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Supporting Three-dimensional Learning on Ecosystems Using an Agent-Based Computer Model

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Abstract

The *Next Generation Science Standards* call for engaging K–12 students in three-dimensional learning, in which students make sense of phenomena or solve problems by simultaneously using science and engineering practices (SEPs), crosscutting concepts (CCCs), and disciplinary core ideas (DCIs). Decades of education research suggest agent-based computer models (ABMs) have the potential to support all three dimensions. However, most existing studies focus on using ABMs to support one or two dimensions (i.e., DCIs and/or SEPs). This article presents a mixed-methods study in which 63 sixth-grade students engaged in ABM-supported, three-dimensional learning to explore the causes of severe bark beetle outbreaks in forest ecosystems. Data collected from pre- and post-assessments, students' written explanations for the outbreak phenomenon, and videos of classroom instruction suggest the ABM of bark beetle outbreaks supported students in using all three dimensions of science learning to make sense of the target phenomenon. Our results show that the ABM-supported unit significantly improved students' understanding of ecosystem concepts. The largest improvement was observed among previously low-performing students. Furthermore, students engaged in sophisticated science practices, reasoning with the computer-generated data to develop an evidence-based explanation for the target phenomenon. The ABM helped students to make sense of the target phenomenon using five different CCCs. Importantly, our results also show that ABMs enabled students as young as sixth grade to predict system outcomes and better understand the nature of models in science. This study contributes to the field by bridging ABM education literature with three-dimensional science teaching and learning.

Keywords NGSS three-dimensional learning · Ecosystem · Educational technology · Agent-based models and simulations

Introduction

The contemporary US science education standards, *Next Generation Science Standards (NGSS)* (NGSS Lead States, 2013), call for engaging K–12 students in three-dimensional learning (3D learning), in which students make sense of phenomena or solve problems using science and engineering practices (SEPs), crosscutting concepts (CCCs), and disciplinary core ideas (DCIs) simultaneously. Features that distinguish 3D learning from previous science learning approaches include (1) student learning is driven by the need to make sense of phenomena and (2) sensemaking is supported by the integration of three dimensions of science learning (SEPs, DCIs, and CCCs). Thus, educators are to explicitly include SEPs, DCIs, and CCCs, a set of conceptual tools used across disciplines (e.g., patterns, causality, systems), when designing and implementing learning tasks (National Research Council [NRC], 2012). According to *NGSS*, students at a young age can begin to examine everyday phenomena and perform relatively simple investigations and then progress to explore phenomena occurring in systems too big, too small, or too complex to be directly observed or investigated in a regular classroom setting. Computer simulations are often used to represent complex phenomena and support interactive investigations (Smetana & Bell, 2012). Relevant science education documents have highlighted the significant role of computer simulations in 3D learning. As stated in *A Framework for K–12 Science Education* (NRC, 2012), students should "progress to using mathematics or simulations to construct an explanation for a phenomenon" (p. 70) and "use (provided) computer simulations

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or simulations developed with simple simulation tools as a tool for understanding and investigating aspects of a system, particularly those not readily visible to the naked eye" (p. 58).

Agent-based computer models (ABMs) are a type of computer simulation that allows its users to manipulate the behaviors of autonomous agents and how they interact within a system (Wilensky & Rand, 2015). ABMs have gained popularity in various fields as a powerful way to simulate complex systems and reveal dynamic, emergent phenomena in the natural and human designed world (Gu & Blackmore, 2015; Macal, 2016). Wilensky and Rand (2015) point out that ABMs may provide intuitive and concrete learning experiences for students to explore dynamic systems and processes. Decades of educational studies suggest that integrating ABMs into K–12 science classrooms may deepen students' understanding of science concepts, engage students in science practices, support systems thinking, and foster productive science discourse (Dickes & Sengupta, 2013; Dickes et al., 2016; Hmelo-Silver et al., 2014; Varma & Linn, 2012; Wilensky & Reisman, 2006; Xiang & Passmore, 2015). However, from a 3D learning perspective, most existing studies focus on using ABMs to develop students' understanding of science content (i.e., DCIs) and/or support science practices (SEPs). Few studies have examined the impact of ABMs on supporting the use of CCCs (Hmelo-Silver et al., 2014) or 3D learning (Yoon et al., 2015).

Here, we report a mixed-methods study that examines the affordances of ABMs from a 3D learning perspective. In this study, a group of sixth-grade students engaged in a 3D learning unit to investigate climate-driven bark beetle outbreaks in forest ecosystems. In this unit, students first examined infested tree bark specimens, read about the bark beetle life cycle, conducted an embodied modeling activity to investigate the interactions between bark beetles and host trees, and identified the possible environmental disruptions to the forest ecosystem. Then, they collected complex data sets from an ABM of bark beetle outbreaks and analyzed the data sets to examine the effect of rising temperature on the frequency and severity of bark beetle outbreaks. Ultimately, students constructed evidence-based arguments to explain the causes of the recent severe bark beetle outbreaks in the western USA. We describe whether and how the ABM supported students in using all three dimensions of science learning (SEPs, DCIs, and CCCs) by integrating quantitative and qualitative data collected from pre- and post-assessments, students' written explanations for the outbreak phenomenon, and video footage of classroom instruction.

Theoretical Framework

The present study is guided by the framework of three-dimensional learning (3D learning) proposed by the National Research Council (2012) in the foundational science education document *A Framework for K–12 Science Education: Practices, Crosscutting Concepts, and Core Ideas* (the *Framework*). Although the relevant components, such as conducting inquiry and recognizing causality and systems, were present in the previous *National Science Education Standards* (NRC, 1996) and education documents like *Benchmarks for Science Literacy* (American Association for the Advancement of Science [AAAS], 1993), the *Framework* officially defines science and engineering practices (SEPs), crosscutting concepts (CCCs), and disciplinary core ideas (DCIs) as three dimensions for K–12 science learning. Furthermore, it stresses that students should use these dimensions together to explain why natural phenomena occur and solve real-world problems. In this section, we elaborate on the three dimensions, their integration, and phenomenon-based 3D learning.

Three-dimensional Learning (3D Learning)

The view that science is both a collection of knowledge and the process of generating that knowledge is foundational to the framework of three-dimensional science teaching and learning. The DCIs capture the knowledge aspect of this view, as they consist of the fundamental ideas that all students need to grasp in four disciplinary domains—physical sciences, life sciences, earth and space sciences, and engineering and technology. These ideas have broad importance across multiple disciplines or are the key organizing concepts of a single discipline (NGSS Lead States, 2013). The SEPs include eight essential activities in scientific inquiry and represent the knowledge-generating aspect of science (NRC, 2012). Students are expected to understand and perform these SEPs to develop, refine, and extend their knowledge (NGSS Lead States, 2013). Combining content ideas and inquiry practices in learning tasks is not new in science education for it has been featured in a range of learning approaches under the names of inquiry-based learning, problem-based learning, project-based learning, and discovery learning. Three-dimensional learning differs from these approaches by explicitly including seven CCCs as the third dimension of science learning.

Quinn (2021) points out that these CCCs are important tools in authentic scientific inquiry because they are consistently used by scientists across various disciplinary areas. Some of the CCCs were formerly known as common themes in science, such as systems, scale, changes, and models (AAAS, 1993), but they had not been given equal status with the practices and content ideas in classrooms prior to *NGSS* (Quinn, 2021). Nordine and Lee (2021) contend that CCCs may strengthen science learning in three ways. First, CCCs may be integrated with DCIs and SEPs to better support students in making sense of phenomena. For example, comparing a two-dimensional task statement, *use a model*

(SEP) of the movements of Earth, Sun, and Moon (DCI) to explain lunar phases, and a three-dimensional task statement, *use a model (SEP) of the movements of Earth, Sun, and Moon (DCI) to explain the pattern (CCC) of lunar phases in a month*, we can see that integrating the CCC of *patterns* better defines what students should learn about the lunar phase phenomenon. That is, students observe the lunar phenomenon to identify the Moon's monthly changing pattern then use a model to explain the pattern. Second, CCCs can be used as lenses to examine a phenomenon from different perspectives. For instance, when examining different living organisms, students may compare their similarities and differences (i.e., patterns) and consider how these properties may determine their functions (i.e., structure and function). These different lenses allow students to ask productive questions and develop a sophisticated understanding of each phenomenon (Nordine & Lee, 2021). Third, CCCs bridge the four disciplinary domains in *NGSS* because they are used across multiple disciplines and can bring coherence to K–12 science instruction and learning.

