Moving from Exploring Patterns to Causal Explanations in Ecosystems Science Reasoning

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Problem/Background

Understanding the difference between correlation and causation is a critical concept in scientific explanation. The distinction is instantiated in the Next Generation Science Standards (NGSS) in the Cross-Cutting Concepts of "Patterns" and "Cause and Effect" (Achieve, 2013). While the standards suggest that "patterns can be used to identify cause and effect relationships" (PAT-M3) and that "patterns of change can be used to make predictions" (PAT-E2), the standards also recognize that "empirical evidence is required to differentiate between cause and correlation and make claims about specific causes and effects" (CE-H1). Helping students to realize that patterns can be used to identify *possible* cause and effect relationships and that scientist have means to intervene on patterns to discern causation—thus differentiating co-variation and causation—are important goals for science education. As science educators, it would help us to more deeply understand these distinctions and how students come to understand them.

Noticing patterns, both in what one observes and in the outcomes from empirical data can spur further observation, investigation and, in some cases, experimentation. Those who study the nature of science and causal inference have argued that intervention is critical to drawing causal conclusions (e.g. Gopnik et al., 2004; Pearl, 2000). A prevailing model of how humans engage in causal reasoning is a Causal Bayes Net (CBN) Model (e.g. Glymour, 2001; Gopnik & Schulz, 2007), which involves summing across multiple causal instances to infer causality despite probabilistic inputs. But simple induction is not enough and can easily lead to confusing correlation with causation, particularly in cases when a plausible (though not necessarily accurate) causal mechanism can be discerned. Therefore, a critical component in CBN models is the ability to intervene and to act empirically on variables to be able to assess their causal potency (Gopnik & Schultz, 2004; Gopnik et al., 2004; Lagnado & Sloman, 2003; Steyvers, Tenebaum, Wagenmakers, & Blum, 2003). CBN models argue that, while one can glean information about potential causal strength from co-variation, it is the ability to screen off variables and assess the outcomes that allows developing an understanding of causal structure to realize a fully causal account. Screening off enables one to investigate plausible causal mechanisms that account for the patterns. As aligned with the NGSS standards, fully causal accounts articulate both *covariation pattern* and *causal mechanisms*.

In order to elucidate causal relationships in the sciences, scientists design experiments that are randomized, replicated, controlled, and conducted at an appropriate temporal and spatial scale for the hypothesis being tested (Tilman, 1989; Carpenter, 1996; Knapp et al., 2012). Ecosystems scientists are no exception, despite the complex environments in which they work. They have developed ways to intervene on relationships to help them to discern causality (Weathers et al, 2007).

However, a long history of research in science education shows an over-reliance on co-variation to suggest a causal relationship and a tendency to view any covariate as causal even in cases where it was merely correlational (Kuhn et al, 1988). Given the opportunity to set up experiments, students in elementary and middle school often generate uninformative experiments and make judgments that were based on inconclusive or insufficient data while ignoring inconsistent data and disregarding surprising results. (See Zimmerman, 2000 for a review.) The tendency to over-rely on co-variation is particularly problematic when reasoning about large complex systems such as ecosystems where covariation in terms of temporal and spatial contiguity can be an important cue to the possibility of a causal relationship. However, as the covariates become increasingly distant or delayed, they tend to be missed—resulting in shortsightedness and a focus on local, immediate factors over temporally and spatially remote ones (Grotzer & Tutwiler, 2014).

Despite these difficulties, research suggests some possible paths forward. Schauble and colleagues (Schauble, Glaser, Raghavan, & Reiner, 1992) found that some learners generate more alternative hypotheses, conduct controlled experiments and more extensively search problem spaces. Studying what these learners do may help educators develop supports for all leaners. Sandoval and Reiser (2005) have argued that students need to understand the epistemological commitments that scientists make—the processes they value for generating and validating knowledge. They call for an understanding of the ways of knowing and finding out in the discipline, for instance, "Good explanations are based on evidence from investigations." And "scientific explanations emphasize evidence, have logically consistent arguments, and use scientific principles, models, and theories. The scientific community accepts and uses such explanations until displaced by better scientific ones. When such displacement occurs, science advances" (NRC, 1995). They call for foregrounding these commitments in the context of inquiry-based approaches. Recent research also reveals that students faced with contextualized problems employ a variety of strategies for experimentation (McElhaney & Linn, 2011). Specifically in the context of developing causal explanations in complex problem spaces, research shows that when students have information about causal mechanisms, they often can override spatial and temporal gaps that separate co-variates (Grotzer & Solis, 2015).

