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Teaching complexity in biology through agent-based simulations: the relationship between students' knowledge of complex systems and metamodeling knowledge

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Real-world complex systems research seeks to understand how systems in the world can follow the same rules of complexity. Scientists have found similarities in processes—such as self-organization, micro-to macro-level emergence, and feedback loops—in seemingly disparate phenomena such as the spread of infectious diseases and how traffic patterns are formed. Our project, BioGraph 2.0, was developed to respond to the issue of students' disjointed understanding of biology due to the fragmented nature of how high school biology is taught in high school classrooms. We hypothesized that by framing multiple biology concepts through the lens of complexity using dynamic simulations, or models featuring complex systems processes, students would be able to see complex systems as a unifying concept throughout biology. We built a series of units modeling phenomena on biological concepts such as gene regulation, ecology, and evolution using an agent-based modeling tool called StarLogo Nova. While previous research over the last decade of this project has highlighted students' growth in complex systems understanding, in this study, we explored the relationship between complex systems and agent-based models. We investigated pre and post intervention data from over 300 high school students to determine how their metamodeling knowledge influenced their understanding of complex systems. Through a regression analysis, we demonstrate that growth in students' modeling understanding significantly predicted growth in complex systems understanding. We further triangulate our findings with interview data from students who highlight the importance of the modeling tool to support their complex systems learning.

KEYWORDS

complex systems, modeling, agent-based simulation, biology, metamodeling knowledge

1. Introduction

The natural and social world that surrounds us is made up of systems that follow the rules of complexity (Servedio et al., 2014; Camazine et al., 2020). *Complex systems* can be defined as macrolevel patterns or structures that emerge from the activity of microlevel interacting agents (Yoon et al ., 2018a). Researchers from different disciplines have noted that, regardless of the kinds of agents (e.g., predator and prey) and the ontological phenomenon under investigation (e.g., ecosystems), complex systems are composed of web-like structures in which individuals follow rules (e.g., wolves eat rabbits; Chi et al., 2012; West, 2014; Bar-Yam, 2016). Complex systems also have intricate interdependencies and structures that exist at different scales (e.g., trophic levels in ecosystems; Bar-Yam, 2016). Because of this web-like nested structure, information travels in nonlinear ways, which makes understanding cause and effect in complex systems behaviors challenging (Grotzer and Tutwiler, 2014). Moreover, often the dynamics that fuel complex systems behaviors (e.g., feedback loops and self-organization) are hidden and take place over large time spans (e.g., evolution) or spatial scales (e.g., climate change), which limits what we can understand about the whole system at any point in time or place (Grotzer and Tutwiler, 2014).

It is not surprising then that students in K–12 education harbor misconceptions about systems. A number of empirical studies have shown that they tend to adopt a linear approach when thinking about the relationships among system components rather than recognizing their nested non-linear nature (Sweeney and Sterman, 2007; Gotwals and Songer, 2010; Riess and Mischo, 2010). For example, Gotwals and Songer (2010) found that students struggled with reasoning about how a disruption in one part of a food chain could impact changes in another part of the food chain that was not directly connected to it. These indirect relationships, as Chi et al. (2012) argue, are hard to comprehend because the perceptual apparatus through which we observe phenomenon is limited to the information about the system we have access to at a particular point in time. Another common challenge that researchers have discussed is the tendency for students to attribute an outcome to a central agent or cause (Penner, 2000; Taber and García Franco, 2010; Levy and Wilensky, 2011). Students are unable to recognize that often control in systems is decentralized and that structures or behaviors at macro levels emerge from micro-level system activities. For example, ecosystems are able to stay in equilibrium (macro-level pattern) because of the combined activities of micro-level components (e.g., predator–prey interactions). But even more fundamentally, in a series of studies, Ben-Zvi Assaraf and colleagues have found that students often struggle to accurately identify the components that comprise a system and how those components are interrelated or exist as an integrated whole (e.g., Assaraf and Orion, 2010; Assaraf and Orpaz, 2010; Assaraf and Knipples, 2022).

To address these learning challenges, researchers have posited that computational modeling tools such as agent-based simulations could provide access to structures and behaviors of systems to support sense making and have been researching their uses and affordances (Wilensky and Jacobson, 2015; Wilensky and Rand, 2015; Yoon et al., 2018a; Mambrey et al., 2022; Yoon, 2022). A majority of this research has examined learning of biological systems. In our recent systematic review of complex systems research in K–12 science education, we found that topics within the field of biology were investigated in 83% of studies (Yoon et al ., 2018a). Within these studies, agent-based simulations have been used to represent the complexity of biology systems in a more tangible and accessible format for students to explore complex systems thinking (Hmelo-Silver et al., 2017; Markauskaite et al., 2020; Housh et al., 2022; Jacobson and Wilenski, 2022; Yoon et al., 2022).

Models and modeling approaches have, in fact, received a great deal of attention in science education research due to their importance in conducting real-world scientific inquiry (NGSS Lead States, 2013). However, while learning and participation outcomes through the study of computational complex systems models have been generally understood to be positive, we found that only two studies in our systematic review (Yoon et al., 2018a) explored the relationship between instructional approaches that use complex systems models and student learning of complex systems. However, there is extensive research into how students conceive of models (e.g., Nicolaou and Constantinou, 2014; Nielsen and Nielsen, 2021). While content knowledge is important for working with models, so is metacognitive knowledge of models or metamodeling knowledge (Schwarz et al., 2009; Upmeier Zu Belzen et al., 2019; Chiu and Lin, 2022). This study explores how the instructional approach of agent-based models to represent complex systems afforded change in students' metamodeling and complex systems knowledge and the relationship between the two.

The research reported here builds on more than a decade of work in which we have explored the use of computational complex systems models to support teaching and learning in high school biology. We built a series of units modeling phenomena of biological concepts such as gene regulation, ecology, and evolution using an agent-based modeling tool (described in more detail below). In this program of research, we have explored various educational goals such as designing curriculum and instruction to support complex systems and biology learning (Yoon et al., 2016), professional development for classroom instruction (Yoon et al., 2017), building teachers' social capital for complex systems teaching (Yoon et al., 2018b), a learning progression for complex systems understanding (Yoon et al., 2019a), and supports for teacher community building to scale complex systems PD in online platforms (Yoon et al., 2020a,b). In this study, we address the need articulated in the review by Yoon et al. (2018a) for more studies that investigate the relationship between instructional approaches and student learning outcomes. Specifically, we investigated how students' understanding of biological models using the modeling tool influenced their understanding of complex systems. To this end, we ask the following questions:

1. To what extent did biology students' complex systems and modeling knowledge change over time?
2. To what extent is there a relationship between students' modeling knowledge and their complex systems understanding for biology systems?
3. What affordances of the modeling tool and process can explain this relationship?

2. Theoretical background

Knowledge and understanding of complex systems and scientific models are inextricably linked due to the nature of complex systems and the need to create models to understand and analyze them, however there is an additional need to understand how high school students perceive and utilize this link in building their complex systems knowledge. The Next Generation Science Standards (NGSS) emphasize the connection in combining the two into a single crosscutting concept, *systems and system models,* which is explained as "defining the system under study—specifying its boundaries and making explicit a model of that system—provides tools for understanding and testing ideas that are applicable throughout science and engineering" (NGSS Lead States, 2013, Appendix C, p. 1). As such, there is a need to explore how both complex systems and scientific models are conceived by students and how those conceptions might influence knowledge development across both areas and their combined real-world applications.

