PART 2: Exploratory and Diagnostic Tools

Don't bite off more that you can swallow.

Chapter 4 - Patterns of Interaction

4.1 Introduction

As mentioned in the first chapter, the environmental/agricultural philosopher Wendell Berry (1981) says there are three ways to act on a problem: first - don't actually solve it, second - push the problem somewhere else, third - solve the problem "in the pattern". It turns out to be very difficult to do this because many of the crucial problems turn out to be those that have ambiguous or hidden patterns. Clear patterns would provide easy-to-follow signals for solutions. What Berry means is that we need to solve the problem in the pattern of its context. The purpose of this chapter is to provide a method for recognizing types of patterns, analyzing them, and scientifically formulating which models are the most likely explanations for those patterns.

The first step in understanding and responding to the environment is looking for patterns. Because humans are innately good at seeing useful patterns, we might take this activity for granted. Instead of limiting our abilities to untrained innate skills, we need to develop both a broader awareness of types of patterns and study the processes that lead to these patterns. In addition to the usual correlations, distributions, periodic cycles and patterns on different scales, we also need to be aware of patterns that stem from underlying processes that maybe non-linear, complex or emergent.

There are three major categories of patterns; 1) those that form as a result of strong, external driving factors in the environment, 2) those that are the result of multiple, internal interactions, and 3) those that result from both strong external factors and internal interactions. The first category is important and we have many examples of this. We will lump the second and third categories together and focus on those. We need to develop a way to look at these systems with a holistic approach. Complex patterns need to be studied so that we will be aware of them, understand how they work, and be able to take some action that works with these interactions

Sidebar – Important terms for Chapter 4
Pattern of behavior - observed position or trace of objects in the environment
Pattern of interaction - the observed pattern that is generated through from internal objects and processes
Metaphor - metaphor is to use one description from a known area to understand another example
Analogy - specify how examples A and B are alike
Model - a simplified description of a system or set of interactions
Simulation - a model that has user-modifiable parameters, used for understanding the behavior
Visualization - the run of a particular model or simulation without ability to change parameters

Table 4.1 External Drivers and Patterns. With high driving forces there are often internal interactions that dissipate that energy.

External driving force	Pattern
Water flow	River basin erosion
Mixing	Eddies

4.2 - An example of the difference between traditional and complex/interactive views

The following example should help illustrate the difference between the traditional, cause and effect, view and the interactive, complex, view.

Imagine that we have a transparent box that contains some ice and we heat it up with a lamp. The traditional approach to studying this would be to measure the amount of heat in the box and how much energy the box and its contents are absorbing. The heat absorbed by this system would be the independent variable and we could relate the amount of ice and the melting rate of the ice to the effect of heat.

Now imagine a slightly more complex system in which there is a sheet of dark material under the ice. As the ice melts the dark material is exposed. We may get a much more complex, interactive pattern of response in which the heat absorbed depends on the amount of ice and dark material, and temperature depends on the absorption. Given enough effort and measurement, this system could be described by equations and appropriate constants, however we might be more interested in observing and then discovering the "pattern of interactions". In this case the pattern is the result of a positive feedback loop in which the more the ice melts the faster the remaining ice will melt.

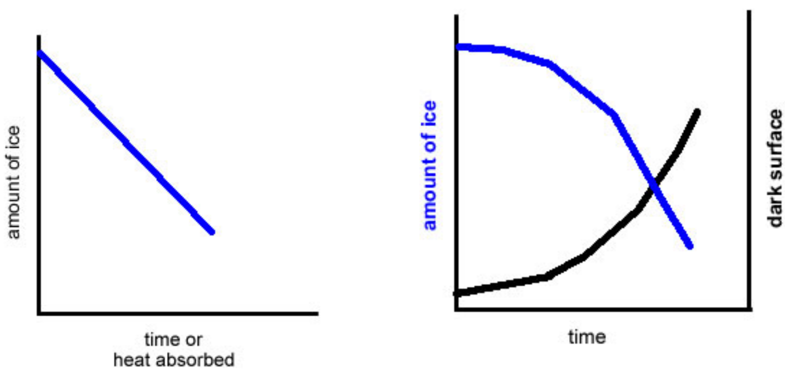


Figure 4-1. Ice melting rates in different configurations. A) ice melts as a result of absorbing heat. The absorption rate of heat is constant and

thus the melting rate is linear with time. B) The absorption rate for the system changes as blacker surface is exposed, resulting in an interaction that changes the rate of melting with time. The difference between the two examples is because the second set up results in a positive feedback interaction for heat absorption. In both cases, the amount of heat absorbed directly causes ice to melt.