Immersive simulated virtual environments provide an opportunity for students to interact with ecosystem components in an experimental manner and to conduct authentic scientific experimentation in a realistic, contextualized, but virtual setting. Offering students opportunities to investigate rich contexts enables them to discover the nuances and complexity within that domain as well as patterns that generalize beyond that domain (Berland & Reiser, 2010). Context rich problems are important in helping students to develop approaches to inquiry that map closely to what scientists actually do, the theory rich contexts that they focus on (Koslowski, 1996), and how an investigation develops and changes over time (Sandoval & Reiser, 2004; Berland & Reiser, 2010). Scientist characters in the immersive world can offer students information about the epistemological commitments that they make as they transition from finding co-variation patterns to intervening upon those patterns and analyzing causality.

This paper reports on the analysis of data collected in May to June of 2017 (as part of a broader study) in which we analyzed the level of students explanations for what was happening in a complex eutrophication scenario in an ecosystem. Specifically, we were interested in the following questions:

1. If given the opportunity, in a virtual world, to gather evidence of correlational patterns, information about mechanisms, and intervene through experimentation to account for the mechanisms in play in a given instance, what would students' resulting explanations look like?
2. How did students' explanations accommodate both covariation patterns and mechanistic accounts of the ecosystems dynamics? Did students typically include one or both in their explanation?
3. What characterized the ways that students spoke about covariation patterns?
4. What characterized the ways that students spoke about causal mechanisms?

Design

A study was conducted with seventh grade students (n = 118) (as part of a larger investigation) in 5 classrooms of 4 teachers with a ten-day, technology-based, inquiry-oriented ecosystems science curriculum that they were using (described below). On the ninth day, students were asked to write their explanation for what had caused the environmental problem in the curriculum. (What causes all of the larger fish in a pond to die overnight?)

Curriculum

Students participated in a problem-based curriculum within a Multi-User Virtual Environment (MUVE). It is based on a virtual world called EcoXPT. (See Figure 1.) Students can make various measurements while in the world using a set of measurement tools. (See Figure 2.) During the first three days, students explored the world and were instructed to “get to know it.” On about the third day, students discovered that a fish die off had occurred on a certain day within the world. They began to investigate possible causes for the fish die off by traveling back and forth in time before and after the event, and collecting data on population levels and water quality measurements. They used data tools in the world to view and graph this data which allowed them to see patterns between the different types of data. (See Figs. 3 and 4.)

Fig. 1 EcoXPT Virtual World

Fig. 2. Measurement Tools

Measurement	June 30	July 6	July 10	July 16	July 22	July 25	July 28	Aug 15
Water temperature (ºC)	22	19	21.5	24.5	26.5		25.5	25
Dissolved oxygen (mg/L)	8.4	9.5	9.4	10.2	5.4	4.1		
Phosphates (mg/L)	0.01	0.1	0.03	0	0.015			0.025
Nitrates (mg/L)	0.15	0.56	0.33	0.2	0.11	0.2	0.3	
Turbidity (NTU)	5	25	35	65				
pH		6.7	8	8.4				
Chlorophyll A (ug/L)		10	50	100				
Air temperature (ºC)	25.5	20	24.5	27.8	31.1			
Wind speed (m/s)	1.5	4.6	3	2.1	1.5			
Cloud cover (%)	20	100	0	20	100			
Bacteria population (cells/ml)	5000			7000			33000	
Bluegill population	189	163	152	123	114		0	
Bluegreen algae population (cells/ml	800		1300	1600	1000			
Green algae population (cells/ml)	1000				4000			
Heron population	2				2			7
Largemouth bass population	38				40		0	
Minnow population	356				250		233	446

Fig. 3. Data Table

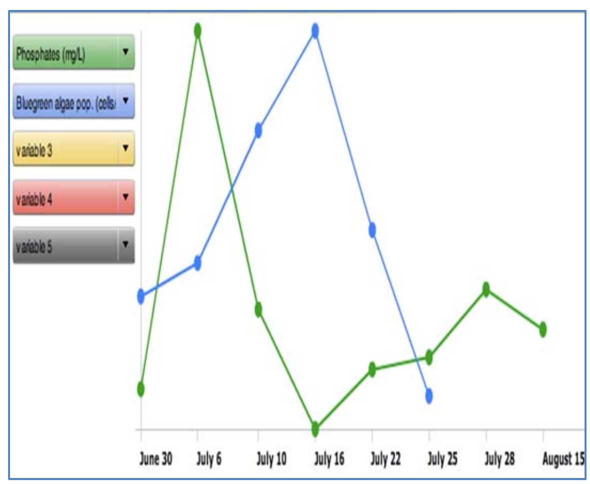

Fig. 4. Graphs of Co-variation Relationships

The problem scenario was complex and involved an eutrophication scenario (that resulted in a fish die off) with interacting, dynamic causes. See Figure 5.

