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Perspective:

In It for the Journey:
The Road to Powerful STEM Learning

By Chad Dorsey

What's the difference between just driving somewhere and taking a road trip? Plenty! Over the past year, I've had the pleasure of opening my children's eyes to the incomparable joys of the road trip: the unexpected roadside attraction, the anticipation of unknown intrigue just around the next curve. So what do road trips have to do with data and STEM learning? As it turns out, just about everything.

This issue of our newsletter highlights some important ideas about STEM teaching and learning. In particular, it addresses significant ideas about teaching and learning with data. And just as a road trip sets the stage for something undiscovered to appear around every corner, these articles describe the rich mysteries of data exploration and scientific investigation. Whether they're describing what it's like for students to uncover experimentation on their own or outlining the many ways learners can reveal a complex dataset's hidden stories, each article tells a tale of excitement and discovery.

Our work on InquirySpace's investigation environment and curriculum makes a strong case for giving students the tools to uncover the world's mysteries themselves. Driven by a sense of ownership over their own learning and empowered by the tools and techniques of scientific investigation, students can arrive at some of the most important ideas in science through their own power of reasoning. Providing students with the means to explore phenomena closely, the tools to analyze and iterate quickly and confidently, and just the right degree of scaffolding can open their eyes to their own personal capacity for discovery.

Allowing students to appreciate and explore a dataset's mystery offers rich opportunities for individual discovery. In particular, the messy, multivariable datasets of today's world are a far cry from the traditional classroom's two-column tables. Such straightforward, bivariate datasets render the very concept of exploring data practically moot. The richness of more complex data, however, not only invites students to explore but makes diving deep practically mandatory. And, when learners are constructively "awash in data," a dozen discoveries await in the next chart or graph. As Isaac Asimov once reminded us, "The most exciting phrase to hear in science, the one that heralds new discoveries, is not 'Eureka' but 'That's funny…'"

Training our road trip eyes

Let's appreciate the view of the road trip veteran whose keen eyes can turn that odd, nondescript road sign into a detour that makes the entire experience unforgettable. So it is when learners acquire a taste for making their own STEM discoveries. Observations that once slipped past unremarked suddenly become excuses to pause, tinker, and observe. When we give learners the opportunity to investigate the world more closely, we outfit them with mental tools that apply far beyond merely a single STEM subject. Once a student begins to see the world as groups of molecules in vibrational harmony, she'll never look at a puddle or a piece of metal the same way again. Once a learner discovers for himself how electricity operates or how the body defeats disease, his perspective on circuit-powered devices or approach to an annual flu shot has been forever altered.

Most importantly, however, the more broad the experience, the more resonant and lasting it becomes. The moment a student discovers that an investigation of her own design reveals new and meaningful understanding, the world of science comes into reach. The instant his personal exploration of a complex dataset yields a novel and useful pattern, understanding data becomes exciting. The effects of these realizations stretch far beyond STEM learning itself. Each glimpse brings learners one

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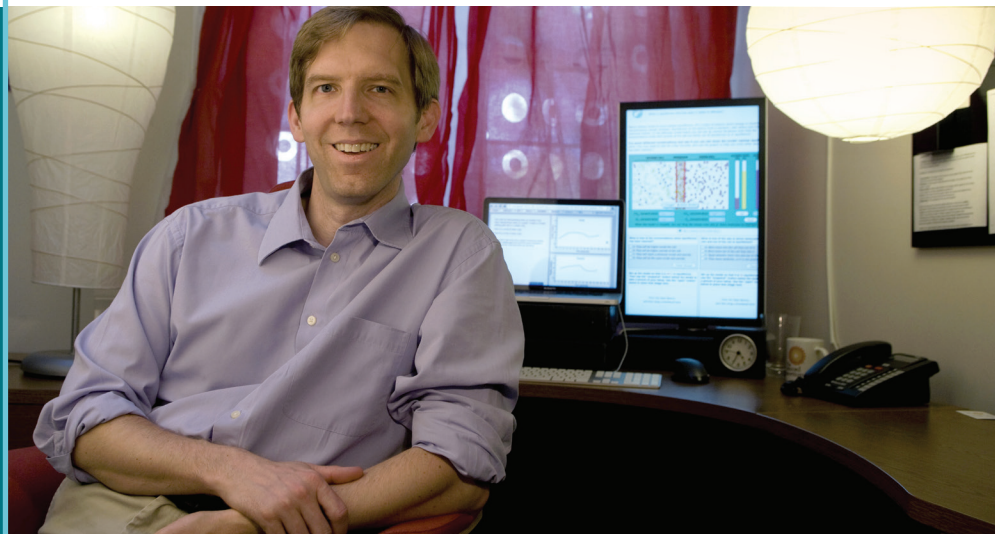
step closer to seeing unanswered questions not as barriers but as invitations to investigation. By providing extended opportunities to grapple with and answer the world's mysteries, STEM learning is actually exercising students' most important muscle of all— the confidence and ability to tackle and solve problems.

STEM learning is certainly not the only place learners can build the essential, lifelong skill of problem solving. But few other places in the formal curriculum offer opportunities as numerous or takeaways as powerful. Because novel discovery is at the core of every concept in every STEM subject, each new idea can become a chance to hone students' abilities and eagerness for problem solving. Seizing these opportunities means viewing all STEM learning through this wider lens.

Technology's role

At first, many critical topics seem improbably far from the realm of individual exploration and discovery. How can a student experiment with climate change? Tease patterns from an especially messy dataset? Test personal ideas about the workings of a complex system? Through tools, models, and simulations, technology can turn all of these questions and more into opportunities for individual exploration.

Technology is a powerful tool for STEM discovery. It allows students to turn improbable topics into opportunities to grapple with and solve problems. In the laboratory, technology can strip away burdensome or time-consuming tasks, tighten cycles of analysis, and bring core elements of scientific investigation into relief. Fast, accurate sensors. Computer-controlled devices and

switches. Customizable data control and collection software. Designed for exploring complex data, these tools transform the classroom from a place where students carry out predetermined procedures to a world where they design and revise unique experiments to ask and answer their own questions. The more we bring learners into this world, the more we help them become part of the process of doing science in all of its stages.

Perhaps most importantly, technology provides a space where learners experience aspects of scientific investigation they may otherwise miss entirely. In particular, technology's flexibility and power can allow productive access to the critical phase of "messing around" with experimental apparatus, procedures, measurement techniques, and datasets, providing easily accessible ways to investigate the questions it generates. The fuzzy margin between initial encounter and systematic experimentation is where problem solving hits its stride and true ingenuity takes off. And it may hold the biggest opportunity for STEM learning in the coming decades.

