Uncertainty and Climate Change with Case Study

Now we're going to talk about uncertainty. Well, uncertainty is infused in virtually every aspect of decision making, specifically natural resources decision making, but also in other decision making processes. Rarely do we have certainty around all aspects of a decision that we're going to make. The challenge that natural resource managers are faced with is recognizing how to work creatively and respectfully with uncertainty to maintain this healthy humility about what we know and what we don't know, and to not be overwhelmed by it all.

In Nichols, et al, 2011, they divide uncertainty into four different categorizations-- you may be familiar with some of these-- environmental variation, partial controllability partial observability, and structural uncertainty. And we'll talk more about those.

So environmental variation probably influences all the components of a decision process. Climate change effects on environmental variation may cause our objectives to evolve as climate change produces changes in habitats, and thus carrying capacity, for different managed populations. So environmental variation is all around us. But recognizing that, as the environment changes and as climate change interacts with that, we may need to change some of our objectives.

Partial controllability is a type of uncertainty that arises because we're not sure if our management actions will actually produce the outcome that we want. So this is the controllability of the outcome according to the action that's taken. And climate change may affect the imprecision of certain management actions.

There's lots of different examples under that. But thinking about, maybe, the rates, and if you're predicting that if you set the harvest quota at this amount, well, climate change could cause a shift in the species range. And then you may not be able to capture the amount of harvest that you had anticipated by setting that quota, even though you had been able to in the past.

Partial observability is when we can only see a portion of the variable that we're looking at, or we can only see it imprecisely. So climate change can influence partial observability. Even through sampling and census estimation, thinking about ways that we monitor and try to detect populations, climate change can cause those through phenological shifts, through rain shifts and other types of changes to the thing that we are measuring. Climate change can also induce changes in the distribution and the behavior of wildlife over both space and time. So thinking about these changes should impact how we develop monitoring programs so that we can detect what it is that we're trying to observe, even with the changes that are induced from climate.

The fourth is structural uncertainty. And this concerns how the models are used to project the consequences of the management on the systems and on the things that we care about. So with climate change, you're dealing with nonstationarity. So it's important to recognize that this impacts environmental variation. And it involves both the ecological systems-- the weather, the precipitation, the different habitats, and animals, and plants, and species we care about-- but it also impacts the socioeconomic systems, and thinking about how those can interact. So it's important to look at the way uncertainty can play a role in the different state variables that we have in the models and in the different models that we use to assess the consequences of these actions.

So one approach would be just modifying the existing models to predict these responses more accurately, or to think more broadly about the potential range of impacts. Maybe you want to expand the monitoring scope to detect those more accurately, or to show greater variation in some of the variables that you have uncertainty around, and to show what that might look like. So you have the power to detect that and to see it so that the model set is encompassing those attributes.

And that's one way to look at uncertainty. There's another paper by O'Regan et al, 2002 that has a different way to divide up and categorize the different types of uncertainty. According to that article, there's two sources of uncertainty. One is epistemic. And the other is linguistic.

So here it's breaking down each of those two types of uncertainty into six different categories. And under epistemic uncertainty, that's where you're thinking about things like measurement error, systematic error, natural variation, inherent randomness, model uncertainty, and subjective judgment. Measurement error, that's looking at imperfections in the management techniques, or the observation techniques. So this is instrument error. And in this instance, if you're measuring something, there will be some variation around that mean. But it won't be skewed to one side or the other because it's just imperfections.

The second is systematic error. And that's the result of bias in the measuring equipment. So that could be if it's calibrated incorrectly initially, it might introduce a skew or a bias into the estimate that you have. The third is natural variation. And we already talked about that. Systems change with respect to time, space, and other variables.

And inherent randomness, in principle, it's saying that the system is irreducible to a deterministic one. And it's important to distinguish from processes that appear to be irreducible than ones that actually are. So here, the authors are saying that they're inherent randomness that exists in certain systems that are not reducible.

And next is model uncertainty. We just talked about that. And that's our representations of physical and biological systems. It could be first that the variables and processes that are regarded as important are featured in the model. And there could be uncertainty around that.

The second would be the way that those constructs are used to observe the processes. And that would be another source of uncertainty. It can be very difficult to quantify and to eliminate. But we've talked about some techniques that you might want to use in light of climate change.

Next is subjective judgment. And again, this is the expert system, the interpretation of data. So here you can do things that we mentioned, like assigning a degree of belief to that uncertainty, or showing the range, or the interval, around that. And there's lots of different techniques for doing that.

Then, if you're looking at linguistic uncertainty, this, I think, is the best area for us to be diligent about trying to reduce the uncertainty in the way that we communicate about the things that we're trying to do and the things that we care about. So in this article, they break down linguistic uncertainty into vagueness, context dependence, ambiguity, indeterminacy of theoretical terms, and underspecificity. Well, that just sounds like a handful of things that are really tough to tell what they're talking about. So I think I just introduced a lot of linguistic uncertainty there.

So let's discuss it. Vagueness. Vagueness arises because a lot of the language that we use, even scientific language, permits these borderline cases. If you think about-- in numerical terms, there can be a set that you've defined. And you say, well, the first 100, 1 to 100, the second 100, 100 to 200-- well, what about that 100? Is it in the first set or the second set? It's a borderline case there.

So you would have to define it as either less than 100 or greater than 100 to know which set it falls into. Very rarely do we actually take the time to develop that degree of precision around the terms that we're using. So vagueness can either be nonnumerical, or it can be numerical, meaning that sometimes, the thing that we're vague about doesn't have a natural number associated with it. So maybe it's not height, or it's not something that's easily quantifiable. So that can be even more challenging. But there are ways to work on reducing the vagueness.