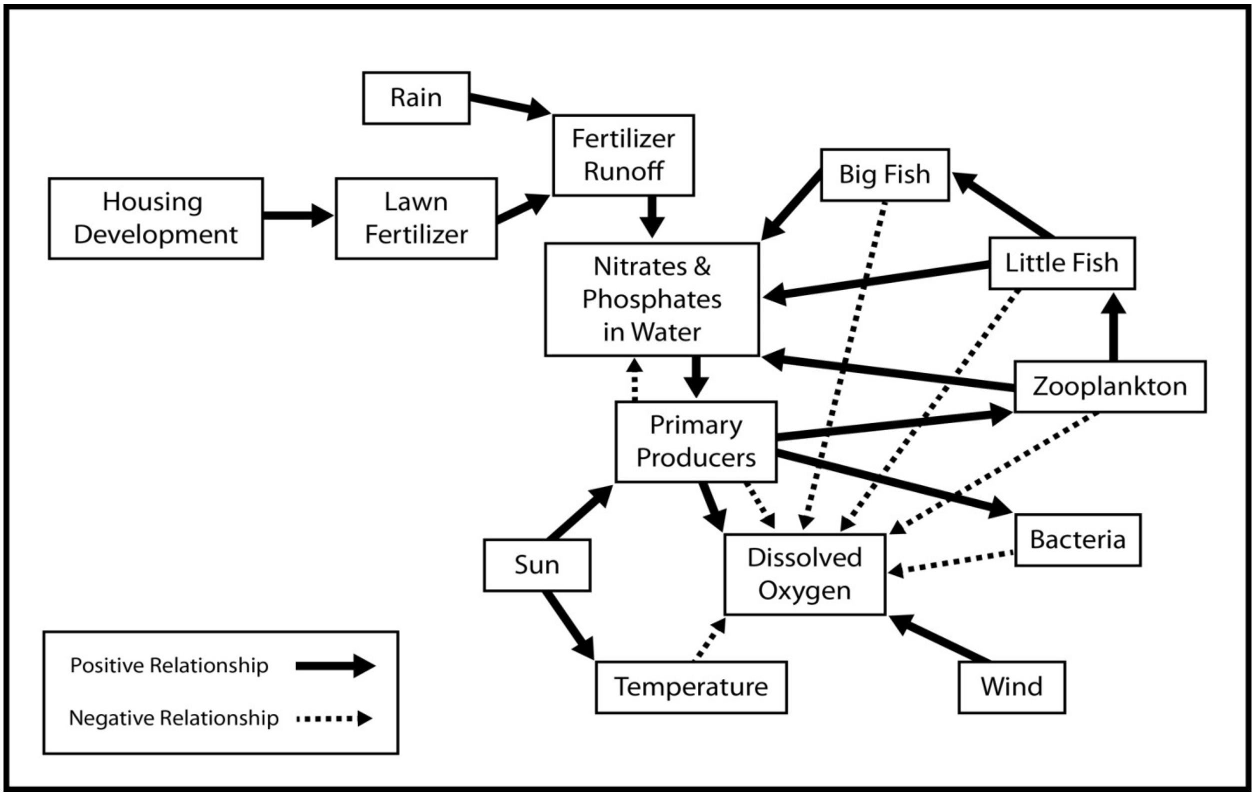

Fig. 5. A Complex Underlying Eutrophication Scenario

Students also had access to experimental tools and to scientists in the world who shared the rationale for certain approaches and their epistemological assumptions. (See Figs. 6 and 7). This included tools that were available in a lab building such as tolerance tanks (See Figs. 8 and 9) and comparison tanks (See Figs 10 and 11) as well as experimental tools that were used out in the virtual world such as the mesocosms (see Fig. 6) and tracer tools (See Figs. 12 and 13).

