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Teaching and Learning Evolution as an Emergent Process: The BEAGLE project

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Evolution, and how to teach it, is perhaps the most controversial topic in American schools today. Biologists attest to the ubiquity of evolution, and assert that evolutionary explanations undergird their entire science and are of fundamental import. Yet, according to recent surveys (Gallup, 2008), 44% of Americans say they do not accept evolution in any form, and a shockingly small number, only 14%, say they believe in naturalistic evolution. A century and a half after the publication of the Origin of Species, there remains considerable cultural resistance to teaching this "controversial" subject in schools. Many explanations have been proffered for this disconnect between scientific consensus and citizen acceptance. Prominent among these explanations is that conflict with religious belief is the principal cause of objections to evolution (Numbers, 1992; Scott & Branch, 2003; Witham, 2002). While acknowledging the importance of religious objections, this chapter proceeds from the assumption that another major cause of rejection of evolution is the cognitive difficulty of understanding the evolutionary process. In this regard, we place evolution in a class of processes known as *emergent processes* that are notoriously difficult for people to understand (Centola, Wilensky & McKenzie 2000; Penner, 2000; Resnick & Wilensky, 1993; Wilensky, 2001; Wilensky & Centola, 2007; Wilensky & Resnick, 1999).

Indeed the history of science is replete with scientific knowledge claims that came into sharp conflict with religious beliefs. To take one example, the claim that the earth is not flat but spherical, which was put forth by the Greeks and Indians before the advent of Christianity, was met with Christian religious objections in the Middle Ages as it conflicted with Biblical verses about "the four corners of the earth". As late as the nineteenth century, even scientists such as William Carpenter (1871) and Samuel Rowbotham (1865) published proofs of a flat earth. Yet these objections eventually subsided. Now, except for a few fringe "Flat Earthers", religious and non-religious alike accept the spherical earth and are not bothered by the "four corners". How did this change in beliefs come about? Major factors in fostering this change of attitude were new technologies that enabled us to view the earth from afar and other celestial bodies from up-close. Those of us old enough to have been conscious in 1965 -- how can we forget the first photograph of the earth taken by Apollo 17 from space and published in Life magazine?

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Figure 1. *Photograph of the Earth from space (Life magazine, December 7, 1972).*

The new technologies made vivid to our eyes the roundness of the earth. Is it possible to develop a technology that would make equally visible and vivid the process of evolution? In this chapter we present a sample collection of computer models from a larger "curriculum" of computer-based activities called BEAGLE (Biological Experiments in Adaptation, Genetics, Learning and Evolution), in which we attempt to do just that – to use the computational technology to enable us to "see" evolution in action. Technologies such as telescopes and spaceships are able to compress space, enabling us to encompass large distances and far-away objects in a single view. Similarly, computational technologies enable us to compress time, so that large stretches of evolutionary time can be seen in a single viewing. Computer-based models of evolutionary processes provide a "sandbox" for students to experiment with mechanisms and analyze the outcomes that lead to population change over many generations. Our unfamiliarity with "Deep Time" (Gee, 2000) is one important component of what makes evolution difficult to comprehend. Ever since the late 1700s when Scottish geologist James Hutton described the seemingly infinite stretches of geologic time (see Taylor, 2006), there has been widespread incomprehension of this vastness. In 1805, Hutton's colleague John Playfair said: "the mind seemed to grow giddy by looking so far into the abyss of time". Deep time is certainly one important barrier to comprehension of evolution. But there is another important factor that we believe is an even greater impediment. Evolution is a process that works on populations. Gene frequencies in a population change as a result of the variation in competitive advantage of individual traits. Processes where changes occur at one level, but subsequently lead to aggregate outcomes and changes at a higher level (e.g., phenotype results from interaction of genes, population levels result from interactions of individual organisms, and speciation results from interaction of populations) are known as emergent phenomena (Penner, 2000; Wilensky, 2001; Wilensky & Resnick, 1999). In previous work (Resnick & Wilensky, 1993; Wilensky, 1997; 1999b; Wilensky & Resnick, 1999) we have shown that emergent phenomena are particularly hard for people to reason about. Commonly people "slip between levels" (Levy & Wilensky, 2008; Sengupta & Wilensky, 2009; Wilensky, 2001; Wilensky & Resnick, 1999) attributing properties of the individual to the population and vice versa. For example, if a colony of ants exhibits intelligent foraging behavior, we commonly attribute that intelligence to the individual ants. But this is a misattribution -- science has shown that in fact while ant colonies are efficient at gathering food, individual ants are not. It's through the accumulation of the actions and interactions of many ants, each with simple behavior, that we get the emergent intelligence of the colony (Holldobler & Wilson, 1991; Robson & Traniello, 1995; Sudd, 1957; Wilson, 1971). This slippage between the level of the ant colony and the level of the individual ant is a prototypical example of how people so easily slip between different levels of an emergent phenomenon or complex system. Evolution, itself an emergent process, engenders these same cognitive difficulties. Like other emergent phenomena (EP) we have studied, we would expect students of evolution to encounter the same cognitive difficulties reported on with these other EP. Indeed, we have seen the levels slippage described above when students reason about EP. For example, if students are told that a population of dinosaurs evolves into a population of birds, by the levels slippage, they envision that this means that an individual dinosaur must morph into a bird. But such a morphing is clearly absurd. By this implicit reductio ad absurdum, they conclude that evolution of species cannot be true.

Understanding Emergent Phenomena

In the early nineties, Wilensky and Resnick conducted interviews about emergent phenomena. They asked individuals to explain classic EP such as the food gathering of ants, flocking of birds, traffic jams, etc. Each of these phenomena exhibits characteristic patterns (e.g., V-shape of a goose flock) that emerge from the interactions of individuals (e.g., goose). They found a surprising regularity in the explanations people gave: they tended to explain the phenomena as orchestrated by a leader as opposed to the distributed control organizing these phenomena and they described the phenomena as deterministic with no role for randomness in their explanations. Randomness was seen as destructive of the order perceived in the patterns whereas, in fact, the random perturbations help to stabilize and maintain the patterns. Resnick and Wilensky attributed these explanations to a prevalent habit of mind, which they called the "deterministic-centralized mindset" (DC mindset) (Resnick, 1994; Resnick & Wilensky, 1993;

Wilensky & Resnick, 1995; 1999). All EP can be perceived at two core levels: the level of the individual element (micro) and the level of the aggregate pattern (macro). A key feature of the DC mindset is the tendency to “slip between levels” (Wilensky & Resnick, 1999), that is to misattribute properties of the aggregate to the individual (as in attributing intelligence to the ant) and to misattribute properties of the individual to the aggregate (as in misattributing forward motion to a traffic jam because the individual cars are moving forward).

Subsequent work has established that this levels slippage presents a significant barrier to people’s understanding of many scientific phenomena. For example, Sengupta and Wilensky (2005, 2008a, 2009) have demonstrated that a primary obstacle for students in understanding electricity arises from their slippage between the levels of individual electrons in a wire and the aggregate current in that wire. The curricular design described in this chapter was based on an identification of levels slippage as a crucial difficulty in understanding evolution; it is easy to slip between properties of individual organisms and those of populations or species.

In previous work we have shown that using computer-based models and simulations, specifically agent-based models, can help people overcome the DC mindset and levels slippage and come to understand emergent phenomena. This has been demonstrated in a wide variety of scientific domains including chemistry (Stieff & Wilensky, 2002; 2003; Levy & Wilensky, 2009a; 2009b); population biology (Wilensky, Hazzard & Longenecker, 2000; Wilensky & Reisman, 2006; Klopfer, 2003); electricity (Sengupta & Wilensky, 2005; 2008b; 2009), materials science (Blikstein & Wilensky, 2004; 2006; 2007; 2009). probability and statistics (Wilensky, 1997; Abrahamson & Wilensky, 2004; 2005). In these studies, it was shown that encoding domain knowledge using agent-based models greatly enhances students’ comprehension of the science enabling the students to connect the micro and macro levels and comprehend how mechanisms operating at the micro level can generate observed regularities at the macro level.

Agent-Based Modeling

The last two decades have seen the creation of the new computer-based methodologies of agent-based modeling. By the term “agent”, we refer to a computer-based object or entity that has properties and behavior. For example, we could create “car agents” that look like little cars. Each car agent has properties such as location and speed, and associated behaviors such as moving and accelerating. Once we set the car agents in motion according to their behavioral rules, a characteristic traffic pattern, such as a traffic jam, will emerge. The key idea of agent-based modeling is that much of the regularity and complexity in the world can be explained by choosing agents and behaviors that through their interaction generate the observed macro patterns and regularities. Agent-based modeling has enjoyed a rapid increase as a method of conducting scientific research (Gilbert & Troitzsch, 2005; Railsback, Lytinen, & Jackson, 2006; Wilensky & Rand, in press). But, equally, it has become increasingly employed as a vehicle for teaching and learning science.

