Introduction to Structural Equation Models

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A multitrophic perspective on biodiversity–ecosystem functioning research

nature ecology & evolution ARTICLES
https://doi.org/10.1038/s41559-020-1280-9

Check for updates

The results of biodiversity–ecosystem functioning experiments are realistic

PROCEEDINGS B
rspb.royalsocietypublishing.org

The strength of the biodiversity–ecosystem function relationship depends on spatial scale

nature COMMUNICATIONS

ARTICLE
Received 12 Nov 2014 | Accepted 17 Mar 2015 | Published 24 Apr 2015 DOI: 10.1038/ncomms7936 OPEN

Biodiversity enhances ecosystem multifunctionality across trophic levels and habitats

ECOLOGY LETTERS
Ecology Letters, (2020) **23**: 757–776 doi: 10.1111/ele.13456

REVIEWS AND SYNTHESES

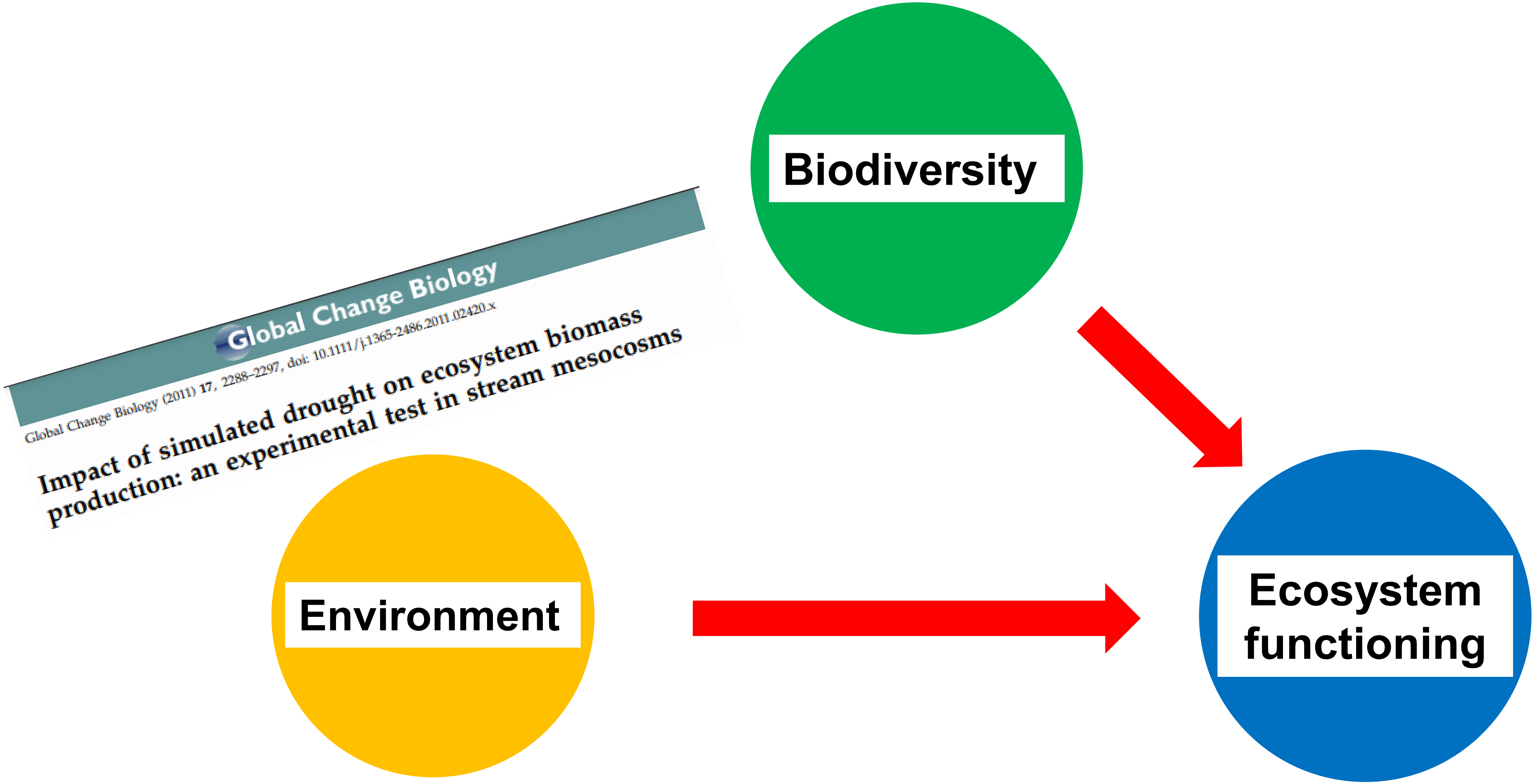
Scaling-up biodiversity-ecosystem functioning research

LETTER
doi:10.1038/nature10282

High plant diversity is needed to maintain ecosystem services

Biodiversity – Ecosystem Functioning

Environment – Ecosystem Functioning



Global Change Biology

Global Change Biology (2011) 17, 2288–2297, doi: 10.1111/j.1365-2486.2011.02420.x

Impact of simulated drought on ecosystem biomass production: an experimental test in stream mesocosms

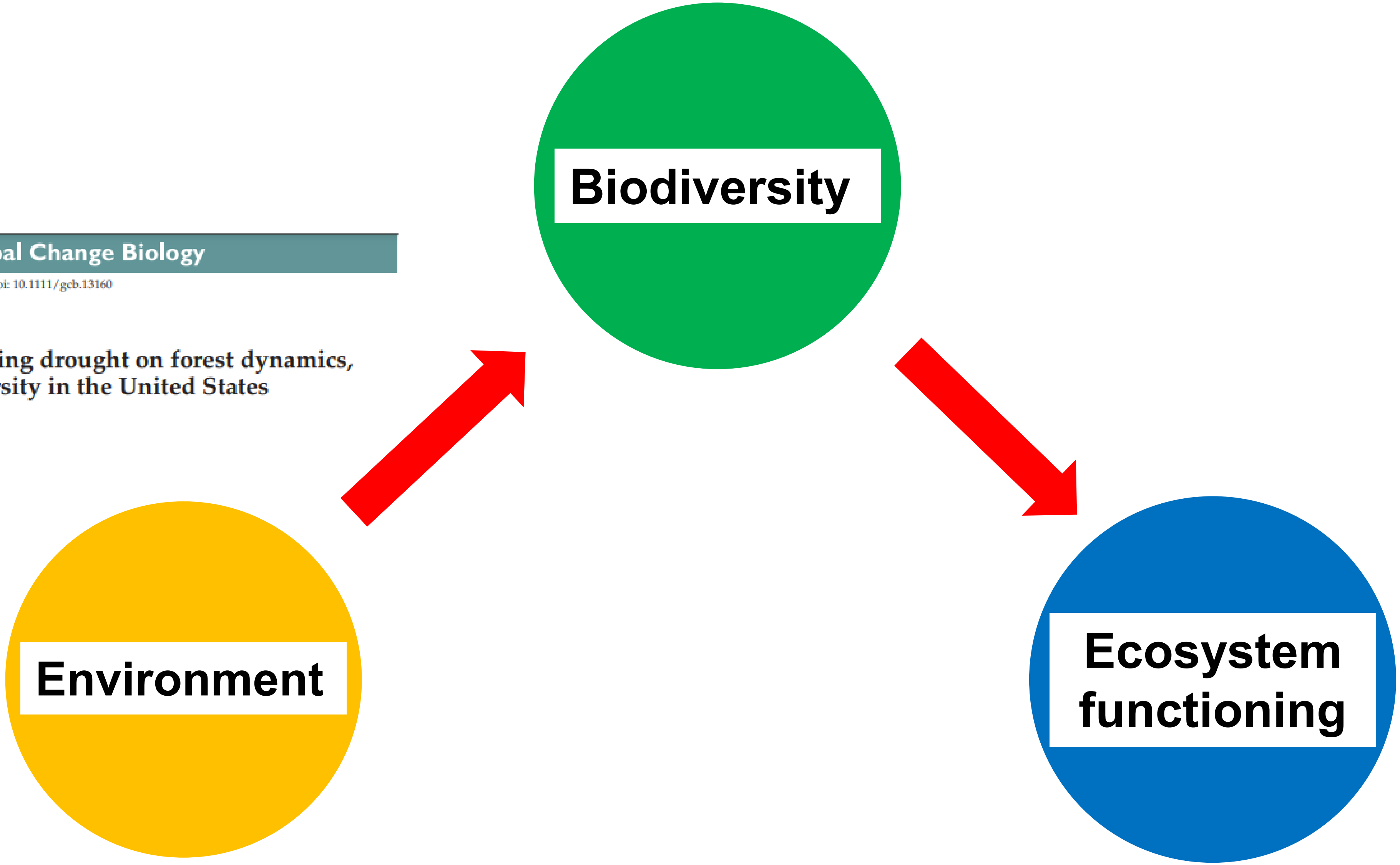
Environment - Biodiversity

Global Change Biology

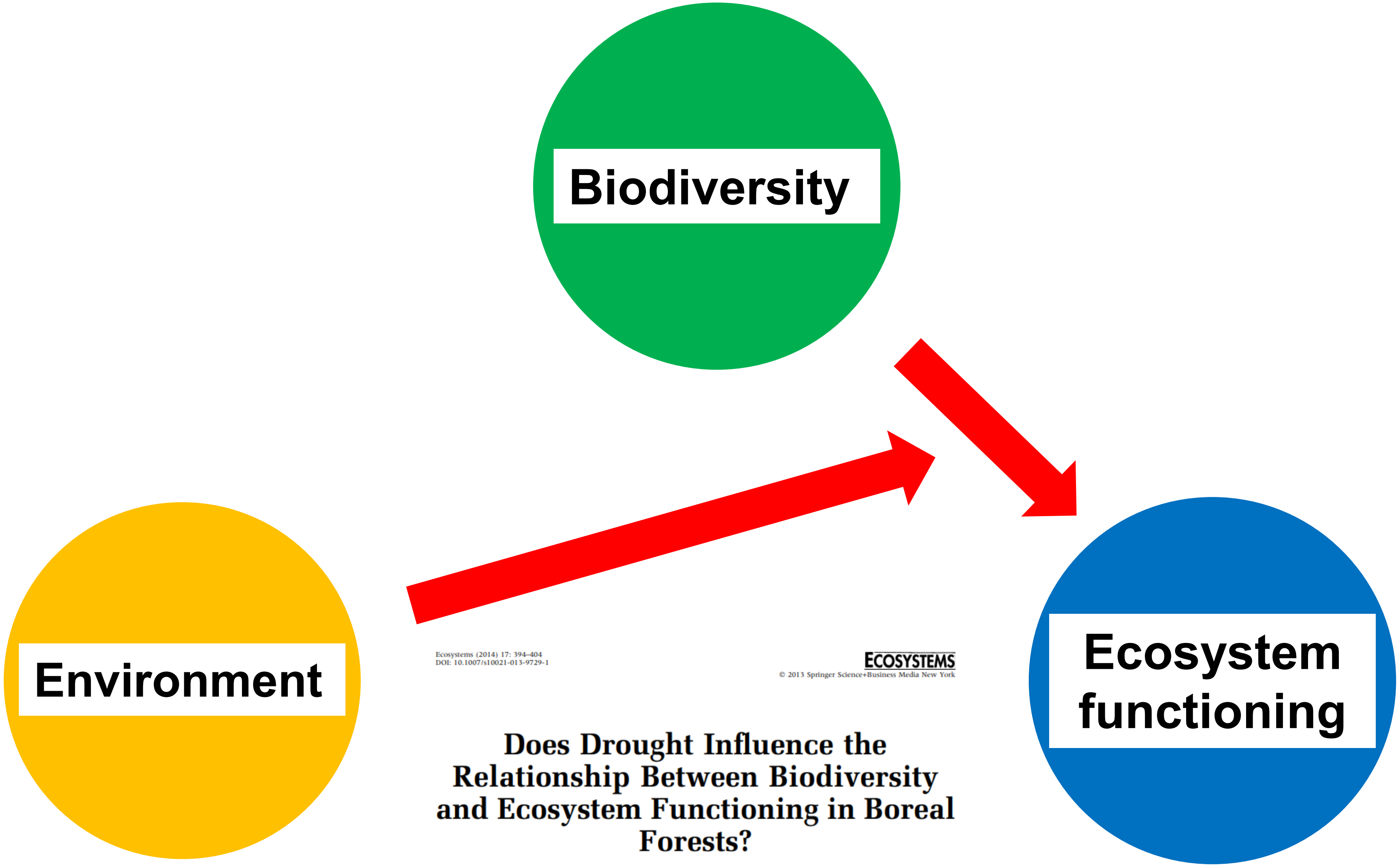
Global Change Biology (2016) **22**, 2329–2352, doi: 10.1111/gcb.13160

SPECIAL FEATURE

The impacts of increasing drought on forest dynamics, structure, and biodiversity in the United States