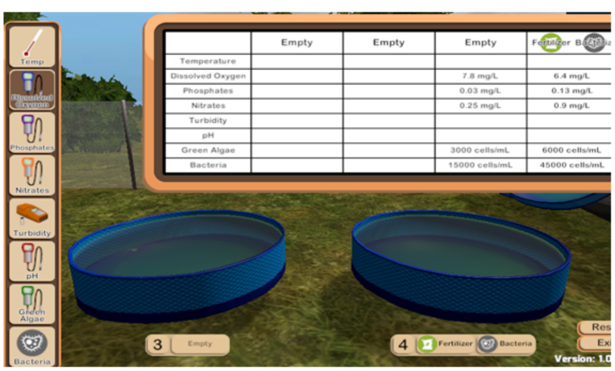

Fig. 6. Mesocosm Experimental Tool

Fig. 7. Scientist Character in the World

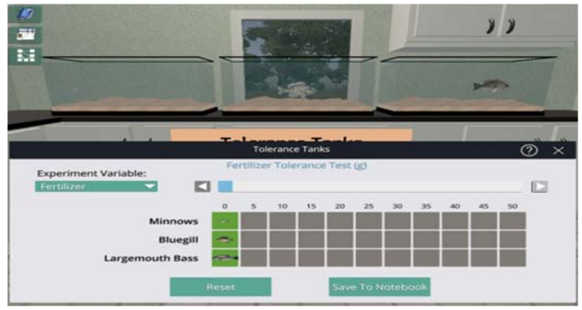

Fig. 8 Tolerance Tanks

Fig. 9. Tolerance Tanks Results

Fig. 10. Comparison Tanks

Fig. 11. Comparison Tanks Results

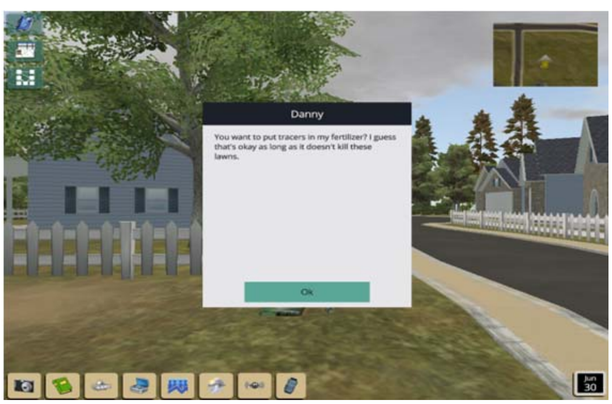

Fig. 12 Tracer Tools

Fig. 13 Tracer Tools Results

Additional supporting structure in the form of Thinking Moves posters and videos were shared with the students. (See Appendix A.)

Coding and Analysis

Emic coding was conducted to assess how students talked about covariation patterns and mechanisms in their explanations. A grounded-theory approach (Glaser & Strauss, 1967; Charmaz, 2006) was used to generate categories from the data. Findings from the extant literature offered insights and focus, however, the intent was not to confirm a theory-driven, etic framework but rather to allow new insights from the data that also were informed by existing research (Strauss & Corbin, 1994).

Findings

As might be predicted from the extant literature, students used the resources available to them in their causal reasoning. Across the data sample, students used information about covariation patterns, mechanisms, and also depended upon testimony from non-player characters in the world including that of scientists. Some students relied upon multiple sources of information, yet students also revealed distinct tendencies in how they relied upon each type of information. Further there were differing levels of sophistication within each framing tendency. Each framing tendency is described below with samples from student protocols:

1. A tendency to rely upon the use of covariation patterns to make a connection.

Covariation patterns can be an important indicator that two variables are linked. The NGSS call for a focus on patterns as a means of identifying causal relationships (PAT-M3). While the NGSS do not frame the Performance Expectation in terms of identifying “possible causal relationships,” science generally recognizes that co-variation is not the same as causation and that it is possible to have 1) spurious correlation; 2) correlation that is indirectly caused by a third variable; and 3) correlation that suggests a necessary but not sufficient condition for causation (where another variable is needed as a co-actor with the first in order to cause the outcome). Some of the students reasoned about patterns in ways that avoided confusing correlation with causality while others did not.

Patterns as Causation. One tendency that students revealed was to frame their explanations in terms of variables changed in relation to each other (co-variation patterns) and to offer this as their causal explanation. They conflated pattern change with causal change. In this framing, students referred to a pattern or correlation in the data. They did not point to a causal mechanism, but substituted correlated patterns of change for causation. For instance, “When the phosphate levels go up, the algae goes up. Then the phosphate levels go down and the algae go down causing bacteria to go up.” (See Appendix B for an example.)

Patterns as Outcomes from Dynamic Balance/Variable Levels as Mechanism. A more conservative response that is potentially also more sophisticated is to focus on the patterns in terms of dynamic balance and levels and to point to levels as the mechanism for the outcome. Taken alone, this pattern does not offer information for what is behind the change in level (though covariation patterns that discuss levels can be combined with mechanism information as discussed below). This framing recognizes that levels of balance are important to the causal dynamics of ecosystems. These students talked about levels going up and down. For instance, “The fertilizer increased the amount of algae as shown when we conducted an experiment. The water temperature (when it is hot) also affected the bacteria increasing it up to 3,000. The bacteria affect the amount of dissolved oxygen by decreasing it… …If the amount of dissolved oxygen reached 3, then both the Bluegill and Large Mouth Bass would die.” This reasoning pattern seems like an important step in developing hypotheses. It does not over-reach beyond the data given.

2. A tendency to use mechanism to make a connection

Some students focused on how the factors that could act as possible mechanisms to result in an outcome.

Token explanation In this framing, students inserted the name of a variable in place of a mechanism. This particular pattern yielded low level explanations that did not attend to non-obvious causes and did not contain substance as to how the mechanism worked. A common pattern is to state a mechanism as a token explanation and then to give a correlation pattern to explain it. "I think that the fertilizer caused the fish to die. The reason is because when the fertilizer was first put in, the water started to look dirtier, then we saw that the population of bluegills and largemouth bass was going down." See Appendix B for examples.

Behavior of a Mechanism. In this framing, students gave an explanation of what the mechanism does in terms of its behavior in order to cause an outcome. "Phosphates and nitrates caused the amount of algae to grow because the algae use the nutrients in it to live." "When algae died, it caused increased in bacteria because they could feed on the dead algae." (See Appendix B.)

