Bifocal Modeling in Biology: Linking and Comparing Virtual and Real Experiments

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Abstract

In this paper we describe a pilot study of an approach to STEM inquiry learning called Bifocal Modeling (Blikstein, 2010) with a group of high school students studying bacterial growth. Students grew and measured real bacteria, and then collaboratively designed a conceptual agent-based model of bacteria. Observations and student notes suggest that the activity helped students demonstrate their knowledge of bacterial growth by formalizing it from a list of unorganized facts into an accurate pseudo-computational model. In the process of completing their task, they also critically reflected on the assumptions built into the modelling activity itself, and demonstrated familiarity with some core principles of complex systems.

Keywords (style: Keywords)

Virtual Experiment, virtual model, physical model, Bifocal Modeling, computer modeling, agent-based modeling.

Introduction

The use of computational models of scientific phenomena has become an increasingly viable option for classroom science learning as technology and accessibility improve. There is a large body of literature on the use of those virtual models to display data, to simulate complex phenomena, and to permit student experimentation in domains that might be costly, impractical, or dangerous (Jaakkola & Nurmi, 2008; Finkelstein et al., 2005; Klahr, Triona & Williams, 2007; Zacharia 2008a, b; Resnick & Wilensky, 1998; PhET, 2011). The potential of a combination of virtual and physical models for science learning has been documented for a wide range of ages and domains. For instance, Liu and collaborators (2006) explored high school students' understanding of chemistry concepts. They found that the combination of a virtual model and hands-on lab activity was more effective than either alone, balanced for time-on-task, in promoting students' conceptual understanding of the gas laws. Recent studies have also investigated the importance of the sequencing of physical and virtual model activities on student learning, with the general result that better learning resulted from the virtual experiment following a physical one (Gire et al 2010, Smith et al. 2010).

However, the literature has focused almost entirely on pre-designed physical and computer models. Pre-designed models can scaffold and direct students to attend to relevant problem information, but they fail to give students opportunities to evaluate the assumptions and limitations of the models themselves (Papert, 1980). Creating and critically evaluating models is an important part of scientific practice, and is being increasingly recognized as a valued educational goal (Levy & Wilensky, 2008; Blikstein & Wilensky, 2010). The literature has also under-explored the potential for deeper support of student comparison between the physical and virtual models. Smith and collaborators (2010) noted that scaffolds in the virtual model, or direct data-sharing between virtual and physical, could help students to see the similarities and differences between model and reality.

In this paper, we present a pilot study that demonstrates a pedagogical framework to augment the comparison between real and ideal systems as an avenue to deeper understanding of biological phenomena. Using a type of scientific inquiry activity called Bifocal Modeling, high school students built virtual and physical models of bacterial growth in order to learn content knowledge, computational thinking, and critical meta-modeling skills. Our main research questions were: (1) how do students' understand the mismatch between idealized and physical models?, and (2) how do they critically evaluate their choice of variables and phenomenal factors to include (or not) in their own theoretical models to iteratively match it to the real-world data?

Research setting

Bifocal Modeling (BM) (Blikstein & Wilensky, 2006, 2007; Blikstein, 2010, 2011; Blikstein, Furhrmann, Greene, & Salehi, 2012) is an approach to inquiry-driven science laboratory learning that challenges students to build and relate in real time physical and virtual models. In these "hybrid-reality" activities, students explore a scientific phenomenon such as heat diffusion, the properties of gases, or wave propagation by designing and building their own physical model and collecting data using embedded sensors. In parallel, they build their own virtual model of the same phenomenon, and can compare the behavior of the virtual model and the physical model in real-time (figure 1). The most common software to implement virtual models has been NetLogo (Wilensky, 1999), a free and open-source environment for agent-based modeling. A NetLogo model typically consists of a set of autonomous agents (such as gas particles or people at a party) moving through a world and interacting to produce emergent outcomes. Students define the variables held by the agents and the world, and specify a set of rules for agent-level behavior, such as "if two gas particles collide, they exchange energy, and bounce off each other." Their goal is to build a model whose behaviour matches the data they collected. This challenge encourages students to refine their content knowledge as they iteratively improve their virtual models, and to question the validity of their own representational choices. For example, a student trying to match a computer model of Newtonian motion to a real experiment may be forced to confront the existence of a missing friction coefficient, to determine how to measure motion using a given set of sensors, or even whether to model an object as a single unit or as a collection of atomic particles. In this way, BM can serve as a method to learn scientific content, modeling skills, and scientific research methods.

