton Conway (described in Conway, 1976) created a cellular automaton that he called the “Game of Life.” Martin Gardner (1970) popularized this game in his *Scientific American* column. Subsequently, millions of readers played the game.

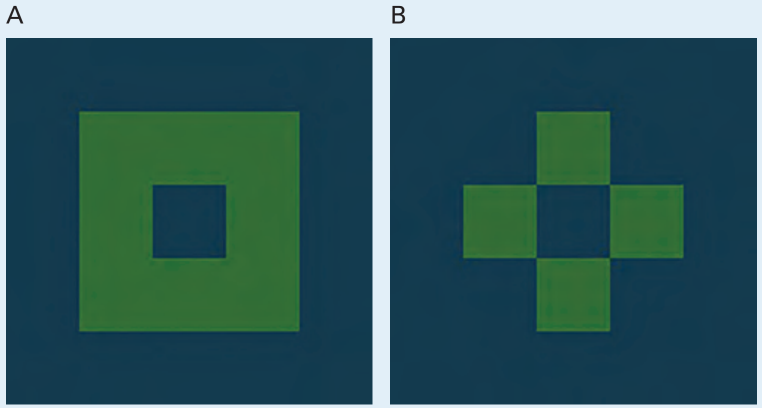


Figure 2.10
(A) Moore Neighborhood. (B) von Neumann Neighborhood. This will be further elaborated in chapter 5.

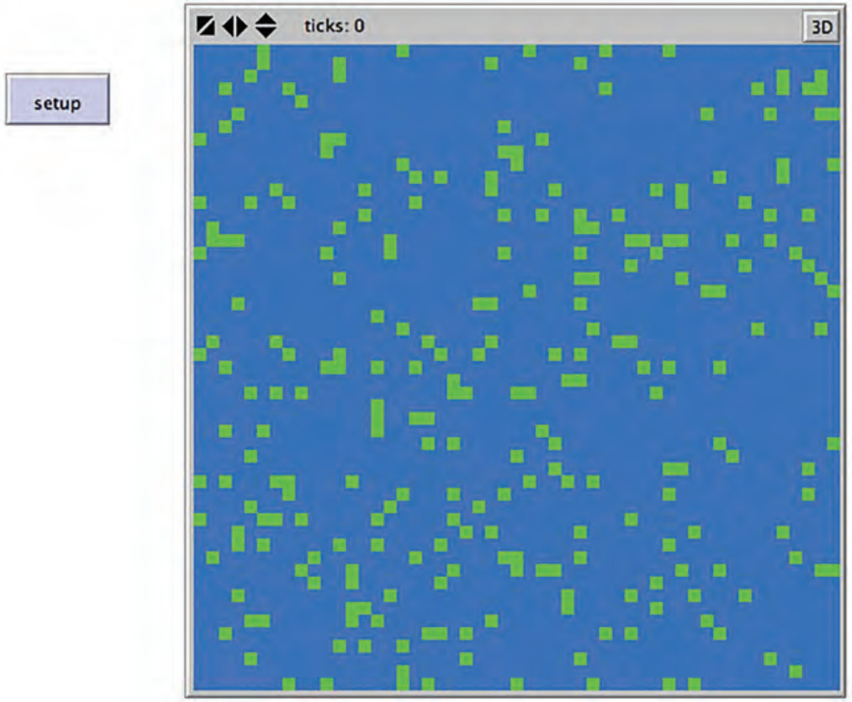


Figure 2.9
A typical random initial configuration of the Game of Life. Approximately 10 percent of the cells are alive and colored green.

3. Exploring and Extending Agent-Based Models

I. Simple rules can be used to generate complex phenomena

- Many of the models that we will look into have very simple rules that do not require complex mathematical formulas or a deep understanding of the knowledge domain that they are attempting to model.
- Nonetheless, they are able to reproduce complex phenomena that are observed in the real world.
- For instance, a model of fire spread may have only a simple rule to describe fire spread from one tree to another, but it still may have interesting things to say about how likely a fire is to spread across an entire forest.