In complex scenarios in which one cannot perceive both sides of the covariation relationship, mechanism can be especially powerful in helping students to discern that a causal relationship exists (Grotzer & Tutwiler, 2014; Grotzer & Solis, 2015). Mechanism knowledge therefore can be a powerful means of getting to know the causal dynamics of a system in which all of the relationships are not salient.

Mechanism explanations often followed a domino-type narrative of what caused what to happen but often spoke as though the dynamics were event-like rather than process like (Grotzer et al., 2013) and as though the events were happening to single organisms as opposed to populations.

3. Integrated use of covariation and mechanism information.

The most common tendency was an integrated use of covariation and mechanism such that they were in explanation of each other. The dynamic pattern was offered and it was followed with causal mechanisms to explain the pattern part of the causal story.

For instance, "The fertilizer contains nitrates and phosphates which caused algae to grow rapidly. After the fertilizer cycled out of the pond, the algae lost the nutrients it had become dependent upon which caused some of the algae to die. The dissolved oxygen levels lowered due to less producers in the pond. There was also 100% cloud cover for three days not allowing the algae to do photosynthesis, lowering the dissolved oxygen…" (See Appendix B.)

These explanations often had significant depth even though they were not free of causal gaps in the explanations.

Overall Findings and Discussion

Table 1 shows the percentage of students offering each type of explanation. The forms of explanation were not mutually exclusive and students could use different approaches for different portions of their explanations. Therefore, the totals do not add up to 100%. While Pattern as Causation is not the most common explanation, it is an instructional issue of concern that 36% of the students offered this type of explanation for at least a portion of their explanation.

Table 2 shows the breakdown of which students used mechanism only, covariation only, or an integrated explanation.

In summary,

- Students with the deepest explanations had well integrated instances of patterns as covariation/dynamic equilibrium with mechanism. This accounted for most of the students.

- Explanations focused only on patterns were not as common and are not wrong, per se, as long as they don't extend beyond the correlations; students viewed these as explanations perhaps confounding correlational and causal patterns.
- Explanations with only mechanism tended to include narratives that told the story of what happened but without clear connection to population data.
- Mechanism only explanations varied in level; some were very low level with superficial features to the explanation (obvious causes) while others included complex, deep level mechanisms such as photosynthesis and respiration.
- Token explanations were present but less common, perhaps due to the support to investigate in the curriculum.

In an instructional sense, these patterns suggest different types of responses. In instances in which students have not included mechanism information, a deeper focus on how particular causal mechanisms behave and how they inform what might be happening in the causal dynamics is warranted. In instances in which students told the story of the mechanisms without the broader population levels, instruction might highlight that the causal dynamics occur at the level of populations and that the changes are dynamic and process like. This might help students to realize that the causal story is not a simple linear narrative but a process of ups and downs.

Understanding the relationship between co-variation and causation is important for helping students to learn causal explanation in the sciences. The role of mechanism is especially important in environmental problems when one cannot necessarily discern co-variation relationships due to spatial and temporal factors. Recognizing that mechanism and covariation can both be primary and powerful modes of causal induction invites further investigation into how students understand the role of each in scientific explanation.

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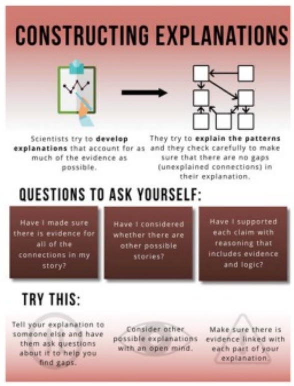
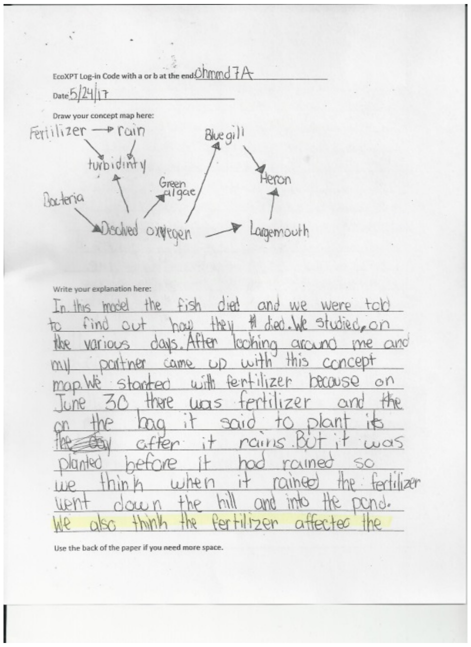
Appendix A: Thinking Moves



Appendix B. Student Responses



EcoXPT Log-in Code with a or b at the end: Ohmmd7A

Date 5/24/17

Draw your concept map here:

Write your explanation here:

In this model the fish died and we were told to find out how they died. We studied on the various days. After looking around me and my partner came up with this concept map. We started with fertilizer because on June 30 there was fertilizer and the on the bag it said to plant its the day after it rains. But it was planted before it had rained so we think when it rained the fertilizer went down the hill and into the pond. We also think the fertilizer affected the

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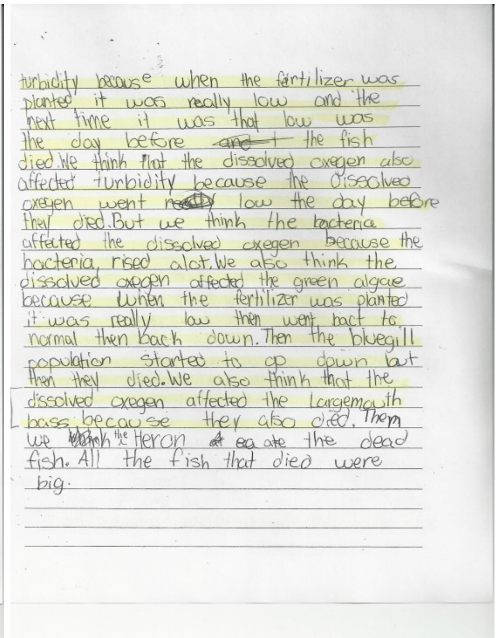
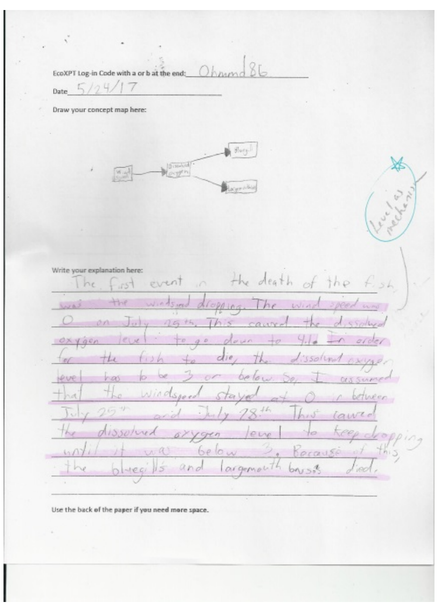


turbidity because when the fertilizer was planted it was really low and the next time it was that low was the day before ~~and~~ the fish died. We think that the dissolved oxegen also affected turbidity because the dissolved oxegen went really low the day before they died. But we think the bacteria affected the dissolved oxegen because the bacteria rised alot. We also think the dissolved oxegen affected the green algae because when the fertilizer was planted it was really low then went back to normal then back down. Then the bluegill population started to go down but then they died. We also think that the dissolved oxegen affected the Largemouth bass because they also died. Then we think the Heron ate the dead fish. All the fish that died were big.

Covariation Patterns as Explanation



EcoXPT Log-in Code with a or b at the end: Ohmmd86

Date 5/24/17

Draw your concept map here:

Write your explanation here:

The first event in the death of the fish was the windspeed dropping. The wind speed was 0 on July 25th. This caused the dissolved oxygen level to go down to 4.1. In order for the fish to die, the dissolved oxygen level has to be 3 or below. So, I assumed that the windspeed stayed at 0 in between July 25th and July 28th. This caused the dissolved oxygen level to keep dropping until it was below 3. Because of this, the bluegill's and largemouth bass's died.

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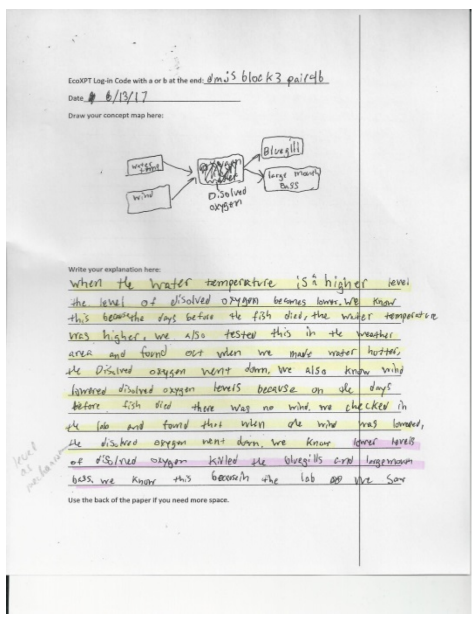

EcoXPT Log-in Code with a or b at the end: dmis block3 pair46

Date 6/13/17

Draw your concept map here:

Write your explanation here:

when the water temperature is a higher level the level of disolved oxygen becomes lower. We know this because the days before the fish died, the water temperature was higher, we also tested this in the weather area and found out when we made water hotter, the Disolved oxygen went down. We also know wind lowered disolved oxygen levels because on the days before fish died there was no wind. we checked in the lab and found that when the wind was lowered, the disolved oxygen went down. we know lower levels of disolved oxygen killed the bluegills and largemouth bass. we know this because in the lab we saw

