Computational Thinking for Using Models of Water Flow in Environmental Systems:

Intertwining Three Dimensions in a Learning Progression

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Abstract

Nearly a decade ago, the *Framework for K-12 Science Education* argued for the need to intertwine science and engineering practices, disciplinary core ideas, and crosscutting concepts in performance expectations. However, there are few empirical examples for how intertwining three dimensions facilitates learning. In this study, we used a learning progressions approach to examine how student engagement in computational thinking (science and engineering practice) intertwines with learning about the flow of water through environmental systems (disciplinary core ideas) and understanding of systems and system models (crosscutting concept). We developed three secondary-level curriculum units situated in current groundwater contamination and urban flooding contexts. Units included specially designed NetLogo computational models. Post-assessments measured student performances in computational thinking processes and understanding of hydrologic systems. Using item response theory in our analysis, we identified distinct levels of performance on a learning progression. At the lower end, Literal Model Users interacted with models and manipulated model interfaces to achieve a specified goal. In the middle, Model Technicians used computational models to solve real-world problems. At the upper end, Principle-Based Model Users used computational thinking processes and principles related to systems modeling and hydrology to explain how the models worked to predict water flow. Differences between performances of Literal Model Users, Model Technicians, and Principle-based Model Users reflected shifts in how students made sense of the systems and system models crosscutting concept. These shifts in performances aligned with progress in computational thinking practices and finally with use of hydrology disciplinary core ideas. These findings contribute to understanding of how science and engineering practices, disciplinary core ideas, and crosscutting concepts intertwine during learning; how computational thinking practices develop; and how computational thinking about system models facilitates learning for environmental science literacy.

Key words: computational thinking, systems and system models, three-dimensional learning, learning progressions, water in environmental systems, environmental science literacy

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A major advance of the *Framework for K-12 Science Education* (National Research Council, 2012) is the depiction of Western science and engineering as cultural endeavors with socially constructed norms for participating in the production, evaluation, and communication of scientific knowledge (Duschl, 2008; National Research Council, 2007, 2012; Osborne, 2014). The science and engineering practices define one dimension of this enterprise, articulating how scientists and engineers create and use scientific knowledge. Inextricably intertwined with the science and engineering practices, like strands of a rope (Krajcik et al., 2014), are two other dimensions: the core ideas of the scientific disciplines and the conceptual tools for sense-making that cut across the disciplines. A second major advance of the *Framework* is that the organization of curriculum, instruction, and assessment, based on this three-dimensional structure, should be informed by empirically based learning progressions of how student participation in and sense-making of science changes across the grade-bands in school.

Learning progression research has attempted to provide an empirical basis for a coherent, three-dimensional approach to curriculum, instruction, and assessment (Alonzo & Gotwals, 2012; Corcoran et al., 2009; Duschl et al., 2011; Jin et al., 2019). There are now numerous learning progressions that trace changes in students' conceptual sense-making about disciplinary ideas (e.g., Alonzo & Steedle, 2009; Furtak & Heredia, 2014; Gunckel, Covitt, et al., 2012; Jin & Anderson, 2012; Mohan et al., 2009; Morell et al., 2017; Plummer & Maynard, 2014) and examples of learning progressions for specific science and engineering practices, such as constructing explanations (Berland & McNeill, 2010), developing models (Schwarz et al., 2009), argumentation (Osborne et al., 2016), and statistical reasoning (Lehrer et al., 2014). However, only a few learning progressions incorporate both content and practice (Gotwals & Songer, 2013; Songer et al., 2009) and only two projects that we are aware of have attempted to build three-dimensional learning progressions across disciplinary core ideas, science and engineering practices, and crosscutting concepts (Kaldaras et al., 2021; Wyner & Doherty, 2017). Many questions remain about how students achieve three-dimensional performance expectations, and if or how their learning along the three dimensions is integrated (Duschl et al., 2011; Sikorski, 2019).

The NGSS identify a specific set of performance expectations that combine science and engineering practices, crosscutting concepts, and disciplinary core ideas. Yet, engaging in science involves many possible combinations of these three dimensions. Our interest is in the combination of science and engineering practices, disciplinary core ideas, and crosscutting concepts that support the development of environmental science literacy, defined as the capacity to draw on scientific core ideas and bring to bear scientific ways of thinking to make sense of environmental issues relevant to people's lives and communities (Anderson et al., 2018; Jin & Anderson, 2012; Mohan et al., 2009). In this paper we focus on how students use computational thinking (science and engineering practice), scientific principles for reasoning about the movement of water (disciplinary core ideas), and the understanding of systems and system models (crosscutting concept) to make sense of groundwater contamination and urban flooding, two environmental issues that people frequently encounter.

As a science and engineering practice, computational thinking is a relatively new focus for science education, not having received widespread attention until the release of the *Framework for K-12 Science Education* (National Research Council, 2012). Since 2012, research related to computational thinking in the K-12 science and engineering curriculum has focused primarily on defining computational thinking and developing frameworks for what students should know and be able to do with respect to computational thinking (Sengupta et al., 2013; Weintrop et al., 2016) and on developing curriculum projects to teach students how to code models (e.g., Leonard et al., 2016; Puttick & Tucker-Raymond, 2018). What has not been studied extensively is how student engagement in the practice of computational thinking changes over time nor how student learning in each dimension might connect to their learning along the other dimensions as they engage in computational thinking.

In this study we examined how students engage in computational thinking while working with agent-based models of water flowing through environmental systems. In the agent-based modeling environment, individual agents that operate independently but are guided by a set of rules are used to investigate interactions within systems (Bonabeau, 2002; Goldstone & Wilensky, 2008; Grimm et al., 2006; Wilensky & Rand, 2015; Wilensky & Reisman, 2006). Our research builds on previous learning progressions for disciplinary ideas relevant to water moving through environmental systems, (Forbes et al., 2015; Gunckel, Covitt, et al., 2012) as well as work on student understanding of systems and system models of water in the environment (Fick et al., 2021; Lally & Forbes, 2020; Sabel et al., 2017).

Background and Conceptual Frameworks

Discourse-based learning progressions are empirically supported descriptions of student learning that trace how student sense-making and engagement in practices change as students learn the cultural ways of thinking and acting that define the discourses of science (Anderson et al., 2018; Gunckel, Mohan, et al., 2012; NRC, 2007; Jin et al., 2019). The lower anchor of a discourse-based learning progression reflects the ways of thinking and acting that students use to make sense of a phenomenon when they initially encounter it. It includes the cultural and social sense-making resources, including ways of talking and writing, that students bring from their home and social worlds (Anderson et al., 2018; Gunckel, Mohan, et al., 2012). Often, these ways of thinking display force-dynamic reasoning, wherein narratives describe relationships with respect to forces that either enable or hinder an action (Pinker, 2007; Talmy, 1988). As students gain experience through instruction with the cultural practices of science, they add new discourse practices and ways of thinking to their sense-making repertoires. The upper anchor of a learning progression represents the goal ideas and scientific practices reflective of the culture of Western science that students should be able to use by the end of high school to explain and predict phenomena (Anderson et al., 2018; Gunckel, Mohan, et al., 2012; Duschl et al., 2011; Jin et al., 2019). Indicators of levels of performance within the learning progression are used to identify the significant shifts in student performance that indicate progress towards achieving the upper anchor.

Learning progressions build on the insights of prior research on student learning (Duncan & Hmelo-Silver, 2009). Below we outline the theoretical framing and existing research on student learning for each of the three dimensions as they relate to water in environmental systems. This is followed by an articulation of how the dimensions intersect in performances reflecting the upper anchor level of our learning progression.

