INTEGRATING COMPUTATIONAL THINKING WITH K-12 SCIENCE EDUCATION
A Theoretical Framework

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Abstract: Computational thinking (CT) draws on concepts that are fundamental to computing and computer science, however, as an approach, it includes practices, such as problem representation, abstraction, decomposition, simulation, verification, and prediction that are also central to modelling, reasoning, and problem solving in many scientific and mathematical disciplines. Recently, arguments have been made in favour of integrating programming and CT with K-12 curricula. In this paper, we present a theoretical investigation of key issues that need to be considered for integrating CT with K-12 science. We identify the synergies between programming and CT on one hand, and scientific expertise on the other. We then present a critical review of literature on educational computing, and propose a set of guidelines for designing learning environments in science that can jointly foster the development of computational thinking with scientific expertise. Finally, we describe the design of a learning environment that supports CT through modelling and simulation to help middle school students learn physics and biology.

1 INTRODUCTION

Wing (2006, 2008) and others (NRC, 2010) have described computational thinking as a general, analytic approach to problem solving, designing systems, and understanding human behaviours. Computational thinking (CT) draws on concepts that are fundamental to computing and computer science, however, as an approach, it includes practices (*e.g.*, problem representation, abstraction, decomposition, simulation, verification, and prediction) that are also central to modelling, reasoning, and problem solving in a large number of scientific and mathematical disciplines (NRC, 2010). Several scholars (Soloway, 1993; diSessa, 1986, 2000; Sherin, 2000; Pea, 1986; Guzdial, 1995) have used the synergies between scientific thinking, analysis and engineering design, and evaluation to establish close links between CT and modeming, reasoning, and problem solving in STEM disciplines.

Developing scientific reasoning and expertise requires sustained, immersive educational experiences, as is reflected in the recent efforts to develop learning progressions for science in K-12 classrooms (Lehrer, Schauble, and Lucas, 2008; Krajick *et al.*, 2008). Similarly, fostering a curriculum that integrates CT with science and mathematics requires the design of coherent, long-term curricula (ACM K-12 Taskforce, 2003). However, there exists no theoretical framework that can support such an endeavour, and empirical studies show that integrating computational modelling and programming with K-12 science and math curricula can be extremely challenging (Sherin *et al.*, 1992). Our goal in this paper is to establish such a framework and present the design of a computer-based learning environment, which supports middle school science learning through Computational Thinking in Simulation and Model-building (CTSiM).

2 REVIEW OF LITERATURE ON EDUCATIONAL COMPUTING

Perkins and Simmons (1988) argued that novice misconceptions in math, science, and programming exhibit similar patterns in that misunderstandings in these domains have domain-specific (*e.g.*, challenging concepts) and domain general (*e.g.*, difficulties pertaining to conducting inquiry, problem solving, and epistemological knowledge) causes. Harel and Papert (1991) argued that programming is reflexive with other domains, *i.e.*, learning programming in concert with concepts in another domain can be easier than learning each separately. Along similar lines, several researchers have shown that programming and computational modelling can serve as effective vehicles for learning challenging science and math concepts (Guzdial, 1995; Sherin, 2001; Hambrusch *et al.*, 2009; Blikstein & Wilensky, 2009; diSessa, 2000; Kaput, 1994; Kynigos, 2007). Table 1 illustrates components of CT that are central to our framework and establishes their relationship to scientific practices.

Table 1. Computational Thinking and STEM Expertise

Computational Thinking and Programming	**STEM Expertise**
Abstractions	Models, laws & other generalizable representations in science; Variables and functional forms in mathematics
Encapsulation	Creating coherent, formal representations of scientific processes and phenomena; Understanding functions as dynamic objects in mathematics
Classes/Agents & Class Inheritance	Agent-based thinking (micro-level reasoning, species vs. individuals, classification & hierarchy – inheritance)
Emergence & Aggregation	Macro-level reasoning; Generating aggregate-level equations and functional forms from individual-level variables
Algorithms (Behaviours) & Causal Reasoning (Interactions & Rules)	Mechanistic reasoning; Natural laws; Mathematical equations and functions
Software Engineering / Iterative Design	Iterative theory refinement through modelling; Model matching; Model Refinement
Unit Testing and Verification	Experimentation; Hypothesis Testing; Verification
Formal representations	Mathematical models & inscriptions

2.1 Pedagogical Benefits of Integrating CT with Science Curricula

We discuss a number of pedagogical benefits that may be derived from integrating CT and K-12 science curriculum units.