Learning materials that employ agent based models can address conceptual barriers caused by levels slippage that make understanding evolution difficult for students. Levels slippage is particularly problematic when teaching evolution because evolutionary mechanisms, properties and outcomes operate at multiple interacting levels. For example, mutations act on genes, predators act on individuals and trait variation is a property of a population. And while competition between species appears to be a population level interaction, it often emerges from competition between individuals or genes. Agent-based models can support student explorations that focus on purposeful inspection of individuals while concurrently comparing the changes and outcomes that are occurring at other levels. Our work suggests that using agent-based models enables students to focus on two levels at a time and to move between them, and that that is a key component of learning and teaching about evolution.

NetLogo is one of the most widely-used agent-based languages and modeling environments (Wilensky, 1999a). It was designed to be "low threshold and high ceiling" (Papert, 1980; Tisue & Wilensky, 2004) – that is, easily accessible to novices in computer programming or modeling yet powerful enough to be a central tool for professional research. NetLogo is indeed in widespread use by both researchers and educators. It comes with an extensive models library of sample models (over three hundred models) that can be used in educational settings. This library also includes a section of curricular models. A large body of educational materials and curricular units has been designed using the NetLogo environment including most of the BEAGLE evolution materials described herein. These materials are all "glass-box", that is, the underlying NetLogo code can be viewed and modified by any user. This ability to easily inspect and modify the code has resulted in educators spawning thousands of variations of curricular materials adapted for their own particular contexts.

Besides its use as a single-user application for demonstrating, modifying and creating agent-based models, NetLogo also has another multi-user mode. Through a module called HubNet (Wilensky & Stroup, 1999a), multiple users can join a NetLogo simulation once it is started, thereby turning it into a "participatory simulation" (Wilensky & Stroup, 1999b, 2000). Users connect to the computer running the NetLogo simulation through their own computer or handheld device such as a calculator. In this mode, an entire classroom can participate in a simulation, each, for example, playing the role of predator or prey in a shared ecosystem. All of these features and considerations are ideally suited for creating powerful and engaging models and simulations of evolution. As such we decided to create the BEAGLE evolution curriculum using NetLogo as a platform.

The BEAGLE project

In the project described herein, we have employed agent-based models and representations to teach evolution. The BEAGLE (Biological Experiments in Adaptation, Genetics, Learning and Evolution)[3] project is based on a suite of NetLogo models and supporting materials designed to facilitate inquiry, teaching, and learning of concepts and phenomena related to evolution, adaptation, and natural selection. We have piloted BEAGLE models and materials in several settings, from middle school science to undergraduate biology classes.

The development of BEAGLE models was guided by multiple sources including national learning goals for science literacy, popular science materials, traditional biology topics, reform-based science curriculum units, and the current state of the art evolutionary research. Each BEAGLE model was developed using design principles distilled from our previous work in designing and researching instructional materials that use agent-based computer models. We particularly relied on interface guidelines learned from the Connected Chemistry curriculum project (Levy, Novak & Wilensky, 2006; Levy & Wilensky, 2009a). Such instructional materials have been shown to be vibrant, compelling, and accessible for adolescents (Stieff & Wilensky, 2003; Levy, 2009b). All models were checked for correctness of code and accessibility of information by a team of students and researchers at the Center for Connected Learning and Computer-Based Modeling (CCL) and were then reviewed for scientific accuracy and importance by university biologists. The curricular materials developed to accompany each model include conceptual scaffolding for students to interact with and explore models, to run experiments, and to use analysis tools to test model outputs and model assumptions.

There are over a dozen models used in our BEAGLE materials on evolution, each one addressing different emergent phenomena related to competition, selective breeding, patterns of inheritance, genetic drift, natural selection, mutation, coevolution, speciation, and adaptive radiation. Each BEAGLE model comes with an information tab[4] that includes instructions for students and teachers on how to use the model. The instructions include a section on what the model is trying to show or explain, how the model works, how to use the model, patterns of behaviors for the user to notice while running the model, some suggestions for activities to try with the model as well as suggestions for possible changes or additions to the model. These embedded model instructions, support open exploration and "playing" with the model in a variety of learning settings.

As part of the BEAGLE project we developed a three-week instructional unit on evolution titled,

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[3] Many of the BEAGLE models can be downloaded from http://ccl.northwestern.edu/simevolution/beagle.shtml. Some instructions for using the models are embedded in the info tab of the models. Much more extensive materials and a BEAGLE curriculum for middle and high school have been piloted {WORD?} in secondary school and university classes and are expected to be published in the near future. If you wish to pilot the materials, please contact us at oas@ccl.northwestern.edu.

[4] All models in the NetLogo model library have information tabs that provide background and guidance to users.

"BEAGLE: Mechanisms of Evolution." The unit can be used in a variety of learning settings ranging from middle school through undergraduate biology classes as well as informal settings or online. The unit includes a set of sequenced instructional activities, discussions, outside the classroom readings and homework assignments, related to each computer model. The unit is structured into four learning sets. The first learning set investigates ecosystems, predator/prey/producer relationships, and competition. The second learning set investigates the mechanisms of evolution (natural selection, genetic drift, mutation) as well as selective breeding. The third learning set investigates outcomes that result from interactions between multiple mechanisms of evolution. Such emergent outcomes include extinction, speciation, co-evolution, and adaptive radiation.

Below, we present four case studies from the "BEAGLE: Mechanisms of Evolution" unit. These cases are developed from middle school students' experiences with pilot implementations of the BEAGLE models and instructional materials. While, as yet, we have not conducted rigorous classroom research on BEAGLE, we have conducted extensive classroom research and iterative redesign based on classroom use. The cases illustrate the affordances of the models to engage students in thinking about evolution as an emergent process. They provide a sample of some of the ways in which students use agent-based models to explore and understand emergent phenomena and emergent processes in evolution. Each case centers around one focal BEAGLE model and describes 1) how the model works and 2) the emergent phenomenon that the model is designed to teach and 3) student activities and understanding while engaged in interactions with the model.

The Case Studies

Model 1: Wolf-Sheep Predation

The BEAGLE curriculum is based on of a set of models and activities. These models and activities can be used in many different ways and need not be run in a fixed sequence. Typically, however, we begin student explorations with ecological models without evolution. A focus on ecology gets students to reason about the interactions between individuals and the subsequent changes in populations and this is an important prerequisite step in understanding evolution. A typical first model that addresses this is the Wolf-Sheep Predation model (Wilensky, 1997) from the NetLogo models library.

The model consists of a simple ecosystem that includes a primary producer (grass) that re-grows throughout the ecosystem over time; grass provides energy for sheep (which eat grass as they move about the ecosystem). Sheep in turn, provide energy for wolves (which eat sheep as they move about the ecosystem). As wolves and sheep move about they lose energy. When sheep or wolves have enough energy they give birth to new offspring and when they run out of energy they die.

This model enables students to explore the interactions between individuals and population in a predator-prey ecosystem. 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. The model exhibits a variety of emergent phenomena that can be analyzed and explored to better understand the interactions between the agents in the system. Through various activities with this model, students develop important ideas related to: 1) interactions between organisms and the environment, 2) individuals and populations, 3) direct and indirect evolutionary pressures, 4) stability and change over time, and 5) competition.

Model 1: Emergent Phenomenon - Competition

Most students have prior knowledge of some basic interactions between organisms and their environment. The topic of ecosystems is commonly revisited in many contexts in primary school science. If asked, "what can cause a population to change?" we have seen that middle school students will readily identify specific food, predators, and habitat as important factors that cause a change in the size of a population. And these same students are able to predict the immediate or short-term effects that these survival factors would have on a population (e.g., more habitat can support a larger population). But the interrelationships between individual organisms and the population and between individual organisms and their environment are typically described only in very simple or very direct terms, where a single proximate cause is solely responsible for a single immediate effect.

