The value of multiple representations for learning about complex systems

Kate Thompson, CoCo Research Centre, Building A35, The Faculty of Education and Social Work, The University of Sydney, Australia 2006, k.thompson@edfac.usyd.edu.au

Abstract: Multiple external representations are a well-researched strategy for understanding phenomena, however, they have yet to be empirically tested with respect to learning about complex systems, and specifically environmental education or learning from models. System dynamics models and agent-based models are tools used to represent complex systems. System dynamics models provide a top-down aggregated representation of a system with an emphasis on understanding time delays and feedback. Agent-based models provide a bottom-up representation, using animation, allowing system-level concepts to emerge from the interaction between individuals. Their joint use is becoming more common among scientists researching complex systems. This experimental study provides empirical evidence for the advantage of using multiple models with Year 9 and 10 students (novices in the use of either model type) to learn about a complex socio-environmental system.

Introduction

Multiple external representations (MER) are a well-researched strategy for understanding phenomena (Ainsworth, 2006), however, they have yet to be empirically tested with respect to learning about complex systems, and specifically environmental education or learning from models. System dynamics models and agent-based models are both well-known tools recommended for learning about complex systems (Jacobson & Wilensky, 2006). System dynamics models provide a top-down aggregated representation of a system with an emphasis on understanding time delays and feedback. Agent-based models provide a bottom-up representation, using animation, allowing system-level concepts to emerge from the interaction between individuals. Their joint use is becoming more common among scientists researching complex systems, and has been recommended for learning about environmental systems (Reimann & Thompson, in press; Wilensky, 2007).

This experiment compares the learning outcomes from students in four groups: a control group (Text group) in which students were exposed to a text-based description of visitor impacts on a national park, and three treatment groups, in which students were either given a system dynamics model to examine (SDM group), an agent-based model of the system (ABM group), or both of these combined (SDM & ABM group). In this study the multiple external representations are fully redundant, that is, the same information is able to be determined from all of the representations (de Jong et al., 1998), however the processes are different. Using Ainsworth & Van Labeke's (2002) functional taxonomy of multiple representations, and considering the inherently different representations displayed by the two model types (stock and flow diagrams in system dynamics models and animations in agent-based models), the guiding hypothesis is that: *a system dynamics model is too abstract for students, and an additional representation that constrained the understanding of the model (one that was familiar to the students, such as an agent-based model) will improve interpretation.*

Background

Learning from multiple external representations

The use of multiple external representations (MER) provides learners with an authentic learning environment because most experts, and scientists in particular, use multiple external representations to explain phenomena (Kozma, 2003). Specific information may best be conveyed in a particular type of representation (de Jong et al., 1998) and so to convey a range of information, a number of different representations may be needed. In addition, using MERs provides a safety net in case the student's reasoning process comes to a halt for some reason with a single representation (Savelsbergh et al., 1998).

MERs may serve one of three different functions (Ainsworth & Van Labeke, 2002): *complement*, *constrain*, and to *construct*. When representations contain different information or cognitive requirements, the representations *complement* each other, either by processes or information. In the *constraining* function, one representation is used to constrain any misinterpretations that may result from the other. This may be done by using something familiar to the learner (such as an animated representation) or by the inherent properties of the representation. The third function is when each representation is used to help learners *construct* a deeper understanding of the learning objective (Ainsworth, 1999b).

The learner's prior knowledge, both domain knowledge and representation knowledge, may also have an effect on learning outcomes. If learners are already familiar with either the domain or the representation, then there should be an increased ability to recognise the connection between the representation and the phenomenon represented (Ainsworth et al., 1998b; Seufert et al., 2007). Students with low prior knowledge were found to have problems relating different representations to each other, and were disadvantaged because of this (Bodemer & Faust, 2006; van der Meij & de Jong, 2006). The ability of students to correctly relate MERs to each other was associated with familiarity of the visualizations in the learning material (Bodemer & Faust, 2006).

Learners have to understand the syntax of each representation (novices may use representations inappropriately); which parts of the domain are represented; they have to relate the representations to each other; and they have to translate between the representations (this is particularly difficult for novices) (Ainsworth, 1999a; van der Meij & de Jong, 2006). Another challenge is the high cognitive load associated with the coordination of information from different representations (de Jong *et al.*, 1998). Regardless of cognitive load, some students still fail to coordinate between MERs (Ainsworth et al., 1998b).

