Introduction to structural equation modelling - advanced modelling techniques

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Overview

Advanced SEM topics:

- Latent variables

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- Latent variables
- Composite variables

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- Interactions

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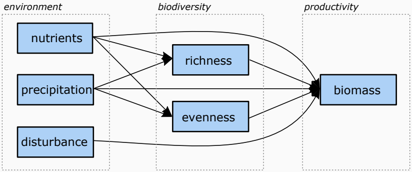
- Latent variables
- Composite variables
- Interactions
- Complex survey designs

Revisiting the meta-model



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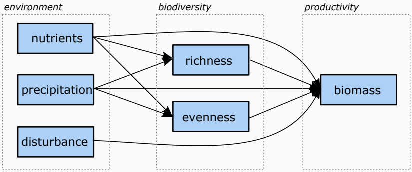

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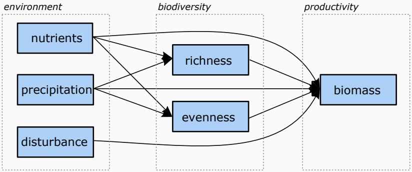

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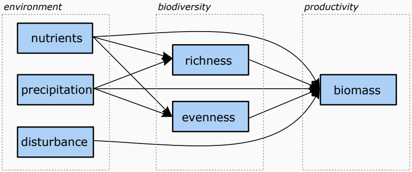

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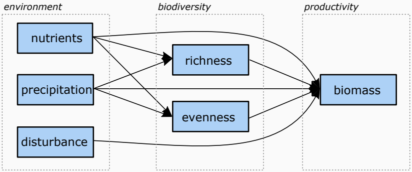

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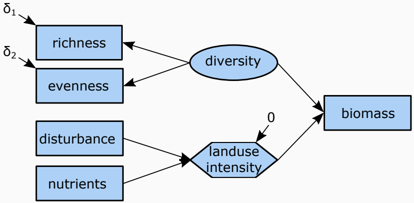
- Or, because we measure variables with error.
- This is where latent and composite variables are needed.

Latent variables



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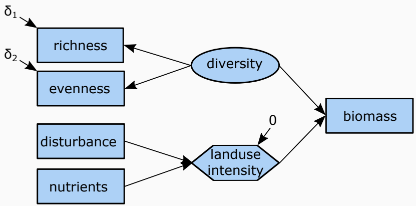

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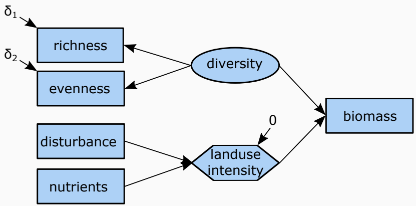

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- Graphically, latent variables are often represented by an oval node shapes (ellipses).

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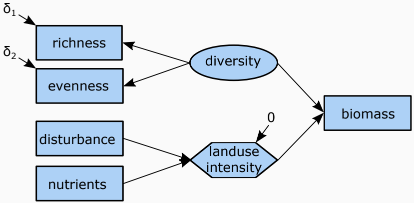

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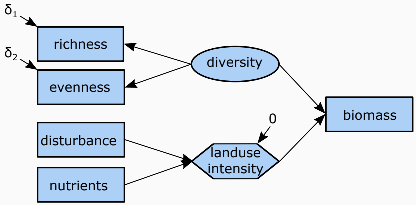

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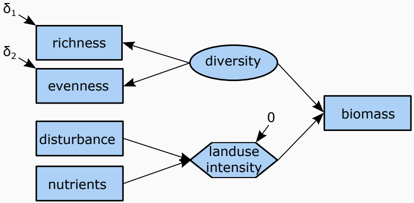

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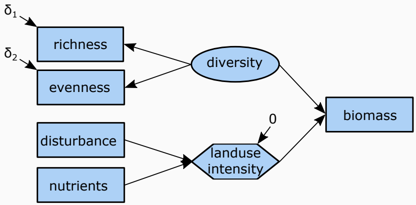

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- Latent variable free of random or systematic measurement errors in contrast to its indicators.

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- *Structural model* is one with directed paths between latent variables.