When asked to consider a simple ecosystem containing only three types of organisms, where grass is the primary producer, sheep are the primary consumer, and wolves are the secondary consumer, it is difficult for students to reason about the indirect effects on the population and individuals within each population for a variety of scenarios. For example, we have seen that students have difficulty connecting how a change in the wolf population would indirectly affect the amount of grass in the ecosystem. To understand this indirect effect, students need to connect at least two relationships: 1) the effect of the number of sheep on the amount of grass and 2) the effect of the number of sheep on the number of wolves. So in order to account for the indirect effect of wolves on grass, they would need to reason out how the change in the grass would affect the scarcity of food for each individual sheep, which in time has an aggregate effect on the population of sheep, which in turn affects the scarcity of food for each individual wolf, which in time has an aggregate effect on the of wolves.

We have also noted that it is frequently difficult for students to connect limitations on resources to their effect on individuals in an ecosystem. While it is easier to understand that there is an upper limit to the number of individuals that can be sustained in a given environment, it is more difficult to reason about how that upper limit would subsequently result in a form of competition between those individuals of the same population for those resources.

Competition is an emergent process. Maximum sustainable population levels (or carrying capacities) arise as an indirect result of competition between similar agents for similar limited resources. Whenever there is variation in the number and distribution of both types of agents and when there are not enough resources to meet the needs of every individual in a population, the interactions between the agents will result in (and is a result of) a continually changing landscape of resource distribution over time. Relative scarcity of these resources will have both a temporal and spatial component. In order to observe the interactions that result in (and are affected by) this distribution, the interactions amongst many different individuals need to be observed many times and under many conditions, in compressed time and space.

Repeated examination of when and where such interactions are occurring helps students recognize that survival of individuals is not only influenced by the immediate conditions of the environment surrounding an individual, but also by recent conditions in the past, and upcoming conditions in the future. When individual survival patterns are examined in the context of the changes in species' population (where births and deaths are occurring at different rates through time), students begin to connect individual survival to cycles in population size. Being able to distinguish between effects at the micro-level and at the macro-level enables students to develop a chain of causal links necessary to explain how individuals of the same species end up indirectly and directly competing against each other. Competition as an emergent process is difficult to understand without this dynamic view of resource distribution in the ecosystem. Many effects that lead to competition between individuals in a population are the result of a delayed sequence of interactions and consequences. For example, rainfall in one year may not immediately affect the number of birds that survive. But it would eventually have an effect, after first affecting the growth of plants which in turn would affect the number of flowers produced, which in turn affects the number of seeds produced, which would affect the amount of food available for birds later this year and the next. Without understanding such indirect and dynamic interactions how can one account for why one individual might thrive while the population simultaneously declines? Or why an individual, in its attempts to survive, is concurrently but unintentionally decreasing the chances of survival for the remaining individuals in the population by decreasing the overall supply of resources available for other individuals?

Model 1: Student Experiences

These ideas are addressed in the BEAGLE Wolf-Sheep Predation activities. Below (figure 2) is a screen capture from the Wolf-Sheep Predation simulation in progress. Notice the window on the right (the "World" or the "View" in NetLogo parlance) displays where different individual wolves and sheep are in space and where the resources necessary for survival are located. Some sheep are very close to large amounts of grass (shown in green), while others are in regions where there is less grass nearby. Likewise, some wolves are close to sheep (which they need to eat in order to survive), while others are further away from sheep. As time progresses, grass grows and sheep and wolves move about the ecosystem, interacting with each other. Students can track the survival of individual sheep and wolves, study their motion, energy levels, and reproduction, while concurrently comparing what is happening to the population. Tracking and analyzing the changes that occur over time in the population is supported by the real-time graph and monitor updates (shown in graphs and monitors on the bottom left side of the screen capture). It is important for students to have access to both the view and the plots in order to analyze and reason through different conditions to account for differences between what is occurring for an individual and what is occurring for the population. For example, a single individual may be thriving (surviving and reproducing) while the overall population is struggling (the total number of individuals are declining).

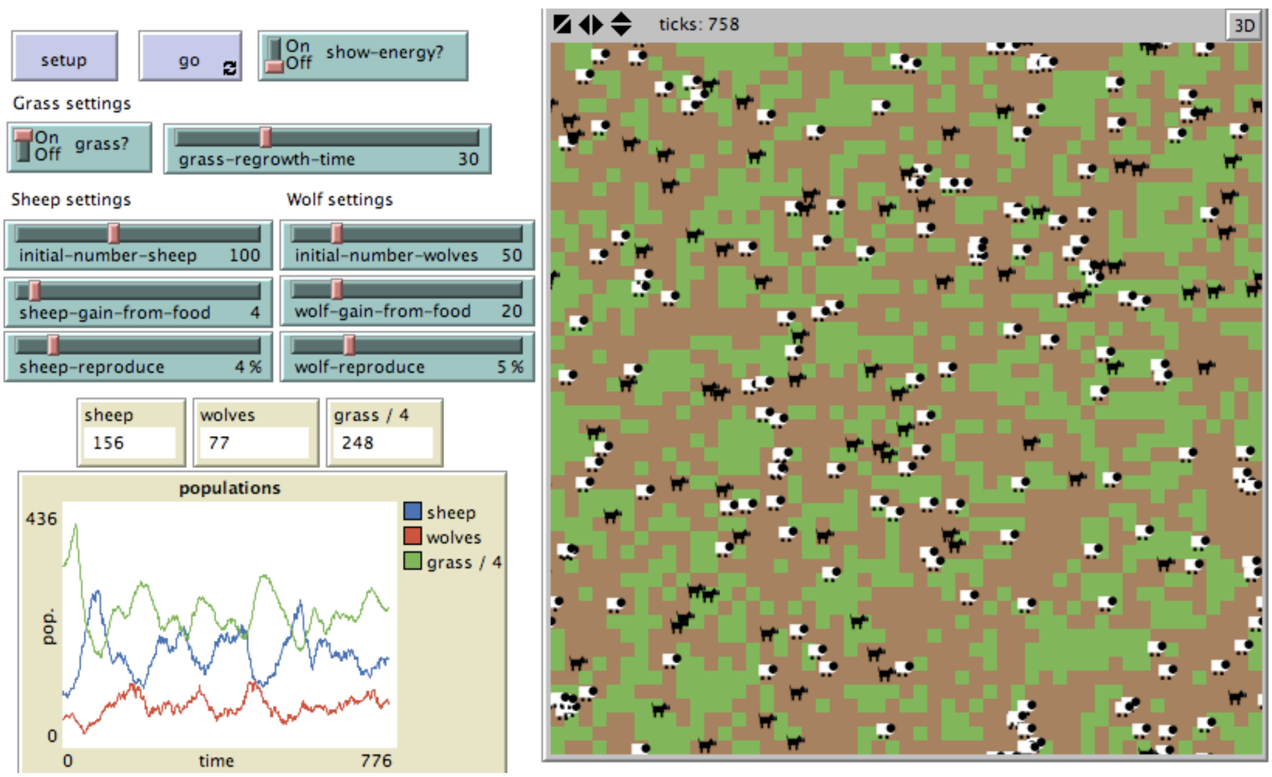

Figure 2. NetLogo Wolf-Sheep Predation Model

The interface in all BEAGLE models supports similar types of analysis (between patterns of change in both populations and individuals). Students can change various parameters in the model using sliders and switches (shown in the top left of the figure above) to design experiments and test various scenarios. Students can use the model to investigate questions such as “What would happen if I started with more wolves?”, or “How would a faster rate of grass growth affect the stability of the sheep population?” or “Why does random placement of individuals have little effect on the overall trend in the cycles in the population?” or “What is the carrying capacity of wolves in this ecosystem?”

One student, Gabrielle, who was engaged with the model, was curious whether the nature of predator-prey oscillations might depend on the parameters of the model. She wondered what would happen if she started the simulation with a very large number of sheep. She guessed that the sheep would then dominate the ecosystem.

When Gabrielle ran the program, she was in for a surprise -- all of the sheep died. At first she was perplexed: she had started out with more sheep and ended up with less. We have seen many students become emotionally involved with the fate of the “creatures” in the models. Often, when they see the creatures endangered by the trough of an oscillation in the population size, they attempt to add more of the endangered creatures to ensure its survival. But, in this case, Gabrielle’s attempt to help the sheep had exactly the opposite effect.

Gabrielle’s initial response is an indication of a typical type of *micro-macro confusion* – between trying to achieve a group-level result by focusing only on the individuals – without considering the interaction among them. It is as if Gabrielle assumed that each sheep had a particular chance of survival, and then added more sheep to increase the chances of a large group surviving. In this way of thinking, their chances of survival just add up. But in fact, there is a feedback mechanism in the system, so that increased numbers of sheep results in increased competition for limited grass which results in reduced chances of survival for all sheep (that outweigh the compensation for the increase in numbers of sheep).

