Introduction to structural equation modelling - basic modelling

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11/11/2020

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- To test hypotheses, we need a way to dissect when they occurr for a reason versus randomness.
- We use statistics to understand, when connections are non-random.
- Research questions are often about understanding cause and effect.

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  - “Understanding the whole rather than the parts in isolation”
- SEM unites multiple variables in a single causal network: simultaneous tests of multiple hypotheses.
- Causality is central: SEM implicitly assumes that the relationships among variables represent causal links.

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- The arrow above indicates a causal relationship.

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- Include interaction terms can test main effects and interaction effects.

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1) Understand the patterns of correlation/covariance among a set of variables.
2) Explain as much of their variance as possible with the model specified.

Thinking about the model

A SEM is usually specified based on theory to determine and validify a proposed causal process and/or model.

Which variables to include?

- Supported by theory.

Good practice: Make a table / graph of putative causal relationships before analysis.

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- Ecologically meaningful.
- Garbage in - garbage out (both data quality and ecologically meaningful).

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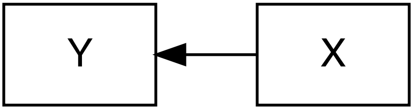
- Important to be explicit about the approach taken.

Graphical models:



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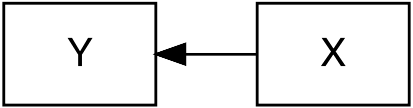

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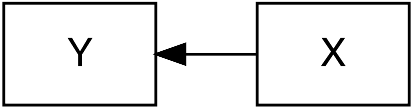

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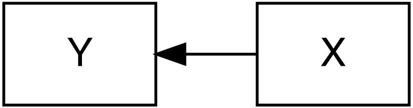

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- Edges (two-headed arrows) are non-causal relationships such as X and Y are correlated.

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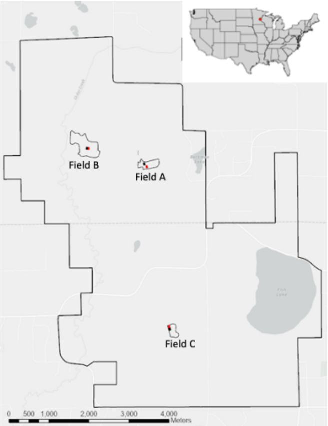
2) How are these effects mediated by diversity?

Introduction to the dataset



Map showing location of the study site (Cedar Creek Ecosystem Science Reserve), the location of the three study fields within the reserve, and location of the 35 x 55 m intact (black) and disturbed (red) plots within each field.

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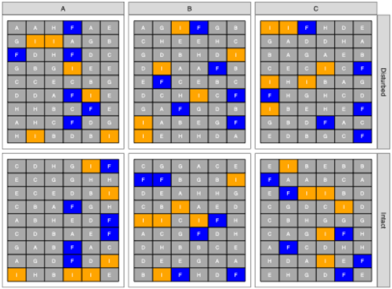

Location of the 4 x 4 m nutrient treatment plots within each 35 x 55 m Intact or Disturbed plot within each of three fields (A, B, and C). Letters indicate the nutrient treatments, and the colored plots are treatments that are the focus of the analyses presented here: Control (orange) and 9.5 g N m-2 yr-1 (blue).

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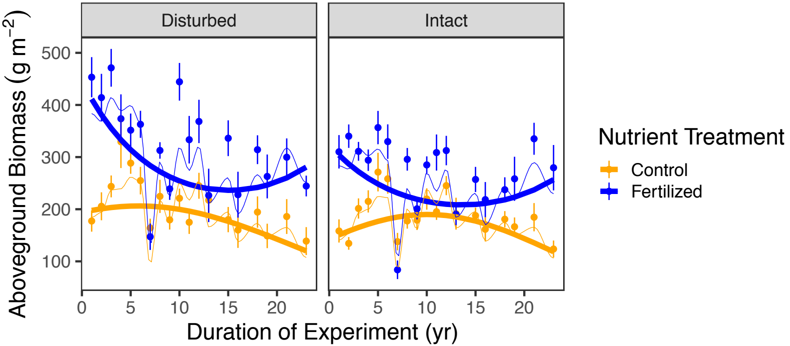
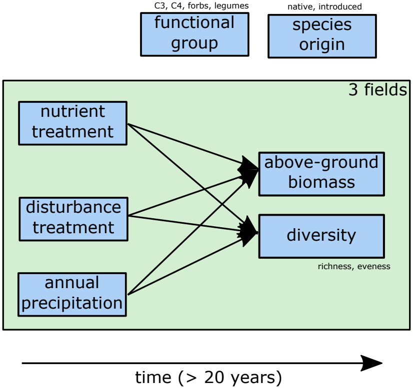


Effect of soil disturbance (disking) and nutrient enrichment on live, aboveground plant biomass. Colors indicate nutrient addition treatment: Control and NPK+ (all nutrients plus 9.5 g N m-2 yr-1).