A. Lowering the learning threshold by reorganizing scientific and mathematical concepts around intuitive computational mechanisms: Several studies have shown that through programming, students can construct representations of physics concepts such as speed and acceleration, which in turn provides motivation for learning programming and leads to a deeper understanding of concepts in both domains (Sherin, 2001; Soloway, 1996; Guzdial, 1995; diSessa, 2000; Papert, 1980). Sherin (2001) and diSessa (2000) argued that programming enables novice learners to access their intuitions about the physical world. Redish and Wilson (1993) argued that computational representations enable us to introduce discrete forms of the fundamental laws, which can be much simpler to explain and understand than the continuous forms traditionally presented in equation-based instruction. Furthermore, these studies also suggest that in the domains of physics and biology, rather than organizing scientific phenomena and domains in terms of abstract mathematical principles, these phenomena can be organized in a more intuitive fashion around computational mechanisms and principles (Redish and Wilson, 1993; Sengupta & Wilensky, 2011; Wilensky & Reisman, 2006). .

B. Programming and computational modelling as embodiments of core scientific practices: Soloway (1993) argued that learning to program amounts to learning how to construct mechanisms and explanations. Therefore, the ability to build computational models by programming corresponds to core scientific practices, such as model building and verification. Lehrer, Schauble and Lucas (2008) indicate that modelling is a fundamental component of inquiry in science. Regardless of the domain, scientists' work involves building and refining models of the world (Stewart & Golubitsky, 1992).

C. Developing pre-algebra concepts through graphing functions and linked representations: Much like computational environments for science, environments like SimCalc (Kaput, 1994; Hegedus and Kaput, 2004) ESCOT (Roschelle *et al*., 1999), and E-slate (Kynigos, 2001, 2007) enable students to learn algebra by creating their own dynamic representations of concepts, such as rate and proportion, through animations of actors. Based on this research, our goal is to provide students with the following opportunities within an integrated modelling platform by (a) linking the underlying computational model (*i.e.*, agent-based program) with the resultant visualization of the programmed behaviours as well as mathematical inscriptions (*e.g.*, graphs) to measure salient aspects of the simulated behaviours; (b) importing physical data into the mathematical realm in active ways, and (c) manipulating functional forms to develop mathematical narratives and explanations of scientific phenomena.

D. Contextualized representations make it easier to learn programming: When computational mechanisms are anchored in real (world) problem contexts, programming and computational modelling become easier to learn. Hambrusch *et al*. (2009) found that introducing computer programming to undergraduate non-CS major students in the context of modelling phenomena in their major domains (physics and chemistry) resulted in higher learning gains (in programming), as well as a higher level of engagement.

2.2 Agent-based Computation

In this work, we focus on multi-agent-based computational modelling (MABM). An example of a multi-agent programming platform widely used by both researchers and educators is NetLogo (Wilensky, 1999; Sengupta & Wilensky, 2009). The term "agent" in the context of MABMs denotes individual computational objects or actors (*e.g.*, cars), which are controlled by simple rules assigned by the user. It is the interactions between agents (based on these rules) that give rise to emergent, aggregate-level behaviour (*e.g.*, formation of a traffic jam – while individual cars move forward, the traffic jam moves backward – see Resnick, 1994).

When students learn using MABMs, they use their intuitive knowledge at the agent level as they are asked to manipulate and reason about the behaviours of individual agents. Then, by visualizing and analyzing the aggregate-level behaviours that are dynamically displayed in MABM simulations, students can develop multi-level explanations by connecting their relevant agent-level intuitions with the emergent phenomena (Resnick, 1994; Wilensky & Resnick, 1999; Klopfer, Yoon, & Um, 2005; Sengupta & Wilensky, 2011; Blikstein & Wilensky, 2009). These scholars have argued that in most science classrooms, aggregate-level formalisms are typically used to teach scientific concepts and phenomena, such as using the Lotka-Volterra differential equation to explain how populations of different species in a predator-prey ecosystem evolve over time (Wilensky & Reisman, 2006). In contrast, when complex phenomena (*e.g.*, microscopic processes of electrical conduction) that are traditionally taught in college are represented in the form of multi-agent based models, much younger students (*e.g.*, 4th and 5th graders) can access and understand those phenomena (Sengupta & Wilensky, 2011; Dickes & Sengupta, 2011).

