From Middle School to Graduate School: Combining Conceptual and Simulation Modeling for Making Science Learning Easier

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Abstract

MILA-S is an interactive open learning environment for scientific modeling (Joyner, Goel, & Papin, 2014). It enables students to build conceptual models of ecological phenomena, evaluate them through simulation, and revise the models as needed. MILA-S automatically spawns simulations from the conceptual models, making modeling easier for the student. Earlier work had described the use of MILA-S in middle school. In this paper, we report an experiment on the use of MILA-S in two college-level classes. In one class, we found that almost half of the students showed improved understanding of scientific modeling; in the other class, about two thirds of the students showed enhanced understanding.

Keywords: education; ecology; learning; modeling; science

Introduction

Most artificial intelligence theories, techniques and tools for aiding learning have focused on K12 education. However, AI has an important role to play from pre-K to graduate school. An important question is whether AI techniques that prove useful in, say, middle school (K6-8), may also be useful at the college level. On one hand, the background knowledge and learning goals of college students are quite different from those in middle school. On the other, many cognitive processes and some learning tasks transcend any given level of education. Let us consider scientific modeling as an example. Although science standards vary widely, lessons in scientific modeling in many school systems begin in the upper elementary school (K4-5) and continue through graduate school. Given that some cognitive processes of scientific modeling likely remain the same from K4-5 through graduate school, though for different kinds of problems and different levels of detail, we may expect that the same set of AI theories and techniques might be useful at the different grades, though perhaps with different types of scaffoldings. Yet, insofar as we know, there has been little work on using the same AI tools to support scientific modeling across the educational spectrum.

MILA-S is an interactive open learning environment for scientific modeling (Joyner et al., 2014), including the full cycle of model construction, evaluation, and revision. It enables students to build conceptual models of ecological phenomena, evaluate them through agent-based simulation, and revise the models as needed. MILA-S's innovation is that it uses AI techniques to automatically spawn simulations from the conceptual models, thus making modeling easier for the student.

When we introduced MILA-S in ecology classes in middle school science, we observed significant gains in learning about the process of scientific modeling as well as in the quality of the final models (Joyner et al., 2014). A key finding from the earlier experiments is that the ability to evaluate conceptual models of ecological systems through simulation leads to qualitatively different and apparently better models (Goel & Joyner, 2015).

In this paper, we report a new set of experiments on the use of MILA-S in two college-level classes. In one class on AI, with a mixture of residential and online students as well as graduate and undergraduate students, we found that almost half of the students showed improved understanding of scientific modeling. In the other class on cognitive science with all residential graduate students, about two thirds of the students showed enhanced understanding. Although the MILA-S tutorial in both classes focused solely on ecology, in both we found spontaneous transfer of the modeling process to other domains.

Scientific Cognition

Cognitive theories of scientific discovery indicate that scientists conduct inquiries by observing a phenomenon, proposing a hypothesis for explaining the phenomenon, elaborating the hypothesis into a predictive model, evaluating the model by verifying its predictions, and then repeating the cycle of model construction, evaluation and revision until they are satisfied with the model or they abandon it in favor of another hypothesis e.g., (Clement, 2008; Nersessian, 2008). Cognitive theories of learning science suggest an authentic inquiry-based approach to learning about scientific modeling, including cycles of model construction, evaluation, and revision e.g., (Schwarz et al., 2009).

However, scientific models can be of various types, with each type having its own unique affordances and constraints, and fulfilling specific functional roles in scientific inquiry

(Magnani, Nersessian, & Thagard, 1999). Conceptual models allow scientists to specify and share explanations of how a system works through qualitative relationships among various entities in a representation language. Simulation models capture relationships between the variables of a system such that as the values of input variables are specified, the simulation model predicts the temporal evolution of the values of other system variables.