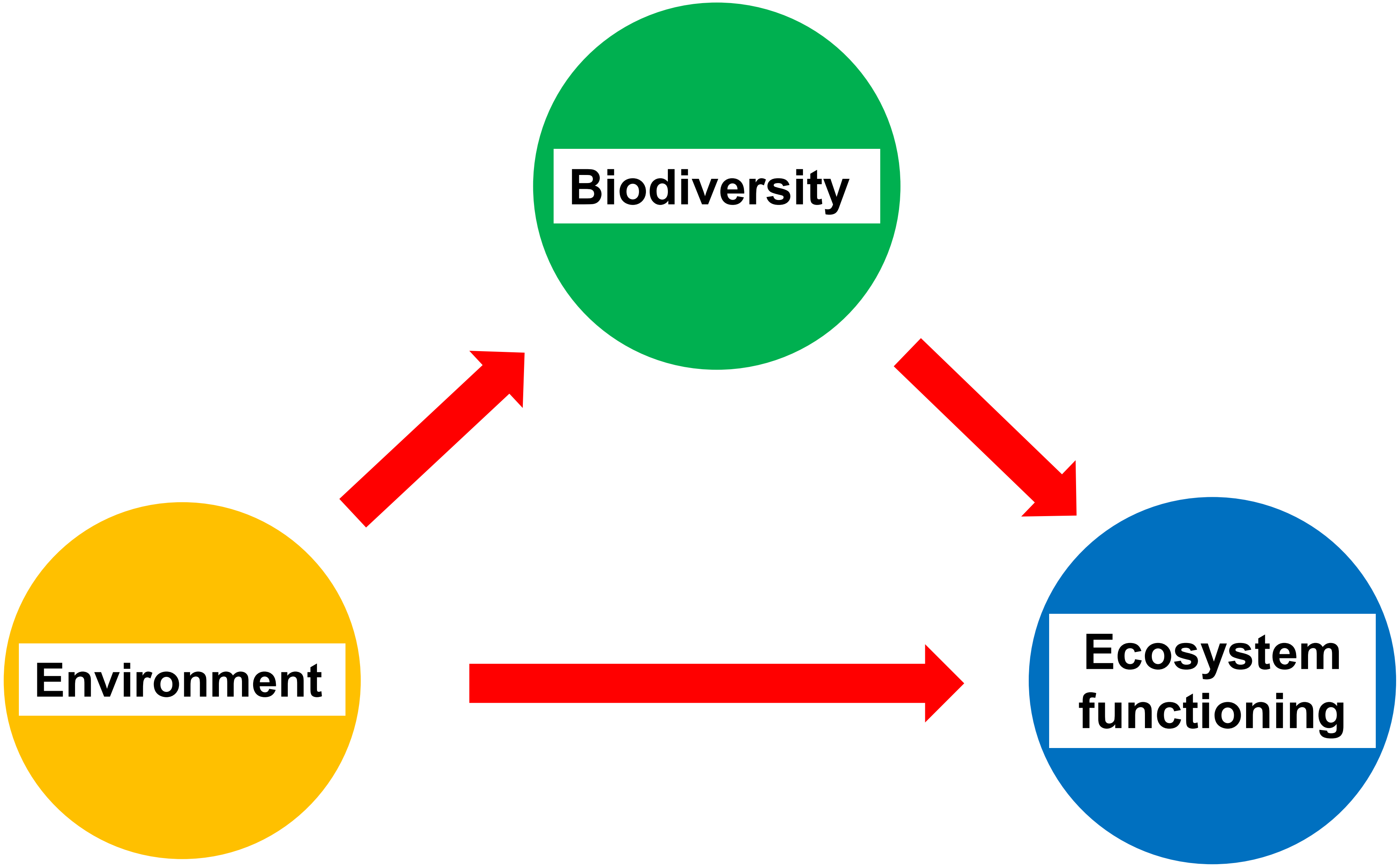
Environment * Biodiversity



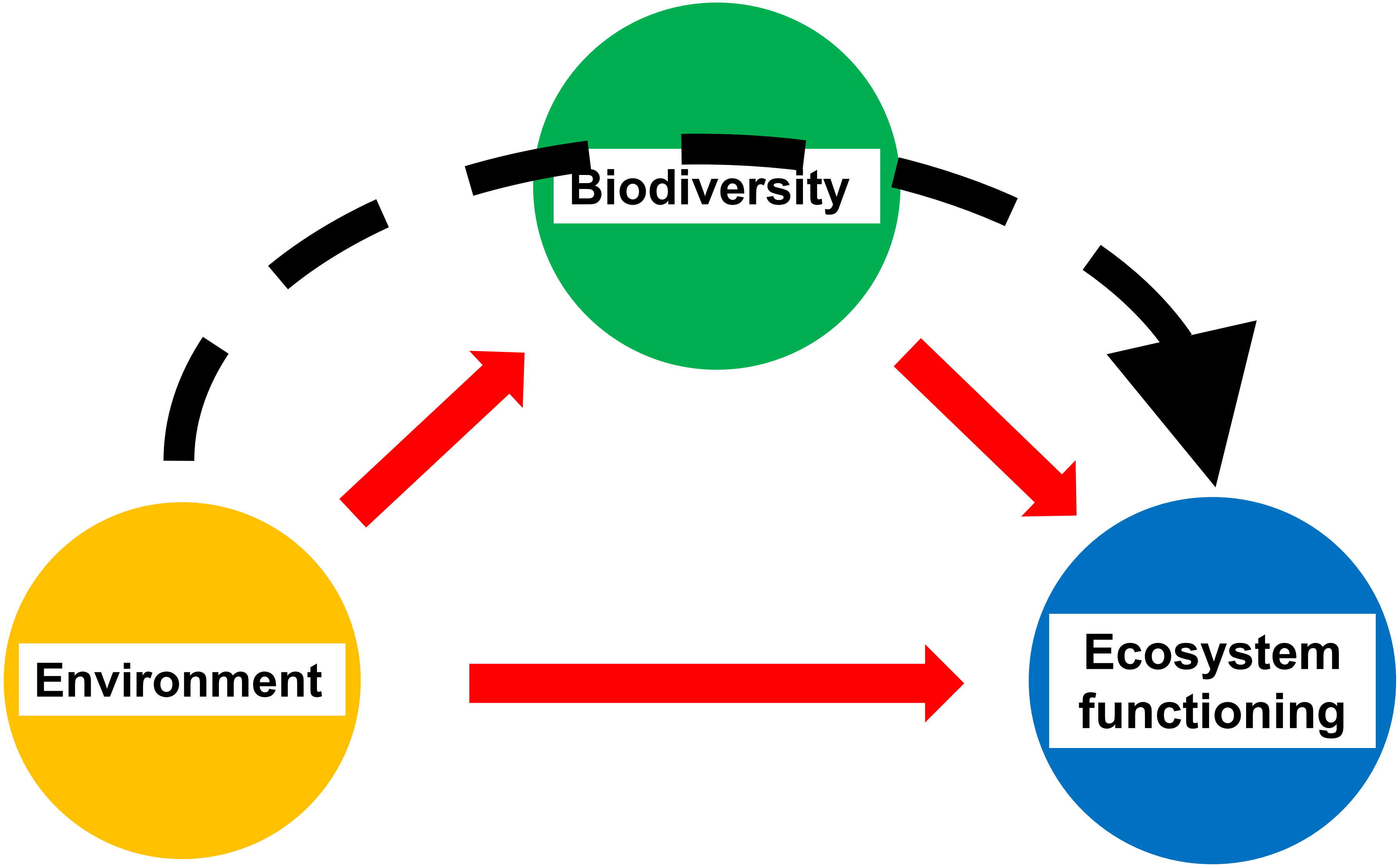
Ecosystems (2014) 17: 394–404
DOI: 10.1007/s10021-013-9729-1
ECOSYSTEMS

Does Drought Influence the Relationship Between Biodiversity and Ecosystem Functioning in Boreal Forests?

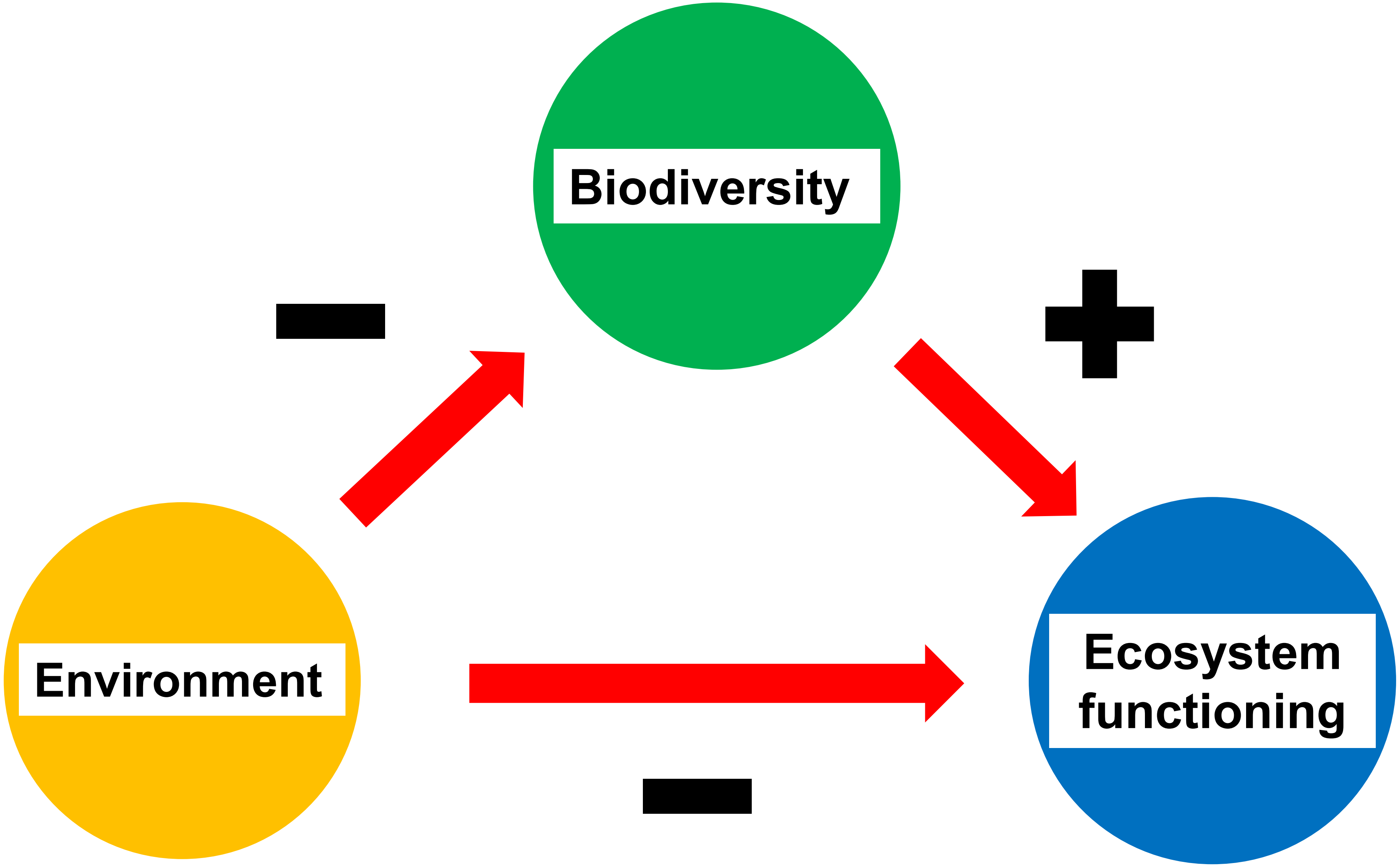
Environment – Biodiversity – Functioning