Among the earliest and best-known agent-based programming languages is Logo (Papert, 1980), which has been widely used to support children' learning through constructionist activities (*i.e.*, through the creation of personally meaningful computational artifacts). The core building blocks for constructionist (or design-based learning) activities in Logo are computational procedures, which facilitate simultaneous learning of concepts about the phenomena being modelled and computational concepts, such as procedure abstraction, iteration, and recursion.

2.3 Visual Programming

In visual programming environments, students can construct programs using graphical and physical objects, typically using a drag-and-drop interface (Kelleher & Pausch, 2005, Hundhausen & Brown, 2007). This significantly reduces students' challenges in learning the language syntax (compared to text-based programming), and thus makes programming more accessible to novices , This is an important affordance of visual programming, because prior research showed that students in a LOGO programming-based high school physics curriculum faced significant challenges in writing programs for modelling kinematics even after multiple weeks of programming instruction (Sherin *et al*., 1992)

Some examples of visual agent-based programming are AgentSheets (Reppening, 1993), StarLogo TNG (Klopfer, Yoon, & Um, 2005), Scratch (Maloney *et al*., 2004), ToonTalk (Kahn, 1996), Stagecast Creator (Smith, Cypher, & Tessler, 2000), Kedama

(Oshima, 2005) and Alice (Conway, 1997). Common characteristics of all these environments are: (a) users can construct or design their programs by arranging icons or blocks that represent programming commands and (b) these platforms employ animations to represent the enactment (*i.e.*, the execution) of the user-generated algorithm (*i.e.*, program), albeit with varying degrees of algorithm visualization (Hundhausen & Brown, 2007).

3 SYSTEM DESIGN FRAMEWORK

Figure 1 illustrates the conceptual framework for our integrated approach to science learning through computational thinking. The framework captures a typical learning-by-design progression, which includes learning the basics of a science unit, modelling the entities and processes in the unit using a visual agent-based computational framework, simulating and studying the behaviour of the model, using explanation and argumentation skills to fully understand and verify the model, and finally applying the developed model and the learned science concepts to problem-solving situations.

In what follows, we outline our key design principles, some of which has been adapted from Sengupta (2011).

A. *<u>Achieving Low Threshold and High Ceiling – The Trade-offs</u>*: For a computing medium to be widely usable in K-12 science classrooms it must have the following affordances: (1) it should be easy to use for novice students; (2) learning activities should be well-integrated with the existing science curricula; (3) teachers, who are likely to have little or no computing background, should be able to master the system with minimal or no professional development; and (4) while *low-threshold* is a definite requirement for our system, it should not impose arbitrary ceilings on the levels of complexity for modelling and analysis by students over time. Therefore, our goal here is to find a sweet spot that encapsulates *low-threshold* (*i.e.*, easy to program, similar to NetLogo and Logo), *wide walls* (*i.e.*, students should be able to design a wide range of artifacts, such as animations, games, and science experiments, much like Scratch), and *high ceiling* (*e.g.*, NetLogo supports advanced programming and modelling of complex phenomena using a library of intuitive programming primitives). While many of these design principles are shared by other modelling platforms (*e.g.*, Logo, NetLogo, and Scratch), CTSiM is being designed specifically for pedagogical use in science classrooms, keeping *both teachers and students* in mind as users. This is reflected in the design of domain-specific programming primitives, scaffolds to make algorithms "live" and to support experimentation, and an explicit focus on curricular integration. We discuss these in detail in the rest of this section.,

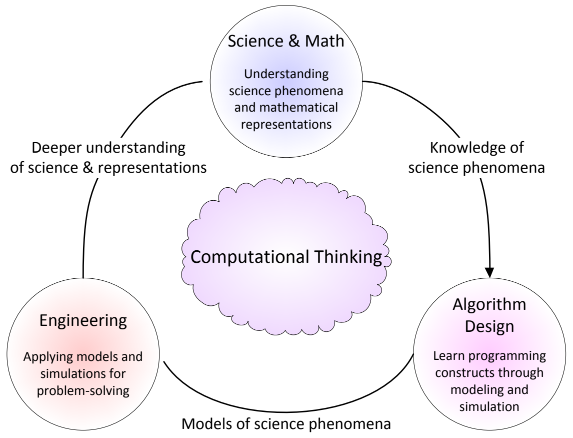

Science & Math
Understanding science phenomena and mathematical representations
Deeper understanding of science & representations
Knowledge of science phenomena
Computational Thinking
Engineering
Applying models and simulations for problem-solving
Algorithm Design
Learn programming constructs through modeling and simulation
Models of science phenomena