4.3 Understanding Patterns

Being able to work with patterns requires a complex set of cognitive skills, however we can break these down into three basic areas.

1. awareness/detection - We have to be aware that the environment contains a pattern that might be useful to examine as a pattern of interactions.
2. characterization/description - We need a method for describing and characterizing these models in a more general way so that we can communicate about them and relate patterns that we are observing to ones that have been studied.
3. decision/action - A key piece of understanding is to take action. We should start any action with the thoughtful review of what has been done in other similar situations and what worked and what didn't.

Drawing on a repertoire of patterns

The architect Christopher Alexander developed an extensive framework for describing patterns in his work on a pattern language *(*Alexander 1964, Alexander 2002). ?? more here??

Appendix 3 provides a catalog of patterns that is organized by the general shape of the response curve or the underlying mechanisms. Studying these examples will help you build a set of metaphors that you can use to detect other complex patterns. In the past, people may have gained a wide range of rich metaphors from their interactions with nature. But since our current society provides most of us with less opportunity for direct, primary experiences in nature, we may have to take time to deliberately study examples of organic or natural patterns. Examining the natural world for biologically inspired solutions, called “biomimicry” by Bayrus (1997) is another example of a deliberate search of natural patterns that was very fruitful for engineering.

Linking patterns to models

Models are simplified descriptions of the world that can be used to characterize, generate hypotheses, and compare predictions. We need models for scientific management. Some models are based on known mechanisms such as a population growth model that is based on birth and death rates. It is straightforward to measure birth and death rates to make the model and to work backwards from the model to show that the predicted population is consequence of those factors. But models of complex systems often loose that connection to observable mechanisms and this makes it even more difficult to explain the gross behavior in terms of actual mechanisms involved. For example, we may observe a population in an ecosystem that fluctuates widely and create a complex simulation of the factors that might lead to those fluctuations. We may not be able to prove (in a traditional sense) that the parameters in our model represent the actual internal structure and factors that lead to the fluctuations. But even with those shortcomings we can use that model to predict changes in the patterns of behaviors if particular management actions are taken. This gap between being able to "show" that the model predicts the basic behavior of a system and being able to "prove" that our model is a faithful representation of the underlying processes is a big sticking point.

One approach that is very useful is to look at the likelihood of the models given the observations. Instead of trying to prove that the model describes particular data set, this approach turns the standard statistical approach on its side, and compares several models to see which is more likely. It asks what is the degree of likelihood of any model given a set of data or observations. In contrast, traditional statistics can be used to tell you how close the data fit to a given model or equation. For starters we can use likelihood approach by generating several complex simulations that might fit the observed pattern and then estimating which model is most likely given the data we have. We could follow that up with more sophisticated analysis, such as Bayesian methods for pattern matching.

Another approach is to use simulation models. For an observed set of data, several simulations are created that match the available data but would have different underlying mechanisms. These simulations could be to generate predictions that are either ambiguous or conflicting. A simple example of this is to compare exponential and sigmoidal models for the growth of the population (Figure 4-2) and to then predict at what point the predictions diverge by more than 10%. Then we can use; 1) isolated experiments, 2) specifically crafted and intentional disturbances

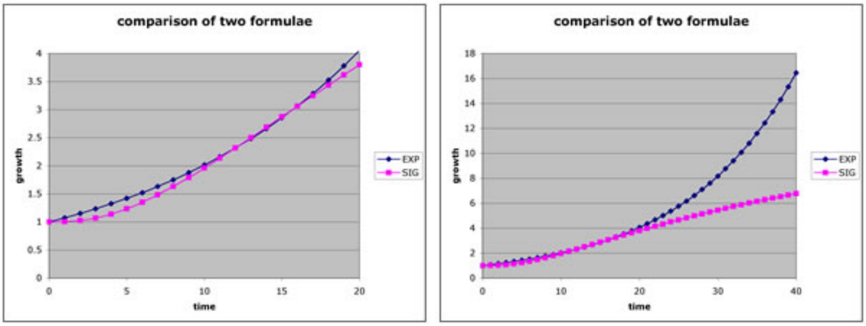


Figure 4-2. Comparison of two growth models. Both figures have the same underlying equations generating the curves, the only difference is that one "simulation" runs twice as long. In the figure on the left, both curves are incredibly close, within the size of the symbols for many points. Only after the simulation runs for another 20 days is the pattern clear that the exponential equation continues to grow explosively and the sigmoidal curve levels off.