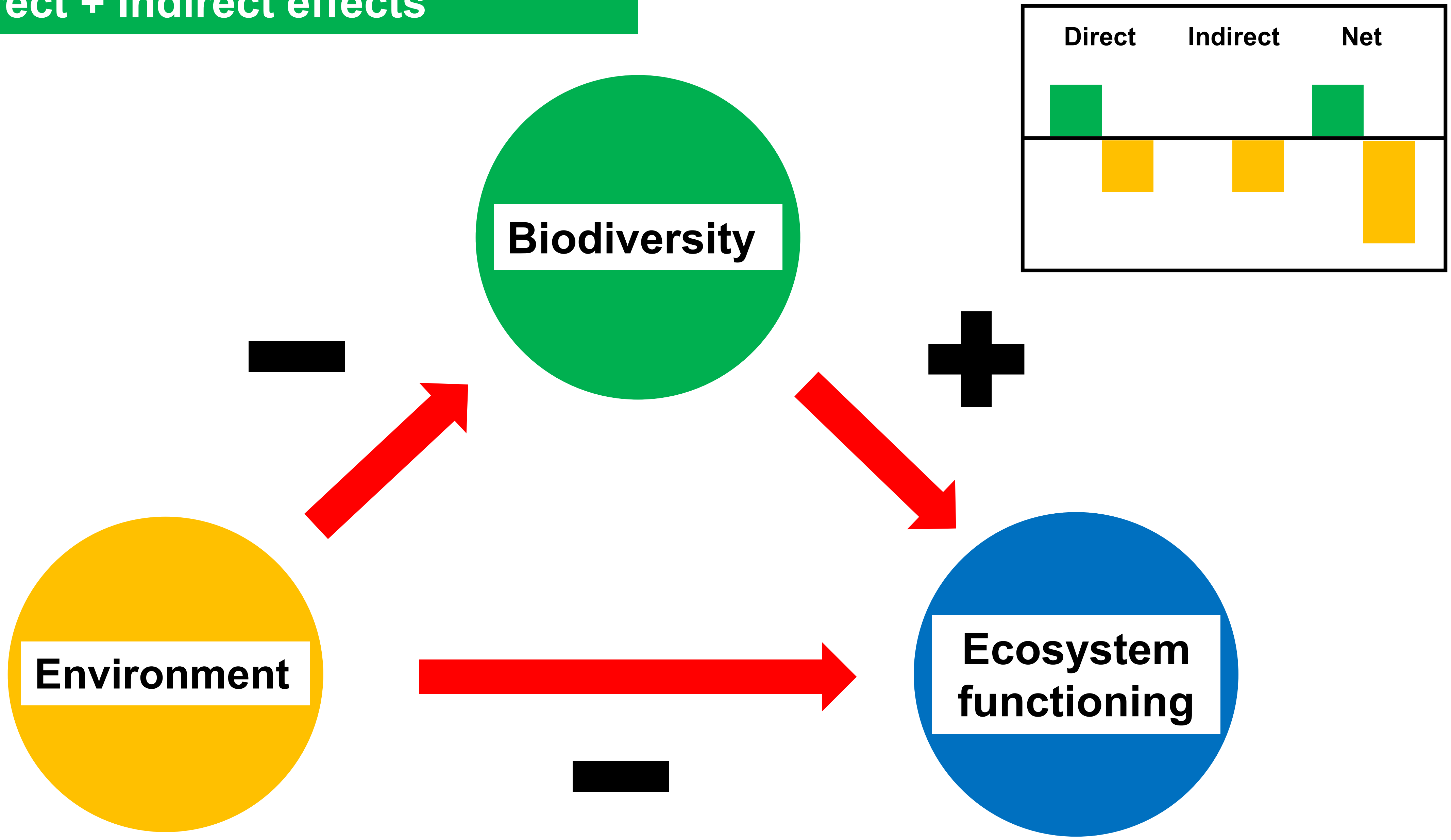
Indirect effects



Direct + Indirect effects



Direct + Indirect effects

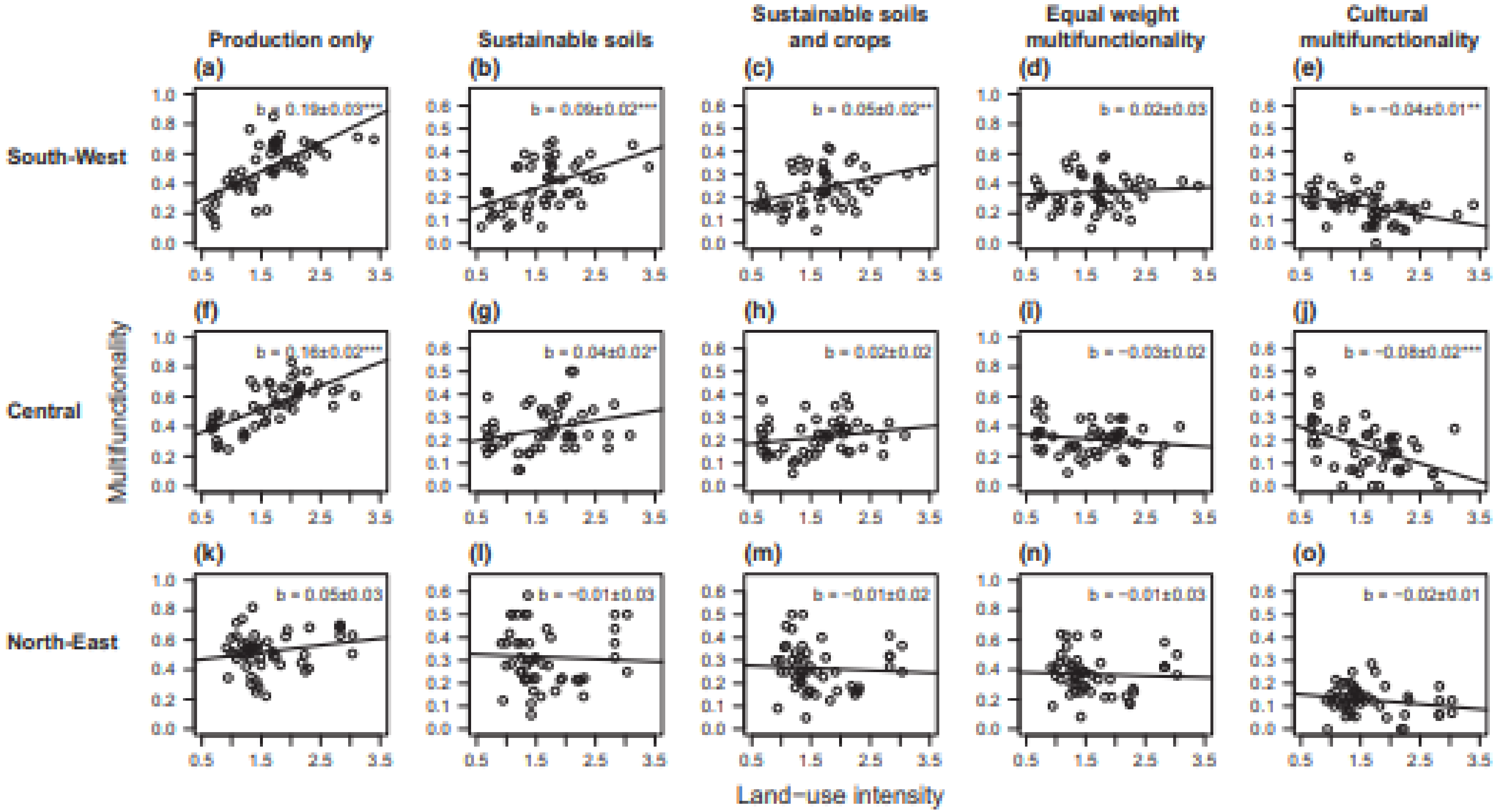


Indirect effects matter

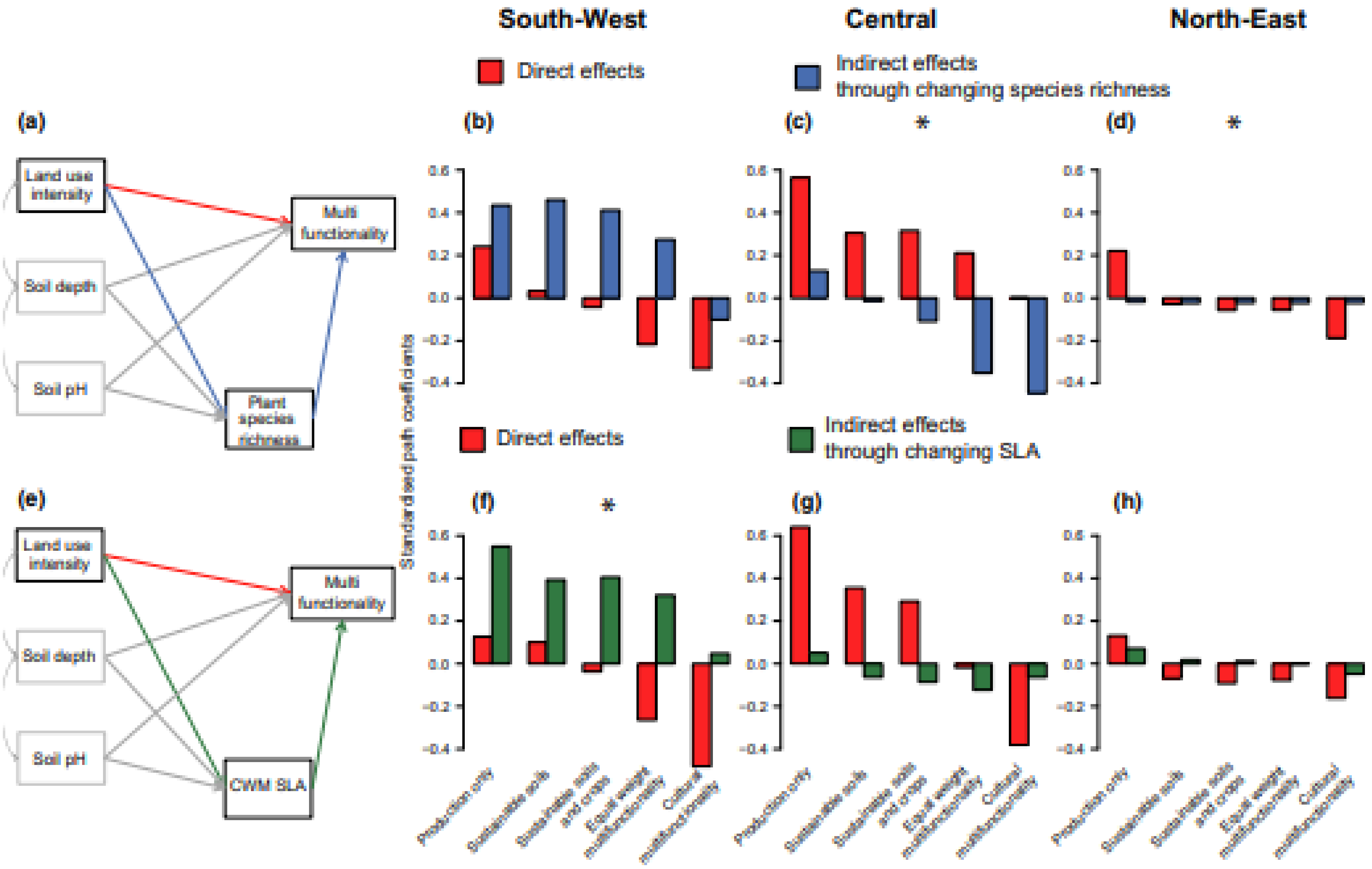
ECOLOGY LETTERS
Ecology Letters, (2015) 18: 834–843 doi: 10.1111/ele.12469

LETTER

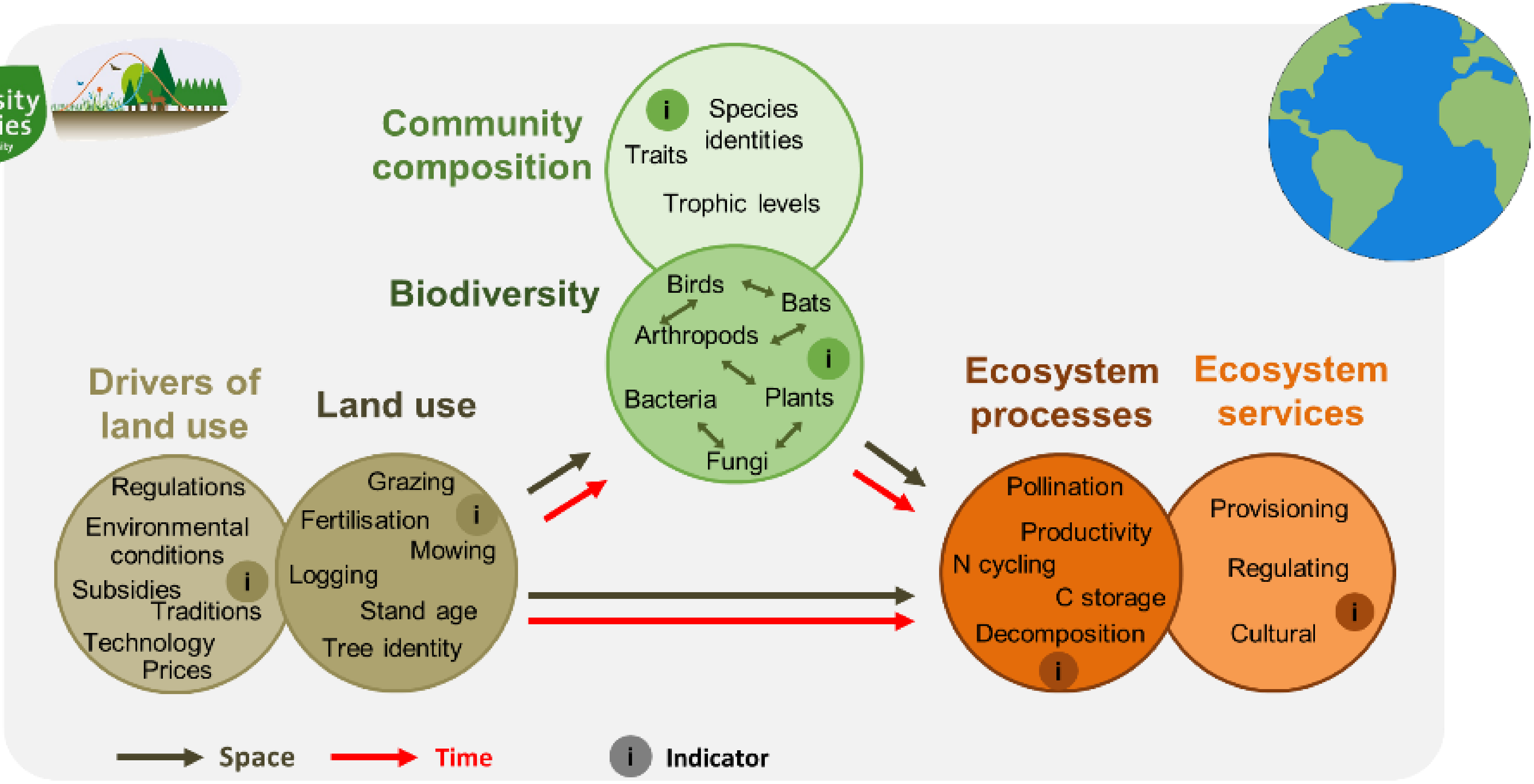
Land use intensification alters ecosystem multifunctionality via loss of biodiversity and changes to functional composition



Indirect effects matter



Never-ending complexity



Everything depends on everything

Phylogenetic, functional, and taxonomic richness have both positive and negative effects on ecosystem multifunctionality

LETTER

https://doi.org/10.1038/s41586-018-0627-8

Biodiversity increases and decreases ecosystem stability

Research

Oikos 118: 1892–1900, 2009
doi: 10.1111/j.1600-0706.2009.17556.x,

Subject Editor: Ulrich Brose. Accepted 26 May 2009

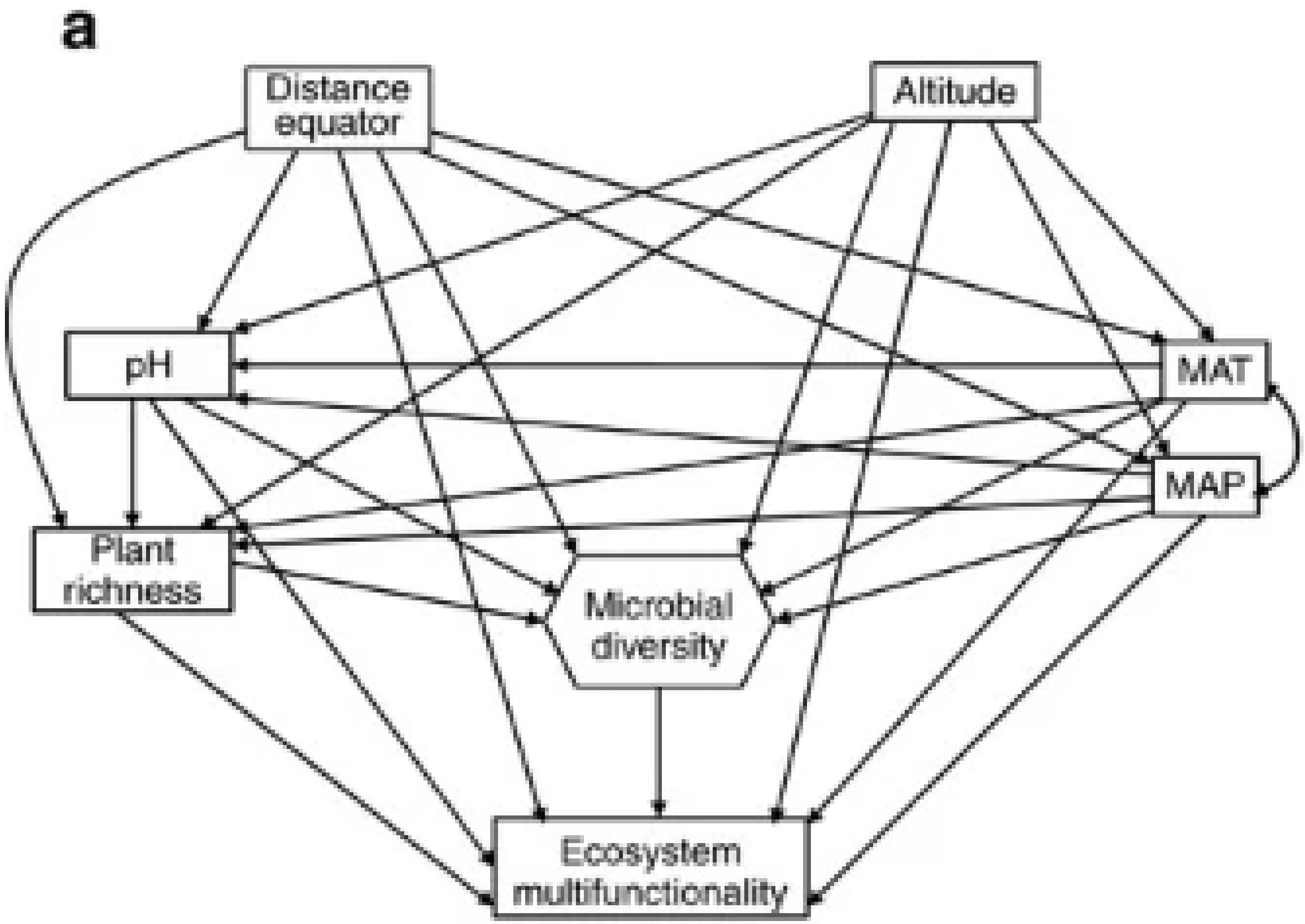
Context dependency of relationships between biodiversity and ecosystem functioning is different for multiple ecosystem functions

Unraveling the complexity

ARTICLE

Received 25 Jun 2015 | Accepted 23 Dec 2015 | Published 28 Jan 2016 DOI: 10.1038/ncomms10541 OPEN

Microbial diversity drives multifunctionality in terrestrial ecosystems



Stop and think for a second

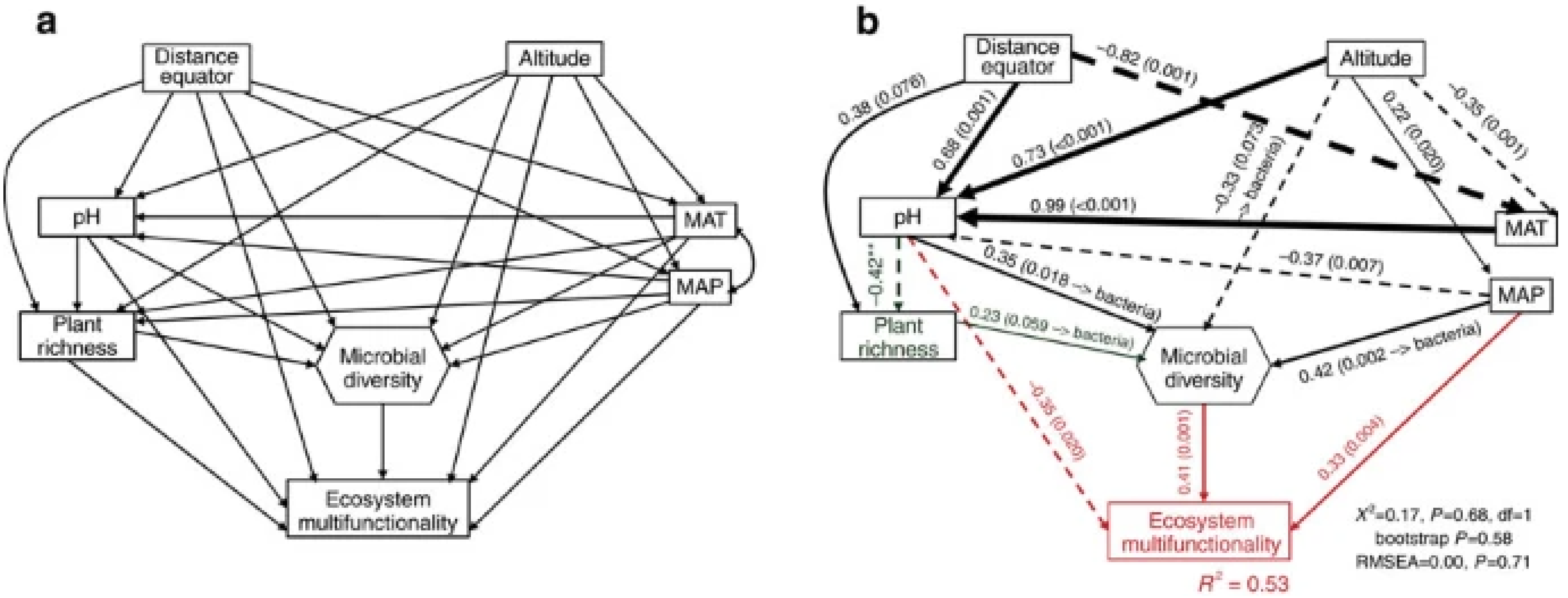
Change ecology for a more relaxing science

Or

Try to disentangle the ecological mess

Unraveling the complexity

Figure 4: Direct and indirect effects of space, climate, soil pH, plant richness and microbial diversity on ecosystem multifunctionality in global drylands.



