**Decision Making Under Uncertainty:**
**Statistical Decision Theory**

**Introduction**

I’d like to start today’s lecture with a reminder about something I said a long time ago when we finished our survey of population viability analysis. Population viability analysis is best seen not as a way of garnering precise predictions about the fate of a population but as a way of ensuring that all relevant life-history variables have been considered, that they have been evaluated appropriately, and that we have a reasonable sense of the trajectory that the population is likely to follow if current trends continue. It provides a way of structuring our thinking about the problem.

That’s precisely the way I think we should regard the approach to decision making that I’m about to describe. One of the most difficult tasks facing conservation biologists, as I have emphasized repeatedly, is that decisions must often, perhaps usually, be made in the face of woefully inadequate data. There is no way to freeze the status quo in a time capsule while we study the situation and come up with a solution. A few years ago one of the small projects in this course involved a critique of the recovery plan for Furbish’s lousewort (*Pedicularis furbishiae*). Many of the students assigned that project expressed dissatisfaction at the amount of data on which the advice was based, even though it was based on more than 10 years of field work. Not only was the amount of information about life history and population dynamics much greater than typically available for endangered plants then, it’s still vastly more than is available for most endangered plants now. Even though you might like to have more data before writing a recovery plan, you have no choice but to write it with the data that’s available at the time.

Similarly, if you’re working for the Fish & Wildlife Service, The Nature Conservancy, or a local land trust and you have an opportunity to buy or accept the gift of a piece of land, you won’t have a lot of time before you have to make a decision on whether or not to accept it. If you’re lucky you may have a chance to walk the property a couple of times and consult some museums, herbaria, or databases about the communities and species present. You won’t have the option of waiting until you have all of the information you’d like to have. We saw this illustrated even more vividly during our recent discussion of setting global conservation
priorities. Our ability to set priorities is limited by the data available.

Does this mean that we should just give up and go home? No, of course not. It does mean that we should take advantage of any techniques at our disposal that can help us make the best decisions possible, given the large amount of uncertainty with which we’ll have to live. That’s what the techniques I’m going to describe are intended to do. But they are valuable not because they provide precise answers to the questions we have to answer when making decisions,¹ but because they help us to structure our thinking about decisions in a way that helps to ensure that we don’t ignore any important features of the problem.

The Framework of Statistical Decision Theory

How do we reconcile uncertainties with the need for a decision now, recalling that a decision not to act until more information is available is still a decision? Risk analysis and statistical decision theory can provide some guidelines.

We’ve already encountered the most basic idea in decision theory in our discussion of the practical problems facing conservation biologists. Namely, the recognition from statistics that there are two types of errors we can make in evaluating an hypothesis:

- We may say that something is happening when it isn’t (Type I), or
- We may say that something isn’t happening when it is (Type II).

In classical statistics, an experimenter must decide beforehand the acceptable level of Type I error and design an experiment with an acceptable level of Type II error. The decision on whether to accept or reject the null hypothesis then depends only on the level of Type I error the experimenter is willing to accept, e.g., the conventional level of 5%. The experimental design problem is then one of determining how large the sample needs to be to detect an effect of a particular size or of how to allocate a fixed sampling effort to maximize the chances of detecting an effect.

One way of looking at the difference between academic biologists and conservation biologists² is that they associate different costs with Type I and Type II errors. Academic biologists don’t want to make a mistake by claiming an effect is real when it’s just a statistical fluke, so they focus on Type I error (as I described in the preceding paragraph). Conservation biologists don’t want to make a mistake by ignoring a problem when it exists,

¹Hint: They don’t give precise answers.
²Please recognize that I’m painting a caricature of the positions here. The differences aren’t as stark as I’m making out. They represent tendencies rather than fixed attributes.
so they focus on Type II error. They’d rather say that there’s a problem and discover that they were wrong than say that there’s not a problem and discover that there is.