The *Framework* (2012) contends that SEPs, DCIs, and CCCs must be integrated such that students use all three dimensions simultaneously to make sense of a phenomenon. The integration of the three dimensions reflects authentic science work and aligns with education research literature, which has shown that students develop and refine their understanding of science better when engaged in relevant science practices and discourses (Berland & McNeill, 2010; Krajcik et al., 2008). The integration of three dimensions is embedded in the standards, curriculum, instruction, and assessment in science education. In *NGSS*, each performance expectation incorporates a SEP, a CCC, and a DCI. When developing and implementing a curriculum, educators should select relevant SEPs, DCIs, and CCCs to engage students in meaningful learning tasks. In assessments, students should be evaluated based on performing 3D tasks rather than knowledge memorization (NRC, 2012).

Compared to the conventional science instruction that often focuses on delivering scientific ideas to students without including further knowledge application, "learning to explain phenomena and solve problems is the central reason students engage in the three dimensions of the *NGSS*" (Achieve, 2016, p.1). Phenomena are observable events in the universe, and scientific knowledge is developed to explain these events. Engaging students in generating evidence-based explanations to explain how and why phenomena occur embodies knowledge application and therefore aligns with the conceptual shifts in *NGSS*. Phenomena also provide a meaningful context for students to use and understand the three dimensions (Achieve, 2016; NRC, 2012). Such interactions positively reinforce the learning process and help students deepen their understanding of the natural world and become scientifically literate.

The middle-school unit and agent-based computer model (ABM) developed by the authors for this study were guided by the 3D learning framework for science teaching and learning. The unit includes multiple opportunities for students to explicitly use DCIs, CCCs, and SEPs as they gather evidence and engage in sensemaking to explain how and why climate-driven bark beetle outbreaks have destroyed plenty of forests in western US over the past few decades.

Literature Review

Agent-Based Computer Models (ABMs)

What sets ABMs apart from other types of computer simulations is that they are constructed from an "agent perspective" (Macal, 2016). ABMs simulate systems based on the behaviors of individual objects, named agents, within the system rather than aggregated variables. In an ABM, each agent behaves according to its "own" rules, i.e., from its own perspective, but together, they lead to the emergence of macro phenomena or patterns at the system level. For example, a predator–prey ABM may be constructed by assigning behavioral rules, such as growth, foraging, predation, reproduction, and death, to the individual predator and prey agents in the model. After the agents faithfully enact these rules over time, a predator–prey population fluctuation pattern emerges (Wilensky & Reisman, 2006).

ABMs are particularly useful for investigating complex systems and emergent phenomena. A complex system is a part of reality consisting of interconnected components and the causal processes that connect the component interactions to yield the system outcomes (Jacobson, 2001). Studying a complex system involves understanding the interdependent relationships of the components within the system and the resulting events. Emergent phenomena are the events resulting from the constant interactions of the system components (Macal & North, 2010; Wilensky & Resnick, 1999). For example, the phenomenon of adaptation emerges from the interactions between organisms and their environments over generations. A solid interpretation of emergent phenomena can only be achieved by understanding the intense and complex interactions among thousands, even millions of individual agents in the system, such as atoms, molecules, or living organisms. Being a technique that directly focuses on the system components and their interactions, ABMs empower users to investigate the internal structures of a system, explore system outcomes under various conditions, and use observed patterns to make predictions (Goldstone & Wilensky, 2008).

ABM-Supported Science Learning

Over the past two decades, K–12 science education researchers have explored the use of ABMs to teach a host of science topics and have shown that ABM-supported learning deepens students' understanding of science ideas, engages students in various inquiry practices, supports system thinking, and fosters productive science discourse (Dickes & Sengupta, 2013; Dickes et al., 2016; Hmelo-Silver et al., 2014; Varma & Linn, 2012; Wilensky & Reisman, 2006; Xiang & Passmore, 2015). Researchers have reported that ABMs facilitate science learning in four ways. First, ABMs help students visualize a complex system at different levels. That is, an ABM simulates a large number of individual behaviors at the micro-level as well as the resulting system outcomes at the macro-level (Hmelo-Silver et al., 2014; Wilensky & Reisman, 2006). Second, ABMs provide multiple external representations of a phenomenon. In addition to the animated simulation, ABMs often use dynamic graphs to visualize the changes in different variables and therefore provide multiple perspectives on a phenomenon (Basu et al., 2015). Third, ABMs allow students to carry out investigations by manipulating the incorporated variables and examining the resulting outcomes to deepen their understanding (Dickes & Sengupta, 2013; Tan & Biswas, 2007). Fourth, many ABMs allow students to code the rules for an individual's behavior to explore the underlying mechanisms of a phenomenon (Basu et al., 2016; Wilensky & Reisman, 2006; Xiang & Passmore, 2015).

Existing studies have suggested that ABMs may support all three dimensions of science learning, but research efforts on each dimension are highly uneven. Most of these studies have focused on developing students' understanding of science content (i.e., DCIs) and/or supporting certain SEPs. Researchers have successfully used ABMs to teach students core ideas about ecosystems (Berland & Reiser, 2011; Hmelo-Silver et al., 2014; Vattam et al., 2011), biodiversity (Jones & Laughlin, 2009), evolution (Dickes & Sengupta, 2013; Xiang & Passmore, 2015), climate change (Pallant & Lee, 2015; Varma & Linn, 2012), gases (Samon & Levy, 2017), and electricity (Sengupta & Wilensky, 2009). Furthermore, it has been reported that using ABMs may naturally engage students in performing multiple SEPs, specifically *developing and using models*, *planning and carrying out investigations*, and *using mathematical and computational thinking* (Sengupta et al., 2013; Xiang & Passmore, 2015), and in turn support other practices, such as *analyzing and interpreting data*, *constructing explanations*, and *engaging in argument from evidence* (Dickes & Sengupta, 2013; Pallant & Lee, 2015). By contrast, studies related to CCCs are limited and primarily concentrate on causality and systems (Hmelo-Silver et al., 2014; Wilensky & Reisman, 2006). For example, Hmelo-Silver et al. (2014) found that using ABMs provided students with a concrete context to understand the CCC of *systems and system models*. Studies conducted from an integrated 3D learning perspective are also very limited. The only study on ABM-supported 3D learning is from Yoon et al. (2015), in which they examined how an ABM-supported unit on digestion enabled high-school biology students to apply SEPs and CCCs. Based on student interviews, Yoon and colleagues (2015) observed that students most used two SEPs, *developing and using models* and *analyzing and interpreting data*, and two CCCs, *cause and effect* and *systems and system models*.

ABM-Supported Learning About Ecosystems

ABMs have been used to learn about ecosystems since multi-agent modeling tools became available for students. In the relevant studies, ABMs supported the SEPs of modeling (Wilensky & Reisman, 2006), investigating (Tan & Biswas, 2007), constructing explanations (Dickes et al., 2016), and engaging in argumentation (Berland & Reiser, 2011) by visualizing predator–prey dynamics and changes in ecosystems across levels, enabling interactive investigations, and generating datasets. However, CCCs were often implicit in these studies. Only Hmelo-Silver and colleagues (2014) explicitly examined the CCC of *systems and system models* in their work. No studies have examined the affordances of ABMs for supporting 3D learning about ecosystems.

Challenges in ABM-Supported Learning and Scaffolding Strategies

Students may encounter various challenges in computer-supported learning, including using ABMs, due to limited knowledge and inquiry skills (De Jong & Van Joolingen, 1998). Basu et al. (2016) identified four challenges to ABM-supported student learning. First, students may possess limited domain knowledge so that they are biased or unable to interpret the ABM representations. Second, students may be unable to identify the entities and conditions in an ABM due to limited knowledge about the simulation. Third, students may have difficulties connecting micro-level behaviors to macro-level results due to a lack of agent-based thinking. Fourth, students may have a hard time creating an ABM to represent a phenomenon due to limited programming knowledge. The first two challenges are general for all computer simulations, whereas the last two challenges are specific to ABMs.