of the environment, 3) management actions, or 4) wait around for natural perturbations to test the model predictions. It is important to elaborate on the differences between these four choices for testing the model. Traditional science would employ isolated and controlled experiments. This allows the investigator to control the conditions and use a matrix of changes in the independent variables. This approach is very effective and powerful and has been the basis for huge advances in environmental sciences in agriculture, limnology, and other areas. Often it is not possible to run isolated and controlled experiments and science has to rely on studying a single, non-replicable event. For example, the modification of unique lakes to see what might happen is sometimes possible. More often however, the only modifications that can be made for an ecosystem is through management action. It is not feasible, affordable or ethical to simply perturb a lake to see what happens. Instead, there are management objectives that can be addressed and studying that action with before, during and after measurements can be extremely valuable. The final option is to observe the changes in natural system due to natural perturbations. The problem with this is that you never quite know when a natural perturbation (such as a fire, drought, flood, pest outbreak, etc.) will happen. You may also not have sufficient pre-perturbation data or you may not be able to mobilize monitoring support and equipment in time during a perturbation. Monitoring plans are designed to be cost-effective and routine, not to wait around for perturbations. I know of an example where people involved in highly organized monitoring plan had difficulty justifying the change in their work schedules when there was an exciting breach of a levee that led to an unexpected perturbation event in the lake they were monitoring. The organization's budget was closely controlled to meet the monitoring goals and there was not enough slack to allow unplanned monitoring. Eventually a compromise was made and valuable data was collected, but it shows that you can't just expect to be able to explore some of these surprises. Scientific adaptive management design (as described later in Chapter 18) tries to build in dealing with novel or unexpected results into the project (and the budget).

4.4 Some patterns are cryptic

Clear patterns in environmental factors allow us to understand the underlying processes and guide our technological applications and policy decisions. For example, increasing pollution in a stream over several years or the appearance of an invasive weed in a natural grassland are clear signals that something is wrong. Some of the most important problems that we face, however, aren't marked by clear signals. In fact, ambiguous or cryptic patterns may be the reason why these problems are persistent and difficult to address. The most challenging problems that we face are both complex and have poor alignment between actors' values and the benefits from alternative solutions. These are classified as "wicked problems" in which neither more scientific information or public awareness will be sufficient to address the problem (see Chapter 1).

One example of a crucial process that is difficult to detect at early stages is runaway positive feedback (Figure 4-2). These type problems have been described as "spiraling out of control", a "vicious spiral" or "crossing the tipping point". At low values the incremental growth is small, but as the value increases so does the increment in any time and can eventually lead to an explosive growth in the system. In the early stages the positive feedback nature can be hidden in the variability in the data or by overlapping cycles. Global warming is a good example of this type of process. **IF** there are positive feedback processes (such as might be caused by increasing temperature releasing more CO2 from tropical soils or methane from the tundra), **THEN** it will be much easier and cheaper to make an incremental reduction as a preventative measure now than to repair extensive damage later. The issue is that we (as environmental scientists) don't know if this is a simple increase or a vicious downward spiral with a threshold.

Biodiversity loss is another crucial issue facing us. Currently is it generally accepted that most processes are linear. That means that a 1% increase in the causative factor will have a proportional change in the output function. However, biodiversity loss may be highly non-linear. There may be a threshold in our level of human disturbance that leads to a rapid and dramatic restructuring of ecosystems and communities to be much more impoverished. Complex models for this type of shift have been constructed that show at a crucial threshold of habitat fragmentation the biodiversity takes a huge loss. These processes are discussed more in Chapter 7:Networks. The scientific burden is how to detect the threshold before we cross it, especially if it is a non-linear response. We may never be able to recover what we lost. One of the favorite metaphors for biodiversity loss is that we are going to remove some random rivets in your airplane. How many rivets can we remove with no effect and how few would we have to remove after that to have a catastrophic failure of the plane. Although very mechanical, this metaphor illustrates the potential to be near failure without crossing, but that when just one more insult is added to the system there can be a catastrophe.

4.5 Catalog of complex patterns

I have compiled a catalog of patterns that can be observed in the environment and may be caused by underlying complex interactions. Example images or identifying characteristics for each category of pattern are given and, in some cases, critical elements that differentiate this pattern from others. This list is useful when scanning a broad range of possible mechanisms but can't be used as a method for proving that one particular underlying mechanism is the cause of an observed pattern.

Remember, scanning this catalog isn't a valid search strategy for proving any relationship, rather it is a starting point for looking for complex mechanisms that may generate the pattern you are observing. Also, this is not valid because no criteria for matching have been established, i.e. there is no stopping rule for when your search would be complete.

Table 4-1. The catalog contains the following patterns that can be related to their dominant metaphor. Please see Appendix 3 and online for images of these classes (and sub-classes).