2.1. Dimensions of complex systems understanding

Within K–12 research, several conceptual frameworks have been applied to what has been generally called *systems learning* (Yoon et al., 2018a). Specifically in biology, three frameworks have been popular for providing the theoretical foundation to understand how students learn: (a) systems thinking; (b) components-mechanisms-phenomena (CMP); and (c) complexity from emergence. Briefly, *systems thinking* focuses on the interrelationships and interdependence of system structures, which first requires identifying the components that comprise the system (e.g., the boundaries) and then considering the dynamic relationships between the components (Assaraf and Orion, 2010; Assaraf et al., 2013). Thus, the focus is on understanding particular qualities of the system under investigation that are unique from system to system. Similarly, a CMP framing emphasizes components, connections, and behaviors that phenomenologically define a particular system (Hmelo-Silver et al., 2017). Researchers have investigated aspects of systems understanding in CMP categories, noting that instruction often only focuses on macro-level structural components (e.g., trees, oxygen) at the expense of learning about mechanisms or behaviors (e.g., photosynthesis, carbon cycle) that underpin the function of a system (e.g., Jordan et al., 2014).

The third characterization of systems learning—*complexity from emergence*—aims to apply common processes that fuel systems. Researchers from this tradition recognize that systems from within and between disciplines often exhibit similar characteristics (e.g., feedback loops, self-organization, nonlinearity) that happen in microlevel interactions to produce macrolevel patterns (Chi et al., 2012; Wilensky and Jacobson, 2015; Yoon et al., 2017). This framing of emergent behaviors from local (simpler) behaviors to global (more complex) structures has supported research in notable organizations, like the Santa Fe Institute, to investigate some of the worlds' most pressing problems such as disease epidemics and climate change. Our own work has taken this approach to learning about systems and has sought to understand how students reason through specific complex systems dimensions (Yoon et al., 2016, 2017) that include (a) the predictability of effects caused by small changes to the system, (b) the dynamism of the mechanisms and processes underlying the system, (c) the level of centralization of the organization of the system, and (d) the scale of the effects and capacities of the system (see Yoon et al., 2016 for more details). These four components are comprehended on a scale that ranges from, on one end, a clockwork framework of systems, in which systems are examined as individual parts, to, on the other end, a complex framework of systems understanding that acknowledges that the whole is greater than the sum of the parts. In other words, the properties of the whole complex system are properties that none of the parts have alone (Jacobson et al., 2011). In order for students to develop their understanding of complex systems, they must shift their ontological categories and move from a clockwork to a complex understanding of systems (Chi, 2005).

2.2. Scientific modeling and the importance of metamodeling knowledge

As the NGSS crosscutting concept *systems and system models* suggests, models and modeling are a vital part of science education but have also been identified as primary tools for achieving STEM integration (Kelley and Knowles, 2016; Hallström and Schönborn, 2019). As technological advances make computational models easier and more accessible, the ability to interpret these models is a driving factor for the integration of technology into other fields of science and engineering that, in turn, creates a need to include modeling as a component of STEM courses (Schwarz et al., 2009; Kelley and Knowles, 2016). To this end, numerous research studies have been conducted to understand and measure how students conceive of scientific models (e.g., Schwarz et al., 2009; Louca and Zacharia, 2012). The knowledge to understand and work with models, to create models within scientific practice, and to apply that knowledge to authentic context is often referred to as modeling competence (Upmeier Zu Belzen et al., 2019; Nielsen and Nielsen, 2021; Chiu and Lin, 2022). In a systematic review of empirical research on assessing modeling competence, Nicolaou and Constantinou (2014) found that modeling competence falls into two primary categories—namely, *modeling practice,* which is the ability to create and use models, and *meta knowledge of models* (also referred to as *metamodeling knowledge*), which is the understanding of the purpose, process, and use of models. This second category, meta knowledge of models, refers to the epistemological awareness about the nature and purposes of models and modeling, which is a form of metacognitive knowledge (e.g., Grosslight et al., 1991; Schwarz et al., 2009; Fortus et al., 2016; Upmeier Zu Belzen et al., 2019; Lazenby et al., 2020) rather than cognitive knowledge of the modeling process. In this project, students did not create their own models but instead engaged in activities that highlighted the utility of the modeling process to interpret simulated biological phenomenon. Thus, we use metamodeling knowledge as a measure of students' understanding of scientific modeling.

In a highly cited article based on their work on the Modeling Designs for Learning Science (MoDeLS) project, Schwarz et al. (2009) sought to develop a set of learning progressions for metamodeling knowledge. They identified three components of metamodeling knowledge: nature of models, purpose of models, and the criteria for evaluating and revising models. The *nature of models* component includes an understanding that models are an abstract rather than literal representation of real-world phenomenon and that different models have different advantages and limitations. *Purpose of models* includes an understanding that models are a tool to advance knowledge about the world and specific phenomena (e.g., for explanation or for prediction). Finally, there should be an understanding that models change based on information that is generated from accumulated empirical data. Thus, the component of *change* as an essential criterion for evaluating and revising models is an important aspect of metamodeling knowledge (Grosslight et al., 1991; Gogolin and Krüger, 2018; Upmeier Zu Belzen et al., 2019).

In comparing student metamodeling knowledge to that of experts, three levels of thinking about models have been identified (Grosslight et al., 1991; Upmeier Zu Belzen et al., 2019). In Level 1 thinking, models are viewed as exact replicas of reality and are assessed based on whether they "correctly" illustrate reality. In Level 2 thinking, models are understood to have a purpose that dictates the nature of the model. The model can be used to communicate something about the already known reality it represents, but the main focus is on the model itself rather than the underlying ideas. A Level 3 understanding identifies models as part of the scientific process from which data can be collected and analyzed. Gogolin and Krüger (2018) found that most high school students have a Level 2 understanding of the nature of models and a Level 1 understanding of the purpose of models, though with some variation across grade level and context. They noted that only a handful of students reached Level 3 understanding about the nature and purpose of models and theorized that this was due to a lack of emphasis on models as tools for hypothesis and prediction within classroom instruction. As models are becoming more ubiquitous in science classrooms and are an integral tool for learning about complex systems, there is a need for a more explicit focus on promoting understanding of scientific models across contexts at the high school level (Nicolaou and Constantinou, 2014; Gogolin and Krüger, 2018; Upmeier Zu Belzen et al., 2019; Lazenby et al., 2020).

2.3. Complex systems modeling

Scientific computational models such as agent-based simulations can help the process of developing systems thinking and an understanding of complexity by enabling students to dynamically observe the interactions and interdependencies of individual parts and emergent system-wide patterns as they develop over time (Chi, 2005; Jacobson et al., 2011; Markauskaite et al., 2020; Yoon et al., 2022). Several studies have been conducted on complex systems modeling using agent-based simulation tools such as NetLogo and StarLogo Nova (e.g., Hmelo-Silver et al., 2017; Yoon et al., 2017; Markauskaite et al., 2020). The use of the agent-based modeling simulation StarLogo Nova allows for three different representations of the complex system being modeled: first, a visual representation of the interactions of the complex system model; second, mathematical representations of specific outputs over time; and, finally, the blocks-based code representation used to build the model (see Figure 1). It has been shown that multiple representations of the same system can support students' understanding of the system (Jacobson et al., 2011; Ryu et al., 2015; Hmelo-Silver et al., 2017).

In our previous research, we have shown that the use of biological agent-based simulation in StarLogo Nova led to improvement in both biology and complex systems understanding (Yoon et al., 2017, 2020b). These findings are supported by the work of others, which showed that agent-based simulations of complex systems support the development of students' understanding of complexity (e.g., Jacobson et al., 2011; Hmelo-Silver et al., 2017). Hmelo-silver et al. (2017) found that the use of an agent-based computational model of an ecosystem led students to a deeper understanding of the causal mechanisms within a complex system compared to students in a control group who did not engage with models. However, a CMP framework for complex systems understanding only focuses on macro-level structural components and does not consider understanding of complexity from emergence. Additionally, the study measured modeling practice against complex systems knowledge, rather than focusing on metamodeling knowledge. Similarly, Markauskaite et al. (2020) examined modeling practices in connection with a specific complex system of climate change but focused more on the content knowledge connections than generalizable components of complex systems knowledge. This suggests there is space for more research into the explicit nature of the relationship between students' metamodeling knowledge and their knowledge of complex systems (Markauskaite et al., 2020) and how the affordances of the models support growth in understanding of complexity.