Science and Engineering Practice: Computational Thinking

As an analytical approach to solving problems, computational thinking relies on abstracting the essential elements of systems to define problems, identify relationships, and search for solutions (Grover & Pea, 2018; National Research Council, 2010; Sengupta et al., 2013; Wing, 2006, 2014). Although the *Framework for K-12 Science Education* and the NGSS refer to computational thinking as a single practice, Weintrop and colleagues (2016) consider computational thinking to include different practices that cut across many aspects of conducting investigations and modeling systems. Among their categories are computational thinking practices for building computational models and practices for using computational models to solve problems. This taxonomy highlights the close relationship between computational thinking and modeling given that modeling systems relies on computational thinking to produce generalizable abstract representations (National Research Council, 2012; Sengupta et al., 2013). Thus, while computational models are useful to explain and predict phenomena, creating and using computational models requires understanding how computational models work and the processes involved in preparing problems for computational modeling (Wilensky & Reisman, 2006; Wofford, 2009).

Computational thinking involves the thought processes necessary to break problems into parts in such a way that a computer could be used to solve them (Grover & Pea, 2018; Lee, 2016; Shute et al, 2017; Wing, 2006). Processes are the actions that are embodied in science practices (Osborne, 2014). For example, familiar scientific processes embedded in science practices include observing, measuring, and inferring, among others (Chamberlin, 1965; Cottingham et al., 2017; Platt, 1964). These processes are actions that are used in science practices, such as planning and conducting investigations, constructing explanations, and developing models. Three processes that are necessary for preparing problems for computational solutions using agent-based models and for using these models to find and test solutions to problems are discretization, parameterization, and setting boundary conditions. Below we describe these processes in more detail.

Discretization

In applied mathematics and computer science, discretization is the process of creating discrete analogues to continuous functions, variables, and equations for the purpose of study using digital computers. Understanding how discretization operates is necessary for preparing a problem space for analysis with computational models.

In hydrologic systems, spatial environments such as watersheds and aquifers have properties that vary continuously. Topography is the continuous surface in three-dimensions that defines the shape of a watershed. Similarly, groundwater systems are defined by the continuous arrangement of stratigraphic layers composed of a variety of Earth materials (e.g., sand, gravel, sandstone). To model hydrologic systems in an agent-based computer-modeling environment, these continuous spaces must be divided into discrete units (Wilensky & Rand, 2015). The number and size of discretized spaces have trade-offs in accuracy, precision, and model performance, depending on the data available or the size of the system being modeled. For example, topographic surfaces can be discretized into contours of equal elevation intervals. Smaller elevation contour intervals may produce smoother representations of slope but may misrepresent the accuracy of the model if elevation data are limited. Groundwater systems can be discretized using a raster matrix of cells (two-dimensional) or blocks (three-dimensional) to which values for certain properties of the system can be assigned. Larger cells dividing the system space may cover the problem area in fewer numbers of cells but may also produce more ambiguities in the model. Engaging in the process of discretization requires balancing these trade-offs when preparing a problem-space for analysis or evaluating arguments based on computational models.

Parameterization

In agent-based models of hydrologic systems, the agents are drops of water that move through the discretized space based on certain attributes of that system. Parameterization is the process of identifying those attributes that control the behavior of the agent and assigning values for them in each discretized unit (Wilensky & Rand, 2015). For example, when modeling runoff in a watershed, important parameters are the rate and amount of precipitation from a storm event and the topography and surface features of the system. These parameters vary continuously across the area influenced by the storm, but values can be assigned to the discretized cells based on rasterized contours and interpolation from nearby data points. Similarly, in modeling groundwater flow in an unconfined aquifer, parameters that influence the rate and direction of water flow include the permeability of the substrate and the total potential energy within any given cell in the model. Algorithms can be written to instruct the computer model how to handle parameter values when solving a problem. For example, a groundwater computational algorithm instructs the model to move a water droplet (the agent) to an adjacent cell with a lower total potential energy parameter value. Understanding which parameters are important to include in a model and how the model treats those parameters is necessary for scientists and students to be able to use computational models to explain and predict the flow of water and contaminants through hydrologic systems.

Setting Boundary Conditions

Boundary conditions are important components of computer models as they define the relationship between the modeled system at its edges to the surrounding systems with which it interacts (Wainwright & Mulligan, 2013). In the agent-based modeling environment, the edges of the model represent special conditions that must be accounted for (Wilensky & Rand, 2015).

The model must have rules for how the agent will behave when it encounters an edge (i.e., a boundary). In models of hydrologic systems, the boundary conditions set within the model have consequences for the behavior of an agent water droplet moving through the system. The boundary conditions of the model must depict the real-world conditions of the system represented by the model as accurately as possible. Typically, hydrologic computational model boundaries can be set as open, allowing the agent water droplet to move into and out of the system, or closed, such that when the agent water droplet encounters the boundary, it can no longer move in that direction. In a model of a watershed, most boundaries would be closed, representing the watershed divides that define the system. In a groundwater system, impermeable layers would dictate a closed boundary whereas permeable edges would let water flow into and out of the modeled space. Understanding the relationships defined by the system boundaries and the consequences for the behavior of an agent within a system model is required to create, use, and evaluate computational models of complex systems.

Research on Student Learning about Computational Thinking

Research on integrating computational thinking into school science is a developing area. To date, much of the work in the field so far has focused on the design of computational thinking learning experiences. The research has mostly focused on students' performances on pre-post instructional assessments as a way to evaluate various learning approaches. The findings that are emerging suggest that there are synergistic benefits; students learn more about disciplinary science when taught using computational thinking approaches and students also show improvements on computational thinking performances (e.g., Aksit & Wiebe, 2020; Arık & Topçu, 2021; Hutchins et al., 2020; Peel et al. 2019).

Recent research has begun to delve into explaining the nature of student learning about computational thinking in science settings. Arastoopour Irgens et al. (2020) examined differences in discourse patterns between students who showed positive learning gains and students who showed negative gains while exploring agent-based models of predator-prey relationships, species competition, and natural selection. They found that students who showed positive gains were more likely to provide justifications for the actions of an agent linked to scientific principles, whereas students who did not show positive gains focused primarily on the actions of the agents and did not provide justifications for these actions. Although Arastoopour Irgens et al. did not use a learning progression lens, their descriptions of these two groups of students reflect the principled model-based reasoning of an upper anchor and force-dynamic narratives of a lower anchor of a learning progression, respectively.

Crosscutting Concept: Systems and System Models

System and System Models is one of the seven crosscutting concepts identified in the *Framework* and NGSS. There is discussion in the literature about what the crosscutting concepts represent and whether they provide coherence across the disciplinary core ideas, as claimed in the *Framework* (Osborne et al., 2018; Rivet et al., 2016). Rivet and colleagues present several metaphors for the ways that crosscutting concepts are represented in the *Framework*, including as lenses for noticing salient aspects of phenomena, as bridges to transfer ideas among connected domains, as epistemic tools for engaging in science practices, and as rules for providing order and structure to student thinking. In one of the few existing attempts to understand the role of crosscutting concepts in three-dimensional learning, Fick (2018) showed that implicit and explicit instruction related to system and system models supported students in clarifying confusions while drawing models of watersheds. We build on this work by looking at how the crosscutting concept of systems and system models can be a tool for engaging in computational thinking while working with models of water systems.