Traditional approaches typically underplay these essential stages. Classrooms that lack technology's power are often forced to push them aside entirely. This is the "final destination" approach to STEM learning—blindly speeding to the last stop. The importance of the road trip is its focus on the journey, which allows us to see the world in all its spectacular nuance. With that in mind, build a detour or two into your classroom, put students in the driver's seat, and use the full potential of technology to empower students. Every time you do, you take them on the journey of a lifetime.

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The InquirySpace
Model of Scientific Experimentation

Laboratory investigations are a mainstay of the science classroom, and have historically been the pathway for students to "experience science." The importance of engaging in science and engineering practices is one of the three dimensions of *A Framework for K-12 Science Education* and the Next Generation Science Standards (NGSS). A naive reading of these practices might leave one thinking that we already do these things.

By Dan Damelin, Hee-Sun Lee, and Lynn Stephens

However, traditional labs typically engage students in only a subset of the practices, such as analyzing and interpreting data, and obtaining, evaluating, and communicating information. One of the key shifts in the NGSS is toward student agency in their scientific explorations. This is exemplified in other practices, such as asking questions, developing and using models, planning and carrying out investigations, and engaging in argument from evidence. Students should be learning science by doing real science, and to do that they need to struggle with the ideas of scientific experimentation, data analysis, and iterative refinement of experiments.

Our National Science Foundation-funded InquirySpace project is developing and researching students' ability to engage in open-ended science investigations of their own design. We are researching what students require to be empowered as learners and what conditions are necessary to foster their ability to conduct robust, data-rich investigations. We are beginning to understand how authentic scientific investigation comes about in the classroom. And we are uncovering some surprising insights.

Doing labs "correctly"

Traditionally, managing the complexity of doing science has been accomplished by providing students with clear instructions and a narrowly scoped, predefined experiment. However, if we're expecting learners to grow, we need to begin by giving them opportunities to exercise independence, take responsibility, and make corrections, right from the start. Giving students agency is central to fostering independent investigation—it may even be central to understanding science itself.

Current laboratory scenarios rarely begin with this premise. Investigating phenomena is complicated and an hour of classroom time is precious. Consequently, the focus becomes ensuring that the lab runs smoothly, which means students follow a pre-set step-by-step procedure, collect data as prescribed, and don't waste time.

But consider what learners take away from this overly scripted exercise. First, they may envision laboratory procedures as something to be followed rather than forged. The idea of designing and refining an investigation, and gaining ownership of the science practices involved, vanishes, or at best is sidelined. Second, students may implicitly learn to consider data as a product rather than a process. Students often try to create a data table with the "right answers" in order to reveal a result they—and the teacher—know is predetermined. In these situations, uncertainty or variability in data is something to avoid and is interpreted as the outcome of incorrect execution (i.e., a "wrong answer"). The concept of unique discovery never really enters the discussion.

The elements of agency

Scaffolding students toward independence means empowering them with agency in three critical aspects of scientific investigation: 1) designing experimental scenarios that include collecting, inspecting, cleaning, and analyzing data, 2) addressing sources of uncertainty
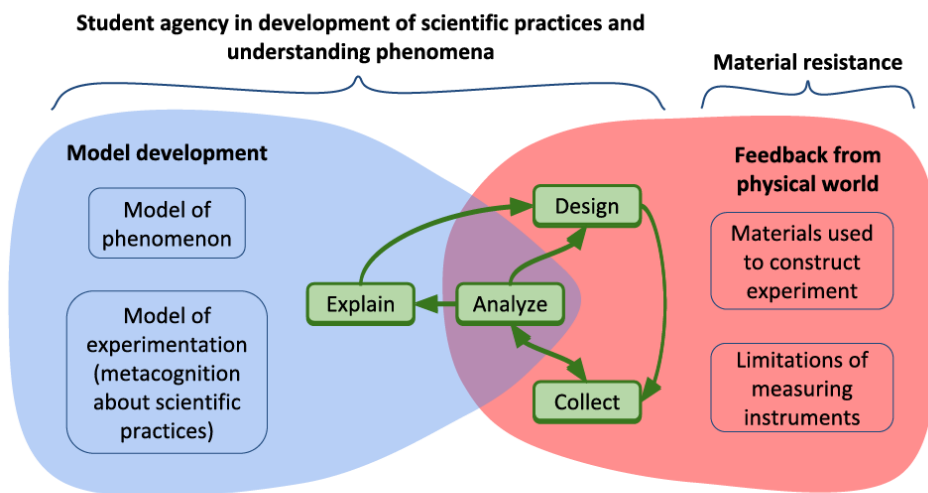
Inquiry Framework

Figure 1. A model of scientific experimentation.

and variability associated with the limitations and constraints of data collection, analysis, and interpretation, and 3) engaging in argument from evidence, developing scientific explanations, and communicating those ideas.

A student preparing for a laboratory investigation has a mental model of scientific experimentation. The model may include: ideas about how data are gathered, strategies for designing experiments, what is involved in collecting data, the role lab apparatus play in investigating and answering a question, and much more. The student also has a mental model of the scientific phenomenon she's preparing to investigate. This model might include ideas about how electricity works, what bacteria need to grow, what mechanism is at the heart of chemical reactions—or a thousand other concepts related to the phenomenon at hand.

In order to help students develop agency in the context of scientific experimentation, we need to recognize that both models are at work when exploring phenomena. Her mental model of the phenomenon influences what she decides to observe and what questions to ask. On the other hand, her mental model of experimentation influences the design of the experiment, including what questions she considers investigable, the structure of her data collection, and what equipment she selects as appropriate to answer those questions. What's critical to recognize is that refining and building students' competence at independent investigation involves a continuous interaction between the two models.

There's another factor as well. Scientific investigations aren't thought experiments. They use real materials, in the real world. A balance has friction between its parts. A microscope is limited by focus and optical resolution. Scientific phenomena are complex and indistinct. Objects being measured—and measuring devices themselves—have finite dimensions. The reality of experimentation is that we must use the materials of the real world to investigate the world's phenomena—and that these materials always resist our efforts in some way or another. In

our attempt to keep things simple for students, we may be tempted to minimize the resistance an experiment's materials introduce, but some measure of resistance is always unavoidable.