II. Randomness in individual behavior can result in consistent patterns of population behavior

- It is common for people when they see an ordered population level behavior such as a flock of birds to assume that there must be deterministic processes that govern the behavior of the individuals (Wilensky & Resnick, 1999).
- In the case of the birds, people tend to believe that there must be specific social rules or communications that tell each bird how to place itself in the flock.
- However, nature has some surprises for us: Many times the individual level rules are quite simple (see point 1) and do not necessarily tell the bird where to position itself in the flock.
- Instead, the rules often contain a certain amount of nondeterminism and are robust to perturbations in the initial conditions. Despite the stochastic nature of these systems, they can still result in the generation of predictable high-level behavior like the flocking of birds.

III. Complex patterns can "self-organize" without any leader orchestrating the behavior

- Similarly, it is common for people when they see a flock of birds, to assume that there must be a leader who orchestrates the behavior—a leader bird who tells each follower bird what to do (Resnick & Wilensky, 1993; Resnick, 1994a; Wilensky & Resnick, 1999).
- However, nature again surprises: a population of individuals, each following very simple rules, can "self-organize," generating complex and beautiful patterns without any orchestrator or centralized controller—these patterns are called "*emergent*" (Wilensky & Reisman, 2006).

IV. Different models emphasize different aspects of the world

- Even after we have completed a good working model of a particular phenomenon, we have not finished with the modeling process.

- Every model foregrounds certain aspects of the world and backgrounds other aspects.

- There can be many models of the same phenomenon, and they may each have something interesting to say about the way the world works.

The Fire Model

- Many complex systems tend to exhibit a phenomenon known as a “critical threshold” (Stauffer & Aharony, 1994) or a “tipping point” (Gladwell, 2000).
- Essentially, a tipping point occurs when a small change in one parameter results in a large change in an outcome. One model that clearly contains a tipping point is the early agent-based model of a forest fire.
- This model is easy to understand, yet exhibits some interesting behavior. Besides being interesting in its own right, the model of forest fire spread is highly relevant to other natural phenomena such as the spread of a disease, percolation of oil in rock, or diffusion of information within a population (Newman, Girvan & Farmer, 2002).

http://www.netlogoweb.org/launch#http://www.netlogoweb.org/assets/modelslib/IABM%20Textbook/chapter%203/Fire%20Extensions/Fire%20Simple%20Extension%201.nlogo

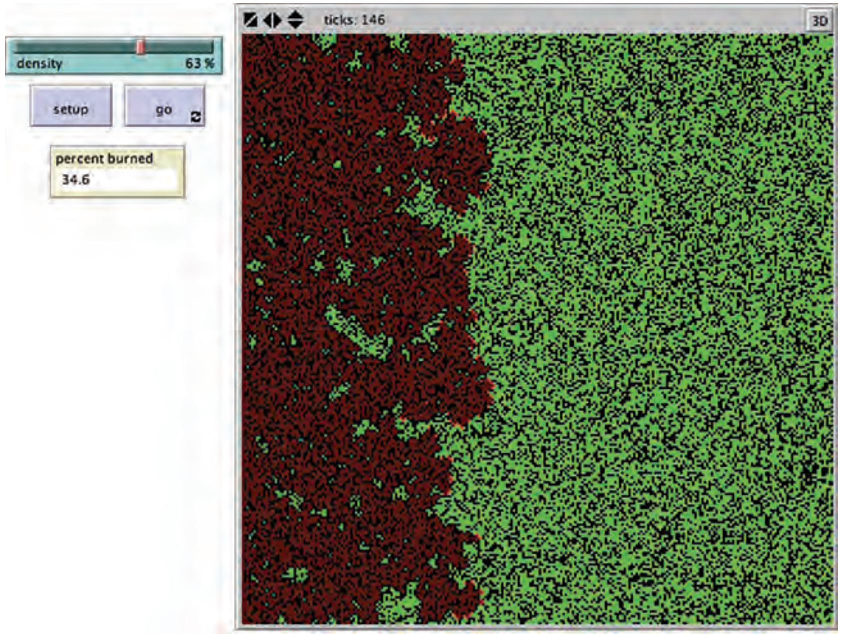


Figure 3.2
NetLogo Fire Simple Model. Based on NetLogo Fire model (Wilensky, 1997). http://ccl.northwestern.edu/netlogo/models/Fire.