3. Methods

This is a mixed methods study that combines qualitative coding and analysis of open-ended responses with quantitative analysis of the coding in order to explore the relationship between students' knowledge of modeling and knowledge of complex systems.

3.1. Intervention details and study parameters

This study is part of a long-standing program of research that has sought to increase engagement with and understanding of biology systems through the design and dissemination of a curriculum to teach common topics in high school biology through agent-based complex systems models. The curriculum is built around the computational modeling tool StarLogo Nova. The curriculum includes five units, each of which utilize their own complex system model, and each of which focuses that model on a particular topic typically taught in high school biology: genetics, evolution, ecology, the human body, and animal systems. They entail working with the scientific models to engage in core scientific practices as outlined in the NGSS, such as analyzing and interpreting data, engaging in argument from evidence, and obtaining, evaluating, and communicating knowledge claims. The student and teacher materials for the units engage learners with the nature and purpose of models by asking students to make predictions about what will occur in the system and then having them change the model parameters to test and observe what happens. Figure 2 presents a page from the student activity packet for the human body model; students are asked to observe the model, predict what the model will do using different input conditions, and then run the model with different conditions and record what the model does. Students normally worked in groups of two to complete the units, each of which take 2 to 3 days to complete. The program of research has been published on extensively; see previously published work for more details on the context of the program (e.g., Yoon et al., 2019b; Yoon, 2022).

This study encompasses data collected during the 2019–2020 and 2020-2021school years. The project shifted from an in-person format for teacher recruitment and training to an online format in 2018; 2019 was the first year that the program was fully accessible online for teachers to participate in training. It is important to note that the Coronavirus pandemic began during spring of 2020 and, as a result, the context of classroom implementation shifted across the time period of this study, as many teachers switched from in-person to hybrid or fully remote learning.

3.2. Participants

One of the goals of the larger study was to understand the efficacy and effects of the curriculum across different contexts. As such, this study involved eight teachers from five different schools in two countries (U.S. and India). These teachers were chosen from the larger group of 42

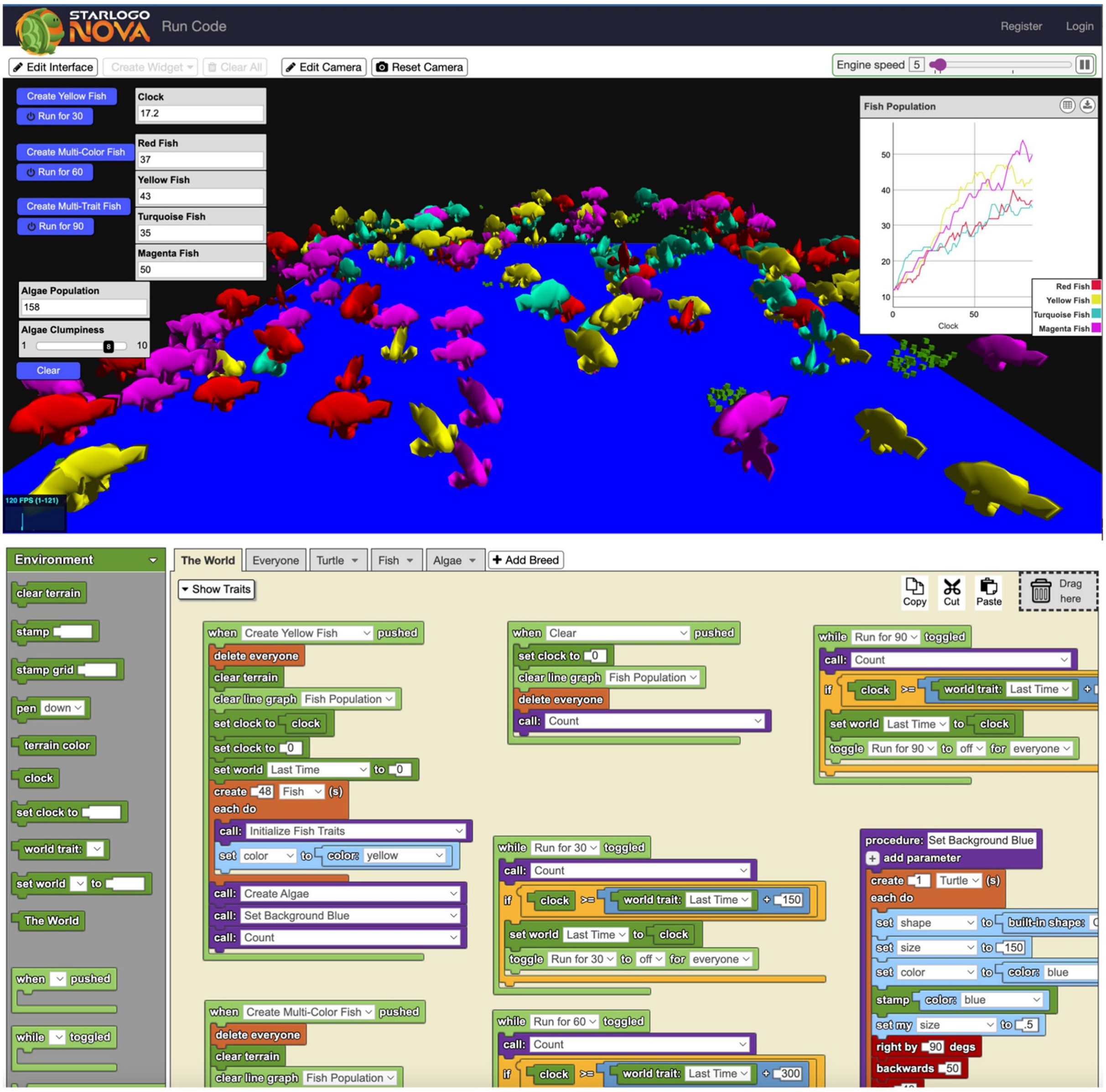


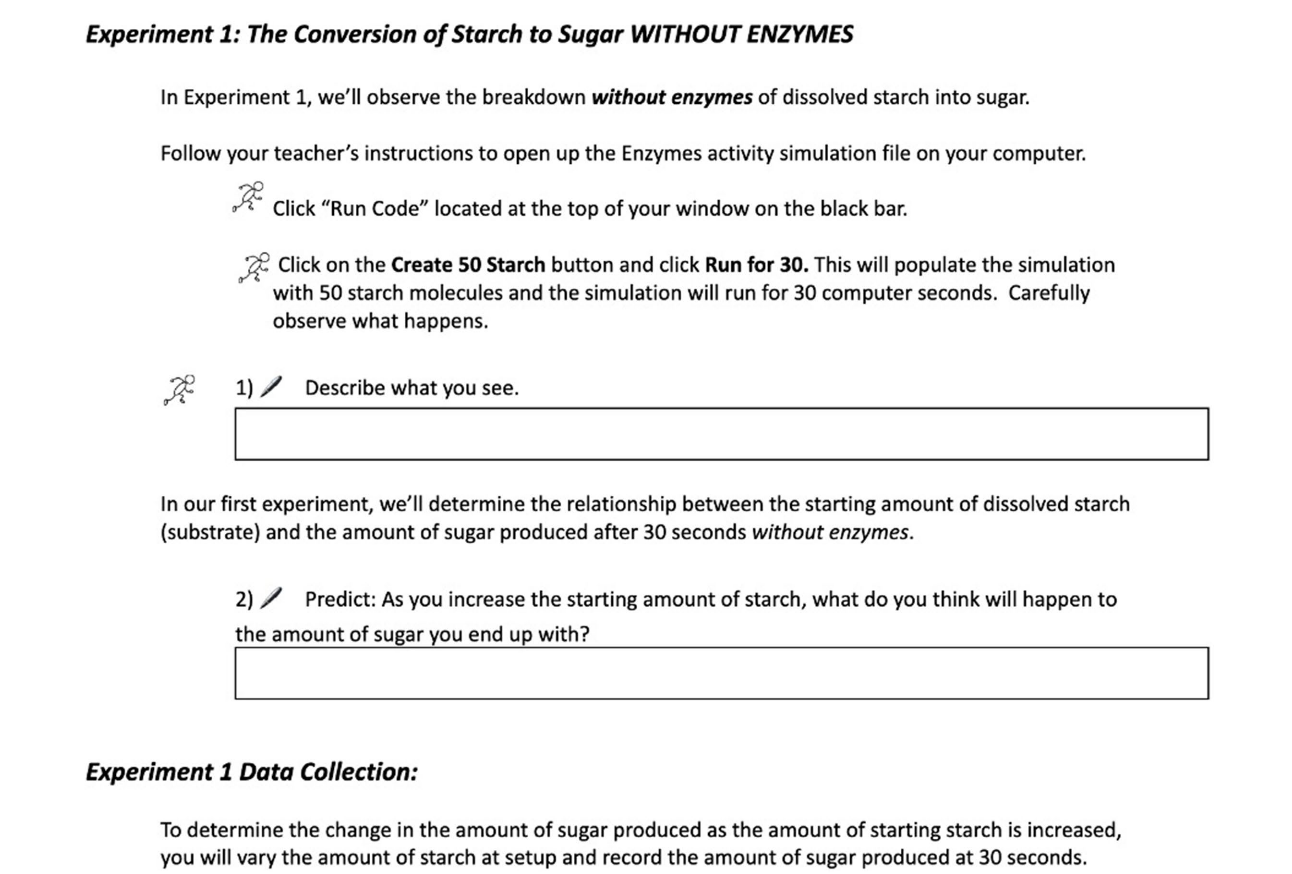
FIGURE 1
StarLogo Nova Interface: Model on Evolution. The top image shows the simulations of the fish interacting in the virtual environment. The mathematical representation can be seen in the top right in the form of a time-series graph, and the bottom half of the figure depicts the code used to build and run the simulation.

