Identifying Curriculum Design Patterns as a Strategy for Focusing Geoscience Education Research: A Proof of Concept Based on Teaching and Learning With Geoscience Data

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ABSTRACT

The geoscience education research (GER) enterprise faces a challenge in moving instructional resources and ideas from the well-populated domain of "practitioners' wisdom" into the research-tested domains of St. John and McNeal's pyramid of evidence (this volume). We suggest that the process could be accelerated by seeking out clusters of instructional materials that share a common design pattern and then researching the affordances, pitfalls, and mechanism for the cluster. As a proof of concept, we sought design patterns that would support the learning goal that students be able to use authentic geoscience data to make inferences about Earth processes and decisions about Earth–human interactions. Analyzing intro-level modules from the InTeGrate project revealed six such patterns, each of which was used in at least three modules. For each pattern, we describe the instructional sequence, provide an illustrative example, describe the variability observed within the pattern, hypothesize mechanisms by which the instructional sequence might lead to improved learning, and pose potential research questions. In order from most to least abundant, the observed design patterns are *Data Puzzles, Pooling Data to See the Big Picture, Make a Decision or Recommendation, Predict–Observe–Explain, Nested Data Sets,* and *Deriving a New Data Type*. We conclude that a research program based on design patterns for teaching and learning with authentic geoscience data is viable, and we offer recommendations for moving forward. © *2017 National Association of Geoscience Teachers*. [DOI: 10.5408/16-217.1]

Key words: data, InTeGrate, design patterns, geoscience education research (GER)

THE PROBLEM: HOW TO HIGH GRADE INSIGHTS FROM PRACTITIONERS' WISDOM

St. John and McNeal (this volume) have characterized the current body of geoscience education knowledge as a pyramid (Fig. 1). Across the broad base of the pyramid is a wealth of information at the evidence level of "practitioners' wisdom or expert opinion." This level includes the Science Education Resource Center (SERC) and Cutting Edge websites, commentaries, and similar curriculum-relevant materials prepared and/or selected by experienced geoscience education practitioners. Going up the pyramid, the body of evidence narrows through qualitative and quantitative case studies at a single institution, followed by cohort studies across multiple institutions with more broadly applicable instruments, followed by meta-analyses, and topped by systematic reviews at the narrow pinnacle of the pyramid.

The practitioners' wisdom body of evidence in undergraduate geoscience education has been accumulating for decades, spurred onward by ambitious, nationwide efforts such as On the Cutting Edge (Manduca et al., 2010) and the Climate Literacy and Energy Awareness Network (2016). However, for the higher levels of the pyramid, the evidence is sparser, because geoscience education research (GER) is a relative newcomer to the field of discipline-based education research (Piburn et al., 2011; Singer et al., 2012). Moreover, the amount of effort needed to move a given pedagogical strategy or curriculum unit from the first level of the pyramid to the second or from the second to the third is far more than was required to get into the bottom level. More students and instructors must be engaged, be incentivized, and give informed consent; assessments or other instruments must be refined, validated, deployed, and rigorously scored; data must be analyzed statistically; papers must be written; and the peer review process must exercise its quality control function.

Given the available human and financial resources across the GER community, we believe that it will not be possible to individually test each program, product, practice, and policy that sits in the practitioners' wisdom level of the evidence pyramid. A more efficient approach is sorely needed.

A PROPOSED SOLUTION: RESEARCH DESIGN PATTERNS RATHER THAN INDIVIDUAL RESOURCES

We suggest that the GER community find a way to cluster instructional materials so that a whole category of materials, sharing a common approach, can be researched in one coordinated study. The individual instructional units, modules, or activities would be considered instances or cases of a specific approach. The study would seek to elucidate the strengths and pitfalls of the features that various instances have in common while exploring the range of variations that they do not have in common.

A viable path forward may lie in the concept of design patterns. A design pattern is a description of a reusable,

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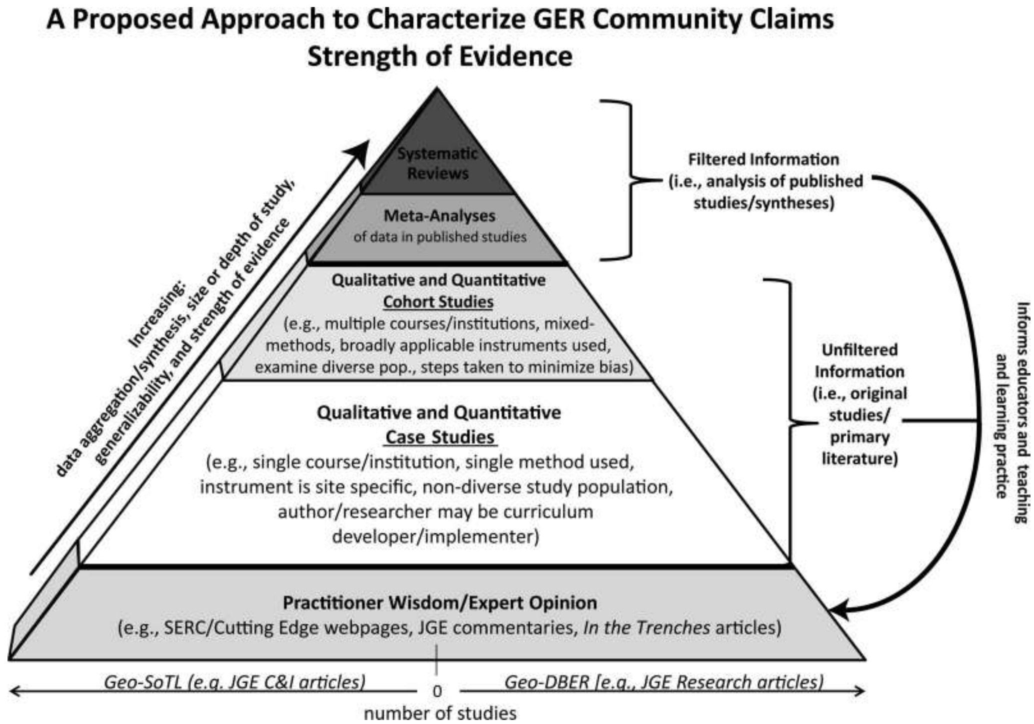

FIGURE 1: St. John and McNeal (this volume) have characterized the current state of geoscience education knowledge as a pyramid, with a large base of material that was vetted at the level of expert opinion tapering up to a small apex of material that was tested and distilled through education research. This paper proposes a strategy to accelerate the movement of materials upward, out of the practitioners' wisdom or expert opinion level.

adaptable solution to a recurring situation that arises as a designer works to shape an environment that will serve humans well. The concept originated in architecture and urban design (Alexander et al., 1977) and has been adapted for many other fields in which design is a key aspect of professional practice (Leitner, 2015). An example from Alexander's classical work in architecture would be an arcade, a partially covered walkway at the edge of a building that tackles the challenge of connecting the private space of the building interior with the public space of the exterior. Design patterns aspire to articulate the essential features that make the pattern work, as embodied in the most effective examples that have emerged from extensive practice.

In education, Linn and Eylon (2006) applied the design pattern concept to K–12 science instructional materials, Bauer and Baumgartner (2011) mapped design patterns for teaching with e-portfolios in higher education, and Kastens et al. (2015) took some first steps toward applying the idea to geoscience education. As applied to instructional activities, we envision that a design pattern lays out a coordinated sequence of actions followed by teachers and students in an instructional setting for the purpose of leading students toward making sense of phenomena in the world. Design patterns are content independent and thus can be used and reused for different topics. As in architecture, each design pattern contains certain essential features required to make the pattern work but also allows room for flexibility to fit the "concrete problem situation at hand" (Leitner, 2015). The well-known instructional strategies of think–pair–share (Starting Point, 2015), *Predict–Observe–Explain* (*P-O-E*; Haysom and Bowen, 2010), and the 5 Es (Bybee et al., 2006) can be considered examples of design patterns.

For curriculum developers, established design patterns can be used as templates for how to organize and sequence instruction in a way that is likely to be both engaging and effective. For education researchers, design patterns may offer a way to group existing educational interventions into clusters that can be tested as a group. The remainder of this commentary will begin the process of exploring whether such an approach is viable in GER. Such an approach would require the following steps:

(1) Identify a recurring set of design patterns that have been used in multiple instances in well-regarded curriculum materials and teach toward an educational goal that is highly valued by the geoscience education community. Traditionally, the design pattern approach draws primarily from observation and experience of practice (Alexander et al., 1977), but during Step 1, the research and practitioner's literature should also be mined for candidate patterns and insights about patterns (Leitner, 2015).
(2) Develop a hypothesis or hypotheses about a mechanism or mechanisms by which the instructional sequence embodied in each design pattern could plausibly lead to strong student learning outcomes. Ideas for mechanisms may draw on practitioners' observations or on insights from learning science and cognitive science. This early thinking about a mechanism or mechanisms will serve as the first draft of a theory of action and as a basis for formulating research questions.
(3) Develop research questions that target the essence of the design pattern rather than the specifics of

each curriculum module. In this process, reflect deeply on what overarching learning goals are embodied in the candidate design pattern. In some cases, these may be geoscience habits of mind or ways of knowing (Manduca and Kastens, 2012; InTeGrate, 2015a), rather than understanding of specific Earth phenomena.

(4) Conduct classroom-based design research spanning multiple instances of a design pattern in multiple classrooms to tease out the common affordances, challenges, and conditions of success characteristic of the design pattern.

(5) Use the insights emerging from Steps 2–4 to sharpen the original curriculum materials, develop new materials, and refine the design patterns. Working with cognitive science colleagues and drawing on the research literature, articulate an evidence-based theory of action that explains what underlying cognitive and social processes are leveraged by the design pattern when it is working well.

This paper undertakes Step 1–3 for one recurring instructional challenge and offers thoughts on how the GER community could undertake Steps 4 and 5. This plan is a substantial methodological departure from conventional education research. Rather than starting from research questions grounded in prior literature, this plan's starting point is a large body of existing educational materials considered to be of high quality by frontline educators. The premise is that embodied in those materials are important insights about how to help students think and learn and that such insights would benefit from being pulled into the daylight, articulated explicitly, and tested methodically. This pathway into research is not meant as a substitute for the more traditional pathway; it is offered as a parallel pathway that is well suited for a field that has a relatively small body of research-tested instructional approaches and a relatively large body of practitioner-recommended materials.

TESTING STEP 1: IDENTIFYING A SET OF DESIGN PATTERNS

We have chosen to seek design patterns that support the learning goal that students are able to use authentic geoscience data to make inferences about Earth processes and decisions about Earth–human interactions. This challenging learning goal spans all geoscience disciplines. Use of data is a well-established component of undergraduate science education (Manduca and Mogk, 2002), features prominently in a consensus set of competencies that geoscience faculty wish to develop in their students (Mosher et al., 2014), and is a key scientific practice in *A Framework for K–12 Science Education* (National Research Council [NRC], 2012).