Taking all this into account, the process of investigation becomes an interplay of three elements: the student's model of scientific experimentation, her model of the phenomenon, and the material resistance* of the world itself (Figure 1). By leveraging and honing her two mental models, she is able to design increasingly focused investigations. She then collects data for analysis, which results in a scientific explanation that demonstrates her understanding of the phenomenon. Initial stages of investigation involve cycles of designing, collecting, analyzing, and explaining based on feedback from the material world. This leads to more formalized and deliberate cycles as she refines her understanding and process.

* Pickering, A. (2010). *The mangle of practice: Time, agency, and science.* Chicago: University of Chicago Press.
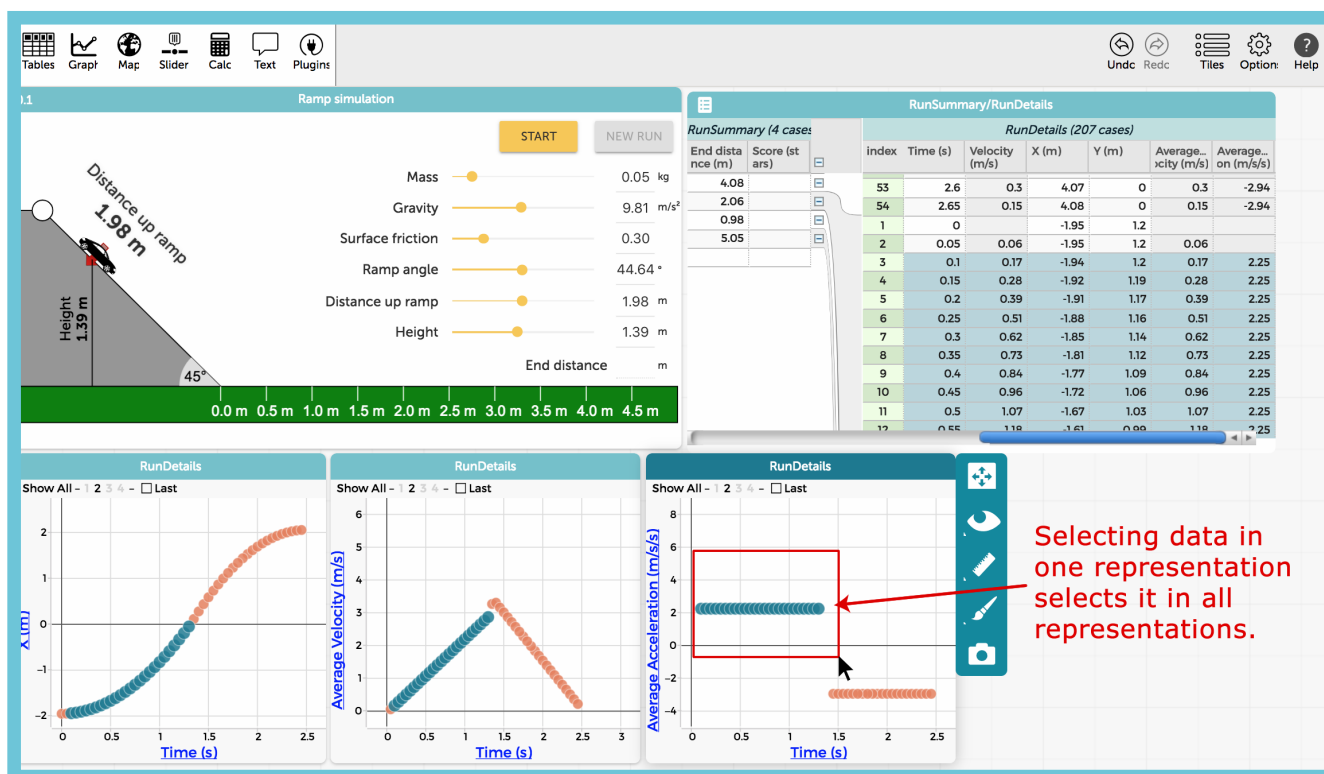
The InquirySpace approach

Our goal is to support students in learning science by doing science. The core of this approach involves students having the skills and the charge to investigate the world around them. Rather than following a recipe such as those found in classical labs, students should be asking questions like: What can I measure and observe? How can I design an experiment to collect data? Once I have data, how certain am I of the patterns or relationships those data suggest? Do I need to collect more data? Do I need to redesign my experiment? Such questions are at the center of the changes in classroom laboratory experimentation we wish to bring about.

Since 2012, InquirySpace has been developing, classroom-testing, and revising software to facilitate student-led inquiry, as well as curricular supports to scaffold students in building the skills and mental models of experimentation necessary to engage in scientific inquiry. The software development includes expansion and refinement of our Common Online Data Analysis Platform (CODAP), an easy-to-use web-based tool, and plugins for CODAP that allow direct data collection via sensors and data generation by simulations. CODAP has been uniquely designed for students to engage in sense-making from data, utilizing a simple drag-and-drop interface for organizing data into hierarchical structures, generating visualizations of the data, and using graphs not just as a means for displaying data, but as a way to filter and explore data across linked representations (Figure 2). Students can visualize and analyze data as they are collected in real time and make adjustments to refine their experiments, e.g., constructing the physical apparatus to collect data, selecting and using measuring devices properly, considering how much data to collect, and identifying and minimizing error sources.

We are developing on-ramps to help students build knowledge over time not only in the technical skills of scientific investigation, but also in the conceptual skills needed to undertake student-led and designed experiments. They begin with significant scaffolding that fades over time, culminating in the exploration of some phenomenon of the student's choosing related to the relevant scientific domain of physics, chemistry, or biology.

Such independently designed student experiments differ from the traditional lab in several ways. Students begin by "messing around," exploring what is possible and how the physical limitations of their measuring devices and experimental materials might influence the questions they can ask and answer. While this may seem a bit chaotic at first, it is a necessary step for students to gain agency in engaging with science practices, and informs their impending work as they home in on a more formalized procedure of their own design. When students no longer follow lab instructions blindly, they become actively engaged with phenomena, working to extract their secrets and taking the first steps in seeing the world through the lens of science.

Figure 2. Simulation of a ramp experiment embedded in CODAP. The same data is linked in the table and three graphs (blue rows in the table and blue points in the graphs).

