Paper Title Model-Based Learning About Climate Change With Productive Failure: Preliminary Findings

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Session Title Technology-Supported Learning in K-12 Science

Session Type Paper

Presentation Date 4/15/2012

Presentation Location Vancouver, British Columbia, Canada

Descriptors Computers and Learning, Science Education

Methodology Mixed Method

Unit Division C - Learning and Instruction

Agent-based Models and Learning about Climate Change: An Exploratory Study[1]

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10 April 2012

Abstract. This paper reports on research being conducted as part of a four year funded project in Australia that involves the use of agent-based computer models to help students learn about climate change. The intervention in this study involved different sequences of structure provided as part of pedagogical guidance for problem solving and learning activities with agent based models. Thirty-three grade nine students in an all girls' school in Australia participated in the study that used two NetLogo models of greenhouse gases and the carbon cycle. There were significant findings of learning gains from pretest to posttest by all students, and qualitative observations and teacher interviews suggest that the students were highly engaged and enjoyed learning with the agent-based computer models. Implications and future research plans are discussed.

Of increasing centrality to the daily practices of many scientists since the late 20th century has been the use of computer modeling and scientific visualization tools to investigate a wide range of complex physical and social systems (Jacobson & Wilensky, 2006; Mitchell, 2009; Pagels, 1988). Related to science education, we are starting to see new national guidelines for science curricula and standards in countries such as Australia (ACARA, 2011) and the United States (National Research Council, 2012). These new science education policy documents articulate new frameworks for the scientific knowledge and skills students learn at the pre-university level that go beyond the traditional topics in biology, chemistry, and physics. For example, there is not only a greater attention to process skills such as scientific inquiry, but also new emphases on overarching ideas such as principles and processes of systems and on computational modeling as a method for doing science. In addition, these science education policy documents propose that students engage with new topics such global systems, including the carbon cycle and interactions involving the biosphere, lithosphere, hydrosphere, and atmosphere, or investigating how human activity affects global systems. Given the well documented challenges students have learning traditional science education subjects (Bransford, Brown, Cocking, & Donovan, 2000; Duschl, Schweingruber, & Shouse, 2007), implementing these types of new frameworks for scientific knowledge and skills and uses of computer modeling tools in Australian schools (as well as in other countries) will likely require changes—perhaps major ones—from more traditional approaches to teaching science.

However, there has been relatively little research to inform approaches to help students learn about scientific knowledge and skills about climate systems. To date, research in this area has been primarily descriptive of what are the important scientific concepts associated with global warming and climate change and what are ways students currently think about these topics. Regarding the former, Jarrett, Takacsa, and Ferry (2011) conducted a Delphi study of 19 academics, researchers, and high-school teachers who have expertise in global climate systems, as well as a comprehensive literature review. A set of 10 major concepts related to understanding climate change were identified: *carbon cycle and fossil fuels, electromagnetic spectrum, interactions between greenhouse gases and electromagnetic radiation, natural climate variability in the past and relationship to CO_2 levels, difference between weather and climate, proportions of greenhouse and non-greenhouse gases in the atmosphere, radiative forcing capacity, feedback, equilibrium of energy, and conservation of energy*. Of these, we observe that only concepts such as feedback, equilibrium, and conservation of energy are emphasized in the Australian and United States science education curricula, and these concepts are generally taught as topics in physics, biology, and chemistry, and not in the context of much larger scale global climate systems in which there are multi-faceted interactions across larger scale chemical, biological, physical, and social systems.

Regarding students' understandings of concepts such as those identified by Jarrett and associates related to climate systems, Shepardson, Choi, Niyogi, and Charusombat (2011), conducted a literature review and identified 16 international studies between 1993 and 2008 that investigated how secondary students understood various concepts about global warming. Four thematic concepts areas were identified in these

[1] Paper presented at the 2012 Annual Meeting of the American Educational Research Association, Vancouver, Canada.