For a body of curriculum materials to analyze in this proof of concept, we have chosen six modules developed, tested, and published by the InTeGrate project (Table I; InTeGrate, 2017). InTeGrate materials are developed by teams of experienced classroom educators and piloted by the developers in their own classrooms, and the materials pass through a curriculum auditing and peer-review process (Savina et al., 2015). The InTeGrate curriculum development and refinement rubric (InTeGrate, 2015b) requires that all instructional materials use "authentic, credible geoscience data," so although the topics and data featured in the six modules vary widely (Table I), all modules have the potential to strengthen students' proficiency with geoscience data. The InTeGrate rubric also requires that materials conform to a set of pedagogical criteria, including having learning strategies and activities that promote student engagement with the materials and having assessments that address outcomes at successively higher cognitive levels (InTeGrate, 2015b). The modules chosen for this study are designed for use in introductory geoscience courses. InTeGrate records show that each of these modules has been used by at least 16 instructors, including the 3 developers (Kathryn Sheriff, pers. comm., July 5, 2017).

The granularity of analysis was the activity, a coherent, sequenced effort on the part of the student that usually results in a student product or performance. Six modules were analyzed, each spanning 2–3 weeks of instruction. Each module is composed of six units, and units contain between two and five activities. For each activity, we recorded a description of the data, the form of data access, and what students do with the data. For the latter, we developed a catalog of data moves, or actions that students take with the data, such as describe patterns, relationships, or trends in data; compare and contrast data; and make a calculation based on data. For each activity, we coded the actions taken by students into a sequence of data moves.

Iterating through our corpus of materials, we gradually discerned recurring sequences of data moves that addressed our chosen learning goal, including the requirement that students should use data to make an inference or decision. These we identified as candidate design patterns. Table II shows examples of how a sequence of data moves coalesces to form a design pattern. Like design patterns in other fields (Leitner, 2015), our teaching-with-data design patterns are characterized by variations on a theme, exhibiting enough similarities to fit within a single template but enough differences to span a range of data types and topics. For each candidate design pattern, we identified characteristic data moves, including a culminating move requiring student insight. In addition, we mapped out the range of variation that could fit within the defined bounds of the pattern and compiled brief descriptions of activities falling within the pattern.

To assemble the final collection of design patterns, we used a threshold of three instances: a candidate design pattern had to occur in at least three units spanning at least three modules to be included in this paper. Passing this threshold meant that three development teams, including nine or more faculty, had drawn on their wisdom of practice and decided that this sequence of actions would be pedagogically valuable for their students.

FINDINGS FROM STEP 1: THE DESIGN PATTERNS

Our analysis yielded six design patterns (Table III). Each of these patterns, while distinctive from one another, addressed through a sequence of data moves our chosen learning goal. Although they employed different strategies and involved a variety of steps specifically appropriate to certain data types and content contexts, they all involved the

TABLE I: Curriculum modules analyzed.

Module	Selected Data Types[1]
Climate of Change: Interactions and Feedbacks Between Water, Air, and Ice	• Maps of sea surface temperature anomaly, wind, ocean current, and reflectivity anomaly • Graphs of ENSO index, ice sheet albedo, atmospheric CO_2, climate forcing, insurance losses, and heat-related deaths • Three-dimensional block diagram of SST and thermocline; Hovmoller diagrams • Survey data from Six Americas climate change attitude survey
Environmental Justice and Freshwater Resources	• Maps of topography, vegetation, precipitation, and groundwater depletion • Tables of water usage, altitude of gauging stations, and precipitation • Google Earth KMZ files and images • Stratigraphic cross section • Online database of groundwater data
A Growing Concern: Sustaining Soil Resources Through Local Decision-Making	• Maps of physiographic divisions, erosion, soil organic matter, crop intensity, and change in precipitation • Photos of agricultural and natural landscapes • Online database of soil types and soil profiles
Humans' Dependence on Earth's Mineral Resources	• Maps of rare earth element localities, plate boundaries, and geological map and gold deposit localities in Yellowstone • Graphs of GDP/capita versus consumption, time series of consumption and extraction, cell phone battery sales, Li and Ni production, abundance of elements in Earth's crust, and time series of production and ore grade • Tables of energy density and cost of batteries, export quotas, and price per ton
Living on the Edge: Building Resilient Societies on Active Plate Margins	• Maps of earthquake epicenters, plate motion vectors, plate boundaries and faults, population density, epicenter locations and magnitude, damage cost, deaths, bathymetry or topography, and liquefaction susceptibility • Table relating instrumental intensity to peak velocity, peak acceleration, perceived shaking, and potential of damage • Photographs and eye-witness accounts of damaging earthquakes • GPS data, tilt data, and seismograms • Time series bar graphs of gas emissions and seismic events
Natural Hazards and Risks: Hurricanes	• Maps of hurricane recurrence time, sea surface temperature, storm tracks, rainfall, wind direction, topography, and cone of uncertainty • Tables of numbers of fatalities, hurricane location and attributes, and damage cost • Graphs and charts of atmospheric composition and density, number of storms per month, and accumulated cyclone energy • Aerial and ground-level photos; LIDAR images

Note: Modules were analyzed in spring and summer of 2016; some have since been modified.
All analyzed modules can be accessed from http://serc.carleton.edu/integrate/teaching_materials/modules_courses.html.
[1]ENSO = El Niño/Southern Oscillation; SST = sea surface temperature; KMZ = keyhole markup language zipped.

use of authentic geoscience data and required students to move beyond simply reading data visualizations to discerning patterns in the data and relating these patterns to Earth processes and Earth–human interactions.

For each pattern, we now describe the essential aspects of the pattern, provide one illustrative example, describe the range of variation within the pattern, and tally how many instances of the pattern were found. The patterns will be presented in order from most to least abundant in the body of materials that we analyzed. In the subsequent section of the paper, we will revisit each pattern and offer possible mechanisms by which the instructional sequence could

TABLE II: How data moves combine to form design patterns.

Examples of *Data Puzzle* Design Pattern	
Humans' Dependence on Earth's Mineral Resources—Unit 2: Activity Option 2.2	**Climate of Change: Interactions and Feedbacks Between Water, Air, and Ice—Unit 5: Case Study 5.2**
Data moves: • Plot data • Answer decoding questions • Describe patterns, relationships, and trends • Develop a potential explanation for each pattern, relationship, or trend *Aha insights:* There is a delicate balance between supply and demand for rare earth elements (REEs), impacted by the intertwined behaviors of consumers, mining companies, and technology companies. Demand exceeds supply for several important REEs.	Data moves: • Answer decoding questions • Describe patterns, relationships, and trends • Plot data • Make a calculation based on data • Compare and contrast data • Make a prediction • Explain the reasoning behind the prediction *Aha insights:* Methane—a greenhouse gas that students may not have previously heard much about—has a powerful impact on atmospheric temperature.

foster student learning and propose candidate research questions.

Data Puzzle

For a *Data Puzzle* (Kastens and Turrin, 2010; Kastens et al., 2015), the curriculum developer has identified snippets of data that embody an important scientific concept or process. The developer has found or created a data visualization or visualizations that clearly display trends or patterns that are the characteristic traces of the concept or process. The data are purposefully selected and represented so as to have a high insight-to-effort ratio. Students view data visualizations on screen or paper and answer a sequence of guiding questions about the system represented by the data. The sequence of questions builds toward a culmination in which students bring forth a substantial insight about Earth, the environment, or Earth–human interactions, termed the "Aha! insight" by Kastens and Turrin (2010; viii). Merely decoding and/or describing data in the absence of a culminating interpretive insight does not meet our stated learning goal. A common form of the *Data Puzzle* aha insight is when students recognize that a concept they have studied in the abstract is concretely manifested in data that they are trying to interpret. With this insight, they can then make meaning from the data by drawing on the concept.

Figure 2 shows an implementation of the *Data Puzzle* design pattern drawn from Perez et al. (2017). In this example, students have done prework to establish the chronology of events that led to the establishment of the nation's first Superfund site, at Love Canal. Working with both aerial and ground-level photographs, they compare and contrast the situation in the late 1970s with the situation today. They combine information about regional stratigraphy, permeability data, and the location of the river and creek to understand how geology and hydrology influenced the flow of toxic materials.

Data Puzzles vary widely by type of data, type of visualization, and the data moves that students are asked to carry out as they are led toward their interpretive insight. Common data moves in data puzzles include describing relationships or trends in the data across time and space, comparing and contrasting data sets, comparing a model with data, performing a calculation on the data, and organizing data using a graphic organizer. In our corpus, most data visualizations were preprepared and presented statically on paper or screen. However, we also included in this pattern instances in which students make visualizations (e.g., in Microsoft Excel or Google Earth or on graph paper), but the parameters of the data visualizations are prescribed by the curriculum or the teacher; the students have no role in deciding what data to access or how best to represent it. Some *Data Puzzles* follow a linear sequence of DV1, *Q* about DV1, DV2, *Q* about DV2, etc. (where DV = data visualization and *Q* = question). Others follow a more complex sequence in which students must draw information from multiple visualizations simultaneously to answer questions later in the sequence.

The *Data Puzzle* design pattern was used in every one of the six modules examined (Fig. 3). Twenty-two instances were found, almost three times as many as for any other pattern. This may be because the *Data Puzzle* pattern can be used for almost any concept or data type. Although it takes more instructional time to work through an activity designed according to the *Data Puzzle* pattern than to present the same content didactically, the *Data Puzzle* design appears to be more time efficient than the other patterns. Anecdotal reports suggest that the *Data Puzzle* design pattern may also be easier for nondeveloper instructors to adapt to their local context than the other design patterns.

Pooling Data to See the Big Picture

The *Pooling Data to See the Big Picture* design pattern begins with students working on separate sets of data that pertain to the same real-world phenomenon. The data sets are selected so that they collectively display a range of attributes associated with the target phenomenon. Then, students share the findings from their data exploration. The culmination comes when the findings are methodically combined to yield a bigger picture and deeper insights than could have been obtained from analysis of any single data set.

Figure 4 shows an example of the *Pooling Data* design pattern, drawn from Goodell et al. (2015). In this instantiation of the design pattern, students work individually to learn about a submarine divergent margin by viewing a data-rich video and blog post. In class, they work in small groups to examine multiple types of data from one of three on-land divergent plate margins. They attend to earthquake hazards, volcanic hazards, and other associated hazards, and they explain how each hazard type is related to divergent

TABLE III: Summary of design patterns identified in InTeGrate curriculum materials.