Learning from models

A system dynamics model is one of the representations investigated in this study. "System Dynamics is a methodology for analysing complex systems and problems with the aid of computer simulation software" (Alessi, 2000, p. 1) and includes cause and effect relationships, time delays and feedback loops. Systems can be represented by *causal loop diagrams* and by *stock and flow diagrams*. Causal loop diagrams are useful for demonstrating feedback (Sterman, 2000). Feedback is a defining element of a complex system. Stock and flow diagrams represent the quantitative nature of the system. A stock is defined as a "quantity of something (such as the quantity of heat in a cup of coffee)" (Alessi, 2000). A stock is represented by a rectangle (see Figure 1). A flow is the rate of change of a stock (Alessi, 2000). Flows are represented by pipes into or out of a stock (Sterman, 2000). A valve can be seen on the pipe that controls the flow. The clouds at the ends of the flows represent the boundaries of the system. STELLA™ is the software used in this study, and is an object-oriented graphical programming language designed specifically for modelling dynamic systems (Costanza et al., 1998). Icons for stocks and flows (see Figure 1) are placed on the screen and connections between these are made.

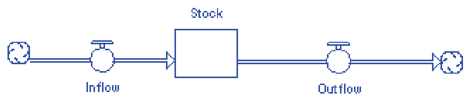


Figure 1. An example of a Stock and Flow Diagram (Sterman, 2000, p. 193).

Although much is written of the value of system dynamics modeling in education in schools, very little empirical data exists to confirm this (e.g. (Doyle et al., 1998)). Instead, case studies and anecdotal accounts from teachers who have used such models are available on the web (e.g. (Verona et al., 2001)). The Core models project was a large scale implementation of system dynamics modeling in a number of schools, and evaluation of the project, while focusing on teacher support, did find that students improved understanding of the scientific concepts underlying modeling, but not their ability to interpret the models (Maryland Virtual High School, 2001). Some studies have focused on university-aged students and examined how students mismanage systems (Moxnes, 1998), or learn about system dynamics concepts (Kainz & Ossimitz, 2002) rather than learn about the domain on which the model is based.

An agent-based model is the other representation investigated in this study. In agent-based modelling the focus is on the interaction between the *agents*, and their *environment*. An *agent* is defined as an object that controls its own behavior, and could be individuals of a species, individuals at a particular stage in the life cycle (a cohort), or a group of individuals that can be considered identical (Ginot et al., 2002). The rules that apply to the agents determine the behavior of the whole system, called *emergence*. By laying down the rules for the agents and the system, behavior may *emerge* that would otherwise not have been predicted (Bousquet & Le Page, 2004). NetLogo was used to build the agent-based model. The software is written in Java (Tisue & Wilensky, 2004), and is a hybrid compiler/interpreter. It also enables users to open simulations and experiment, exploring the effects of their decisions and was designed for use in both research and education.

When used in education, agent-based models allow students to explore the relationship between the agents' rules of behaviour and the patterns that emerge (Stieff & Wilensky, 2003). Students are able to make predictions and test them by exploring model outcomes as they manipulate variables (Stieff & Wilensky, 2003). The use of agent-based models in education "narrows the gap" between school biology and research biology (Wilensky & Reisman, 2006). The main advantage of using agent-based models is that students are able to employ their knowledge of the behaviour of individuals in the construction of theories about the behaviour of populations (Wilensky & Reisman, 2006). Agent-based models have been used in chemistry, biology and physics and have allowed students to make predictions, and connections between abstract and concrete concepts (Levy & Wilensky, 2005; Sengupta & Wilensky, 1999; Wilensky & Reisman, 2006).

System dynamics modelling is well suited to studying systems containing a complex web of feedback loops, and agent-based modelling is well suited to incorporating spatial and probabilistic aspects of the system, further, system dynamics models can be useful for conceptual understanding, and agent-based models for the representation of the processes (Wakeland et al., 2004). Agent-based models establish a link between the micro and macro level of the model, system dynamics models establish a link between the system structure and the system behaviour (Schieritz & Milling, 2003). These authors suggest that an integrated approach may help decision makers to be able to think of the two levels that are modelled at the same time.