LINKS

InquirySpace
https://concord.org/inquiryspace

CODAP
https://codap.concord.org

Monday's Lesson:

Using Artificial Intelligence to Design a Solar Farm

By Charles Xie

Charles Xie
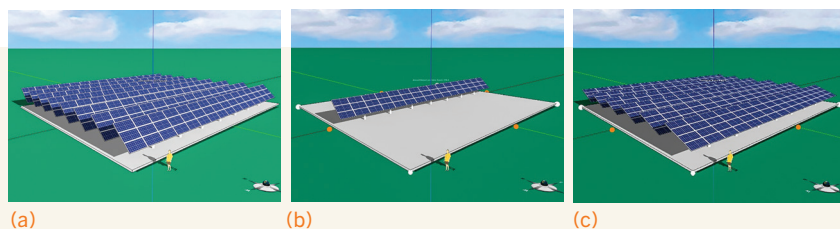(qxie@concord.org)
is a computational scientist.

A large part of engineering is about searching for good designs. But an optimal design is often hard to find. Artificial Intelligence (AI) is about to change that. Design is an evolution of solutions, and AI tools such as genetic algorithms are an excellent fit. They can generate a variety of designs in the same way genetics does for biology—and help people learn, design, and discover new things. This Monday's Lesson unveils the incredible power of AI with a classroom-ready application.

Designing a solar farm

A solar farm is a power station consisting of photovoltaic panel arrays mounted on the ground. Since it usually involves large capital, engineers must design it carefully to achieve a maximal return on investment. We will use solar farm design as an example to show how students can work with AI to solve complex problems. To begin, download Energy3D (http://energy3d.concord.org).

How does AI work?

AI must know your objective in order to find a solution. For instance, if the objective is to maximize the output without concern for the cost, a design in which the solar panels are closely packed may be a good choice (Figure 1a). If the objective is to maximize the output from each panel, a design with rows of panels far away from one another would be better (unsurprisingly, a single row shown in Figure 1b was found to be the best in this case). If the objective is to maximize the profit, as is often the case in the real world, a design that falls between the two would fit the bill (Figure 1c). You can verify these results with an example provided in Energy3D by opening the menu "Tutorials > Methods of Engineering Design > Solar Farm Optimization."

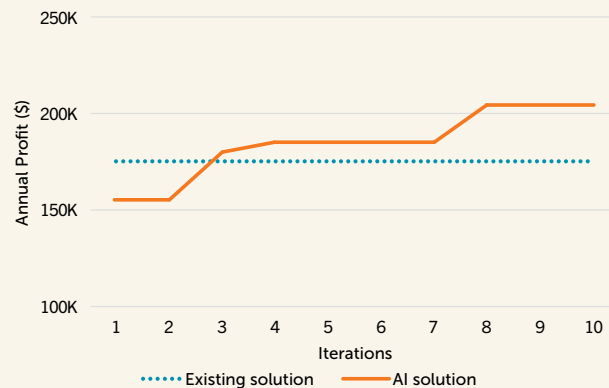### Applying to a real-world project

With Energy3D, you can experiment with a real-world project found through Google Maps. If there is a solar farm in your area, you can easily import its satellite image into Energy3D (using "View > Ground Image > Use Image from Earth View…") and start modeling it by adding solar panels on top of the image. Alternatively, you can download an existing model on the Virtual Solar Grid (http://vsg.concord.org) as a starting point. Once you have an Energy3D model, draw a minimum polygon that confines all the solar panels on the foundation (Figure 2). This is the area within which AI will search.

Let's use the solar farm in Figure 2 as an example and show how AI can hypothetically improve it. Figure 3 shows that the AI-generated solutions are inferior to the existing one in the first two iterations, but they surpass it after that. After 10 iterations, AI had evaluated 2,000 solutions (no one can single-handedly do that in the same amount of time) and arrived at a design 16% better than the existing one.

Welcome to the future of design!

For the full curriculum module, visit
http://energy.concord.org/energy3d/projects.html

(a)   (b)   (c)

Figure 1. AI designs that generate as much (a) total electricity, (b) electricity per solar panel, and (c) total profit as possible within a rectangular area in Massachusetts over the course of a year.

Figure 2. An Energy3D model of an existing solar farm in Massachusetts.

Figure 3. The result of 10 iterations of design evolution.

Exploring the
Essential Elements
of Data Science Education

By William Finzer and Frieda Reichsman

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She scans the numbers, scrutinizing thousands of cases and dozens of attributes. Something doesn't look right. Missing values? Incorrect coding? Fixing those will be a start. Cleaning, checking, re-sorting—gradually she cajoles the enormous array into a workable form. Now the fun part begins: teasing out hidden relationships and laying the groundwork for deeper analysis. She merges the tamed dataset with another and digs in, stacking, filtering, creating graph after graph, hot on the trail of unseen patterns and new insights.

This is an increasingly common scenario. As complex datasets begin to underpin every aspect of modern life, data scientists are everywhere, applying their advanced programming and statistics knowledge, disciplinary understanding, and data wrangling skills. In high-tech science labs and enormous automotive assembly lines, in tiny fashion startups and standalone agricultural greenhouses, people with data science skills and understanding are finding patterns and guiding decisions. From combating global warming to feeding the growing population, reducing violence, and increasing equity, data science will be at the heart of future solutions to every significant problem in society. In this data-rich future even everyday life decisions such as choosing a health care provider or political candidate will demand new fluency in interpreting, tempering, and critiquing claims derived from large or complex datasets.

At the Concord Consortium, we believe that basic data fluency must be a skill offered to all, which is why we've worked to foster learning with and about data for decades. We believe building understanding and habits of mind around data is critical, and we believe all students should be able to understand and analyze complex data without hours of coding lessons or years of advanced mathematics. To that end, we're spearheading the field of data science education at the pre-college level. In an effort to identify and further the essential elements of data science education, we have developed software and curricula, hosted dozens of webinars and meetups, and researched student learning with data.

Modes of working with data

Thanks in part to an increased emphasis on data in both the Common Core State Standards for mathematics and the Next Generation Science Standards, students are examining data in more and more classrooms. However, data can be used in many different ways. We've studied student learning with data and have identified six different modes through which students can work with data. Each mode has the potential to bring simplicity or sophistication to the study of data:

- Entering data
- Examining data displays
- Collecting data
- Exploring data
- Discovering with data
- Problem solving with data

These six modes overlap and reinforce the organic, cyclical nature of working with data. And importantly, they engage students with an essential aspect of data investigation—what one might call "messing around." Spending time "playing" with data is a critical step in providing students a feel for what the data might tell them—and very different from many traditional activities in science or math class. When students approach a dataset by initially messing around—often through one of the modes outlined below—they build familiarity and understanding that sets the stage for key questions and conjectures to emerge.