The model enables students to gain powerful insights into how interactions between the individuals within the same population indirectly affect the overall populations (of the same species and of different species). These population effects can be more clearly understood through observing and inspecting what is happening to individuals as these effects emerge within the ecosystem over time. Populations of predators, for example, undergo cyclical fluctuations that are an indirect result of their own behaviors (the more sheep there are, the more likely it is for each individual wolf to get enough food to survive and reproduce, this in turn leads to more wolves, which eat more prey, which reduces the amount of prey available for the wolves now which allows for more grass to grow back. With the sheep population now low, less grass will be eaten and it is less likely for each wolf to find enough food to survive, which results in less wolves. Both of these changes benefit the sheep that survive and reproduce more frequently -- and the cycle repeats).

Reasoning about these types of indirect forces that affect survival in the model serves as an entry point to developing forms of reasoning that can connect indirect and direct competition effects to a variety of emergent outcomes in populations. Competition for limited resources itself is an important mechanism of evolution. But fluency with reasoning about indirect pressures and effects is also necessary to understand even more complex mechanisms of evolution.

Model 2: Bug Hunt Drift

Other sets of introductory models and activities in the BEAGLE curriculum help build familiarity with important mechanisms related to evolution. For example, selective breeding models introduce students to mechanisms that include selection, variation, inheritance, and time. The interaction of these mechanisms in the context of selective breeding helps provide students a basic model of selection that can be expanded on to account for changes that emerge from other forms of selection such as genetic drift.

Genetic drift is a powerful form of selection and, though not well known to the public, it is one of the primary mechanisms of evolution. The phenomenon of genetic drift is the result of purely random selection events or interactions over time. Random interactions (either random breeding or random predation), are events that result in the removal or duplication of a trait (or set of traits) within a population. Within a population where such random events are continually occurring, some traits are carried into future generations while others, over time, disappear.

To explore this emergent outcome, each student uses the Bug Hunt Drift model (Novak & Wilensky, 2008). In this model, a student adopts the role of a "selective agent" and then transitions to the role of a "random agent" and eventually to the role of an observer of "random agents". Students initially use their mouse to select bugs from a multi-colored population of bugs that are moving randomly around the screen, Students can select bugs they wish to die or bugs they wish to reproduce (create an identical offspring). They can be given a variety of scenarios or goals such as: How long does it take you to generate a population with only one variation of the color trait? If a bug dies, a new offspring bug is automatically created that is an exact duplicate in color to a randomly selected bug (of the remaining bugs in the population). Likewise, if a student adds a bug (by selecting a bug to have an offspring), another randomly selected bug is removed from the population.

Alternatively, students can also employ progressively more random selection mechanisms for which bug they are selecting, thereby removing themselves from the selection process. One such scenario gives students a "color blind" view of the population of bugs, but keeps them in control of which bug to select for reproduction or removal. Another scenario available to students is automated random removal or reproduction of individuals. Both of these "blind" mechanisms (for randomly selecting bugs to remove or reproduce) result in genetic drift. One mechanism keeps students in a more participatory role, and the other moves the students to more of an observer role in the simulation.

Model 2: Emergent Phenomenon – Genetic Drift

Accounting for how intentional selection (e.g., selective breeding) can lead to changes in frequencies of trait variations in populations is a more straightforward form of reasoning then trying to account for how random selection in a population can lead to the same outcome. Becoming familiar with random interactions and how they lead to similar emergent outcomes is critical to understanding genetic drift. Many types of random interactions (such as random reproduction or random predation), always lead to a similar outcome in populations– loss of genetic diversity and eventually the emergence of only a single variation of a trait in a population over time. Different initial conditions (e.g., size of the population) and different sequences of interactions result in different pathways or histories of events that leads to this outcome (sometimes genetic drift takes longer to observe than other times, due to its basis in random events). Different trait variants disappear from the population in different amounts of time, in part due to the accumulated effect of the random interactions: some causing relative trait frequencies to increase, while other interactions cause them to decrease. And these differences in initial conditions and sequence of interactions will also yield an unpredictable end state for each model run (the resulting population may be one color at the end of a model run one time (e.g., green), and a different color the next time the same experiment is performed (e.g., blue)).

Initially, it is difficult for students to understand the similarities and differences in outcome across model runs. without conducting multiple experiments and carefully monitoring their experience with the vast number of interactions that occur within the population. For example, a similar outcome in every model run is that there is a loss of diversity. However, there is a difference in outcome for each run -- the final bug color (or colors) is different for different runs and is unpredictable. The length of time for each model run to result in a single-colored bug population also varies from run to run. For example, in a relatively small population of sixty bugs , on average, it takes over 1000 clicks to remove all but one type of variation, but sometimes it takes more and sometimes less.

Model 2: Student Experiences

Students are led through three scenarios, each employing different selection mechanisms. In the first scenario, students are asked to start with a multi-colored bug population and try to produce a single-colored bug population by selecting individual bugs for either reproduction or death. Students observe that selecting a bug for reproduction always results in a bug with exactly the same trait produced (a clone) from the parent selected. At the same time a random bug is removed from the population. The student knows the color of the new bug since she is intentionally selecting for it. And so with each single selection, the student can observe the resulting shift in the distribution of traits in the population and also observe how changes in the population accumulate over time.

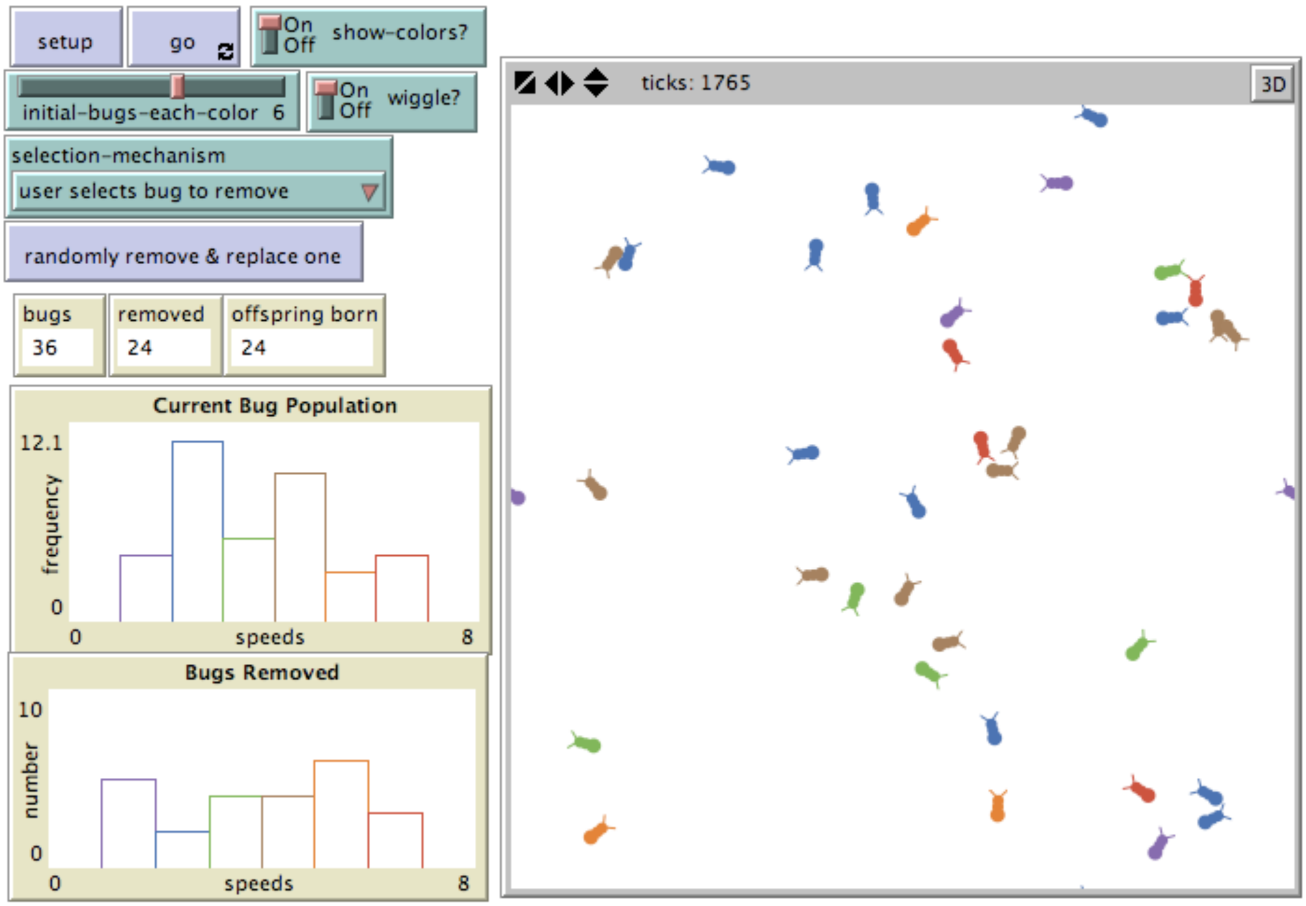

Figure 3. NetLogo Bug Hunt Drift

Repeating this selection over time, the target color for the student becomes more prevalent in the population, but the progress toward a completely uniform color in the population does not move at a steady rate. Sometimes the colors that are almost gone from a population, rebound in frequency, and some times they disappear quickly. The non-linear route toward eliminating other colors from the population helps students recognize how random selection converges on a different end state each time, through a different path, but with the same general pattern of result.