studies: *conceptions about global warming and the greenhouse effect, causes of global warming and climate change, environmental impact of global warming and climate change, and resolution of global warming and climate change*. Overall, students had inaccurate or conceptually incomplete understandings about global warming concepts in these areas. To extend this research to the context of the United States, Shepardson and colleagues also noted that the *National Science Education Standards* (National Research Council, 1996) had recommended that students should begin to learn about climate systems in grade seven. They then conducted a qualitative study involving 91 seventh grade students in the USA about their understanding of selected topics related to global warming and climate change. A set of categories emerged the content analysis of the students' responses that were associated with different degrees of conceptual sophistication the students had about global warming and climate change, such as the *impact of global warming, understanding the greenhouse effect, and explaining the change in atmospheric carbon dioxide levels*. Overall, the qualitative data that was collected suggests that these students did not have a scientifically sophisticated understanding of important concepts about global warming and climate change, and that these findings were overall similar to those in the earlier research.

There appears to be a reasonable agreement about the importance of having students learn scientific knowledge about climate systems and research documenting that few secondary level students understand concepts in this area, so there is now a need for research into how students might deeply *learn* this knowledge. An important recent approach for helping students to successfully learn more standard science education topics involves model-based learning (MBL) (Clement, 2000; Gordin & Pea, 1995; Penner, 2001; Zhang, Liu, & Krajcik, 2005). In general, MBL approaches engage the learners in working with computer simulation and visualization systems and learning the targeted science concepts in an interactive manner while problem solving. There has also been research involving the use of agent-based models (ABM), which computationally represent phenomena as a number of agents or elements that each has particular rules they follow, and for which the apparent complexity of the system being modeled emerges from the interactions of the agents in the systems (Railsback & Grimm, 2011).[2] A number of recent studies have documented significant learning with ABMs, especially for learning scientific concepts about various types of complex physical and biological systems (Blikstein & Wilensky, 2010; Goldstone & Wilensky, 2008; Jacobson, Kapur, So, & Lee, 2011; Levy & Wilensky, 2005; Penner, 2000; Sengupta & Wilensky, 2009; Wilensky & Reisman, 2006). Given our focus on helping students learn important concepts about climate systems, we use ABMs in this study that are described below.

It has been recommended that learning activities involving computer models should follow a "gradual progression from well-defined problems to ill-defined problems in developing expert modeling practices" (Zhang et al., 2005, p. 598). While there is research that has documented significant learning associated with pedagogical guidance for learning with computer models that is initially more structured to less structured, this does not mean that alternative approaches for pedagogical guidance might not also be effective. Indeed, there is a current debate about how pedagogical guidance should be provided to learners, for which we next provide an overview. We then report on an exploratory study that investigated contrasting approaching for the structure and sequencing of agent-based model learning (ABML) activities that target selected conceptual aspects of climate change related to the carbon cycle and greenhouse gases. The paper concludes with a consideration of new research we are planning as well as more general implications of this research.

Issues in the Structure of Pedagogical Guidance

The issue of how pedagogical guidance should be provided to learners is a practical one that confronts all educators and at all levels. This issue is also one that has been disputed in the research literature for at least three decades, if not more (Mayer, 2004). To understand current theory and research perspectives about pedagogical guidance, Kirschner, Sweller, and Clark (2006) provide a critical review of a number of studies of human learning, which they broadly categorize as (a) *direct instructional guidance* and (b) *minimal instructional guidance*. They contrast and compare direct instruction approaches such as research involving worked examples (Miller, Lehman, & Koedinger, 1999; Quilici & Mayer, 1996; Sweller & Cooper, 1885), and process work sheets (Nadolski, Kirschner, & van Merriënboer, 2005) with research involving minimally guided instructional approaches such as constructivism (Jonassen, 1991), experiential learning (Kolb, Boyatzis, & Mainemelis, 2001), discovery learning (Mayer, 2004), problem based learning (Hmelo-Silver, 2004), and inquiry learning (Van Joolingen, de Jong, Lazonder, Savelsbergh, & Manlove, 2005).[3] In their analysis of the research on learning with these various approaches, Kirschner and associates (2006) conclude there should be

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[2] Agent-based modeling contrasts with equation-based modeling (EBM) in which the execution of the model provides an evaluation of the equations. There are, of course, advantages and disadvantages of all computational modeling techniques. For a discussion, see Parunak, Savit, and Riolo (1998).

