Preparing MILA-S for College

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ABSTRACT

Scientists use both conceptual and simulation models to make sense of the world. MILA–S is an interactive system for authoring conceptual models of ecological phenomena and spawning agent-based simulations of the ecological systems directly from models. We have used MILA–S in middle school science to foster learning about both ecological systems and scientific modeling. We now seek to use MILA–S to promote learning about ecological systems and scientific modeling in college-level introductory biology classes. Compared to middle school students, college-level students typically study more complex ecological systems. In this paper, we present extensions and enhancements to MILA–S in preparation for deployment in college.

INTRODUCTION

Much cognitive systems research on science education seeks to introduce authentic practices of real scientists into science classrooms (Edelson, Gordon & Pea 1999). Scientists in general make sense of the world through cycles of model construction, use, evaluation and revision (Clement 2008; Darden 1989; Halloun 2000; Nersessian 1989, 2008; Schwarz et al. 2009). Further, scientists use many kinds of models to generate, specify, share, test and critique their ideas [Carruthers et al. 2002]. Two of the techniques scientists commonly use are construction of conceptual models and execution of simulation models of the phenomenon or system of interest (Clement 2008; Nersessian 2008). Conceptual models are abstract representations of the components, relations, and processes of the phenomenon (Clement 2008; Darden 1989; Nersessian 1989, 2008; Novak 2000; White & Fredriksen 1990). A conceptual model specifies a scientist's current understanding of a phenomenon and evidence for the understanding, allowing externalization, sharing and critiquing of that understanding, as well as use of the model to guide further investigation Like conceptual models, simulation models too specify the scientists' current understanding of the system and guide further investigation. Simulation models are executable with specific values for the system's input variables, enabling determination of the temporal evolution of the values of the system's output variables (Clement 2008; de Jong & van Joolingen 1998; Jackson, Krajcik & Soloway 2000; Nersessian 2008; White & Fredriksen 1990).

MILA-S is an interactive technology for authoring conceptual models of ecological phenomena and generating simulations based on the conceptual models, preserving the capacity for rapid revision and knowledge sharing allowed by the conceptual models while extending them to provide the repeated testing and feedback of more precise simulations (Goel & Joyner 2015; Joyner & Goel 2015; Joyner, Goel & Papin 2014). MILA-S uses agent-based simulations (Bonabeau 2002) because the paradigm of agent-based simulation is especially well suited for ecological systems (Grimm et 2006). MILA-S uses Component-Mechanismal. Phenomena models (Joyner, Majerich & Goel 2013; Joyner, Goel, & Papin 2014) for authoring the conceptual models of ecological phenomena and the NetLogo simulation engine (http://ccl.northwestern.edu/netlogo) for agent-based simulations of ecological systems [Wilensky & Resnick 1999]. MILA-S implements a translator that directly compiles the conceptual models into agent-based simulations.

A pilot study entailed deployment of MILA–S in middle school science classrooms in metro Atlanta, and its use by about 50 students for modeling a local aquatic ecosystem. Preliminary results from the study indicated that the students used MILA–S to engage in the desired cycle of mode; construction, use, evaluation and revision (Joyner, Goel, & Papin 2014). Similar studies have also shown that using the MILA family of tools leads to an improvement in both the quality of the conceptual models of ecological phenomena and understanding of the process of scientific modeling –of ecological systems (Goel & Joyner 2015, Joyner & Goel 2015).

Much cognitive systems research has explored interactive tools for qualitative modeling and qualitative simulation and their use for promoting science education (Bredeweg & Forbus 2003). MILA-S parallels Bredeweg et al.'s (2009) Garp-3 system that allows the user to create first qualitative models of ecological phenomena and then qualitatively simulate them. In contrast to Garp-3, MILA-S uses Component-Mechanism-Phenomena modeling for authoring conceptual models, the off-theshelf NetLogo engine for running agent-based simulations, and a translator between the two for directly spawning the simulations from the conceptual models.



Figure 1: A conceptual model constructed by a team of 7th grade students using MILA-S.