Systems theory is a deep and rich field and others have looked at how students develop systems thinking (Ben-Zvi Assaraf & Orion, 2005; Hmelo-Silver & Azevedo, 2006; Jacobson & Wilensky, 2006). Two aspects are relevant to how students use basic concepts about systems and system models to engage in computational thinking. The first is a foundational awareness of systems as units of analysis for isolating and studying a portion of the world (National Research Council, 2012). Systems are typically defined as the set of bounded, interrelated entities that interact to form a whole (von Bertalanffy, 1968). In systems theory, systems are described by their structure, function, and dynamics. The structure of a system includes the parts of the system, their interactions, and their relationships (Ben-Zvi Assaraf & Orion, 2005; Fick, 2018; Fick et al., 2021; Hmelo-Silver et al., 2007). In groundwater systems, for example, the structure includes the organization of the substrate layers that define an aquifer and the physical properties of these layers, such as permeability, that influence the movement of water through the ground. In watersheds, the structure includes the topography and permeability of the land surface. System function describes how a system works. In the case of water systems, this includes the processes that move water through systems, such as infiltration and runoff. System dynamics describes how a system responds to changes and the nature of that response. In analyzing a contaminated groundwater system, for example, dynamics can describe how the system reacts during remediation. In watersheds, dynamics can describe how the system responds to a rain event (e.g., potentially resulting in a flood).

The second aspect of systems and system models relevant to computational thinking is recognizing the purpose of a system model. Studying systems requires building abstract representations, called models, that are used to recognize patterns and explain and predict phenomena (Harrison & Treagust, 2000; National Research Council, 2012; Passmore et al., 2009; Schwarz et al., 2009; Windschitl et al., 2008). System models are thus bounded representations of portions of a system and include the component parts, the processes that operate within the system, and the relationships among the parts and processes. The classic water cycle diagram is one such example. Computational models, especially agent-based models, can represent the nature of system functions and dynamics (Wilensky & Rand, 2015).

Recognizing the relationship between system models and the real-world systems that they represent is an important aspect of this crosscutting concept. Learning progressions research by Schwarz et al. (2009) and also by Pierson et al. (2017) examined how students engage with system models while modeling. Both found that students initially view models as literal illustrations (i.e., models as descriptions) but are later able to conceptualize the relationships between the models and the real world (i.e., models as tools for explaining, predicting, and asking questions), noting what is highlighted and what is hidden. In another study of student understanding of systems across domains, Cisterna et al. (2020) found that secondary students (grades 6-10) were able to identify system components and relationships but had difficulty explaining how the components worked together.

Disciplinary Core Ideas: Principles for Tracing Water in Environmental Systems

Within the *Framework*, a disciplinary core idea in Earth and space science is that water continually moves among and through various reservoirs within the Earth's hydrosphere (ESS2.C). Understanding these movements requires unpacking the components and processes that operate within groundwater and surface water systems. These systems, however, do not operate separately from human actions (ESS3.A and ESS3.C). Environmental systems, such as groundwater and surface water systems, include both natural and connected human-engineered components and are inseparably linked to human social and economic systems (Gunckel, Covitt, et al., 2012; Lally & Forbes, 2020). Groundwater and surface water systems provide fresh water necessary for living systems, including the global human population. Human actions and decisions, situated within political and economic systems, impact the structure and function of hydrologic systems, which in turn also has implications for human socio-political systems (Clark et al., 2016; Collins et al., 2011; Millennium Ecosystem Assessment, 2005; Rockström et al., 2009).

Scientific explanations and predictions of water moving through surface water and groundwater systems include detailed descriptions, at various scales from atomic-molecular through global, of multiple pathways along which water moves (Gunckel, Covitt, et al., 2012). They also include scientific principles that govern the movement of water along these pathways (Gunckel, Covitt, et al., 2012). For example, water flows from areas of higher potential energy to areas of lower potential energy along pathways constrained by topography and permeability. These principles account for the direction and rate water flows on the Earth's surface through watersheds, whether and where water infiltrates into the subsurface, and the rate and direction of water flow in groundwater systems. Furthermore, human actions, such as decreasing permeability of surface systems by increasing the areas covered by pavement or increasing rates of pumping in wells, have implications for the volume of water that flows through the system.

Previous work on a learning progression for water in environmental systems identified four levels of student responses (Gunckel, Covitt, et al., 2012). Level 1 and Level 2 responses provide variations of force-dynamic accounts of water moving through systems. For example, accounts may include evidence of reasoning about where water will flow based on how close two locations are to each other, whether there is an entity that does something to the water (e.g., "… the ground that sucks up the water" or "… the sun dries up the water"), or whether there is something in between two locations that might block a potential pathway (e.g., "…the dam holds back the water."). Level 3 accounts are largely phenomenological in that they describe the phenomenon that is happening. These accounts generally provide incomplete school science narratives that trace water along multiple pathways and identify processes that move water, such as evaporation or infiltration, but do not yet identify the scientific principles that govern the flow of water. Level 4 responses provide mechanistic accounts that include scientific principles (e.g., movement of matter from areas of high to low total potential energy) to explain or predict the flow of water through systems.

A Three-Dimensional Upper Anchor for Computational Thinking about Water in Environmental Systems

The upper anchor for our three-dimensional learning progression for making sense of computational models of water moving through environmental systems builds on and integrates the research on the three dimensions described above. Students performing at the upper anchor would be able to identify watersheds and aquifers (disciplinary core idea) as bounded systems through which water flows (crosscutting concept) and use computational models to abstract the essential elements of those systems for defining problems, identifying relationships, and searching for solutions (science and engineering practice). They would be able to define the structure of groundwater and watershed systems (crosscutting concept) as continuous spatial environments (disciplinary core idea) and be able to manage the trade-offs associated with discretizing relevant variables for computational analysis (science and engineering practice). Furthermore, they would be able to identify parameters and develop rules for using those parameters (science and engineering practice) to predict and explain pathways of water (disciplinary core idea) through these water systems (crosscutting concept).

Combined, these dimensions would produce an emergent capacity for addressing environmental issues that none of the dimensions provides alone. For example, groundwater contamination is a common problem with which communities all over the world must contend. Experts provide maps and cross-sections showing the sources, pathways, and concentrations of the contamination and use complex computational models to predict future conditions under various scenarios or action alternatives. Government agencies, environmental organizations, and parties responsible for the pollution use these predictions to weigh potential responses, including health advisories, engineered solutions, and legal actions. Using an understanding of both how water flows through aquifer systems and how computational models function to interpret experts' arguments positions an environmentally literate public as participants in community discussions about the contamination rather than as merely spectators, or worse, collateral damage. Similarly, land use and climate change affect regional precipitation and runoff patterns, with resultant changes in flooding and water quality that impact many communities. Resilience requires being able to comprehend how water moves through watersheds to understand claims, evaluate risks, and take actions based on computational models. These types of water issues often disproportionally affect marginalized communities (e.g., Balazs & Ray, 2014; Hsiang et al., 2017). Being able to marshal the power of computational thinking about models of water systems could empower communities to push back on the systems and structures that create environmental injustice.

To contribute towards this vision, the research presented in this paper focuses on identifying the lower anchor and intermediate steps of a three-dimensional learning progression for water moving through environmental systems. Our research questions were:

1. At each level of the learning progression, what are the characteristics of students' performances along the three dimensions of computational thinking (science and engineering practice), water flow (disciplinary core ideas), and systems and system models (crosscutting concept)?
2. At each level of the learning progression, what are the relationships among the three dimensions that are evident in students' performances?