[3] The references for these various instructional approaches listed in this sentence are drawn from the Kirschner and associates (2006).

"direct, strong instructional guidance rather than constructivist-based minimal guidance during the instruction of novice to intermediate learners (p. 84).

We broadly characterize the direct instruction approaches described by Kirschner and colleagues, as well as other didactic teaching approaches, as pedagogically providing *high structure*, whereas the minimally guided approaches provide *low structure* during learning activities.[4] We also observe that in many of the studies they discuss in their review, the main independent variables vary the approach of direct (i.e., high structure) versus minimally guided (i.e., low structure) instruction, with the dependent variables being various assessments of learning or problem solving success, such as the Albanese and Mitchell (1993) review of medical PBL research and the Klahr and Nigam (2004) study of direct instruction versus discovery learning for students about experimental design. However, a weakness of the studies discussed by Kirschner et al. (2006) is they primarily control for high structure or low structure. Further, they do not discuss studies that involve *different sequences of structure during learning activities*, such as Schwartz and Branford (1998) and VanLehn, Silar, and Murray (2003).

A Framework for Sequences of Pedagogical Structure in Learning

As background to our research, we propose a basic framework for sequencing structure for learning and problem solving activities that consist of: (a) high-to-high structure (HH), (b) high-to-low-structure (HL), (c) low-to-low structure (LL), and (d) low-to-high structure (LH). Of course, the factor of time (i.e., duration) is also important for each sequence component, but for this high level discussion of a framework for sequencing of learning activities, we assume that the duration of the phases is approximately the same (although this could be an interesting research area to investigate). We further assume the time of the phases in each category aligns with typical classroom period durations as either fractions or multiples there of (e.g., two sequences within a 60 minute class, two sequences spread over different class periods), perhaps with some time devoted to formative or summative assessments.

For convenience of discussion, we regard a learning activity that is completely high structure as being in the HH sequence, and completely low structure as being in sequence LL. Thus, the majority of the direct instruction studies referenced in Kirschner, Sweller, and Clark (2006) would be regarded as HH, whereas minimally guided instruction studies would be LL. The sequence HL does not seem to be represented in studies cited by Kirschner and colleagues, however, we suggest that approaches such as cognitive apprenticeship (Collins, Brown, & Newman, 1989; Collins, Brown, & Holum, 1991) seem aligned with HL in terms of the sequence of expert modeling of the targeted knowledge or skill (high structure) and the fading of scaffolding for the learner (low structure). The sequence LH is exemplified by research related to productive failure (Kapur, 2008, 2009, 2010), where the initial solution failure during the elicitation phase reflects low structure and the consolidation phase providing high structure. Other learning designs for the LH sequence are found in the work of Schwartz and Branford (1998), VanLehn and colleagues (2003), and Bjork and Linn (2006).

Given the interesting findings about the physics problem solving performance of students in Kapur (2008), we elected to do a study that employed a similar research design, but using agent-based computer models of the carbon cycle and greenhouse gases (see below). Briefly, Kapur's design compared a group of students engaged in a HH sequence (i.e., a sequence of two well-structured problems) with a group in a LH sequence (i.e., an ill-structured problem followed by a well-structured problem). In our experimental design, the two treatment groups were given model-based learning activities that were either HH or LH structure. We hypothesized given the representational affordances of the agent-based models for depicting micro- and macro-level aspects of the climate system related to the carbon cycle and greenhouse gases that both the HH and the LH approaches would lead to learning gains associated with declarative knowledge about these topics. However, based on the earlier research by Kapur, we also hypothesized that the LH approach would lead to more successful problem solving compared to the HH treatment by the posttest. We were also interested in the subjective impressions students had about using the agent-based computer models in these two different pedagogical approaches, and expected that all students would enjoy using this approach to learn about science topics related to climate change.