The second is context dependence. And this is definitely one that we can work on both in our objectives, and in our alternatives. So uncertainty arising in context dependence would be the failure to specify the context in which a proposition is to be understood. You'd say, well, the species size is small. Well, is that small for a mammal, or small for a plant, or small for some other organism? So thinking about how we interpret meanings differently depending on the context, that we can definitely improve.

The next is ambiguity. Ambiguity is uncertainty that arises from the fact that a word can have more than one meaning. And it's not clear which meaning is intended in this case. So we use the word percent cover. Well, is that foliage cover? Is that an aerial level? Or is that ground level? Is that mid-level, canopy level? There can be a lot of different interpretations of that. So there's ambiguity around which meaning of that word is intended in this instance.

Under-specificity, this occurs when there is unwarranted generality. So in the future, there will be rainy days. How many? How far into the future? What seasons will they occur in? We can do a lot to increase the specificity around the different terms in the statements that we make just to clarify the meaning of them.

The next one is indeterminacy of theoretical terms. So those are things that are terms that may be used in the future that are not completely fixed by the past usage. So if you think about a species name that we give to, say, a plant species, then someone else identifies it in the future, or it may then be re-classified as a sub-species, or then merged with another species that, at this point in time, we don't recognize all the potential forms and shapes that it can take in the future-- so what the authors recommend, in this instance, is to be as conscientious as possible about the future usage of those terms. And that I don't see applying as directly with the decision processes that we have at hand.

So we may not be able to reduce uncertainty around the indeterminacy of theoretical terms. But if we can reduce some of the linguistic uncertainties associated with vagueness, with ambiguity, with context dependence, and underspecificity, then we'll go a long ways to communicating more clearly about the things that we're trying to do and about the things that we care about.

Use measurable attributes that describe consequences unambiguously and consistently. You could also think about generating verbal descriptions instead of just using probabilities so that people understand what those numbers mean in the context of that situation. And you can also look at ways to map, or draw out, these expressions of uncertainty into numeric probability ranges. Particularly, if you're using expert opinion or expert assessment, then that's another way to do that.

But there are cases when probability assignments may not be appropriate. And let's take a look at those. The authors in the *Structured Decision Making* text highlight three situations when it might not be appropriate to use probability assignment. And the first is when problems are characterized by overwhelming uncertainty.

Not just the magnitude, but the direction of the response is unknown. This is often referred to as deep uncertainty. But a more common situation is that the managers are just overwhelmed by what they feel like are a large number of sources that are external to what they can do, and external to their decision, but which will have significant influence on their decision.

So in that case, you might consider using scenario analysis to look at those different plausible scenarios of how those could influence your objectives. But the authors caution here that if you're not referencing explicit probabilities associated with these scenarios, then the human tendency is often to a, either assume that each of these scenarios are equally likely, or b, just to start believing strongly in one of those scenarios because it's presented in a way that's very compelling. And both of those are logical flaws that could actually be worse than just assigning an uncertainty range that's very wide. So that is when problems are characterized by overwhelming uncertainty.

And the second is problems that are involving very low probabilities. So consequences are thought to be severe or catastrophic should an event take place, but where the probabilities associated with that event are extremely low, for example, the authors mention a meteor striking in a dam, releasing a bunch of water. So the probability is so low that people tend to ignore that. And then they just focus on the severity of those consequences should it happen.

So if, for whatever reason, it's necessary to discuss this highly unlikely event, then it makes more sense to describe the odds than the probability. So talking about the odds as a frequency, there's one chance in 10 trillion of a meteor striking the dam and releasing a large amount of water.

The third situation is when problems have probability assignment that does not inform a decision. So for the media problem, is there anything that the managers are going to do in their decision that's currently being weighed? Maybe there's nothing they can do to reduce the chance of this occurrence. And there may not be any reason to spend time or your resources to model the probability around that situation. So it doesn't add any insight to the decision at hand.

And the authors provide a note of caution. To guard against the argument, the quantitative probabilities should be avoided, because we don't know them. There are concerns about creating an illusion of false knowledge, or precision. Well, those are relevant concerns. But it's not an excuse for willful ambiguity or for vagueness.

Even very large uncertainties can be characterized precisely by asking for confidence intervals, for example. And the information can prove to be invaluable in decision making.

So in exploring these risk preferences, you wanted to ask the risk profiles of the alternatives and elicit those from the decision makers. You may want to generate probability distributions, and summarize those, and figure out which parts of those distributions matter most. Think about things like what are the competing hypotheses, and how uncertain are they? How much information is enough?

What are the consequences of being wrong? Are the estimated consequences close to a recognized or legal standard? Are we approaching a threshold? And are the estimated consequences approaching a threshold beyond which they are likely to escalate? And that's something that you would want to think about, as well.

The authors present eight key messages when you're dealing with uncertainty. In addition to some of those approaches that we talked about in the alternatives generation phase, they say to explore ways to structure the key uncertainties to lend insight to the decision. Secondly, be specific about probability and consequences. Third, recognize that there are times when estimating probabilities is meaningless. Fourth, explore the risk profiles of the alternatives and the risk tolerance of the decision makers.

Fifth, characterize the degree of agreement among the experts if they're being used. Sixth, look for ways to improve the quality of the information. Seventh, remember that the goal is good environmental management decisions. And eighth, to use an iterative approach to exploring uncertainty, thinking about when it may be useful to do an initial run through and then go back and revisit it, and revisit it, adding in more information as appropriate and as it informs the decision context.