Given the success of MILA–S for fostering learning of ecological systems as well as scientific modeling in middle school science, we now seek to use MILA–S to promote learning about ecological systems and scientific modeling in college-level introductory biology classes. However, college-level students are cognitively more developed than middle school students, the ecological systems they study are more complex, and they have more prior knowledge of ecological systems and scientific modeling. This raises the question of how to extend and enhance MILA–S to match complexity of systems that they study? In this paper, we summarize MILA–S and its use for learning about ecological systems and scientific modeling, and then describe extensions and enhancements to MILA–S in preparation for its deployment in college.

DESIGN OF MILA-S

MILA (Modeling & Inquiry Learning Application)_ is a family of interactive tools for supporting student learning about scientific discovery. The core MILA tool enables middle school students to investigate and construct models of complex ecological phenomena. MILA–S also allows students to simulate their conceptual models (Goel & Joyner 2015; Joyner, Goel & Papin 2014).

MILA builds on a line of exploratory learning environments including the Aquarium Construction Toolkit (ACT; Vattam et al. 2011) and the Ecological Modeling Toolkit (EMT; Joyner et al. 2011). ACT and EMT were shown to facilitate significant improvement in students' deep, expert-like understanding of complex ecological systems. For conceptual modeling, ACT used Structure-Behavior-Functions models that were initially developed in AI research on conceptual design of technical systems (Goel 2013; Goel, Rugaber & Vattam 2009). 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). Both ACT and EMT used NetLogo simulations as the simulation models (Wilensky & Reisman 2006; Wilensky & Resnick 1999). Like most interactive tools for supporting modeling in science education (vanLehn 2013), both ACT and EMT provided one set of tools for constructing and revising conceptual models and another tool set for generating and using simulations.

Conceptual 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 causal model constructed by a team of 7th grade life science students early in their interaction with MILA-S. 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 that 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.

CMP modeling draws causal relations between the variables associated with the different components. For example, the presence of a chemical like ammonia in the ecosystem that is poisonous to fish may decrease the lifespan of the fish, or it may directly decrease the population of the fish (additional information on the difference between the two is provided later in this paper). MILA-S provides the user with a set of prototypes that describe causal relationships among 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, 'consumes', 'produces', or 'becomes upon death,' etc. Similarly, a relation from an abiotic Amount to a biotic Population could be 'destroys' or 'feeds'. 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 variables of two components indicates the direction of causal influence. For example, the arrow from Fish to Oxygen in



Figure 2: The results of NetLogo simulation of the conceptual model illustrated in Figure 1.

Figure 1 indicates that the Population of Fish influences the Amount of Oxygen.

A Mechanism in CMP modeling is a causal chain of component variables connected by causal relations. For example, Figure 1 illustrates a mechanism hypothesized by a team of students 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 for the mechanism illustrated in Figure 1 is a change in the Amount of Oxygen in an aquatic ecosystem.

A user starts the process of CMP causal modeling using MILA–S with the goal of constructing a causal explanation for explaining a given phenomenon. She then specifies a mechanism as the explanation for the phenomenon, incrementally composing the mechanism from the components of the system, their variables, and the relations between the variables. As Figure 1 illustrates, a CMP model in MILA–S is an external visual representation with textual annotations.

NetLogo Simulations

Figure 2 illustrates the result of the NetLogo simulation for the conceptual model of Figure 1. Note that all three components of the causal model (Figure 1) are represented in the simulation (Figure 2): 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 depicts the agents in a window showing their actions and behaviors. Also 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 the simulation's start condition. The input variables are set through the sliders and toggles on the left side of the simulation window illustrated in Figure 2. The user then clicks the Setup button to apply those changes to a new simulation. The user next clicks the Go button to start the time steps of the simulation.

NetLogo simulations are typically designed with its 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 nontrivial changes to the way in which the simulation operates: these changes can involve writing all-new methods, creating new variables, or defining new agents. Clearly, it would be useful if the cost of generating NetLogo simulations could be controlled.

MILA–S provides one technique for controlling the cost of generating NetLogo simulations: it automatically generates the simulations from user's casual model. Note also that the generation of the CMP causal model illustrated in Figure 1 does not require any knowledge of programming. Instead, MILA–S provides a visual syntax for CMP modeling.



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 system, and then clicks a 'Run Sim' button for simulation generation. MILA-S iterates through some initial boilerplate settings, then gathers together all the components for initialization along with their individual parameters. After this, 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 the higher-level rapid model revision process that is the learning objective of this project. Figure 3 illustrates the general scheme for translating the semantics of CMP conceptual models into the semantics of the Netlogo agent-based simulations; Joyner, Goel & Papin (2014) provide a more detailed account of the translation scheme and process.