Figure 1. CTSiM conceptual framework

B. *<u>Incorporate Multiple "Liveness" Factors as Support for Programming and Learning by Design</u>*: Our challenge is to design a system that lets students seamlessly progress through cycles of construction, execution, analysis, reflection, and refinement using timely feedback from the simulation environment and scaffolding provided by the system. To support learning activities that involve rapid prototyping, our CTSiM system will offer learners a range of "liveness" factors for algorithm construction, visualization, analysis, and reflection (Tanimoto, 1990). This primary design objective is to enable the learners to identify the relationship between their programs (*i.e.*, algorithms) in the Construction World (see Section 4.1), and the resultant enactment of their simulations in the Enactment World (see Section 4.2). This involves developing scaffolds for supporting algorithm visualization (*e.g.*, highlighting step-by-step execution of commands; controlling the delay between execution of successive commands). The goal is to provide timely feedback to students in order to avoid situations where lack of feedback and scaffolding may cause errors to accumulate late into the construction process, which makes the source of errors harder to detect. Accumulation of errors often leads to students being overwhelmed in terms of their cognitive abilities, resulting in their applying *trial and error* rather than *systematic* methods to conduct scientific inquiry (Segedy, Kinnebrew, and Biswas, in review).

C. Verification and Validation to Support Learning of Expert Models: True scientific expertise involves understanding how knowledge is generated, justified, and evaluated by scientists and how to use such knowledge to engage in inquiry (Driver, Newton, & Osborne, 2000; Duschl & Osborne, 2002). Novice science learners engaging in these aspects of inquiry often struggle without extensive scaffolding (*e.g.*, Klahr, Dunbar, & Fay, 1990; Schauble, Klopfer, & Raghavan, 1991; Sandoval & Millwood, 2005). This is a challenge in computational modelling environments, where learning is often assumed to arise as students build their models and then verify them by comparing the behaviours generated against real data or behaviours of reference models representing the actual phenomena (Bravo *et al.*, 2006). Therefore, building appropriate scaffolding and feedback is vital to the success of such environments. In CTSiM, learners will iteratively refine their programs by effectively comparing results of their simulation to an "expert" (*i.e.*, canonically correct) simulation, understand the differences, and then map elements and constructs in their model to behaviours exhibited by their simulation and vice-versa. We will extensively scaffold this process to support experimentation and measurement activities, as discussed in Section 4.3.

D. Choice of Curricular Topics: The phenomena we have chosen as contexts for disciplinary learning are kinematics (physics) and ecology (biology), which are common and important curricular topics. Researchers have shown that K-12 students find these phenomena quite challenging to understand (Chi, Slotta & Leauw, 1994). Furthermore, it has been argued that students' difficulties in both the domains have similar epistemological origins, in that both kinematic phenomena (*e.g.*, change of speed over time in an acceleration field) and system-level behaviours in an ecosystem (*e.g.*, population dynamics) involve understanding *aggregation of interactions* over time (Reiner, Slotta, Chi & Resnick, 2000; Chi, 2005). As discussed in Section 2.2, agent-based modelling is ideally suited for representing such phenomena, as it enables the learner to recruit their intuitions about agent-level behaviours and organize them through design-based learning activities (Kolodner *et al.*, 2003), in order to explain aggregate-level outcomes.

4. IMPLEMENTING CTSiM: ARCHITECTURE AND MODULES

The CTSiM environment will be made up of three primary modules:

1. *The Construction World*: This module provides the visual programming interface for the student to build a computational model by composing programs. Students select primitives from a library of commands and arrange them spatially, using a drag-and-drop interface to generate their programs. These programs control behaviours of individual-level agents in a NetLogo simulation.
2. *The Enactment World*: This module is a microworld (Papert, 1980; White & Frederiksen, 1990) in the form of a NetLogo simulation, which simulates the agent-level behaviours modelled by the student in the Construction World.
3. *The Envisionment World*: This module works closely with the enactment world, helping the student to set up experiments to analyze the behaviour of their models and to compare their model against an expert model. Much of the scaffolding and feedback to help students refine, understand, and verify their models is also provided in this module.

