Introduction to structural equation modelling - advanced modelling techniques

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Overview

- Interactions

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- Latent variables

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- Composite variables

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- Complex survey designs

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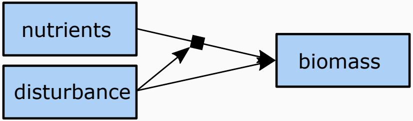
- Spatial autocorrelation

Interaction questions (Moderation)



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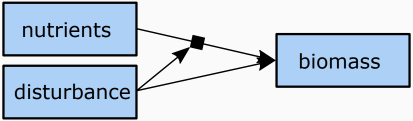

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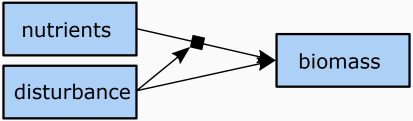

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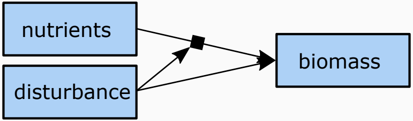

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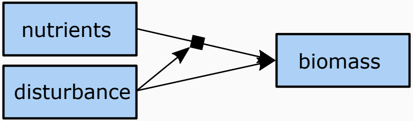

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- For instance, the effect of nutrients on plant growth, may depend on how disturbed the environment is.
- Such a behaviour is called an interaction, which indicates that the effect of the two main effects are different when combined.
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- In regression, the interaction is represented by a coefficient that estimates the effect of the product of the two predictors.

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2) Composites

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- Lavaan offers the “group” argument to specify for which groups coefficients should be estimated.
- Importantly, groups have to be of categorical nature.

```
mod <- sem(model, group = "age_class", data = dd)
```

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")
```

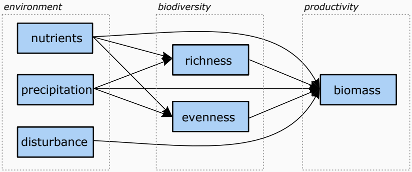
Interactions (Moderation)

- 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.

Revisiting the meta-model



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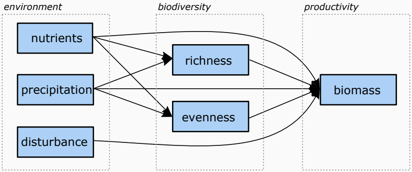

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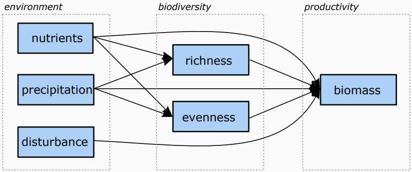

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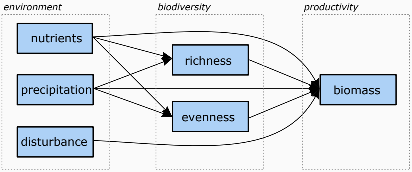

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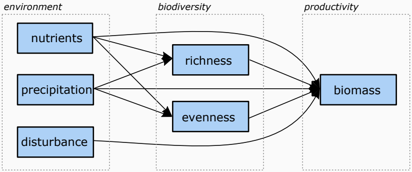

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- However, some of the parts of the model may be difficult to quantify and measure directly.
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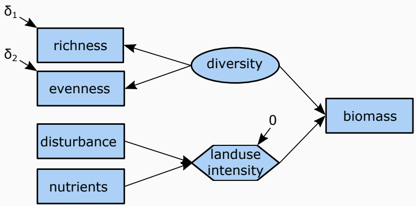
- Or, because we measure variables with error.
- This is where latent and composite variables are needed.

Latent variables



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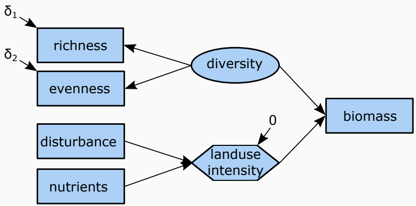

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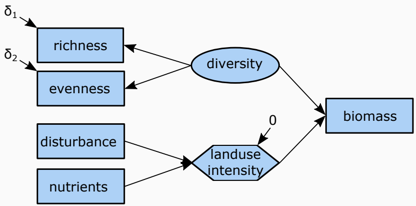

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- Latent variables are often represented by an oval node shapes (ellipses).

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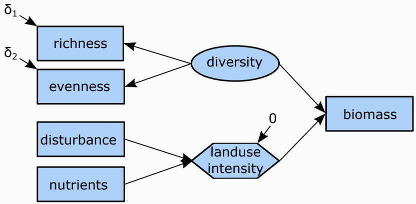

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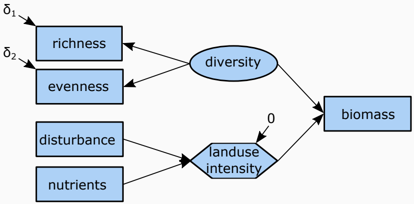

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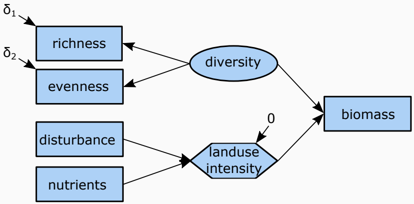

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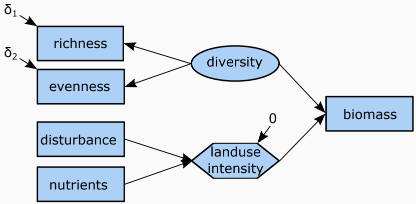

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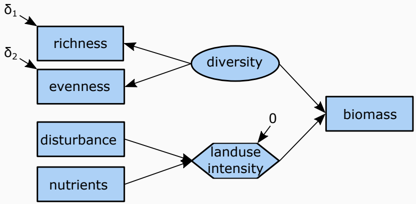
- A latent variable is free of random or systematic measurement errors in contrast to its indicators

Composite variables



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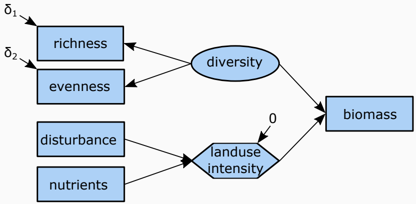

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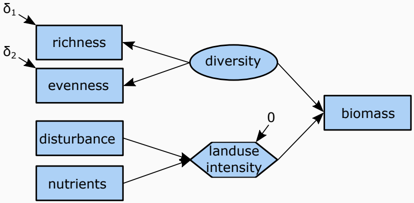

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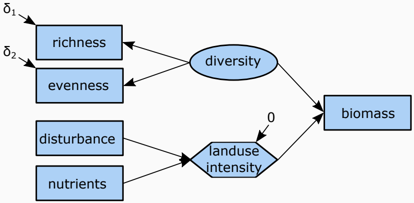

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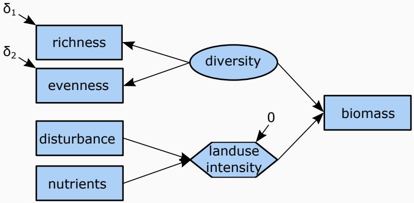

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- Composites are often shown as hexangular shapes or ellipses (latent composites).

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- 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 variable.

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    3) Result is a corrected lavaan object.

Spatial autocorrelation

Questions?