AI tools for science education have used both conceptual models (e.g., (Novak, 2010)) and simulation models e.g., (De Jong & Van Joolingen, 1998; Jackson, Krajcik, & Soloway, 2000). However, past research typically has used the two kinds of models independently from each other (VanLehn, 2013): students use one set of tools for constructing, using, and revising conceptual models, and another tool set for constructing and using simulation models. In contrast, cognitive theories of scientific inquiry suggest a symbiotic relationship between conceptual and simulation modeling e.g., (Nersessian, 2008; Clement, 2008): scientists use conceptual models to set up the simulation models, and they run simulation models to test and revise the conceptual models. This led us to MILA-S.

MILA-S

MILA-S builds on a long line of exploratory learning environments including the Aquarium Construction Toolkit (ACT) (Vattam et al., 2011) and the Ecological Modeling Toolkit (EMT) (Joyner, Goel, Rugaber, Hmelo-Silver, & Jordan, 2011). ACT and EMT were shown to facilitate significant improvement in student's deep, expert-like understanding of complex ecological systems. Both ACT and EMT, provided one set of tools for conceptual modeling and another tool set for simulation modeling, and used the NetLogo platform for agent-based simulations (Wilensky & Resnick, 1999). For conceptual modeling, ACT used Structure-Behavior-Function models (Goel et al., 1996). In contrast, EMT used Component-Mechanism-Phenomenon (or CMP) conceptual models that are variants of Structure-Behavior-Function models adapted for modeling natural systems (Joyner et al., 2011).

Conceptual Models

Figure 1: Example of conceptual model

MILA-S uses CMP models. Components in CMP modeling can be either biotic or abiotic. Each component has a set of variables associated with it, four for biotic components, and one for abiotic components. Biotic components are defined by their population quantity, lifespan, energy level, and likelihood to breed; abiotic components are defined only by their quantity. Figure 1 illustrates a conceptual model constructed by a team of 7th grade life science students in an earlier study. In this model, there are three components: Sunlight, Oxygen, and "Fishies". The Sunlight and Oxygen are abiotic components, and they have only Amount as a variable which is designated on the node for the component. "Fishies" is a biotic component, and thus has Population, Age, Birth Rate, and Energy as variables; Population is designated on the "Fishies" node itself, while the notations for the other three variables extend downward from the main node.

MILA-S provides the user with a set of prototypes that describe causal relationships among the system variables. The choice among the available prototypes is determined by the variables on either end of the relation and the type or direction of the relation. For example, a relation from the Population of a biotic component to the Amount of an abiotic component, such as that from Fish Population to Oxygen Amount, could be 'consumes', 'produces', or 'becomes upon death,' etc. Similar relationship prototypes are available for links between two biotic and two abiotic components. In the model shown in Figure 1, the prototypes chosen are 'consumes' for the relationship between Fish and Oxygen, and 'produces' for the relationship between Sunlight and Oxygen. The direction of the arrow between the two components indicates the direction of causal influence.

A Mechanism in CMP modeling is a chain of component variables connected by causal relations. For example, Figure 1 illustrates a mechanism according to which the Amount of Sunlight (an abiotic component) influences the Amount of Oxygen (another abiotic component) and the Population of Fish (a biotic component) also influences the Amount of Oxygen. A Phenomenon in CMP is an observation about the system of interest. For example, the phenomenon is a change in the Amount of Oxygen in an aquatic ecosystem for which the mechanism illustrated in Figure 1 provides an explanation.