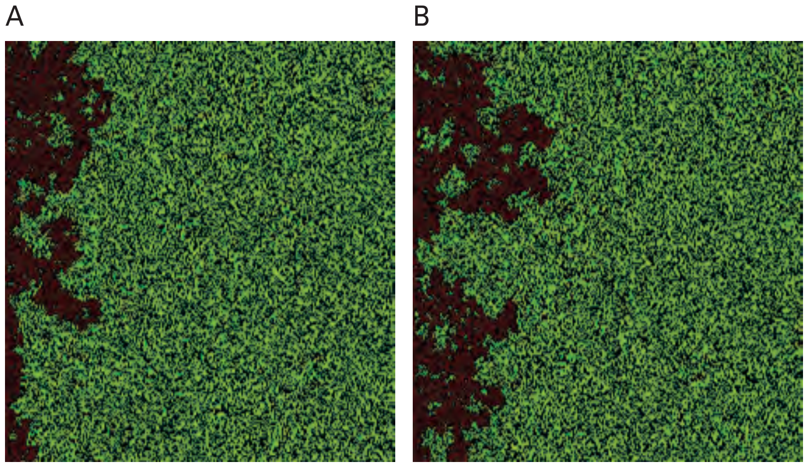


Figure 3.3
Two typical runs of the Fire Simple model with density set to 57 percent.

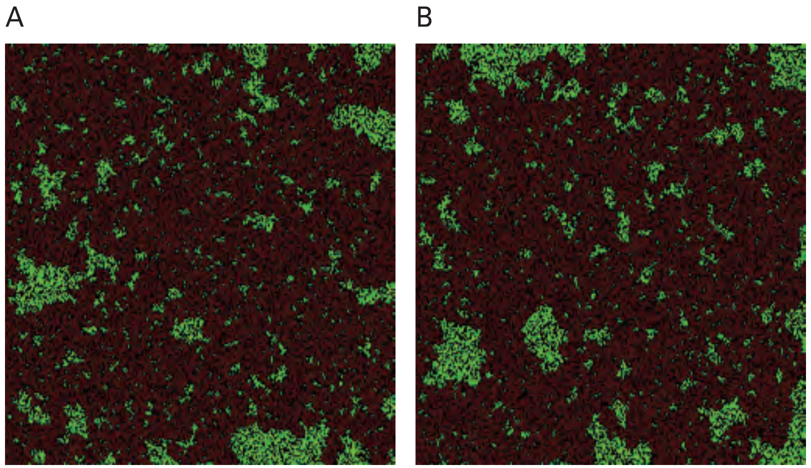


Figure 3.4
Two typical runs of the Fire Simple model with density set to 61 percent.

4. Creating Agent-Based Models

- Choosing a question may seem to be a separate issue from model design. After all, the natural progression seems to be: *first* choose a question, and *second* build a model to answer that question.
- Sometimes, that may indeed be the procedure we follow, but in many instances we will need to refine our questions when we start to think about it in an agent-based way.
- Our original question for the Wolf Sheep Simple model was: *"How do the population levels of two species change over time when they coexist in a shared habitat?"*
- We will now evaluate whether this question is one that is amenable to ABM and refine our question within the ABM paradigm.

A Concrete Example

- We have identified our research question in detail it can be useful to consider a particular context for this research question.
- We discussed reference patterns as a source of phenomena-based agent-based models. Sometimes that reference pattern is the original inspiration for the model.
- Other times, as now, we have refined our research question enough that we seek out a reference pattern that will help us test whether our model is a valid answer to the question.

In the case of the predator-prey relations, there is a famous case of cohabiting small predator-prey populations in a small geographic area. This is the case of fluctuating wolf and moose populations in Isle Royale, Michigan.