An alternative approach, derived from Bayesian statistics, treats the probability quite differently. Prior beliefs are combined with the likelihood of the data to produce posterior probabilities about the hypothesis. More importantly, a decision-theory approach treats the decision of whether to accept or reject the null hypothesis as a real decision, i.e., as an action that has consequences. Moreover, they recognize that the cost of being wrong depends on how you’re wrong. It may be probably worse, for example, to decide that there is no evidence of a worldwide decline in amphibian populations when they are declining than to decide that there there is evidence for a worldwide decline when they are not declining. We have to remember that in conservation planning, you don’t have the option of not deciding. At most you have the option of deciding not to decide, which is still a decision. Saying

“I don’t know whether species X poses a significant threat to conservation values in area Y. Let me study the problem for five years and get back to you.”

is equivalent to saying

“I don’t know whether species X poses a significant threat to conservation values in area y. But I know that any threat it poses is mild enough that I can afford to investigate the problem for five years before doing anything to reverse the threat.

So in a decision-theory approach you assign costs to the various possible outcomes and try to minimize them.

**Decision Trees**

The most basic technique in decision theory is the decision tree. Take, as an example, the question of whether to regulate air pollution to improve forest health.

Suppose you are asked to provide an opinion on whether or not air pollution should be regulated to improve forest health. Three responses are possible:

1. Pollution is affecting forest health and should be regulated.

---

3Those of you who know me will be astonished that it’s taken me this long to get to a discussion of Bayesian approaches.

4Alternatively, you can assign benefits to the outcomes and attempt to maximize them.

5There are obviously other reasons why we might want to regulate air quality as well, but we’re only going to consider this aspect of the problem.

6This example is taken from [2].
2. Pollution is *not* affecting forest health and should not be regulated.

3. The evidence is inconclusive (so I need some grant money to study the problem, and I’ll get back to you).

Of course, regardless of how you interpret the evidence about whether pollution is affecting forest health, pollution either *is* having an effect or it is *not* having an effect. Even if you regard the evidence as inconclusive, pollution either is or is not having an effect.\(^7\)

In addition, regulators will either decide to regulate air pollution or not. We hope that their decision is informed by the advice we give them, but their decision on whether to regulate or not depends on whether they think that pollution is affecting forest health,\(^8\) and just as our opinion can be wrong, their decision can be wrong too.\(^9\) Notice that there are 12 possible outcomes: 3 answers we might give to the question, 2 possible states of the world, and 2 possible decisions by the regulator.

These possibilities and their consequences can be summarized in a decision tree (Figure 1).

- The squares represent points in the tree over which you have control as a decision-maker, i.e., they represent the decisions you can make. In this case our decision is what to tell the person who asked for our opinion.
- The circles represent points in the tree over which you have no control.
- Along each branch of the tree, all possibilities are considered.

The consequences of following each branch of the tree can be evaluated for several different variables. Notice that the payoffs to the scientist and the forest are not the same. More importantly, they payoffs are measured in different units. They’re not easy to compare.\(^10\)

**Statistical Decision Theory**

For many purposes, simply laying out all the alternatives and their consequences is sufficient to arrive at a reasonable solution. The preponderance of effects in one direction may be so

---

\(^7\)The effect may not be particularly large or important, but it’s unlikely that there is *no* effect. A complete discussion would phrase the question differently and ask whether pollution is having a large enough effect on forest health to make it worth regulating. To keep things simple, we’ll ignore that subtlety.

\(^8\)For simplicity we’ll ignore the possibility that their decision is influenced by other factors, like economic impact.

\(^9\)Although we hope that we’re less likely to be wrong than they are.

\(^10\)This is a point we’ll come back to just before Thanksgiving break.
Figure 1: Decision tree for analysis of regulation on air quality intended to improve forest-health.
overwhelming that you don’t need to do anything more. In other cases, it may be difficult
to decide on a course of action based on the tree skeleton and consequences alone.