Structural Equation Models

(SEM)

Give credit to the experts

Jim Grace

Special Section: Observational Studies

Structural Equation Modeling for Observational Studies

JAMES B. GRACE,[1] *United States Geological Survey National Wetlands Research Center, 700 Cajundome Boulevard, Lafayette, LA 70506, USA*

Ecological Monographs, 80(1), 2010, pp. 67–87

On the specification of structural equation models for ecological systems

JAMES B. GRACE,[1,4] T. MICHAEL ANDERSON,[2,5] HAN OLFF,[2] AND SAMUEL M. SCHEINER[3]

Ecology, 101(4), 2020, e02962

Scientist's guide to developing explanatory statistical models using causal analysis principles

JAMES B. GRACE[1,3] AND KATHRYN M. IRVINE[2]

Give credit to the experts

USGS
science for a changing world

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Wetland and Aquatic Research Center

Quantitative Analysis Using Structural Equation Modeling

Overview Related Science

USGS scientists have been involved for a number of years in the development and use of Structural Equation Modeling (SEM). This methodology represents an approach to statistical modeling that focuses on the study of complex cause-effect hypotheses about the mechanisms operating in systems. SEM is increasingly used in ecological and environmental studies and this site seeks to provide educational materials related to that enterprise. This site serves up tutorials, exercises, and examples designed to help researchers learn and apply SEM. Please click on the “Science” tab to learn more.

How to Use This Site

This site provides tutorials, examples, and exercises for those wishing to learn basic or specialized structural equation modeling methods. A description of what has been added and when can be found in the document **What's New**.

Contact

Comments on existing tutorials and suggestions for additional tutorials can be sent to sem@usgs.gov. Please note that while emails to this address will be read, we cannot provide individual replies given time constraints. For this we apologize, but we do hope the materials provided will be helpful.

Status - Active

Contacts

James Grace

Research Ecologist
Wetland and Aquatic Research Center
Email: gracej@usgs.gov
Phone: 337-298-1671

Explore More Science:

tutorials
structural equation modeling
SEM
quantitative analysis
statistics

Give credit to the experts

Jon Lefcheck

Methods in Ecology and Evolution

British Ecological Society

Methods in Ecology and Evolution 2015 doi: 10.1111/2041-210X.12512

APPLICATION

PIECEWISESEM: Piecewise structural equation modelling in R for ecology, evolution, and systematics

Jonathan S. Lefcheck*

Give credit to the experts

SAMPLE(ECOLOGY)

RANDOM THOUGHTS ON ECOLOGY, BIODIVERSITY, AND SCIENCE IN GENERAL

ABOUT ME • PUBLICATIONS • CV • PHOTOS • CONTACT • BLOG

TEACHING

STRUCTURAL EQUATION MODELING

This introductory short course is designed to familiarize participants with the philosophy and practice of structural equation modeling / confirmatory path analysis. All course materials, including lectures, datasets, and R scripts, are available for download below. Thanks to Jarrett Byrnes for generous donation of lecture slides: visit his site for more materials!

READINGS

Grace et al. (2013) "Guidelines for a graph-theoretic implementation of structural equation modeling." *Ecosphere*. PDF

Search …

- LATEST TWEETS -

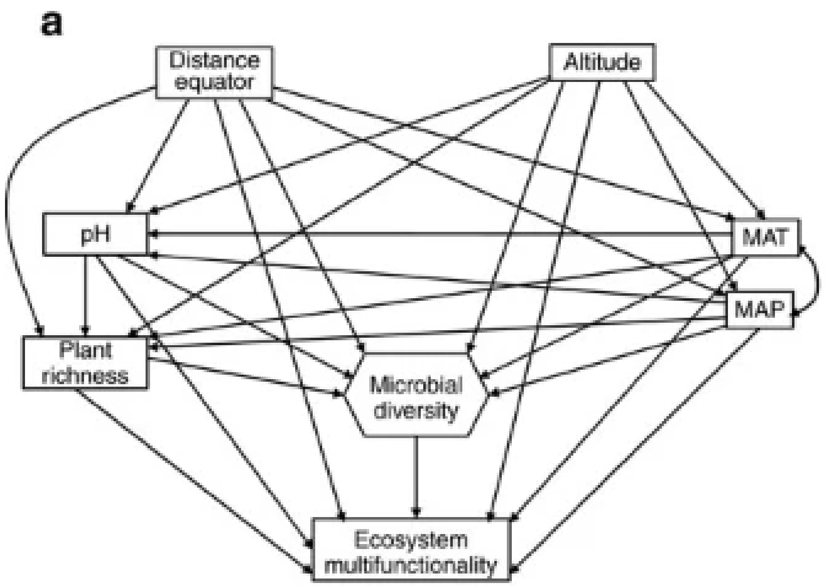
RT @stefanako71: Imagine doing something so wacky that prompts Pauly and Hilborn to be in total agreement. 2 days ago

RT @bethaniey15: Don't forget to email me before 16 May if you would like to apply for this PhD opportunity on understanding the role of #s… 3 days ago

Structural Equation Models

Structural Equation Model is a **modelling framework** for building and evaluating hypotheses about cause-effect connections in systems

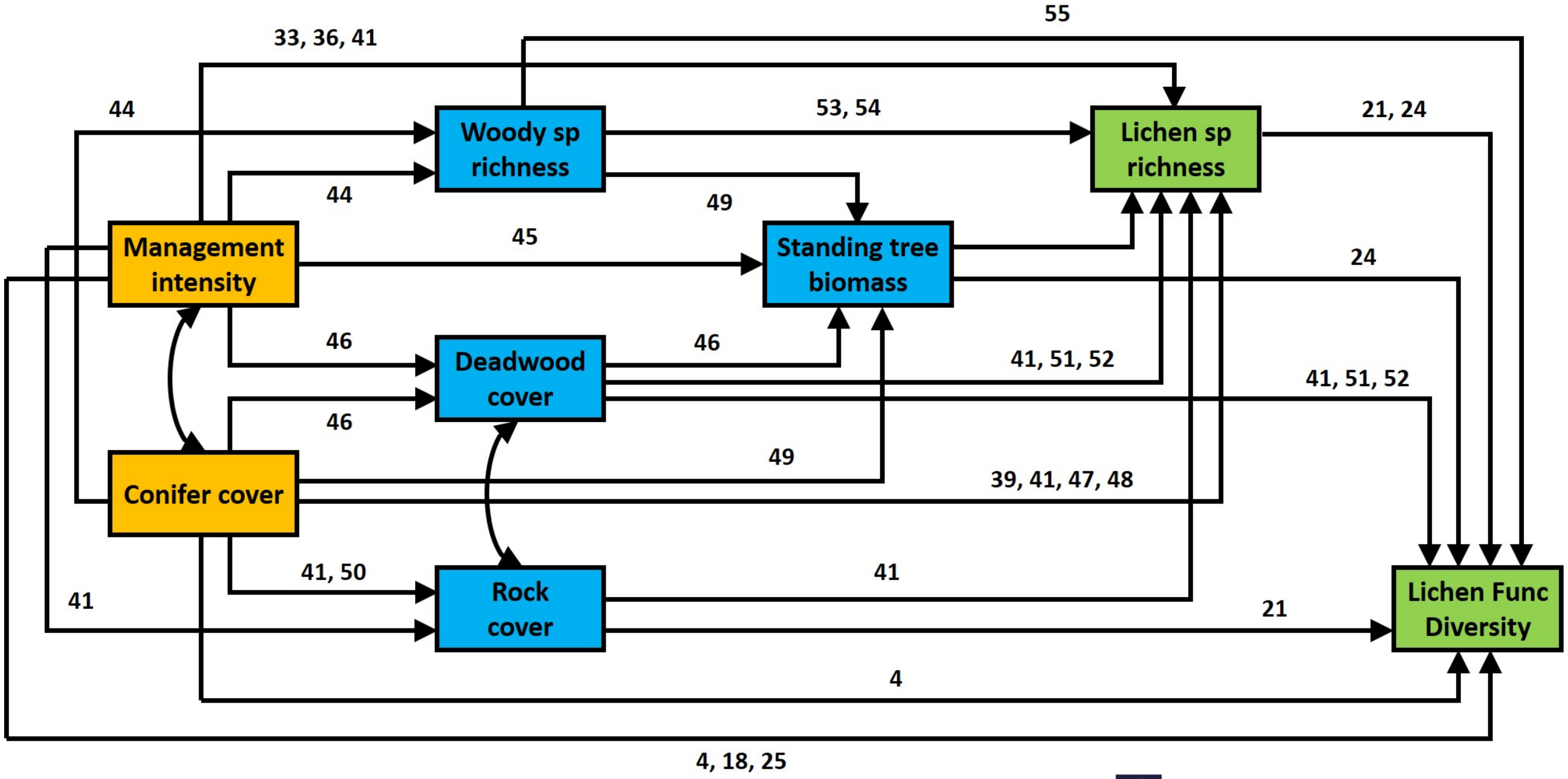
It is a **system level** approach to explore the interrelations among the components of the study system



Warning with modelling

Structural Equation Model is not a proof of **causality**

All the causal relations must be built based on theoretical knowledge



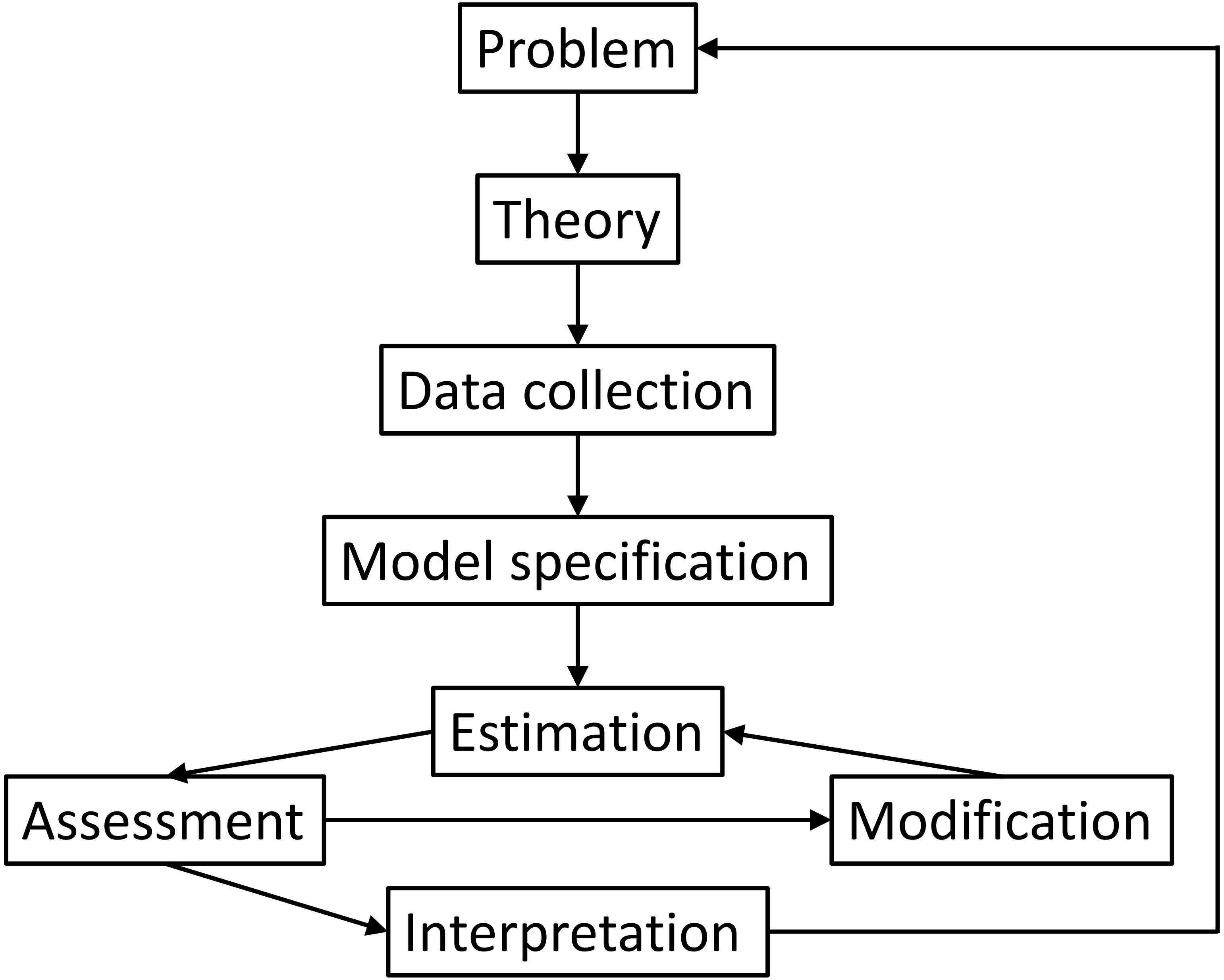
microorganisms

MDPI

Article

Direct and Indirect Effects of Management Intensity and Environmental Factors on the Functional Diversity of Lichens in Central European Forests