The growth of bacteria has been an exciting object of study for centuries. We chose bacteria as a subject because of their simple cellular structure and quick reproduction rate, allowing them to be used to address many biological questions as model systems. Bacteria can also be used to demonstrate exponential growth, which can be used to model more complex ecological dynamics.

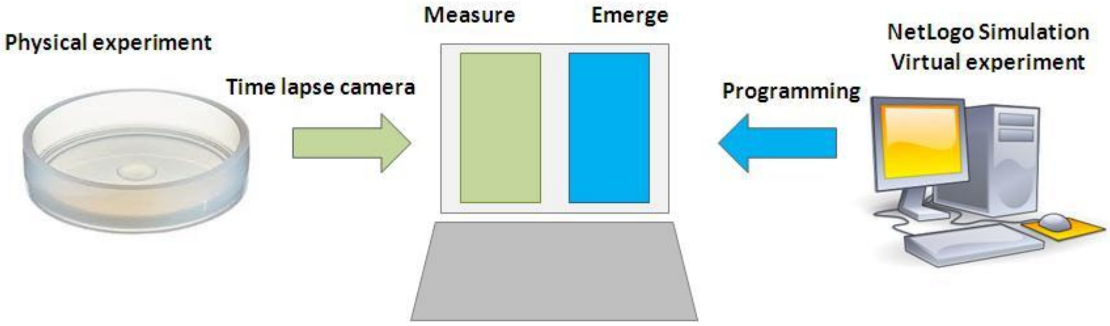

Figure 1. Bifocal Modeling platform, linking a physical experiment and a computer simulation in real time.

Methods

The authors conducted a pilot study in the form of an after-school workshop for four high school students, all female and ranging from 9^{th} to 11^{th} grade. Two had previously learned about bacteria in class, but knew nothing about the growth pattern of bacteria, and had never grown real bacteria. The workshop was conducted in a laboratory setting and lasted for a total of about five hours, split across three afternoon sessions. Even though Bifocal Modeling activities typically take 20+ hours, for this study we attempted a design experiment to fit the activity within a format that would be more realistic for a school implementation within a typical biology unit. Therefore, we attempted to shorten the activity while trying to keeping its core design principles. The first change was to shorten the data collection phase by offering students the opportunity to create their own experiments (growing bacteria), but also providing some previously collected data (movies of bacteria growing). The second decision, which emerged during the activity (Design-Based research, Confrey, 2005; Edelson, 2002), was to teach only the conceptual principles of the computational modeling language, since learning a programming language in a 3-hour period would be challenging for most students. Therefore, we adopted a version of "paper modeling" (Blikstein, 2009) and students collectively built agent-based rules of the computer model on a whiteboard, going through their pseudo-code and animating it "frame by frame."

During the first session, the students were tasked with growing real bacteria using supplied tools. They collected bacteria samples from different places around their environment (e.g. doorknob, touch screen, hand, and keyboard), and each student prepared a Petri dish with agar and applied the bacteria to the dish. When finished, they installed a provided time-lapse camera that captured images of the dishes every 30 minutes for five days. The images were automatically compiled into a video that showed the students the growth pattern of the bacteria. For this particular design, we condensed the physical data-collection portion by also providing students with previously-captured movies of bacteria growth and a growth curve, so that they could start the modeling task earlier. We explained that the growth curve was what they could expect to see in their own bacteria cultures, and challenged them to learn about the growth curve in order to make a model of bacteria that could reproduce it and fit the curve.

During the second session, the students were grouped into two pairs and each pair used a computer to do web research on the bacterial growth curve. As they searched, they took notes on information they thought was relevant. The authors were present to remind the students that their goal was to understand what causes the characteristic growth curve. An acceptable answer would be that a typical growth curve contains several distinct phases as the bacteria adapt to their new environment, consume food and release waste, rapidly multiply, and eventually die out from their own waste products and lack of food.