In such cases it may be useful to do the analysis quantitatively by assigning probabilities
to various outcomes along the decision tree. Numerical values may also be assigned to the
various outcomes, and a mathematical criterion may be chosen to identify the “best” decision.

One of the most difficult parts of doing a formal, quantitative analysis of the decision
tree is arriving at probability estimates for the various outcomes. After all, the whole reason
we’re even exploring this approach is that we don’t have as much information as we’d like.

- This is one place where you can use some interesting techniques to elicit subjective
  probabilities from “gut” reactions. In that way, you take advantage of the intuitive
  “feel” many will have for the situation and explore their consequences. In the absence
  of solid data, we can even use guesses. This approach guarantees that we are at least
  consistent in how we use those subjective impressions.\(^\text{11}\)

- We’ll also talk about a couple of alternatives that don’t require us to estimate these
  probabilities before introducing a couple of less structured approaches.

Of course, if you have a formal population viability analysis with persistence probabilities
specified over some time period,\(^\text{12}\) so much the better. This approach allows them to be
incorporated directly.

The Procedure

1. Define a gain function or a loss function. This is the thing that measures the value
   or cost of a particular outcome. The value function may be qualitative—allows per-
   sistence, doesn’t allow persistence—or it may be quantitative—the probability of
   extinction in 100 years is \(p\) or the present value of the population expected to exist 100
   years from now is \(x\).\(^\text{13}\)

\(^{11}\) The limitations of this approach are probably pretty obvious, but we’ll delve into a little more detail
about the use of expert opinion next time.

\(^{12}\) Or an equivalent projection of outcomes for an ecosystem your managing or a reserve system you are
designing.

\(^{13}\) For those of you who’ve had a little economics (and especially for those of you who haven’t), let me
remind you that if you’re using dollars as your measure, it’s not enough to calculate how much something is
worth 100 years from now. Investment decisions are generally, and reasonably, based on the amount of money
you’d have to invest now at some specified interest rate (the discounting rate) to have the amount you’re
interested in at the end of that period. To have $1,000,000 100 years from now, I would need $10,051.84
today, assuming a 5% discount rate (the magic of compound interest). Thus, the present value of $1,000,000
in 2100 is $10,051.84 today. We’ll return to these ideas when we discuss the economics of valuing biodiversity.
2. Associate utility values with each possible outcome in your decision tree. Utilities are a measure of how valuable (or how costly) a particular outcome is. Costs are often measured in dollars (or other currencies), but properly speaking the money is used merely as a metric to make different choices comparable. The dollar value *per se* isn’t important. It’s what the dollar value represents. To make this concrete, let’s take a look at the decision tree Maguire and her co-authors [3] present for management of the Sumatran rhino (Figure 2). In this case, we have two possible *loss* functions: (1) an estimate of the probability of extinction associated with the particular management alternative and (2) an estimate of how much it would cost to implement each of the management alternatives.

3. Having associated values with each possible outcome, you associate probabilities with each branch on the tree that’s outside your control. These probabilities should reflect the probability of a particular outcome, given the events that have preceded it in the tree. Thus, the probabilities of particular events may depend on their context, as they should if we really think our management decision is going to have an effect.
4. Now that you have values associated with each possible outcome and probabilities associated with each branch of the tree, it’s possible to calculate the expected values associated with each possible decision. The expected value of a decision is the weighted average of all outcomes associated with that decision, where the weights are the probabilities associated with each step in the decision tree.

So for example, if we were to intervene by establishing a captive breeding program, the diagram tells us that

- There is an 80% chance that the captive breeding program will succeed, in which case there’s zero chance of extinction in 30 years.
- There is a 20% chance that the captive breeding program will fail, in which case there’s a 95% chance of extinction in 30 years.
- The expected probability of extinction is

\[(0.8)(0.0) + (0.2)(0.95) = 0.19\]

This compares with a 0.53 expected probability of extinction if reserves are simply expanded.

If we take the probability of extinction as our loss function, we’re done. We simply choose the alternative that has the lowest probability of extinction, namely captive breeding, which has \(pE = 0.19\).