A range of scaffolding strategies has been suggested for overcoming these challenges. For example, De Jong and Van Joolingen (1998) suggest providing students with direct domain information and supporting their exploring processes. Reiser (2004) proposes structuring problem-solving tasks and problematizing subject matter to provoke students to actively utilize the resources in the computer-supported environment. Dickes et al. (2016) propose implementing an embodied modeling activity to foster student agent-based thinking before using an ABM. Basu et al. (2016) suggest encouraging students to use productive pre-instructional ideas, de-emphasizing incorrect pre-instructional ideas (i.e., misconceptions), and helping students to identify corresponding correct ideas in ABM-supported learning.

The goal of this study is thus to bridge findings from the ABM education literature with the 3D learning framework to help science teachers and curriculum developers incorporate ABMs in science classrooms productively. We examined the extent to which an ABM supported middle-school students in using all three dimensions of science learning to make sense of a real-world phenomenon during a 6-day science unit. We also identified the characteristics of the class discourse to provide a richer description of this ABM-supported 3D learning process. The research questions we address are as follows:

1. To what extent does the ABM support students in using disciplinary core ideas (DCIs) about ecosystems to explain the bark beetle outbreak phenomenon?
2. To what extent does the ABM support students in performing the targeted science practices (SEPs)?
3. To what extent does the ABM support students in using crosscutting concepts (CCCs) to make sense of the bark beetle outbreak phenomenon?
4. What are the main features of the classroom discourse that influenced the ABM-supported 3D learning outcomes?

Methods

Study Design

A mixed-methods approach was applied in this study to generate an enhanced understanding (Greene et al., 1989; Johnson & Onwuegbuzie, 2004) of student learning and the effectiveness of the ABM-supported unit. Both quantitative and qualitative data were collected from three sources: pre- and post-assessments, students' written explanations for the phenomenon, and video footage of classroom instruction. Qualitative and quantitative techniques were used to analyze the data. Specifically, the textual data, including students' short-answer responses on the assessments and written explanations for the phenomenon, were coded using content analysis methods (Cole, 1988; Elo & Kyngäs, 2008). Then, the coding results were quantified and subject to quantitative statistical analyses. Wilcoxon signed rank tests (Whitley & Ball, 2002) were used to compare pre- and post-assessment results. Effect sizes were calculated using the equation recommended by Rosenthal (1991) to convert the *Z*-score to effect sizes, $r = Z/\sqrt{N}$, where *N* is the total number of students compared. Cohen (2013) criteria (i.e., 0.1, small effect; 0.3, medium effect; 0.5, large effect) were used to determine the effect size. The detailed analysis processes are specified in the following sections.

Context of the Study

The Bark Beetle Outbreak Unit

Over the past three decades, two bark beetle species native to North America, mountain pine beetles (*Dendroctonus ponderosae*) and spruce beetles *(D. rufipennis)*, have attacked and killed enough coniferous trees in the western USA to cover the entire state of California. Research points to climate change as one of the major causes of the severe beetle outbreaks because warm temperatures both accelerate the beetle life cycle (i.e., reproduction) and decrease beetle mortality over winter (Bentz et al., 2010; Logan et al., 2010). We chose this phenomenon to develop a 3D science unit to address the following NGSS performance expectations: (1) analyze and interpret data to provide evidence for the effects of resource availability on organisms and populations of organisms in an ecosystem (MS-LS2-1) and (2) construct an argument supported by empirical evidence that changes to physical or biological components of an ecosystem affect populations (MS-LS2-4). In the bark beetle outbreak (BBO) unit (Xiang & Mitchell, 2019), students use an ABM to investigate the effects of climate change on the number of bark beetle outbreaks over time in a forest ecosystem.

The target DCIs of the BBO unit are *Interdependent relationships in ecosystems (LS2.A)* and *Ecosystem dynamics*, *functioning*, *and resilience (LS2.C)*, in which four specific ideas relate to the bark beetle outbreaks: organisms and populations of organisms are dependent on their environmental interactions both with other living things and with nonliving factors (LS2.A); growth of organisms and population increases are limited by access to resources (LS2.A); predatory interactions may reduce the number of organisms or eliminate whole populations of organisms (LS2.A); and ecosystems are dynamic in nature; their characteristics can vary over time, and disruptions to any physical or biological component of an ecosystem can lead to shifts in all its populations (LS2.C). Students apply these core ideas in the BBO unit to explain the bark beetle outbreak phenomenon, including that bark beetles depend on host trees for food and shelter; bark beetles consume host trees, and therefore, a bark beetle outbreak may reduce the number of host trees and even eliminate entire forests; the growth of a bark beetle population is limited by access to resources (i.e., trees for food and shelter); temperature, a physical factor, influences the bark beetle life cycle and survival; and changes in global climate are disturbing the stability of forest ecosystems, shifting bark beetle populations and causing large-scale tree mortality.

The two SEPs featured in the target performance expectations are *analyzing and interpreting data* and *engaging in argument from evidence*. In the BBO unit, students plot and analyze population data from an embodied model and interpret graphical displays of ABM-generated data to identify factors that limit the growth of bark beetle populations over time, including resource availability and temperature. Students then construct a written argument, based on evidence from their own investigations, for how the rising temperature has caused an increase in the number of bark beetle outbreaks over the past few decades. Since the *Framework* (NRC, 2012) and current research findings suggest that multiple SEPs and CCCs should be integrated into 3D learning to effectively support student learning (Barth-Cohen & Wittmann, 2020; Fick et al., 2018), the BBO unit also includes the SEPs of *asking questions*, *obtaining and communicating information*, *using models*, *carrying out investigations*, and *constructing explanations*, to engage students in a coherent inquiry process.

The two CCCs featured in the target performance expectations are *cause and effect* and *stability and change*. The BBO unit invites students to identify the *cause* of the recent *changes* in Western forest ecosystems. To do so, it requires students to use the additional CCCs of *patterns*, *scale*, and *systems and system models*. That is, students identify patterns in the ABM-generated data and use the patterns as evidence to explain the underlying cause of the changes in the system. Students must also connect how interactions at the micro-level (between organisms) result in patterns at the macro-level (forest ecosystems).

Design of the Bark Beetle Outbreaks ABM

Researchers have found that some common misconceptions may prevent students from fully understanding ecosystem dynamics. Many students fail to recognize the interconnections among various organisms and environmental variables within an ecosystem (Allen, 2014) and fail to perceive multiple causal processes exist in a complex system and that system behaviors are often dynamic (Yoon et al., 2018). Therefore, students often think populations either constantly grow or decline, and that those changes do not affect other parts of the ecosystem (Butler et al., 2015; Munson, 1994). In the case of bark beetle outbreaks, we anticipated that many students would not understand how tiny insects as small as a grain size could be so destructive and kill billions of large trees, and students might fail to connect these micro-scale interactions to macro-scale changes in the forest ecosystem or recognize the conditions under which a population or system is stable or changing. Therefore, it is crucial to reveal the complex and iterative interactions among beetles, host trees, and the environmental factors, as well as help students recognize the stability and changes in this forest ecosystem. An outbreak ABM was developed to address these needs.

The ABM of bark beetle outbreaks (Fig. 1) was developed using NetLogo (Wilensky, 1999) to visualize beetle-tree interactions and the emergence of outbreaks, support students in investigating the effects of climate change on the number of bark beetle outbreaks, and generate complex data sets that may elicit rich discussion and strong arguments on the cause of the bark beetle outbreaks in a forest ecosystem. The outbreak ABM consists of two sets of agents, host trees and bark beetles, and two environmental factors, temperature and drought. Table 1 presents the model components and the behavioral rules for each agent in a hypothetical "year." These behavioral rules represent six ecosystem interactions among bark beetles, host trees, and physical factors in the environment (Fig. 2) based on the reports in primary ecological research (Bentz et al., 2010; Logan et al., 2010). Four of the six ecosystem interactions are relevant in this study: (1) beetles use trees as food and shelter, (2) beetles mass attack to kill a tree, (3) warm temperatures accelerate beetle reproduction, and (4) warmer temperatures decrease overwinter beetle mortality.

Unit Instruction and Strategies

In the current study, the BBO unit was co-taught by an experienced in-service teacher and a student teacher to three 6th-grade classes over 6 days (Supplementary Table 1). Both teachers taught the unit for the first time, but the experienced teacher had participated in 2 h of professional development on teaching the BBO unit and using ABMs. Each day, the student teacher first observed the experienced teacher teaching in one to two classes and then taught the following class under supervision.