Design Pattern	Key Characteristics	Number of Instances
Data Puzzle	• Snippets of high insight-to-effort ratio data preselected by the curriculum designer • Data moves that require observation and description of data (e.g., describe patterns, relationships, and trends or compare and contrast data) • Data moves that require interpretation of data (e.g., develop a potential explanation for each pattern, relationship, or trend or consider the consequences for humans of the phenomenon shown in the data) • Culmination: Experience an "Aha!" while interpreting concrete data in terms of processes previously learned in the abstract	22
Pooling Data to See the Big Picture	• Individually or in groups, interpret different data sets pertaining to the same phenomenon • Compare and contrast data • Culmination: Combine insights from multiple data sources to make an inference, see a pattern, or explain a phenomenon	8
Make a Decision or Recommendation	• Data moves that require observation, description, and/or interpretation of data • Scenario about a situation that requires a decision about a human action to be made in regard to Earth–human interaction • Culmination: Make a decision or recommendation grounded in data and explain and defend the reasoning behind the decision	8
Predict–Observe–Explain	• Gain familiarity with a system through data and/or models • Make a prediction of how data will look under not-yet-observed conditions • Explain the reasoning behind the prediction • Propose how to test the prediction with further data • Culmination: Test the prediction with data, compare and contrast predicted behavior with data, and discuss agreements and discrepancies	5
Nested Data Sets	• Interpret a local data set, drawing on local knowledge and personal observations • Access data covering a larger area, longer time span, or larger populations • Describe patterns, relationships, and trends in a larger data set • Culmination: Leveraging experience with local data, interpret a larger data set of make an inference, see a pattern, or explain a phenomenon	3
Deriving a New Data Type	• Perform a series of calculations based on data • Convert units to develop a derived data type • Culmination: Leveraging insights into how the new data type was derived, interpret a data set of the derived data type to make an inference, see a pattern, or explain a phenomenon	3

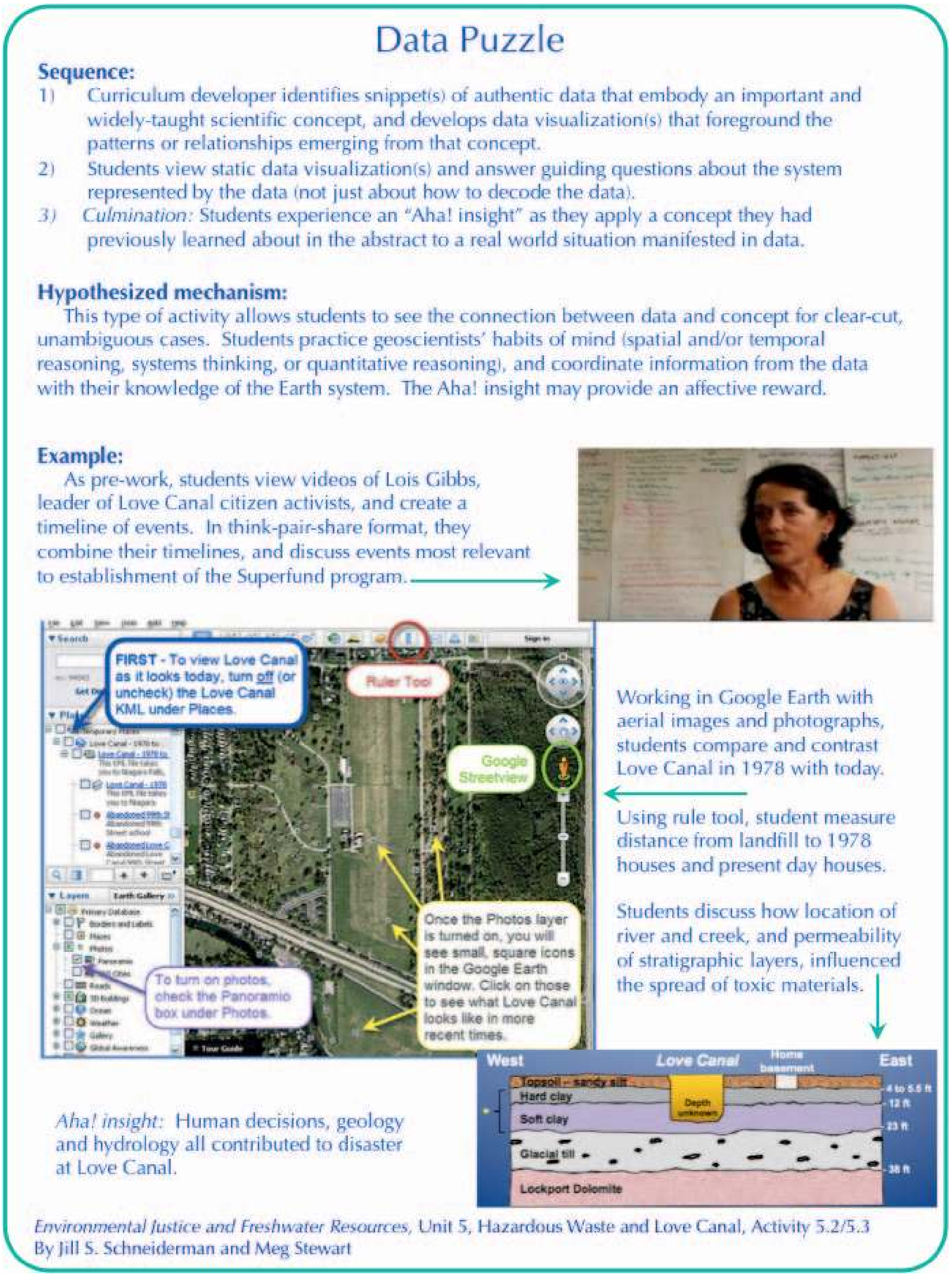

FIGURE 2: The *Data Puzzle* design pattern was found in every one of the six modules examined. It is adaptable for a range of content areas and data types. Color for this figure is available in the online journal.

motion. Then, as a full-class activity, they compare and contrast the three on-land divergent margins and on-land versus submarine divergent margins. This activity makes extensive use of graphic organizers (Fig. 4, lower right) to scaffold the compare-and-contrast efforts.

The pooling data design pattern was found in four of the six modules examined, for a total of eight occurrences (Fig. 3). Within this design pattern, data sets can be differentiated along several dimensions. We found differentiation by spatially distinct localities (e.g., different cities and different mountain ranges), by temporally distinct events (e.g., different hurricanes), and by different data types (e.g., oceanic and atmospheric data covering the same sequence of El Niño and La Niña events). Although not found in the present analysis, previous work (Friedman et al., 1997; Gould et al., 2012; Kastens et al., 2015) describes instances in which students pool data to increase their data's signal-to-noise ratio and enable meaningful patterns to emerge more clearly.

Most often, the distribution of data sets across the class is done by small groups, with the assembly of the big picture then completed as a full-class activity. However, we saw variants in which individuals rather than groups took responsibility for data sets, and other variants in which the

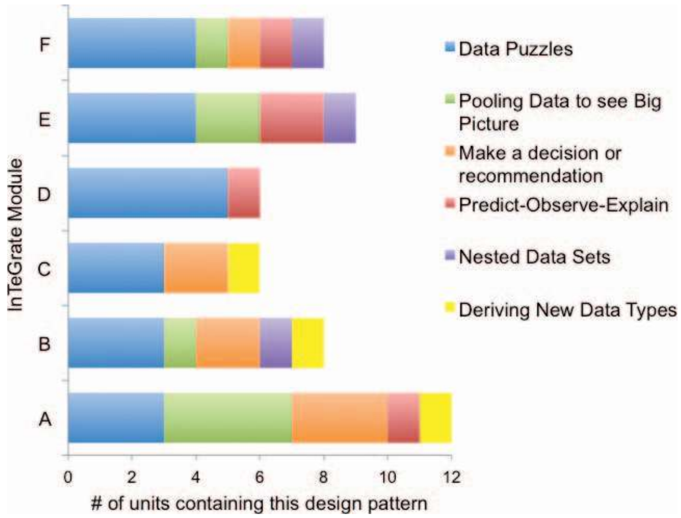

FIGURE 3: For each of the six modules (labeled A–F), bars indicate which design patterns were employed and how many units within the module contained each one. Across the six modules, we discovered six different design patterns that were each used in three or more modules. Color for this figure is available in the online journal.

big picture assemblage was carried out as homework rather than through discourse. The small-group version of the *Pooling Data* design pattern is related to the jigsaw design pattern (Aronson et al., 1978; Tewksbury, 1995, 2016). However, in the jigsaw approach, students need not look at data; they might, for example, read articles with different viewpoints on the same issue (Tewksbury, 1995, 2016). In addition, the classic jigsaw is built around two sets of small groups: a first set of homogeneous teams that all prepare the same material and a second set of heterogeneous groups in which students peer-teach what they learned in their first groups. In the second group, "success is measured by how well a student helps others learn what he/she knows" (Tewksbury, 1995, p. 324). Only one of the activities we reviewed had this distinctive sequence of initial homogenous groups followed by peer teaching in heterogeneous groups.

Make a Decision or Recommendation

In the *Make a Decision or Recommendation* design pattern, students are provided with data that are relevant to making a decision of consequence to humans or society and a scenario that calls for a decision about action or actions that humans could take with respect to an Earth–human interaction. The culminating move is to make a decision or recommend a course of action to stakeholders and to justify the choice. The justification always draws on Earth data but may also take into account other factors, such as economic, political, ethical, or equity concerns.

Figure 5 shows an example of *Make Decision or Recommendation* from Gilbert et al. (2015). In this in-class or homework activity, students confront a scenario concerning a cargo ship docked in Miami, Florida. The ship is scheduled for imminent departure for Galveston, Texas, but a hurricane is bearing down on the city. Using provided data about historical hurricane tracks and a cone of probability forecast for the approaching storm, the seafarers have to decide whether to remain in port or sail for Galveston. One's instinctive response might be to stay in port. But the data-informed answer is to sail immediately, get out of the storm's track, deliver the cargo on time, and be in port ahead of the storm even if it swerves westward toward Galveston.

The *Make a Decision or Recommendation* design pattern was found in four of the six modules examined, for a total of eight occurrences (Fig. 3). In most cases, the scenarios created a sense of tension or urgency, but the nature of the dilemma faced by the decision-maker or stakeholders differed: insufficient funding to take all desired actions, two competing actions that both involve risks, or multiple competing actions with varied cost–benefit ratios. The role or agency of the student relative to the decision also varied: students might be positioned as experts or scientists making a recommendation to stakeholders or as the actual decision-maker (as in Fig. 5), or they might role-play various stakeholders who would be differently affected by the decision.

Predict–Observe–Explain

In the *P-O-E* design pattern, students gain some familiarity with a system through data moves that involve observation, description, and interpretation. They are then asked to make and justify a prediction about how the system will behave under circumstances to which they have not been exposed. The culmination comes when they test their prediction with further data or observation and confront the success or failure of their prediction. *P-O-E* is a widely used design template in K–12 hands-on inquiry curricula (White and Gunstone, 1992; Linn and Eylon, 2006; Haysom and Bowen, 2010), in which the prediction usually involves a classroom demonstration or experiment with physical apparatus. Kearney et al. (2001) extended the *P-O-E* pattern to multimedia computer environments, and Kastens et al. (2015) extended it to student analysis of professionally collected data.