**Expected value of outcomes**

Recall, however, that there’s another loss function included in this figure, one with a dollar sign at the top. Different management options will require different amounts of money. Because resources, including money, people, time, and energy, are limited, we need to consider the possibility that choosing the option with the lowest probability of extinction may cause us to lose opportunities to do other things. Simply fencing reserves, for example, would provide a 45% expected probability of survival. Is it really worth spending six times as much money for a captive breeding program that would increase the expected probability of survival to 81%?

One way of answering that question is simply to think about the decision as if we were gambling.\(^{14}\) To make it simple, let’s suppose that our two choices are:

1. Spend $0.6M to fence reserve and have a 45% chance of survival.

\(^{14}\)Which we are, in some sense.
2. Spend $3.7M on a captive breeding program and have an 81% chance of survival.

Let me change the wording of those options a little:

1. Buy a lottery ticket for $0.60 that gives you a 45% chance of winning a million bucks.
2. Buy a lottery ticket for $3.70 that gives you an 81% chance of winning a million bucks.

Which one of those would you choose? Well, the expected return from the first option is

\[ 0.45 \times 1000000 - 0.60 \approx 450000 \]

While the expected return from the second option is

\[ 0.81 \times 1000000 - 3.70 \approx 810000 \]

Not too hard to pick, is it? The second option is clearly better. What if instead of that lottery ticket winning you a million bucks, though, it won you only five. Then the return from the first option is

\[ 0.45 \times 5 - 0.60 = 1.65 \]

and the return from the second option is

\[ 0.81 \times 5 - 3.70 = 0.35 \]

Again, not too hard to pick, but now we’d pick the first option instead of the second one.

What does this have to do with rhinos? Well, think about that lottery in this way. In the first case, I’m telling you that preventing extinction of rhinos is worth $1 trillion$^{15}$ while in the second case it’s only worth $5 million. Just an illustration of the simple point that it’s not only how much it costs to save rhinos that matters, but also how much it benefits us to save them, i.e., how much its worth it to us to save them. The challenge that we’ll talk more about in a couple of weeks is that we can measure costs fairly easily in dollars and cents (or Euros or pounds or Rand or ...). It’s typically a lot harder to measure the benefits.

**Sensitivity Analysis**

One problem with this approach is that we may be captured by the apparent precision of the numerical results. One way of combating this, and sometimes of producing agreement where there was none, is through a sensitivity analysis. In a sensitivity analysis we try to identify which aspects of the decision tree have a big impact on the decision.

\footnote{15$0.6 million in actual expense instead of $0.60 for the fencing option.}
• change probability that captive breeding is successful to 0.5

\[
E(pE) = (0.5)(0.0) + (0.5)(0.95) = 0.475
\]

instead of 0.81.

• change probability that new reserve prevents timber harvest to 0.8

\[
E(pE) = (0.2)(0.9) + (0.8)(0.37) = 0.476
\]

instead of 0.69.

Sensitivity analysis allows us to explore how different things would have to be for us to change our minds about the decision. Indicates how robust our decision is and points out areas where uncertainty is particularly problematic.

Alternatives to expected value

Suppose we don’t want to (or can’t) come up with reasonable probabilities for our decision tree. Then we can’t use all that nice mathematical machinery I just described. Are we dead in the water?\(^{16}\) No. There are a couple of alternatives we can try.

Let’s return to our example of whether to regulate air pollution.\(^{17}\) Suppose that there could be either no damage, low damage, or high damage to forest trees and there could be either lax pollution control, moderate control, or stringent control. That makes nine possible combinations of levels of regulation and damage. With each of those combinations there’s a cost: the cost of regulation and the costs associated with damage to the forest. Those costs are summarized in Table 1.

If we knew the probability of each outcome given a choice of control measures, we could calculate the expected cost associated with each choice (low, moderate, or stringent control) and choose the one with the lowest expected cost. But that’s not the only choice we could make.