USE OF MILA-S IN MIDDLE SCHOOL SCIENCE

Prior to engagement with MILA–S, the 50 students in our pilot study received a two-week curriculum on modeling and inquiry, featuring five days of interaction with CMP conceptual modeling in MILA. In the first part of the study using MILA, students also used pre-programmed NetLogo simulations that did not respond to students' models, but nonetheless provided students experience with the NetLogo interface and toolkit. Thus, when given MILA–S, students already had significant experience with CMP conceptual modeling, NetLogo simulations, and the interface of MILA.

Constructed Models

During engagement with MILA, students produced models that can be described as retrospective and explanatory. Students started from an observable phenomenon, the aforementioned fish kill, and recounted a series of events that led to that result. Causal relationships were captured throughout the model, but only those that lay directly in the causal path leading to the observed phenomenon, and only in the specific way in which the chain occurred in the phenomenon. For example, one team modeled multiple feedback cycles to explain the phenomenon. In their model, a heat spike caused algae populations to grow out of control, then die off due to a lack of carbon dioxide to breathe and a lack of sunlight to produce energy (due to the thick algae clouding the lake). This led to a spike in algaedecomposing bacteria which suddenly had an ample food supply, as well as a drop in the population of oxygenproducing algae. These bacteria, then, consumed an enormous quantity of oxygen, causing the fish population to suffocate. This led to more dead matter in the lake, thus encouraging more bacteria reproduction, exacerbating the fish kill further.

This model presented a complete explanation for why and how the fish kill occurred in the lake; however, the model only captured a retrospective view of the series of events applicable in this situation. Although students could use mental simulation to imagine the results, these models do not explicitly capture dynamic relationships in the system, and thus are of limited use describing what would have happened under different circumstances. For example, had the temperature changed more slowly and allowed the algae to grow steadily rather than exploding and plummeting in quick succession, could the lake have sustained the increased algae population? Would the increased algae population have produced sufficient oxygen to allow the fish population to grow and thrive as well? Thus, models constructed with MILA were explanatory and retrospective.

With MILA-S, students constructed fundamentally different kinds of models that aimed not to capture the series of events that occurred, but rather to capture the dynamic relationships that gave rise to that series of events. Thus, the models constructed in MILA-S invoked a layer of abstraction and generalization away from the models constructed in MILA. For example, one team constructed an initial model that captured the three relationships they considered most pertinent in the system. These students already believed that the fish kill was caused by a sudden drop in oxygen, suffocating the fish. Thus, their first relationship was that fish consume oxygen. They similarly knew that oxygen is produced from sunlight, and thus included the relationship between sunlight and oxygen. These connections differed fundamentally from those modeled in MILA, such as accounting for trends in multiple directions (i.e. oxygen



Figure 4: Long-durable stability of agent-based simulations.

production varies directly, up or down, with sunlight presence). The model was not constructed to directly explain the phenomenon, but rather to provide the relationships necessary so that under the right conditions, the phenomenon may arise on its own.

Model Construction Process

During prior engagement with MILA, we observed students engage in the model construction cycle. Model construction occurred as students constructed their initial hypotheses, typically connecting only a cause to a phenomenon with no mechanism in between. This was then used to guide investigation into other sources of information such as observed data or other theories to look for corroborating observations or similar phenomena. The conceptual model was then evaluated according to how well it matched the findings; in some cases, the findings directly contradicted the model, while in other cases, the findings lent evidence or mechanism to the model. Finally, the conceptual models were revised in light of this new information (or dismissed in favor of stronger hypotheses, reflecting revision at a higher level) and the process began again.

During engagement with MILA–S, however, we observed a profound variation on the model construction process. The four phases of model construction were still present, but the nature of model use and evaluation changed. Students started by constructing a small number of relationships they believe to be relevant in the system, the model construction phase. After some initial debugging and testing to become familiar with the way in which conceptual models and simulations fit together, students generated simulations and used them to test the implications of their conceptual models. After running the simulation a few times, students then evaluated how well the results of the simulation matched the observations from the phenomenon. This evaluation had two levels: first, did the simulation accurately predict the ultimate phenomenon (in this case, the fish kill)? Once this basic evaluation was met, an advanced evaluation followed: did other variables, trends, and relationships in the simulation match other observations from the phenomenon? For example, one team successfully modeled a fish kill by causing the quantity of food available to the fish to drop, but evaluated this as a poor model nonetheless because nothing in the system indicated a disturbance to the fish's food supply. Finally, equipped with the results of this evaluation, students revised their models to more closely approximate the actual system.

