Overview of the Modeling Process

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This very brief module provides a very general set of points about the overall modeling process.

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SEM is a process designed to lead to scientifically interpretable models. It relies on sequential learning and a general multi-step process to build confident knowledge.

In SEM, we first translate our ideas into models, test those models, modify our models if need be, and then use that knowledge to inform where we start with the next study.
Theory translation should be as explicit as possible. Most modeling exercises have historically translated theory to models using an informal approach and have often omitted many important steps.

In Grace et al. 2010. Ecological Monographs, we propose meta-modeling as a process for defining the family of more specific hypotheses we will examine.

In meta-modeling, we start with a general view of the problem. Background (a priori) knowledge is often only defined at the linguistic level. We strive to show how our model specifics (shown in later slides) relate to the general a priori knowledge. Here I show the a very general meta-model that represents the most general logic for the analysis.
Considering the available data, we can build out our theoretical (a priori) expectations. At this point in the process we remain conceptual and do not yet consider statistical issues like linear relations or response variable distributions.

Causal diagrams are meant to serve as a template for modeling. The can include variables that we do not have measurements for and are meant to represent more deeply the mechanisms of interest. Pearl also means for these diagrams to help us identify the observations that would be needed to estimate various parameters using limited data.
The next major step in the process to fully specify our models. Now we have to work with the variables for which we have observations. In this case, “water conductivity” serves as our indicator of nutrient loading in these very soft-water systems. SEM procedures allow us to test whether the data are consistent with the implications of this architecture. This means we can test for whether there are any linkages we have omitted or any linkages that cannot be supported by the data.
Here is a cartoon to represent the sequence of steps in traditional global estimation. For alternative estimation approaches, consult the module on Estimation.
Once tested with data, we did indeed find evidence for a number of linkages (and associated processes) that we did not initially anticipate.

(1) It seems that species richness is lower where there is higher landuse intensity for some additional reason beyond altered duration of flooding.

(2) Sphagnum moss communities, a characteristic element of the natural system, seems to have been impacted through some additional methods shown as direct paths from soil disturbance and hydrologic alteration.

(3) Surprisingly, no real indication in this sample that impounding (increasing the duration of flooding) affects cattail invasions.

(4) So far, cattails don’t seem to have had a detectable impact on Sphagnum or native species richness, though we certainly expect such effects could occur.
This slide presents Figure 13 from our 2012 Ecosphere paper. Here we show an alternative structural equation model that uses latent variables to represent the generalized system responses (Eutrophication, Bog Development, and Diversity) that lead to the observed biological metric values. Error variables are not shown for simplicity.
Once we have parameter estimates, it is possible to ask "what if" questions and get quantitative answers.

Scenario 1: Observed System, Model M
- Human activities, $H$
- Water conductivity, $W$
- Typha cover, $T$

Scenario 2: Partial Control of $W$, Model $M_{x3}$
- Human activities, $H$
- Water conductivity, $W$

Scenario 3: Complete Control of $W$, Model $M_{x2}$
- Human activities, $H$
- Water conductivity, $W$

Here we first ask, "What would happen if we could set the effects of human activities on water conductivity to zero?" Then, "What if we could also set natural variations in water conductivity to 'pristine'?"

This figure is Figure 11 from Grace et al. 2012 Ecosphere. Queries about predicted effects of interventions on water conductivities and cattail abundance. Scenario 1 is status quo; Scenario 2 is elimination of buffer intrusion and soil disturbance; Scenario 3 is reduction of water conductivity to reference conditions. The “O” variables refer to unknown and unspecified causes of variation (sometimes referred to as U for unspecified). The operator “do($H=0$)” refers to reducing the values of land use and soil disturbance on conductivity to 0. The operator “do($O_w=0$)” refers to reducing the value of other (unknown) factors on conductivity to 0.
Figure 12, Grace et al. 2012 Ecosphere. A. Observed distribution of values of cattail abundance. B. Predicted distribution for case where effects of human activities are eliminated (Model $M_{x1}$ in Fig. 11). C. Predicted distribution for case where conductivity is controlled (Model $M_{x2}$). Consult the original reference for more details.
I have published three different treatments of the SEM workflow process. In my book, I walk through an example to illustrate the intent of sequential learning about a problem. In 2010, we expounded on model specification choices and the grounding needed for decisions in the field of ecology. In 2012, we proposed a 3rd-generation implementation for SEM and some additional steps in the process.
From a science perspective, one of our objectives has been to expand the advice given, as well as the procedures that link questions to answers. There has been a substantial gap in the literature on SEM dealing with the ends of the process. On the front-end, how do we formally translate theoretical ideas into models in a “revealed” fashion. On the back-end, there are many possible uses for our hard-earned parameter estimates. This potential is largely untapped because of a lack of attention by SEMers to issues that are bread-and-butter of “modelers”.

What we aspire to is a comprehensive system for quantitatively examining general theoretical ideas.
These are the guidelines given in the Ecosphere paper. They are also elaborated on in a book chapter*.

A digression on sample size.

Rules of thumb for sample size –
• First, there are problems with any guidance on sample size.
• Second, simulations show we would really like to have huge sample sizes (see Model Evaluation module)
• People often talk about absolute sample sizes (e.g., 200 best, 100 OK, 50 minimal). But, it depends on model complexity (and signal-to-noise ratios)

(1) We would love to have 20 samples per parameter
(2) It would be helpful to have 10 samples per parameter
(3) We hope to have a minimum of at least 5 samples per estimated parameter
(4) It is claimed that Bayesian estimates are stable with as few as 2.5 samples per parameter.

Here is just a very little bit about sample size giving some common rules of thumb. A general reference for the topic is Kline, RB 2015. Principles and Practice of Structural Equation Modeling. Guilford Press.