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- Precursor to evaluation of any structural models in which the latent variables appear.

Heywood cases

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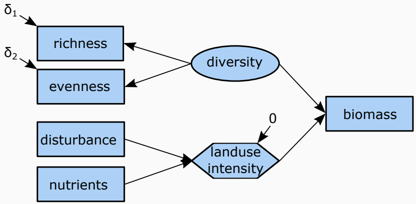
  3) local non-identification
  4) general misspecification

Composite variables



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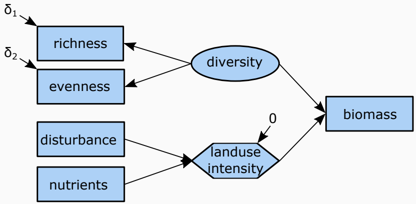

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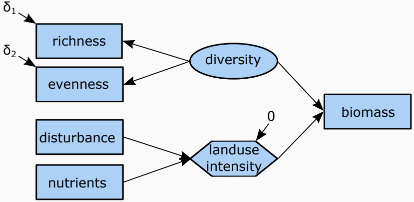

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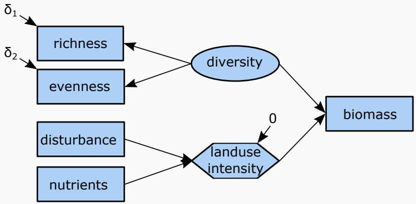

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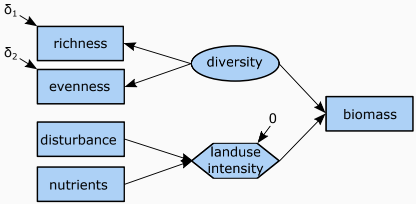

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- Composites are often shown as hexangular shapes or ellipses (latent composites).

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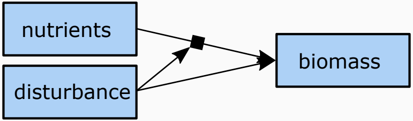
- Rule of thumb 2: If the meaning of the construct changes after dropping one of the indicators, the construct likely is a composite.
- As a latent variable represents an underlying, data-generating process, its indicators need to be correlated to each other.
- In the case of a composite variable, there is no assumption about the relation between the indicators. Thus, correlation among indicators are uninformative about the direction of the causal flow, but a lack of such contraindicates that the construct is a latent

Interactions (Moderation)



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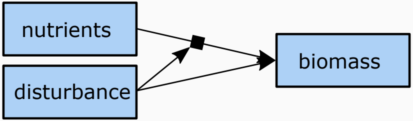

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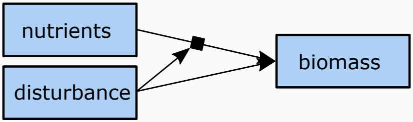

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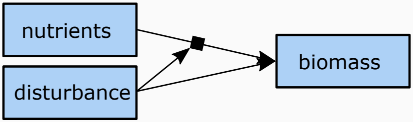

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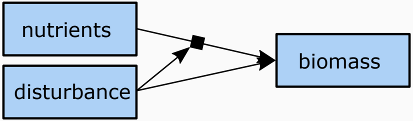

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- In regression, the interaction is represented by a coefficient that estimates the effect of the product of the two predictors.

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- Importantly, groups have to be of categorical nature.

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Lavaan allows to introduce equality constraints on various aspects via the `group.equal` argument:

```
mod <- sem(model, group = "age_class", group.equal =
c("regressions"), data = dd)
```

Additional constraints could be:

```
group.equal=c(
"intercepts",
"means",
"regressions",
"residuals",
"residual.covariances")
```

- Even more control by having the same name for different parameters:

```
model <- '
y ~ c("b1", "b1") * x1 + c("b2", "b2") * x3
x2 ~ c("b3", "b4") * x1
x3 ~ c("b5", "b5") * x2
'
```

Same coefficients for all but the effect of x1 on x2.

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- lavaan objects can be processed further with a specific data structure:
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    2) post-process the lavaan object and compute the adjusted results.
    3) Result is a corrected lavaan object.

Questions?