Several scaffolding strategies were used to help students make sense of the phenomenon. First, students learned about the micro-scale interactions between organisms and their environment early in the unit before thinking about macro-level or system-level outcomes (de Jong & Van Joolingen, 1998). Second, students used an embodied model (Dickes et al., 2016) to observe the effects of beetle-tree interactions, develop agent-based thinking, and gain experience with graphically representing data on changes in populations over time. Third, students followed a structured inquiry process (Banchi & Bell, 2008), i.e., a worksheet guided them without providing a conclusive answer, when using the ABM to investigate the effects of rising temperature on the number of bark beetle outbreaks over time. Students were also reminded by their teachers that they should hold all variables constant except the one being studied and run multiple trials when using the computer model to collect data on the number of

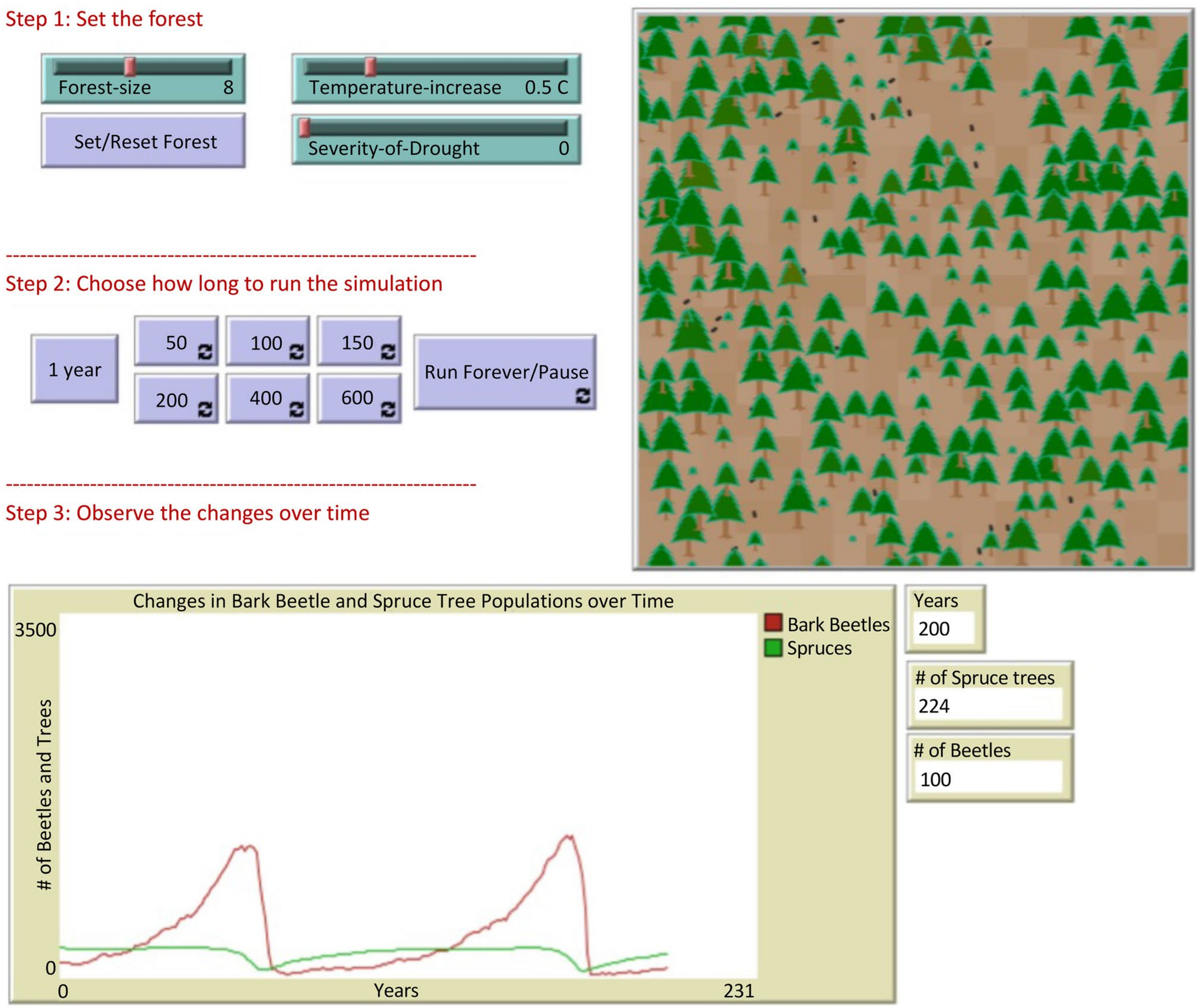

Fig. 1 A screenshot of the agent-based computer model of bark beetle outbreaks

bark beetle outbreaks. Fourth, students were encouraged to work in collaborative groups to analyze and interpret the collected data, identify patterns, predict the future trend, and discuss any uncertainties.

Table 1 Components and behavioral rules of the agent-based model of bark beetle outbreaks

Model components		Model behavioral rules
Agents	Beetles	• Every beetle infests a host tree if there is one nearby, otherwise the beetle dies • Every beetle produces offspring after the infestation and then dies. The number of offspring is influenced by the increase of temperature • A certain percentage of beetles die in winter. The percentage is influenced by the increase of temperatures
	Host trees	• Each patch grows one host tree. If the host tree dies, grow a new host tree next year • A host tree dies when infested by a certain number of bark beetles. The number is determined by the severity of droughts
Environmental factors	Temperature	• A rising temperature allows more offspring to be produced in summer, and fewer beetles die in winter
	Drought	• The severer a drought is, the fewer beetles it takes to kill a tree

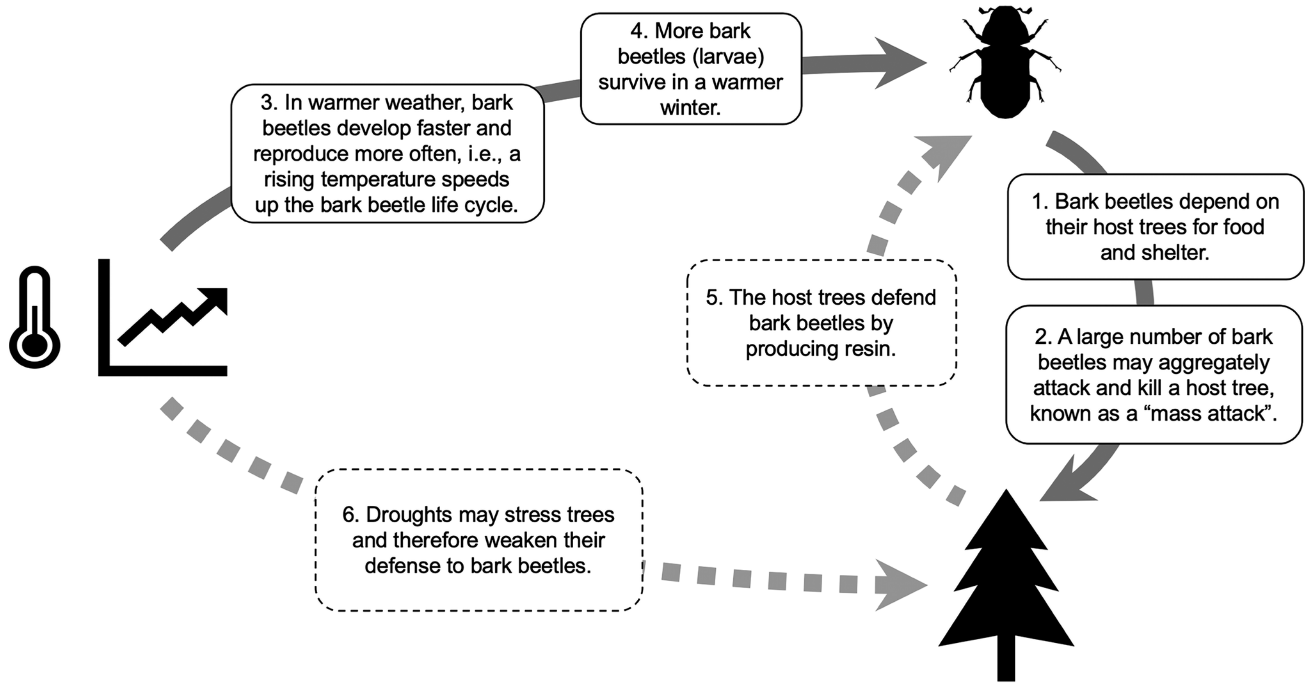

Fig. 2 The interactions among bark beetles, host trees, and environmental factors in the agent-based model. In this study, the learning activities primarily focused on the impact of rising temperatures and interaction ideas 1–4 (shown on the solid arrows)

Participants

This study occurred in a public school in the Mountain West region of the USA in the 2017–2018 academic year. During the year, 82% of the enrolled students were white, 14% were Hispanic, and 4% were from other ethnic groups. At the beginning of Spring 2018, all sixth-grade students were provided with informed consent forms, which were returned by a total of 63 students allowing them to participate in the study. These students, including 30 girls and 33 boys, represented 80% of the sixth-grade students in the school. Of the participants, 83% were white, 11% were Hispanic, 2% were Asian, and 5% were Middle Eastern. Additionally, 8% of the participants were identified as English learners.