Figure 6 shows an example of the *P-O-E* design pattern, drawn from Bhattacharyya et al. (2015). In the previous unit (not shown), students were introduced to interactions between mineral resource use and economic activity, and in the prework for this unit, they considered what mineral resources are used in batteries. At the start of the *P-O-E* activity, the teacher introduces a concept map system model (Fig. 6, middle), which diagrams the direction of influences among mining and processing cost, price, mineral supply, consumer demand, and other factors. This model is intended to be applicable to any mined mineral, and use of the model is introduced through an unrelated example (e.g., cobalt and wars in Congo). After working through guiding questions about lead (Pb), nickel (Ni), lithium (Li), and batteries, students are asked to predict, based on the concept map, how each of a series of events should have affected the price and rate of production of Ni and/or Li. Only after the predictions are articulated and explained are students provided with time series data for Ni and Li price and production (Fig. 6, bottom) spanning the time interval of the prediction. Finally, students are asked to explain how the data support or refute their predictions.

In the example of Fig. 6, the prediction is based on a conceptual system model expressed as a flowchart concept map. All *P-O-E* activities require some kind of model, but the nature of the model is variable and can be conceptual,

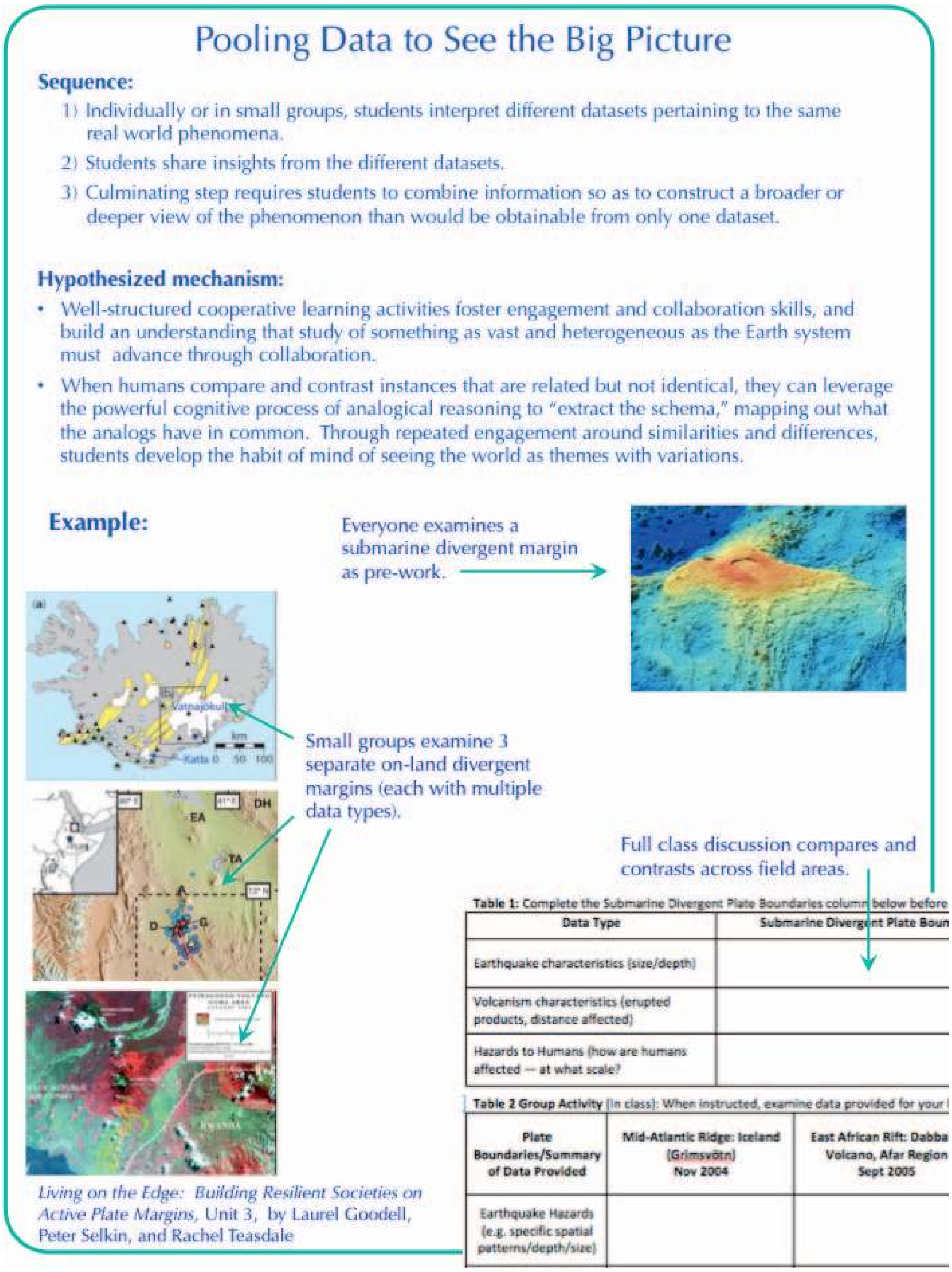

FIGURE 4: In *Pooling Data to See the Big Picture*, students combine insights from related data sets to construct deeper insights than they could get from any single data set. Color for this figure is available in the online journal.

mathematical, diagrammatic, or computational (e.g., Gould et al., 2012). The form of students' predictions can also vary. Most commonly, students are asked to state their predictions in writing, but sketching is another option. The manner in which students are directed to compare the predicted and actual behavior of the system also varies, from fairly open to tightly scaffolded. To create reusable, sharable curricula, the data revealed in all examined modules were data that already existed, so strictly speaking, students were making retro-dictions rather than pre-dictions. It is possible to have students make true predictions of events that have not yet happened by having them collect and interpret real-time data from rapidly evolving systems, such as estuaries (e.g., Adams and Matsumoto, 2011).

We found the *P-O-E* design pattern in four of the six modules, with a total of five occurrences. We found numerous additional occurrences in which students were asked to make a prediction to answer a guiding question, but the prediction was not tested with data; such instances were not counted as *P-O-E*, because they lacked the culminating step.

Nested Data Sets

The *Nested Data Sets* design pattern begins with students analyzing and interpreting data from their own locality. They

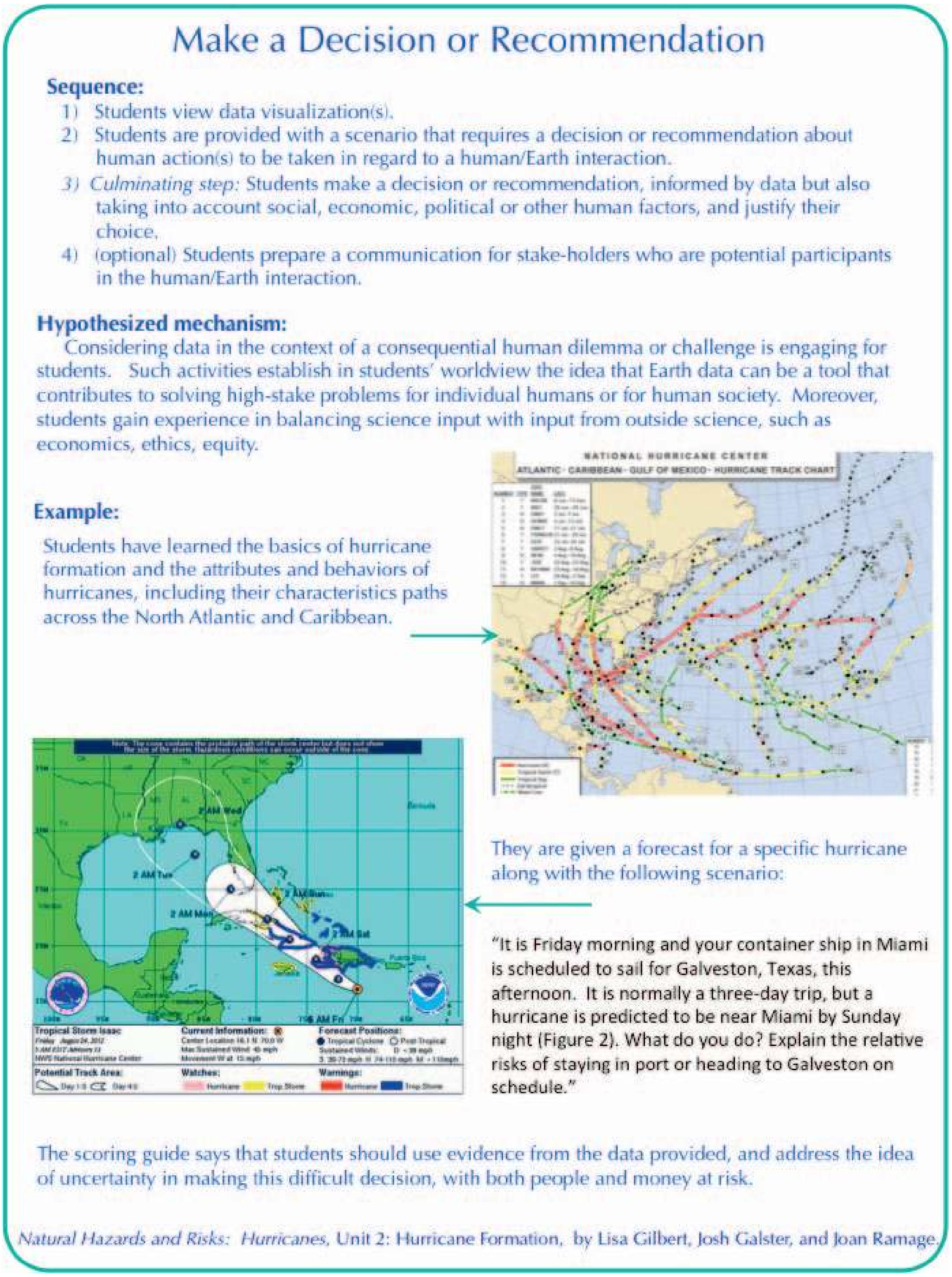

FIGURE 5: In *Make a Decision or Recommendation* students use data about what action stakeholders should take with respect to an Earth–human interaction. Color for this figure is available in the online journal.

then access and interpret professionally collected data of the same data type or types that extend the realm of study outward in space and/or time, typically to a regional, national, or global scale. The culmination comes when understandings built with the local data are leveraged in interpreting the broader data set.

Figure 7 shows an example of the *Nested Data Sets* design pattern, drawn from Shellito et al. (2015). In this unit on adapting to a changing climate, students collect survey data on themselves to assess their climate change personality according to the Six Americas scale (Roser-Renouf et al., 2015). They also assess the social vulnerability to environmental hazards of themselves and their community, drawing on their lived experience in the community with respect to socioeconomic status, race or ethnicity, age, employment loss, family structure, and other factors. In class, they pool their findings and calculate the classwide distribution of climate change personalities. They then compare their class data to the national data, leveraging their local knowledge in explaining any differences observed.