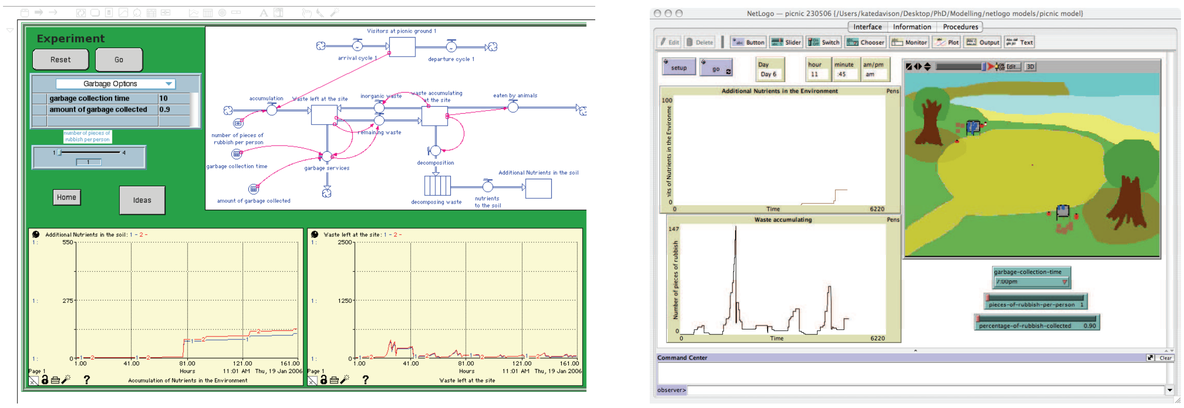
System dynamics models and agent-based models themselves are multiple external representations. System dynamics models include a stock and flow diagram, equations, graphs, tables and text. Similarly the agent-based model is a multiple external representation with the animation, code, text, graphs and tables. Thus, all the potential issues with multiple external representations apply to learning with system dynamics and agent-based models alone, as well as together.

This study uses text and a system dynamics model in order to determine whether learning about a complex system is enhanced by the addition of an agent-based model. An agent-based model may be useful when learning about a complex system because keeping a dynamic system in mind when resolving a localised problem can be challenging (Milrad et al., 2003). This is appropriate for the high cognitive load assumed to be involved with interpretation of new models with this level of complexity (Sweller & Chandler, 1994).

Methods

The models used in this study showed a National Park picnic area used by visitors for seven consecutive days (based on real data of the number of visitors per day (Davison, 2000)) (for a full description of the model see (Thompson & Reimann, 2007)) Both models contained sliders and items allowing students to input values for variables. Changing one variable allowed students to examine the extremes of any effects on the system. The other two variables were decisions that a park manager could make. Students were also able to see the stock and flow diagram (system dynamics model) or the animation (agent-based model), and two graphs. By observing the two graphs, students could see how the accumulated waste was increasing and decreasing as a result of their interaction and the time delay in the corresponding change to nutrients in the environment.

The system dynamics model was built using STELLA™. The user interface included a number of screens, the first of which was the *home* screen, an introduction to the model containing directions with regards to the other screens. The second screen was the *information* screen, containing the text information describing the system. The third screen was the *explore* screen, which allowed students to explore the model "step-by-step" using Stella's™ storytelling feature (isee Systems, 2007), or in full which provided students with the entire model. The final screen was the *experiment* screen, in which students could interact with the model (Figure 2).



System dynamics model — Agent-based model

Figure 2. System dynamics and agent-based models used in the study.

The agent-based model was built using NetLogo™. The combination of features seen in Figure 2 is typical for a NetLogo model with a graphics window, plotting window and sliders and buttons that students could manipulate (Stieff & Wilensky, 2003). Students using the agent-based model also had access to the *Information* screen (with a text description) and the *Procedures* screen (model code).

Students were given an environmental knowledge test and a system dynamics knowledge test as a *pre-test* and a *post-test* (for a full description of all instruments used see (Thompson & Reimann, 2007)). The environmental knowledge test contained questions related directly to the learning materials and questions that required students to apply the knowledge that was available in the learning materials to other ecosystems. The system dynamics knowledge test assessed general and applied system dynamics concept knowledge. General system dynamics concepts are important in the field of system dynamics, and prior knowledge may influence interpretation of a system dynamics model. In addition, assessment of these concepts after the treatment would also be useful to determine whether simple exposure would help to improve knowledge of these areas. The applied system dynamics questions asked students to identify a system from a stock and flow diagram.