teachers who completed the online training course in 2019 based on several parameters, including their high level of engagement with the PD course, their commitment to implementing at least three of the five modules throughout the school year, their student populations and the degree of survey completion, and their interest in and enthusiasm for participating in the study. Ultimately the primary reason for selection was the teachers' agreement to participate in the research. The study encompasses 2 years of implementation. Three of the eight teachers implemented the curriculum in both years of the study. The teachers all identified as female, and their teaching experience ranged from 3 to 28 years in the classroom. A summary of the teachers' descriptive statistics can be found in Table 1. Each of the participating teachers implemented at least three of the units; therefore, the participating students worked with at least three different agent-based simulations of complex systems.

A total of 369 students participated in this study. Descriptive statistics for the student participants can be found in Table 2. Most of the teachers implemented the curriculum with ninth-grade students; however, a few of the classes were mixed grade and therefore included upper classmen.

3.3. Data sources

To investigate our research questions, survey tests of students' pre-and post-implementation complex systems knowledge and metamodeling knowledge were conducted in both years, and student focus group interviews were conducted in Year 2 to further probe the relationship between modeling and complex systems knowledge.



Experiment 1: The Conversion of Starch to Sugar WITHOUT ENZYMES

In Experiment 1, we'll observe the breakdown ***without enzymes*** of dissolved starch into sugar.

Follow your teacher's instructions to open up the Enzymes activity simulation file on your computer.

Click "Run Code" located at the top of your window on the black bar.

Click on the **Create 50 Starch** button and click **Run for 30.** This will populate the simulation with 50 starch molecules and the simulation will run for 30 computer seconds. Carefully observe what happens.

1) Describe what you see.

In our first experiment, we'll determine the relationship between the starting amount of dissolved starch (substrate) and the amount of sugar produced after 30 seconds *without enzymes*.

2) Predict: As you increase the starting amount of starch, what do you think will happen to the amount of sugar you end up with?

Experiment 1 Data Collection:

To determine the change in the amount of sugar produced as the amount of starting starch is increased, you will vary the amount of starch at setup and record the amount of sugar produced at 30 seconds.

FIGURE 2
Student Activity Packet: Enzymes in the Human Body.

TABLE 1 Teacher descriptive statistics.

Teacher	School	Country	Years of teaching experience*	Year implemented	# Students 2019–2020	# Students 2020–2021
1	A	India	28	2019–2020	7	
2	A	India	15	2019–2020	26	
3	B	India	20	2019–2020	10	
4	C	U.S.	7	2019–2020	14	
5	C	U.S.	13	2019–2020, 2020–2021	51	33
6	D	U.S.	8	2019–2020, 2020–2021	46	58
7	D	U.S.	5	2019–2020, 2020–2021	36	57
8	E	U.S.	3	2020–2021		31
Total					190	179

*At end of 2019–2020 school year.

Students completed two surveys pre-implementation and two surveys post-implementation. Though the surveys contained the same questions, they were administered 9 months apart, to mitigate the effects of item exposure. The first survey consisted of one open-ended question to measure their knowledge of complex systems (i.e., "Imagine a flock of geese arriving in a park in Philadelphia, where geese have not lived before. Describe how the addition of these geese to the park may affect the ecosystem over time. Consider both the living and nonliving parts of the ecosystem."). The second survey included three open-ended questions about scientific models. These were: (a) How would you describe what a scientific model is to someone who did not know what a model is?; (b) Describe what models are used for and how they could be used in science; and (c) What, if anything, would cause a scientist to change a model of a scientific concept? These three prompts about models were designed to solicit understanding of the three components of metamodeling knowledge (Schwarz et al., 2009).

In Year 2, which was taught mostly remotely or through hybrid remote and in-person learning, virtual semi structured focus group

TABLE 2 Student descriptive statistics.

Student characteristics	2019–2020 cohort	2020–2021 cohort
Number of students	190	179
Gender		
Male	84	75
Female	98	101
Nonbinary	0	1
Other	1	0
Grade		
8th	NA	1
9th	126	156
10th	33	7
11th	6	3
12th	20	11
Nationality		
United States	147	179
India	43	NA
Ethnicity		
White	74	97
Black	4	7
Asian & Pacific Islander	91	51
Hispanic	4	7
Multi-ethnic or other	9	14

Bold values are the combination of Years 1 and 2.

interviews were conducted over Zoom with one or two groups of three to five students from each class for a total of six focus group interviews across the four teachers participating in Year 2 implementation. These interviews sought to explore how students experienced the models in relation to their understanding of complex systems and conduct deeper exploration into the affordances those models and the process of modeling provided in order to more fully answer the third research question. Some example questions from these interviews include: Based on your understanding of biological systems, what characteristics do they exhibit, and *how* do you know this from the models? and What do you think are characteristics of good scientific models or explanations in terms of helping you learn or understand the science behind them? These interviews ranged in length from 52 to 66 min and were recorded and transcribed for analysis.

3.4. Data analysis

Analysis for this study was conducted using a mixed methods approach that combined qualitative and quantitative strategies for measuring student learning of scientific models and complex systems.

3.4.1. Coding of students' complex systems and metamodeling knowledge

Three separate rounds of qualitative analysis were conducted on the data for this study: coding of the open-ended responses on content knowledge for complex systems; coding of the open-ended responses on metamodeling knowledge; and mining of interview transcripts for information that supported the findings from the coding and quantitative analyses.