After repeating this selection process as a predator, the user then studies how his or her own actions (when blinded to their effect) would again lead to the same genetic drift outcome. Shifting their predator abilities so that they may still select individuals to reproduce or remove from the population, but now using "color blind" eyesight, leads to the same end result, although the path to the result is different. Random variation in trait frequencies are slow to accumulate (since there is no preferred selection being performed by the student), but even minor changes in frequencies tend to cascade into increases in probabilities of further genetic drift. For example, a doubling of the number of red individuals in the populations, and a halving of the number of blue individuals, makes the odds of selecting a red bug for removal far greater than for choosing a blue bug. So while in this scenario, the time to achieve the outcome is greater, requiring many more interactions than with intentional selection, the outcome is similar – a diverse population with many traits becomes a population with only one trait over many "generations."

From here, students explore a third variant scenario using "automated rules" for random (e.g., blind) removal of individuals. By automating the computer to perform selection on individual bugs (e.g., one a second), the student shifts to an observer of the ecosystem, watching the population as a whole as it changes over many generations. These shifts in perspective of how the selection is done (selection as an intentional first person mechanism, ,unintentional first person mechanism or an unintentional third person mechanism) and comparison of the results of each scenario helps students to appreciate the power of genetic drift and understand that it can arise from a variety of different mechanisms.

One student, Nicholas, exploring this automated selection scenario, initially predicted that random selection would cause trait variations to disappear. This prediction is correct, but his reasoning was connected to the idea of migration events in the real world and an intuition about small populations having less diversity, instead of the role of random selection and changing proportions of trait variations.

When he first explored the model in the first scenario, he directly engaged in the selection process. He made a noticeable effort to intentionally select different colored bugs with each mouse click. Then when he switched to "color blind" mode, he changed his predicted outcome. At this point, 3 of the 6 initial color variations were no longer in the population, but these 3 variations had been relatively stable for some time during the exploration. "I think it (number of bugs) will just go down to a few bugs for each (color) and then go up and down (fluctuate)". He then switched to automated computer selection and noticed that one of the colors of bugs did disappear and decided to run the model again to see if this would happen again, then stated, "Ok…so not as many bugs have that (color) disappear. One trait would disappear because less bugs had the trait…cause they keep getting selected and then it's down to one and then none and now there is only the others (colors). Its the one that's not most likely for the offspring, probably because the parent or grandparent didn't have that trait." Here he was starting to connect the relative proportions of the trait in the population to his predicted outcome, recognizing that the previous history of selection in the population is changing these proportions which further influences the chances of what will happen next.

When asked to predict how changing the population size would affect the population, he initially predicted larger populations would show genetic drift quicker. But immediately upon restarting the model with a larger population size and starting the model run, he revised his prediction and reasons, "There is more of each (color) population, so it takes longer for each trait to die out. And when, subsequently, asked to make a prediction for a smaller population size he stated, "One trait would disappear quicker because less bugs had the trait…". Notice how his reasoning has changed to account for the role of proportions of trait variations in the population. The AAAS, Project 2061, Benchmarks for Science Literacy document, argues that in order to understand evolution students need to, "shift from thinking in terms of selection of individuals with a trait to changing proportions of a trait in populations." This is what Nicholas has started to do in his exploration of genetic drift with this BEAGLE model.

Model 3: Bug Hunt Camouflage and Bug Hunters Camouflage

In the Bug Hunt Camouflage model (Novak & Wilensky, 2006a), students explore how the interplay of predator actions and environmental conditions can lead to natural selection. The emergent phenomenon in this model is that natural selection develops camouflaging for the bugs -- that a population hunted by a predator can develop camouflage to increase their chances of survival. For example, in a forest rife with green leaves, green bugs emerge as the predominant bug color.

Using this model, students are placed in the role of a predator to experience how their predatory actions can lead to the emergent outcome of a "more fit" population of prey over time. As a student "bug hunts" (by clicking on bugs in the environment as fast as she can) she plays the part of a predator. Students are simply trying to find and eat bugs as fast as they can (so they do not starve from lack of food), without consciously choosing a particular set of traits in one bug over another.

Each bug in the model has an individual genotype that determines the relative proportion of red, green, and blue pigments it produces. This genotype results in a single phenotype (its visible color as produced on the screen). When a bug is eaten, a new one replaces it. This new bug is reproduced asexually from a parent in the remaining population. The new bug has a near duplicate genotype as its parent but with a slight mutation in the proportions of red, green, and blue pigments that it produces.

Since the student naturally uses color and shape to identify the location of prey in an environment, color grants a level of survival fitness for the bugs in a given environment. Environments are real world photographs of natural settings that are displayed in the background of the model view. If some prey tends to blend into the background photo better, it is more likely to evade detection and survive longer and reproduce more often. If this continues over many generations, the distribution of colors in a population will tend to shift to become better camouflaged in the surrounding environment. The resulting color may give the bugs a competitive advantage for blending into the surrounding environment, but may or may not give them such an advantage in another environment. The environment can be changed selecting from a large number of different photorealistic backgrounds.

Model 3: Emergent Phenomenon – Natural Selection

To understand natural selection, students need to connect their understanding of how variation of heritable characteristics exists within every species, to the idea that some of these characteristics give individuals an advantage over others in surviving and reproducing in certain environments. The advantaged offspring then, in turn, are more likely than others to survive and reproduce. And, as the proportion of individuals that have advantageous characteristics increases, the competitive advantage of the population also increases. In this manner the characteristics of the bug population, do not drift randomly, but move in a general direction that makes them more fit for their environment than the previous generation (most of the time).

When a predator uses color and shape to identify the location of prey in an environment, then the colors and patterns in the environment provide additional selective pressure on the prey. If some prey tend to blend into the background better, they tend to survive longer and reproduce more often. If this continues over many generations, the distribution of colors in a population may shift to become better camouflaged in the surrounding environment. The contribution of mutation can further speed this process, since it can introduce variations that may not have been present in the original population or that were removed because they were not well suited for the previous environment, or it can reintroduce variations that were in the original population, but were removed through the effects of genetic drift.

From previous model explorations in BEAGLE, students will have become increasingly proficient at shifting their reasoning back and forth between individuals (micro reasoning) and populations (macro reasoning). Furthermore, the role of random interactions will have been explored in previous models and can be extended at this point to account for the effect of mutations. They will have also reasoned about how competition is an emergent phenomenon within any population that shares needs for the same resources. What they need to explore further are two new ideas: 1) that certain traits can grant a "competitive advantage" to the survival of individuals in particular environments, making it more likely that organisms with those traits will be more likely than others to survive and have offspring, and 2) that mutations result in new variations of traits within the population, some of which are more advantageous, some of which are less advantageous, and some of which grant little or no competitive advantage.

Model 3: Student Experiences

In one variation of this model, called Bug Hunters Camouflage (Novak & Wilensky, 2006b), students use HubNet to connect their individual computers to participate and interact with each other in a single NetLogo host model. To do this, a single user (teacher or student) launches the host model that other client computers will connect to. A screenshot of this model is shown below.