Question of interest

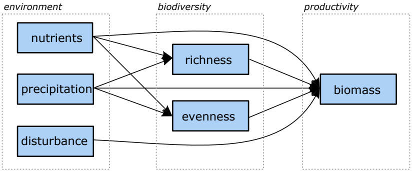


- What is the effect of richness on biomass?

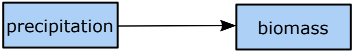
Meta-model

A metamodel summarizes the concept behind a model and links it to theory.

Productivity (biomass) is directly influence on the one hand by the environment (nutrients, disturbance and precipitation) and on the other hand by biodiversity (richness and evenness). Also some elements of the environment influence biodiversity and thus, have an additional indirect effect on productivity via biodiversity.



A simple bivariate model.

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lm(biomass ~ precipitation)
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- Linear regression

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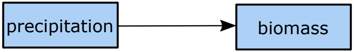


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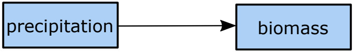


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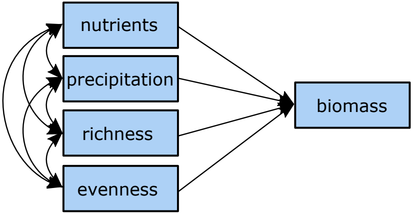
- Regression coefficient quantifies the strength of relationship
- Change in Y for one unit change in X

Multiple independent variables

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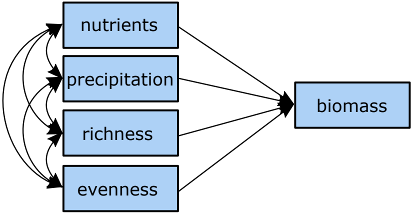


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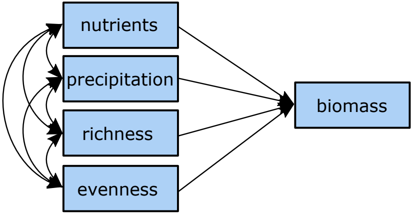


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- All effects are direct.

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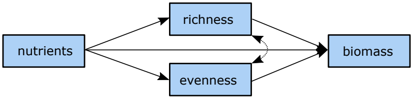


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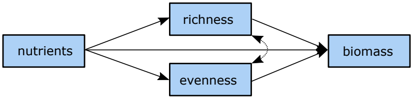


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- Indirect effects can be quantified by the product of the compound path.

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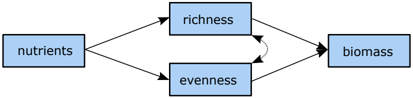

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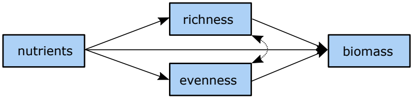

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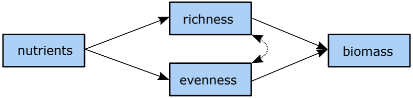

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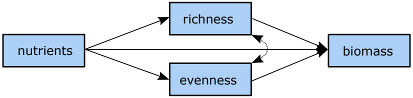

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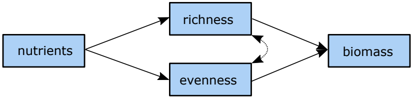

- Tests whether a particular variable has a mediating effect.
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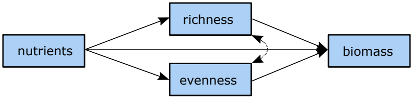
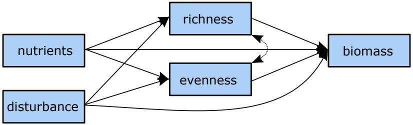
- Full mediation versus partial mediation.



System level approach



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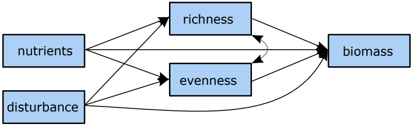

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- Variables for which arrows are also directed into are called endogenous. An endogenous variable can also have arrows directing out of it, but the sole condition is that they must be predicted

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8) The total effect (including undirected paths) is equivalent to the total correlation.

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- Comparative fit index (CFI): this statistic considers the deviation from a 'null' model. In most cases, the null estimates all variances but sets the covariances to 0. A value $>$0.9 is considered good.
- Standardized root-mean squared residual (SRMR): the standardized difference between the observed and predicted correlations. A value $<$0.08 is considered good.

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10) Interpret and present results visually