\(^{16}\)Would I be asking this question if the answer were “Yes”?

\(^{17}\)This example is adapted from [4].
Table 1: Total costs associated with different combinations of regulation and forest damage (modified from [4]).

<table>
<thead>
<tr>
<th></th>
<th>No damage</th>
<th>Low damage</th>
<th>High damage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stringent control</td>
<td>9</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Moderate control</td>
<td>1</td>
<td>5</td>
<td>14</td>
</tr>
<tr>
<td>Lax control</td>
<td>0</td>
<td>10</td>
<td>30</td>
</tr>
</tbody>
</table>

The mini-max cost choice

We could decide that we want to pick the alternative that makes our maximum cost as small as possible, i.e., the one that minimizes our maximum cost. Looking back at Table 1, it’s easy to see that (a) the maximum loss associated with each choice occurs when there is high damage and (b) the minimum loss in that column is associated with stringent pollution controls. Therefore, the minimax choice would be to enact stringent pollution controls.

As Polasky et al. [4] point out, the mini-max choice is **very** conservative. It puts all of the weight for the decision on the worst possible outcome.

The mini-max regret choice

An alternative is to calculate the “regret” associated with making the “wrong” choice under each possible outcome. For example, if we knew that the actual outcome would be low damage, the best choice would be to enact moderate pollution controls, because it’s the least expensive. We’d lose 5 units if we chose either lax or stringent regulation. The “regret” matrix is shown in Table 2. Each entry is calculated by identifying the smallest number in a column and subtracting it from all of the numbers in that column.

Now we might pick the alternative that makes our maximum “regret” as small as possible, i.e., the one that minimizes our maximum “regret.” Looking at Table 2, it’s easy to see that (a) the maximum regret for the stringent control choice is 9, for the moderate control choice is 3, and for the lax control choice is 19 and that (b) the choice that minimizes the maximum “regret” is moderate control.

It’s vital to note that neither mini-max on cost nor mini-max on “regret” can be said to be the “right” choice. They balance tradeoffs in different ways related to how risk averse you might be. It’s also important to notice that even if you *can* estimate probabilities and

---

18Because I’ve changed their example a bit, what they call a maxi-min choice is the same as the mini-max choice as I’ve described it here. Sorry for the confusion, but I find it easier to make costs positive than to leave them negative. That’s the cause of the difference.
calculate the expected cost associated with each action, you might still prefer a mini-max choice based on either cost or “regret”.

### Table 2: “Regrets” associated with different combinations of regulation and forest damage (based on Table 1).

<table>
<thead>
<tr>
<th></th>
<th>No damage</th>
<th>Low damage</th>
<th>High damage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stringent control</td>
<td>9 = 0 = 9</td>
<td>10 = 5 = 5</td>
<td>11 = 11 = 0</td>
</tr>
<tr>
<td>Moderate control</td>
<td>1 = 0 = 1</td>
<td>5 = 5 = 0</td>
<td>14 = 11 = 3</td>
</tr>
<tr>
<td>Lax control</td>
<td>0 = 0 = 0</td>
<td>10 = 5 = 5</td>
<td>30 = 11 = 19</td>
</tr>
</tbody>
</table>

Less structured approaches

While I think there’s a lot to be gained from the systematic attention to detail that structured approaches provide, Polasky et al. [4] describe less structured alternatives that may also be useful in some circumstances.

- **Thresholds approach**: Rather than trying to choose explicitly among alternatives it may be sufficient to identify boundaries that define acceptable from unacceptable or safe from dangerous outcomes. If the we are approaching a threshold that would lead to drastic changes, e.g., loss of the stratospheric ozone layer, it may lead to a policy response. One danger of a focus on thresholds is that it may lead to the impression that values below the threshold are harmless or without risk.