Methods

A foundational commitment of learning progressions is that the pathway for student growth from lower anchor to upper anchor performances is shaped by curriculum and instruction (Corcoran et al., 2009; Duschl et al., 2011; Wiser et al., 2012). Therefore, in this study, we used a design-based research approach to curriculum design and classroom instruction (Cobb et al., 2003; Collins et al., 2004; Design-Based Research Collective, 2003) as the context for research on learning progressions (Gotwals & Songer, 2013). Our process involved three phases, shown in Figure 1. Each phase took approximately one year to complete. Phase 1 involved developing curriculum materials, initial learning progression level descriptions, and assessment items. Participating teachers taught the lessons in their classrooms to their students and administered the assessment items. Analysis and interpretation of student responses to the assessment items informed revision of the curriculum materials, learning progression levels, and assessment items. In Phase 2, the teachers taught the revised lessons and administered the revised assessments in their classrooms. Phase 3 involved developing the measurement model of the learning progression using item response theory. Below we describe each of these phases in detail.

Phase 1: Development

Curriculum Design

We conducted this research within a project called Comp Hydro, in which we designed curriculum units at the high school level to integrate computational thinking into instruction about hydrologic systems. The project engaged students in using agent-based computational models of hydrologic systems produced in NetLogo (Wilensky & Reisman, 2006). In these models, the agents were water droplets that moved through groundwater and surface water systems. The advantages of using agent-based models over other types of computational models in this context include their visual interface, their ability to represent continuous processes as discrete steps, their reliance on simple rules grounded in first principles, and their leverage of embodied experience as students learn to analyze the motions of the agent within the model (Farris et al., 2019; Sengupta et al., 2013; Wilensky & Reisman, 2006).

Our study included students in school districts in Arizona, Maryland, and Montana. We wrote three curriculum units incorporating computational thinking processes and systems and system models, with each focusing on either a groundwater contamination issue or a surface water flooding issue that had relevance to the students in the participating schools in each state (Bennett et al., 2007). In the Arizona version, the lessons focused on a groundwater contamination plume caused by historic use of trichloroethelyne (TCE) and 1,4 dioxane to clean military airplane parts at the nearby airport in the 1950s (Tillman, 2009). Similarly, the Montana version explored arsenic and selenium contamination in a groundwater plume emanating from a former lead and zinc smelter (Burns & Marcussen, 2016). The Maryland version focused on surface water flooding related to urban runoff (Smith & Smith, 2015). Each unit incorporated physical models and computer-based NetLogo models to illustrate the computational thinking processes, system models, and hydrologic principles incorporated into the units. The units included lessons for three weeks of instructional time. Curriculum materials included teacher guides, student materials, NetLogo models, and the physical supplies necessary to conduct all lessons.

Learning Progression Levels

In Phase 1, we outlined an initial learning progression from the lower to the upper anchor. The levels of this initial learning progression were based on previous research on student learning and functioned as a hypothesis about how student thinking develops over time, given a set of instructional experiences, which in this case were the lessons in the curriculum materials (Wilson, 2009). The water systems learning progression (Gunckel, Covitt, et al., 2012), described above in the frameworks section, provided the initial levels of performance for the disciplinary core ideas strand about water moving through environmental systems. We established the initial upper anchors for computational thinking based on the literature cited in the conceptual frameworks section above, identifying discretization, parameterization, and boundaries as important aspects of computational thinking. We did not develop separate upper and lower anchors for the crosscutting concept systems and system models because we hypothesized that concepts of systems and system models were intimately connected to student understanding of both hydrologic systems and computational thinking. Instead, we used aspects of systems and system models to interpret student responses to the assessment items, as described in the assessment analysis and interpretation section below.

Assessment Design

To gather evidence of student thinking to test and revise our learning progression levels, we developed assessment items to provide insight into student understanding of hydrologic principles and computational thinking processes in the context of groundwater and watershed systems. Items were situated in water scenarios similar to the scenarios students studied during the Comp Hydro lessons. For example, one scenario involved reading maps to trace water through a watershed and another involved interpreting maps and cross-sections of a groundwater contamination situation. All items were constructed response and asked students to explain their reasoning.

Assessment items were distributed across pre- and post-assessments so that assessments were tailored to the focus of each curriculum unit (i.e., groundwater or watersheds). Each version of the assessment included 15 - 18 items. The pre-assessments did not include some of the items related to computational thinking processes. We assumed items about processes such as discretization would likely be initially unfamiliar to students and thus might not provide rich data for student performances until after students had encountered these processes during instruction.

All versions of the pre- and post-assessments (i.e., Arizona, Maryland, and Montana) included two linking items that were the same on all assessments. In addition, at least 50% of the items on each version overlapped with items on the other two versions. The linking items and overlap items allowed us to equate student performances across the groups of students who took each assessment (Embretson & Reise, 2013). We used an online assessment system to administer the assessments to students.

To understand how students were making sense of these items, we conducted semi-structured think-aloud interviews (Ericcson & Simon, 1993; Leighton, 2017) with 23 students after the students had completed the Comp Hydro instructional activities. Students were asked to share their answers to the assessment items aloud, and we used follow-up questions to probe their thinking. Interviews were audio and video recorded and transcribed.

Classroom Instruction

The Comp Hydro team included researchers who have strong partnerships with school districts in three states in the United States of America (i.e., Arizona, Maryland, and Montana). This arrangement allowed us to recruit teachers from schools reflecting a diversity of racial and ethnic populations (i.e., predominantly Latino/a/x, Black, and White) and contexts (i.e., urban, small city, and rural). Teachers from schools in these districts were invited to integrate the Comp Hydro lessons into their instruction. Teachers volunteered based on their perceptions of the relevance of the lessons to their students and the standards addressed in their courses.

Lead researchers at each site conducted professional development activities with groups of four to eight high school teachers. The participating teachers taught Earth science, integrated science, environmental science, honors biology, computer science, and/or engineering. Professional development activities ranged from four days to two weeks in length, depending on the school district constraints at each site, and introduced teachers to hydrologic principles, system models, and computational thinking processes; the instructional activities; and the NetLogo models. The teachers enacted the Comp Hydro lessons in their classrooms. Comp Hydro research staff were available, either in person or via email, to support teachers in enacting the lessons.

Analysis and Interpretation

Analysis and interpretation focused on looking for patterns in student responses that would help us more thoroughly describe and revise the levels of the learning progression

(Doherty et al., 2012; Gunckel, Covitt, et al., 2012; Wilson & Sloane, 2000). We began by randomly sampling 50 student responses to an assessment item from the pool of all responses. Using an iterative process of analysis and refinement, we identified groups of responses that had similar characteristics, looking for coherence and consistency in how students responded to the items. We focused on how students were making sense of systems and system models as criteria for grouping the responses. During this process we used students' responses to the think-aloud interview questions to gain insight into their written answers. We then developed exemplar coding documents to capture the defining characteristics of each group. The groups of student responses were then ordered based on increasing similarity to the upper anchor and assigned a score value for level of performance (Level 1, 2, 3, 4). We also included a level 0 for students who did not answer the item or said that they did not know the answer.

Next, two researchers independently used the coding exemplar to code another randomly selected sample of 50 responses. A weighted Cohen's Kappa was calculated. The two researchers discussed disagreements and revised the categories and coding documents as new features of student responses emerged. We repeated this process several more times, using 50 new randomly selected student responses each time, until the categories became stable with little need to revise the coding document and a weighted Cohen's Kappa of at least .85 was reached for all items.

Phase 2: Revision

Curriculum Design

After the first implementation, the curriculum materials were revised based on assessment results and post-instruction teacher feedback. For example, teacher feedback led to modifications to the visual graphic interface of the NetLogo models to make it easier for students to use the models. The assessment results identified difficulties students were experiencing with the core concepts, leading to the modification of instructional sequences or the addition of new instructional activities.