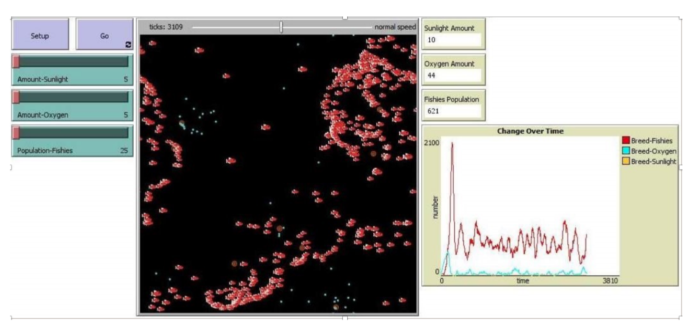

Figure 2: Result of Netlogo Simulation of conceptual model

Agent-Based Simulations

Figure 2 illustrates the result of a NetLogo simulation spawned from the conceptual model of Figure 1. Note that all three components of the conceptual model are represented in the simulation: the Fish are in red, Sunlight hits the water at the location of the brown dots, and the Oxygen produced by that interaction appears as blue dots. As Figure 2 illustrates, NetLogo provides graphs and counters for illustrating the temporal evolution of various variables of the simulation. Before running a simulation, the user sets values of input variables to the simulation through the sliders and toggles on the left side of the simulation window illustrated in Figure 2.

NetLogo simulations are typically designed with their own dedicated programming language, which allows for enormous flexibility. However, this flexibility of designing simulations makes rapid evaluation and revision of models difficult. First, it requires at least a rudimentary background in programming. Secondly, even if the simulation designer is relatively experienced in NetLogo, it can still take significant time to make non-trivial changes to the simulations: these changes can involve writing all-new methods, creating new variables, or defining new agents.

MILA-S provides a technique for controlling the cost of generating NetLogo simulations: it automatically generates the simulations from a users conceptual model. Note also that the generation of the CMP conceptual model illustrated in Figure 1 does not require any knowledge of programming. Instead, MILA-S's CMP language provides a visual syntax for setting up the simulations.

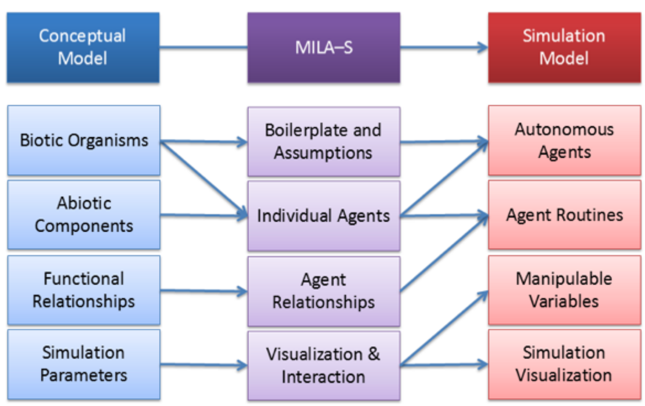

Figure 3: Scheme of translation of CMP conceptual models into NetLogo agent-based simulations

Translating Conceptual Models into Simulations

After constructing a CMP conceptual model, a student first uses a template to set values of the input variables to the simulation system, and then clicks a 'Run Sim' button for simulation generation. MILA-S gathers together all the components for initialization along with their individual parameters. Next, MILA-S writes the functions based on the relations specified in the CMP model. A key part of this is a set of assumptions that MILA-S makes about the nature of ecological systems. For example, MILA-S assumes that if a biotic component consumes a certain other component, then it must need that other component to survive. A model with 'Fish' that contains 'consumes' connections to both 'Plankton' and 'Oxygen' would infer that fish need both Plankton and Oxygen to survive. MILA-S also assumes that species will continue to reproduce to fulfill their carrying capacity rather than hitting other arbitrary limitations. These assumptions do limit the range of simulations that MILA-S can generate, but they also facilitate higher-level rapid model revision. Figure 3 illustrates the general scheme for translating the semantics of CMP conceptual models into the semantics of the Netlogo agent-based simulations. Note that this also combines qualitative conceptual models with numerical simulations.

The simulations created by MILA-S are emergent simulations. The results of the simulation are dictated by the properties and variables of the CMP model interacting with one another as well as the initial values of the variables set by the user. Students can now experiment with their conceptual models and the initial values of the variables rather than just plugging the numbers into an equation until one gets the right answer. Iteratively and incrementally exploring how the simulation results change through small revisions in the conceptual model allows users to develop a deeper understanding of scientific modeling and discovery.