The coding manual used for coding the complex systems open responses has been reported on previously (see Yoon et al., 2016, 2020b). The coding manual was originally constructed from theories presented in Pavard and Dugdale (2000) and refined based on Jacobson et al. (2011) and through over a decade of use in studying complex systems understanding. The manual consists of four components each scored on the level of understanding as 1 (clockwork), 2 (emerging complexity), or 3 (complex) for a possible total score from 3 to 12. Table 3 presents descriptions of the components and example responses from students at the clockwork and complex levels of understanding. For example, the student response provided below is an example of a Level 3 (completely complex) understanding in the component of predictability because the student lists many different options for potential directions the ecosystem could take and uses the word "could" to show unpredictability:

> *Since the geese arrive at a place they haven't ever been before, there are many ways they can affect the ecosystem and it is impossible to say exactly how. For example, they could drive other birds away so that they can lay eggs. They could drive other birds away because they compete for the same kind of food. They could cause the increase of other animals who feed on geese. They could cause the increase of other birds because the geese have become an alternative food source for existing predators. It's really hard to tell.*

However, despite representing completely complex thinking for predictability, this response also depicts a Level 2 (emerging complexity) understanding for the other three components. For example, while acknowledging the existence of other species with agency in the ecosystem, the response is still centered on the geese as the central driving factor in the changes that occur in the system, which is scored as a Level 2 understanding in the category of order.

Responses to the complex systems survey were coded by three members of the research team in two rounds, one for each year of the study. As there were two responses that needed coding for each student (pre-and post-test), there were 380 responses from Year 1 and 358 responses from Year 2. One of the researchers was involved in coding responses from previous iterations of the project and conducted training on the codebook for the other two researchers. After multiple rounds of test coding, an inter-rater reliability test was conducted on 80 responses (21%), and a Cronbach alpha correlation coefficient of $\alpha = 0.863$ was achieved, which represents good reliability (Stemler and Tsai, 2008). After the disagreements were discussed and resolved, the remaining responses were divided evenly among the three researchers for coding. For Year 2 coding, the three researchers reconvened about 9 months later and conducted a second inter-rater reliability test on 72 of 358 responses (20%) from Year 2 and received a correlation coefficient of $\alpha = 0.858$. The disagreements were again discussed and resolved, with the remaining responses divided evenly among the three researchers for coding.

The coding manual for the modeling responses was adapted from prior work conducted on measuring metamodeling knowledge (Grosslight et al., 1991; Schwarz et al., 2009; Fortus et al., 2016; Gogolin and Krüger, 2018; Lazenby et al., 2020). Responses were scored on a scale of 1 (models as copies of reality) to 3 (models as tools for understanding and predicting reality) for each of three different

TABLE 3 Properties of complex systems knowledge.

Complex systems components	Descriptions	Level descriptions and example responses
Predictability	The emphasis is on the predictability of the effects caused by the agent in question. In a complex framework, it is impossible to precisely anticipate the behavior of the system. This is because the actions of agents cannot be predicted (as random forces or chance factors can affect an agent's actions) even if we know the rules or characteristics of the agent.	*Level 1: Clockwork – Agent actions/effects are predictable.* No alternative possibility is offered in the response. Certain words may hint at predictability of the effects of agents: "will," "is going to lead to/cause." Example: *When the geese are there, I think that it would greatly affect the people who go there. A lot of people would leave because of the bird poop.* *Level 2: Emerging Complexity – Agent actions/effects are largely predictable consider alternative possibilities.* The tone of the response indicates that agents' effects are somewhat predictable. However, some randomness in the system is suggested. More than 1 alternative is offered, or the answer has a minimum of two instances that indicate uncertainty in the outcome (e.g., the use of "probably" or "maybe"). Example: *If the geese arrive, they would probably help the ecosystem. The bird droppings might make the soil fertile [1st alternative]. It would start to look a lot greener. However, the increase of plants and roots might cause paths or walkways to be damaged [2nd alternative].* *Level 3: Complex – Agent actions/effects are unpredictable.* There are many alternative possibilities suggested in the response. Certain words discuss the unpredictability of the effects of agents: "may," "perhaps," "maybe," "evolve." Example*: Since the geese arrive at a place they have not ever been before, there are many ways they can affect the ecosystem and it is impossible to say exactly how. For example, they could drive other birds away so that they can lay eggs. They could drive other birds away because they compete for the same kind of food. They could cause the increase of other animals who feed on geese. They could cause the increase of other birds because the geese have become an alternative food source for existing predators. It's really hard to tell.*
Processes	The focus is the dynamism of the mechanisms that underlie the phenomena (i.e., how the system works or is thought to work). In a complex systems framework, there is no definite beginning and end to the activity. System processes are ongoing and dynamic.	*Level 1: Clockwork – Characterized by static and punctuated events* Response indicates that the system is composed of static events. While perturbations (actions by/on parts) in the system may cause change to occur, the change terminates once an outcome is achieved (i.e., there is a definite end). Example*: When geese arrive in the park, it would greatly affect the people who go there. A lot of people would leave because of the amount of bird poop. People would also leave because of all the birds flying around. The statues in the park would be corroded and fall off, which also cause people to leave.* *Level 2: Emerging Complexity – Somewhat static but recognizes that changes occur over a long period of time.* Response indicates that the system reflects some continual movement, fluctuations, and changes. There is indication of various components in the system increasing and decreasing. Responses that include a word or phrase that indicate a significant passage of time, such as "over time" or "eventually" would also warrant a level 2 code. Fundamentally however, there is an end. Example: *Geese may chase off other animals which could stop geese from eating the food they normally eat. These animals would have to adapt [dynamic – signals emerging complexity] or die. The other animals in the park will have to fight with the geese for food, and shelter. Once a species wins [suggests an end], the other types of animals may move away or die [possible end].* *Level 3: Complex – Continual state of activity and fluctuation to maintain balance* Response indicates that the system is an ongoing, dynamic process. Perturbations cause changes to the system, and the system continues to be in a state of flux (i.e., continual, and reoccurring changes happening to the system). The parts adapt or evolve and continue to do so accordingly. There is a sense that despite these changes, the system is maintained. Example: *The geese would eat some animals to survive. This may increase the competition for the same food with other animals. The other animals may leave the park to seek greener pastures. They and the geese may also simply starve, and their populations decrease. However, over time, with more geese in the park, the amount of nutrients in the soil is likely to increase as there is more decaying matter (feces and dead geese). This allows the park to support more producers and consumers. At the same time, overcrowding may occur. The lack of space may again decrease the populations.*

(Continued)

TABLE 3 (Continued)

Complex systems components	Descriptions	Level descriptions and example responses
Order	The focus is the organization of the system or phenomenon as centralized or decentralized. In a complex systems framework, control is decentralized and distributed to multiple parts or agents. Order in the system is self-organized or 'bottom-up' and emerges spontaneously.	*Level 1: Clockwork – Central agent has the power or force to impose order on the system* Response indicates that the system is perceived to be controlled by one central agent (i.e., all action is dictated by a leader). Order in the system is established 'top-down' or determined with a specific purpose in mind. Example*: Since the geese have not lived in the park, they probably do not know where to get food from. No goose from the population would be able to tell the rest [a central actor] so there is little effect of geese on the park ecosystem.* *Level 2: Emerging Complexity – Order of the system is distributed amongst several agents.* Response indicates that the system is largely perceived to be controlled by at least 2 agents but that these agents dictate how the system behaves. Thus, order in the system is still established 'top-down' with a specific purpose in mind. Example: *When the geese [a central actor] are there, it would affect the people who go there. A lot of people would leave because of the amount of bird poop, and the birds are constantly flying around. All the fountains and benches would be corroded by the bird poop, and since there are so much poop around, there would be more flies. The predators [a central actor] that usually hunt the geese would move to that area too.* *Level 3: Complex – Numerous agents* Response indicates that the system is decentralized (i.e., there is no central agent controlling the system). (Response indicates at least 3 agents.) Order in the system is self-organized or 'bottom-up' and emerges spontaneously. Example*: When geese come to the park, they will eat most of the grass. There will be a decrease in the food that geese eat. The caterpillars and the other grass-eaters will starve, die or move to another place. This means the decomposers will have less to eat, and probably decompose any dead geese faster. The soil may have less nutrients and the trees may grow less green.*
Emergence and scale	Emergence refers to the phenomenon where the complex entity manifests properties that exceed the summed traits and capacities of individual components. In other words, these complex patterns simply emerge from the simpler, interdependent interactions among the components. In a complex system, because parts or agents are interdependent in multiple ways, an action (small or large) that is imposed on the system may have large and far-reaching consequences on the numerous parts and agents of the system. This may in turn result in large-scale change and evolution.	*Level 1: Clockwork* Response indicates that (a) the parts of a system are considered to be isolated, where there is no interdependency among them; and (b) there is a sense that the action causes localized changes only. Example: *The geese are staying because they probably have a good resource of food here. The number of bugs will therefore decrease.* *Level 2: Emerging Complexity* Response indicates one complex component of emergence: either (i) a small action creates a large effect (scale) OR (ii) initial action has a cascading effect on several components of the ecological system that indicates interdependence, for example a change in the food chain (emergence) Example: *The geese arrival would drive the other birds away so they can lay eggs. There would be less worms that geese eats. People may see the geese and try to feed them. A lot of these things can fall into the lake and cause the fish to eat them and they may die. (Interdependency is evident between geese and worms, geese and fish, geese and other birds, etc.)* *Level 3: Complex* Response indicates that (a) the parts cannot be understood by decomposing them from the larger system because of their interdependency in multiple (2 or more) ways; and (b) there is a sense that the action can produce both localized changes and cascading effects (small actions → large effects). Example*: The geese will probably help the ecosystem. First, their droppings might make the soil more fertile, and plants will grow better. There may be more O2 as a result. The result of O2 and plant increase could cause a wet and warm ecosystem. However, geese may also eat most of the grass. Other grass-eaters will die or move. This would mean that the decomposers will have less to eat. The soil may have fewer nutrients, and the trees will grow less well. The geese may also damage statues with their droppings.*