Learning Progression Levels

The analysis and interpretation from Phase 1 provided insights into how student thinking across each of the dimensions progressed and interacted along each level of the learning progression. We used these insights to revise our descriptions of the levels of the learning progression. The results reported in this paper are based on this revised version of the learning progression levels.

Assessment Items

Based on the insights provided by our analysis of the assessment results and the think-aloud interviews, we revised some of the assessment items. For example, we clarified the wording of some of the assessment prompts that may have led to misunderstandings about what the item was asking students to do. We also revised some of the illustrations to help direct student attention to relevant or important features.

Classroom Instruction and Student Participants

Lead researchers at each site conducted additional professional development to introduce teachers to the revised lessons. Teachers shared experiences teaching the lessons the previous year and how they would revise their instruction for the coming year. This process allowed teachers to learn from each other’s experiences as well as their own.

Teachers taught the revised lessons to their students. Table 1 shows the number and characteristics of the schools, teachers, and students who participated in the second year of classroom instruction and assessment.

Analysis & Interpretation

Using the revised levels of the learning progression, we refined our exemplar coding documents. We then used this coding document to code all the student responses to the assessments administered in Phase 2. We divided the student responses between two researchers, with 25% overlap. Weighted Cohen's Kappa for the overlap items ranged from 0.83 to 0.91. Items in which there was a disagreement were discussed among the researchers until agreement was reached. These codes were used in Phase 3 described next.

Phase 3: Measurement Model

In Phase 3, the final pool of assessment items and student responses was selected for developing the measurement model of the learning progression using Item Response Theory. We selected 8 items across which analysis of student performances would inform measurement for all dimensions and processes included in the learning progression (i.e., hydrologic principles, computational thinking, and systems and system models). All the items were about hydrologic systems. Items 1 and 2 asked students to trace water through surface and groundwater systems. We used these items to measure student understanding of hydrology principles for tracing water. These items were also the linking items, meaning they were on all versions of the assessment. Items 3 through 8 incorporated computational thinking by providing students with maps of watersheds and cross-sections of groundwater systems and asking students about how they would use computational thinking processes to discretize (Items 3-5), paramaterize (Item 6), and set boundary conditions (Items 7 & 8) in preparing a computational model to trace water through these systems. Because these items required understanding of hydrologic principles and computational thinking processes, we used these items to measure student understanding of computational thinking processes within hydrologic contexts. We used all of the items to analyze student understanding of systems and system models. Items used in the measurement model are included in the supplementary materials. For this phase, we included data only from post-assessments administered after the students had completed the instructional activities.

From the pool of 804 students who took the assessments in the Phase 2, we eliminated students who did not answer at least five of the final eight items. This process resulted in responses from 587 students, of which Arizona students (n= 427) were overrepresented compared to students from Maryland (n=55) and Montana (n=105). To approach a more balanced sampling across the three sites and yet maintain a pool large enough for good statistical analysis (Embretson & Reise, 2013), we used all students from Maryland and Montana and randomly selected 150 students from Arizona to produce our final pool of 310 students. Table 2 shows how many responses were used for each item. Of the final sample of responses, approximately 66% were from students of Latino/a/x or Black ethnic and racial backgrounds from urban Title 1 schools and approximately 33% were White students from small city and rural schools.

The final scores for the selected items were then analyzed using Item Response Theory with a unidimensional, partial credit model (Embretson & Reise, 2013). The model was calibrated on the sample of 310 students. Item fit for all items ranged between 0.75-1.33, indicating acceptable random variation in responses (Wilson, 2005). A Wright Map, which plots item difficulty (right side of the map) on the same scale as student ability (histogram on the left side of the map), was produced (Embretson & Reise, 2013). The points plotted for each item represent the Thurstonian thresholds for each level of difficulty (point at which a student at that ability level has a 50% probability of performing above or below that point) (Embretson & Reise, 2013). No overlaps in thresholds in item difficulties were observed for seven of the eight items, providing evidence that the assessments were able to distinguish between levels of performance on the learning progression (Wilson, 2005). Interpretation of the Wright Map is presented in the results section below.

Results

To address our research questions, we first present the Wright Map and identify the levels of the learning progression. We then use these levels to describe student performances for each of the three dimensions at each level (Research Question 1) and how the three dimensions interact in performances at each of the levels of the learning progression (Research Question 2).

Figure 2 shows the Wright map analysis output. A few patterns are prominent. First, the thresholds for the step between Levels 3 and 4 (diamond shape) for all items except item 7 are approximately equivalent, meaning that these items have similar difficulty at the upper levels. Second, items 1 and 2 had the lowest difficulty and good separation between the threshold for the step between levels 0 and 1 (triangles) and the step between levels 1 and 2 (squares), whereas items 3-8 became progressively more difficult at the lowest levels. Item 7 was the most difficult item and had no threshold for the step between levels 3 and 4, meaning no students performed at level 4 on this item. Furthermore, items 3-6 and item 8 had little to no separation between the levels 0/1 threshold (triangles) and levels 1/2 threshold (squares), indicating that there is little meaningful difference between Levels 1 and 2 for these items. Therefore, we reduced the learning progression to three levels: a combined Level 1-2, Level 3, and Level 4.

Levels in the Learning Progression (Research Question 1)

Our first research question asked about the characteristics of students' performances along each dimension for each of the levels of the learning progression.

Level 1-2: Literal Model Users

Level 1-2 was the entry level in the learning progression. The responses in this category (Tables 3, 4, 5 & 6) indicate that students answered the assessment items by focusing primarily on the visible features of the representation included in the item prompt.

Hydrology Disciplinary Core Ideas. We used Items 1 and 2 to analyze student thinking about water flowing through surface and groundwater systems. Students were shown an aerial photo of a pair of sports fields bounded on one side by a river and on the other side by a parking lot. Students were also shown a corresponding topographic profile extending from the parking lot across the sports fields and through the river. The items asked students to predict whether rain falling on the sports fields (Item 1) and the parking lot (Item 2) would flow to the river.

Table 3 shows example student responses to these items. Level 1-2 responses identified potential pathways based on the photos, often relying on a subjective interpretation of whether the sports field or parking lot was connected to the river (e.g., "the field is near the river") or whether there was something blocking the pathway of the water to the river, such as a small hill or the sports field itself. The focus on water flowing along visibly connected pathways and the invocation of agents to enable or block water flow indicates that students were using force-dynamics to reason about potential water pathways.

Computational Thinking. Tables 4, 5, and 6 show example responses to the assessment items that incorporated the computational thinking processes (Items 3-8). Items 3, 4, and 5 addressed discretization. These items included a topographic map of a watershed overlain by a grid. Students were asked the purpose of the grid (Item 3), and to identify an advantage (Item 4) and a disadvantage (Item 5) for using a grid of smaller cells versus a grid of larger cells. At the 1-2 level, students said that the cells were used “to see closer,” “to get a better look at the area,” and to “mark off certain areas” (see Table 4). These types of responses suggest that the students viewed the grids overlaying the maps as tools helpful for making information on the map visible for study. Such responses indicate that the students focused primarily on reading the map; they did not yet recognize the grid as a tool for abstracting information.