Method

The agent-based models of the carbon cycle and the greenhouse effect used in the study were co-created by the project team and a collaborating teacher with a PhD in physics, and were then verified by an earth sciences graduate. These models were programmed in the NetLogo agent-based modeling system (Wilensky, 1999). The *carbon cycle* is represented by a fixed number of carbon molecules within a closed system. Carbon molecules exchange at the boundaries between atmosphere, land, and ocean. Students can alter the rates of transfer at these

[4] "Structure" may be broadly conceived in a variety of forms such as structuring a problem, scaffolding, instructional facilitation, providing worksheets or scripts, and so on. See also the discussion in section *A Framework for Sequences of Pedagogical Structure in Learning*.

boundaries as well as control the rate of release of deeply stored carbon into the atmosphere. Carbon moves in different regions as well as in different life forms, represented as trees (plants) and sheep (animals).

The *greenhouse effect* (Figure 1) is modeled by introducing the sun's energy into the model of the carbon cycle. Additionally, in order to model the greenhouse effect, H_2O molecules are present in the atmosphere, and the Earth's albedo or reflectiveness. Within this model each "light ray" (indicative of electromagnetic radiation from the sun) is represented as an agent. Rules are specified for the interaction between light rays and the Earth's surface (reflection, absorption) as well as for heat released from the Earth's surface (infrared radiation) and greenhouse gases (the CO_2 and H_2O agents). The resulting complex system has emergent properties of "global heat" that changes based upon the amount of solar radiation/greenhouse gas/reflection in the system. These NetLogo agent-based models generates output that is in line with IPCC data for carbon and temperature (Intergovernmental Panel on Climate Change, 2007).

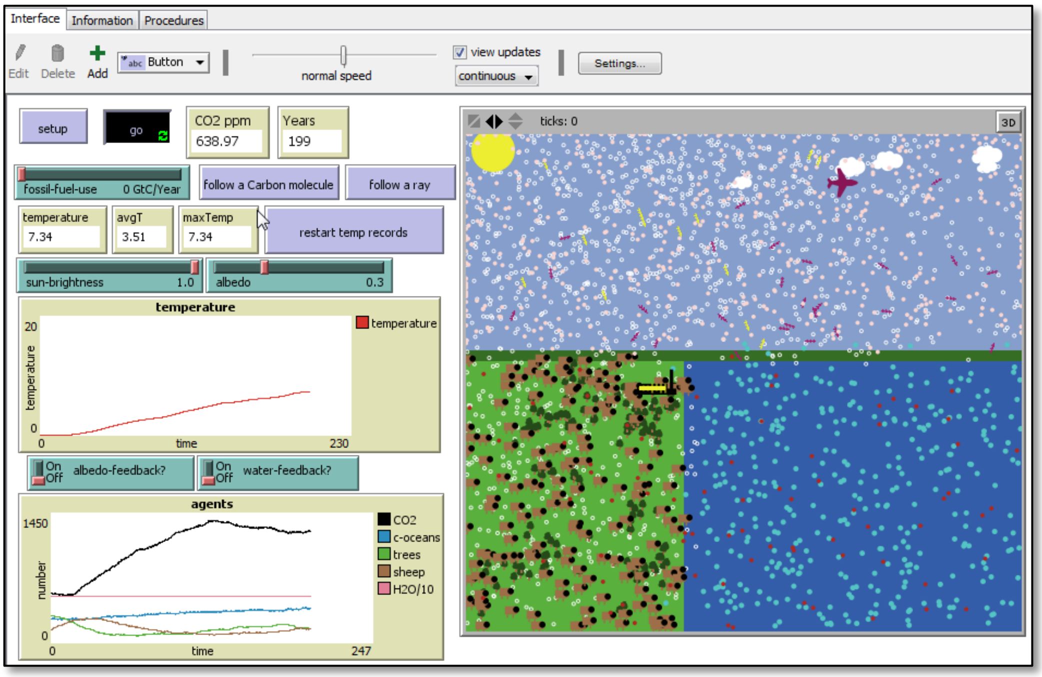

Figure 1. A NetLogo model of the greenhouse effect showing slide bars and buttons for student interaction, real-time graphs of outputs, and a visual representation of the simulation.