Modelling process



Graphical models

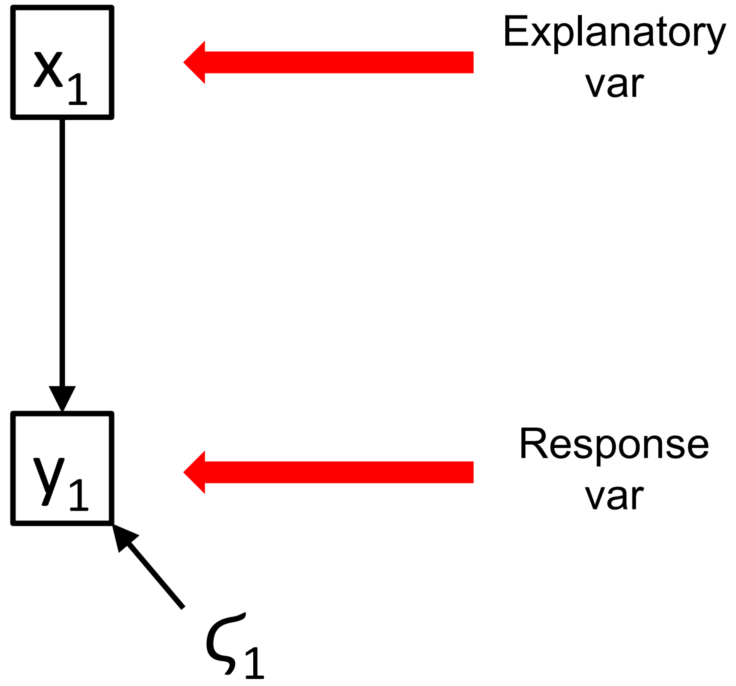
Equational form

$$y_1 = f(x_1)$$

Response var

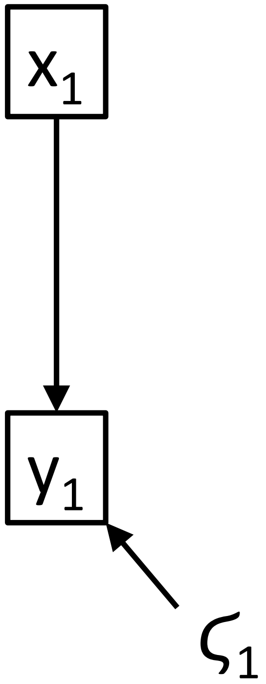
Explanatory var

Graphical form



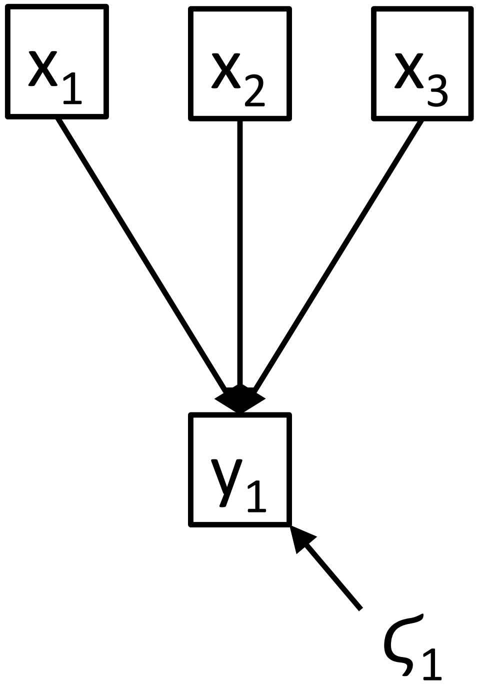
Graphical models for stats

Regression model



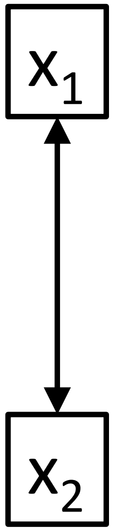
$y_1 = a + x_1$

Mult Regression model



$y_1 = a + x_1 + x_2 + x_3$

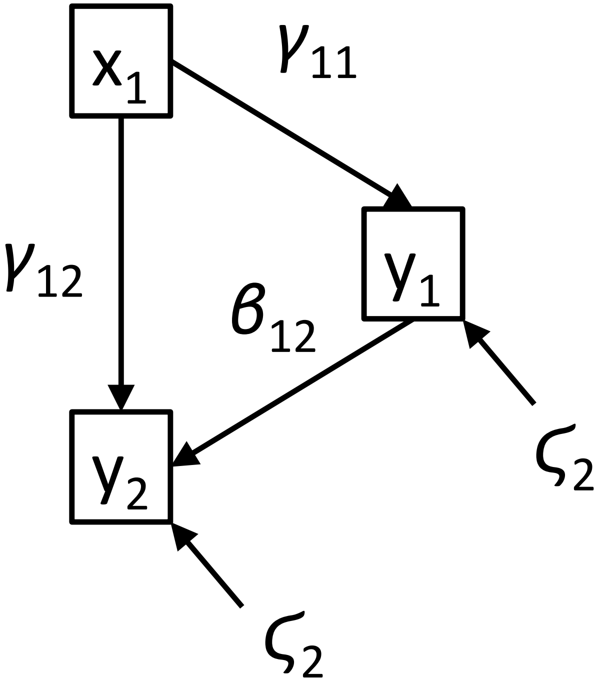
Correlation



$x_1 \sim x_2$

SEM test multiple equations

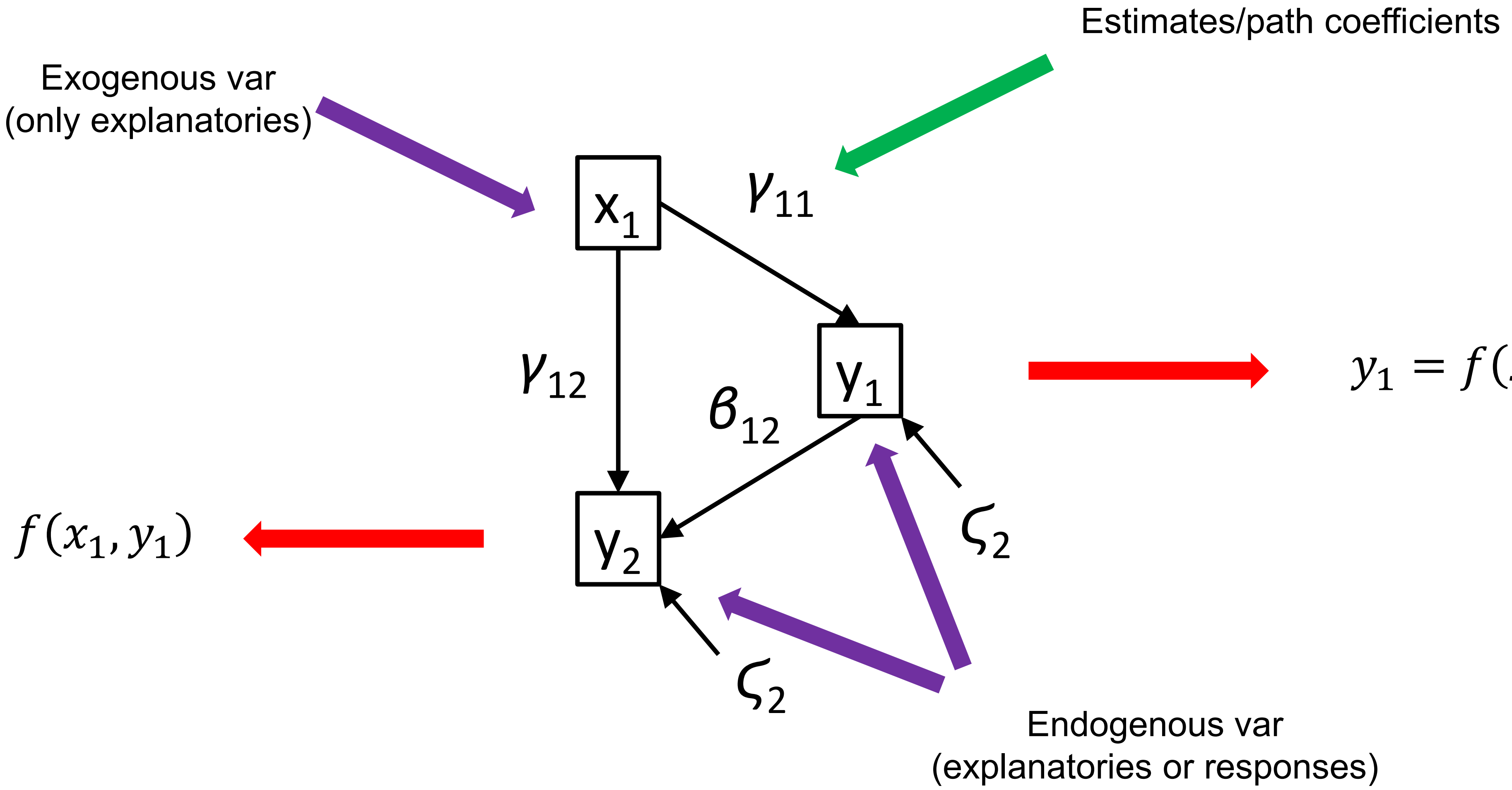
Linear-normal relations



$$y_1 = f(x_1)$$

$$y_2 = f(x_1, y_1)$$

SEM test multiple equations

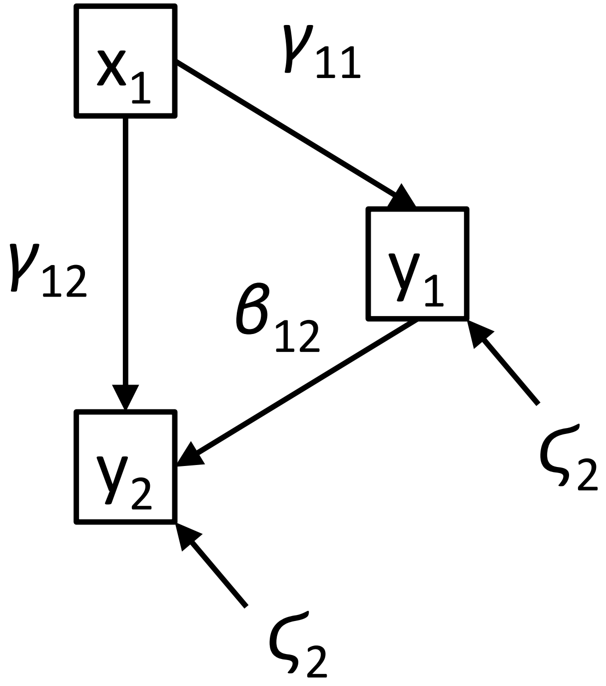


$$y_1 = f(x_1)$$

$$y_2 = f(x_1, y_1)$$

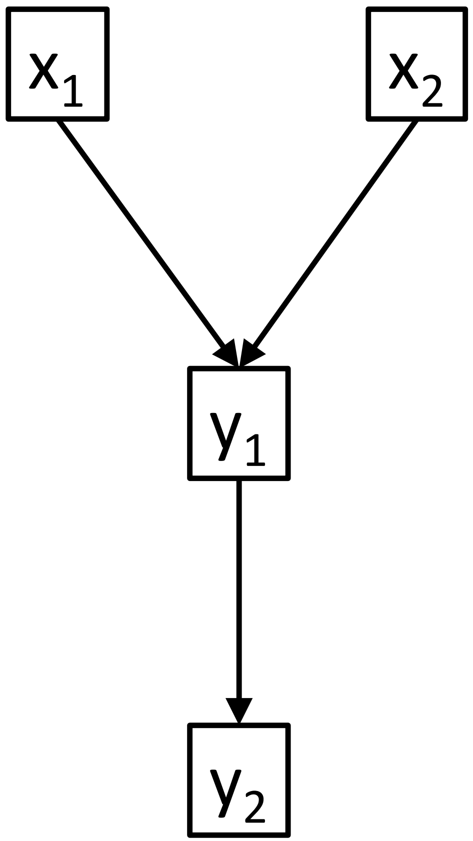
SEM test multiple equations

Direct effect $X_1 \rightarrow Y_2 = \gamma_{12}$

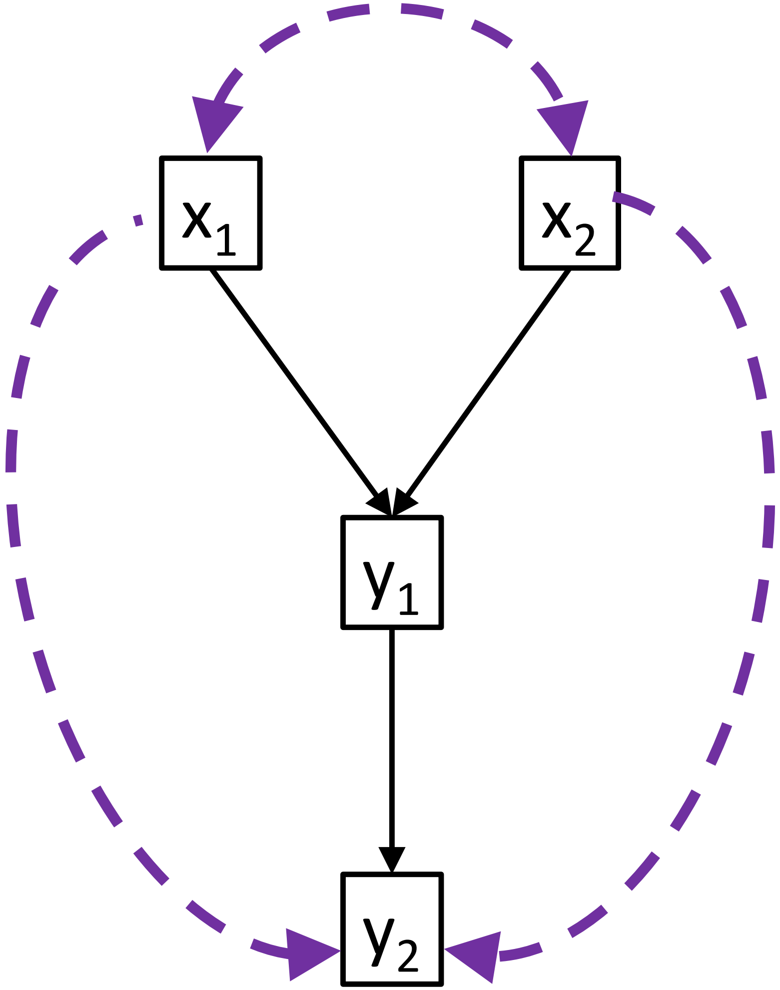


Indirect effect $X_1 \rightarrow Y_2 = \gamma_{11} * \beta_{12}$

Relation + Absence of relations



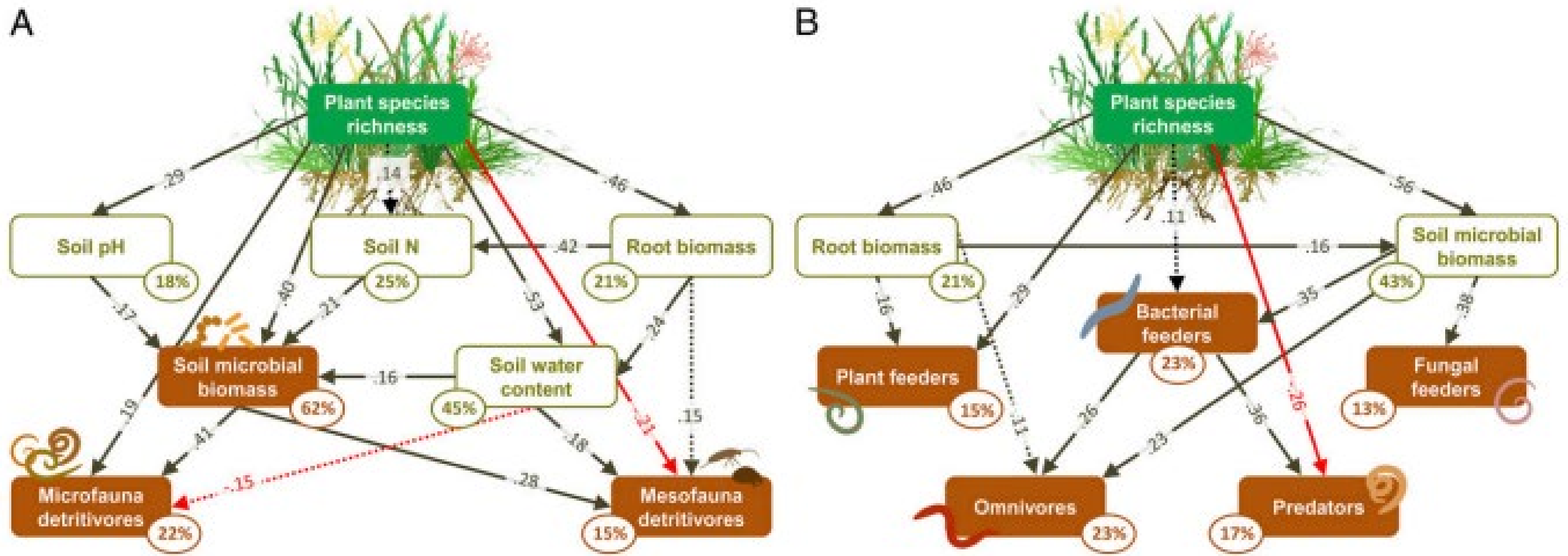
Non saturated



Saturated (if included)

Nice pictures for your work!