Item 6 addressed parameterization. It showed a discretized cross-section model of a contaminated aquifer and asked students for the information about each cell in the grid that would be necessary to compute and predict the flow of contaminated water through the system. In Level 1-2 responses (Table 5), students made predictions about where they thought the contamination would go (e.g., “the contamination is definitely going into the creek”). However, the responses did not identify the hydrologic principles that would govern such flow. When students did provide more detailed reasoning, they described features visible in the cross-section representation, such as the slope of the water table or the type of material labeled in the cross-section. As with the discretization items, student responses focused on what was visible in the picture of a computer model interface. Students used the picture to explain and predict, but they did not provide evidence that they recognized that a computer model could also be useful for explaining and predicting.

Items 7 and 8 asked students about setting boundary conditions in a model. These items showed students a cross-section of a groundwater system and asked how the right and lower boundaries of the model should be set. The Wright map shows that these items were particularly difficult for students performing at this level. Student responses at this level (Table 6) provided reasoning such as “I chose open so that the water can flow away from the creek on the left.” This response and the many others like it suggest that students mostly interpreted the boundaries as barriers to water flow, consistent with force-dynamic reasoning.

Systems and System Models. Responses at Level 1-2 for all items provide insight into how students made sense of systems and system models. The responses identified structural features of hydrologic systems, such as stratigraphic layers and rivers visible in photos, maps, and pictures of model interfaces. As noted in the responses to Items 1 and 2 on hydrologic systems, students’ descriptions of processes moving water used force-dynamic reasoning.

What is interesting at this level is how students’ answers to Item 6 (parameterization) and Items 7 & 8 (boundary conditions) provide clues to the sense students made of what the depicted models represented and what they could be used for. Responses to Item 6 described what the students thought they would see on the computer screen based on the visible features (e.g., location of the contamination source relative to the river or the type of sediment that composed the aquifer). On the items about setting boundary conditions, students made statements such as, “I would open the boundary so that water could flow down,” and “I chose closed because you don’t want any water flowing through or near the gasoline tank” (Table 4). These types of statements suggest students were responding to the items as if they could manipulate the model interface to control the flow of water and contamination within the view of the picture. It was as if they were seeing the model as a simulation that they could operate, much as they might interact with a computer game, with the goal being to keep the contamination contained or isolated. However, these responses also suggest that students did not see the models as abstractions of real-world systems. Instead, to them, the system resided simply on the picture or graphic interface shown.

We labeled this level Literal Model Users because responses at Level 1-2 relied on visible features in photos, maps, and cross-sections and force-dynamic reasoning to trace water or make predictions about the pathway of water flow, and did not yet recognize system models as abstractions of real-world systems.

Level 3: Model Technicians

Responses at Level 3 had moved beyond literal use to use of computational models for problem-solving.

Hydrology Disciplinary Core Ideas. In contrast to Level 1-2 responses, Level 3 responses to the items we used to analyze student understanding of hydrologic systems (Items 1 & 2) traced the water from the sports fields and the parking lot along multiple possible pathways (see Table 3). They often described pathways (e.g., “it would travel through the ground into the river”) or named processes (e.g., “it would probably evaporate”) to trace the water. Many noted that water runs downhill. However, responses did not include principles of hydrologic flow to explain how or why the water would move along the pathways identified.

Computational Thinking. Responses to the items that incorporated computational thinking showed that students performing at Level 3 were beginning to recognize computer models as useful for solving problems. Example responses to the items incorporating discretization (Items 3-5, Table 4) include, “it [the smaller cell sizes] is easier to locate a cell in specific areas that you would want with more detail,” suggesting that the students viewed the discrete cells as grids for locating information on maps and cross-sections, much like latitude and longitude lines. Some responses, such as “the purpose is to color code your map with the different colors that determine the contamination and where it is strongest at,” indicate that students also thought that the cells could be useful for organizing information related to hydrology, such as water flow, rainfall, or water contamination. Responses such as “this makes more grids that you have to label” recognized that the size of the cells mattered for how much work would be required to identify and organize the information.

Level 3 responses to the items that incorporated parameterization (Table 5, Item 6) named at least one relevant parameter for modeling groundwater flow and in some cases described how that parameter was relevant. These responses did not, however, explain the hydrologic principle that governed water flow that would be useful for writing rules for computational models. For example, many students named sediment type as a relevant parameter, but only stated that it affected the rate of water flow; they did not explain that water flows more easily through sediment that has a higher permeability. These responses suggest that students were beginning to recognize that computational models rely on information input into the model and rules for operating on that information to produce a solution to a problem.

Student responses to the items about boundary condition (Items 7 & 8, Table 6) suggest that students thought of models as useful for seeing what would happen in the real world under various possible conditions and to look for potential solutions to problems (e.g., containing groundwater contamination). They talked about using the models to find out where the contamination would go under conditions that would be “as real as possible.” However, as in the parameterization item, the responses indicate that the students did not connect the relevant hydrologic principles to their computational reasoning about boundary conditions. Usually, either their use of hydrologic principles was incorrect, or they did not use a hydrologic principle to make their choice about the boundary conditions of the model.

Systems and System Models. Level 3 responses to the items incorporating computational thinking (Items 3-8) indicate that students had moved beyond manipulating the computer interface to achieve a goal and instead viewed the system models as tools for solving problems. Students could use the system models to trace water through hydrologic systems, using school science rules. Responses to the items addressing discretization and parameterization identified system structures and described system functions that were not visible on the representation given, such as rainfall amounts or contamination concentrations, suggesting that students were beginning to think abstractly about physical systems. Furthermore, their responses to the boundary items indicate that students recognized computational models as abstractions of those physical systems where they could test ideas and learn about aspects of systems hidden from view.

We labeled Level 3 the Model Technicians because we interpreted from these responses that students who performed at this level recognized computational models as tools for solving real-world hydrologic problems. Nevertheless, although students performing at Level 3 used computer models to produce solutions to problems, their responses did not explain how or why the model would run or produce the results that were given.

Level 4: Principle-Based Computational Model Users

Level 4 of the learning progression describes item responses that reflect principle-based reasoning about water flowing through systems as well as principle-based understanding about how computational models work.

Hydrology Disciplinary Core Ideas. At Level 4, the student responses to the items that we analyzed for student thinking about hydrologic systems (Items 1 & 2, Table 3) included explanations for how and why the water would move downhill. For example, students said that the water would reach the river because, “the elevation goes down so that the gravity will pull the water down into the river,” or “because groundwater flows from high hydraulic head to low.”

Students also included reasoning about other pathways, such as evaporation into the atmosphere or infiltration into the groundwater, as well as factors such as permeability that would constrain potential pathways. These types of responses included principles upon which the students' explanations and predictions were based.

Computational Thinking. Level 4 responses to the items incorporating computational thinking indicate that students are not only able to use models, but they also are now able to explain how the models function to produce a solution to a problem. For example, on the discretization items (Items 3, 4, & 5, Table 4), responses such as, "The purpose of dividing the areas into cells is so that the computer can read one cell at a time" indicate that students recognized discretization as a step necessary to break down continuous data to make the data tractable for computational processing. In contrast to Level 3 responses that focused on locating data on the representation shown, Level 4 responses referred to the computational thinking process of dividing a continuous space into chunks to input as data into a computer model. On the parameterization item (Item 6, Table 5), responses such as "the hydraulic head; water flows from high hydraulic head to low hydraulic head. If you knew that information for each of the boxes you could calculate where the water would go," identified a relevant parameter and gave an explanation, based on a hydrologic principle, for why that parameter was necessary. Responses to the items about boundary conditions item (Items 7 & 8, Table 6) correctly identified the boundary conditions necessary to model the groundwater flow and provided a reason based on the hydrologic flow of water through the aquifer system shown in the item. These responses suggest that students understood that the problem space had to be prepared (discretization items), that hydrologic principles constrain how information about the system is used by a model (parameterization), and how to set the model conditions so that it accurately reflected the system being modeled (boundary condition items).