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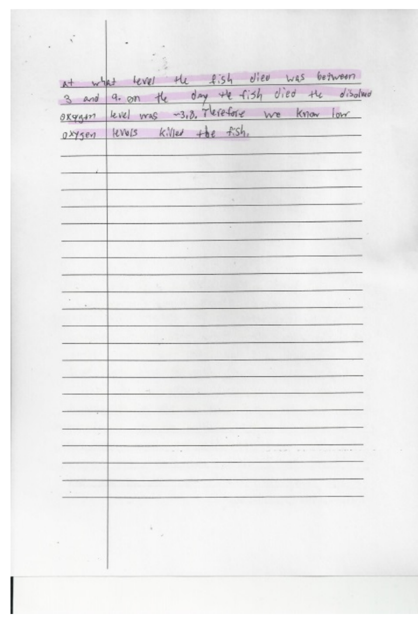
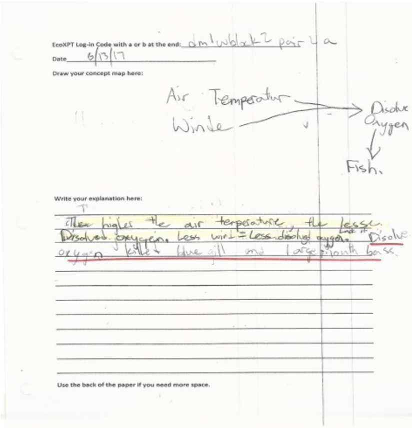
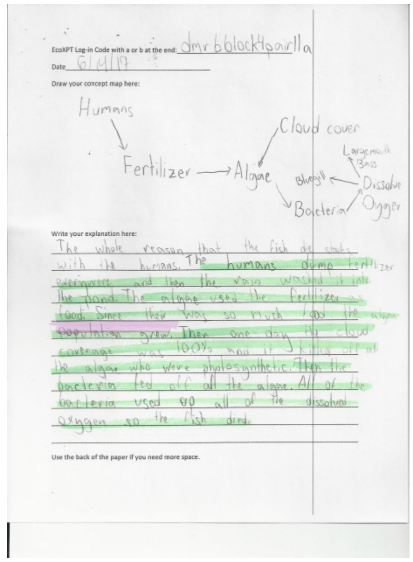
level as mechanism



at what level the fish died was between 3 and 4. on the day the fish died the disolved oxygen level was ~3.8. Therefore we know low oxygen levels killed the fish.

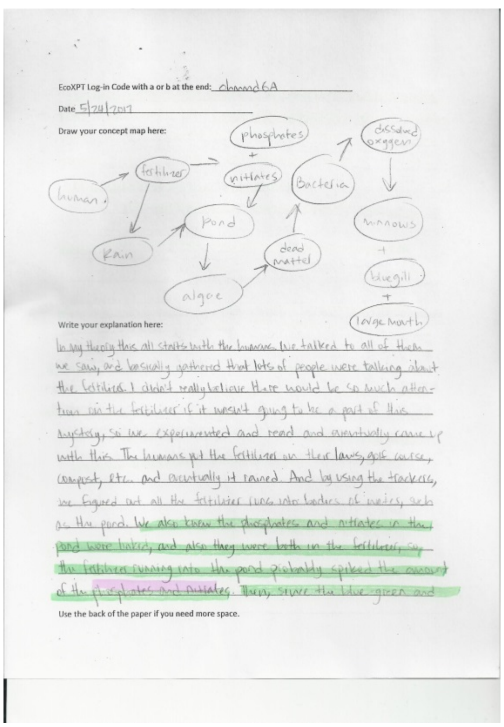
Level as Mechansim

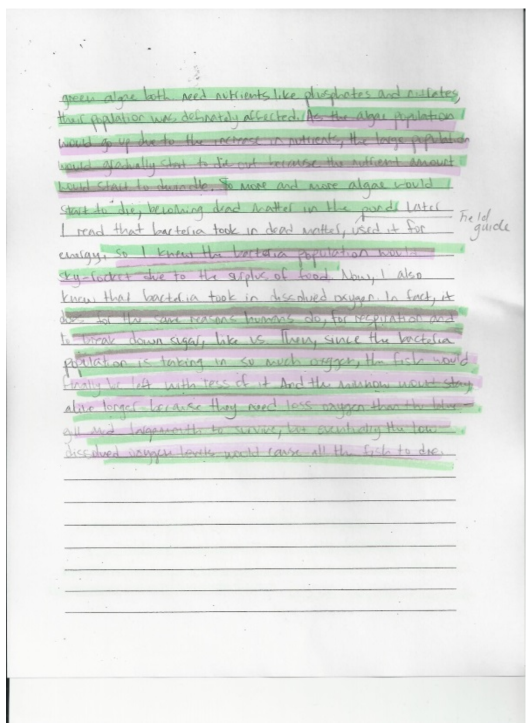




Token Explanation (And Pattern as Explanation)