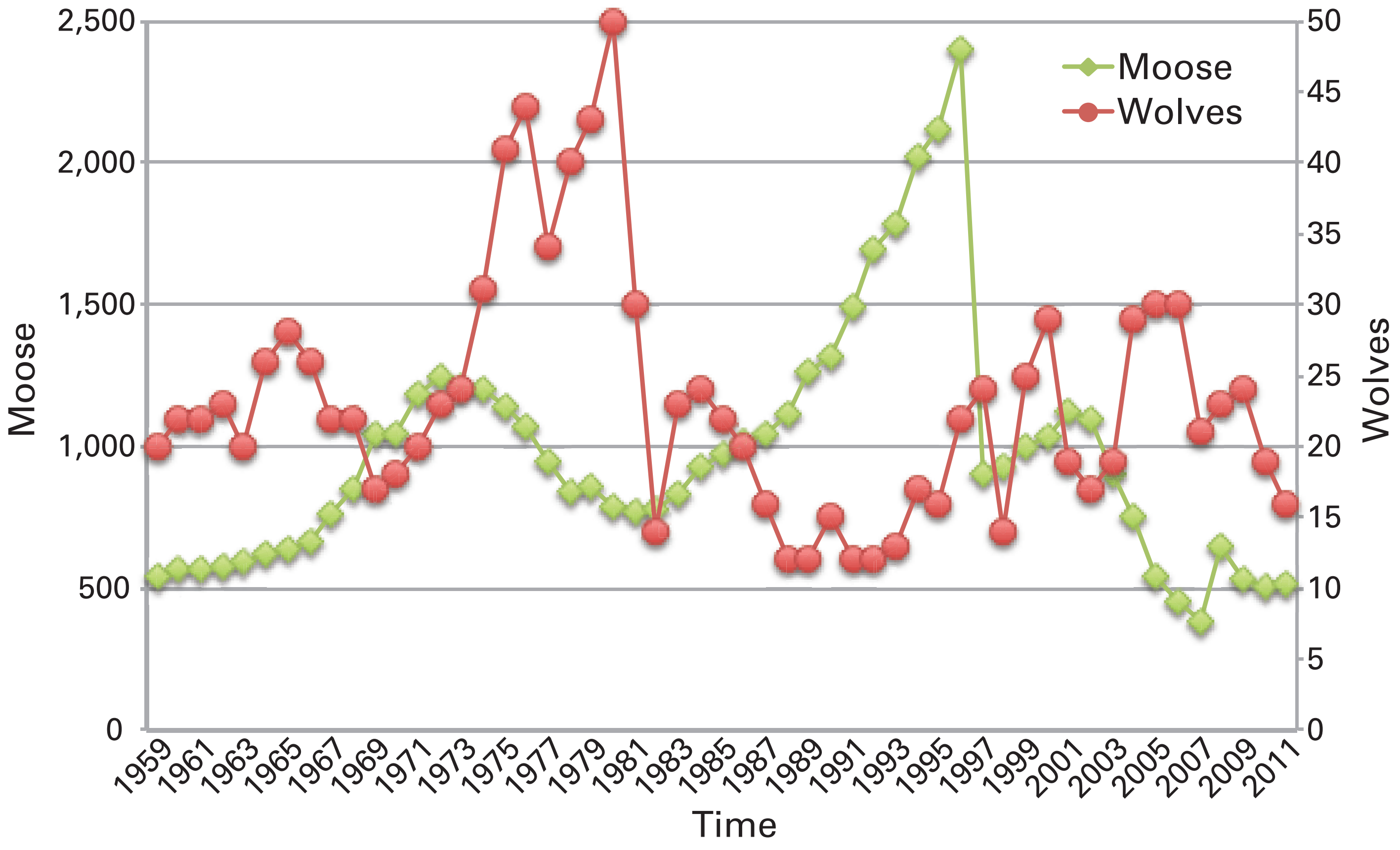


Figure 4.2
Five decades of fluctuating wolf and moose populations at Isle Royale. Note that when the wolf population peaks, the moose population is at a low point and, similarly, when the moose population peaks, the wolf population is at a low point.

- As we can see in the data from Isle Royale, the wolf and moose populations in Isle Royale have been sustaining themselves for more than fifty years without either species going extinct.
- The populations also exhibit a rough oscillation, with moose at a low when wolves peak and vice versa.
- This data can serve as a reference pattern for our phenomena- based modeling. It allows us to further refine our research question to this:
- “Can we find model parameters for two species that will sustain *oscillating* positive population levels in a limited geographic area when one species is a predator of the other and the second species consumes resources from the environment?”

Process

1. What part of your phenomenon would you like to build a model of?
2. What are the principal types of agents involved in this phenomenon?
3. In what kind of environment do these agents operate? Are there environmental agents?
4. What properties do these agents have (describe by agent type)?
5. What actions (or behaviors) can these agents take (describe by agent type)?
6. How do these agents interact with this environment or each other?
7. If you had to define the phenomenon as discrete time steps, what events would occur in each time step, and in what order?