27 students from two schools participated in this study. School 1 was an academically selective girls high school; students who participated from this school were in year 10. School 2, was a girls 7-10 middle school; students who participated from this school were in year 9. There were 5 students in the Text group, 6 students in the ABM group, 9 students in the SDM group and 7 students in the SDM & ABM group.

Due to the scheduling requirements at each school, the progression through the experiment was different for each. At school 1, students were introduced to the experiment and completed the background questionnaire, and one week later the remainder of the experiment was conducted. At this point, students were given 20 minutes to complete the pre-test, 20 minutes to look at the materials, and 20 minutes to complete the post-test, ten minutes to complete the final assessment and five minutes to complete the evaluation. At school 2, students were introduced to the experiment and completed both the background questionnaire and the pre-test during the first meeting. The following day students were given 20 minutes to examine the materials, and the remainder was as for school 1.

Results

Kruskall Wallis tests were carried out to compare independent data with more than two groups (learning outcomes between the four groups) (Field, 2005). Medians and ranges are reported on instead of means and standard deviations because of the non-parametric nature of the data. The proportion of students who scored more than 50% and the proportion of students who increased their score are also reported to get a sense of students' performance. The Wilcoxon signed-rank test was used to test the differences between the pre- and post-tests for environmental knowledge and system dynamics knowledge (Field, 2005). Spearman's rho was calculated to determine the significant correlations between learning outcomes for each group. Significant, positive correlations between pre-test scores and learning outcomes indicate those learning outcomes for which pre-test scores were related to the final answer. Between other learning outcomes, positive significant correlations suggest relationships between environmental knowledge and system dynamics knowledge

Environmental and system dynamics knowledge pre- and post-test scores

Table 1: Median, range of scores and proportion of students who scored more than 50% for the environmental knowledge and system dynamics knowledge pre-tests and post-tests for each group.

	Pre-test				Post-test				Pre-test vs. Post-test (T)
		Range		More than 50% score		Range		More than 50% score	
Group	*Mdn*	Lower	Upper	(%)	*Mdn*	Lower	Upper	(%)	
ABM									
EK	16.25	0	25	67	15.75	5.5	28	50	**2.5**[a]
SDK	3.5	0	10	33	6.5	0	10	67	**0.0**
SDM									
EK	11.5	2	31	44	15.5	3	24	44	17.0
SDK	1	0	7	11	2	0	7	22	8.0
SDM & ABM									
EK	14.5	2	20.5	43	17	10	22.5	86	**0.0**[*]
SDK	3.5	0	7	29	5	1.5	7.5	29	**0.0**
Text									
EK	14	7	27	40	19	12	27	80	**1.0**[a]
SDK	1	0	7.5	20	5	2	7.5	40	**0.0**[a]

Note. EK = environmental knowledge test. SDK = system dynamics knowledge test.
Bold typeface indicates large effect size ($r > | .50 |$)
[a]$p < .10$. [*]$p < .05$

Table 1 shows that the ABM group had the highest median pre-test environmental knowledge score and the Text group had the highest median post-test environmental knowledge score. The ABM group also had the highest proportion of students who scored more than 50% in the pre-test. The SDM & ABM group had the highest proportion in the post-test. Pre-test scores were not significantly different ($H(3) = 0.30$, $p = .96$). Similarly, post-test scores were not significantly different ($H(3) = 2.34$, $p = .51$).

The ABM and SDM & ABM groups had the highest median pre-test system dynamics knowledge score, and the ABM group had the highest median post-test system dynamics knowledge score. Only 33% of students scored more than 50% in the pre-test in the ABM group, but 67% scored more than 50% in the post-test. Pre-test scores were not significantly different when the groups were compared ($H(3) = 2.93$, $p = .40$). Post-test scores were also not significantly different ($H(3) = 2.16$, $p = .54$).

There was a large effect size associated with the comparison of the pre-test to the post-test environmental knowledge score in the ABM group (significant at $p < .10$). The range of scores for this group decreased between the pre-test and post-test, and the lower range of the scores was higher in the post-test than the pre-test. There was a non-significant difference between the pre- and post-test environmental knowledge scores for students in the SDM group. There was a significant difference and a large effect size associated with an increase in the median environmental knowledge score when the pre- and post-test scores were compared in the SDM & ABM group. There was a large effect size associated with an increase in the environmental knowledge score in the Text group (significant at $p < .10$).