Easily identifiable spatial patterns generated by:

Banded vegetation – facilitation in 1D (NetLogo model)
ILP – facilitation in 2 dimensions
Forest mosaic (my-forest-fire.nlogo)
Fractal watershed erosion or delta deposition
Percolation of oil into soil (Netlogo)
Swarms resulting in structures
Swarms resulting in dynamic behavior, such as flocking
Dunes

Dissipative structures that are the result of large energy flux

Bernard cells
River meanders
Geisers

Temporal patterns

Water pulsing in a sluice way
Box-car effect on the freeway
Logistic growth curve to deterministic chaos, chaos does not equal complexity

Phase transitions

Time for forest fire to proceed through landscape – dramatic increase near threshold
ILP (Reichart)
O2 flux causing variations in DO (STELLA)
Green-Desert transition (Sole')

Social collapse – sunk cost model (Sole')

4.6 Using simulations to generate patterns

Wolfram (2002) has described a "New Kind of Science" in which he uses rule-based cellular automata to generate patterns and then analyzes these patterns for where the complexity comes from. Using a simple rule set for each cell, a method for calculating a new row of cells with each time step, and a starting "seed" row; you can iteratively generate new rows until a pattern emerges. The pattern comes from the simultaneous interaction of the current row of cells with the rule set to give a changed pattern in the next row. You might be familiar with this type of cellular automata in the game of Life or have seen a grid-based version of this in models of forest fires.

Several patterns in the catalog (Table 4-1) can be generated using simulations that have very simple rules. The fourth column indicates the type of model used to simulate the pattern. These described in more detail and with links to on-line simulates in the appendix.

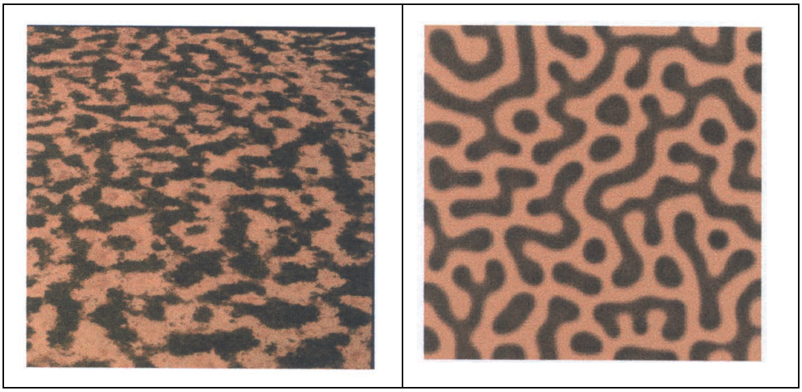


Figure 4.x An aerial photograph of the vegetation pattern in a xeric region of Niger (left) and a simulation of that same pattern created with a cellular automata (right). The simulation demonstrates that the lateral flow of water, accompanied by nearfield plant-on-plant inhibition and farfield promotion, results in a similar pattern. From Reitkerk 2002. *These images haven't been cleared for use.*

4.7 Two examples of employing patterns to address an environmental problem

An illustrative example: Pollution levels in a stream

Let's compare two ways to examine the amount of pollution that is introduced into a stream by a point source. This is an over-simplified example to illustrate the difference between a deductive and inductive approach. The deductive approach would start from a set of known laws and apply them *a priori* to hypothesize a cause and effect relationship. The inductive approach would be to collect observations and then to look for patterns to expand our understanding. Both of these approaches are valid and powerful types of science.

Deductive approach - starting with the laws

The law of conservation of mass should apply to mixing problems such as pollution input to a river. You consider this law and come up with the following hypothesis: The total mass of pollutant in the river will always be the same, but the concentration might increase of decrease depending on the relative amount of dilution from the flow of the river. Following this approach, you measure the mass of pollutant, the flow rate and predict the concentration of pollutant that will be measured downstream.

Inductive approach- starting with observations

You measure the pollution put out by the point source (such as a single sewer outlet) and get the following data in Table 3:

Table 4-3: Example data from a stream-monitoring project.

date	**point source g per hour**	**stream g per liter**
1/15	3	0.030
2/15	5	0.033
3/15	7	0.035
4/15	6	0.040
5/15	7	0.070
6/15	6	0.080
7/15	4	0.080
8/15	5	0.200

Plotting this data you get a bunch of points as shown in figure 4-3.