Plant diversity effects on soil food webs are stronger than those of elevated CO_2 and N deposition in a long-term grassland experiment

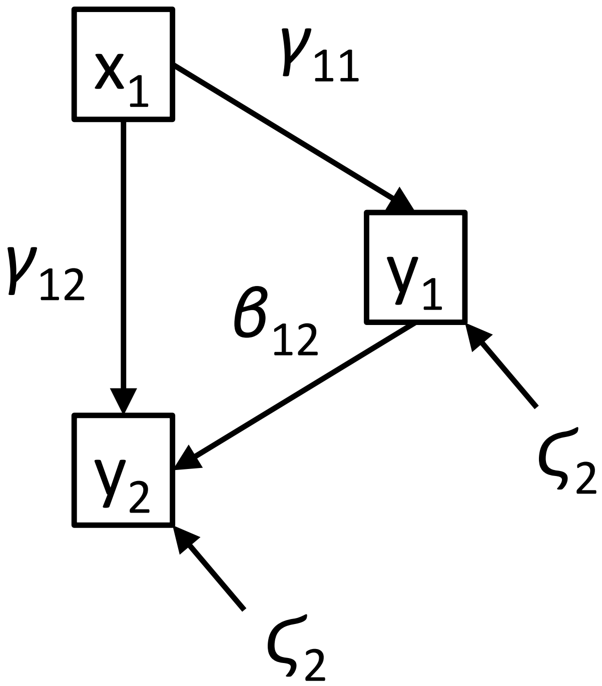


SEM is based in covariance matrix

Covariance matrix is a square matrix including the covariance between elements in a vector

$$\begin{bmatrix} \text{Var 1} \\ \dots \\ \text{Var x} \end{bmatrix} \longrightarrow \begin{bmatrix} \text{Cov 11} & \dots & \text{Cov 1x} \\ \dots & \dots & \dots \\ \text{Cov x1} & \dots & \text{Cov xx} \end{bmatrix}$$

SEM is based in covariance matrix



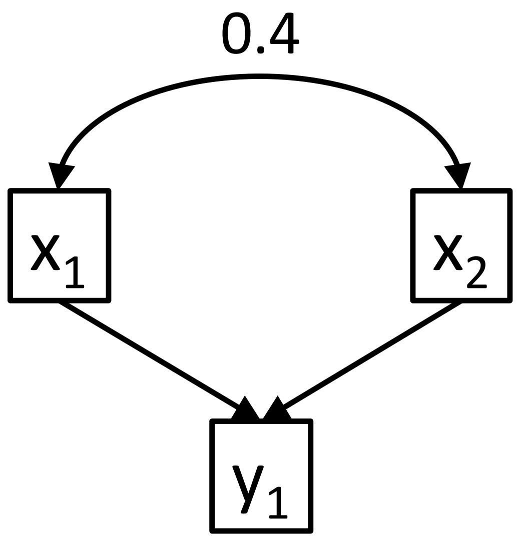
Standardized covariances (correlation)

	X_1	Y_1	Y_2
X_1	1.0		
Y_1	0.4	1.0	
Y_2	0.5	0.6	1.0

γ_{12}

Path calculation

Correlations are just covariances

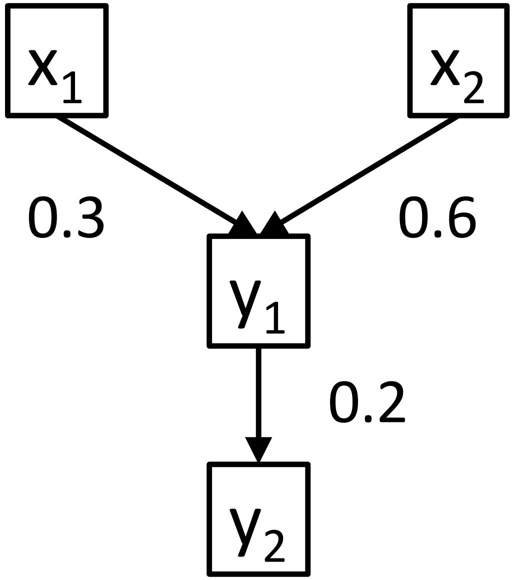


	X_1	X_2	Y_1
X_1	1.0		
X_2	0.4	1.0	
Y_1	0.5	0.6	1.0

Path calculation

Correlations are just covariances

Direct paths are just covariances



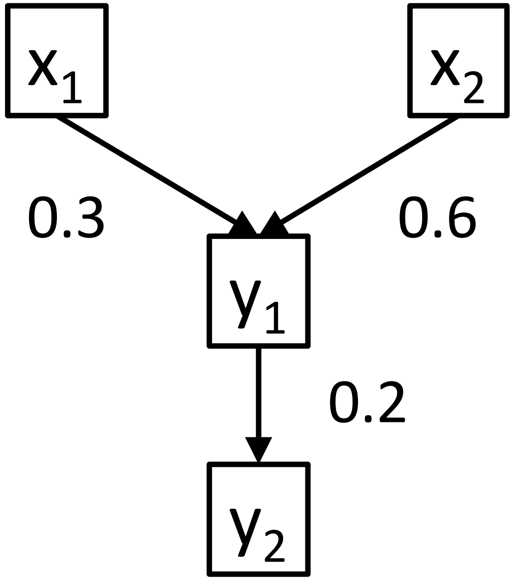
	X_1	X_2	Y_1	Y_2
X_1	1.0			
X_2	0	1.0		
Y_1	0.3	0.6	1.0	
Y_2	0.06	0.12	0.2	1.0

Path calculation

Correlations are just covariances

Direct paths are just covariances

Compound paths are the product of covariances



$$X_1 \rightarrow Y_2 = 0.3 \ * 0.2 = 0.06$$

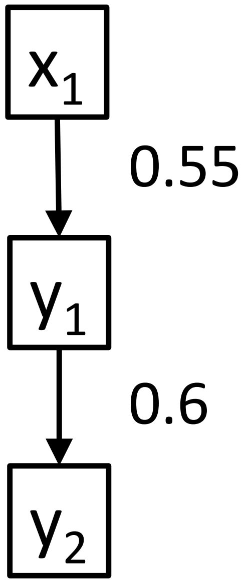
$$X_2 \rightarrow Y_2 = 0.6 \ * 0.2 = 0.12$$

	X_1	X_2	Y_1	Y_2
X_1	1.0			
X_2	0	1.0		
Y_1	0.3	0.6	1.0	
Y_2	0.06	0.12	0.2	1.0

Conditional independence

Compound paths can be different from covariance

$$X_1 \rightarrow Y_2 = 0.55 * 0.6 = 0.33 \neq 0.5$$



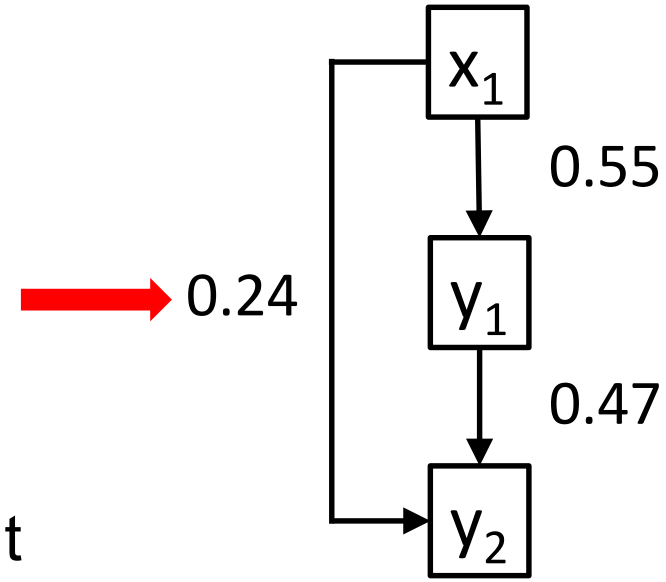
	X_1	Y_1	Y_2
X_1	1.0		
Y_1	0.55	1.0	
Y_2	0.5	0.6	1.0

Conditional independence

Compound paths can be different from covariance

$$X_1 \to Y_2 = 0.55 \, * 0.6 = 0.33 \neq 0.5$$

Partial effect



In this case, x_1 and y_2 are not conditional independent and additional paths are required

$$X_1 \to Y_2 = 0.55 \, * 0.47 + 0.24 = 0.26 + 0.24 = 0.5$$

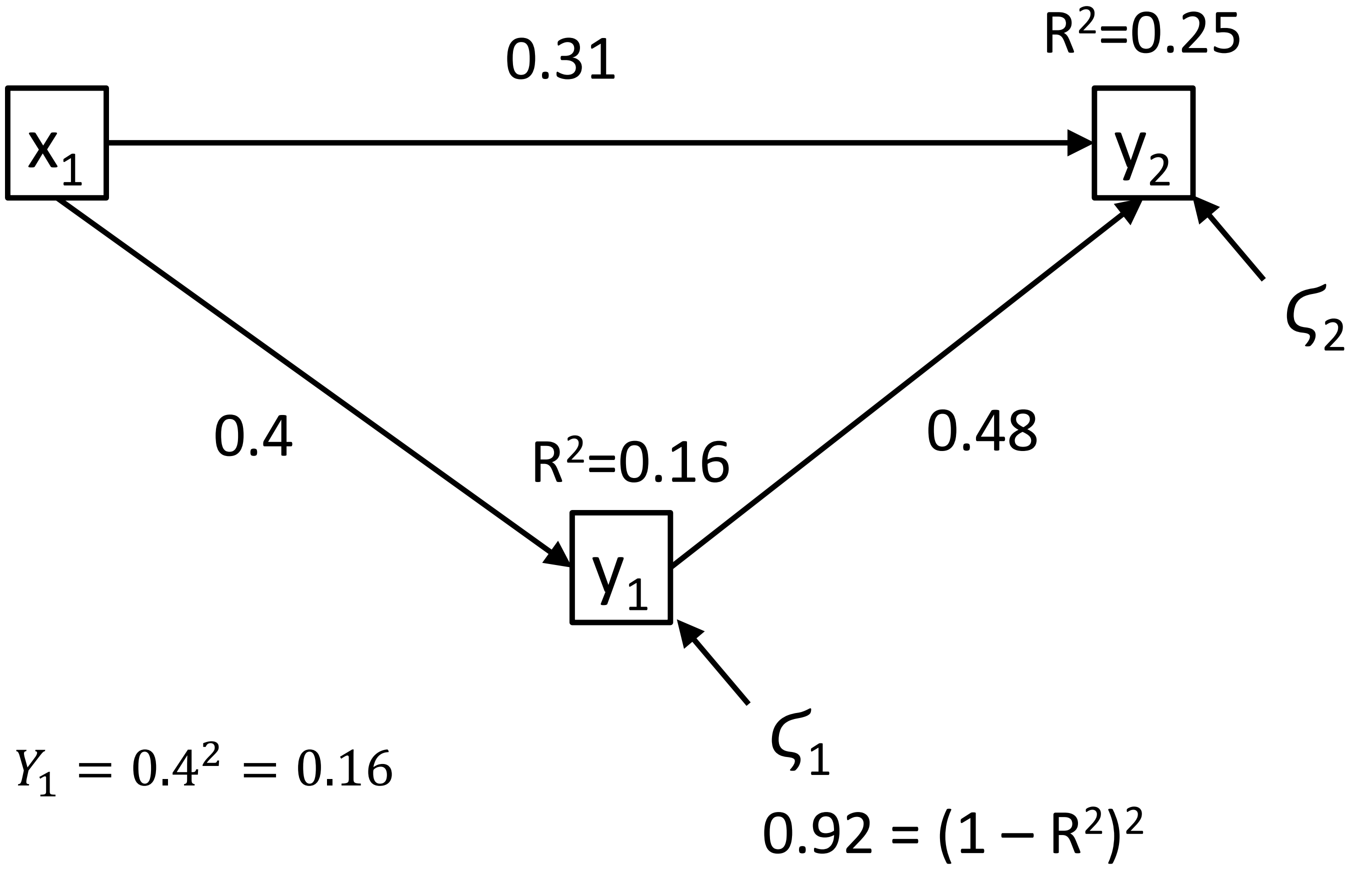
$$Y_1 \to Y_2 = 0.47 + 0.55 * 0.24 = 0.47 + 0.13 = 0.6$$

	X_1	Y_1	Y_2
X_1	1.0		
Y_1	0.55	1.0	
Y_2	0.5	0.6	1.0

Also considers correlations

Paths and errors

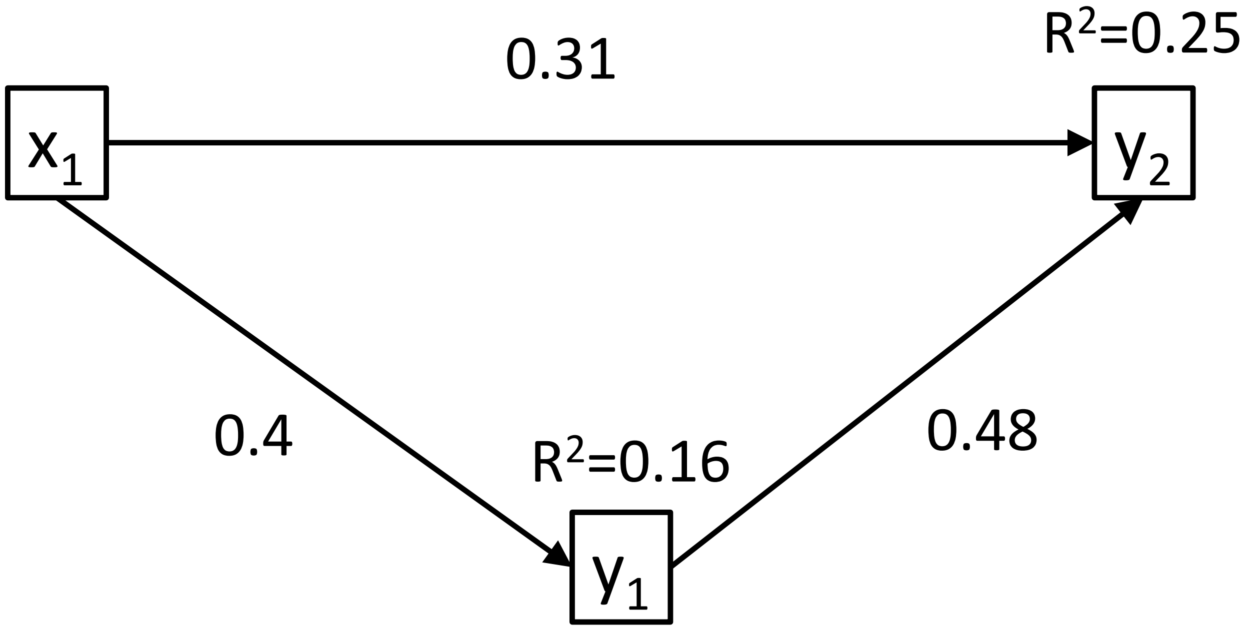
Errors represent influence of unmodeled factors