Based on discussions with collaborating teachings, we elected to refer to the experimental activities for the students in the LH structure sequence as *Challenge and Guided Learning* (CGL), and the HH structure sequence as *Guided Learning* (GL). Experimental materials were developed for learning activities involving two NetLogo agent-based models of: (a) the carbon cycle; and (b) the greenhouse effect. For each of the two models, three problem-based activities were prepared for the CGL and GL conditions. The experimental design for the study is shown in Table 1. The two conditions differed only in the structure provided in activity 1.

Table 1
Study Sequence

	Activity 1 (A1)	Activity 2 (A2)	Assessment (A3)
Guided Learning	Structured	Structured	Not Structured
Challenge and Guided Learning	Not Structured	Structured	Not Structured

To illustrate what the participants in the two treatment groups did, for Activity 1 with Model 2 Greenhouse Gases (Figure 1), the GL group received these instructions:

Instructions

A greenhouse gas is a gas within the atmosphere that absorbs and emits infrared energy.

Working with NetLogo Model 2 of the Greenhouse Effect, carry out the activity and then answer the three questions provided.

Activity M2.1
Note that there is a button labeled "follow a ray". Pressing this button follows a ray of energy from the sun as it enters the atmosphere.

We are going to see what happens to an individual ray when the model runs, by following these instructions:

1. Press the setup button.
2. Press the go button. The button will turn black and rays will start to enter the system from the top left corner
3. Press the "follow a ray" button. The button will turn black and the screen will focus on an individual ray.
4. Record a tally in the table below to indicate what happens to this ray of light.

Repeat steps 1 – 4 for three different rays of light, recording years in the table below. Notice what happens to the energy once it is released back into the atmosphere and record your observations in the final column.

	Bounces off albedo?	Becomes a ball of heat	Re-enters atmosphere	What do you notice about the activity of rays in the atmosphere?
Ray 1				
Ray 2				
Ray 3				

Questions
M2.P1.1 What is the difference between the behaviour of visible light (yellow rays) and infrared light (red rays)?

M2.P1.2 What is the difference between the interaction of energy with CO2 particles and H2O particles?

M2.P1.3 Which of the two do you think are greenhouse gases?

In contrast, the participants in the CGL group received these instructions:

Instructions (CGL)
A greenhouse gas is a gas within the atmosphere that absorbs and emits infrared energy.

Working with NetLogo Model 2 of the Greenhouse Effect, carry out the activity and then answer the three questions provided (same questions as above for CGL group).

Note that each group is given the same general instructions to use the NetLogo carbon cycle model and answered the same questions, however the GL group received a set of structured "worksheet-like" instructions for how to run the model systematically in ways intended to guide the learner toward more successfully answering the questions.

For Model 2 Activity 2, each of the treatment groups received the identical problem instructions, structured worksheet instructions, and questions to answer the same questions (see Appendix). The low structure assessment (A3) for Model 2 was also completed collaboratively. The Model 1 activities for the GL and CGL treatment groups were similar, but involved working with a simpler NetLogo model of the carbon cycle also developed by our team.

Table 2
Assessment Instruments and Sample Items

	Description	Sample Items
Background knowledge (20 minutes)	• 5 personal information questions • 30 multiple choice questions about science learning, skills, and beliefs	I am not confident about understanding difficult science concepts.
Pre- and Post-test (20 minutes x 2)	• 4 short answer questions testing declarative knowledge about complex systems • 6 true/false questions about scientific knowledge • 6 short answer questions explaining the true/false responses • 10 short answer questions relating to scientific knowledge about climate change	• What does it mean to say that the carbon cycle is an example of a closed system? • I will see the effects of climate change within my lifetime: true or false? Explain your answer • Explain the greenhouse effect.
Model 1 and 2 Assessment Activities (20 minutes x 2)	Open ended problem scenario to assess conceptual understanding	From what you have observed in the models, what argument could be made for a link between CO2 emissions and climate change?

The participant's knowledge about targeted climate change topics was assessed in two ways (see Table 2). First, pre- and post-tests were administered that consisted of 20 questions (six multiple choice and 14 open-ended short answer questions), which were intended to assess both declarative and conceptual knowledge of climate science. Students were given 20 minutes to complete each test. Second, after the two model activities (A1 and A2), the students completed the problem scenario assessment task (A3).