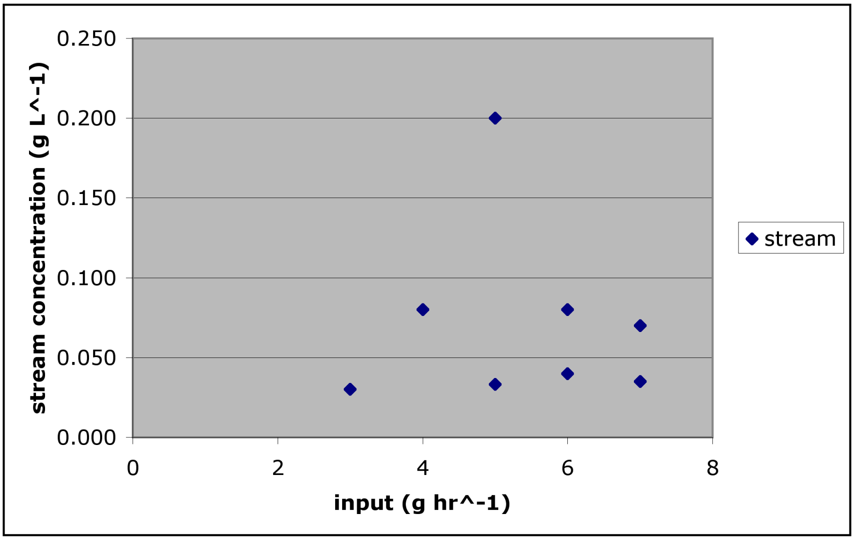


Figure 4-3. Data from Table 3 plotted as the stream concentration related to pollution input rate.

After seeing this you think about it and realize that you need to know the volume of the stream flow at any time to calculate the resulting concentration. You retrieve that data from a gauging station and add it to the table (Table 4):

Table 4-4: Recalculated data from Table 3 that includes stream flow rate.

date	stream flow L ^hr-1	concentration of pollutant g/liter	mass of pollution transported by the stream

			flow * stream conc.
1/15	100	0.030	3
2/15	150	0.033	5
3/15	200	0.035	7
4/15	150	0.040	6
5/15	100	0.070	7
6/15	75	0.080	6
7/15	50	0.080	4
8/15	25	0.200	5

Thus the highs and lows in stream flow change the stream concentration independently of the point source input. Multiplying the stream flow by the concentration in the stream will give the mass of pollutant that has been put into that total volume of water. This calculation (column 2 * column 3 = column 4) compared to the data column 2 in Table 4.3 confirms that you have accounted for all of the pollutant.

What is the difference between the inductive and deductive?

In the traditional scientific approach that focuses more on deterministic processes, there is a gap between concepts and the application of this knowledge with scientific tools. For example, how do you know that the total mass of pollutants in the stream is conserved? However, most of the analytical tools used in the traditional context are based on deductive approaches and the power that comes from that generality.

Instead of having to jump to this assumption (that the general approach will apply), investigators using the more inductive approach wade through the swamp of rich, personal exposure to some complex systems. From this experience and simulations they realize that only some of the features of the system can be captured. Collection of information can be guided by experience and from simulations but shouldn't be constrained by the presupposing certain relationships. The data from a more inductive approach can be analyzed with appropriate tools that search for patterns. These inferential tools can be applied to simulation output for the researcher to gain experience at detecting and rejecting patterns.

Both approaches have a gap. In the deductive approach, invoking the laws of science early presents a gap between what the investigator actually sees and experiences and the process of collecting measurements. By crossing this gap early, powerful measurement and analysis tools are readily available. In the inductive approach, the investigator must collect data and form it into information without the efficient constraints of laws, and then cross a gap when attempting to apply inferential statistics of similar tools to help decide between possible patterns in the data.

A more complex example: Sand pile model for landslides

The previous example illustrated how some problems could be addressed with either deductive of inductive approaches. This example will show that even though simple governing rules can lead to complex behavior the investigation of a phenomenon might have to work backwards from inductive, experiential start. Simulations of the system demonstrate how the behavior can be different each time, but that there are generalizations about the pattern of behavior that can be made. These complex systems have simple rules but multiple possible outcomes, i.e. they aren't deterministic.

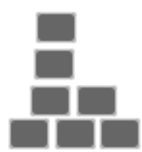
Dropping sand grains one at a time onto a pile is one example of the complex behavior that can arise from a very simple set of rules. The rules are that:

- sand grains are added one at a time
- if, anywhere on the sand pile, there are two grains right on top of each other, there is a good chance that this pile of grains will fall over.

Below is a sketch a few steps in the building of a sand pile. There are simulations of this process available on the internet.

1. pile of sand develops

2. new grain added to top



3. grain could fall either direction

4. it happens to fall to the right

5. and then further tumbles

6. and finally ends up

At step 3 it could have fallen to the left, causing a bigger avalanche.