There was a large effect size associated with an increase in the system dynamics knowledge score when the pre-test and post-test scores were compared in the ABM group. There was a non-significant difference between the pre- and post-test system dynamics knowledge scores for students in the SDM group. There was a large effect size associated with an increase in the median system dynamics knowledge score when the pre- and post-test scores were compared in the SDM & ABM group. There was a large effect size associated with an increase in the system dynamics knowledge score in the Text group (significant at $p < .10$).

Correlations between learning outcomes

Table 2: Correlations between learning outcomes in the ABM group using Spearman's rho.

	Pre-test environmental and system dynamics knowledge scores		Learning outcomes	
	EK_{pre}	SDK_{pre}	EK_{post}	SDK_{post}
ABM group[1]				
Pre-test environmental and system dynamics knowledge scores				
EK_{pre}	--			
SDK_{pre}	.60	--		
Learning outcomes				
EK_{post}	$.89^{*}$	.43	--	
SDK_{post}	$.83^{*}$	$.83^{*}$	.60	--
SDM group[2]				
Pre-test environmental and system dynamics knowledge scores				
EK_{pre}	--			
SDK_{pre}	-.29	--		
Learning outcomes				
EK_{post}	.47	.36	--	
SDK_{post}	-.16	.14	-.21	--
SDM & ABM group[3]				
Pre-test environmental and system dynamics knowledge scores				
EK_{pre}	--			
SDK_{pre}	$.79^{*}$	--		
Learning outcomes				
EK_{post}	$.93^{**}$	.60	--	
SDK_{post}	$.78^{*}$	.74	$.76^{*}$	--
Text group[4]				
Pre-test environmental and system dynamics knowledge scores				
EK_{pre}	--			
SDK_{pre}	$.98^{**}$	--		
Learning outcomes				
EK_{post}	.70	.56	--	
SDK_{post}	.70	.56	1.00^{**}	--

[1]$n = 6$, [2]$n = 9$, [3]$n = 7$, [4]$n = 5$

Note. EK = environmental knowledge score. SDK = system dynamics knowledge score. $_{pre}$ = pre-test score. $_{post}$ = post-test score

$^{*}p < .05$; $^{**}p < .01$

Table 2 shows that in the ABM group, students who had a higher pre-test environment knowledge score also had high post-test scores for the environmental knowledge and system dynamics knowledge tests. Similarly, students who had a higher pre-test system dynamics knowledge score had a higher score for the system dynamics knowledge post-test. In the SDM & ABM group, students who had a higher pre-test environmental knowledge score also had a higher pre-test system dynamics knowledge score. Students who had a higher pre-test environmental knowledge score had a higher post-test score for the environmental knowledge test and for the system dynamics knowledge test. Students who had a higher post-test environmental knowledge score had a higher system dynamics knowledge post-test score. In the Text group, students who had a higher pre-test environmental knowledge score had a lower pre-test system dynamics knowledge score.

Discussion

The guiding hypothesis was that: *a system dynamics model is too abstract for high school students, and an additional representation that constrained the interpretation of the model (one that was familiar to the students, such as the animated representation included in the agent-based model) will improve interpretation.*

Students in the control group increased both knowledge scores between the pre- and post-test. Students in all groups were given a text description, and due to the experimental design, it can be assumed that results calculated for treatment groups that differ from the control group may be a result of the treatment. Non-significant correlations between pre-test scores and learning outcomes indicated that the text had an effect on learning outcomes.

Agent-based models have been shown to be successful in allowing students to link multiple representations and levels to gain a deeper understanding of concepts, and is suited to representation of a process or a dynamic system due to the animation involved as part of the model (e.g. (Milrad et al., 2003; Stieff & Wilensky, 2003)). However, with these advantages comes a high cognitive load related to the extent to which the elements interact with each other (Sweller & Chandler, 1994), which may prevent links between the levels from being made by students. In the ABM group, increases in both knowledge test scores were reported. The results of the correlations support those of Ainsworth et al. (1998b) who suggested that if learners are already familiar with either the domain or the representation, then there will be an increased ability to recognize the connection between the representation and the phenomenon represented. In the ABM group, students who had higher pre-test scores for environmental knowledge and system dynamics knowledge scored highly on the post-test questions. It may be that prior knowledge facilitated students' exploration of the model so that students who had this knowledge were better able to improve their environmental and system dynamics knowledge scores.