$Y_1 = 0.4^2 = 0.16$

Total effects

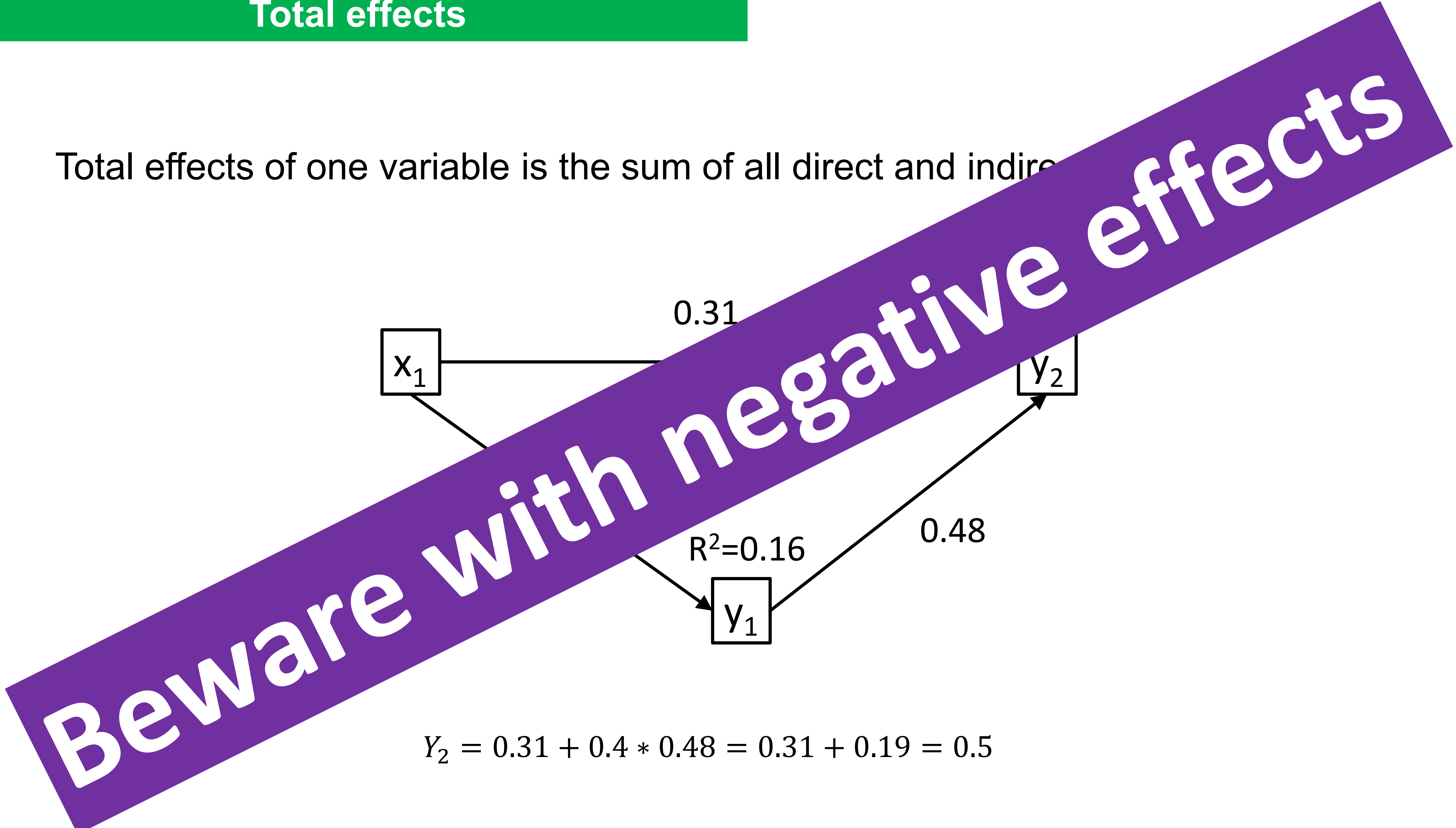
Total effects of one variable is the sum of all direct and indirect paths



$$Y_2 = 0.31 + 0.4 * 0.48 = 0.31 + 0.19 = 0.5$$

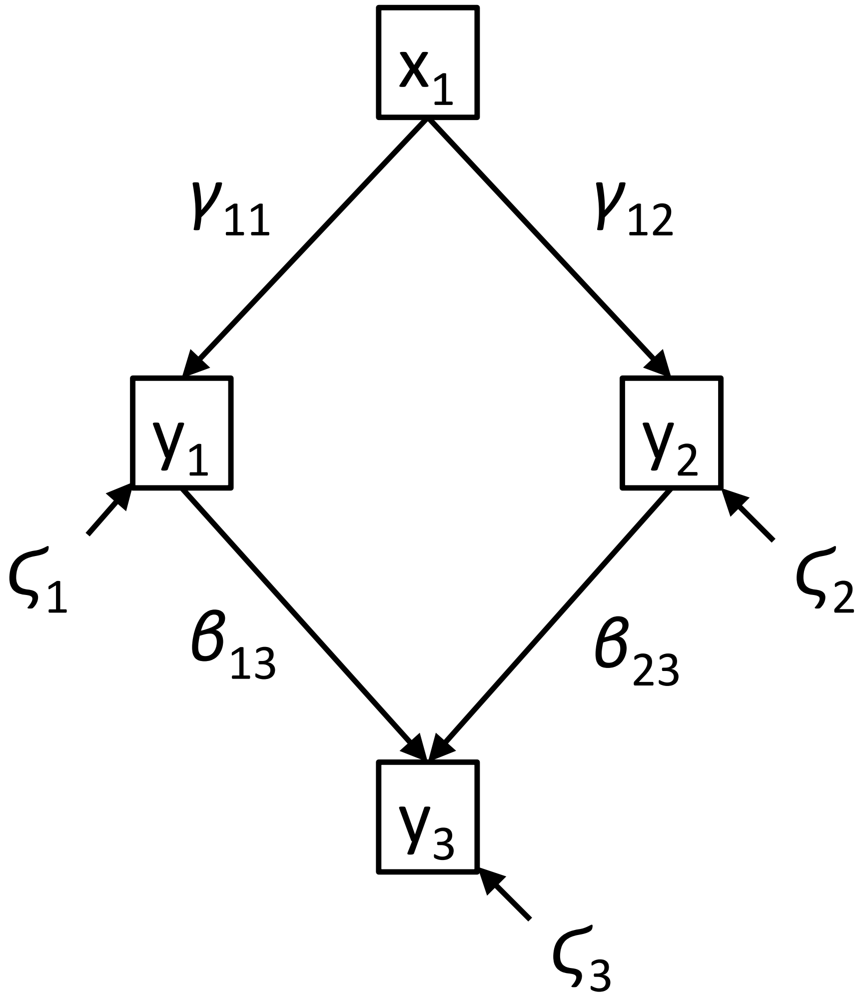
Total effects

Total effects of one variable is the sum of all direct and indire



$$Y_2 = 0.31 + 0.4 * 0.48 = 0.31 + 0.19 = 0.5$$

Calculating SEM

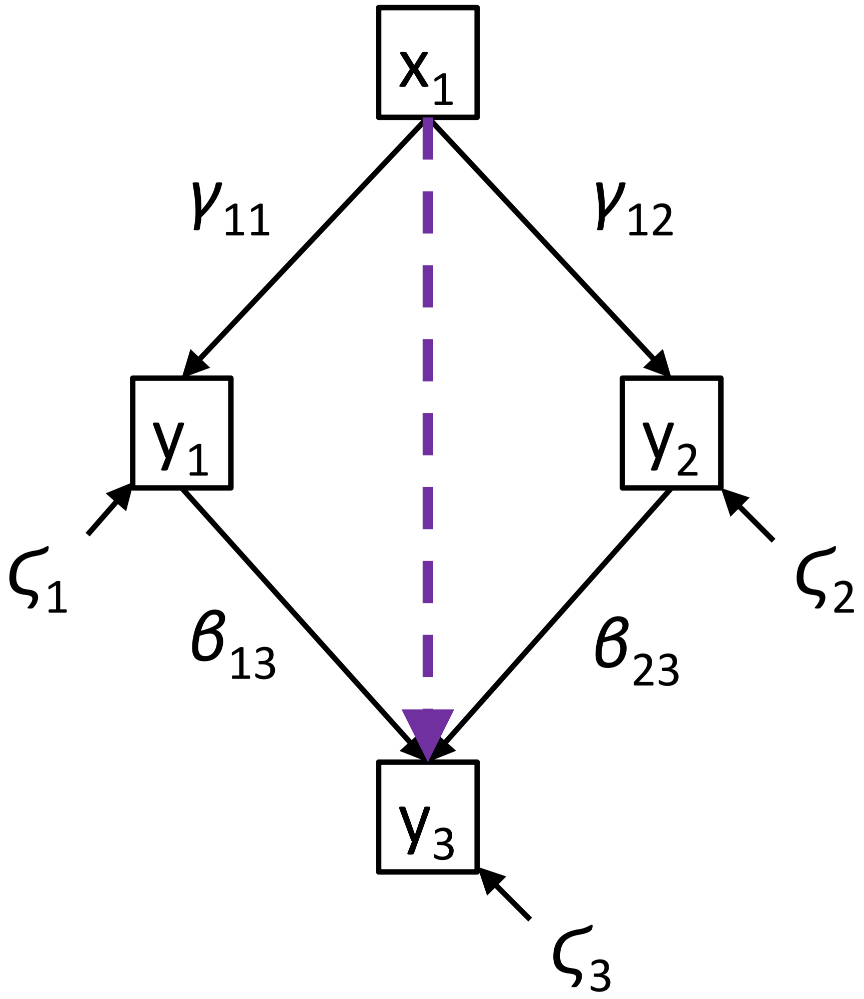


$$y_1 = a + \gamma_{11}x_1 + \varsigma_1$$

$$y_2 = a + \gamma_{12}x_1 + \varsigma_2$$

$$y_3 = a + \beta_{13}y_1 + \beta_{23}y_2 + \varsigma_3$$

Calculating SEM



$$y_1 = a + \gamma_{11}x_1 + \varsigma_1$$

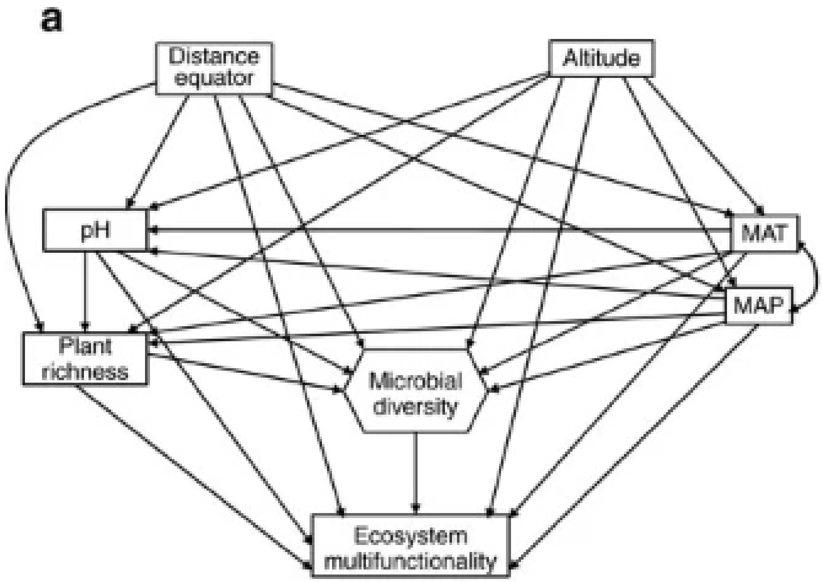
$$y_2 = a + \gamma_{12}x_1 + \varsigma_2$$

$$y_3 = a + \beta_{13}y_1 + \beta_{23}y_2 + \varsigma_3$$

$$X_1 \rightarrow Y_3 = \gamma_{11} * \beta_{13} + \gamma_{12} * \beta_{23}$$

Hoping for no significance

We accept SEM when $p > 0.05$



Global vs Local estimation

Global estimation

Considers the model as a whole

Compares observed covariances to model covariances

Allows correlation between variables

lavaan R-package

Local estimation

Breaks the model in sub-models

Evaluates the importance of missing paths for the model

Allows generalized mixed models

piecewiseSEM R-package

Getting started with *lavaan*

All examples used here come from:

https://www.usgs.gov/centers/wetland-and-aquatic-research-center/science/quantitative-analysis-using-structural-equation?qt-science_center_objects=0#qt-science_center_objects

Big thank you to James Grace for open his teaching material to anyone interested in working with SEMs

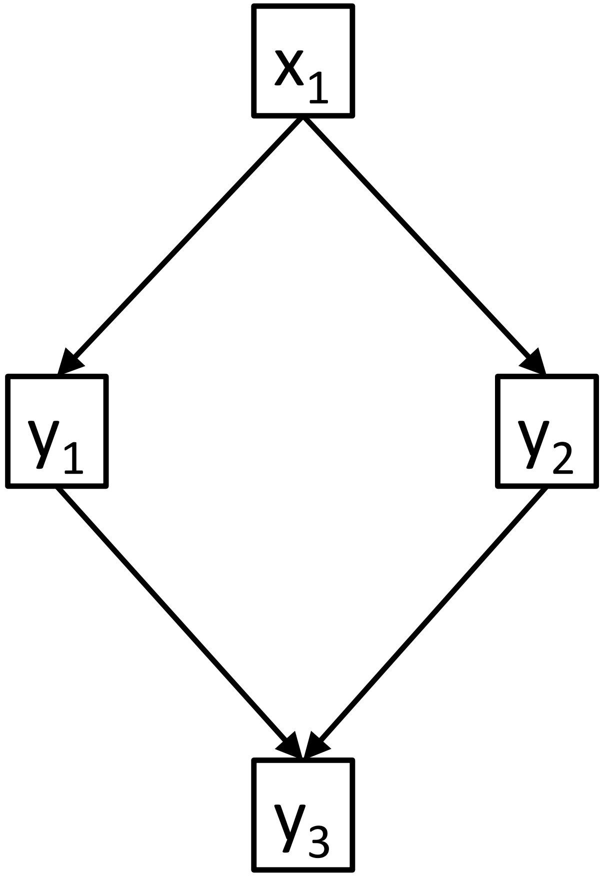
Getting started with *lavaan*

Working with *lavaan* requires R statistical software

Prior to SEM analysis:

- Install and load *lavaan* library
- Load the data
- Explore the data
- Standardize and transform the data when necessary to meet model assumptions (assumptions for linear modelling)

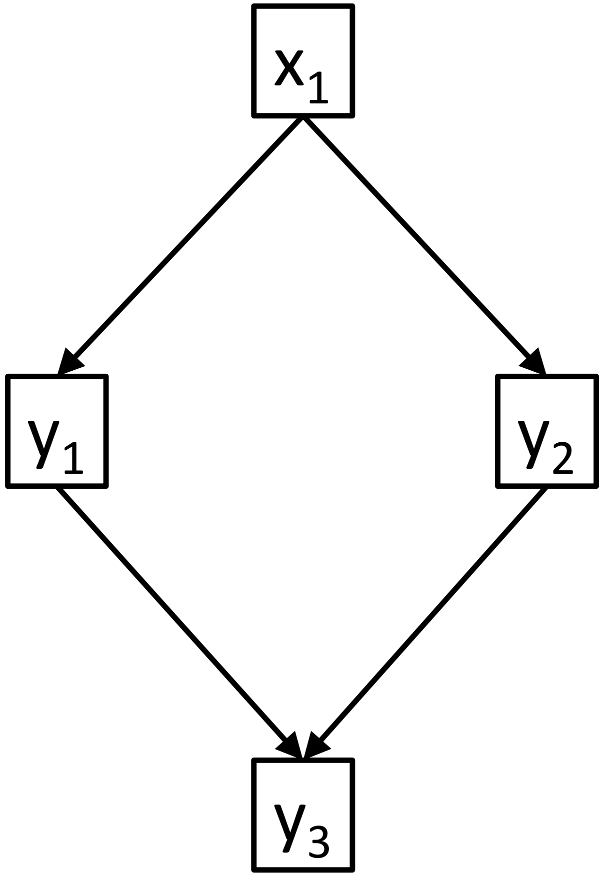
Doing SEM in *lavaan*




```
# Step 1: Specify model

mod.1   <-         'y1 ~ x1
                    y2 ~ x1
                    y3 ~ y1 + y2'
```