For the third and final session, the authors intended to have the students use the NetLogo simulation environment to make a virtual model. But due to the challenge of learning NetLogo programming in a short period of time (see above), the authors instead conducted a variation of "paper modeling" (Blikstein, 2009) in which students collectively designed and ran an agent-based model of bacterial growth on a whiteboard. This required articulating the variables in the model (such as bacteria count, food, waste, and moisture), and agent-level rules such as "each bacterium subtracts 2 units of food from its location and emits 1 waste."

The students would "run the model" by enacting its rules on the board to progress the model by a single time step at a time, and then stop to add or change rules and variables. The authors scaffolded the modeling session with minimal questions, such as "What is still missing from our model?" and "How can you express the idea of eating food in terms of the variables we have?" The resulting model was "executed" on the whiteboard for enough time steps to give students a sense of the growth curve, and simulated a colony of bacteria that moves, consumes food and moisture, excretes waste, reproduces, and can die from starvation or poisoning from toxic waste. We are well aware of the differences between computational and non-computational media (diSessa, 2000; Papert, 1980), but for the research goals of this study, this adaptation was successful at enacting the initial stages of the computational modeling process, which was enough for our specific research questions. In fact, after the whiteboard activity, students did interact with actual computer models, but that data is not reported here since our focus in on the early exploration of agent rules and real-world data.

Students were given two open-ended questionnaires about bacteria and the growth curve -- before and after the entire session. They were also videotaped during all activities, their computer usage was documented with the Camtasia screen-capture software, the researchers took field notes, and their notes and sketches in all three sessions were preserved.

Data and Discussion

This section will consist in a commented narrative of several classroom episodes centered around the perceived and hypothesized affordances of BM, namely: (a) resolving model mismatch, (b) converging on appropriate variables, (c) critically evaluating the assumptions of models, and (d) translating between micro and macro perspectives.

Iteratively improving the virtual model to resolve mismatch

Overall, the group's method was to "run" their whiteboard virtual model in order to see how the bacteria grew, to compare the results to their goal of the growth curve from the physical data, and to resolve the perceived differences between the two by adding rules and variables to the virtual model. They repeated this process a total of four times in the 1.5 hours of the session, developing an increasingly accurate model in the process (figure 2).

For example, a student observed at one point after "running" the virtual model that their growth curve was increasing exponentially from the start. She noted that this was not correct, because the real growth curve had an initial flat "lag phase" before beginning to grow. After a moment's reflection, she remembered that this was because real bacteria have an initial phase of settling into a new environment before multiplying. She said "We need to make a rule that it takes time before the bacteria grow." Another student chimed in, saying that this would have to be different from a maturation period for individual bacteria, because it would apply only to the first bacteria on the dish. After more discussion about how to code the lag phase in their system, they came up with the following rule: "If a bacterium is in the first generation, it has to wait two time steps before reproducing." Upon running the model again, students could see from the resulting curve that they had successfully created the lag phase. The students went through a similar process to add all of the variables in their model.

- add bacteria, food, moisture, temperature

- add rule: bacteria move around randomly

- RUN MODEL: results were a flat growth curve

- add food rule: bacteria absorb food and moisture

- add waste rule: bacteria release waste

- add reproduction

- RUN MODEL: results are exponential growth and no death

- add death rule: if bacteria don't get food/moisture, they die

- RUN MODEL: results were exponential growth and then death

- add lag phase rule: first generation takes longer to multiply

Figure 2: A chronological list of the additions the students made to the model, and the instances in which they ran it. The results of each run prompted a subsequent rule addition that made the model more accurate.

Converging on appropriate variables

When the students were searching the web for information about bacteria, they collected and wrote down a great deal of information that was not necessary for the modeling task they were given. For example, some students noted that bacteria are prokaryotes, eat many types of human food, and live in a range of conditions. However, during the whiteboard virtual modeling session, the students only included variables that were necessary to define the shape of the growth curve - food/moisture, waste, and bacteria health. Global variables like temperature and oxygen affect bacterial growth, but the dynamics of the curve assume that these global variables are constant or the variations are too small. The fact that the students left these variables out without prompting suggests that they implicitly understood this instance of a controlled variable.