System dynamics models are useful for conceptual understanding (Wakeland et al., 2004), they establish a link between the system structure and the system behaviour (Schieritz & Milling, 2003). Students have been shown to improve understanding of the scientific concepts underlying modelling, rather than their ability to interpret the models after a long-term intervention (Maryland Virtual High School, 2001). However, the high cognitive load involved in interpreting the abstract, scientific diagram may result in small learning gains (Lowe, 1993; Sweller & Chandler, 1994). In the SDM group, there was a non-significant difference between the pre- and post-test environmental knowledge test scores, and the system dynamics knowledge test scores. These results and those of the correlations indicate that the treatment had an effect on learning outcomes. Students who had high pre-test environmental knowledge and system dynamics knowledge scores did not have high post-test scores for these tests.

Students in the SDM & ABM group significantly increased their environmental knowledge score ($p < .05$). Significant increases were also noted in both the control group and the ABM group. By comparison with the lack of change in the SDM group, the increased score in the SDM & ABM group indicates that for students given a system dynamics model, the addition of an agent-based model provided students with an advantage with respect to environmental knowledge scores. Significant correlations between the pre-test environmental knowledge score and the post-test score indicated that students used prior knowledge in addition to the representation, as was suggested for students in the ABM group. Additionally, correlations between learning outcomes suggested that students were able to learn about both areas (environmental knowledge and system dynamics knowledge). A number of authors suggest that learners who are already familiar with either the domain or the representation, should have an increased ability to recognise the connection between the representation and the phenomenon represented (e.g. (Ainsworth *et al*., 1998a; Seufert et al., 2007)).

A large effect size was associated with an increase in the system dynamics knowledge score for students in the SDM & ABM group, and also in the control group and the ABM group. Comparison with the non-significant change in the SDM group indicates that for students given a system dynamics model, the addition of the agent-based model provided students with an advantage in terms of system dynamics knowledge scores. Correlations between knowledge scores suggest that the treatment may have had an effect on this score. It may be that students with higher prior environmental knowledge were able to concentrate on learning about areas not related to environmental knowledge (such as system dynamics concepts) covered by the materials.

Of those groups that were given a model, the SDM & ABM group was the most successful, in terms of a greater increase in their environmental knowledge score, and a similar increase in their system dynamics knowledge score to those in the ABM group. These results support the findings of many authors who suggest that using multiple external representations is a useful strategy for learning about a complex system (Ainsworth, 1999b; Savelsbergh et al., 1998).

Research on expert and novice use of representations for problem-solving may be relevant in explaining some of these results. It has been suggested that experts use pictorial and dynamic representations to evoke a recognition process allowing them to reason with the external representation rather than maintain the internal representation (Tabachneck-Schijf et al., 1997). The domain 'experts' in this study were able to use the multiple representations more successfully than the domain 'novices'. This difference in the use of single and multiple representations may indicate the difference between using the models to reason with, or as a mindtool, and to build mental models. Students with lower domain knowledge learned about particular areas, improving their mental model in one section. When given two models, these domain novices were able to use them, and were able to arrive at a similar level of knowledge of all three learning outcomes, but particularly improved knowledge about the environment. The domain experts may have been more successful in the final assessment task because they were able to link these areas together. This has implications for both environmental educators and system dynamics educators. The SDM & ABM group and the Text group provided a learning environment in which students with any level of prior knowledge could improve their knowledge about the environment.

This study had two main limitations. The first was the small sample size which is common in educational research, and in all relevant instances in this study, effect sizes were reported which take sample size into account. The sample size limits the generalisability of the study, and conclusions are limited to these experiments. The second was the short treatment time, 20 minutes is a short amount of time during which to expect learning to occur. For practical reasons, it was necessary for this study. However, the results do show that increases in knowledge scores and understanding can be achieved in a short amount of time. This is relevant for environmental educators who often have time restrictions in their programs.

The hypothesis has been supported, and students who had both the system dynamics model and the agent-based model had a greater increase in their environmental knowledge score than the other groups. However, the Text group also increased their system dynamics knowledge tests scores more than students in the other groups, and students in both the ABM group and the Text group increased their environmental knowledge scores (although to a lesser extent). These results do not provide any explanation of whether students were using the agent-based model to *constrain by familiarity* their understanding of the system dynamics model, or using the system dynamics model to *construct deeper understanding by abstraction* or *by relations* of the agent-based model. Differences in how students in these groups interacted with the models in terms of the strategies used (Levy & Wilensky, 2005) and the representational preferences of students may also help to explain differences between the learning outcomes.

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