3. it could fall either way

4 - alternate. it falls to the LEFT

5 - alternate. causing a larger cascade

In one case one grain of sand tumbled down the pile, and in the other case it caused a larger event.

In a sand pile buildup there are lots of little tumbles, more small avalanches and only a few large avalanches. This is because if there hasn't been an avalanche for a while the pile gets steeper and steeper until it causes a large event. This model and the explanation have been explored in great deal in other sources (for example Bak 1996).

For the purposes of this example, we are interested in the frequency of the events and how big they are. It turns out from many observations that avalanches that are about twice as big are half as frequent. If you plot the frequency of events (Y axis) vs. the size of the event (X axis) you would get a plot that looks like this:

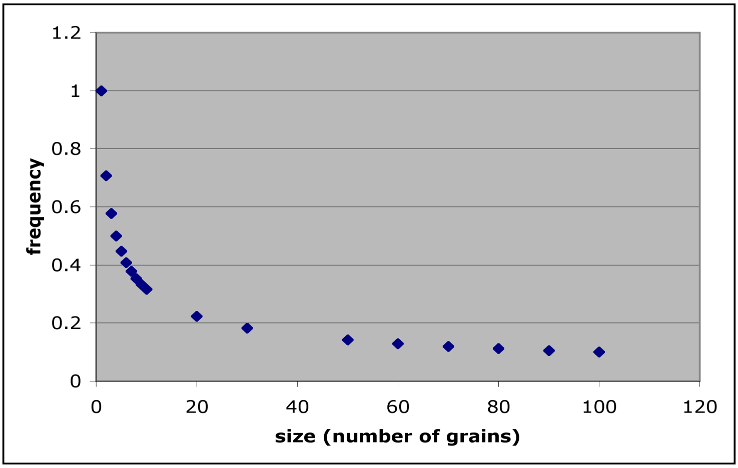


Figure 4-4. Frequency of landslide as a function of the magnitude of the landslide. There are very few large events, but many small events.

If you use a log-log plot, by simply making each axis a log scale, it looks like this:

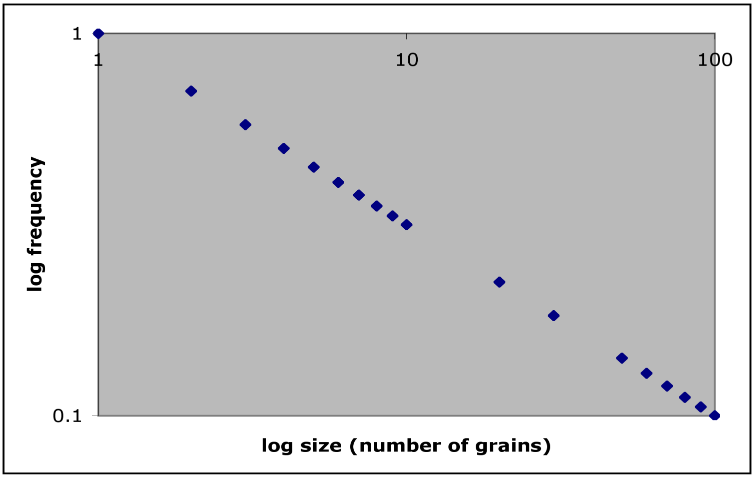


Figure 4-5. The same data as in Figure 4-4 plotted on a transformed set of axis: log of frequency vs. log of the size of the landslide.

The log-log transformation (Figure 4-5) works because we are dealing with constant ratios of change; if the size increases by a certain ratio, then the frequency decreases by a related fraction. It doesn't matter where you are on the graph, whether you are at the second, or 82nd most frequent event, the ratios hold. This is an example of a scale independent relationship. Other examples of this pattern of behavior can be seen in landslides, earthquakes (Gutenberg Richter Law), and the size of cities (Zipf's Law).

4.8 Likelihood of mechanisms given a pattern

This section describes a method to establish the likelihood that an observed pattern is similar to one that has been described in the catalog, with the implication that we might understand which processes formed it. This does not prove that the observed pattern was caused by a particular mechanism. The steps are: 1) observe a pattern, 2) create a simplified representation, 3) look for likely patterns in the catalog that are candidates for explaining the observed pattern, 4) analyze the candidate models to see which is more likely.

For example, a stream drainage basin may look like Figure 4-8.