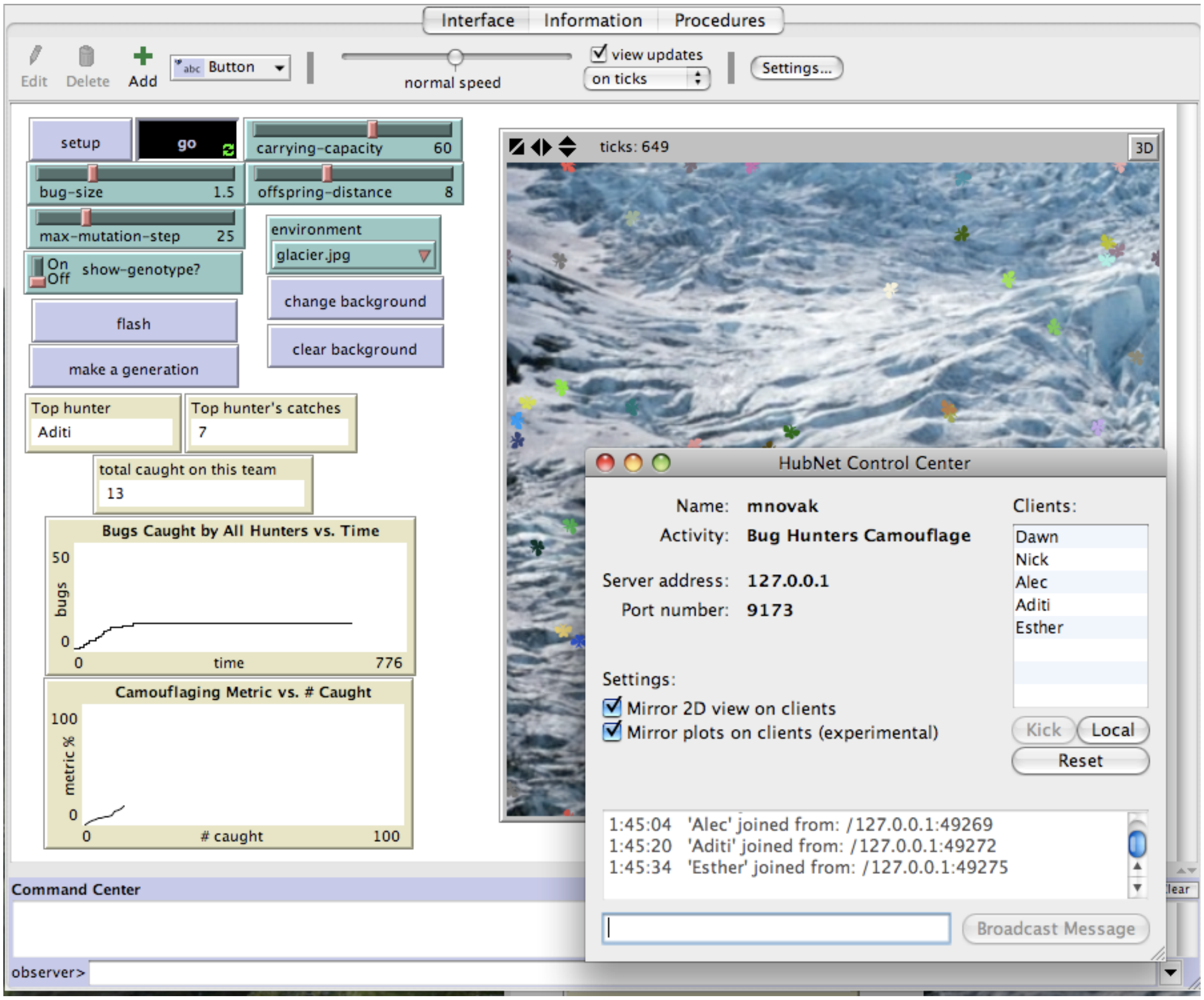

Figure 4a. NetLogo Bug Hunters Camouflage **(host model)**

Once launched, the person who launches the host model accepts clients who join the model from across a network. Each client who joins (one per student) receives a HubNet Client Window to use to interact with the model. This Client Window looks similar to the host model, but has less interface elements for controlling the setup and start of the simulation. A screen shot of the client window is shown below.

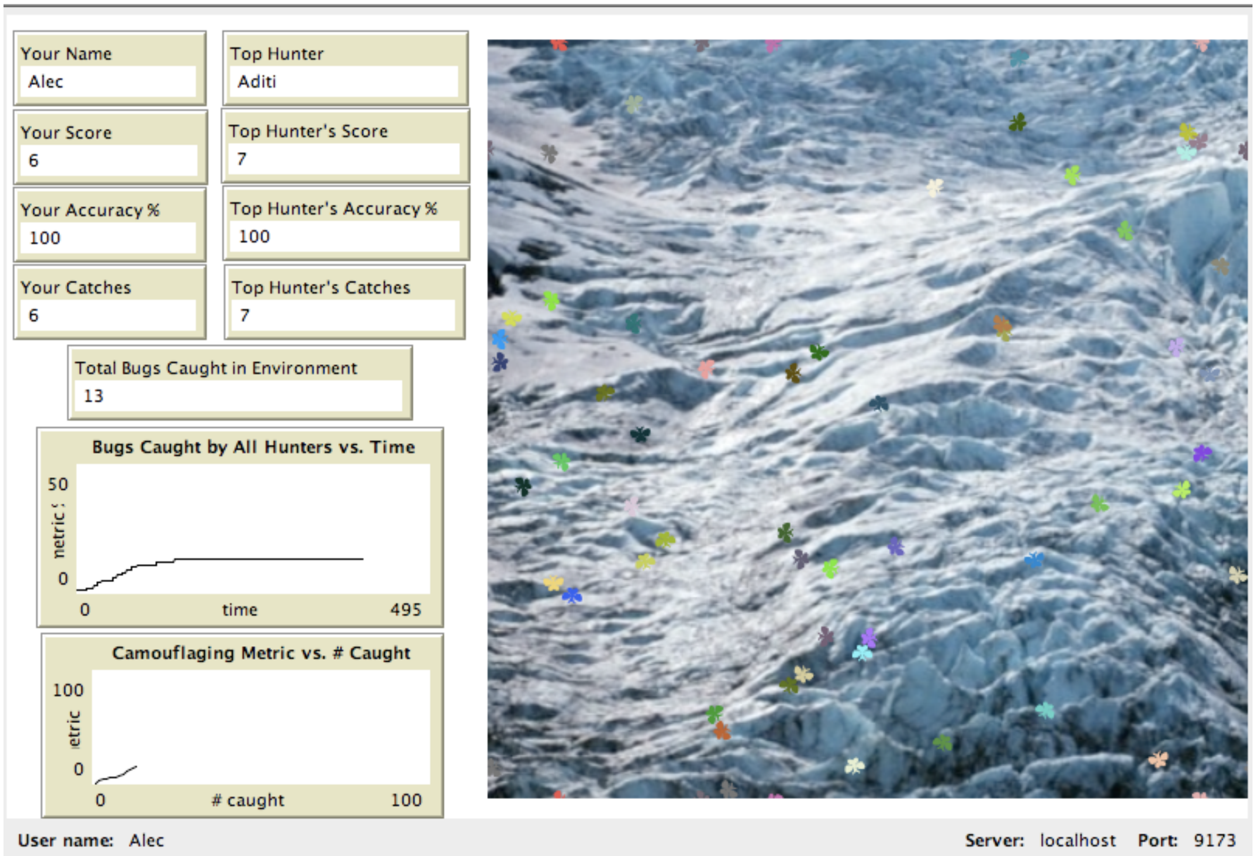

Figure 4b. NetLogo Bug Hunters Camouflage **(HubNet Client Window)**

Each student who receives a client window is given control of a single agent in the model. In Bug Hunters Camouflage, each student controls a predator. All the students simultaneously compete for finding prey in the same ecosystem by clicking on the same population of bugs that appear on their screen. . When one student finds a bug and clicks on it, it is removed from the screen of all the clients. This classroom wide competition for the same resources (bugs) is the mechanism that drives the emergence of camouflaging in the bugs. The students' own actions are responsible for generating natural selection. And the harder they compete against each other, the quicker the effects of natural selection emerge.

We observed the use of this model in a seventh and an eighth grade classroom. The students' joy of participating in a risk free form of competition and their sense of play generated high levels of engagement. For five minutes, their verbal interactions mimicked the sound and feel of a playground, even while each student was focused closely on their own client interface and the dynamics of the simulation. One student asked the whole class "who is winning?", while another student responded that the lead (winning) hunter (or "top predator") had just changed. A third student complained that someone just ate "his bug" (i.e., the bug that he was just about to eat).