8. What do you hope to observe from this model?

Choosing Your Agents

- We have identified and contextualized our driving research question, we can begin to design the components that will help us answer it.
- The first question we should ask ourselves is: What are the agents in the model? When designing our agents, we want to choose those components of our model that are autonomous and have properties, states, and behaviors that could possibly have bearing on our question.
- When choosing what are to be the agents in a model, it is important to concentrate on those autonomous entities which are most relevant to our research question.
- In the Wolf Sheep Simple model, *Wolf, Sheep, Grass are agents*!

Choosing Agent Properties

- Agents have properties that distinguish them from other agents. It is important to determine these properties in advance so we can conceptualize the agent and design the agents' interaction with each other and with the environment.
- In the Wolf Sheep Simple model, we give the sheep and wolves three properties each: <u>(1) an energy level</u>, which tracks the energy level of the agent, <u>(2) a location,</u> which is where in the geographic area the agent is, and <u>(3) a heading,</u> which indicates the direction the agent is currently moving or would be moving.
- The energy property is not merely describing temporary energy (such as whether an animal is fresh or fatigued). Rather, "energy" incorporates some notion of the amount of "vitality" in a creature, abstracting away the messy details of metabolism, calorie storage, or starvation, and condensing it all into a single measure.

Summary of the Wolf Sheep Simple Model Design

- The Wolf Sheep Simple model can be described in the following way:
- *Driving Question:* Under what conditions do two species sustain oscillating positive population levels in a limited geographic area when one species is a predator of the other and the second species consumes limited but regenerating resources from the environment?
- *Agent Types:* Sheep, Wolves, Grass
- *Agent Properties:* Energy, Location, Heading (wolf and sheep), Grass-amount (grass)
- *Agent Behaviors :*Move, Die, Reproduce (wolf and sheep), Eat-sheep (wolf only), Eat-grass (sheep only), Regrow (grass)

Summary of the Wolf Sheep Simple Model Design

- *Parameters:* <u>Number of Sheep, Number of Wolves, Move Cost, Energy Gain From Grass, Energy Gain From Sheep, Grass Regrowth Rate</u>

- *Time Step*: 1. Sheep and Wolves Move
  2. Sheep and Wolves Die
  3. Sheep and Wolves Eat
  4. Sheep and Wolves Reproduce

  5. Grass Regrows

- *Measures :* <u>Sheep Population versus Time, Wolf Population versus Time</u>

Examining a Model

- What parameters of two species will sustain oscillating positive population levels in a limited geographic area when one species is a predator of the other and the second species consumes limited but regrowing resources from the environment?

[Wolf Sheel Predation](http://www.netlogoweb.org/launch#http://www.netlogoweb.org/assets/modelslib/Sample%20Models/Biology/Wolf%20Sheep%20Predation.nlogo)

http://www.netlogoweb.org/launch#http://www.netlogoweb.org/assets/modelslib/Sample%20Models/Biology/Wolf%20Sheep%20Predation.nlogo