Data Collection

The results presented here were yielded from three data sources: pre- and post-assessment questionnaires, students' written explanations of the outbreak phenomenon, and video footage of classroom instruction. The self-developed pre- and post-assessment questionnaires (Supplementary Table 2) examined (1) the changes in students' understanding about the ecosystem interaction ideas and the cause of bark beetle outbreaks and (2) the changes in students' ability to analyze and interpret outbreak data. An open-ended question, "Tell us how using a computer model helps you learn about bark beetle outbreaks," was used in the post-assessment to gather students' perceptions of the ABM-supported learning. Both questionnaires were validated and piloted in the previous semester. The participating students independently responded to the assessments through a Google Form using a class Chromebook before and after the unit.

At the end of the BBO unit, students constructed a written argument about the cause of severe bark beetle outbreaks using a claim, evidence, and reasoning (CER) framework (McNeill & Krajcik, 2008). In particular, students were instructed to make a claim and support their claim with (1) evidence from their investigation and (2) reasoning with ecosystem interaction ideas. Before students constructed their written arguments, they first reviewed as a whole group what they had learned about the cause of the recent bark beetle outbreaks and the evidence they had gathered in the previous 5 days. Students then wrote up the CER argument individually. A total of 51 written arguments were collected from the participants. In this study, the entire 6 days of teaching in all three classes was video-recorded to support our interpretation of the quantitative results obtained from the assessment tasks.

Data Analysis

To answer *RQ*1 about students' use of disciplinary core ideas (DCIs), we examined how well students grasped the four ecosystem interaction ideas (i.e., among beetles, trees, and temperature) and how well the students could appropriately and sufficiently reason with these ideas to explain the cause of severe bark beetle outbreaks. Students were regarded to grasp certain ideas if they correctly answered the multiple-choice questions or appropriately used the ideas in their short-answer responses and written arguments. To determine whether students appropriately and sufficiently applied the interaction ideas, we adopted the propositions from McNeill and Krajcik (2008) to define *appropriate* reasoning as including relevant scientific ideas that support the claim, and *sufficient* reasoning as providing adequate information that reveals students' knowledge and reasoning processes. Two research team members first independently coded a subset of data and then discussed the coding results until reaching a consensus. Next, we applied the refined coding criteria to the rest of the data and then compared and discussed the results again. At last, student responses and written arguments were coded at four reasoning levels (Table 2). The two coders agreed on 77% of the coding results. The discrepancies were discussed until consensus was reached.

Level 0 was referred to as reasoning *not present*, as students did not use any core ideas (DCIs) about ecosystem interactions or only reasoned with irrelevant or erroneous ideas in these responses. Level 1 included two forms: *fractional* and *fragmental*. We regarded a response as *fractional* reasoning if it mixed appropriate and erroneous ideas, or if it cited appropriate ecosystem interaction idea(s) but the reasoning process was inappropriate to justify the claim. We regarded a response as *fragmental* reasoning if it only provided the relevant data patterns or mentioned the ecosystem interaction idea(s) but did not make connections between the ideas and the data patterns to their claims. Level 2 was referred to as *linear* reasoning, because these students were able to appropriately reason with one ecosystem interaction idea as it connected to a data pattern. Level 3 was named *complex* reasoning, as these students could sufficiently and appropriately reason with more than one interaction idea in their responses.

To answer *RQ2* about students' use of the targeted SEPs, we compared students' ability to analyze and interpret the graphical displays of ABM-generated data in the pre- and post-assessments based on how well they correctly answered multiple-choice questions using Wilcoxon signed rank tests. We also examined how many students included relevant data patterns from the ABM as evidence to support their written arguments. The two coders agreed on 96% of the coding results. The discrepancies were discussed until consensus was reached.

Assessing students' use of CCCs is challenging as CCCs are integrated with SEPs and DCIs. Furtak et al. (2021) point out that CCCs can be assessed by prompting students to demonstrate their ability to use CCCs to address different phenomena. To answer *RQ3*, we examined students' responses to the open-ended question, "Tell us how using a computer model helps you learn about bark beetle outbreaks," in the post-assessment to identify whether the ABM involved students in using CCCs. We first coded student responses based on the general ABM support

Table 2 Levels of reasoning and examples of responses in post-assessment and written arguments

Levels of reasoning	Level coding criteria	Example responses
Level 0: Reasoning Not present	*Inappropriate* Not provide any relevant information, OR Provide completely irrelevant or erroneous information, OR Make an incorrect claim	-I don't know -I know this because even if the tep. [temperature] is low in the winter it dose [does] not matter because bark beetles can live in any enviorment [environment]
Level 1a: Fractional Reasoning	*Partially appropriate* Mix relevant and erroneous information, OR Include interaction idea(s) but the majority of the reasoning is inappropriate and cannot lead to the claim	I chose that an increase in temperature will result in more beetles because all insects rely on heat to live
Level 1b: Fragmental Reasoning	*Appropriate but insufficient* Briefly provide the relevant patterns but no explanations, OR Briefly mention the interaction idea(s), but do not reason with it/them	I heard that because the temp is going up than that speeds up the life cycle
Level 2: Linear Reasoning	*Appropriate and sufficient* Provide relevant information that reveals an explicit reasoning process based on one piece of evidence or one interaction idea	I chose that because I know that when the temperature is hotter beetles go through their life cycle faster resulting in more beetles
Level 3: Complex Reasoning	*Appropriate and sufficient* Provide relevant information that reveals an explicit reasoning process based on more than one piece of evidence or multiple interaction ideas	I chose option 1 because we learned that when the temperature has increased or is warm, they produce more offspring and they mature more quickly, ending up with more adult beetles to attack trees. Also, the warmer temperatures help adult beetles survive the winter

Table 3 Comparisons on the students correctly answering the questions in pre- and post-assessments ($n=63$)

Question	Three dimensions	Pre-assessment		Post-assessment		Wilcoxon signed rank test		
		n	%	*n*	%	*Z*	*p*	*r*
Question 1	DCI	53	84%	62	98%	−2.714	0.007	0.34
Question 2*	DCI	31	49%	58	92%	−5.014	<0.001	0.63
Question 3	DCI-SEP-CCC	54	86%	60	95%	−2.121	0.034	0.27
Question 4	DCI-SEP-CCC	34	54%	61	97%	−5.196	<0.001	0.65
Question 6	SEP-CCC	38	60%	49	78%	−2.294	0.022	0.29
Question 7	CCC	44	70%	63	100%	−3.771	<0.001	0.48
Question 8:01	CCC	41	65%	47	75%	ns	-	-
Question 8:02	CCC	42	67%	43	68%	ns	-	-
Question 8:03	CCC	35	56%	51	81%	−3.266	0.001	0.41
Question 8:04	CCC	36	57%	47	75%	−2.2	0.028	0.28

*Question 2 only reports the students who correctly chose the option of the rising temperature

perspective (i.e., visualization, manipulation, data-generation) and the use of CCCs separately and then connected the ABM supports to identified CCCs. The two coders agreed on 67% of the coding results. The discrepancies were discussed until consensus was reached. Last, we also compared students' pre- and post-understanding about the use of computer models in science using the Wilcoxon signed rank test.

To answer *RQ*4 about the classroom discourse, we analyzed all the dialogue that occurred during whole-class discussion and teacher interactive lectures over the 6 days to identify how often DCIs about ecosystem interactions were explicitly taught or used to make sense of the phenomenon of bark beetle outbreaks along with the relevant SEPs and CCCs. Two research team members first open-coded the video from one class on each day independently and then discussed the coding results until reaching a consensus. Next, we applied the codes to the other two classes taught on the same day. If new codes arose, we thoroughly discussed them to ensure that all coders had a common understanding. The two coders agreed on 62% of the coding results. The discrepancies were discussed until consensus was reached.