The overall system architecture is illustrated in Figure 2. The rest of this section provides a brief description of the three modules, and illustrates their functionality using a biology learning unit – a simple fish tank ecosystem that includes fish, algae, and bacteria that break down organic waste.

4.1. Construction World

The construction world allows students to build the relevant science model using an agent-based framework with relevant computational constructs. Figure 3 presents a mock-up of the drag-and-drop modelling interface (illustrated on the left side of the figure) in which students define their computational models for a simplified fish tank microworld. The students define the model for each type of agent by arranging and parameterizing a set of visual primitives, as illustrated for a partial fish agent model in Figure 3.

The visual primitives are named and iconically depicted in terms of their scientific function. These primitives are of three types: agent actions in the microworld (*e.g.*, movement, eating, reproducing), sensing (*e.g.*, vision, colour, touch, toxicity), and controlling the flow of execution in the computational model (*e.g.*, conditionals, loops). Each visual primitive, in turn, is defined in terms of an underlying computational primitive (with appropriate constraints and parameters), as illustrated in Figure 4. The computational primitives provide a domain-independent set of computational constructs in a variety of categories: 1) changing (*e.g.*, increasing or decreasing) a property of the agent, 2) sensing conditions of the agent or its environment (*e.g.*, reading local or global variable values), 3) creating or destroying agents (*e.g.*, to model birth and death), and 4) conditionals and logical operators for controlling execution flow.

4.2. Enactment World

The enactment world interface allows the student to define a scenario (as a set of initial parameters) and visualize the multi-agent-based simulation driven by their model. The CTSiM environment, implemented in Java, includes an embedded instance of NetLogo to implement the visualization and mechanics of the simulation. As the student builds a model, it is represented in the system as a code graph of parameterized computational primitives, illustrated in Figure 4. This code graph remains hidden from the end-user (the learner), who accesses the environment using the UI as shown in Figures 3 and 5. The code graph enables the system to simulate the user-generated model for a given scenario by stepping through the graph and executing the computational primitives. The execution of the computational primitives indicated by the current (user) model drives the NetLogo simulation, as illustrated in Figure 2. NetLogo visualization and plotting/measurement functionality (illustrated in Figure 4) provide the students with a dynamic, real-time display of how their agents operate in the microworld, thus making explicit the emergence of aggregate system behaviours (*e.g.*, from graphs of the population of a species over time).

Furthermore, since there is a one-to-one correspondence between the visual primitives in the construction world model and the computational primitives in the execution model (code graph), the system can highlight each primitive in the construction world as it is executed in the enactment world. This model-tracing functionality will be leveraged to provide important scaffolding that supports model refinement and debugging activities.

4.3. Envisionment World

The envisionment world provides students with a space where they can systematically design experiments to test their constructed models and compare their model behaviours against behaviours generated by an "expert" model. A typical experimental setup would involve assigning values to agent parameters and variables defined in the student model, and simultaneously simulating the expert model with the same parameter values. Although the expert model is hidden, students may observe its behaviour in comparison to their own model with side-by-side plots and microworld visualizations. With additional scaffolding and support, this allows students to make decisions on what components of their models they need to investigate, develop further, or check for errors to correct. Figure 5 illustrates a mock-up of the envisionment world window that we are designing from CTSiM.