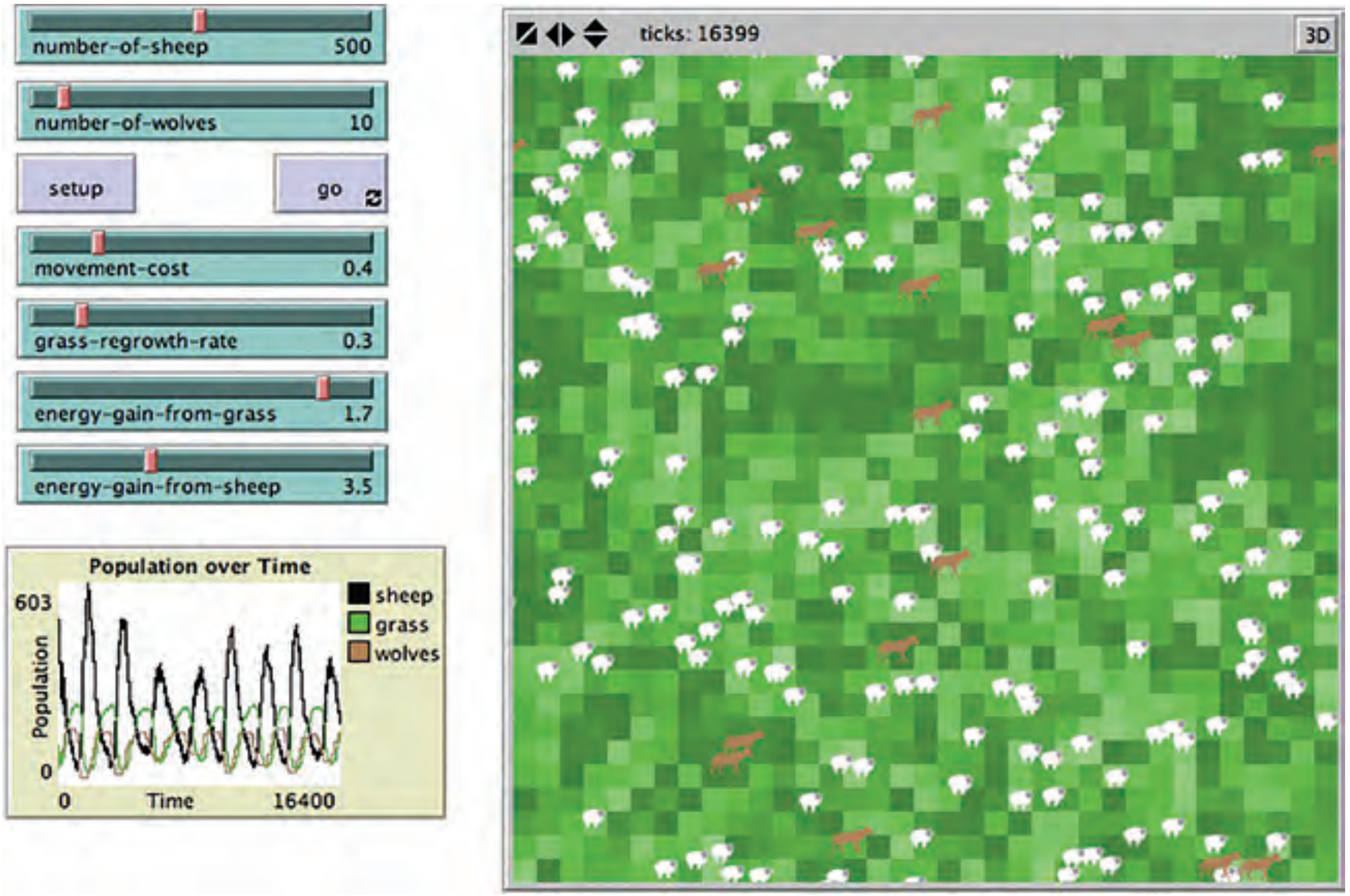


Figure 4.9
The Wolf Sheep Simple model, now including wolves. (See Wolf Sheep Simple model 5 in the supplementary materials.)

Parameter Sweeping and Collection of Results As we mentioned in the introduction, just because you have found one set of parameters that seem to answer your question does not mean that you are done.

Analysis of Data

Summarizing data can be done in a variety of ways. Not only does data analysis enable us to describe complex data results in a much more compact form, but it also gives us a uniform way of looking at data so we can compare and contrast data sets.

Having lots of data is nice, but it is difficult to make claims about three (3) different variables with ten (10) different random number seeds and eleven (11) different initial parameter settings. Altogether that combination produces 330 different values. Thus, we need to summarize and analyze this data in some way, so that it is comprehensible. One typical way to summarize the data is to average it across the runs.