Results

Significant learning gains were identified among the participating students after the BBO unit (Table 3). No statistically significant differences were identified about students' understandings, abilities to perform 3D tasks, or attitudes towards using the ABM in terms of students' gender, ethnicity, English proficiency, or the class they attended in this study.

Students' Use of Ecosystem Disciplinary Core Ideas (DCIs)

Significantly, more students grasped the ideas of *trees as food and shelter*, *mass attack*, and *accelerated life cycle* in the post-assessment. The effect sizes of the student increases ranged from medium to large. The largest gain showed with the idea that a rising temperature would accelerate the life cycle of bark beetles. However, the number of students who grasped the idea of *overwinter mortality* remained low in both pre- and post-assessments (Table 4).

After the BBO unit, significantly more students understood that a rising temperature would increase the bark beetle population (Questions 2 and 4 in Table 3). Significantly more students, increasing from 16 to 49% ($n=61$), were able to provide a *linear* explanation of why a rising temperature will result in more beetles in the post-assessment (Wilcoxon signed rank test, $n=61$, $Z=-5.023$, $p<0.001$, $r=0.64$). No students provided a *complex* explanation in the pre-assessment, but five students (8%) provided a *complex* explanation in the post-assessment (Fig. 3). Such improvement primarily occurred among the students whose responses were ranked as *not present* (Wilcoxon signed rank test, $n=37$, $Z=-4.817$, $p<0.001$, $r=0.81$) and *fractional*

Table 4 Comparison of students who grasped the four ecosystem interaction ideas in pre- and post-assessments based on questions 1, 3 and 5 ($n=63$)

Interaction ideas	Pre-assessment		Post-assessment		Wilcoxon Signed Rank test		
	n	%	*n*	%	*Z*	*p*	*r*
Trees as food and shelter	53	84%	62	98%	−2.714	0.007	0.34
Mass attack	54	86%	60	95%	−2.121	0.034	0.27
Accelerated beetle life cycle	8	13%	37	59%	−5.209	<0.001	0.66
Overwinter mortality	3	5%	9	14%	ns	-	-

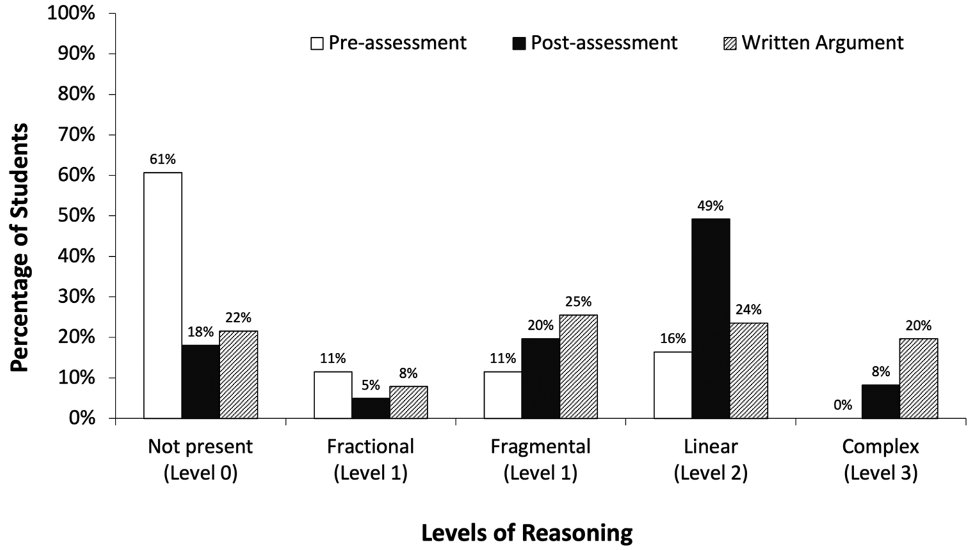

Fig. 3 Distribution of the levels of reasoning about the cause of recent bark beetle outbreaks in students' responses in pre- and post-assessments ($N=61$) and written arguments ($N=51$)

(Wilcoxon signed rank test, $n=7$, $Z=-2.333$, $p<0.02$, $r=0.88$) in the pre-assessment. Before the unit, 37 explanations were ranked as *not present*; 16 of these students provided a *linear* explanation and two of these students provided a *complex* explanation after the unit. Before the unit, seven students' explanations were ranked as *fractional*, and five of these students provided a *linear* explanation and one of these students provided a *complex* explanation after the unit. No significant changes occurred among students whose explanations were ranked as *fragmental* or *linear* reasoning level in the pre-assessment.

In the CER written arguments, 22 students (43%, $n=51$) provided a *linear* or *complex* argument, 13 students (25%) expressed a *fragmental* argument, five students (10%) provided a *fractional* argument, and 11 students (22%) could not provide a quality argument (Fig. 3). Up to 43 students (84%) appropriately claimed the rising temperature as a factor contributing to the severe bark beetle outbreaks (Fig. 4a). Students most often used the idea of *accelerated life cycle* (69%) in their written arguments. Only 29% of students cited the idea of *overwinter mortality* (Fig. 4c).

Students' Ability to Engage in Target Science Practices (SEPs)

Significantly, more students, increasing from 60 to 78% ($n=61$), correctly identified the relationship between the rising temperature and bark beetle outbreaks (Wilcoxon signed rank test, $n=61$, $Z=-2.294$, $p=0.022$, $r=0.29$, Question 6 in Table 3), and significantly more students, increasing from 70 to 100% ($n=61$), properly predicted the future outbreak trend (Wilcoxon signed rank test, $n=61$, $Z=-3.771$, $p<0.001$, $r=0.48$, Question 7 in Table 3).

In the written arguments, 34 students (67%, $n=51$) cited appropriate results from the ABM as evidence to support their claims. These students presented two types of evidence. Twenty-three students (45%) pointed out that the numbers of bark beetle outbreaks were associated with the rising temperature, and six students (12%) described that the bark beetle populations increased in the ABM when the temperature rose. In addition, four students (8%) cited that the ABM showed the interconnections between the bark beetle and host tree populations (i.e., more trees lead to more bark beetles and more beetles lead to fewer trees) (Fig. 4b).

Students' Use of Crosscutting Concepts (CCCs) with Support of ABM

A total of 57 students responded to the open-ended question, "Tell us how using a computer model helps you learn about bark beetle outbreaks." Visualization and manipulation stood out as the two most-cited supports provided by the ABM, reported by 32 students (56%) and 19 students (33%), respectively. We found that 38 students (67%) indicated CCCs when describing how the ABM supported their learning. The CCC of *cause and effect* was most present, indicated by 19 students (33%). Fifteen students (26%) mentioned *stability and change*, and 14 students (26%) mentioned *patterns*. The CCC *of systems and system models* and *scale* were indicated by five (9%) and four students (7%), respectively. We also found that 18 responses included more than one CCC. Table 5 summarizes the observed connections between the two most-present ABM supports (i.e., visualization and manipulation) and the five cited CCCs. Visualization was mentioned with *patterns*, *cause and effect*, *and stability and change* to a similar extent, whereas manipulation was more often mentioned with *cause and effect* than with other CCCs (Table 5).