Results From Previous Studies

We have conducted several studies on using the MILA family of tools in middle school science. The most relevant to the present discussion is a 2014 study at a middle school in Georgia in which 50 "gifted" students used MILA-S for inquiry-based learning in the ecological domain. We discovered that the students found the MILA-S tool easy to use, and that the use of the tool helped improve their understanding of the process of scientific inquiry and modeling (Joyner et al., 2014). However, our most salient finding from the previous study in middle school science was that students constructed qualitatively different conceptual models when they could test them through simulation: instead of constructing mostly explanatory models, they constructed conceptual models that were both explanatory and predictive (Goel & Joyner, 2015).

However, when we introduced MILA-S in a unit on ecology in a college-level introductory biology course for non-majors we found little gain in learning or understanding . This could have been because of the very limited duration of the intervention in the college-level class on introductory biology: while the intervention in middle school unfolded over several days, the college students had only a single class period of 50 minutes to take a pre-test, learn about MILA-S from a brief tutorial, use MILA-S to address a new problem, and address a post-test. In subsequent studies described below, we made the intervention more open-ended, allowing the students to work with MILA-S outside the class, and also provided the students incentives for completing the study. In addition, we tweaked the questionnaire as well as the MILA-S tool itself, making ecological modeling more authentic as described in (Goel, Joyner, & Hartman, 2016).

Table 1: Participant Distribution

Level of Study	# Students CogSci	# Students KBAI
Undergraduate	0	25
Masters Oncampus	10	15
Masters Online	0	103
Doctoral	13	3

Experiment Design

We have now conducted two new studies in using MILA-S for inquiry-based scientific modeling.

Human Subjects

The first study in Fall 2016 engaged students from a class on Knowledge-Based AI (KBAI). Different sections of the class contained residential and online students, as well as undergraduate and graduate students. The second study involved graduate students in a residential class on Cognitive Science (CogSci). Table 1 indicates the distribution of students in the two classes. Of the 146 KBAI students, 142 students had STEM background, while 4 did not. Most of the students with STEM background were computer science students. Of the 23 CogSci students, 21 students had STEM background while 2 did not; most of the students with STEM background again were computer science students. In the KBAI class, the MILA-S study was offered for extra credit. In CogSci class the study was presented as a small project that all students had to complete. Participants from the CogSci class were additionally asked to form small groups, discuss their experiences with MILA-S, and submit a report on the same.

Materials

There were three components of the both studies:

1. Tutorial: single page tutorial of MILA was provided to students which also contained video links of different ecological phenomena e.g. starfish dying along western coast. A five minute video demonstrating use of MILA was also shared.
2. Questionnaires: The students were asked to answer three questionnaires as part of the study.
   (a) Initial Survey
   (b) Pre-Test:- comprised of a total of 10 MCQs.
   (c) Post-Test:- consisted of the same questions as pre-questionnaire (and additional feedback questions).
3. MILA-S: The students were given access to MILA-S after they had completed the initial survey and the pre-questionnaire. Once the participant got access to MILA, they were asked to complete three tasks:
   (a) Build a sheep-grass model
   (b) Build a wolf-sheep-grass model
   (c) Model(s) of their choice.

   Tasks a and b above were included to help students become familiar with the MILA-S tool, as well as understand the parameters such as birth rate that affect ecological systems. From an analytical perspective, the first two models provided data for qualitative analysis of differences in student behaviors. The third task was aimed at understanding the degree of familiarity students developed with the abilities of MILA-S, and the scope of transfer and innovation in model building. Overall, the study was kept a little open, without too many constraints on student interactions with the tool. While instructors were not present during student work, students always had the option of reaching out and asking questions, and we saw that many students did utilize this to inquire about the tool, development of conceptual models and understanding of the simulation results.

Question Categories

The initial survey focused on gathering demographic information such as study level, self reported curiosity scores, STEM experience. All questions were multiple choice questions.