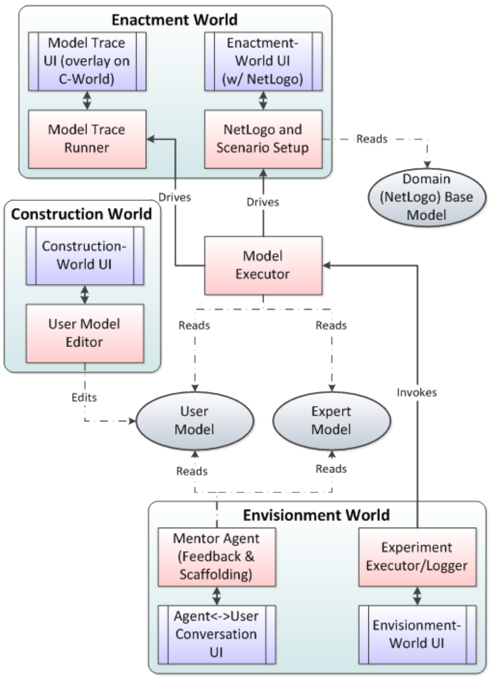


Figure 2. CTSiM architecture

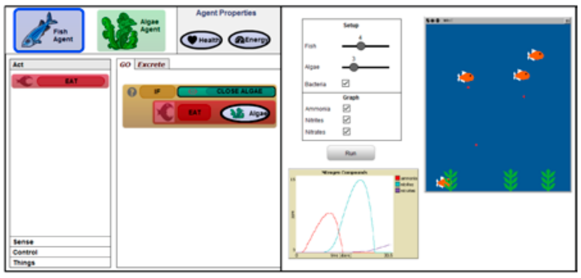


Figure 3. Construction- & enactment-worlds interface mock-up

Work by Basu, Sengupta, and Biswas (in review) details our approach to simulation investigation and discusses the scaffolds that we have developed to help students study and understand underlying model concepts and relations in a desert ecosystem microworld. With proper support and scaffolding, we believe that the overall process of model construction, analysis, comparison, and refinement will help students gain a better understanding of science (*e.g.*, science phenomena and the scientific reasoning process), mathematics (*e.g.*, measurement, graphs, and equations), and computational constructs and methods.

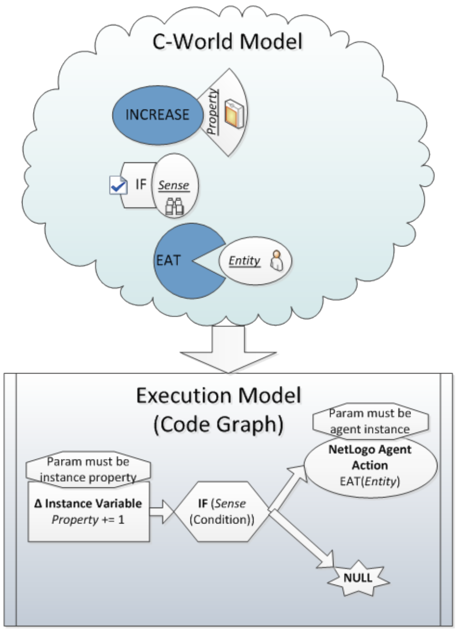
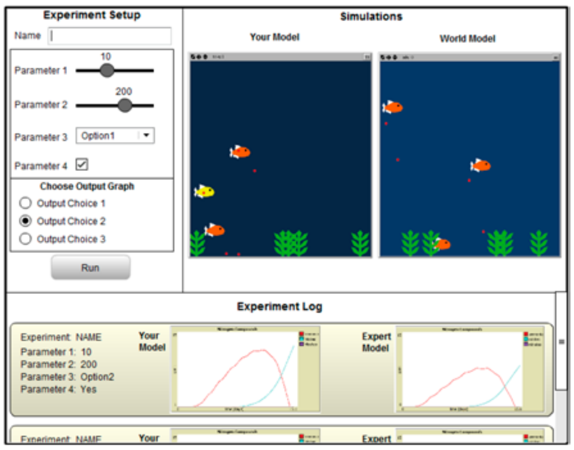


Figure 4. Construction-world and execution models

To further support learning science by model building, analysis, and verification, we plan to develop a module for critique, explanation, and argumentation that will engage students in authentic analysis and inquiry practices. For example, each cycle of modelling will begin with students critiquing the fit between the current version of their model, and the target agent- and aggregate-level behaviours generated from the expert model. If differences in system behaviour (between the expert model and the student's model) are identified through the critique phase, the student will then be scaffolded in creating an explanation/claim about the mechanisms in their constructed model that could lead to the observed differences. The methods discussed in the construction and enactment worlds will support this interaction and help students identify the segments of their model that are contributing to differences in system behaviour. The goal is to scaffold explanation about the underlying causal mechanism that simultaneously identifies an issue and proposes corrective action.



Experiment: NAME
Parameter 1: 10
Parameter 2: 200
Parameter 3: Option2
Parameter 4: Yes

Figure 5. Envisionment world interface mock-up

After creating an explanation about the source of differences between the agent-level program and aggregate-level outputs, the student will be scaffolded to identify and collect further evidence for, or against, the proposed causal mechanism. This can include evidence collected during the critiquing phase or during subsequent experimentation. Research has shown that students initially tend to focus only on evidence that supports their claims and ignore the evidence that contradicts their claims, in a manner very similar to the ways in which scientists have historically dealt with anomalous data (Chinn & Brewer, 1993). Therefore, the scaffolding should help students search for evidence that might contradict their claims, as well as evidence that supports their claims.