Figure 2 shows the experimental sequence. In each of the two classes there were 30 students, and the activities were carried out in pairs, for a total of 30 dyads. Students participated in a pre-test of their knowledge of climate science and complexity, which was repeated as a post-test. Students were paired in order to carry out the activities A1 and A2 with each of the two models, and the A3 assessment. Each pair was randomly assigned to one of two conditions (as explained above): (a) CGL where dyads had a low structure A1 followed by a high structure A2 for each model; and (b) GL where dyads had a high degree of structure for A1 and A2 for each model. Students were allocated 80 minutes for working with each of the two models and completing given activities. For six dyads, computer screen recordings were made and log files were collected of all NetLogo interactions and webcam audio and video recordings. Another phase of this overall research program is developing data mining techniques to analyze the NetLogo log files, which we then validate through qualitative analysis of the audio, video, and screen recordings we have of the learners.

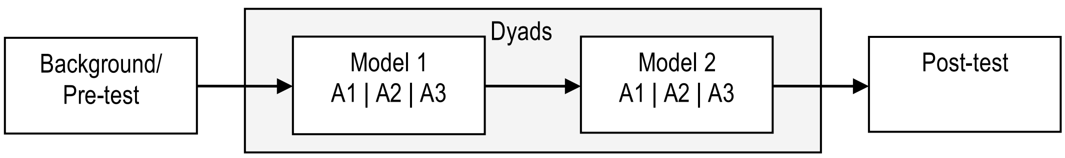

Figure 2. Experimental sequence.

Results

Due to student absences for the pre- and post-tests or for the two class periods in which models were used, the data analysis was carried out with 33 students who completed all tasks. Ten short answer questions related to scientific knowledge of climate change phenomena were coded using an adapted five-point knowledge integration rubric (see Table 3) that elucidates students' capabilities to make connections between different elements of the phenomenon (Gerard, Spitulnik, & Linn, 2010). One question did not have relevant responses (perhaps because of the wording of the question) and was removed, leaving nine questions. Initially, two coders each coded 60% of the results with a 20% overlap for reliability. Cohen's Kappa on this 20% was 0.64. Coders met to discuss discrepancies and coded the remaining results so that each coder had rated all of the results. Following discussion of discrepancies 100% agreement was reached.

Table 3
Knowledge integration coding scheme

Criteria	3	2	1	0	NA
Reasons	A full response that includes at least one scientifically valid connection	A partial response including at least one scientifically valid connection.	Partial response: unelaborated connections with relevant features.	Incorrect response or off-task	No response

These scores were scaled to a mark out of one hundred. Table 4 summarizes results. Taking into account the covariate of instructional method, there was a significant difference between the pre- and post-test scores of the students, $F(1,31)=9.367$, $p=.005$. However, repeated measures ANOVA on the summed short answer responses with a between-subjects factor of the CGL/GL grouping was not significant, $F(1,31) = 1.532$, $p = .225$.

Table 4
Pre- and Post Test Results

	N	Pre-Test		Post-Test	
		Mean	*(SD)*	*Mean*	*(SD)*
Challenge & Guided Learning (LH)	15	31.73	(15.81)	41.07	(14.38)
Guided learning (HH)	18	34.67	(12.27)	38.89	(13.22)
All students	*33*	*33.33*	*(13.84)*	*39.88*	*(13.58)*

The model problem solutions (A3) that the dyads worked on were similarly coded and scaled (see Table 3). Repeated measures ANOVA on the activity question responses with a between-subjects CGL/GL factor found no significant differences, $F(1,12) = 0.300$, $p = .594$.

Table 5
Results of Model Problem Solutions (A3)

	N (dyads)	Model 1 (Carbon Cycle)		Model 2 (Greenhouse Effect)	
		Mean	*(SD)*	*Mean*	*(SD)*
Challenge & Guided Learning (LH)	6	61.11	(16.39)	38.89	(18.26)
Guided Learning (HH)	8	55.21	(9.90)	37.50	(18.72)
All dyads	*14*	*57.74*	*(12.85)*	*38.10*	*(17.82)*

Qualitative observations by the research team during the sessions suggest that overall the students were very engaged and interested in working with the computer models. The teachers of the classes involved with the study also commented that they felt having the students learn climate change ideas using the NetLogo models seemed to be an effective and engaging approach for learning science.