dimensions of metamodeling knowledge (Schwarz et al., 2009). These dimensions are listed and explained in Table 4. The responses to three separate open-ended questions were combined into a single response for coding, and codes of 0 were allowed for responses that consisted of "I do not know" or blank answers for one of the dimensions. Therefore, total possible scores ranged from 0 to 9.

To explain the coding in a little more detail, below is a sample response from a student:

> *I would describe [a scientific model] as something that shows or represents in detail what the science is trying to show. Models are used to visualize things and to get a better look and understanding.*

TABLE 4 Properties of metamodeling knowledge (MMK).

MMK property	Description	Level descriptions and example responses
Nature	The "nature of models" property represents how a model is conceptualized. This includes how literal models are believed to be and how general or specific they can be.	*Level 1*: Models are literal replications of a single phenomenon that can be perceived by human senses. At this level, a model is believed to be "correct" or "wrong" based on its adherence to reality. Example: *"A model is a miniature replica of the original concept aiming to provide a better understanding about the concept. It is a detailed visual representation."* *Level 2:* Models are idealized representations of a phenomenon that may not be accessible to the human senses. Though models might not be literal replications of reality, they are based entirely on existing data from reality. At this level, models are understood to be created by a modeler with a purpose that dictates certain choices about how the model represents reality. Example: *"A scientific model is a model used to describe a scientific process of concepts. It can either be either physical or virtual but in some way, it will model either the concept of the process that it was supposed to represent."* *Level 3:* Models are a reconstruction of a phenomena (or a series of related phenomena), based on theoretical understanding, data, and hypothesis. Importantly, at this level there is an understanding that models can extend beyond rigid adherence to existing data and can include hypothetical theories. At this level, models are known to represent multiple interrelated systems or phenomena. Example: *"A scientific model is a creative representation or formulation of an idea that is created in order to analyze how that idea would fit into the real-world using evidence and scientific knowledge."*
Purpose	The "purpose of models" property represents the reason for a model's existence and what can be achieved with it. This includes the way it is used to communicate and to conduct predictions or discover new information and understanding.	*Level 1:* Models are used to demonstrate how something looks or operates on a superficial level. Their purpose is to describe only. Example: "*Models are used to visually show about the real thing*." *Level 2:* Models are used to explicitly highlight underlying mechanisms or key concepts within a phenomenon. This differs from Level 1, where representations aim for superficial replication and direct representation of the overall phenomenon. At Level 2, models have been shifted from direct visual replications of reality to communicate something specific about how the phenomenon functions. Example: "*It is a representation of a concept or system of ideas used to provide further explanation or clarification. Models are used for organizing ideas and explanations to understand systems or complex ideas in science. They could be used by a presenter or scientist explaining ideas to another, or to simply record discoveries.*" *Level 3*: Models are used to interpret or predict the process or outcome of a phenomenon or system. The purpose of models is to serve as a thinking aid to guide the construction and interpretation of data. Models can lead to new understandings and hypotheses. Example: "*Scientists use models to identify patterns in the world. Based on their knowledge with these models and scientific knowledge they can make predictions on future patterns.*"
Change	The "changeability of models" property demonstrates how and when a model could or should be changed and the reason or purpose for doing so.	*Level 1:* Models may be changed if there is something wrong with them, if errors are found, or if the model is not communicating effectively. There is one "correct" model. Example: *"If their model was incorrect or not used properly."* *Level 2:* Models may be changed if new data or information is discovered about the underlying phenomenon. At Level 2, responses may be referring to the process of aligning the model with more modern or contemporary understandings of the underlying science. Example: *"If new information comes out disproving the previous scientific model."* *Level 3:* Models are revised as part of a cyclic process of prediction, data collection, and analysis. The interpretation of data from the model is the agent of change. Example: *"Based on their new findings and new concepts that they are developing in their experiment."*

> *[A scientist might change a model if] they saw that their model didn't accurately represent the data they're trying to show.*

In this response, the use of the words "show" and "accuracy" demonstrates an understanding of a model as a static representation of an intended outcome whose role is to depict that outcome in alignment with expected reality. This response was scored as a Level 1 for all three properties. In contrast, the following example response demonstrates a more advanced level of metamodeling knowledge:

> *A scientific model is a concept to make something easier to understand. It could be any type of model to visualize something that is being experimented. Models are used to represent something in the real world. It is a way that scientists can make predictions and propose new ideas. [A scientist might change a model] based on their new findings and concepts that they are developing in their experiment.*

In this second response, the student recognizes the active role of models in the scientific process (scored as a 3 for purpose) and cycle of changing models as part of that process (scored as a 3 for change). While they still connect models to real-world representations, they understand that a model is not an exact replica (scored as a 2 for nature of the model).

We worked with a member of the research team who was not involved in creating the codebook to test the coding manual for understanding and clarity. Two additional researchers were trained on the codebook who achieved an inter-rater reliability Cronbach alpha coefficient of $\alpha = 0.90$ on 70 responses (9% of the total of 738 over the 2 years). We realize that this is less than the standard of 20% of the data used to obtain interrater reliability, there were additional time constraints and availability of the coders decreased substantially due to the time of year that coding was requested. However, as the alpha coefficient is well over the 0.70 limit indicating good reliability (Stemler and Tsai, 2008), and as the sample is large, we deemed this was a sufficient measure of reliability and decided to proceed with coding of the remaining responses. After the differences were discussed, one researcher (first author) coded the remaining responses.

The student focus group interviews were mined by the first author for responses that could explain how the curriculum and models afforded better understanding of complex systems. Responses were then grouped into themes that supported the three categories of metamodeling knowledge.

3.4.2. Relationship between students' complex systems and metamodeling knowledge

The resulting codes were compared pre-to post-test scores for both modeling knowledge and complex systems understanding. A paired samples t-test was conducted to determine whether there was positive significant growth in both measures. The results were then analyzed to understand whether there was a relationship between the two measures through hierarchical regression modeling. The analysis was conducted to determine whether there was a significant effect on complex system understanding beyond their prior knowledge of modeling and understanding of complex systems measured at the pre-test survey.

4. Findings

Results from the analysis of the coded open-ended survey responses revealed significant growth in both metamodeling and complex systems knowledge. The results of the regressions analysis showed that modeling knowledge had a significant positive effect on complex systems understanding when holding all other variables constant. Finally, the student focus group interviews supported these findings with quotes from students depicting how aspects of the models were viewed to enhance their learning of the complex biological systems.