We found three occurrences of this design pattern in the InTeGrate corpus, plus we previously described another example from the Hudson estuary (Kastens et al., 2015, their Fig. 4). The instantiations differ widely in the types of data

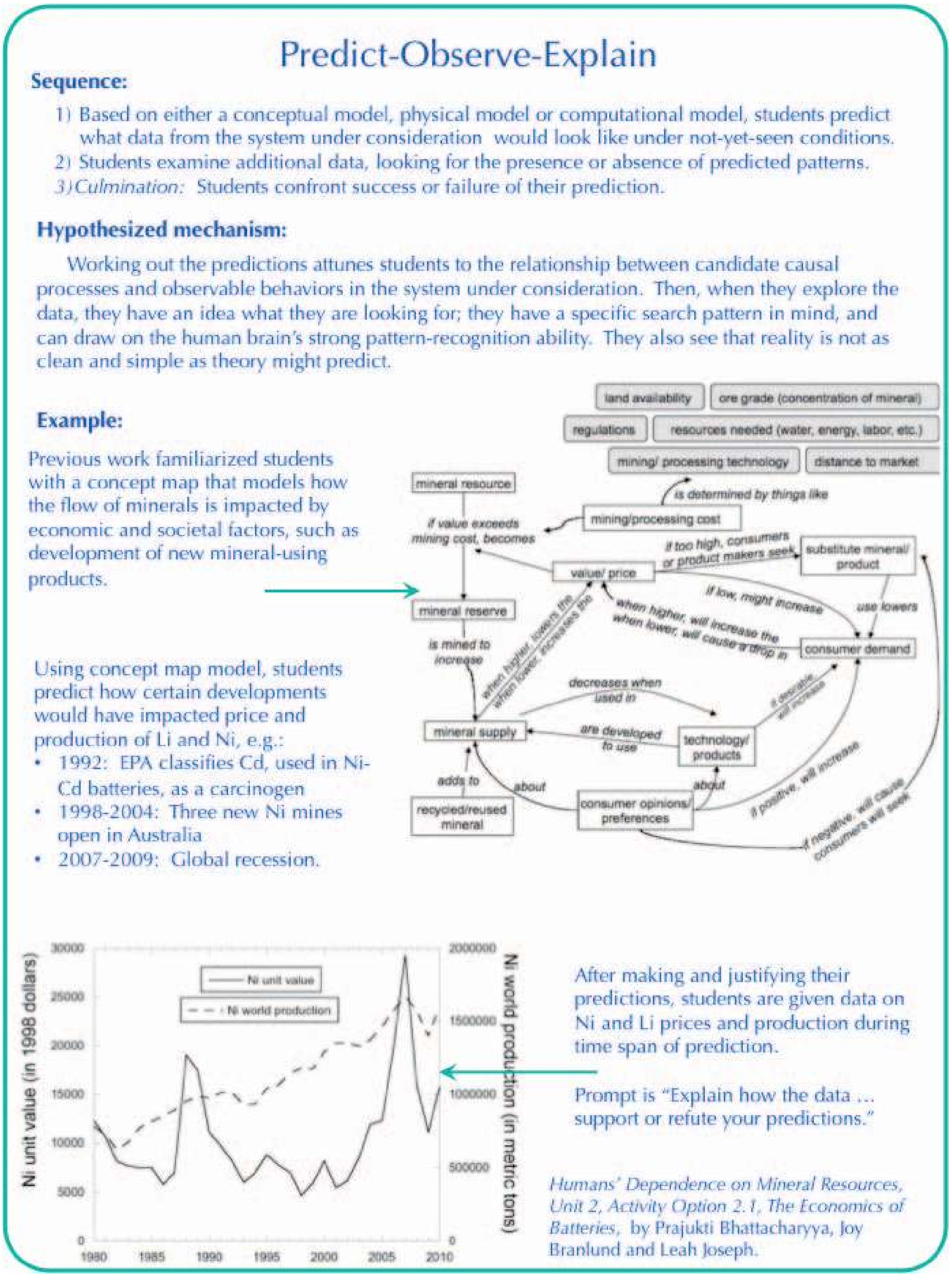

FIGURE 6: The *P-O-E* design pattern is widely used with hands-on demonstrations in K–12 education, but in the InTeGrate modules, we found it used for data-based investigations. Color for this figure is available in the online journal.

involved and the nature of the task that connects the large- and small-scale data sets. Most use Earth data, but the example of Fig. 7 shows that the pattern can apply to human subjects' data as well. When we first described this design pattern, we envisioned that students would always be collecting the local data themselves. However, in analyzing the InTeGrate modules, we found that certain types of very local data can now be obtained from the Internet, such as the highly localized soil profiles that users of *A Growing Concern* (Fortner et al., 2015) access via SoilWeb (University of California–Davis, 2016). Moreover, appropriate exercises can mobilize local knowledge that students have from just living in the environment, as in the social vulnerability to environmental hazards assessment described above. So now we have broadened this pattern to admit instances in which students do not collect the data themselves, provided that the essential elements of an instructional progression from local to large scale is present and local insights substantially inform the large-scale questions.

Deriving a New Data Type

The parameters that are directly measurable from the Earth system or the Earth–human system are sometimes not what scientists or technologists want to be thinking about.

FIGURE 7: In the *Nested Data Sets* design pattern, students leverage insights obtained from local data to interpret data on a regional, national, or global scale. Color for this figure is available in the online journal.

For example, an oceanographer or a harbor dredger may want to know water depth, but the sonar echo sounder measures acoustic travel time. In such cases, a protocol is developed to convert the available data type into a new data type, called a derived data type, that is useful for specific scientific or practical purposes. The process of converting the available data type into the desired data type may incorporate assumptions, empirically derived coefficients, nonlinearities, and other complexities.

The *Deriving a New Data Type* design pattern seeks to open the black box of a derived data type. Through scaffolded work with selected data or observations, students build familiarity with what is being measured or observed and work through the process of building the derived data type step by step. The culmination comes when students use their hard-won understanding of the derived data type to do something interesting or useful, such as make an inference, see a pattern, or explain a phenomenon.

Figure 8 shows an example of the *Deriving a New Data Type* design pattern, drawn from Fortner et al. (2015). In this soil erosion activity, the derived data type is the revised universal soil loss equation (RUSLE; Institute for Water Research, 2002). RUSLE is built from five factors, each of which has a complicated relationship to its empirical

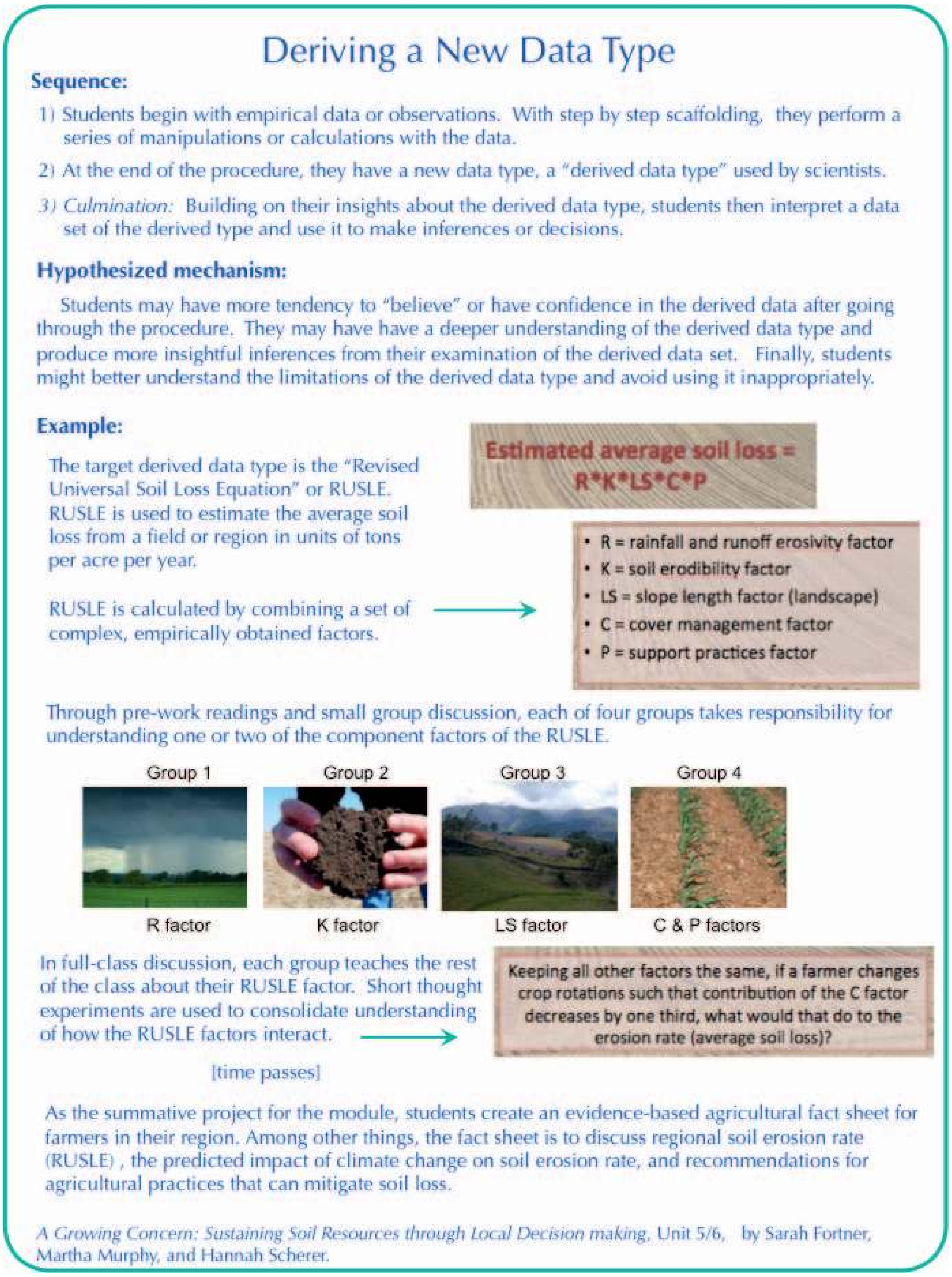

FIGURE 8: The three occurrences of *Deriving a New Data Type* were all concerned with data types used in societal or economic problem-solving, in this case for agriculture. Color for this figure is available in the online journal.

underpinnings. Students are split into small groups, each of which is responsible for reading about, understanding, and explaining one factor. In a full class discussion or in think–pair–share format, the class then works through several thought experiments to dig into how the factors combine to create the derived data type. As the culminating activity of the module, students create an agricultural fact sheet advising farmers in their region on how to mitigate soil loss both today and under anticipated conditions of climate change. To do so, they must draw on their understanding of RUSLE and its constituent components.