The 10 MCQs on the pre- and post-tests asked questions in three broad categories:

1. Basic concepts and processes of scientific modeling.
2. Understanding of conceptual and simulation models of complex systems in general as well as ecological systems in particular.
3. Understanding of ecological systems, for example, how ecological systems respond to different changes. In particular, students were asked about effects of different parameters such as birth rate, initial energy and lifespan on the simulation.

Results

We assume that learning occurs if a student correctly answers more questions on the post-test as compared to the pre-test. Table 2 summarizes the main results, where the pre- and post-test scores are on a scale of 1-10. We note that 45% of the KBAI class participants and 65% of the participants from the CogSci had improved post test scores. The higher number in the CogSci class might be because of the larger incentive given to the students.

Moving away from a binary interpretation of learning, Table 3 gives details about the pre- and post-test scores in KBAI and CogSci classes. While more CogSci students showed learning gains compared to the KBAI students, the KBAI class on average showed slightly larger learning gains. We observe that the learning results are statistically significant (p-value was calculated by performing the paired t-test).

We also calculated the correlation between level of study and learning, and STEM background and learning. Here, we assigned numerical values to level of study e.g. undergraduate:1, masters:2, doctoral:3. For STEM Experience, we created bins based on whether a person had studied/worked in

Table 2: % Participants with improved post-test scores

#	KBAI	CogSci
Total Learning	66 / 146 (45.2%)	15/23 (65.2%)
Undergraduate	11/25 (14%)	NA
Masters	54/118 (45.7%)	7/10 (70%)
Doctoral	1/3 (33.33%)	8/23 (61.53%)
Participants from STEM field	64/142 (45%)	1/2 (50%)
Participants not from STEM field	2/4 (50%)	14/21 (66.66%)

Table 3: Learning Statistics

Group	#Users	Pre Test	Post Test	P-Value
KBAI	146	mean:6.82	Mean:7.65	0.0035
		Stdev:1.55	Stdev:1.77	
CogSci	23	Mean:5.44	Mean:5.81	0.004
		Stdev:1.81	Stdev:1.8	

a STEM related field prior to taking the KBAI/CogSci class as well as their self reported score on familiarity with STEM concepts. We then calculated the Pearson coefficient of these variables against difference in the pre- and post-test scores, and observed that the values were small, less than 0.02. This indicates that learning occurred independent of the Level of Education, or STEM Experience.

Student Models

Figures 4 and 5 illustrate two conceptual models built by the students in the KBAI class. We note that these models are not from ecology: students in our studies apparently were spontaneously able to transfer the CMP language for modeling complex systems and the MILA-S methodology for scientific modeling to other agent-based domains.

To assess the quality of models constructed by the students, we calculated the model complexity scores for 27 randomly selected participants from KBAI class and for 16 students from CogSci class. Model complexity score was calculated only for the model(s) that students themselves built. In case of multiple models we selected the model with the highest complexity score.

Complexity Score = cc + lc + uc

where, cc = number of components in the conceptual model, lc = total number of links between components in the conceptual model, and uc = undirected cycles in conceptual model.

We observed that for the KBAI class, complexity scores ranged between 3-13 with mean of 7 and standard deviation of 3.46, and for the CogSci class, they ranged between 5-15 with mean of 7.56 and standard deviation of 5.67. This indicates that the complexity of models in the two classes was about the same. The p-value (based on the paired t-test between the complexity score and the difference of post-pre test scores) in both classes was p less than 0.01.