4.1. Knowledge growth in both scientific modeling and complex systems

The results of the surveys showed growth from pre-test to post-test for both measures, where a paired samples t-test showed positive significant growth $t\ (368) = 6.03$, $p < 0.001$ with a Cohen's d effect size of 0.39 for students' modeling knowledge which is a small to medium effect (Lakens, 2013), and positive significant growth $t\ (368) = 4.62$, $p < 0.001$ with a Cohen's d effect size of 0.27 which is a small effect for students' complex systems understanding (see Table 5 for more details).

While these results supported previous findings that students experienced growth in their complex systems knowledge, in this study we were primarily interested in the relationship between change in modeling knowledge and complex systems knowledge. This relationship was explored through a regression analyses.

4.2. Change in metamodeling knowledge has significant positive impact on change in complex system understanding

To test if students' metamodeling knowledge improved their understanding of complex systems beyond their prior knowledge of modeling and understanding of complex system measured at the pre-test, a hierarchical regression was conducted with two blocks of variables. The first block included students' pre-test of knowledge of modeling and pre-test of knowledge of complex system as the predictors, and with students' post-test measure of understanding of complex system as the dependent variable. In block two, students' post-test measure of metamodeling knowledge was also included as the predictor variable, with students' post-test measure of understanding of complex system as the dependent variable (see Table 6 for a summary).

Overall, the results show that the first model was significant $F\ (2{,}366) = 28.85$, $p < 0.001$, $R^2 = 0.14$. But only students' pre-test measure of understanding of complex system was significantly associated with the post-test measure of understanding of complex system ($b = 0.37$, $t = 6.81$, $p < 0.001$). The second model ($F\ (1{,}365) = 32.49$, $p < 0.001$, $R^2 = 0.21$), which included students' post-test measure of modeling knowledge ($b = 0.33$, $t = 5.70$, $p < 0.001$), showed significant improvement from the first model, $\Delta R^2 = 0.07$, $p < 0.001$. Overall, when students' pre-test of knowledge of modeling and pre-test measure of understanding of complex system were included in the model, the variables explained 14% of the variance. The final model, including students' post-test measure of understanding of modeling, accounted for 21% of the variance. Thus, with the addition of the second independent variable of students' post-test modeling scores, results showed that it significantly predicted students' complex systems understanding in the post-test beyond students' prior knowledge of modeling and understanding of complex systems measured at the pre-test.

TABLE 5 Scientific metamodeling and complex systems knowledge.

		Scientific metamodeling knowledge			Complex systems knowledge		
Year	N	Pre-test avg (SD)	Post-test avg (SD)	Diff	Pre-test avg (SD)	Post-test avg (SD)	Diff
Year 1	190	4.47 (1.51)	5.31 (1.33)	0.84	5.97 (1.46)	6.28 (1.56)	0.31
Year 2	179	4.79 (1.41)	5.05 (1.35)	0.26	6.04 (1.51)	6.58 (1.63)	0.54
Both Years	**369**	**4.63 (1.47)**	**5.18 (1.34)**	**0.56**	**6.01 (1.48)**	**6.43 (1.60)**	**0.42**

Bold values are the combination of Years 1 and 2.

TABLE 6 Results of regression of post measure of understanding on predictors.

Predictor	Variables	B	*t*	Sig.
Model 1				
	Pre-test of understanding of complex system	0.37	6.81	< 0.001
	Pre-test of modeling	0.83	1.52	= 0.130
Model 2				
	Pre-test of understanding of complex system	0.34	6.46	< 0.001
	Pre-test of modeling	0.03	0.52	= 0.602
	Post-test of modeling	0.33	5.70	<0.001

$R^2 = 0.14$ for Model 1, $p < 0.001$; $\Delta R^2 = 0.07$ for Model 2, $p < 0.001$; Total $R^2 = 0.21$, $p < 0.001$.

4.3. How metamodeling knowledge supports complex systems learning

To answer our third research question about the specific affordances that allowed for the connection between metamodeling knowledge and complex systems understanding, an analysis of the student focus group interviews was conducted. The three components of metamodeling knowledge: nature of models, purpose of models, and the criteria for evaluating and revising models (Schwarz et al., 2009) were identified within the interviews and three themes emerged that connect those components of metamodeling knowledge to complex systems understanding and highlight specific affordances of the StarLogo Nova models that support students' complex systems understanding development. For the nature of models, students focused on the "realistic" quality of the models, which allowed for aspects of complex systems in biology to be viewed and explored. Students understood the purpose of the models to have a role in communicating different aspects of the system through the different representations within the model. Finally, students engaged with the changeability of models through manipulating parameters to highlight characteristics of complex systems such as randomness and interconnectedness.

4.3.1. The nature of models as "realistic" representations of complex systems

While viewing scientific models as exact copies of reality supports a low-level understanding of the nature and purpose of models, it is important to understand that models are used to represent reality in some way that is useful. The connection to reality was a component of the models that students were drawn to, and which was brought up by multiple students in response to a question about the nature of good scientific models. For example, a student from a focus group for Teacher 5 said, "They model a real-life system, so we can see how, in real life, they work. We can actually see each component of every system, and that really helped me, at least, understand how all these things work." In response to the same prompt, a student from Teacher 8's class identified the importance of keeping models close to reality while also modifying them to make them simple:

> *I generally think of things that are easy to navigate, but also keeping it realistic. So, they're not so simple that it's not enough information, but just the right amount that it still looks relatively real to what you're learning about. Keeping it simple but realistic at the same time, because if it's not realistic, it's not benefiting you for learning what that system really looks like.*

These quotes support students' metamodeling knowledge of the nature of models as *useful* representations of reality. Students also connected the realistic nature of the models to characteristics of complex systems. One student from Teacher 8's class said, for example, that "Even if you would test [the model] again and again, it was super unlikely you'd come to the same answer twice just because they are trying to make it as realistic as possible." A student from Teacher 5's class had a similar observation, saying "Getting different outcomes with different numbers or even that the same numbers, just like a more realistic model, and I think that's how scientific models should be." These quotes show that students were making connections between the nature of models and the nature of complex systems.

4.3.2. The purpose of models: to communicate through different representations of the system

Most of the students interviewed spoke about the purpose of models to communicate and explain complex systems through multiple representations of the system and the data within it. While the students did not talk about the code representation, both the visual and mathematical representations were highlighted as important factors in building their understanding of the complex systems and underlying concepts. A student from a focus group for Teacher 8 mentioned that having the visual representation was an added benefit over auditory methods she was more used to encountering, saying:

> *I feel like it really helped just to put a visual to the things that we were learning. Not just have the words in an auditory explanation of what was going on, but to see what was actually going on and have a good visual of it.*

Mathematical representations, in the form of graphs that tracked output data from the simulations, were also a source of information that students used to interpret complex systems. In the focus group with students from Teacher 5, one student responded to a comment about tracking changes in the system by highlighting the graphs, saying, "We could usually tell that by the two graphs on the side, which would kind of help to see how dramatic or undramatic the changes were."

Students also made connections between the visual and mathematical representations within the simulations. One student from a focus group for Teacher 6 talked about how the visual representation helped simplify the complexity while the mathematical representation helped him understand the process:

> *These models, they help simplify a very complex scientific idea and it helps me visualize and, for example, the graph for the gene*

> *regulation, it helps you understand how the graph was developed and instead of making biology feeling like it's something that's just needs to be memorized, it helps you understand the process more.*

The students recognized that having multiple representations of the model in the StarLogo Nova simulation allowed them to explore complex systems in multiple ways that helped them understand the concepts and complex systems in general. For these students, the model was a tool for building understanding.