4.4. Sequence of Curricular Modules & Activities

We are currently developing two curricular models in the CTSiM environment: (1) a kinematics unit that focuses on modelling Newtonian mechanical phenomena such as the trajectory, velocity, and acceleration of balls placed on different inclined planes, as well as using mathematically meaningful aesthetic representations (*e.g.*, geometric shapes) to represent various classes of kinematic phenomena (*e.g.*, constant speed, constant acceleration) (Sengupta, 2011; Sengupta, Voss Farris, & Wright, under review); and (2) an ecological unit (Tan and Biswas, 2007) that emulates a simplified fish tank environment, which includes fish, algae, and bacteria for breaking down organic waste; it primarily models a simplified food chain and the waste cycle focusing on how organic waste is broken down in steps by bacteria to produce nitrates, which provide nutrition for algae. The focus of this unit is on the study of interdependence and balance in ecosystems.

In terms of learning programming, these modelling activities will introduce students to fundamental programming constructs (*e.g.*, agents, conditionals, loops, variables, etc.). For example, the first two modelling tasks in both kinematics and ecology involve students using three main types of constructs: agents (various species of organisms in ecology; physical objects in kinematics), conditionals (indicating need-based interactions between agents in ecology, and effect of different conditions, *e.g.*, terrains, in kinematics), and loops (for repetitions of an action(s) based on the current value of an agent's or environmental property/variable). In subsequent modelling activities, students will learn to define variables (*e.g.*, defining attributes of agents and breeds of agents), as well as code-reuse and encapsulation (*e.g.*, using portions of existing code to model behaviour of new agents). In later, more complex, modules, students will explore class hierarchy/inheritance connected to science through relation to taxonomy and class/type properties and behaviours, as well as the nature of physical "laws" that apply to all objects (*e.g.*, in kinematics).

From the mathematical perspective, students in both curricular units will focus on: (1) generating graphs of aggregations (*e.g.*, averages) over time, (2) identifying and developing basic mathematical relationships between variables and statistical properties of populations evident from graphs (*e.g.*, linear vs. quadratic relationships, averages, range, variance/standard-deviation), and (3) understanding rates through designing multiple, linked representations of rates and other time-based/time-variant relationships. For example, students would start out visualizing a variable's value changing over time, either step-by-step or plotted on a graph, and then learn to represent it as a simple equation.

5 DISCUSSION & CONCLUSIONS

In general, computational thinking involves being able to reason at multiple levels of abstraction (Kramer, 2007), mathematical and design-based thinking (Wing, 2008), as well as using these kinds of reasoning for contextual problem solving (Guzdial, 2008; Wing, 2008). Our paper proposes a theoretical framework through which these aspects of CT can be integrated with curricular modules in K-12 science classrooms via agent-based modelling. We also presented the computational architecture of a learning environment based on this theoretical framework that includes a visual programming language and a modelling environment. In designing this system, our goal is to integrate computational thinking with existing K-12 science curricula (as has been recommended by the ACM K-12 Taskforce (2003)), *without necessitating the development of new curricular standards* or introducing a programming course separately from the curricular science. This also lays the groundwork for the development of a long-term curricular progression in which students can engage in learning science using computational modelling and thinking over a span of multiple years. This is consistent with the findings from research in developmental psychology and science education, which show that the development of scientific thinking, even when it builds on students' intuitive knowledge and competencies, happens over a period of multiple years through meaningful immersion in authentic learning experiences (Lehrer, Schauble, & Lucas, 2008).

By engaging students in agent-based modelling across multiple domains, but using the same programming constructs and modelling environment, our primary goal is to enable students to realize the commonalities across domains in terms of the underlying computational/mathematical constructs and practices (*e.g.*, control flow, variables, debugging), as well as the domain-general representational practices involved in modelling (*e.g.*, problematizing, experimentation, generating inscriptions, verification, and validation). We will run classroom studies with the first prototype of our system in Spring 2012, to study some of these claims and to collect data for refining and continuing the development of CTSiM.

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