Systems and System Models. Level 4 responses for all items showed that students were bringing a systems-based approach to working with computational models (Tables 4-7). Not only did responses identify relevant structures and processes, but they also reflected a principle-based understanding of how water moves through systems. Furthermore, the responses to the computational thinking items used these principles of hydrologic systems to explain how the computer models were able to trace water through these systems. For example, as described above, the Level 4 responses to the parameterization items often named not only relevant parameters and the hydrologic principles that govern their use, but they also indicate that students recognized how a computer model would use that parameter to trace water based on the appropriate hydrologic principle. Level 4 responses to the boundary conditions items, such as, "I would leave the right boundary open so that water can flow through it and through the path of the contaminations so that I can study its effects," recognized not only that the boundaries had to be set relevant to the structure of real-world systems, but also how those boundaries functioned in the computational modeling space to facilitate explaining, predicting, and problem-solving.

Level 4 Principle-Based Computational Model Users reflect the upper anchor of the learning progression. They can use scientific principles for how water moves through hydrologic systems to not only use models to explain and predict the flow of water through systems, but also to explain how agent-based models function to model the flow of water through systems.

Relationships Among the Dimensions: Computational Thinking, Systems and System Models, and Hydrologic Principles (Research Question 2)

Reading across the levels of the learning progression described in the previous section, changes in student responses are traceable along all three NRC *Framework* dimensions. Student accounts of water moving through hydrologic systems moved from force-dynamic (Level 1-2), to using school science stories (Level 3), to identifying and using scientific principles of how water moves through systems (Level 4). Evidence for computational thinking showed that student responses shifted from describing visible features of computational models (Level 1-2), to using computational models for solving problems (Level 3), to being able to explain how to use computational thinking processes (e.g., discretization) to model water systems (Level 4). Finally, students' application of the *systems and system models* concepts in their responses progressed from viewing system models as simulations isolated from the physical world that can be manipulated to achieve a goal (Level 1-2), to recognizing models as abstractions of physical systems (Level 3), to being able to explain how computational models function to trace water through systems (Level 4).

Shifts along each of these dimensions also showed that student performances at higher levels were more three-dimensionally intertwined compared with student performances at lower levels. At Level 1-2, the force-dynamic accounts focus on the visible aspects of the models, and approach to the models as simulations suggests that students' understanding of hydrologic principles, engagement in computational thinking, and application of systems and system models concepts were not well integrated. Further evidence for this separation at Level 1-2 includes the increasing difficulty of the post-assessment items at Level 1-2, as shown on the Wright Map. Items 1-2, which were about hydrologic systems, were easier for students to answer than items 3-

8, which incorporated computational thinking into questions about hydrologic systems. The items about setting boundary conditions (Items 7 & 8) were most difficult. For students to respond to these items, they needed to intertwine hydrologic concepts (disciplinary core idea) with computational thinking (science and engineering practices) about system models (crosscutting concepts). That these items were so difficult at Level 1-2, compared with items querying only about hydrologic systems indicates the three dimensions remained separate at the lowest levels.

Because items 3-8 were difficult at the lower levels, reaching Level 3 performance for these items represented a significant achievement on the learning progression. The Wright Map shows that the item difficulties at Level 3 exhibited little variation (save Item 7). Level 3 also represented a large increase in difficulty for items 1-5, which were easier at the lower levels. At this point, student responses show a major shift along the *systems and system models* dimension as students moved from viewing computational models as isolated simulations to seeing them as abstractions of real-world systems. This shift corresponded with a shift from describing what was visible on a model representation to using computational models and computational thinking processes to solve problems, such as using discrete contours and raster cells to locate and organize information and using models to see how water moves through hidden parts (e.g., aquifers) of hydrologic systems.

Thus, responses at Level 3 suggest that the *computational thinking* dimension and the *systems and system models* dimension were beginning to integrate. However, the responses also show that students were not yet accessing hydrologic principles to trace water through systems. Although at Level 3 students could name processes that moved water along multiple potential pathways, they were not yet using hydrologic principles to explain how and why water would flow along some pathways but not others. Because a principle-based understanding of water in environmental systems is necessary to understand how agent-based models of water systems work, students' use of school science stories about water may have inhibited their ability to explain how computational models functioned to trace water through systems.

It was not until Level 4 that students began to use hydrologic principles to trace water in groundwater and surface water systems. Students performing at level 4 could explain and predict the flow of water through hydrologic systems, and they could also explain how computational models of hydrologic systems use these same principles to trace and predict water flow. At Level 4, the three dimensions become integrated in students' responses. Figure 3 summarizes the levels of the learning progression and how the three dimensions of the NRC *Framework* become more intertwined at each level of performance.

Discussion

The findings from our analysis provide insights into three areas of interest in science education research: 1) How the three dimensions of the NRC Framework may intertwine during learning, 2) How student performances in computational thinking may become more aligned with the norms of scientific practice, and 3) How computational thinking fits into environmental science literacy. We discuss these insights below.

Intertwining of Three Dimensions

Prior to the *Framework for K-12 Science Education*, science content, scientific inquiry, and the unifying themes of science were taught as separate strands with standards or grade-level benchmarks for each (American Association for the Advancement of Science, 1993; National Research Council, 1996). Grounded in the understanding that learning science involves enculturation into the practices of science (Driver et al., 1994), the *Framework for K-12 Science*

Education and the NGSS moved towards integrating disciplinary science knowledge with the capacity for doing science. The foundational argument is that science education should engage students in instructional experiences that integrate knowledge and practice. Throughout the *Framework*, the authors argue for the integration of these dimensions into curriculum, instruction, and assessment. Towards that end, the NGSS established standards that incorporate science and engineering practices, disciplinary core ideas, and crosscutting concepts into single performance expectations. As Krajcik at al. (2014) explained, these dimensions are supposed to work together, “like strands of a rope” to make learning stronger (p. 159).

Our findings illustrate how these “strands of a rope” may come together when learning with computational models of water moving through environmental systems. We found that at Level 1-2, we could only characterize student performance along each dimension separately. However, as student performances reflected higher levels on the learning progression, their progress on one strand influenced the progress that they were able to demonstrate on a different strand. There is evidence from other studies that understanding of disciplinary core ideas influences how students engage in science practices (Kaldaras et al., 2021; National Research Council, 2007; Songer & Sawyer, 2006). Our findings that students’ Level 3 school science accounts of water moving through systems (versus principle-based Level 4 accounts) may have inhibited their ability to explain how computational models trace water through systems aligns with this previous research. At Level 3, the disciplinary core dimension had not yet intertwined with the strand for science and engineering practices and it is not until these two dimensions work in concert that student performances reflect Level 4 knowledge and practice.

What is new in our study is how the crosscutting concept may have played a role in the enactment of a science practice. We found that a shift in how students made sense of systems and system models changed how they were able to engage with the computational models and advance their computational thinking. This finding suggests that progress towards a performance expectation that intertwines science and engineering practices, disciplinary core ideas, and crosscutting concepts is not simply a matter of making progress along each strand separately nor simultaneously. Rather, as students make progress towards a three-dimensional performance expectation, the dimensions become more tightly connected, making advances along each dimension possible. Using the rope metaphor, the science practice (computational thinking) and crosscutting concept (system and system models) became intertwined first and the disciplinary core ideas (hydrologic principles) twisted in only at the upper level.