Thus, students still constructed and revised conceptual models, but through the simulation generation framework of MILA–S, the model use and evaluation stages took on the practical rigor, repeatable testing, and numeric analysis facilitated by simulations. Rather than speculating on the extent to which their model could explain a phenomenon, students were able to directly test its predictive power. Then, when models were shown to lack the ability to explain the full spectrum of the phenomenon, students were able to quickly return and revise their conceptual models and iterate through the process again.

Challenges

MILA-S provided an effective framework at simulating the interactions between a small number of components and their variables. However, some of the systems that students were examining involved several more components than these, along with multiple relationships between their variables. Upon reaching a level of complexity slightly higher than shown in Figure 2, the NetLogo simulations generated by MILA-S stopped providing meaningful feedback to students. The number of agents would explode based on the multiple consumption and production relationships at play. slowing the simulation down and rendering the visualization elements indistinguishable. Repeated runs of the same simulation with the same initial parameters sometimes generated wildly varied responses as the number of agents and methods exacerbated the influence of random chance on the simulation's outcomes.

It is likely that with proper parameters and relationships, MILA–S could still have generated usable simulations that gave meaningful feedback. The challenge was that most executions of the simulations gave limited or no feedback as to the changes that needed to be made to more closely replicate the phenomenon. The simulations contained too much noise to facilitate the process of model evaluation and revision.



Figure 5: Enhancement of the CMP conceptual models by adding spatial relations.

FROM SCHOOL TO COLLEGE

In preparing MILA-S for use in college-level introductory biology classes, three factors are especially noteworthy. First, compared to middle school students in US in the 11-14 years range, college level students typically are 18-22 years old and therefore are cognitively more developed. Second, college-level students typically have more prior knowledge both about the systems of interest and the process of scientific modeling. Third, compared to middle-school science, college-level biology classes typically entail modeling of more complex ecological systems, with larger numbers and variety of species and larger number and range of interactions among them. Thus, to deploy MILA-S in college, we need to extend and enhance its capability in several ways.

Long-Duration Stable simulations

While ecological phenomena do not always sum up to a neat mathematical equation, there are emergent behaviors in an ecosystem that one comes to expect. For example, when a simple food chain ecosystem is modeled, one expects the resultant simulations to show the fluctuating predator-prev population cycles that can be mathematically modeled by the Lotka-Volterra equations. At the time of initial experimentation, it was difficult to get MILA-S to produce this expected behavior when simulating a food chain consisting of all biotic populations. In order to correct this, the concept of a "base population" was added to the conceptual model. This base population was implemented in NetLogo as patches instead of turtles like every other component. We found that in order to produce the cyclic behavior of predator-prey relationships the organism present at the bottom of the food chain needed to have the ability to repopulate and keep its population in tact without relying on it interacting with other members of the population. Essentially, once the base population could produce agents without interacting with other members of its species the simulations immediately stabilized and could be created much faster and with more success than experimenting with the organism's parameters. Figure 4 illustrates the stable results of this implementation.

Spatial Simulation

In addition to simulating food chain ecology and simple relationships between biotic and abiotic organisms, we are integrating spatially explicit relationships into the simulation. Integrating a spatial dimension allows users to model where organisms are allowed to exist and how they interact or are affected by their habitat. These simulations could be used to explore phenomena such as boundary effects, migration patterns, and urbanization effects. Figure 5 illustrates an initial expansion of the CMP language to include spatial regions such as meadow and pond, and spatial relations such as adjacency.