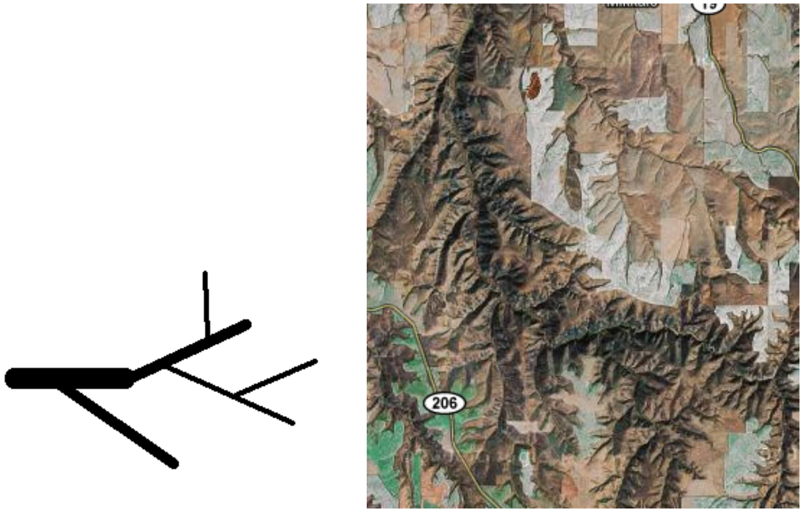


Figure 4-8. The pattern of a stream basin with several small tributaries. The image at the right is a Google Maps image of one of the upper stems of the John Day River in Oregon (Copy right by Terrametrics 2010 and Map data Google 2010)

Looking at the catalog of patterns (Appendix 3) there are several patterns that are similar to this one. Picking several as candidates to explain this pattern:

> Pattern 1.1 - This is bigger pattern is just a combination of straight lines, implying that the main forces causing this pattern are just those that cause water to flow down hill in the shortest path.
>
> Pattern 3.4 - A fractal stream basin, implying that historical erosion pattern has lead to the one main stream and the tributaries.

Pattern 3.6 - A biological fractal, such as the lines on the bottom of a sand dollar.

The representation of our observation is important in the analysis. If we were to look at the stream on a road map, we might see that the stream width was not accurately represented and the stream might be very similar to a set of connected straight lines such as shown in figure 4-9.

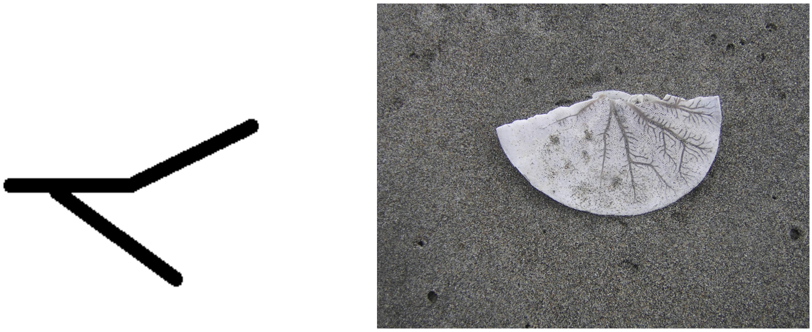


Figure 4-9. (a) Steam basin pattern as it might look on a road map with stream sizes all the same and smaller ones dropped off. (b) The bottom of a sand dollar (pattern 3.6).

Given that we know it's a stream pattern, pattern class 3.4 makes sense and the images in the catalog are very similar. However, just by looks, pattern class 3.6 looks most like our pattern. So unless we had some other information about how these were formed we might have to conclude that our observed stream was more likely to be similar to the fractal patterns (3.4 or 3.6) than a straight line (pattern 1.1). We would probably need to add more detailed observation and representation of the streams to differentiate (based just on the pattern) between pattern 3.4 and 3.6.

In this approach we are looking for likelihood not "truth" or a "provable" mechanism. This makes an important link to the concept of the "precautionary principle" in which we are looking for likely problems that might crop up and cause trouble or damage, and we are willing to suffer some false positives to get a better chance in including those mechanisms in the mix. The same holds here, we are looking for models that may describe the observed data and we would much rather include a candidate model (because we can deal with it) than we are trying to eliminate models. Each subsequent round of study should help us discriminate between the likelihood of the models.

4.9 Learning from and communicating about patterns

Metaphors, similes and analogies

These definitions are from Rigney (2001).

> "Metaphor is a mode of thought wherein we interpret one domain of experience through the language of another."
>
> "Simile is more literal than metaphor, asserting not that A is B, but only that A is like B in certain implied respects."
>
> "Analogy goes one step beyond simile, specifying ways in which A and B are alike. We develop an analogy when we begin to explicate the points of resemblance that metaphor and simile only hint at."