While these modes are not the only ways students can engage with data, they are all important for providing students a natural feel for data's complexity and nuance.

Entering data. Data only exist after they have been recorded, and there are myriad ways of doing this. A kindergartner adds a sticker in the "dog" column of a dot chart to record his pet. A third grader counts the different kinds of books on the bookshelf and writes it down on paper. A seventh grader measures and records the distances her classmates throw a shot put in the cells of a spreadsheet. And a high school biology student takes photos of plants in an experiment, loading them into an online database. Entering data can feel mundane or exciting, but to enter data is to know its origins and take ownership of it.

Examining data displays. Science textbooks are full of data displays: tables, plots of distributions, data-rich maps, scatterplots, pictograms, and lists, just to name a few. But data displays also appear on scoreboards, on computer screens, on automobile dashboards, and in science journals. Though often students are tasked with "reading" a graph or with showing how a data display illustrates a given concept, there is potential for considerable challenge in extracting from the display puzzling phenomena, arguments in favor of a point of view, and deep relationships that only become apparent after multiple encounters.

Collecting data. Data do not collect themselves. They emerge from a designed process. As students gain experience with making use of data, they increasingly appreciate the thought that goes into figuring out how to relate investigative questions

with decisions about what will be the "case" or unit of observation, what attributes of the case are relevant, how many observations are needed, and how to most usefully record and store that data. What at first appears simple reveals itself as the subtle process of modeling the world with data.

Exploring data. The sheer volume of easily accessible, unexamined data puts students in the role of explorer. Students probe the data landscape, familiarizing themselves with data sources, data structure, and types of attributes, and dive into a data world rich with possibility.

Discovering with data. With exploration comes the possibility of discovery. Students may set out to find a particular relationship only to discover that there is none, or, conversely, happen on an unexpected strong correlation. Today students can also work with data that are previously unexplored. When they do, the discoveries they make are actually new discoveries.

Problem solving with data. At a certain stage students reach a level of comfort with data where data become a tool for solving problems. When a student recognizes the need to solve a problem and recognizes that having data about the problem could help yield a solution, using data begins to become second nature, and looking for data a habit of mind.

Making great data experiences

To ensure that students engage in these modes of working with data, they must have access to datasets of appropriate size. Data that have many more than two attributes compels students to look at the data from different dimensions, make multiple representations, and ultimately find original discoveries. Large datasets also help learners become comfortable feeling "awash in data" and foster necessary data habits of mind.

At the same time, students must have access to intuitive data tools that allow them to visualize relationships and make sense of data. Our easy, web-based Common Online Data Analysis Platform (CODAP) is designed for this purpose and has tools for beginners as well as advanced features for experienced users. One key feature is that representations link dynamically across tables, graphs, and maps.

By working with data frequently and repeatedly, learners develop experience and competence, gaining fluency with the data moves necessary for structuring, examining, and diving into data, and ultimately building excitement for their ability to work with data. This enthusiasm is the cornerstone of deepening students' understanding of data as a tool for solving problems in the world, and is key to preparing them for life in a world immersed in data.

CODAP
https://codap.concord.org

A Dashing New Look
into Dragon Genetics

By Trudi Lord and Frieda Reichsman

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Our popular dragon genetics games have been used by tens of thousands of high school biology students to learn about heredity and genetics. In hundreds of classrooms we have watched students light up when they solve a virtual breeding challenge and create an offspring drake with the right traits. However, it isn't always obvious—to us or to the teacher—how well or poorly a student is progressing in the game and understanding the genetics concepts.

The GeniGUIDE project, funded by the National Science Foundation, seeks to improve student learning using game data in two ways: by supporting the student with just-in-time help and by sending valuable information about student progress to the teacher. We partnered with North Carolina State University to design an Intelligent Tutoring System (ITS) and integrate it with our newest dragon genetics game, Geniventure. While students try to solve the challenges in Geniventure, the ITS works in the background, monitoring student performance and building a model of student knowledge. If students struggle with Geniventure challenges, the ITS provides hints and extra practice for genetics concepts, and passes information to the teacher via a real-time dashboard system.

To build the ITS, we identified specific game challenges with traceable on-screen actions that could be used to show evidence of learning. At the same time, we used an Evidence-Centered Design (ECD) approach to simplify broad genetics learning goals, generating a comprehensive list of individual concepts. We then mapped these bite-sized concepts to the game challenges. This process led to an initial version of the ITS—a rules-based system that evaluated student understanding of a handful of basic concepts, such as the need for two recessive alleles to produce a recessive trait

and the ability to map from a genotype to phenotype and vice versa. Using this system, the Geniventure game was able to provide students with three levels of progressively more directed hints.

After piloting this system in multiple classrooms, observing students, and gathering teacher feedback, we upgraded the rules-based ITS to utilize a more advanced student model based on Bayesian Knowledge Tracing (BKT). While using BKT is common in software addressing more algorithmic topics (think mathematics and computer programming), it is a novel approach in an open-ended genetics game.

A model of student understanding

The data-driven, BKT-based system creates an initial student model using data collected from previous classroom implementations. As a student works through the six levels and over 60 challenges of Geniventure, the BKT-based ITS tracks their in-game actions (for instance, changing an allele or choosing particular parent drakes to breed) and modifies the initial model accordingly, making it specific to the student and continuing to refine it as the student plays Geniventure. The ITS calculates a probability that the student understands the genetics concept identified by the ECD process. The probability represents the likelihood that the student has learned the concept that is being addressed by their behavior as they set alleles, sort drakes by predicted phenotype, or attempt to breed offspring that match a target. Using machine learning, the BKT-based ITS takes into account all observations of the student's performance to constantly model a student's knowledge of genetics concepts. This information is used to estimate the probability that the student already knows the concept, is guessing correctly, or is making a mistake in applying a concept that he or she actually does understand.

The resulting student model yields a more complete representation of student knowledge, which results in improved tutoring actions, such as delivering contextualized hints in a timely fashion. In addition, the BKT-based ITS also provides remediation for students who are truly struggling. When the
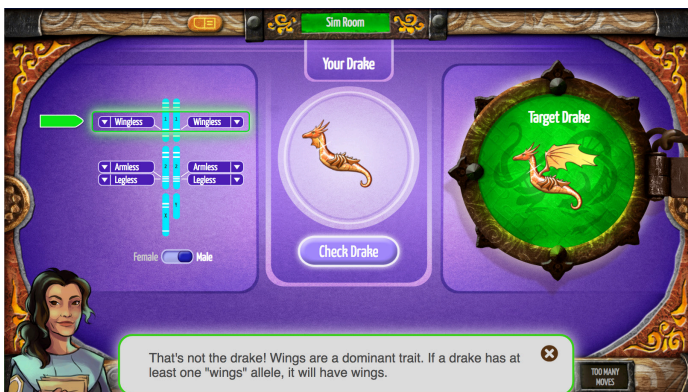
Figure 1. The Intelligent Tutoring System (ITS) delivers a text-based hint along with a visual cue.