Figure 4.10
Results of Wolf Sheep Simple model analysis

Equation-based model

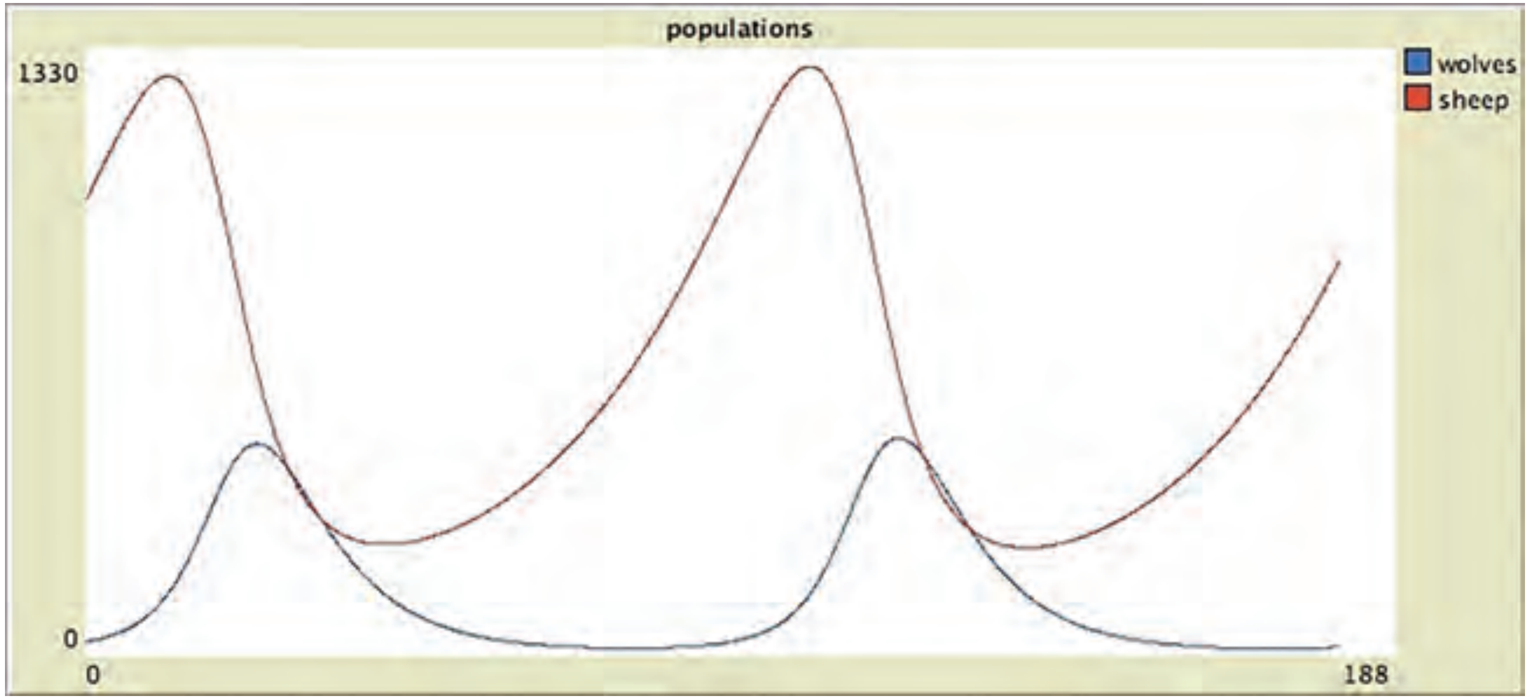


Figure 4.11
Lotka-Volterra relationship (Wolf Sheep Predation System Dynamics model) (*Wilensky, 2005*).

[Wolf Sheel Predation](http://www.netlogoweb.org/launch#http://www.netlogoweb.org/assets/modelslib/Sample%20Models/Biology/Wolf%20Sheep%20Predation.nlogo)

http://www.netlogoweb.org/launch#http://www.netlogoweb.org/assets/modelslib/Sample%20Models/Biology/Wolf%20Sheep%20Predation.nlogo

- **WHAT IS IT?**
- This model explores the stability of predator-prey ecosystems. Such a system is called unstable if it tends to result in extinction for one or more species involved. In contrast, a system is stable if it tends to maintain itself over time, despite fluctuations in population sizes.
- **HOW IT WORKS**
- There are two main variations to this model.
- In the first variation, the "sheep-wolves" version, wolves and sheep wander randomly around the landscape, while the wolves look for sheep to prey on. Each step costs the wolves energy, and they must eat sheep in order to replenish their energy - when they run out of energy they die. To allow the population to continue, each wolf or sheep has a fixed probability of reproducing at each time step.
- In this variation, we model the grass as "infinite" so that sheep always have enough to eat, and we don't explicitly model the eating or growing of grass. As such, sheep don't either gain or lose energy by eating or moving. This variation produces interesting population dynamics, but is ultimately unstable. This variation of the model is particularly well-suited to interacting species in a rich nutrient environment, such as two strains of bacteria in a petri dish (Gause, 1934).