Three occurrences of *Deriving a New Data Type* were observed, spread across three modules (Fig. 3). One might expect that this design pattern would lean heavily on calculation and quantitative reasoning. That is sometimes the case, such as when students learn to calculate the 30-year probability of earthquakes in Goodell et al. (2015). But in the example of Fig. 8, the hard work comes in building a conceptual understanding of the component factors that combine to form the derived data type; the actual combining step is computationally simple. In each of the instantiations we observed of this design pattern, the derived data type was used to inform a societal or economic activity: agriculture, seismic hazard mitigation, and hurricane risk assessment. One can imagine applying this design pattern to derived data types used for purely scientific inquiry, but this group of curriculum developers did not choose to do so.

Others

Our six-module exploration has surely not uncovered all potentially useful design patterns for learning with authentic geoscience data or all strategies and variations that might be employed within a particular design pattern. Additional analyses of curricula from other sources should be undertaken. We did not find the hypothesis array design pattern that was previously identified by Kastens et al. (2015), building on the work of Mayer et al. (2002). Backward fading scaffolding, as developed in astronomy education (Slater et al., 2010; Slater, 2013), could be an effective design pattern in geoscience education as well. The K–12 Earth Science education research community may also have useful insights to offer GER as they investigate the scientific practice of analyzing and interpreting data from *A Framework for K–12 Science Education* (NRC, 2012).

STEPS 2 AND 3: HYPOTHESIZED MECHANISMS AND POTENTIAL RESEARCH QUESTIONS

The presence of these design patterns in at least three of the six analyzed modules tells us that experienced educators think that these approaches will be useful and practical. An ambitious GER program will be needed to see whether these conjectures are correct. As an intermediate step between practitioners' wisdom and full-out GER, we now consider by what mechanism or mechanisms each of these instructional approaches might plausibly work to improve student learning and see whether it is possible to pose interesting research questions that span the variations within each design pattern.

Data Puzzle

In discussing the value of *Data Puzzles*, Kastens and Turrin (2010) note that the ability to extract insights from observational Earth data is a fundamental aspect of geoscience expertise. *Data Puzzles* offer students the opportunity to hone their abilities to draw connections between Earth processes and data traces that those processes have left on Earth, using geoscientists' methods of spatial–visual reasoning, temporal reasoning, quantitative reasoning, and concept-based reasoning. Like drills in sports, *Data Puzzles* build proficiency by providing clean, clear-cut situations with which to practice before facing the messiness of data that sit at the frontiers of knowledge. *Data Puzzles* provide a controlled dose of the uncertainty and ambiguity that are inherent in authentic data without overwhelming the student.

Kastens and Turrin also advance an affective claim that reaching an aha insight about Earth by wrestling with authentic data provides students with "a rewarding burst ... of illumination ... the true reward of doing science, the intrinsic thrill that keeps scientists going through thick and thin" (2010, p. viii). The curated data snippets and the sequenced guiding questions are intended to position students to experience this thrill of discovery earlier and more often than they would otherwise.

In addition, *Data Puzzles* typically require students to coordinate three types of intellectual resources: (1) information obtainable from the data, (2) knowledge of the Earth system, and (3) representational competence or data interpretation skills (Kastens et al., 2016). Using the terminology of the revised Bloom taxonomy (Anderson et al., 2000; Armstrong, 2016), the first of these is a type of factual knowledge, the second is a type of conceptual knowledge, and the third is a type of procedural knowledge. Pulling together these three types of knowledge to reach a conclusion or form an inference requires an additional cognitive skill known as knowledge integration (Linn, 2006; Kastens and Manduca, 2012). Recent work (Resnick et al., in press) suggests that in the context of a challenging geoscience data interpretation task, it is possible for undergraduates to have in hand knowledge types 1–3 and yet to be unable to pull them together into the scientifically normative interpretation.

Considering various aspects of the mechanisms above, potential research questions related to the *Data Puzzle* design pattern are as follows:

- What pedagogical supports help students progress from the idealized data sketches common in textbooks to the carefully curated high-insight snippets used in *Data Puzzles* to the messiness of large professionally collected data sets?
- Relative to students who were didactically presented with a scientifically accepted concept, model, or conclusion, do students who worked through the process of analyzing the underlying data show better understanding of that concept, model, or conclusion? If so, in what ways do the learning outcomes of the two groups differ?
- Is it true that students, or at least some students, get an affective boost from solving a *Data Puzzle*, from creating a new-to-them data-based insight about how the world works? If so, what are the attributes of *Data Puzzles* that are better and worse at achieving this outcome?

Pooling Data to See the Big Picture

Writing about the closely related jigsaw design pattern, Tewksbury (1995, 2016) outlines several advantages of the approach. Well-structured cooperative learning activities are engaging for students. In addition, the jigsaw technique gives students the opportunity to practice self-teaching, which is important for lifelong learning, and peer teaching, which motivates a deeper level of understanding.

Beyond the benefits associated with cooperative learning in general, three other potential learning processes may be triggered by the *Pooling Data* design pattern. The first is a form of analogical reasoning called extracting the schema, in which humans compare and contrast two or more analogous situations, identify the commonalities among them (Kurtz et al., 2001; Gentner and Colhoun, 2010; Jee et al., 2010), and articulate the commonalities as an abstraction that is independent of the specific instances. Analogical reasoning is most likely to produce new insights if the analogical mapping deals with higher-order relations and processes rather than surficial attributes (Gentner, 1983, 2010) and if the pedagogical scaffolding requires learners to explicitly articulate the correspondences between the analogs (Kurtz et al., 2001). In a problem-solving task, Gick and Holyoak (1983) showed that students who had extracted a relevant schema by comparing two analogs were more likely to recall and tap into that schema than if it had been presented to them in sentence form.

A second possible learning process is that *Pooling Data* may, over time, help to build the geoscientists' habit of mind of looking at the world with the expectation of seeing variations within themes. Whereas every carbon-12 atom exhibits the same structure and behavior, and every lever conforms to the same equation, the same is not generally true of the phenomena that geoscientists categorize. All divergent plate margins share enough essential similarities to justify placing them into a shared category, yet they vary substantially across several dimensions (Fig. 4). The same is true for the variations within other geoscience themes; think of hurricane, earthquake, estuary, and batholith. Each of these terms covers multiple instances of Earth phenomena that are similar yet different, and both the similarities (the themes) and the differences (the variations) are important.

The final learning mechanism is that *Pooling Data* inculcates future geoscientists into collaboration patterns that they will use throughout their lives. Manduca and Kastens (2012) make the case that collaboration is a central feature of geoscience research, driven by the vastness and heterogeneity of the Earth system.

Potential research questions related to the *Pooling Data* design pattern include the following:

- Are learners who have extracted the schema from a cluster of analogous phenomena in geoscience data more skillful at interpreting new instances of the phenomena than are learners have been told the schema didactically? If so, in what ways do learning outcomes differ between the two groups?
- What kinds of prompts, scaffolding (e.g., the compare-and-contrast matrix of Fig. 4), classroom facilitation, etc., are most effective at moving students from an understanding of their detailed case to the big picture view that incorporates data and findings from the other cases?
- When tested with an instrument that measures understanding of the nature of science, do students taught through *Pooling Data* activities show a strong understanding of science as a collaborative process of social construction of knowledge?

Make a Decision or Recommendation

Decision-making under conditions of risk or uncertainty involves a complex suite of cognitive processes that evolved to allow humans' ancestors to function in everchanging natural and social environments and to satisfy a variety of often contradictory goals (Weber, 2014). *Make a Decision or Recommendation* activities allow students to experience some aspects of this complexity as it plays out for decisions related to Earth–human interactions. Psychologists depict risk perception as a feeling–an intuitive assessment of the likelihood and severity of adverse effects (Weber, 2014). Activities that place students in the role of decision-maker can tap into that set of feelings and juxtapose the intuitive decision (e.g., stay safely in port) with the analytical decision (e.g., set sail for Galveston immediately.) Through such activities, students may gain facility at balancing science input with considerations from outside science, such as economics, ethics, or equity. They may internalize the world view that Earth data are a useful tool in solving high-stakes problems for individual humans and human society.

Potential research questions related to the *Make a Decision or Recommendation* design pattern are as follows:

- Do students' decisions and/or their understanding of those decisions vary depending on the role in which they are positioned: as scientists or experts making a recommendation to stakeholders, as the decision-maker, or as stakeholders affected by the decision?
- What lines of evidence, warrants, and reasoning do students put forward to justify their decisions or recommendations? This line of research would parallel the argumentation from evidence research of McNeill and colleagues (McNeill and Krajcik, 2007; Berland and McNeill, 2010), but the end point of the student's line of reasoning would be a recommended or decided-upon human action rather than an explanatory claim.
- What curricular scaffolds encourage students to use evidence-based reasoning?

Predict–Observe–Explain

White and Gunstone (1992) and Haysom and Bowen (2010) discuss the value of *P-O-E*s in terms of students constructing their own understandings of the world and in terms of teachers and researchers gaining access to students' misconceptions. However, the *P-O-E* activities in our corpus, such as the example in Fig. 6, did not center on typical student misconceptions.

Kastens et al. (2015) conjecture that working out predictions attunes students to the relationship between candidate causal processes and observable behaviors of the system under consideration. Then, when students explore the data, they know what they are looking for; they have a specific search pattern in mind and can draw on the mind's strong pattern-recognition ability (Gersmehl and Gersmehl, 2007).

In addition, using a model to make predictions is a central activity of 21st century science and a high-order cognitive skill. Due to the asymmetry of time (Cleland, 2001), humans can think about the past with data alone, but to contend with questions about the future—and modern society is asking geoscientists many such questions–one needs some kind of model (Kastens, 2009). When scientific progress is conceptualized as an iterative, cyclic, or spiraling process (e.g., Windschitl et al., 2008; Kastens, 2015), a pivotal activity is to make predictions about the behavior of the system in not-yet-observed situations and then compare the behavior of the system as captured in data with the behavior of the current model or models.

Potential research questions related to the *P-O-E* design pattern include the following:

- What are effective ways to structure students' comparison of prediction versus data? One challenge is that data have noise and that any specific data snippet chosen as the basis of comparison has idiosyncrasies in it.

- How do students respond if they have made a wrong prediction? In some cases, their reaction may be to tweak or cherry-pick the data to match their prediction. What kinds of curricula and teacher supports can effectively nudge such students to go back and reconsider the reasoning behind their prediction and deepen their understanding of the phenomenon?
- When tested on an instrument that probes understanding of the nature of science, do student taught through *P-O-E* activities show a strong understanding that scientific models improve through cycles of prediction, testing, and revision?
- Many activities have students make a prediction as part of a discussion or written assignment but without then testing the prediction. What is the added value (both affective and cognitive) of having students test their prediction with additional data?

Nested Data Sets

The *Nested Data Sets* approach seems to be grounded in the premise that situated, embodied cognition—thinking that responds to real-world situations that are being directly perceived in real time by the human senses—differs importantly from cognition that is mediated through symbolic abstractions and representations (Wilson, 2002; Mogk and Goodwin, 2012). The concept of embodiment would imply that by moving through, living within, or collecting data from an environment, a person constructs a richly textured, nuanced knowledge of that environment, which is absorbed through the senses and marinated in strongly felt experiences. (“Environment” in this context can be natural, human built, or a combination of both.) This deep, rich knowledge of the local setting can then support students in interpreting local data (Mitchell, 1934; Ault, 2008; Semken and Freeman, 2008). They can draw on local knowledge to form hypotheses about causal processes or influences and to anticipate potential problems with the local data.