4.3.3. Changing the model parameters to explore randomness and connectivity as components of complex systems

Though the students did not change the underlying code of the simulations, they did change the parameters that were used as initial conditions for running the model and chose different scenarios to model, which served as examples for thinking about model changeability. This ability to change the model in response to the data produced by the model in order to further explore the system being simulated supported students in developing complex systems knowledge. A student from Teacher 6's class explained this process:

> *Something else I noticed with this simulation was that you could customize the different scenarios, so that it fit with what you were trying to learn. I remember we would put in different barriers in different types of sugar. I remember that was really helpful because we could, and with all of the simulations too, you could create these different scenarios to separately explore different concepts.*

The changeability of the models allowed students to observe the connected nature of the complex systems and the way that the models were able to make those connections observable to them. In talking about the ecology model, one student in Teacher 5's class said,

> *What we learned was how when one species is affected, it's not just affected individually. It's kind of like a domino effect that affects the organisms it feeds on and the organisms that feed on it, which was really interesting.*

A student from Teacher 6's class made an explicit connection between this interconnectedness of the components of the models and the fact of that as a defining characteristic of complex systems saying,

> *There are a lot of different parts to all of [the models], it's just part of what a complex system is, and they all work together, and there are different outcomes based on how they work together, so I would say that's the characteristic that they exhibit.*

The students also noticed the ability of the models to simulate the emergent nature of complex systems, which can seem like randomness due to the complexity of the interactions of the components within the system. One student from Teacher 5's class noted the relationship between the randomness displayed by the models and what might happen in real life, saying,

> *One thing I noticed about these [models] is that the outcomes were kind of different every time. If multiple people in the class did the same numbers or same data, it wasn't guaranteed to get the same response and the same outcome. Obviously, that's how it is in real life.*

A student in Teacher 6's class made a connection between the randomness displayed by all the models and the unpredictability of complex systems, showing a high-level understanding of both the nature of models and of complex systems, saying, "All the models had different models of different parts of things, and they all moved randomly, and you have that element of unpredictability, which would be a characteristic of complex systems." Finally, a student from Teacher 7's class summed up all three of the themes from the interviews in a single quote, saying,

> *The graph there in the Gene Regulation, that's useful. So, it's not just that I think there's more of these over time and then they decrease, you can see the graph, you can see it's actually happening. Also, I think the randomness … In all of these, if you run the simulation multiple times, it's not just the same exact thing. The factors are working off each other with a bit of randomness. You can tell that whatever is happening is actually happening. In the real world, it's not going to be the same every single time. It's more realistic.*

These three themes and the quotes that illustrate them add further support to the quantitative analysis of the student knowledge surveys and suggest that there is a significant connection between students' metamodeling knowledge and their learning about complex systems. Students' ability to see models as useful representations of an aspect of reality and to understand that they could be manipulated to view that reality from different angles and different starting scenarios allowed them to develop a deeper understanding of complex systems and their emergent nature.

5. Discussion

Our findings answer our research questions in the following ways. There was significant growth both in students' metamodeling knowledge and in their complex systems understanding across both years of the study. The hierarchical regression analysis also showed a significant effect of students' growth in metamodeling knowledge on their growth in complex systems understanding. Furthermore, student interviews identified three distinct ways that their modeling experiences supported learning about complex systems, highlighting supports for metamodeling knowledge reported in the literature review (i.e., the nature, purpose, and changeability of models; Schwarz et al., 2009). From the focus interview responses about the *nature of models*, the agent-based simulations in our study enabled students to observe system structures through visualizations of system component interactions (Chi, 2005; Jacobson et al., 2011; Markauskaite et al., 2020). These dynamics are normally hidden to the naked eye, which makes it challenging to understand how system patterns emerge (Yoon et al., 2018a). Emergent patterns in biology, such as climate change or natural selection, are also difficult to witness in real time because they appear over large geographic and temporal scales (Grotzer and Tutwiler, 2014). Many students in our study noted that being able to see the system all at once was important to their learning. Regarding the *purpose of models*, the existence of multiple representations of the scientific phenomenon under investigation provided students with strategies to interpret data generated from multiple runs and to develop explanations of the system (Gogolin and Krüger, 2018; Upmeier Zu Belzen et al., 2019). Finally, regarding the *changeability of models*, the ability to manipulate initial conditions and the ability to compare varying results allowed students to develop more sophisticated scientific theories (e.g., that there is built-in variation and randomness in all systems) than what only a single run of the simulation would otherwise afford. These findings support previous research showing the affordances of computational models as tools for increasing students' complex systems understanding (e.g., Hmelo-Silver et al., 2017; Yoon et al., 2017; Markauskaite et al., 2020; Nguyen and Santagata, 2021).

While these findings support previous research and add to the research on modeling and complex systems by explicitly demonstrating a quantitative significant effect of metamodeling knowledge on complex systems understanding, there are limitations to the study. The sample of teachers in the study were self-selecting into the professional development for the StarLogo Nova simulations and resources, and into the study. As such, the teachers were highly motivated and likely represented an ideal population of students. Additionally, the Covid-19 pandemic made working with the teachers and students in India impossible for the second year of the study which limited the diversity of the students in the study and may have skewed the regression model. Another limitation is that, while this study focused on students' metamodeling knowledge, modeling practices were not measured and certain components of modeling competence such as *multiple models* and *testing models* (Upmeier Zu Belzen et al., 2019) were not included in the study. Finally, we acknowledge that this work is embedded firmly within the context of Biology and while metamodeling knowledge is conceived as content general knowledge, it has been found that there exists a difference between contextualized and decontextualized metamodeling knowledge so our results may only speak to contextualized knowledge (Göhner et al., 2022).

While acknowledging some limitations, the findings reported here emerge from over a decade of research on this project that involved years of iterative design and implementation cycles to reach a point where the curriculum and PD experiences fully supported teachers and students in using models to support learning of complex systems (see Yoon et al., 2016, 2020b; Yoon, 2022). Our research has produced significant outcomes for student learning and supported attempts to scale up access to project resources more globally (Yoon et al., 2020b). Developing greater understanding of complex systems (Yoon et al., 2018a) and systems more generally (NGSS Lead States, 2013) has also been a focus of educators and educational researchers for many years. Despite this longstanding interest, however, complex systems curricula and tools have still not made their way widely into biology classrooms (Gilissen et al., 2020; Markauskaite et al., 2020). Perhaps this slow progress is related to the lack of studies that make explicit the connection between growth in student understanding of complex systems and specific instructional approaches such as agent-based modeling, as noted in a previous literature review (Yoon et al., 2018a). Without assurances that learning outcomes will improve, it may be difficult to convince teachers to adopt new pedagogies and tools like ours that add additional time to the standard biology curriculum. That we found improvements in both student measures of metamodeling knowledge and complex systems understanding even in Year 2 of the project—where teaching and learning happened fully online—is also worth highlighting given the documented learning losses that we have experienced due to the pandemic (Nowicki, 2022).

6. Conclusion

In this study, we investigated how students' understanding of biological models using an agent-based modeling tool influenced their understanding of complex systems. Through many years of design iterations, we developed a curriculum that supports growth in students' knowledge of scientific models and complex systems understanding in high school biology. Through a regression analysis of 2 years of student data, we demonstrated that growth in students' modeling knowledge significantly predicted growth in their understanding of complex systems. We further showed that students perceived multiple aspects of the agent-based modeling tool as important to supporting their understanding of complex systems. Studies that demonstrate explicit relationships between instructional approaches and improvements in complex systems content learning are rare, which underscores the overall value and contribution of this research. We hope that future research will continue to explore the relationship between metamodeling knowledge and complex systems understanding both to replicate our work with different systems' representations to show that the effects are significant in other contexts and content areas, and to expand upon our work to include more components of modeling competencies (Schwarz et al., 2009; Fortus et al., 2016; Upmeier Zu Belzen et al., 2019). Specifically, embedding agent-based simulations within the scientific inquiry process to support students' deeper exploration of complex systems and their development of systems thinking.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving human participants were reviewed and approved by University of Pennsylvania IRB. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

Author contributions

KM and SY contributed to conception and design of the study. KM performed the analysis and wrote the first draft of the manuscript. SY wrote sections of the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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