More Powerful Agent-Based Simulation Engines

As we noted above in the discussion on deploying MILA-S into middle school classroom, as the number of species and the variety of interactions among the species in the conceptual model increased, the NetLogo simulations became too slow to be useful. This means that for college-level ecological systems we may need more powerful agent-based simulation engines. Thus, we are integrating another off-the shelf agent-based simulation engine called Repast Simphony (http://repast.sourceforge.net/) into MILA-S. We chose Repast Simphony because it is an open-source agentbased simulation engine compatible with MILA-S, because it is similar to NetLogo in many respects but more powerful, and because it supports modeling of complex ecological systems. In the current version of MILA-S, we have partially integrated Repast Simphony into MILA-S; we are now testing the MILA-S' compiler for translating CMP conceptual models into the simulator's constructs.



Figure 6: The output of Repast Simphony's agent-based simulation engine.

CONCLUSIONS

Cognitive systems research on qualitative reasoning typically focuses on qualitative modeling and qualitative simulation. Thus, in a parallel project on evaluating conceptual designs early in the design process, we have developed a technique for qualitative simulation of functional models of design concepts (Wiltgen & Goel 2016). In contrast, agent-based simulations are especially appropriate for modeling ecological systems. The question then becomes how can we use agent-based simulations in conjunction with qualitative modeling?

This paper has described the design of an interactive system called MILA-S for generating agent-based simulations from qualitative conceptual models of ecological systems. MILA-S not only enables construction of causal models of components and mechanisms in an ecosystem, but it also takes as input the causal model and autonomously generates an agent-based simulation that shows the temporal evolution of the system according to the causal model. The user needs to simply use a visual syntax for generating causal models and the interactive tool automatically generates the corresponding simulation. Further, because the simulation directly corresponds to the causal model, the results of the simulation directly evaluate the model and point to the revisions needed to the model.

Initial results from a pilot study with 50 students in a middle school provided preliminary evidence in favor of the hypothesis. Firstly, students approached the modeling process from a different perspective from the outset, striving to capture dynamic relationships among the components of the ecological system. These dynamic relationships then promoted a more abstract and general perspective on the system. Secondly, the process of model construction, use, evaluation, and revision presented itself naturally during this intervention, with the simulations playing a key role in supporting the cyclical process of constructing conceptual models.

Compared to middle school students, college-level students typically study more complex ecological systems. In this paper, we present extensions and enhancements to MILA–S in preparation for deployment in college. In particular, we described three extensions to MILA–S. (1) The ability to generate long-duration stable simulations. (2) The ability to take spatial relationships into account in both the conceptual and simulation models. (3) The ability to generate simulations that can capture a range of interactions in a variety of species. The next step will be to introduce MILA–S into college-level biology classes.

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REFERENCES

- Bonabeau, E. (2002) Agent-Based Modeling: Methods and Techniques for Simulating Human Systems. In *Procs. National Academy of Sciences*, 99(3).
- 2. Bredeweg, B., & Forbus, K. (2003) Qualitative Modeling in Education. *AI Magazine*, 24(4): 35-45.
- 3. Bredeweg, B., Linnebank, F., Bouwer, A., Liem, J. (2009) Garp3 Workbench for Qualitative Modeling and Simulation. *Ecological Informatics*, 4: 263-281.