For *Nested Data Sets* to be effective, we must then conjecture that some of the skills and insights built from consideration of local phenomena can be transferred, with appropriate pedagogical scaffolding, to scales that can be experienced only indirectly through representations. Part of this transfer has to do with building representational competence: Hutchins and Renner hypothesize that “practitioners can reason more deeply about the meanings of inscriptions if they have previously produced and interpreted similar inscriptions through transformations of their own perceptual–motor–cognitive experiences in the real world” (2012, p. 182). Part of this transfer would seem to be reasoning by analogy, in which a person projects understanding from a well-understood source domain onto a less-well-understood target domain by analogical mapping between the two domains.

Our research questions related to the *Nested Data Sets* design pattern center on the assertion that students will have a deeper understanding of large-scale professionally collected data sets as a result of having worked with data from a locality (physical or biological data) or group (survey data) with which they have personal experience. Potential research questions follow:

- Relative to students who went directly to the larger-scale professionally collected data, is it true that students who first worked with local data have deeper insights about the regional- or global-scale data? If so, what is the nature of their deeper understanding? (Are they more attuned to error sources and natural variability? Are they better able to make causal inferences? Are they better able to anticipate implications of the data?)
- How do learning outcomes differ between students who collected their own local data and students who worked with data from their locality but collected by others?
- Do students tend to overgeneralize when using analogical reasoning to transfer locally constructed insights to the regional, national, or global scale? If so, what pedagogical scaffolding best supports students in walking the tightrope between leveraging local insights and overgeneralizing?

Deriving a New Data Type

Working step by step through the process of constructing a derived data type is expensive in instructional time and student patience. What additional learning could justify this investment, especially given that these modules are intended for introductory students rather than majors? In the instances analyzed, students did not have to figure out how to do the derivation, as might be expected in a math class; instead, the steps were spelled out, and students walked a well-marked path. One potential form of added value is that students will gain a deeper understanding of the derived data type and will, therefore, make more insightful inferences. They might better understand the limitations of the derived data type and avoid using it inappropriately, or they might be more inclined to believe the derived data type and trust it in making consequential decisions about Earth–human interactions.

Our research questions for this design pattern center on comparing students who have worked through the process of constructing a derived data type with students who have merely been provided with a final data visualization and definition. Potential research questions follow:

- Do students who worked through the process of creating the derived data type interpret visualizations of derived data more accurately or more insightfully?
- Do they demonstrate more willingness to use the derived data for making decisions that have consequences for humans and human society?
- Do they demonstrate more understanding of the limitations of the derived data type?

THE PATH FORWARD: ANTICIPATING STEPS 4 AND 5

This thought experiment has shown that it is possible to formulate research-worthy questions that span an entire design pattern, despite the considerable range of variation in content and in details of sequencing and framing. In this section, we reflect on how the GER community could advance a research program built around design patterns.

Most of these research questions would be well served by classroom-based research in the tradition of design research or design-based research (Design-Based Research Collaborative, 2003; Wang and Hannafin, 2005; Kelly et al., 2008; Anderson and Shattuck, 2012). In such research, data are collected in authentic instructional settings, the instructors are coresearchers, and the research has the dual goals of improving the instructional materials and producing generalizable knowledge about how learning occurs via the type of educational approach under examination. This research agenda is well suited for collaborative action research, in which multiple instructors across differing institutions with varied instructional contexts contribute. In selecting specific instructional materials to include in a research program into a given design pattern, it would be best to choose clear-cut instantiations with a strong culminating move and avoid activities that intertwine multiple design patterns.

An important early step would be to articulate clearly the learning goals for each design pattern that transcend the specific content of the individual lessons. This might be done enjoyably and productively through discourse among developers and users of multiple lessons that have the same design pattern. All of these design patterns are expensive in instructional time, and to justify their use, they need to be fostering higher-order thinking and important learning goals.

Having agreed on learning goals, the next step would be to agree on or develop ways to assess the desired learning. In some cases, this might be done by means of a common instrument. For example, if an agreed-on learning goal of *Pooling Data* is "students will understand that geoscience advances by combining evidence from different field areas and kinds of measurements to make inferences about Earth processes," a shared instrument probing understanding of the nature of science might be appropriate. In other cases, a shared research protocol rather than a shared instrument might be needed. For example, an agreed-on learning goal of *Nested Data Sets* might be "students will recognize potential sources of error in data and take them into account in their data interpretation." In such a case, context-specific assessments would be needed for each data type, but the common element across the design pattern could be that students who collected and interpreted local data would be contrasted with students who only worked with regional, national, or global data.

Our hypothesized mechanisms suggest that these design patterns tap deeply into powerful human cognitive, affective, and social processes: analogical reasoning (*Pooling Data*), ability to create and run mental models of future developments (*P-O-E*), quantitative reasoning (*Deriving New Data Types*), embodied cognition (*Nested Data*), decision-making under conditions of risk and uncertainty (*Making a Decision or Recommendation*), and problem solving (*Data Puzzles*). This suggests that geoscience education researchers would be well advised to seek collaborations with cognitive scientists who have specialized expertise in these ways of knowing in order to maximize the chances that the research will yield generalizable knowledge rather than merely measures of efficacy. Such collaborations will be valuable both in shaping the research plan and in interpreting the findings so as to upgrade the best supported of the hypothesized mechanisms into evidence-based theories of action.

In parallel with pursuing research into design patterns for teaching with data, the GER and geoscience education communities could explore whether other aspects of geoscience teaching and learning would benefit from the design pattern approach. Design pattern practitioners use the term "pattern language" for a related set of patterns within a field of expertise (Alexander et al., 1977). We could imagine pattern languages related to supporting diverse learners (Kastens and Orr, 2017), teaching in physical laboratories, teaching in the field, involving citizens in scientific research, or fostering temporal, spatial or systems thinking.

The ultimate research goal for pattern-based research should not be to find out "Does the intervention work?" or even "How well does it work?" but rather to dig into the mechanism of learning to find out "How does it work?" Developers and instructors intuit that these approaches add educational value that more than repays the invested time and effort. As geoscience education researchers, our challenge is to find out exactly what that added value is and how it gets added, drawing on the full toolkit of educational research methodologies and our deepest insights about geoscientific ways of knowing.

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REFERENCES

Adams, L.G., and Matsumoto, G.I. 2011. The benefits and challenges of using real-time data in the classroom: Perspectives from students, educators, and researchers. *Marine Technology Society Journal,* 45:55–58.

Alexander, C., Ishikawa, S., and Silverstein, M. 1977. A pattern language: Towns, buildings, construction. New York: Oxford University Press.

Anderson, L.W., Krathwohl, D.R., Airasian, P.W., Cruikshank, K.A., Mayer, R.E., Pintrich, P.R., Raths, J., and Wittrock, M.C. 2000. A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives. London, UK: Pearson.

Anderson, T., and Shattuck, J. 2012. Design-based research: A decade of progress in education research. *Education Researcher,* 41:16–25.

Armstrong, P. 2016. Bloom's taxonomy, CFT teaching guides. Vanderbilt University Center for Teaching. Available at https://cft.vanderbilt.edu/guides-sub-pages/blooms-taxonomy/ (accessed 17 August 2016).

Aronson, E., Stephan, C., Sikes, J., Blaney, N., and Snapp, M. 1978. The jigsaw classroom. Beverly Hills, CA: Sage Publications.

Ault, C.R., Jr. 2008. Achieving Querencia: Integrating a sense of place with disciplined thinking. *Curriculum Inquiry,* 38:605–637.

Bauer, R., and Baumgartner, P. 2011. Showcase of learning: Towards a pattern language for working with electronic portfolios in higher education. *In* Proceedings of the 16th

European Conference on Pattern Languages of Programs. Irsee, Germany: Association for Computing Machinery.

Berland, L.K., and McNeill, K. 2010. A learning progression for scientific argumentation: Understanding student work and designing supportive instructional contexts. *Science Education,* 94:765–793.

Bhattacharyya, P., Branlund, J., and Joseph, L. 2015. Human's dependence on mineral resources. InTeGrate. Available at http://serc.carleton.edu/integrate/teaching_materials/mineral_resources/index.html (accessed 15 August 2016).

Bybee, R.W., Taylor, J.A., Gardner, A., Van Scotter, P., Carlson Powell, J., Westbrook, A., and Landes, N. 2006. The BSCS 5e instructional model: Origins and effectiveness. Available at https://bscs.org/sites/default/files/_media/about/downloads/BSCS_5E_Full_Report.pdf (accessed 6 July 2017).

Cleland, C. 2001. Historical science, experimental science, and the scientific method. *Geology,* 29:987–990.

Climate Literacy and Energy Awareness Network. 2016. Collection of climate and energy educational resources. Available at http://cleanet.org/index.html (accessed 31 August 2016).

Design-Based Research Collaborative. 2003. Design-based research: An emerging paradigm for educational inquiry. *Educational Researcher,* 32:5–8.

Fortner, S., Murphy, M., and Scherer, H. 2015. A growing concern: Sustaining soil resources through local decision making. InTeGrate. Available at http://serc.carleton.edu/integrate/teaching_materials/sustain_agriculture/index.html (accessed 15 August 2016).

Friedman, E., McGrath, B., and Baron, J. 1997. Web adventures in K–12 science. *Technos,* 6:21–24.

Gentner, D. 1983. Structure-mapping: A theoretical framework for analogy. *Cognitive Science,* 7:155–170.

Gentner, D. 2010. Bootstrapping the mind: Analogical processes and symbol systems. *Cognitive Science,* 34:752–775.

Gentner, D., and Colhoun, J. 2010. Analogical processes in human thinking and learning. *In* Glatzeder, B., Goel, V., and Muller, A.V., eds., On thinking, vol. 2. Towards a theory of thinking. Berlin, Germany: Springer-Verlag, p. 35–48.

Gersmehl, P.J., and Gersmehl, C.A. 2007. Spatial thinking by young children: Neurologic evidence for early development and "educability." *Journal of Geography,* 106:181–191.

Gick, M.L., and Holyoak, K.J. 1983. Schema induction and analogical transfer. *Cognitive Psychology,* 15:1–38.

Gilbert, L., Galster, J., and Ramage, J. 2015. Natural hazards and risks: Hurricanes. InTeGrate. Available at http://serc.carleton.edu/integrate/teaching_materials/hazards/index.html (accessed 30 August 2016).

Goodell, L., Selkin, P., and Teasdale, R. 2015. Living on the edge: Building resilient societies on active plate margins. InTeGrate. Available at http://serc.carleton.edu/integrate/teaching_materials/living_edge/index.html (accessed 31 August 2016).

Gould, P., Sunbury, S., and Krumhansl, R. 2012. Using online telescopes to explore exoplanets from the physics classroom. *American Journal of Physics,* 80:445–451.