- **Scenario planning**: There may be a host of variables that are difficult to quantify or unravel. Nonetheless, it may be possible to develop plausible scenarios that describe different possible outcomes, e.g., the different emission scenarios envisioned by the IPCC. If the consequences of different scenarios are clear, that may be sufficient to facilitate decision making. One danger is that those who identify the scenarios may fail to identify important possibilities. Scenario planning requires a great deal of creativity, and it’s difficult to be sure that all relevant scenarios have been considered.

- **Resilience thinking**: In my mind, resilience thinking could be considered a subset of the thresholds approach: first, identify the critical thresholds a system might cross; second, develop early warning systems to identify when the system is approaching those thresholds; and third, develop plans that will either pull the system back from those thresholds or allow it to function appropriately under the new regime.
A risk analysis approach

Let’s try a little experiment. It will be a hypothetical experiment, because none of us have enough cash to make it a real experiment. I’m going to give you two options, and I want you to tell me which one you would pick.

- **Option 1**: I give you $50.

- **Option 2**: I flip a coin. If it comes up heads, I give you $125. If it comes up tails you give me $25.

Now suppose I give you a new version of Option 2.

- **Option 2∗**: I flip a coin. If it comes up heads, I give you $100. If it comes up tails, you don’t get anything, but you don’t owe me anything either.

I’m guessing that most of you will prefer Option 1 to Option 2 and that most of you will also prefer Option 2∗ to Option 1. It will be interesting to see if I’m right. If I am, here’s why it’s interesting.

Calculate the expected value of each choice:

\[
E(\text{Option 1}) = \$50
\]
\[
E(\text{Option 2}) = (0.5)(\$125) - (0.5)(\$25)
\]
\[
= \$62.5 - \$12.5
\]
\[
= \$50
\]
\[
E(\text{Option 2∗}) = (0.5)(\$100)
\]
\[
= \$50
\]

If you were basing your choice among the options based on the expected outcome, there’d be no reason to prefer any of these options to another.

So why did I guess that most of you would prefer Option 1 to Option 2? Because most people are risk averse, i.e., they tend to avoid risk, when there’s the possibility of losing something they have. On the other hand, most people are risk seeking when there’s only the possibility of coming out ahead, which is why I guessed that most of you would prefer Option 2∗ to Option 1.

What does this mean for making conservation decisions? As we saw from the preceding discussion, it may often (perhaps always) be appropriate to consider not only the expected outcome of a decision but also the risks associated with different choices. Once we do that we also have to realize that different people have different tolerances for risk\(^\text{19}\) and that those

---

\(^{19}\)Think basejumpers *versus* an airline safety officer for the Federal Aviation Administration.
Tulloch et al. [5] illustrate the consequences of different attitudes towards risk in an analysis of 700 of the most threatened species in New Zealand. The considered two scenarios:

- **Threshold approach**: Any species conservation projects with less than some probability of success are excluded from consideration when constructing a portfolio of conservation projects.

- **Variance-discounting approach**: Rather than using estimated probabilities of success directly, calculate an “adjusted feasibility” as

  \[ F_i = S_i - \alpha S_i (1 - S_i) \]

  where \( S_i \) is the probability of success, \( S_i (1 - S_i) \) is the variance in success and \( \alpha \) is a subjectively chosen factor between 0 and 1 indicating the extent to which you care about risk, 0 meaning you don’t care at all and 1 meaning that you care as much about risk\(^{20}\) as you do about the expectation.

In their analysis Tulloch et al. set \( \alpha \) equal to the threshold for unacceptable risk used in the threshold approach. Table 3 shows part of what they found.

Not surprisingly, if you’re not too worried about risk, it doesn’t make much difference how you include it in your decision making. If you’re worried about making mistakes, though, it

\(^{20}\)As measured by variance.

### Table 3: The total number of taxa designated for conservation (Total) and the probability of success (mean, standard deviation in parentheses) given a limited conservation budget in New Zealand (from [5].)