- 4. Carruthers, P., Stitch, S., & Siegal, M. (editors, 2002) *The Cognitive Basis of Science*, Cambridge University Press.
- 5. Clement, J. (2008). Creative Model Construction in Scientists and Students: The Role of Imagery, Analogy, and Mental Simulation. Dordrecht: Springer.
- Darden, L. (1998). Anomaly-driven theory redesign: computational philosophy of science experiments. In T. Bynum, & J. Moor (Eds.), *The Digital Phoenix: How Computers are Changing Philosophy*, (pp. 62– 78). Oxford: Blackwell.
- de Jong, T., & van Joolingen, W. (1998). Scientific discovery learning with computer simulations of conceptual domains. *Review of Educational Research*, 68(2), 179-201.
- Edelson, D., Gordin, D., & Pea, R. (1999). Addressing the challenges of inquiry-based learning through technology and curriculum design. *Journal* of the Learning Sciences, 8(3-4), 391-450.
- Goel, A. (2013) One Thirty Year Long Case Study; Fifteen Principles: Implications of an AI Methodology for Functional Modeling. AIEDAM 27(3): 203-215, 2013.
- Goel, A., & Joyner, D. (2015) Impact of a Creativity Support Tool on Student Learning About Scientific Discovery Processes. In *Procs. Sixth International Conference on Computational Creativity*. Provo, Utah.
- 11. Goel, A., Rugaber, S., & Vattam, S. (2009). Structure, Behavior & Function of Complex Systems: The SBF Modeling Language. *AIEDAM* 23: 23-35.
- 12. Grimm, V. et al (2005) Pattern-Oriented Modeling of Agent-Based Complex Systems: Lessons from Ecology. *Science*, 310 (5750).
- 13. Halloun, I. (2007). Mediated Modeling in Science Education. *Science & Education*, 16(7), 653-697.
- Jackson, S., Krajcik, J., & Soloway, E. (2000) Model-It: A Design Retrospective. In M. Jacobson & R. Kozma (editors), *Innovations in Science and Mathematics Education: Advanced Designs for Technologies of Learning* (pp. 77-115). Lawrence Erlbaum.
- 15. Joyner, D. & Goel, A. (2015). Improving Inquiry-Driven Modeling in Science Education through Interaction with Intelligent Tutoring Agents. In *Procs. 20th International Conference on Intelligent User Interfaces.* Atlanta, Georgia.
- Joyner, D., Majerich, D. & Goel, A. (2013) Facilitating Authentic Reasoning about Complex Systems in Middle School Science Education. In Procs. Fourth Conference on Systems Engineering Research, Atlanta, March 2013; pp. 1043-1052.
- 17. Joyner, D., Goel, A., & Papin, N. (2014). MILA-S: Generation of Agent-Based Simulations from

Conceptual Models of Complex Systems. In Proc. 19th International Conference on Intelligent User Interfaces, Haifa, Israel.

- Joyner, D., Goel, A., Rugaber, S., Hmelo-Silver, C., & Jordan, R. (2011). Evolution of an Integrated Technology for Supporting Learning about Complex Systems. In *Proc. 11th IEEE International Conference on Advanced Learning Technologies*, Athens, GA.
- Joyner, D., Goel, A., & Papin, N. (2014). MILA-S: Generation of Agent-Based Simulations from Conceptual Models of Complex Systems. In Proc. 19th International Conference on Intelligent User Interfaces, Haifa, Israel.
- 20. Nersessian, N. (1998) Conceptual Change in Science and Science Education. *Synthese* 80: 163-183, 1989.
- 21. Nersessian, N. (2008). *Creating Scientific Concepts*. Cambridge, MA: MIT Press.
- 22. North, M., et al. (2013) Complex Adaptive Systems Modeling with Repast Simphony, Complex Adaptive Systems Modeling, Springer, Heidelberg, FRG.
- 23. Novak, J. (2010) Learning, Creating and Using Knowledge: Concept Maps as Facilitative Tools in Schools and Corporations. New York: Routledge.
- 24. Schwarz, C., Reiser, B., Davis, E., Kenyon, L., Achér, A., Fortus, D., Shwartz, Y., Hug, B., & Krajcik, J. (2009). Developing a learning progression for scientific modeling: Making scientific modeling accessible and meaningful for learners. *Journal of Research in Science Teaching*, 46(6), 632-654.
- 25. VanLehn, K. (2013). Model construction as a learning activity: a design space and review. *Interactive Learning Environments*, 21(4), 371-413.
- Vattam, S., Goel, A., Rugaber, S., Hmelo-Silver, C., Jordan, R., Gray, S, & Sinha, S. (2011) Understanding Complex Natural Systems by Articulating Structure-Behavior-Function Models. *Journal of Educational Technology & Society*, 14(1): 66-81.
- 27. White, B, & Frederiksen, J. (1990) Causal Model Progressions as a Foundation of Intelligence Learning Environments. *Artificial Intelligence*, 42(1): 99-157.
- 28. Wilensky, U., & Reisman, K. (2006). Thinking Like a Wolf, a Sheep, or a Firefly: Learning Biology Through Constructing and Testing Computational Theories-An Embodied Modeling Approach. *Cognition and Instruction*, 24(2), 171-209.
- 29. Wilensky, U., & Resnick, M. (1999). Thinking in levels: A dynamic systems approach to making sense of the world. *Journal of Science Education and Technology*,8:3-19.
- Wiltgen, B., & Goel, A. (2016) Functional Model Simulation for Evaluating Design Concepts. Advances in Cognitive Systems, 4.