Haysom, J., and Bowen, M. 2010. Predict, observe, explain: Activities enhancing scientific understanding. Arlington, VA: NSTA Press.

Hutchins, E., and Renner, N.O. 2012. Situated and embodied learning in the field. *In* Kastens, K.A., and Manduca, C.A., eds., Earth and mind II: A synthesis of research on thinking and learning in the geosciences. Geological Society of America Special Paper 486. Boulder, CO: Geological Society of America, p. 181–182.

Institute for Water Research. 2002. RUSLE: Online soil erosion assessment tool. Available at http://www.iwr.msu.edu/rusle/about.htm (accessed 31 August 2016).

InTeGrate. 2015a. Geoscience habits of mind. Available at http://serc.carleton.edu/integrate/teaching_materials/habits.html (accessed 31 August 2016).

InTeGrate. 2015b. Working with the InTeGrate materials development and refinement rubric. Available at http://serc.carleton.edu/integrate/info_team_members/currdev/rubric.html (accessed 31 August 2016).

InTeGrate. 2017. About the InTeGrate Project. Available at https://serc.carleton.edu/integrate/about/index.html (accessed 7 July 2017).

Jee, B.D., Uttal, D.H., Gentner, D., Manduca, C., Shipley, T.F., Tikoff, B., Ormand, C.J., and Sageman, B. 2010. Commentary: Analogical thinking in geoscience education. *Journal of Geoscience Education,* 58:2–13.

Kastens, K.A. 2009. Extrapolating beyond the last data point. Earth and mind: The blog. Available at http://serc.carleton.edu/earthandmind/posts/extrapolating_b.html (accessed 17 August 2016).

Kastens, K.A. 2015. Philosophy of Earth Science. *In* Gunstone, R., ed., Encyclopedia of science education. Dordrecht, Netherlands: Springer, p. 354–357.

Kastens, K.A., and Mandua, C.A. 2012. Fostering knowledge integration in geoscience education. *In* Kastens, K.A., and Manduca, C., eds., Earth and mind II: Synthesis of research on thinking and learning in the geosciences. Geological Society of America Special Publication 486. Boulder, CO: Geological Society of America, p. 183–206.

Kastens, K.A., and Orr, C.H. 2017. Using design patterns as a strategy for capturing generalizable knowledge from educational interventions. Available at https://serc.carleton.edu/earth_rendezvous/2017/program/posters/friday/179945.html (accessed 29 June 2017).

Kastens, K.A., and Turrin, M. 2010. Earth Science puzzles: Making meaning from data. Arlington, VA: National Science Teachers Association Press.

Kastens, K.A., Krumhansl, R., and Baker, I. 2015. Thinking big: Transitioning your students from working with small student-collected data sets towards "big data." *Science Teacher,* 82:25–31.

Kastens, K.A., Shipley, T.F., Boone, A., and Straccia, F. 2016. What geoscience experts and novices look at, and what they see, when viewing data visualizations. *Journal of Astronomy and Earth Science Education,* 3:27–58.

Kearney, M., Treagust, D.F., Yeo, S., and Zadnik, M.G. 2001. Student and teacher perceptions of the use of multimedia supported predict–observe–explain tasks to probe understanding. *Research in Science Education,* 31:589–615.

Kelly, A., Baek, J.Y., Lesh, R.A., and Bannan-Ritland, B. 2008. Enabling innovations in education and systematizing their impact. *In* Kelly, A., and Lesh, R., eds., Handbook of design research methods in education. New York: Routledge, p. 3–18.

Kurtz, K.J., Miao, C.-H., and Gentner, D. 2001. Learning by analogical bootstrapping. *Journal of the Learning Sciences,* 10:417–446.

Leitner, H. 2015. Patterns of commoning. Working with patterns: An introduction. Amherst, MA: Commons Strategy Group, in cooperation with Off the Common Books. Available at http://patternsofcommoning.org/working-with-patterns-an-introduction/ (accessed 4 July 2017).

Linn, M. 2006. The knowledge integration perspective on learning and instruction. *In* Sawyer, R.K., ed., Cambridge handbook of the learning sciences. Cambridge, UK: Cambridge University Press, p. 243–264.

Linn, M.C., and Eylon, B.-S. 2006. Science education: Integrating views of learning and instruction. *In* Alexander, P.A., and Winne, P.H., eds., Handbook of educational psychology, 2nd ed. Mahwah, NJ: Lawrence Erlbaum Associates, p. 511–544.

Manduca, C.A., and Kastens, K.A. 2012. Geoscience and geoscientists: Uniquely equipped to study the Earth. *In* Kastens, K.A., and Manduca, C.A., eds., Earth and mind II: Synthesis of research on thinking and learning in the geosciences. Geological Society of America Special Publication 486. Boulder, CO: Geological Society of America, p. 1–12.

Manduca, C.A., and Mogk, D.W. 2002. Using data in undergraduate science classrooms: Final report on an interdisciplinary workshop at Carleton College April 2002. Available at http://d32ogoqmya1dw8.cloudfront.net/files/usingdata/UsingData.pdf (accessed 4 July 2017).

Manduca, C.A., Mogk, D.W., Tewksbury, B., Macdonald, R.H., Fox, S.P., Iverson, E.R., Kirk, K., McDaris, J., Ormand, C., and Bruckner, M. 2010. On the Cutting Edge: Teaching help for geoscience faculty. *Science,* 327:1095–1096.

Mayer, R.E., Mautone, P., and Prothero, W. 2002. Pictorial aids for learning by doing in a multimedia geology simulation game. *Journal of Educational Psychology,* 94:171–185.

McNeill, K., and Krajcik, J. 2007. Middle school students' use of appropriate and inappropriate evidence in writing scientific explanations. *In* Lovett, M., and Shah, P., eds., Thinking with data: Proceedings of the 33rd Carnegie Symposium on Cognition. Mahwah, NJ: Lawrence Erlbaum Associates.

Mitchell, L.S. 1934. Young geographers: How they explore the world and how they map the world. New York: Bank Street College of Education.

Mogk, D., and Goodwin, C. 2012. Learning in the field: Synthesis of research on thinking and learning in the geosciences. *In* Kastens, K.A., and Manduca, C.A., eds., Earth and mind II: A synthesis of research on thinking and learning in the geosciences. Geological Society of America Special Publication 486. Boulder, CO: Geological Society of America, p. 131–163.

Mosher, S., Bralower, T., Huntoon, J.E., Lea, P., McConnell, D., Miller, K., Ryan, J., Summa, L., Villalobos, J., and White, L. 2014. Future of undergraduate geoscience education. Available at http://www.jsg.utexas.edu/events/files/Future_Undergrad_Geoscience_summit_report.pdf (accessed 31 August 2016).

National Research Council (NRC). 2012. A framework for K–12 science education: Practices, crosscutting concepts, and core ideas. Washington, DC: National Academies Press.

Perez, A., Schneiderman, J.S., Stewart, M., and Villabos, J. 2017. Environmental justice and freshwater resources. InTeGrate. Available at https://serc.carleton.edu/integrate/teaching_materials/freshwater/index.html (accessed 10 July 2017).

Piburn, M., van der Hoeven Kraft, K., and Pacheco, H. 2011. A new century for geoscience education research. Commissioned paper prepared for the National Research Council Board on Science Education, Committee on the Status, Contributions and Future Directions of Discipline Based Education Research. Available at http://sites.nationalacademies.org/cs/groups/dbassesite/documents/webpage/dbasse_072590.pdf (accessed 31 August 2016).

Resnick, I., Kastens, K., and Shipley, T.F. in press. How students reason about visualizations from large professionally collected data sets: A study of students approaching the threshold of data proficiency. *Journal of Geoscience Education*.

Roser-Renouf, C., Stenhouse, N., Rolfe-Redding, J., Maibach, E., and Leiserowitz, A. 2015. Engaging diverse audiences with climate change: Message strategies for global warming's six Americas. *In* Hanson, A., and Cox, R., eds., Routledge handbook of environment and communication. London, UK: Routledge, p. 368–386.

Savina, M., Steer, D., Iverson, E., Manduca, C., and O'Connell, K. 2015. A curricular audit process for faculty developers of student-centered curricula that meld geoscience and societal issues. Available at https://serc.carleton.edu/earth_rendezvous/2015/program_table/abstracts/100936.html (accessed 22 August 2017).

Semken, S., and Freeman, C.B. 2008. Sense of place in the practice and assessment of place-based science teaching. *Science Education,* 92:1042–1057.

Shellito, C., Walker, B., and Fadem, C. 2015. Climate of change: Interactions and feedbacks between water, air and ice. InTeGrate. Available at http://serc.carleton.edu/integrate/teaching_materials/climate_change/index.html (accessed 31 August 2016).

Singer, S.A., Nielsen, N.R., and Schweingruber, H.A. 2012. Discipline-based education research. Washington, DC: National Academies Press.

Slater, S.J., Slater, T.F., and Lyons, D.J. 2010. Engaging in astronomical inquiry. New York: W.H. Freeman and Company.

Slater, T.F. 2013. Educational underpinnings of backward faded scaffolding and engaging in astronomical inquiry. Available at http://astronomyfacultylounge.wordpress.com/2013/03/01/educational-underpinnings-of-backwards-faded-scaffolding-and-engaging-in-astronomical-inquiry/ (accessed 29 June 2017).

Starting Point. 2015. Think–pair–share. Available at http://serc.carleton.edu/introgeo/interactive/tpshare.html (accessed 31 August 2016).

Tewksbury, B. 1995. Specific strategies for using the "jigsaw" technique for working in groups in non-lecture-based courses. *Journal of Geoscience Education,* 43:322–326.

Tewksbury, B. 2016. Jigsaws. Available at http://serc.carleton.edu/sp/library/jigsaws/index.html (accessed 17 August 2016).

University of California–Davis. 2016. SoilWeb. Available at http://casoilresource.lawr.ucdavis.edu/gmap/ (accessed 31 August 2016).

Wang, F., and Hannafin, M.J. 2005. Design-based research and technology enhanced learning environments. *Educational Technology Research and Development,* 53:5–23.

Weber, E.U. 2014. Understanding public risk perception and responses to changes in perceived risk. *In* Bennear, L., Balleisen, E., Krawlec, K., and Wiener, J., eds., Recalibrating risk: How regulatory institutions respond to shifts in public risk perceptions. Available at http://kenan.ethics.duke.edu/wp-content/blogs.dir/2/files/2013/10/weber_final_1_22.pdf (accessed 30 August 2016).

White, R.T., and Gunstone, R.F. 1992. Probing understanding. London, UK: Falmer Press.

Wilson, M. 2002. Six views of embodied cognition. *Psychonomic Bulletin and Review,* 9:625–636.

Windschitl, M., Thomson, J., and Braaten, M. 2008. Beyond the scientific method: Model-based inquiry as a new paradigm of preference for school science investigations. *Science Education,* 92:941–967.