Figure 2. The Geniventure teacher dashboard displays real-time student progress and performance.

ITS detects that a student is struggling, the game presents the student with a simplified "bonus challenge" that focuses on one specific concept. After completing this challenge, students can continue with the regular challenge sequence. The ITS also evaluates unnecessary actions made by the student while attempting to complete Geniventure challenges—a type of "gaming the system" that can be caught automatically.

Hints help students

With the integrated ITS, students who get stuck aren't stuck for long. The hints enable students to master simple concepts quickly and with less repetition. In fact, the speed with which students can now work through the challenges has allowed us to introduce more complex concepts and more difficult challenges earlier in the game, reducing the overall length of time needed to complete all game challenges from two or three weeks to just over one week. When the ITS determines that a student is struggling with a concept, it provides a hint. Early challenges provide hints that include both a textual explanation as well as a visual cue (Figure 1). As the game progresses, some of the hint scaffolding is removed. The hints and bonus challenges are designed to look like the regular game screens so the screens of students who are getting several hints or remediation do not alert curious peers.

Following completion of each challenge, students are rewarded with different colored crystals based on their skill and efficiency. Each student is charged with earning crystals; the color of the crystal determines its in-game value. Students can track their progress in the game by viewing the crystals they have earned for each level. The game narrative encourages repeating challenges when low-level crystals are earned. For some students, achieving blue crystals—the highest level in the mythical dragon kingdom—has been a great motivator.

Teacher dashboard

In a small class, it's easy to catch a student who is disengaged. With a class of 20 or 30, however, these students can easily escape a teacher's attention. The Geniventure teacher dashboard displays real-time student progress and performance, functioning as an extra set of eyes in the classroom (Figure 2). To help teachers determine where students might be struggling, the dashboard offers two views. The game progress view displays the crystals students have earned for each attempted challenge, whether they entered remediation for a challenge, and the challenge that students are currently working on. The genetics concept view shows their ITS-estimated level of understanding of each concept.

In both views, the dashboard displays individual student reports and class-level summaries. By sorting the data, teachers can quickly identify students who are behind or having trouble and intervene. As one teacher said, "I saw a student get a black crystal several times in a row, and before he got too frustrated and gave up, I was able to help him." After all, the teacher is the most intelligent tutor in the room!

Next steps

We have piloted Geniventure in a small number of classrooms. In the next phase, we will collect pre- and post-tests of content knowledge, surveys of students' attitudes of the game, and logs of teachers' experiences. This spring, we plan to field test with teachers who want to use Geniventure with their students and are willing to give us their feedback on all aspects of the game, including our teacher support materials. Geniventure, teacher guides, and other classroom support materials will be freely available in summer 2019.

LINKS

GeniGUIDE
https://concord.org/geniguide

Solving Big Problems
Requires Understanding Complex Systems

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The 21st century is full of complex and perplexing problems that have proven tough to solve: pandemics, market crashes, global warming, poverty, and crime. If these problems could be explained by simple cause-and-effect relationships, we'd have a solution by now.

Understanding complex problems demands a different type of thinking, one that embraces the big picture as well as individual causal factors—a combination of "top down" and "bottom up" thinking—one that sees the world as interacting processes in which small-scale changes give rise to emergent properties on a larger scale. What's needed is "systems thinking."

While systems thinking is an essential skill needed by a modern workforce, it largely goes unaddressed in the classroom, in part because it is so difficult to teach. Our three-year Linking Complex Systems project, funded by the National Science Foundation, is beginning to explore whether students can learn about complex systems using computer-based models and simulations that enable students to visualize and manipulate systems and parts of systems in a way not often possible in the real world.

> *What we observe is not nature itself but nature exposed to our method of inquiry.*
> ~Werner Heisenberg, physicist, 1901–1976

Two modeling approaches

Systems thinking is recognized by the Next Generation Science Standards as an important crosscutting concept across multiple science and engineering disciplines. It recently has become a major focus for developing instructional technologies and curricular activities. Working with MIT's Scheller Teacher Education Program and the Argonne National Laboratory Systems Science Center as advisors, we are developing curricula around epidemics and evolution that utilize two modeling perspectives—systems dynamics (top down) and agent based (bottom up)—in order to evaluate learning when students use more than one approach to complex systems thinking.

Our project uses two well-established modeling applications to test two approaches. SageModeler, developed by the Concord Consortium, takes a systems dynamics approach, and StarLogo,

developed at MIT, is an agent-based application. While systems thinking has been notoriously hard to implement in the classroom, we approached the challenge with two applications we knew were free, web based, and student friendly.

SageModeler looks at the big picture first. Students start by designing and building their own overall systems diagram using pictorial variables. They can then connect related component parts, quantify the relationship between variables, and run input and output analyses of the system, all without the burden of writing equations or programming. And since SageModeler is embedded in CODAP, our web-based data analysis application, students also can view the relationships between variables using tables and graphs. SageModeler takes a "stocks and flows" approach: stocks or "collectors" (e.g., CO_2 in the atmosphere) go up or down in the system over time according to rates of change or flows (e.g., parts per million per year).

StarLogo, on the other hand, is an agent-based model that looks at individual components first. It simulates the interactions of particular agents and how they affect the whole system. StarLogo combines a graphical drag-and-drop programming language with a 3D gaming interface in which students can manipulate variables and their values to determine how the variables behave in the system as they interact over time.