Mechanism as Explanation

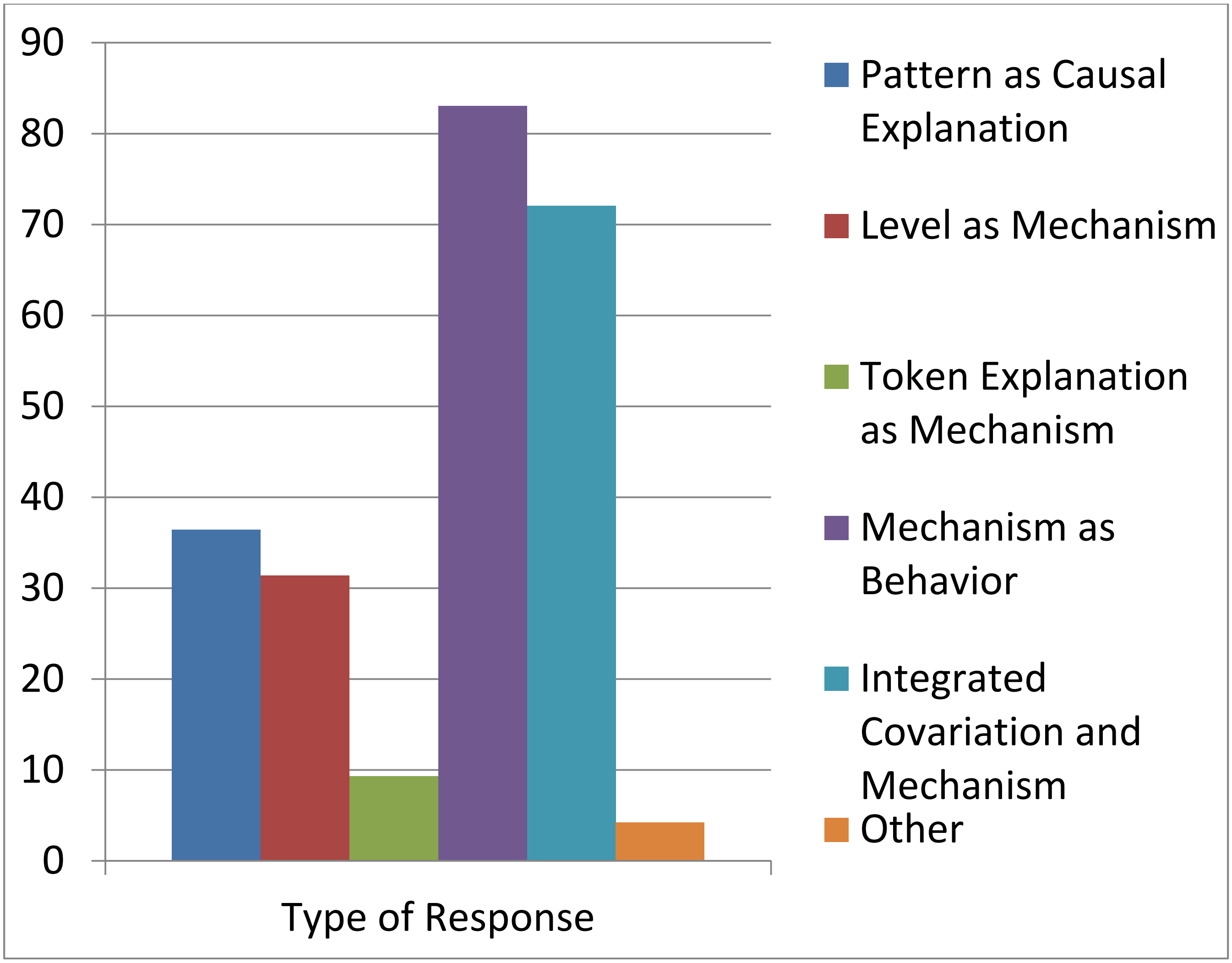




Integrated Covariation Pattern and Mechanism

Type of Response	Pattern as Causal Explanation	Covariation Pattern Level as Mechanism	Token Explanation as Mechanism	Mechanism as Behavior	Integrated Covariation and Mechanism	Other**
Percentage of Students	36.44%	31.35%	9.32%	83.05%	72.03%	4.24%
Notes: *Responses fall into more than one category. Thus, the total is more than 100% of the students. **Other accounted for two responses that did not fit any categories; an unreadable response, and a blank response.						

Table 1. Percentage of Responses



Type of Response	Integrated Covariation and Mechanism	Mechanism Only	Covariation Only	Neither
Percentage of Students	72.03%	10.17%	9.32%	8.47%

Table 2. Percentage of Integrated Response, Mechanism Only, and Covariation Only

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