This finding has implications for how progress along a three-dimensional learning progression is conceptualized. While it is important to be able to identify the characteristics of each dimension at each level of performance on a learning progression (Kaldaras, 2020), expecting that progress from one level to the next along each dimension is equally difficult does not reflect what we observed. Our Wright map shows that integration of dimensions makes assessment items more difficult, especially for students performing at the lower levels. Sikorski (2019) questioned whether requiring progress along all three dimensions to make progress towards higher levels of performance overly constrains student learning to the point that progress is no longer visible or possible. Our findings point towards the importance of recognizing the separateness of the dimensions at the lower levels and attending to how the dimensions come together as students gain experience.

These results suggest that growth in understanding of water in environmental systems (i.e., learning) coincides with the degree to which the disciplinary core ideas about water intertwine with computational thinking (science practice) and systems and system models (crosscutting concept). Progress along each dimension was synergistic, not isolated nor parallel. Progress in the crosscutting concept made possible progress in the science and engineering practice and eventually in the disciplinary core ideas necessary to provide principle-based accounts of water moving through environmental systems.

Implications for Student Learning about Computational Thinking

A fundamental problem in learning progressions research is identifying what progresses as students advance toward a desired learning goal (Corcoran et al., 2009; Duschl et al., 2011; Jin et al., 2019; National Research Council, 2007). Our findings suggest that becoming more competent in computational thinking in a science context is not just a matter of getting better at computational thinking. What we see change across the levels in the learning progression as students engage in computational thinking is how students understand the nature of what they are doing and for what purpose.

At the lower level (Level 1-2), students interacted with computer interfaces to achieve a goal, such as stopping the flow of contamination in an aquifer as represented on the screen. The computational thinking in which they engaged was focused on manipulating the visible features on the screen to help them achieve this goal. When students began to see the computer model as a representation of a system (Level 3), their computational thinking shifted towards using discretization, parameterization, and setting boundaries as tools for using the model to solve a problem grounded in the physical world. This growth, from Literal Model Users to Model Technicians is a significant accomplishment because it reflects a major shift in understanding of what a model is, how to interact with it, and how it can be useful. Students' goals for using the computer model also shifted, as students moved from seeing the model interface as a computer game to recognizing a computer model as a tool for generating solutions and providing answers to questions.

The transition from Level 3 Model Technicians to Level 4 Principle-based Computational Model Users also reflects a shift in how students interacted with computer models and their goals for interacting with the models, although this shift may not be as seismic as the shift from Level 1-2 to Level 3. Level 4 computational thinking is about understanding how the computational model works, not just what it does. Students progressed from recognizing computational models as tools for generating answers to figuring out how the tool functions. At Level 4, they were able to use discretization, parameterization, and boundary conditions to think critically about the answers and solutions that the computer models generated.

This type of shift in practices is akin to other types of discourse shifts that we have observed in accounts of water moving through environmental systems (Gunckel, Covitt, et al., 2012), carbon cycling (Mohan et al., 2009), and energy (Jin & Anderson, 2012). In these discourse-based learning progressions, accounts change based on changes in the types of communities in which they participate. As students gain access to new discourse communities, such as school science discourse communities and scientific discourse communities, their accounts of water, carbon, and energy shift to align more with the purposes for and ways of explaining and predicting phenomena in those communities. In the context of tracing water, the purpose for accounting for where water goes and what happens is different based on the community in which one participates. In the context of computational thinking, we saw a similar shift in how students engage in computational thinking based on how students viewed the nature of what computational models are and the purposes for using them. Thus, we argue that achievement of higher levels of performance for computational thinking coincides with changes in how students view the purpose for using computational models.

Contributions to Environmental Science Literacy

We preserved labels for the upper levels of our learning progression as Level 3 and Level 4, even though we collapsed the lower two levels into one (Level 1-2) to align it with other environmental science literacy learning progressions (Gunckel, Covitt, et al., 2012; Jin & Anderson, 2012; Mohan et al., 2009). The disciplinary core idea strand of the learning progression is directly based on the learning progression for water in socio-ecological systems (Gunckel, Covitt, et al., 2012) and we did see four levels of performance in the two items that primarily addressed hydrologic concepts. Furthermore, we felt it was important to show that Level 1-2 Literal Model Users in this learning progression is aligned with and has similar characteristics to Levels 1 and 2 of the water, carbon cycle, and energy learning progressions, all of which rely on force-dynamic reasoning. Similarly, Level 3 Model Technicians in this learning progression is aligned with Level 3 Incomplete School Science Narratives from the water and carbon cycle learning progression (Gunckel, Covitt, et al., 2012; Mohan et al., 2009), and Level 3 Inconsistent Tracing of Matter-Energy category in the energy learning progression (Jin & Anderson, 2012). Across these progressions, Level 3 accounts re-tell school science stories that describe the phenomena but do not include model-based mechanisms or principles to explain and predict (Windschitl et al., 2008). Likewise, our Level 4 Principle-based Computational Model Users is aligned with and has similar characteristics to Level 4 Scientific Model-Based Accounts in the water, carbon cycle, and energy learning progressions. By preserving the labels for the upper levels in our learning progression, the connections across these learning progressions for environmental science literacy are explicit and the new insights into computational thinking from this research can add to the general understanding of the levels of performance for environmental science literacy of socio-ecological systems.

Making sense of environmental issues that have relevance to one's life and community requires the ability to intertwine the science and engineering practices, crosscutting concepts, and disciplinary core ideas. Researchers have described students' explanations of water in environmental systems (Covitt et al., 2009; Forbes et al., 2015; Gunckel, Covitt, et al., 2012)), modeling practices with respect to the water cycle (Pierson et al., 2017; Schwarz et al., 2009), and systems thinking about water (Ben-Zvi Assaraf & Orion, 2005; Fick, 2018; Fick et al., 2021; Lally & Forbes, 2020). Our research shows how student engagement in computational thinking can be an integral component of environmental science literacy. We contend that achieving Level 4 three-dimensional performance expectations for computational thinking using agent-based models of water systems positions students for more scientifically informed participation in community decision making about socio-ecological water issues. Importantly, our research shows that computational thinking is not something that should just be added onto instruction about water, but rather, is an essential element of facilitating deeper learning of how and why water moves through environmental systems. Our post-instructional assessment results, which show that most students performed at Level 3 but that a large number achieved level 4 (Figure 2), indicate that this goal is within reach for high school students.

Conclusion

Nearly a decade ago the *Framework* argued for the need to intertwine science and engineering practices, disciplinary core ideas, and crosscutting concepts in performance expectations; this study provides empirical evidence for how intertwining these dimensions facilitates learning. We found that student understanding of water in environmental systems emerges from the intertwining of the three dimensions of the *Framework for K-12 Science Education* - science and engineering practices, disciplinary core ideas, and crosscutting concepts. While there is more to be learned about how the three strands intertwine, our work revealed that differences in student performance were related to the degree to which these dimensions intertwined, rather than being in additive or parallel development to each other and that computational thinking was an essential component of this process of intertwining.

The findings point to future research directions for examining how students make progress in computational thinking. We focused on three computational thinking processes for using agent-based models, but there are other types of models, such as equation-based models, that require different or additional computational thinking practices and processes. Investigating how students learn to engage in computational thinking with these types of models will expand how the field understands computational thinking in science. Initially, our work focused on computational thinking with respect to environmental science literacy and how students can become better prepared to understand water issues that affect their communities. Investigating how students engage with these computational thinking processes in other domains, such as ecology or physics, could be fruitful given the ways that science and engineering practices and understanding of disciplinary core ideas might interact. Future work could further investigate how students use computational thinking processes related to other socio-scientific issues that are relevant and important in their lives.

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