Research in the classroom

Depending on the type of problem, one modeling perspective may be more appropriate than another. But experiencing both perspectives demonstrates to students how there is more than one way to solve a problem, and ultimately helps them develop a more nuanced understanding of systems.
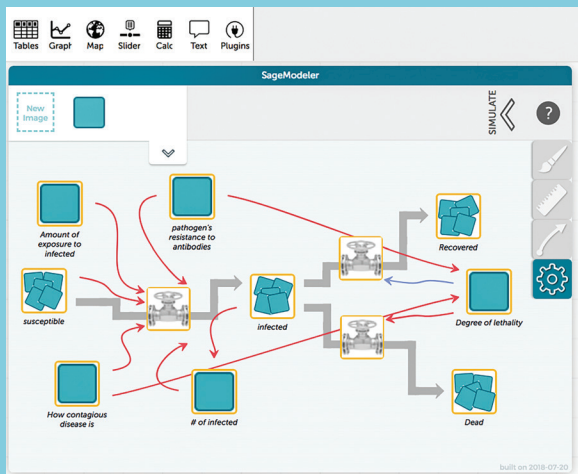
Figure 1. In this SageModeler systems dynamics model each node represents a variable associated with a system element and the arrows between the nodes represent the relationships between variables.
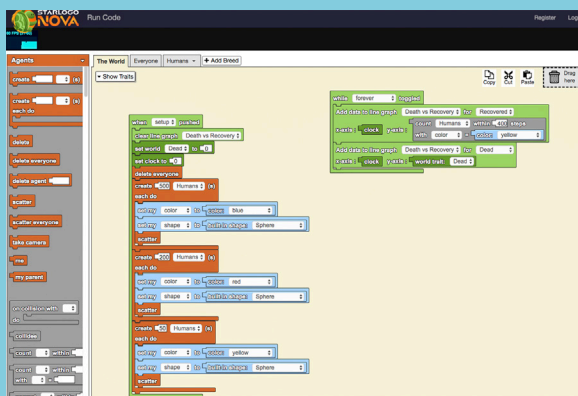
Figure 2. Agent-based StarLogo models are built through a blocks-based programming interface in which students control properties of their virtual systems.
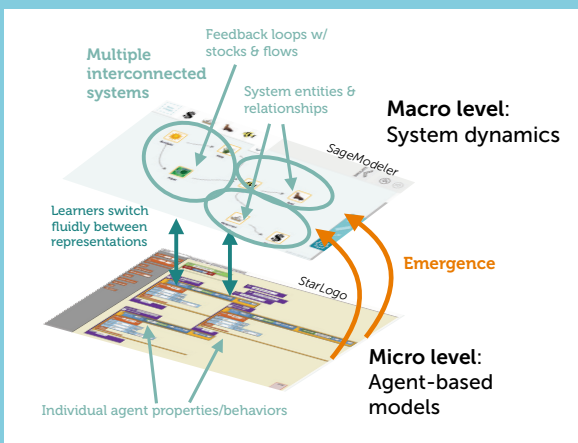
Figure 3. Schematic overview of linked-hybrid modeling perspectives shows both micro and macro views: top down (systems dynamics) and bottom up (agent-based) models.

Following a focus group meeting and training, we pilot tested this idea with a group of 11th grade students in a Massachusetts school district. Using an epidemic as the subject, half the students used SageModeler (Figure 1) and the other half used StarLogo (Figure 2) to analyze the epidemic. We then surveyed them about the experience.

When asked to describe what models describe or explain, most students responded that models were for describing, representing, or explaining how something works or looks. While the generally accepted view is that agent-based modeling allows system outcomes to emerge from individual interactions, and thus making the system outcome less predictable, and systems dynamics modeling is better suited to work with real-world data to test system models, student experiences were mixed in this regard.

In general, students understood that complex issues have multiple causes, and based on those multiple causes, the system can be influenced in a number of ways. But they had a harder time understanding the relationships between components. Students also had different comfort levels with each approach—some preferring StarLogo over SageModeler and vice versa. For example, one student stated: "StarLogo is very detail oriented and SageModeler shows you exactly how the epidemic would play out." But given that this was a pilot study, a definitive evaluation of student responses to the two modeling systems will depend on further study.

Next steps

The purpose of teaching systems thinking is to give students an important problem-solving skill set, and more flexibility when creating and evaluating mental models. If students are exposed to different ways of approaching a problem, they are less likely to fixate on one type of model.

We are planning a new round of research in early 2019 with students in two high school biology classes using a new curriculum developed around genetics and evolution. We hope to unite the two core modeling technologies, SageModeler and StarLogo, and marry the strengths of each to form a new technological genre, called "linked-hybrid modeling," aimed at supporting learning and reasoning in interconnected complex systems (Figure 3). In addition, we're developing a set of core learning exemplars for high school students involving complex systems.

For students, as well as educators, to be comfortable with complex systems thinking, these ideas and approaches need to become part of learning across subjects. Our Linking Complex Systems research is one step towards understanding how to give students this critical 21st century skill.

Under the Hood:
Using Raspberry Pis and WiFis to Do More with Data

By Lisa Hardy and Matt Lewandowski

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For decades students have been using sensors in science classrooms to collect real-time data. In this age of the "Internet of Things" (IoT), sensors are now commonplace, cheap, and amenable to DIY projects. Beyond just creating more data, how can we improve the ways that students interact with and understand data?

The goal of the InSPECT (Integrated Science Practices Enhanced by Computational Thinking) project is to help students do more than simply look at graphs of sensor data. We want them to do things with data: to build dynamic systems that can both sense changes in the environment and respond to them—whether it's turning on a fan when a room gets too stuffy or stabilizing temperature using a Peltier cooler. With our partners at Manylabs, we're developing Dataflow, a browser-based application that (unlike other IoT platforms) not only lets students collect and view sensor data, but also allows them to write programs that transform that data to control physical actuators.

To do this we needed to develop WiFi-connected devices that could execute students' programs and control actuators based on sensor data. Since we want students to understand how Dataflow works, they also need a real-time display of all the collected sensor data and how that data flows through their programs to determine actuator states.

Dataflow uses Raspberry Pis as WiFi-enabled devices that can execute these control programs because they are inexpensive but powerful computers. The Pis run a client program that reads data from all USB-connected sensors, runs student programs, and sets the states of USB-connected actuators. When a Pi boots up, it is available to respond to requests for sensor data and to run students' programs.

In the browser, students connect onscreen "blocks" and "wires" to create the Dataflow programs that are serialized and sent to a Raspberry Pi, where they are run (Figure 1). The client software de-serializes the program as a set of linked, executable "blocks." Each block has:

- other blocks linked as inputs,
- a function to execute when those inputs are defined, and
- a single output value.

To run these programs, the Pi client first fills all sensor-type blocks with values from the connected sensors, then loops over the entire set of blocks, requesting each to attempt to execute. In each loop iteration, the sensor values "flow" through the program and are processed by each block, until each block in the program has a defined output value. The client then uses any actuator-type block values to set the states of connected actuators and any storage-type block values to send data to the server to be persisted in a database and accessed later.