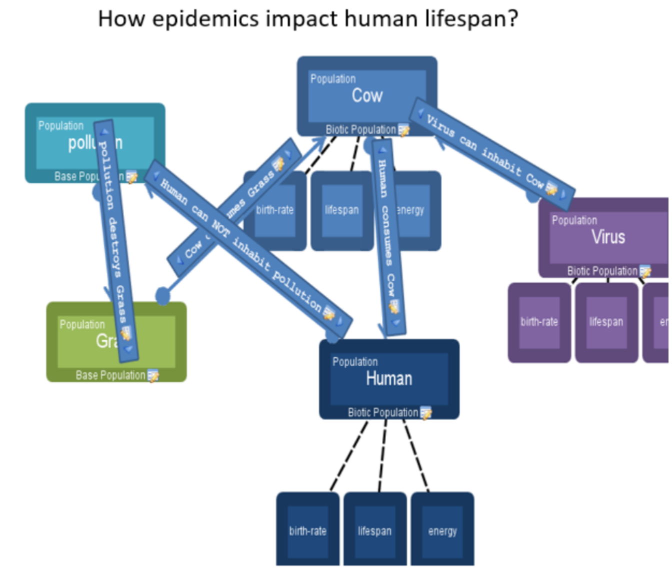

Figure 4: Impact of Epidemics - KBAI

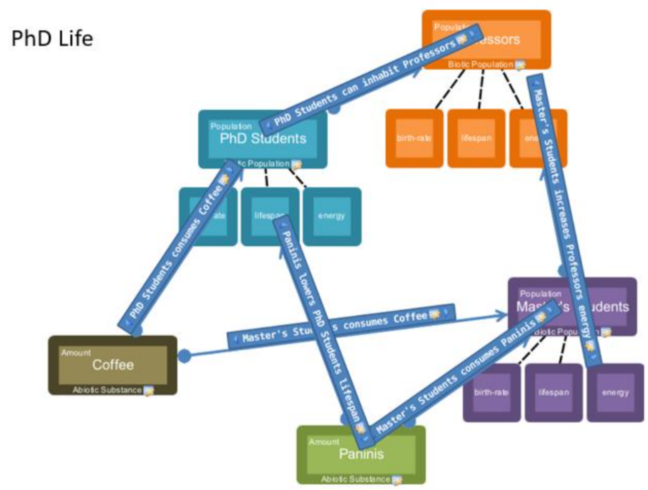

Figure 5: Model of PhD Life - KBAI

Ease of Use

In this study, the students were given with a single page tutorial on MILA-S including basic terms such as ecological systems, conceptual modeling, simulation modeling, and agent-based simulation, along with a 5 minute video about how to use MILA-S. In their feedback on MILA-S, students indicated that they were able to easily use MILA-S to model ecosystems, and asked very few questions regarding how to build conceptual or simulation models. This provides positive feedback regarding MILA-S's ease of use.

Other Observations and Future Work

1. MILA-T (Joyner & Goel, 2015) uses intelligent tutors to help middle school students learn about the process of scientific modeling as well as the content of models of ecological phenomena. However, the experiments in this paper were limited to MILA-S.

2. In future work, we would like to extend the study by providing interventions based on a students progress on a particular task or assignment.

3. In future, we would like to conduct a controlled study in order to focus on specific parameters of learning.

Conclusion

Our goal in this work was to study the use of MILA-S for learning about model construction, evaluation, and revision among college-level students in contrast to middle school students in earlier studies. Our hypothesis in this study was that MILA-S would enable college students to learn about scientific inquiry and modeling much like it helped middle school students. Preliminary results from two studies on the use of MILA-S in two college-level classes provide evidence supporting this hypothesis. In the first study in an AI class consisting of 146 students, over 45% of the students showed improved understanding of scientific modeling. In the second study in a class on cognitive science with 23 students, more than 65% of the participating students showed improved understanding and indicated that the application helped them learn about some of the intricacies of ecological modeling.

When coupled with similar results from earlier studies in middle schools, these results suggest three conclusions. First, learning about scientific inquiry and modeling is an important issue at all levels of education, from middle school to graduate school. Second, MILA-S with its combination of conceptual and simulation modeling can support the cycle of model construction, evaluation and revision not only in ecology but in several agent-based domains. Third, use of MILA-S enhances understanding about scientific modeling for more than half of all graduate students.

Acknowledgements

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