As the students competed to consume bugs, asexual reproduction of the remaining population continued to replace those eaten with near duplicates of individuals in the remaining population (with, random slight variation of offspring genes for red, green, and blue pigmentation). This led to an unexpected result. Since the students tended to eat the easier to see bugs more often, the population that remained became more and more difficult to see over time. Soon some students were claiming they couldn't find anymore bugs or that the bugs had simply disappeared (even through there is a constant number of bugs in the environment). The second author, who was the instructor in an eighth grade class paused the model for a moment and pressed a button in the interface that highlighted where the "hidden" bugs were (by temporarily removing their color and creating brief flashes of white and black at their location). The students' responses were a mix of surprise and puzzlement as they now had been cued into where to look for the bugs, "They blended in," said some students in unison. The teacher then changed the environmental background from a picture of a beach (with pastel colored shells), to a poppy flower field (with a bright green and red palette dominating the composition of the photo). The same population of bugs was now much more visible against this background. He asked the students to predict what would happen to the population of bugs overtime if they hunted them again. There was a debate about what would result. The teacher then asked students to make a specific claim about what would happen the next time and to gather evidence to support or reject their claim. After issuing this challenge and conducting the supporting student activity sheet, where students carefully analyzed and recorded the changes that occurred and discussed (with a partner) possible mechanisms for such change, the teacher led a discussion identifying the new scientific principles that were emerging from the model, drawing on experiences of the whole class. These principles were 1) the variability of traits in offspring increases due to mutation and 2) selection by predators within a particular environment results in removal of easy to hunt variations of the trait over time and 3) the continued removal of easy to hunt variations and birth of individuals with hard to hunt variations of the trait results in a preferential shift in the distribution of traits in the population so that all subsequent generations of individuals become progressively harder to find over time. Students in the class were then prompted to suggest some ways to test these principles with the model. Some asked to run the model again from the start to see if the exact same outcome would result – and were surprised when a similar, but not exactly identical result emerged most of the time (camouflaging, but of distributions of different hue, saturation, or brightness). Another student suggested a class wide coordinated attempt to force the emergent result of the model in a different direction by having everyone try to hunt the ones that blend in and leave the easy- to-find colored ones behind to see if they can intentionally drive the selection process in the opposite direction compared to when they were unintentionally causing camouflaging to emerge.

Model 4: Bug Hunt Coevolution

The Bug Hunt Coevolution model (Novak & Wilensky, 2007) returns to the study of a simple ecosystem. In this model, the ecosystem consists of two populations – a population of prey (bugs) and a population of predators (birds). It is a model that supports multiple roles for the student. In one role the student can assume the role of a single predator in the ecosystem, directly responsible for generating different types of selective pressures on a population through her own actions as the predator. In another role, the student can assume the role of an outside observer of predators and prey (similar to the Wolf-Sheep Predation model), watching individuals interact, compete, and eventually evolve over time.

When students assume the role of a sole predator, they again attempt to hunt bugs in the world, using their mice to click on bugs. In this scenario, bugs have genetic information for a trait that represents their speed of movement. When the student hunts bugs by chasing after them, they unwittingly select for faster moving bugs (which are harder to catch) and select against slower moving bugs (which are easier to catch). When the student changes the hunting strategy they use to catch bugs by waiting for bugs to come to them (placing the mouse down at a fixed location and clicking on all bugs that arrive where they are positioned), the student unwittingly is now selecting for slower moving bugs (which arrive less often at their location) and select against faster moving bugs (which run into the student's mouse cursor more often).

After exploring the opposing selective pressures that the student can generate by simply changing their predation strategies, the student shifts to the role of an observer, watching what happens when both prey and predators (bugs and birds) are allowed to evolve in tandem without intervention by a person playing the part of the predator. Automated bugs and birds (similar to the wolf and sheep in the first model) move about the screen. Unlike the first model, there is variation in the traits for how fast the organisms move and the "depth of vision" of each organism. And further variation for these traits can arise from random mutations in offspring of individuals in the population (for example a fast moving bug may have an offspring that is either the same speed, slightly slower, or slightly faster). Likewise, the depth of vision trait which determines how far away a bug or bird can see a potential target within a cone of vision (if they are a predator it is the distance at which they can see prey and, if they are a prey it is the distance at which they can see a predator) also has a variety of values in both the predator and prey population. Predators (birds) use this trait to help them follow prey (bugs) they can see, and prey (bugs) use this trait to help detect when to turn away from predators (birds) they can see.

The model yields a variety of rich coevolutionary outcomes, depending on the environment (the size of the world) and the rates of mutation of the genes for the traits (settable by the student). For example, both the predator and prey co-evolve increasingly faster rates of movement in the model. But, under the same model settings, the prey will evolve an optimal vision value that is between the minimum and maximum possible values. Vision that is too nearsighted does not permit the prey to see predators in time to avoid them, but alternatively vision that is too farsighted causes the prey to overreact to predators that aren't near enough to catch them forcing them to turn into the path of predators that are chasing them. There is selective pressure for reacting to prey quickly as well as an opposing selective pressure to not overreact .

Model 4: Emergent Phenomenon – Coevolution

The bug and bird coevolution model returns students to a familiar context, predator and prey interactions. By returning to a variation of the original model they explored with wolves and sheep, students' experiences are scaffolded to help connect their initial ideas about individuals and populations and competition, to the mechanisms of selection they discovered in the other models (genetic drift and natural selection). The coevolutionary "arms race" that emerges through interactions of simple automated predators and prey can be explained through careful reasoning about strings of indirect effects between individuals and populations and connecting these to previously learned mechanisms of natural selection (Dawkins, 1998; Hillis, 1991; Ottino-Loffler, Rand & Wilensky, 2007; Ridley, 1993). For example, an increase in speed, due to random variation, of the offspring of a few bugs, results in a slightly different selective pressure on birds; if a bird with a variation of a trait that gives it a competitive disadvantage does not catch enough bugs it will eventually die. The competition between birds for this population of bugs, results in selective pressure for faster birds and birds with optimal eyesight. Each interaction of bird with bug reinforces this dynamic, causing a selective pressure on the predators, which results in a population with greater competitive advantage in its trait variations over time, which causes increased selective pressure on the prey, which results in a greater competitive advantage in the trait variations in this population. And so the cycle of interactions continually repeats, reinforcing and speeding up the effects of natural selection through positive feedback.

Model 4: Student Experiences

Students can change and experiment with each of the elements in this model. They can control how fast prey reproduce by taking the role of the predator. They can adjust the rate of mutation for individual genes in the prey and predator. They can adjust the strategies that the predators and prey use to react to each other when they see each other. And they can adjust the size of the environment and the carrying capacity of the ecosystem. Each of these adjustments often leads to different coevolutionary outcomes. Below is a screen shot of the model for one setting a student was using:

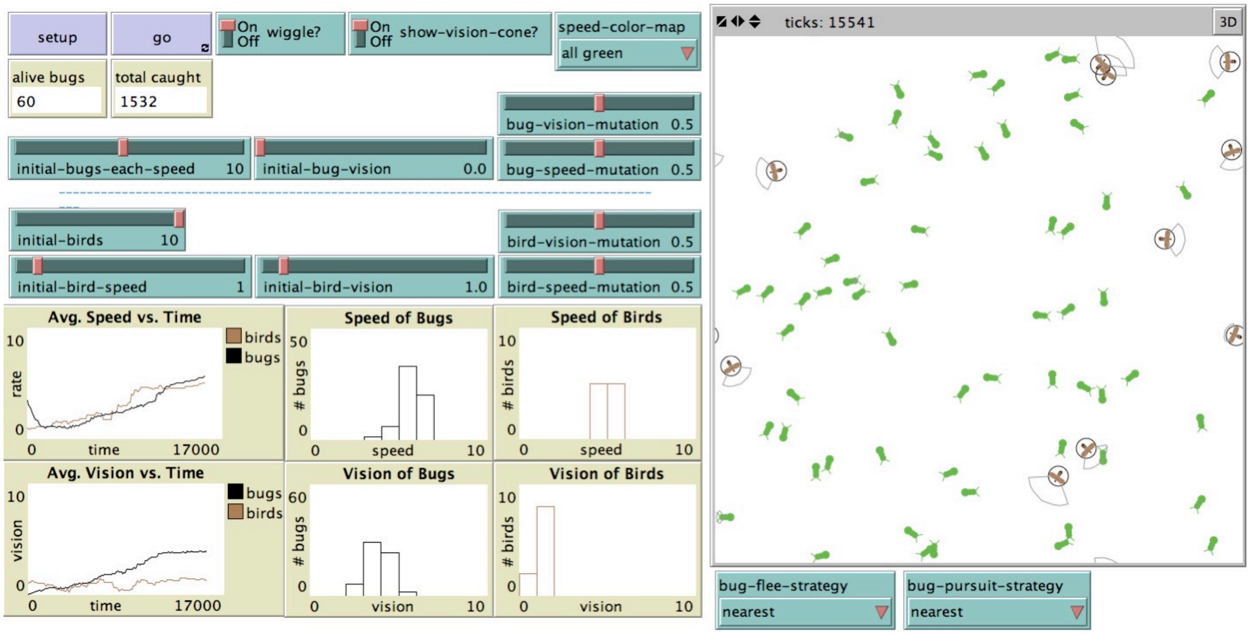

Figure 5a. The NetLogo BugHunt Coevolution Model

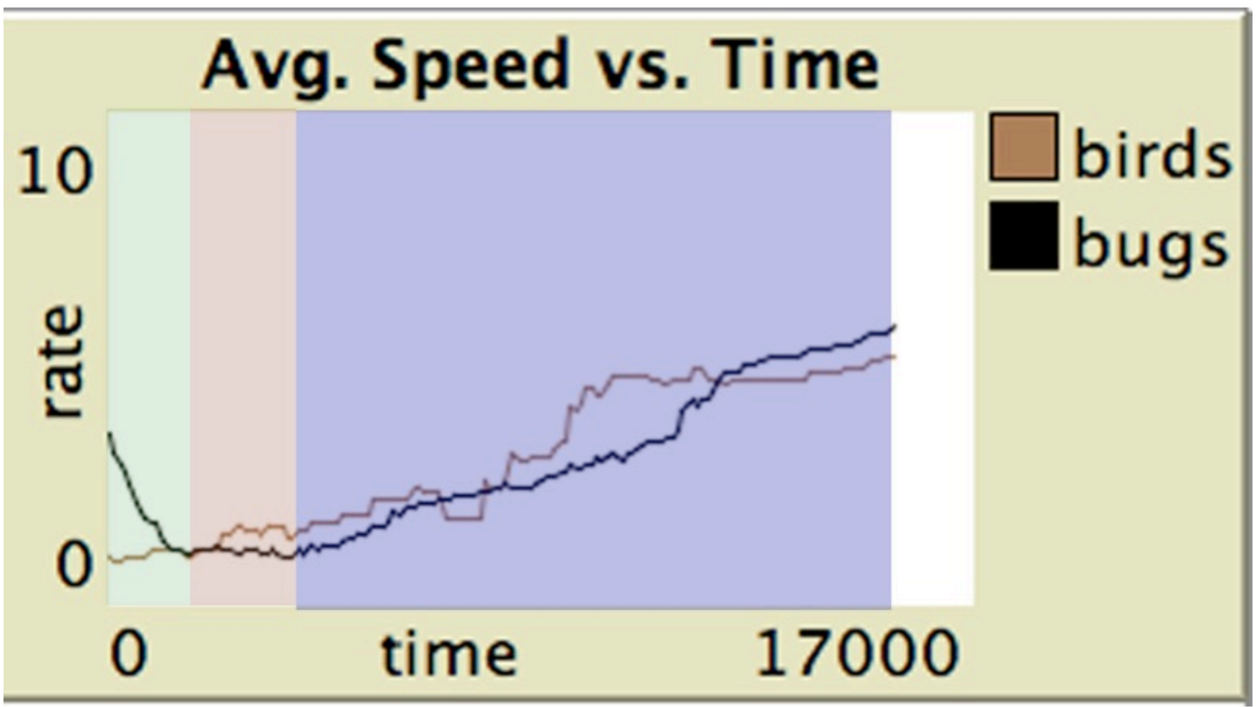

Figure 5b. A zoomed view of a graph at the bottom left of the BugHunt Coevolution Model

Notice the graphs in the bottom left of the model interface (see figure 5a). They show that the populations of predators and prey have already undergone substantial evolution. This is shown as a zoomed in graph of the Average Speed vs. Time for both the birds and bugs in Figure 5b. Notice that at first, in the green portion of the graph, bird speed is evolving to become slower. Fast birds speeds are disadvantageous at this point in the model run. This is due in part to the fact that birds have poor vision during this portion of the model run. As bird vision evolves to become better, eventually a point is reached where bird speed is no longer decreasing. This occurs during the pink portion of the graph. Here Bug speed is increasing some, but bird speed is not. Then in the purple portion of the graph both bug and bird speed increase over time at nearly the same rate. Both populations are coevolving to become faster and faster, since it is disadvantageous for either prey or predator to have a slower speed than the other. Studying the histograms of each population, students can see the relative proportion of different traits and also watch this change in real time as the model continues to run.

Students are asked to account for various evolutionary outcomes in this model using the scientific principles they have developed in the previous activities and models. They account for, explain, and support their explanations with evidence from the model for various questions such as: "What causes bugs to become faster over time?" "Why do bugs evolve different speeds of movement, depending on whether they can see or not?" "Birds and bugs are both changing over time, what is causing each of them to change?"

When using a simpler variation of this model (Bug Hunt Speeds (Novak & Wilensky, 2005)) that included only speed variation but not vision, students in a class of eighth graders investigated the question, "What causes bugs to become faster over time?" In a whole class discussion at the end of the student explorations, one student suggested that maybe the bugs were trying to get away from the birds. Many other students immediately challenged that claim, arguing that the bugs could not see the predators and that their actions were completely random. When intentionally pressed by the second author, to try to get students and the class as a whole to use (misuse) a Lamarckian explanation for changes they perceived (e.g., that since the bugs were trying to go fast, their offspring would be faster), the students in class agreed by consensus that they had no evidence for this since everything they observed suggested the change in speed of the offspring bugs was wholly random. Other students suggested that the effect of a faster moving population over time was quite simple, explaining that if you remove the easy to catch individuals and duplicate the faster individuals, that eventually the only thing you will have left in the population would be fast moving individuals. When the teacher pressed these students on the choice of the word eventually, typical responses included explanations that both took account of the inevitability (and obviousness) of the outcome and of the uniqueness in the possible series of interactions that leads to the outcome. Furthermore, other students explained that the reason the outcome could take longer sometimes would be due to whether you were particularly unlucky/lucky as to which speeds (individuals with a particular trait) were reproducing when you were hunting.

This ability to reason about changes in individuals and populations over larger spans of time, to connect how selective pressure, variation and inheritance results in populations more fit to survive is not an intuitive form of reasoning for most of us. But the reasoning and discussion of students who have explored BEAGLE models and activities suggests an increased level of literacy regarding the mechanisms of evolution that would have been difficult to develop without the use of agent based models.

Concluding Remarks

We have described herein the design rationale of BEAGLE and presented four cases of its use in a classroom context. Each case centered on a single BEAGLE model and was designed to present the target evolutionary concepts as emergent phenomena. To review, we started with the Wolf-Sheep Predation model which targets population fluctuations. We followed with Bug Hunt Drift which targets the fixation of a trait in a population without selection, Bug Hunt Camouflage and its participatory simulation activity places students in the role of direct "natural" selecters, targeting natural selection as an emergent process. Finally, we presented Bug Hunt Coevolution targeting positive feedback mechanisms that lead to evolutionary arms races. These four vignettes demonstrate how agent-based modeling can be used for learning and teaching about evolution. The BEAGLE curriculum contributes two principal innovations: 1) conceptualizing evolutionary phenomena, mechanisms and processes as emergent and 2) employing agent-based models both to represent individuals in a population and as microworld environments in which students can explore and experiment with evolutionary scenarios.

Our observations of students engaged with the BEAGLE materials lead us to believe that these two innovations can be highly effective – both in getting students deeply engaged with and excited by evolution and in developing a sophisticated understanding of how evolution works. Students learned to think about evolution emergently, to look for the individual level mechanisms that might account for an evolutionary change and to test if those mechanisms can plausibly account for the results. In this way the students are not just learning historical evolutionary accounts but are engaged as young scientists, as evolutionary theorists.

The BEAGLE project is ongoing and further models are in development. We continue to engage in a cycle of designing, testing and refining the BEAGLE materials. The research reported on herein is preliminary yet highly suggestive. We are now engaged in more formal research, including the development of interview protocols and rubrics, in depth interviews of students before, during and after using BEAGLE models, and systematic classroom implementations of BEAGLE at several levels of instruction. We are investigating many questions such as what level of scaffolding to give the students, how to deliver the supporting materials, what is the right mix of individual models and participatory simulations, can the same models be used at multiple levels of instruction? We are hopeful that widespread access to an emergent agent-based approach to learning about evolution will enable students to overcome the significant cognitive obstacles to understanding evolutionary processes and mechanisms and, in so doing, will lead to increasing widespread sophistication in understanding of and appreciation of the importance of evolution.

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