In this module I revisit causal modeling principles in a little more depth, now that we have a few models under our belts.

An appropriate general citation for this material is


An additional important reference for the topic of causal modeling is


Notes: IP-056512; Support provided by the USGS Climate & Land Use R&D and Ecosystems Programs. I would like to acknowledge formal review of this material by Jesse Miller and Phil Hahn, University of Wisconsin. Many helpful informal comments have contributed to the final version of this presentation. The use of trade names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

Last revised 17.02.05.

Source: https://www.usgs.gov/centers/wetland-and-aquatic-research-
center/science/quantitative-analysis-using-structural-equation
There is a very important distinction to make between causal linkages and causal estimates.

Establishing that links are causal and that manipulations of one variable lead to responses in the other can be difficult.
There are a whole additional set of issues surrounding whether parameter estimates are pure causal effects.

In ecology we don’t usually require our quantities to be exact in order to declare our model results a useful approximation. However, in some other fields (e.g., medical trials) people can be sticklers about the coefficients. We ignore that these are standardized coefficients for the moment, though we really should be dealing with unstandardized estimates to be more careful.

A second question, “How strongly can we defend the parameter estimates as unbiased causal predictions?”

This one is much harder.
A strong causal prediction would be that any individual plot in a hypothetical population of plots would increase in fire severity by 0.45 if we increased stand age by one unit.
There is skepticism about causal modeling from some quarters.

Caution is OK, but we should not be afraid to do science!

How far down the rabbit hole does this debate go?
Even in controlled experiments we cannot know for sure how individuals assigned to one treatment group would have behaved had they been in the other treatment group. For example, we might ask

“If Ms. X had been given the drug, would she have then survived?”

At a certain level, this counterfactual cannot be answered with certainty.

If you read widely enough, you will find some very deep debates about causal modeling here and there. These are usually not from scientists, but from some statisticians who are concerned that our causal estimates may not be perfect.
Bottom line: we should not be cavalier about the limits of interpretation.

Generally, with SEM we are evaluating causal hypotheses. Building confidence about causal conclusions requires persistent investigation.

Therefore, we might say, “Our model results support the conclusion that X affects Y through Z.”

Best not to speak as if by doing SEM we automatically have causal conclusions.

Understanding of the issues brings with it a respect for the need to pursue a causal understanding seriously. It also brings with it an understanding of the need to clarify our dependence on assumptions.
Confounding is one of the big issues. There are other issues as well, such as whether causes are reversible and whether each individual in the population is equally affected by a causal influence. There is a deep literature here and I would suggest another reference that is a bit more accessible than Pearl. Berzuini, Dawid, Bernardinelli (eds) (2012) *Causality*. John Wiley & Sons.

Note also that when the front door is open there are procedures for removing the bias from the effect of age on fire severity as well.