[Wolf Sheep Predation](http://www.netlogoweb.org/launch#http://www.netlogoweb.org/assets/modelslib/Sample%20Models/Biology/Wolf%20Sheep%20Predation.nlogo)

http://www.netlogoweb.org/launch#http://www.netlogoweb.org/assets/modelslib/Sample%20Models/Biology/Wolf%20Sheep%20Predation.nlogo

- The second variation, the "sheep-wolves-grass" version explictly models grass (green) in addition to wolves and sheep.
- The behavior of the wolves is identical to the first variation, however this time the sheep must eat grass in order to maintain their energy - when they run out of energy they die. Once grass is eaten it will only regrow after a fixed amount of time.
- This variation is more complex than the first, but it is generally stable. It is a closer match to the classic Lotka Volterra population oscillation models.
- The classic LV models though assume the populations can take on real values, but in small populations these models underestimate extinctions and agent-based models such as the ones here, provide more realistic results. (See Wilensky & Rand, 2015; chapter 4).
- The construction of this model is described in two papers by Wilensky & Reisman (1998; 2006).

- **HOW TO USE IT**
- Set the model-version chooser to "sheep-wolves-grass" to include grass eating and growth in the model, or to "sheep-wolves" to only include wolves (black) and sheep (white).
- Adjust the slider parameters (see below), or use the default settings.
- Press the SETUP button.
- Press the GO button to begin the simulation.
- Look at the monitors to see the current population sizes
- Look at the POPULATIONS plot to watch the populations fluctuate over time

HOW TO USE IT

- Parameters: MODEL-VERSION: Whether we model sheep wolves and grass or just sheep and wolves
- INITIAL-NUMBER-SHEEP: The initial size of sheep population INITIAL-NUMBER-WOLVES: The initial size of wolf population
- SHEEP-GAIN-FROM-FOOD: The amount of energy sheep get for every grass patch eaten (Note this is not used in the sheep-wolves model version)
- WOLF-GAIN-FROM-FOOD: The amount of energy wolves get for every sheep eaten
- SHEEP-REPRODUCE: The probability of a sheep reproducing at each time step
- WOLF-REPRODUCE: The probability of a wolf reproducing at each time step
- GRASS-REGROWTH-TIME: How long it takes for grass to regrow once it is eaten (Note this is not used in the sheep-wolves model version)
- SHOW-ENERGY?: Whether or not to show the energy of each animal as a number

- Notes: - one unit of energy is deducted for every step a wolf takes - when running the sheep-wolves-grass model version, one unit of energy is deducted for every step a sheep takes
- There are three monitors to show the populations of the wolves, sheep and grass and a populations plot to display the population values over time.
- If there are no wolves left and too many sheep, the model run stops.

THINGS TO NOTICE

- When running the sheep-wolves model variation, watch as the sheep and wolf populations fluctuate. Notice that increases and decreases in the sizes of each population are related. In what way are they related? What eventually happens?
- In the sheep-wolves-grass model variation, notice the green line added to the population plot representing fluctuations in the amount of grass. How do the sizes of the three populations appear to relate now? What is the explanation for this?
- Why do you suppose that some variations of the model might be stable while others are not?

THINGS TO TRY

- Try adjusting the parameters under various settings. How sensitive is the stability of the model to the particular parameters?
- Can you find any parameters that generate a stable ecosystem in the sheep-wolves model variation?
- Try running the sheep-wolves-grass model variation, but setting INITIAL-NUMBER-WOLVES to 0. This gives a stable ecosystem with only sheep and grass. Why might this be stable while the variation with only sheep and wolves is not?
- Notice that under stable settings, the populations tend to fluctuate at a predictable pace. Can you find any parameters that will speed this up or slow it down?

EXTENDING THE MODEL

- There are a number ways to alter the model so that it will be stable with only wolves and sheep (no grass). Some will require new elements to be coded in or existing behaviors to be changed. Can you develop such a version?
- Try changing the reproduction rules -- for example, what would happen if reproduction depended on energy rather than being determined by a fixed probability?
- Can you modify the model so the sheep will flock?
- Can you modify the model so that wolves actively chase sheep?

THANK you