Discussion and Conclusion

In terms of the implications of these findings for the research interest related to sequences of pedagogical structure, the participants in both the LH (Challenge and Guided Learning-CGL) and HH (Guided Learning-GL) sequences made significant learning gains. Although there were not significant learning differences between the two treatment groups, the main findings were actually in the hypothesized directions, with the LH group scoring higher on the model problem solutions (especially Model 1 A3) and on the posttest than did the HH group. We note that this study involved a relatively small sample size of just 33 with 12 participants in the CGL condition and 16 in the GL condition on the pretest and posttest results. We are planning future studies that will involve larger numbers of students by collecting data in additional schools, which should provide us greater statistical power to further investigate the aspects of the sequencing of pedagogical guidance for agent-based models and learning.

Still, given there have been few reported empirical studies of learning in this area, an important finding in this study is that on average all participants significantly enhanced their understand of important scientific knowledge about greenhouse gases and the carbon cycle. Our findings are consistent with theory and research discussed in Goldstone and Wilensky (2008). They propose in their paper that the representational affordances of agent-based models may activate the highly evolved visuospatial system of students to “perceptually ground” learning in ways that are impossible with equation-based representations that are generally used in teaching science. Indeed, they recommend that:

> simulations be designed or student-constructible so as to mesh well with idealized mental models. For transportable knowledge, realism is sometimes disadvantageous. Computer models, like their corresponding mental models, should be spatially–temporally grounded to take advantage of individuals' highly evolved perceptual capabilities but idealized in other respects to reduce cognitive load and increase generality. (p. 507)

From this perspective, we hypothesize the problems we had the student engage with activated a range of prior knowledge resources that the learners had about weather and climate systems (some relevant, some erroneous), and then the agent-based models allowed the learners to *perceptually* "see" phenomena that are beyond the every day experiences of people, from the visualizations of micro-level molecular behaviors of CO_2 and H_2O and electromagnetic radiation from the sun to macro-level emergent properties such as carbon concentrations in different aspects of the global climate system (e.g., atmosphere, ocean, vegetation, animals) and average global temperature at different atmospheric carbon levels that align with IPCC climate data. The representational affordances of the agent-based models (i.e., dynamic visualizations and graphical representations of quantitative information) provided perceptually grounded feedback that in turn help the learners construct mental models that were more aligned with scientific "idealized mental models." We plan to explore this hypothesis in future research through the use verbal protocols for individual students and discourse analysis for collaborative dyads in conjunction with screen recordings as students use our agent-based models, as well as data mining techniques we are developing in another phrase of our research.

Overall, this initial study in our four-year project demonstrated that students were engaged and enjoyed using NetLogo agent-based models to learn difficult scientific topics such as greenhouse gases and the carbon cycle. The project team and our main collaborating teacher have discussed enhancements and revisions that we will make in the computer models and how we might the sequence of a range of climate change concepts over a greater number of class periods (perhaps 6-8). We are also planning to investigate whether helping students to learn more general principles about complex systems might lead to deeper understanding of climate system concepts as well as enhancing far transfer, which is a conjecture that the first author and others (Goldstone & Wilensky, 2008; Jacobson, 2001; Jacobson & Wilensky, 2006). Overall, we hope that the results of this exploratory study into ways in which students may learn challenging conceptual knowledge about climate systems might contribute to the literature in this relatively new area of science education research.

Acknowledgements

The research discussed in this paper has been funded by grants to the first and third authors from the Australian Research Council Linkage program, LP100100594, and from the Curriculum Learning and Innovation Centre in the New South Wales Department of Education and Communities. We acknowledge the support from the teachers in the collaborating school. Also, we thank Dr. Kate Thompson for her work on the early development phase of this project. Finally, we greatly appreciate the feedback from our international collaborators on this project, Professor Uri Wilensky and Dr. Sharona Levy, on the NetLogo agent-based models we developed and on the overall program of research we are conducting.

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