<table>
<thead>
<tr>
<th>Risk (%)</th>
<th>Total</th>
<th>( S_i )</th>
<th>Total</th>
<th>( S_i )</th>
<th>% above threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>300</td>
<td>0.61 (0.29)</td>
<td>300</td>
<td>0.61 (0.20)</td>
<td>0</td>
</tr>
<tr>
<td>20</td>
<td>296</td>
<td>0.62 (0.29)</td>
<td>287</td>
<td>0.63 (0.28)</td>
<td>7</td>
</tr>
<tr>
<td>40</td>
<td>280</td>
<td>0.64 (0.28)</td>
<td>284</td>
<td>0.64 (0.28)</td>
<td>21</td>
</tr>
<tr>
<td>60</td>
<td>235</td>
<td>0.73 (0.23)</td>
<td>279</td>
<td>0.66 (0.27)</td>
<td>39</td>
</tr>
<tr>
<td>80</td>
<td>165</td>
<td>0.87 (0.17)</td>
<td>277</td>
<td>0.68 (0.26)</td>
<td>57</td>
</tr>
<tr>
<td>100</td>
<td>80</td>
<td>1.00 (0.00)</td>
<td>267</td>
<td>0.70 (0.25)</td>
<td>76</td>
</tr>
</tbody>
</table>
can make a very big difference. What say you, would you rather be 100% sure of protecting 80 species or would you prefer to include that risk via variance discounting and be 70% sure of protecting 267 species (expecting protection of about 187 species, but you’re not sure which ones)?

**Multicriteria decision analysis**

I glossed over at least two real difficulties in making decisions, beyond the obvious one that we never have all of the data we’d like to have:

1. We are usually interested in several different outcomes, and those outcomes are usually measured, if they’re measured at all, in different units. Although methods of combining these incommensurable outcomes exist, they’re not easy to use, and in the end, you simply end up with some kind of subjective weighting of different alternatives.

2. In any real world problem, many people are involved, and it’s unlikely that all of them place similar values on the possible outcomes. A Sierra Club member, for example, is likely to place a much higher value on a landscape showing little evidence of human influence than is an employee of a company involved in mountain-top coal mining.

Multi-criteria decision analysis doesn’t solve either of these problems, but it does provide a structured, sensible way for groups to work through the difficulties and, with a little luck and goodwill, reach a decision that everyone can live with (Figure 3). The sequence of steps it lays out should look very familiar. We’ve seen much the same sequence repeatedly in other contexts already.

**Conclusions**

- Decision theory provides a useful framework to explore alternatives.
  - It forces us to recognize that deciding not to take action is just as much a decision as deciding which action to take.
  - It forces us to recognize that we may err either by taking an unnecessary action or by failing to take a necessary action.

---

21 In case you hadn’t guessed this already, there isn’t a “right” answer. The answer is determined by how much risk you’re willing tolerate and what kind of risk you’re willing to tolerate.

22 Even if no one is happy with it.
Figure 3: Steps in a multi-criteria decision analysis process. The seven items listed in the center of the figure are areas where disagreements are likely (from [1]).
• It helps us formalize and categorize our thinking to make sure that we have considered all relevant possibilities.

• Quantitative analyses must be viewed as explorations of possibilities, not hard predictions, but
  
  – the process of quantification may help us to clarify our thinking, and
  
  – it provides us a way of assessing which parts of the decision tree have a particularly large impact on the outcome and of determining how robust our preferred course of action is to other possibilities. In complex problems this may not be evident from the outset.

• It makes clear that many of the political conflicts involving environmental and conservation decision-making arise because different participants in the process place different values on different aspects of the outcome. That’s why we’re going to try to talk a bit about values in the last few lectures of this course.

References


Creative Commons License

These notes are licensed under the Creative Commons Attribution-NonCommercial-ShareAlike License. To view a copy of this license, visit http://creativecommons.org/licenses/by-nc-sa/3.0/ or send a letter to Creative Commons, 559 Nathan Abbott Way, Stanford, California 94305, USA.