A multiple-answer question, "Why are computer models useful to scientists" was used to examine students' understanding of system models before and after the BBO unit. In

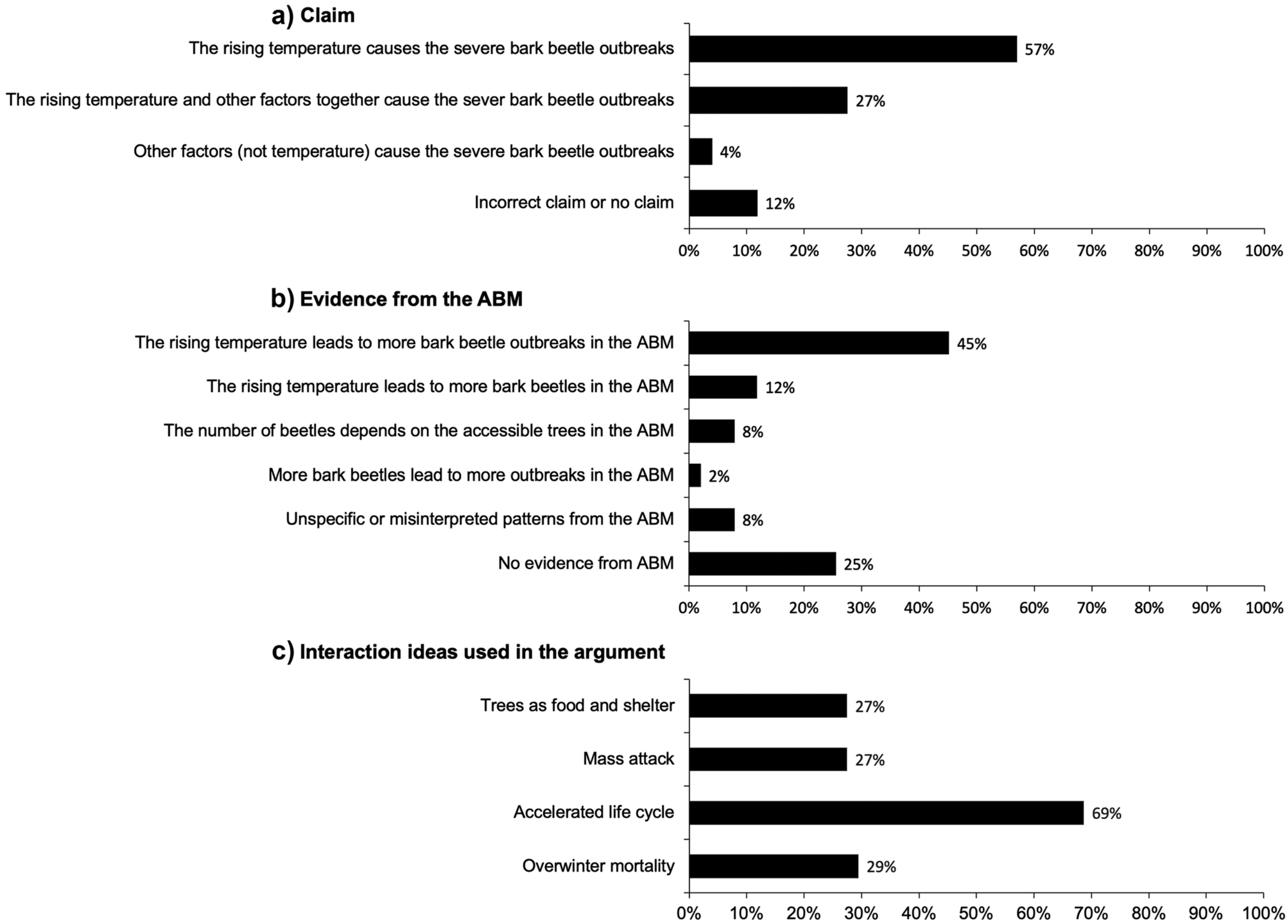

Fig. 4 Percentage of students making a certain claim (**a**), citing evidence from the ABM (**b**), and citing the four ecosystem interaction ideas as reasoning (**c**) in their written arguments ($N=51$)

post-assessment, significantly, more students, increasing from 56 to 81%, chose that computer models are useful for predicting changes (Wilcoxon signed rank test, $n=62$, $Z=-3.266$, $p=0.001$, $r=0.41$, Question 8:03 in Table 3), and significantly more students, increasing from 57 to 75%, chose that computer models are useful for investigating phenomena at a large scale (Wilcoxon signed rank test, $n=62$, $Z=-2.200$, $p=0.028$, $r=0.28$, Question 8:04 in Table 3). In addition, 92% of the participants reported they enjoyed using the ABM.

Characteristics of the Class Discourse in the BBO Unit

The video footage revealed four learning modes in the studied classroom: interactive lecture, small-group work, whole-class discussion, and individual work. Depending on the day, the whole-class discussion and the interactive lectures took from 20 to 60% of the class time. We analyzed the dialogue that occurred during the teachers' interactive lectures and the whole-group discussions and identified a total of 219 incidents that involved teaching/learning about the DCIs along with SEPs and CCCs. We classified the incidents into 11 different categories (Table 6). Three characteristics were revealed in these incidents. First, there were more DCI-learning incidents (i.e., students learned the core ideas about ecosystem interactions) (76%) than DCI-applying incidents (i.e., students used the core ideas to explain or predict) (24%). Second, the ideas of *accelerated life cycle* and *trees as food and shelter* were most often addressed in class, 36% and 33% of the total incidents, respectively. In comparison, the idea of *overwinter mortality* was least addressed, only 12% of the total incidents. Third, the idea of *accelerated life cycle* was most present (40%) among the DCI-learning incidents, and the idea of *trees as food and shelter* was most present (56%) among the DCI-applying incidents. The idea of *overwinter mortality* was least present in both types of incidents, 14% and 6%, respectively.

Table 5 Observed connections between two ABM supports and five crosscutting concepts

ABM supports	CCCs	*n* (%)*	Example responses
Visualization ($n=32$)	Cause and effect	13 (40%)	It helps me learn by showing what is happening and what different variables can do to change what is happening
	Stability and change	13 (40%)	I think that the computer model helped me understand more because I could see what the changes would be over time
	Patterns	11 (34%)	It tells about what can happen in the future and has a specific pattern
	System and system models	3 (9%)	The model helped show me all the things that can affect the beetle population
	Scale	2 (6%)	It helps me see how bark beetles are affecting the forest ecosystem on a larger scale
Manipulation ($n=19$)	Cause and effect	14 (74%)	You can change the amount of trees. You can also change the temperature and see if there is more beetles when there is warmer or colder temperature
	Stability and change	6 (32%)	If you change the year and the temperature there is a lot of change over time
	Patterns	2 (11%)	I can see what is going on and how many outbreaks there are and see how I could help
	System and system models	3 (16%)	It helps me learn by letting me change the drought, temperature, number of trees, and number of diversity
	Scale	2 (11%)	It helped me learned what would happen if the temp went up or down. And if the forest was big or small

*The percentages do not add up to 100% because one response may contain more than one CCC

Discussion and Implications

The present study examines the extent to which students use the three dimensions of science learning, including disciplinary core ideas (DCIs), science and engineering practices (SEPs), and crosscutting concepts (CCCs), during an ABM-supported unit in which students are asked to develop a written argument for a phenomenon. By triangulating data from three sources:

Table 6 A contingency table of four interaction ideas and eleven types of teaching/learning incidents in the BBO unit

		Trees as food and shelter	Mass attack	Accelerated life cycle	Overwinter mortality	Subtotal	%
Learning about the ideas	Teacher elicits students' thoughts about the idea	18	11	26	3	58	26%
	Teacher presents the idea	12	11	13	9	45	21%
	Teacher helps students identify the idea in the reading	9	5	7	6	27	12%
	Teacher explains the idea	3	2	11	2	18	8%
	Students learn the idea from a video	0	4	5	2	11	5%
	Students propose the idea in class	1	1	1	1	4	2%
	Students discuss the idea with peers	0	1	1	0	2	1%
	Students write about the idea	0	0	2	0	2	1%
	Subtotal	43	35	66	23	167	76%
	Sub %	26%	21%	40%	14%	-	-
Applying the ideas	Teacher elicits students' thoughts about using the idea to explain a phenomenon	18	6	11	3	38	17%
	Students use the idea to predict a phenomenon or trend	7	0	1	0	8	4%
	Teacher explains how the ideas can be used to explain a phenomenon	4	2	0	0	6	3%
	Subtotal	29	8	12	3	52	24%
	Sub %	56%	15%	23%	6%	-	-
	Total	72	43	78	26	219	100%
	%	33%	20%	36%	12%	100%	

pre- and post-assessments, students' written explanations for the phenomenon, and an analysis of classroom discourse, we provide evidence that the bark beetle outbreak ABM supported students in using all three dimensions of science learning to make sense of the target phenomenon.