To display a real-time representation of the "flow" of data through those programs as they run, we implemented bi-directional communications between the server and the Raspberry Pis. We send students' control programs to the Raspberry Pis over a websocket, and in response have the Pis send back (once per second) the current state of each block in the running student program. We then feed those states into the real-time representation of the student's blocks-and-wires program in the browser.

Students are learning about computation and control systems as they create control programs and see how the sensor data flows through those programs to determine actuator states. We're adapting low-cost IoT technologies to give students new ways of doing things with data— beyond just looking at it.

Note: Find the open-source Dataflow code on GitHub at the link below.

Figure 1. A Dataflow program to turn on a relay when the temperature is above 25 degrees.

LINKS

InSPECT
https://concord.org/inspect

Manylabs
https://www.manylabs.org

Dataflow repo
https://github.com/concord-consortium/flow-server

Innovator Interview:

Colin Dixon
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When Colin was young, he thought science was a set of procedures to follow. Now, one of his main goals is helping students see that science is about discovery and exploration, done in and with community.

As an undergraduate at Northwestern University, Colin majored in communications and poetry. But through his work with Chicago SCORES, teaching soccer and creative writing to elementary and middle school children in the afterschool program, he discovered the importance of linking the development of the mind and body. He also saw the value for young people of being active in their communities—of "finding your voice and sharing your experience."

After teaching English and working on youth development projects in Uzbekistan for the Peace Corps, he made his way to the Washington, D.C., area, where he was the founding director of a nonprofit bicycle shop. With local grants, fundraising, and revenue from sales and service, the store employs and trains youth, many of whom are recent immigrants. "Some of these kids didn't feel like they had a place in the larger community," observes Colin. Learning how a bike works and being able to repair it provided them with technical expertise "that helped them to know there was a chance to be present in the community in a way that was not possible in other places," says Colin. "Being not just present, but valued for your knowledge and ability is central to the value of 'making' and citizen science."

Intrigued by these ideas, Colin set out to the University of California Davis to study the intersection of technical learning with participation in public life. He surveyed local citizen science projects with Heidi Ballard, founder of the UC Davis Center for Community and Citizen Science, and connected with researchers and educators at the East Bay Academy for Young Scientists. The work "focused on communities not well served by the science infrastructure and kids not necessarily already tied into science," explains Colin, who did a case study of one youth citizen science group that monitors water quality to help restore a local creek.

With another UC Davis faculty advisor, Lee Martin, he converted a van into a mobile maker space, outfitted with both traditional crafting and high-tech tools. They set out to foster and research the development of adaptive expertise, especially within STEM disciplines. Colin was surprised by the variety of projects that young people pursued when given the chance to direct their learning, like one young man's embroidered patches based on Mexican Air Force participation in WWII. In one of Colin's favorite projects, students collected air quality data in the Oakland transit system, then used a laser cutter and Arduinos to create objects that shared the data with community members in real time.

Colin recently completed his Ph.D. in Learning and Mind Sciences. As a research associate at the Concord Consortium, he works on the InSPECT project, which uses inexpensive DIY lab instruments in open-ended, technology-enhanced high school biology experiments designed to facilitate inquiry. Colin sees the excitement as students use and interact with sensors and see data appear on a screen. These students may never have used a Clapper to turn on a light, observes Colin, but "seeing that they can produce and control flows of data in the same way is very powerful."

On the Paper Mechatronics project, which is developing new ways to advance engineering education through computationally enhanced children's papercrafts, Colin says, "Magic happens when technology becomes secondary and in service of something like telling a story." He hopes that all students will come to view science as a disciplined yet creative pursuit, a reflection of the world they live in and the world they want to live in.

"Magic happens when technology becomes secondary and in service of something like telling a story."

The Concord Consortium is happy to announce the following new grants from **The National Science Foundation.**

Learning About Geohazards

From severe flooding and powerful earthquakes and volcanoes to the sustained winds of hurricanes, natural disasters around the globe have caused devastation and have had a major impact on millions of people's lives. How can understanding natural hazards help people plan for and recover more quickly from these impending threats? Two new projects explore innovative instructional approaches for studying geohazards.

GeoHazards: Modeling Natural Hazards and Assessing Risks is collaborating with Pennsylvania State University, TERC, and National Geographic Society to develop a set of computational models that allow students to explore geoscience systems responsible for natural hazards. Students compare data generated from Earth systems models with real-world data in order to develop an understanding of the cause and progression of natural hazards, as well as to make predictions and evaluate future risks in a certain location.

Visualizing Geohazards and Risk with Code (GeoCode) is partnering with UNAVCO and the University of Florida to engage students in the study of geohazards through the integration of computational thinking and science practices. Students transform real-world GPS data into interpretable visualizations. GeoCode also asks students to formulate scientific arguments about predicting impacts and assessing risks.

Both projects support students in applying their understanding of the processes underlying each hazard to build models and visualize data. Curriculum will include scaffolds to assist students in the development of scientific arguments as they consider both risk assessment and mitigation strategies.

Scaffolding Computational Thinking Through Multilevel Systems Modeling

Systems thinking and modeling are essential for addressing some of our most challenging scientific and societal problems—from climate change to economic policy. However, few students are exposed to systems thinking as an approach to understanding phenomena, and even fewer have the opportunity to build their own runnable system models. Computational thinking plays a key role in developing solutions to scientific and engineering problems that involve a systems modeling approach. The Concord Consortium and the CREATE for STEM Institute at Michigan State University are conducting research on student engagement in computational thinking while developing and testing systems models. High school students will use SageModeler to develop models of increasing complexity in physics, chemistry, biology, and Earth and environmental science. The goal of the project is to further the understanding of how the intersection of student modeling and computational thinking develop over time.

Connections of Earth and Sky with Augmented Reality

Augmented reality (AR) systems hold the potential to immerse users in 3D virtual holographic models of scientific systems embedded in a room with both objects and other people present. Multiple people can view and manipulate these holographic models from their own vantage point to support collaborative learning. The Concord Consortium and the University of Illinois, Urbana–Champaign are examining how the visual, physical, and psycho–social affordances of AR can be leveraged and extended to optimize small group interaction and cultivate collaboration and problem solving. We will develop and test learning scenarios that include models of planetary astronomy.

Researchers will work with community college professors in Massachusetts and Illinois to develop scenarios that equip students with problem-solving skills that build from foundational science understandings, and test them with community college students. The project aims to contribute to the research on human–computer interaction and produce design guidelines to support future AR workplace collaboration.