Students also made decisions regarding the granularity with which to describe variables. One student noted multiple types of bacteria nutrients in her web research, but went along with the group in representing food as a single variable of just one type. When asked about this issue, she replied that "I don't need to be that specific for this model."

Critically evaluating the assumptions of models

In addition to learning about the relevant variables for modeling bacterial growth, the students in the Bifocal Modeling workshop spontaneously reflected on the underlying assumptions of their models themselves - in this case, their representations of space and time. Space is represented in NetLogo as a grid of square "patches", units of space that can possess variables like location or food concentration. This patchwork representation of space was explained to the students at the start of the whiteboard modeling session, but at the time of introduction it was only relevant as a way to explain how to represent environmental variables like food. However, as the session progressed the students noticed that their bacteria were scattered randomly across the surface in their model, and filled the entire surface uniformly as they multiplied. In contrast, the real bacteria that they grew formed small circular spots. How could they explain the difference? A discussion on how far bacteria can move quickly led to the question of the size of whole grid square itself. As one student put it, "This square could be a whole dish, or it could be just a tiny spot in the real Petri dish… if we were looking through a microscope, zooming in, they [the bacteria] will move much more. " At the end of their discussion, they decided that it was up to them to define the size of the virtual world they designed.

Similarly, time in NetLogo and the whiteboard model is represented as a series of discrete steps called "ticks." While discussing the proper time delay for the lag phase, one student realized that they had no agreed conversion between ticks and real time. She asked, "Do bacteria get food and moisture each minute? Each hour? Each day? Right now we are just doing this with ticks... how can we translate the tick into real time?" At the end of another discussion about the time scale of bacteria growth in the real world and in NetLogo program, the students decided that if bacteria can multiply every 20 minutes, they will agree that one tick in the virtual world equaled 20 minutes in the physical world. Though they did not entirely resolve their questions about representing time and space in their model, the students were asking the "right" questions; that is, they were asking questions about the assumptions that models make about the world, which are at the heart of scientific critical thinking (Blikstein & Wilensky, 2007).

Finally, the whiteboard modeling activity demonstrated the usefulness of computer models to the students. Once the whiteboard model was slightly complex, it became virtually impossible for a person to track the variable values of all of the bacteria and patches. As one student noted, "…it's going to be really hard to imagine this in our heads. This is definitely where a computer model is relevant."

Translating between micro and macro perspectives

A final theme that arose during the modeling session was the continual switching of perspectives, from the rules for an individual bacterium to the emergent behavior of its entire colony. The literature on complex systems education suggests that people find it difficult to move in either direction between macro and micro perspectives -- either inferring the emergent result of a micro-level change to a system, or predicting the micro level changes that could cause a given macro-level result (Wilensky & Reisman, 2006; Wilkerson-Jerde & Wilensky, 2010). Complex system dynamics are also typically taught only in highly advanced math and science settings. However, the literature also suggests that properly designed activities can help people to grasp complex systems concepts much more easily. The iterative process of modeling that students went through can be seen as a process of writing rules at the level of the individual bacterium in order to create emergent outcomes at the level of the colony. With no prior academic knowledge of agent-based modeling or complex systems, the students in this study managed to describe and manipulate a complex system at both levels, micro and macroscopic. While BM is not inherently bound to a complex-systems framework, the data suggests that the process of modeling a phenomenon was an effective way to intellectually engage students with the dynamics of complex systems.

Conclusions and next steps

Instructed to make a model that recreates the bacterial growth curve, students used their previously-learned knowledge about the curve and the physical appearance of the bacteria as a benchmark for what their model should produce. The clash between the virtual and real models defined a clear goal for the students in recreating the bacterial growth curve. In the process of this reconstruction, we claim that the students demonstrated learning in three areas - content knowledge about bacterial growth, critical evaluative skills for scientific models, and an understanding of the concepts of emergence and exponential growth in complex systems. Future work will continue to develop BM as a platform for real-time linking of physical and virtual models, and for real-time collaborative programming with computational media.

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