Metaphors are very useful if the audience has some other domain of knowledge that can be called upon to jumpstart their understanding. If the audience is aware of features that define the metaphorical system and can use those features as cues in a new domain. For example, you could use an agricultural metaphor to describe biodiversity to farmers or you could use an economic metaphor to talk to financial group. It might not be as productive to talk to financial people using a farm practice metaphor, they might not get the connection. It's only a good metaphor in the context of the receiving group. In the process of learning about complex systems, such as networks of research faculty, the metaphors that we are using are primarily from biological systems that the reader would associate with complex networks, even though they don't really understand how complex networks function. Thus to link a thought to ants, food webs, spatial neighborhoods of farmers, and others, is limited to the metaphor. After the basic comparisons are made, we can't rely on gaining any more understanding of the system by pushing the metaphor further.

We often use machine metaphors to describe how living systems work. For example, the heart is like a pump. If you know how pumps work (with flow, stroke volumes, back pressure, valves, etc.) this can be a useful start. Not surprisingly these can be oversimplifications. For example, using a thermostat metaphor to describe how humans regulate their temperature (too hot, turn on cooling) is deceptively simple. Humans cool themselves using at least 5 mechanisms with overlapping time scales (skin flushing, blood flow, sweating, ventilation, behavior). All together these overlapping rate scales (some faster and some slower) provide a highly resilient control mechanism for keeping our bodies within a workable range of temperature. It is fashionable to use living system metaphors to describe industry, such as an eco-industrial park or survival of the fittest. These metaphors can be misleading unless you really understand the underlying system (ecosystem or evolution) and know the legitimate boundaries of the metaphor.

We acquire metaphors through an exposure to a range of systems that generate patterns. This will help us recognize patterns as being the result of some processes that we are familiar with. The pattern may be the process in action (oscillation of a pendulum) or it may be the trace left by a process (debris line at high tide mark). There are probably many shapes and patterns that you might have seen but didn't realize the complex mechanisms that caused them. Here are some examples:

Table 4.5 Common patterns and the mechanism of formation.

offset of plant stems	
spiral in a sunflower seed	
streams in a drainage basin	
distribution of airport hubs across the US	
patches of weeds in your yard	
irruption of caterpillars	
water changing from smooth to turbulent flow as you increase the flow out of the faucet	
the grain of wood around a knot	
clumps of grass in a marsh and little ponds in the marsh	
the way flies dance around each other in a shaft of light	

Use of metaphors in environmental science

There are many required skills to work in environmental science and policy. Some of these are obvious such as understanding how science really works and to be able to perform the technical aspects of scientific monitoring and experiments. Additionally you need to be able to deal with uncertainty, be able to communicate with a range of audiences, and to help design monitoring and research schemes. In order to be a leader, you have to know where you are going and how to get people to consider your view. A powerful way to do that is to use appropriate and favorable metaphors to frame the conversation. You also need to be able to recognize when other people are using non-favorable metaphors to frame the discussion. This may seem manipulative or unethical, but if you do this openly and identify the different sets of assumptions that are implied by alternative metaphors, it can lead to a more productive and transparent discourse. Table 4-6 shows a comparison of simple mechanistic metaphors vs. not-so-simple ecological metaphors.

Table 4-6. Mechanistic vs. Ecological metaphors.

simple (mechanistic)	**not-so-simple (ecological)**
ecosystem as a homogeneous area	spatial and temporal connectivity
competition	cooperation
stability	resilience
natural selection through survival of the fittest	importance of maintaining biodiversity in evolution
competitive exclusion	survival
equilibrium	pulsing
steady-state	dynamic
global homogeneity	heterogeneity

Metaphors are often abused in public discourse

Invoking powerful and scientific metaphors can be dangerous. I call these “fractured metaphors”, when only part of the system is used. People employ these to provide the imprimatur of science, complexity, or “natural-system-ness” to descriptions as part of their argument in support of their approach. Some of the most abused examples are:

Describing an organization as a tree with all the branches deriving their support from the trunk (i.e. central organization). This image seems to lend credibility to the trunk as an important part of the tree when in fact it is just a conduit between roots and fungi in the soil and the branches and leaves.

Describing a competitive, winner-take-all process as some sort of natural selection. The invocation of Darwinian natural selection makes this seem like a tested and efficient process, when in fact natural selection relies on built in processes that create diversity in the gene pool.

Describing an industrial process as "eco-industrial" because there are significant internal processes. It sounds organic, environmentally friendly and efficient. But many of the examples are violating all laws of ecology by concentrating waste toxins against gradients (such as fly ash or sulfur by-products of coal consumption).

4.10 Summary

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