First, the participating students made significant progress in their understanding and use of the DCIs, indicated by significantly more students using the core ideas at the end of the unit to describe the interactions between organisms (bark beetles and host trees) and their environment (bark beetles and warming temperature) in a forest ecosystem. Significantly more students were also able to connect core ideas about ecosystem interactions to explain changes in populations at the systems level. That is, up to 57% of the students appropriately and sufficiently applied the interaction idea(s) to explain the outbreak phenomenon after using the ABM. Students' responses in the post-assessment to the open-ended question, "Tell us how using a computer model helps you learn about bark beetle outbreaks," suggest the ABM enhanced this part of 3D learning by representing the interaction ideas and phenomenon. For instance, one student described that the ABM represented the phenomenon, "I learned that there are a lot of bark beetle outbreaks and that we need to stop global warming." Another student responded that the ABM revealed that bark beetles depend on the host trees, "It shows that the more tree the more beetles and the fewer tree shows the low [beetle] population." It is remarkable that the students who previously possessed a lower-level understanding showed the most growth. These results are consistent with the existing studies that the use of ABMs increases students' understanding of natural phenomena (Pallant & Lee, 2015; Varma & Linn, 2012) and closes the understanding gap (Dickes & Sengupta, 2013).

However, students' gains in reasoning with the four ecosystem interaction ideas were uneven. For example, students more often used the idea of *accelerated life cycle* as reasoning to support their claim in their written arguments than the idea of *overwinter mortality*. The class discourse and ABM design provide some insights into the reasons for this difference. Although both ideas were presented in the BBO unit, the teachers more often elicited the idea of *accelerated life cycle* from students and involved students in applying this idea to explain the outbreak phenomenon. Furthermore, the temperature variable in the outbreak ABM encapsulated both ideas. When students adjusted the temperature variable, they could view the resulting changes in the bark beetle population but could not distinguish the impacts of the two underlying causal processes. Morrison et al. (2000) pointed out that educators must make the relevant conceptual knowledge apparent for students to interpret animated representations properly. Thus, we may improve the ABM by creating two separate temperature variables for *accelerated life cycle* and *overwinter mortality*. Also, the teachers should explicitly clarify to students that the temperature variable in the ABM involves two causal processes.

Secondly, our results suggest that the ABM successfully supported students in using the SEPs of *analyzing and interpreting data* and *engaging in argument from evidence*. Significantly more students could properly identify the relationships between variables (temperature and beetle population size) in the graphical displays of ABM-generated data in the post-assessment. In addition, more than 60% of students' written arguments used evidence from the ABM to support their claim at the end of the unit. That is, students improved their ability to analyze data, identify relationships between variables, and use the data patterns as evidence to construct a written argument to explain a phenomenon. We attribute this growth largely to the use of the ABM. Qualitative data gathered in the post-assessment supports our conclusion. For example, one student responded: "It [ABM] helps me a lot because when I took the CER [the written argument using the claim-evidence-reasoning format] I felt like I had so much evidence."

We acknowledge that there is still room for growth. First, not all students realized the ABM outcomes could serve as evidence. Second, similar to the study from Pallant and Lee (2015), some students simply included the ABM outcomes as evidence in their written arguments without connecting them to the ecosystem interaction ideas for supporting their claims. As stated in *NGSS*, students should understand that "data aren't evidence until used in the process of supporting a claim. Students should use reasoning and scientific ideas, principles, and theories to show why data can be considered evidence" (NGSS Appendix F, p.33). Our findings suggest the need to improve students' understanding about the concept of evidence. Some pedagogical strategies have been proposed to help students understand and use evidence in argumentation (Duncan et al., 2018; Schwarz et al., 2017). For example, teachers may discuss with students why ABM outcomes could serve as evidence and how to include the data as evidence in written arguments properly.

Third, an analysis of qualitative data collected in the post-assessment revealed that students used crosscutting concepts (CCCs) to reason about the ABM outcomes and make sense of the bark beetle outbreak phenomenon. In this study, we found that the ABM helped students to approach the unit phenomenon using five different CCCs. Consistent with Yoon et al. (2015), the CCC of *cause and effect* was the most cited by students. More of our students (25%) cited the CCC of *stability and change*, compared to less than 10% of students reported by Yoon et al. None of our students mentioned the CCCs of *energy and matter* or *structure and function*. We believe these differences are because the phenomenon and learning tasks in the BBO unit are different from those in the digestion unit implemented by Yoon and her colleagues (2015). Our results further add to the existing research by revealing how ABMs supported students in using these different CCCs to make sense of a phenomenon. Students self-reported the visual representations in the ABM best supported their learning by helping them "see" *cause and effect* relationships, *stability and change*, or *patterns* that could be used to make predictions. The manipulative feature of ABMs was mentioned by a smaller, but noticeable, portion of students as supporting the CCC of *cause and effect*. These students' responses are highly important because they explain the finding from Tan and Biswas (2007) that students who used an ABM to investigate an ecosystem outperformed the students who only analyzed the ABM-generated data. That is, involving students in both observing the visual representations and manipulating variables may strongly support students in identifying *cause and effect* relationships. Only observing the ABM visualizations may help students to perceive the *patterns* and *changes* in a *system*, but it is not as effective in helping students recognize the underlying mechanisms.

Another important finding of our study is that using the ABM helped students develop their understanding of the nature of models in science. It is highly interesting that many participating students recognized that computer models are useful for predicting changes. Gogolin and Krüger (2018) reported that very few students, even in grades 9–12, recognized the predictive power of models. However, our results show that a dynamic computer model, such as an ABM, may enable students as young as sixth grade to predict system outcomes. In fact, 100% of the students correctly predicted the future outbreak trend at the end of the unit. A student stated in the short-answer response, "We learned that they [outbreaks] happen more frequently and we can predict changes in the future." Here, the student made the prediction based on a pattern (i.e., happen more frequently), which aligns with an NGSS specification of *patterns* at 3–5 grades that students should "identify patterns related to time, including simple rates of change and cycles, and to use these patterns to make predictions" (NGSS Appendix G, p. 4). Thus, using ABMs develops students' understanding of the nature of models in science as generative tools for making predictions.

The findings from this study have important implications for ABM-supported, three-dimensional teaching and learning. First, this study connects the *NGSS* language about 3D learning to the ABM education literature. Studies on ABM-supported learning often involve concepts in learning sciences that are less accessible for classroom teachers. By interpreting the study results using the three dimensions of science learning (DCIs, SEPs, & CCCs), we help more teachers to recognize the multiple means by which ABMs may support 3D learning. Second, manipulating ABMs to carry out investigations and collect data can provide opportunities for students to analyze and interpret data and construct written arguments based on evidence. Knowing this, teachers may purposefully use ABMs to design and implement 3D learning tasks that involve these and other SEPs. Third, teachers and curriculum developers should recognize that ABMs support students in using multiple CCCs. Namely, ABMs represent *system* components and interactions at different *scales*, reveal the *patterns* and *changes* in a phenomenon over time, and allow users to identify underlying *causal mechanisms*. These perceptions can be generalized to most of the complex systems and relevant phenomena in the natural world and be intentionally used to involve students in using these crosscutting concepts to reason about emergent natural phenomena.

We acknowledge several limitations of this study. First, this study largely focused on whether the ABM supported students' *use* and *application* of the targeted DCIs, SEPs, and CCCs rather than their *understanding* of them. Except for their understanding of the DCIs, we cannot tell how well students improved their understanding of the relevant SEPs and CCCs. Second, our data sources were mainly students' written responses, so we might have missed some deeper misconceptions and thought processes that can only be revealed in interviews. Third, this study involved a relatively small group of students and did not include a control group in which no ABM was used. Although we believe the ABM provided the students with first-hand experience in manipulating a system model and examining real-time dynamic changes, which is unavailable in non-technology-supported learning modalities, testing our findings at a large scale and including a non-ABM control group in the future studies will certainly further our knowledge of ABM-enhanced 3D science learning. Future work with this unit will also involve refining the ABM of bark beetle outbreaks, designing relevant 3D learning tasks with differing inquiry levels, and identifying teacher scaffolding strategies that help students use ABMs to deepen their understanding of the target disciplinary core ideas, science and engineering practices, and crosscutting concepts.

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Author Contribution Lin Xiang conceptualized, designed the agent-based model and the science unit, designed and implemented the study, analyzed the data, wrote and edited this paper. Sagan Goodpaster analyzed the data and edited the paper. April Mitchell designed the science unit, reviewed the assessment questionnaires, and edited the paper.

Availability of Data and Material Due to the nature of this research, the data for this project are confidential. The participants of this study were under age 18 and their parents did not agree for data to be shared publicly, so supporting data is not available.

Code Availability See Supplementary Model code.

Declarations

Ethics Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. The study was approved by the Human Subjects Committee/Institutional Review Board of the Weber State University (Approval Number: 2017-COS-8).

Consent to Participate Informed consent was obtained from all individual participants included in the study.

Conflict of Interest The authors declare no competing interests.

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