Doing SEM in *lavaan*



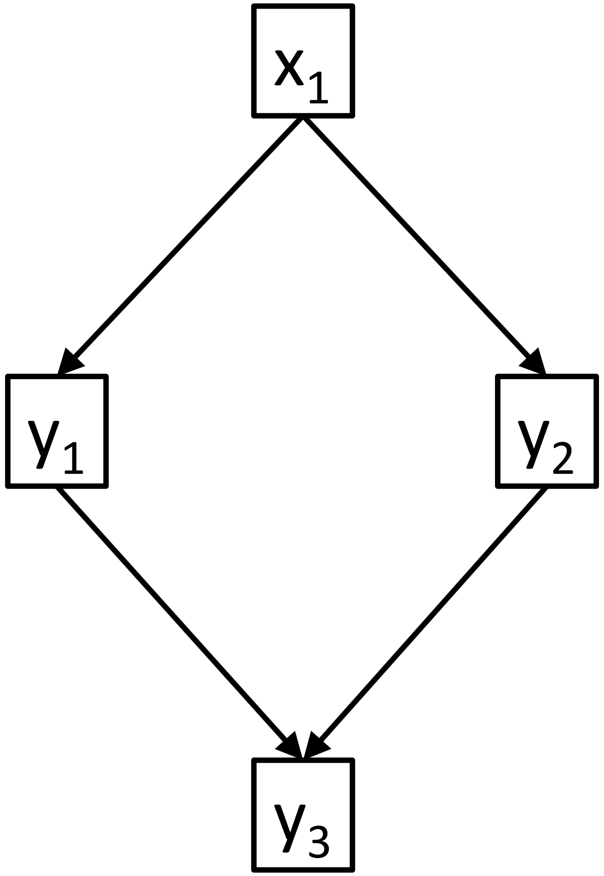

```
# Step 1: Specify model

mod.1   <-         'y1 ~ x1
                    y2 ~ x1
                    y3 ~ y1 + y2'

# Step 2: Estimate model

mod.1.fit <- sem(mod.1, data=dat)
```

Doing SEM in *lavaan*



Step 1: Specify model

```
mod.1   <-       'y1 ~ x1
                  y2 ~ x1
                  y3 ~ y1 + y2'
```

Step 2: Estimate model

```
mod.1.fit <- sem(mod.1, data=dat)
```

Step 3: Extract results

```
summary(mod.1.fit)
```

Interpreting SEM output

```
lavaan 0.6-7 ended normally after 27 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                          7

  Number of observations                            90

Model Test User Model:

  Test statistic                                17.729
  Degrees of freedom                                 2
  P-value (Chi-square)                           0.000

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)
  y1 ~
    x1                0.400    0.081    4.911    0.000
  y2 ~
    x1                0.875    0.367    2.381    0.017
  y3 ~
    y1                0.935    0.171    5.475    0.000
    y2                0.129    0.041    3.121    0.002

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)
   .y1                0.005    0.001    6.708    0.000
   .y2                0.094    0.014    6.708    0.000
   .y3                0.015    0.002    6.708    0.000
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```

Model info and evaluation

Valid model: p-value > 0.05

Interpreting SEM output

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   .y3                0.015    0.002    6.708    0.000
```

Paths info

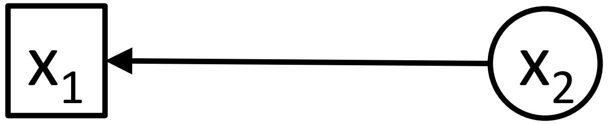
Regression estimate: equation parameters

Variances estimates: error estimates

SEM definition in *lavaan*

regression x2 ~ x1

correlation x2 ~~ x1



Latent variable x2 =~ x1
(unmeasured effect)

Composite variable x2 <~ x1
(caused by)

SEM model evaluation

When evaluating a SEM we asked two questions:

Are we missing important links?

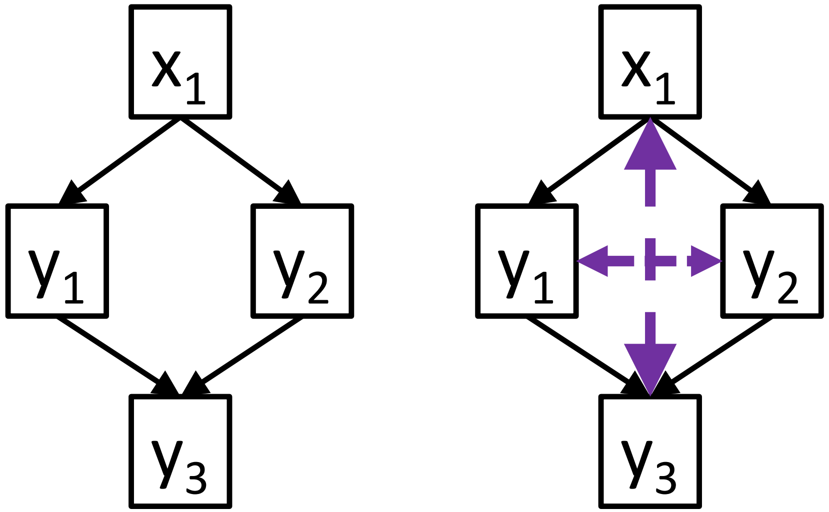
All included paths are supported by the data?

Are we missing important links?

If model is significant, important paths are missing

We compare our model to a saturated model

Saturated model will be identical to data (p-value =1)



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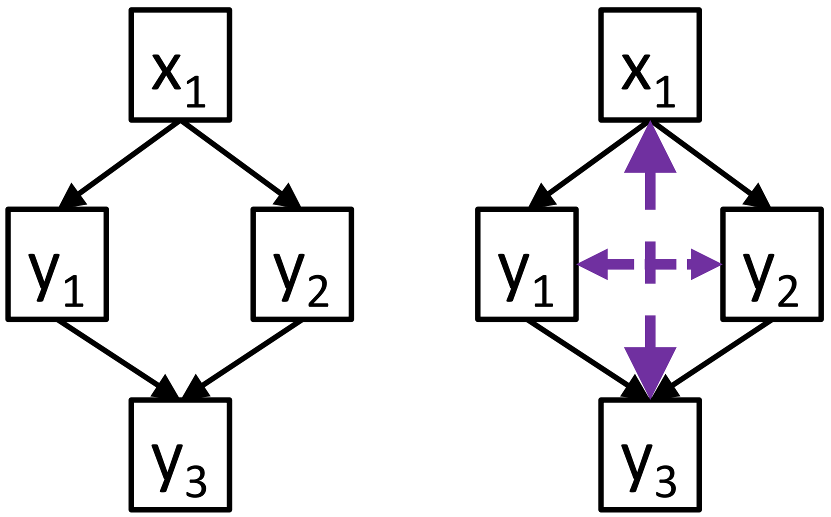

Modification Indices:

	lhs	op	rhs	mi	epc	sepc.lv	sepc.all	sepc.nox
8	x1	~~	x1	0.000	0.000	0.000	0.000	0.000
9	y1	~~	y2	0.014	0.000	0.000	0.012	0.012
10	y1	~~	y3	16.119	-0.008	-0.008	-0.943	-0.943
11	y2	~~	y3	16.119	-0.073	-0.073	-1.945	-1.945
12	y1	~	y2	0.014	0.003	0.003	0.011	0.011
13	y1	~	y3	10.215	-0.337	-0.337	-0.662	-0.662
14	y2	~	y1	0.014	0.056	0.056	0.014	0.014
15	y2	~	y3	2.107	-0.681	-0.681	-0.324	-0.324
16	y3	~	x1	16.119	0.683	0.683	0.400	4.556
17	x1	~	y1	0.000	0.000	0.000	0.000	0.000
18	x1	~	y2	0.000	0.000	0.000	0.000	0.000
19	x1	~	y3	15.946	0.345	0.345	0.590	0.590

```
# Modification indices

summary(mod.1.fit, modindices = T)
```

High mi (>3.64) indicates a missing path

Are we missing important links?

We compare our model to a saturated model

Saturated model will be identical to data (p-value =1)

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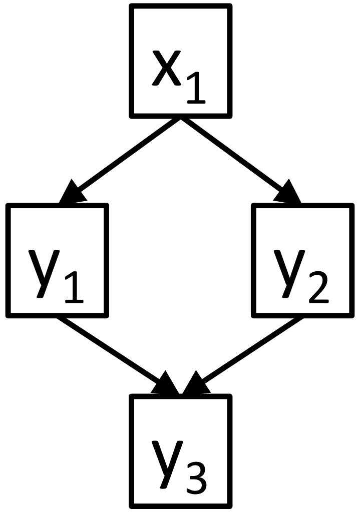

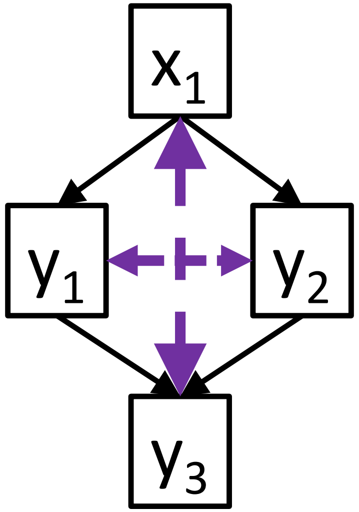

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	lhs	op	rhs	mi	epc	sepc.lv	sepc.all	sepc.nox
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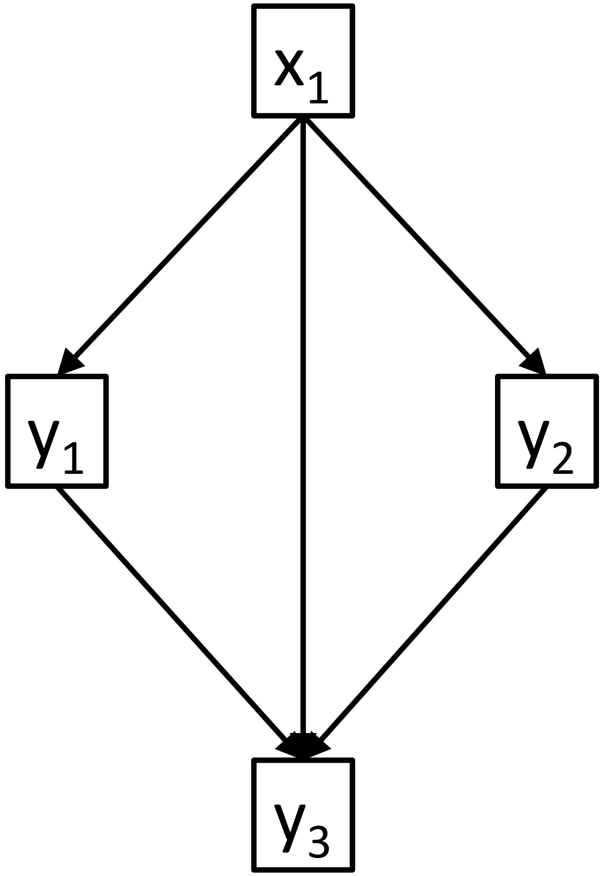
10	y1	~~	y3	16.119	-0.008	-0.008	-0.943	-0.943
11	y2	~~	y3	16.119	-0.073	-0.073	-1.945	-1.945
12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
13	y1	~	y3	10.215	-0.337	-0.337	-0.662	-0.662
14	y2	~	y1	0.014	0.036	0.036	0.014	0.014
15	y2	~	y3	2.107	0.681	0.681	0.324	0.324
16	y3	~	x1	16.119	0.683	0.683	0.400	4.556
17	x1	~	y1	0.000	0.000	0.000	0.000	0.000
18	x1	~	y2	0.000	0.000	0.000	0.000	0.000
19	x1	~	y3	15.946	0.345	0.345	0.590	0.590

Modification indices

summary(mod.1.fit, modindices = T)

High mi (>3.64) indicates a missing path

Testing the improved model



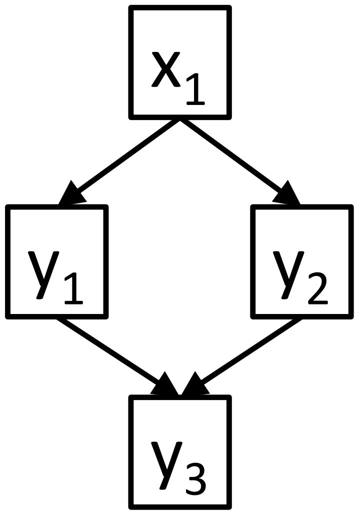
Specify new model

```
mod.2 <- 'y1 ~ x1
          y2 ~ x1
          y3 ~ y1 + y2 + x1'
```

```
Model Test User Model:

  Test statistic                                 0.014
  Degrees of freedom                                 1
  P-value (Chi-square)                           0.906
```

All included paths are supported?



We evaluate each path independently

Some paths can be not supported (p-value > 0.05)

```
Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)
  y1 ~
    x1                0.400    0.081    4.911    0.000
  y2 ~
    x1                0.875    0.367    2.381    0.017
  y3 ~
    y1                0.935    0.171    5.475    0.000
    y2                0.129    0.041    3.121    0.002
```

How to select the best model

Statistical model selection is an important issue, not only for SEM

Some approaches:

Based on theory, model includes relations that make sense theoretically

Based on data, model includes relations that are statistically supported

How to select the best model

Statistical model selection is an important issue, not only for SEM

Some approaches:

- Based on theory, model includes relations that make sense theoretically
- Based on data, model includes relations that are statistically supported

Not best option,
Up to your philosophy

Qualities of a good SEM

Included paths make ecological sense

Model is not significant

Options:

Keep as many paths as possible (highlights the importance of weak effects)

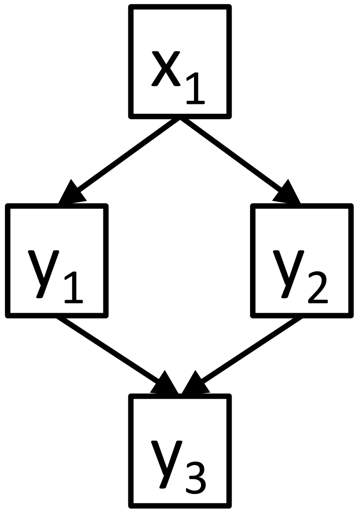
Remove paths to get the most parsimonious model (highlight important effects)

Selecting the most parsimonious model

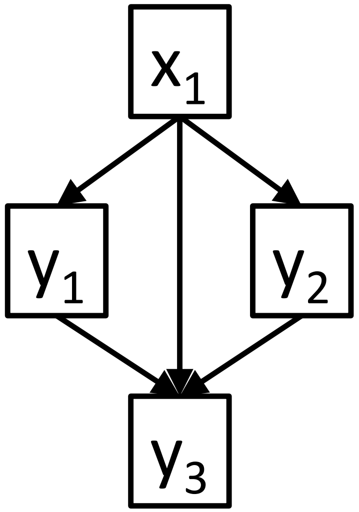
We can select models using AIC (lowest AIC = better model)

```
# Comparing models

anova(mod.fit.1,mod.fit.2)
```



mod.fit.1



mod.fit.2

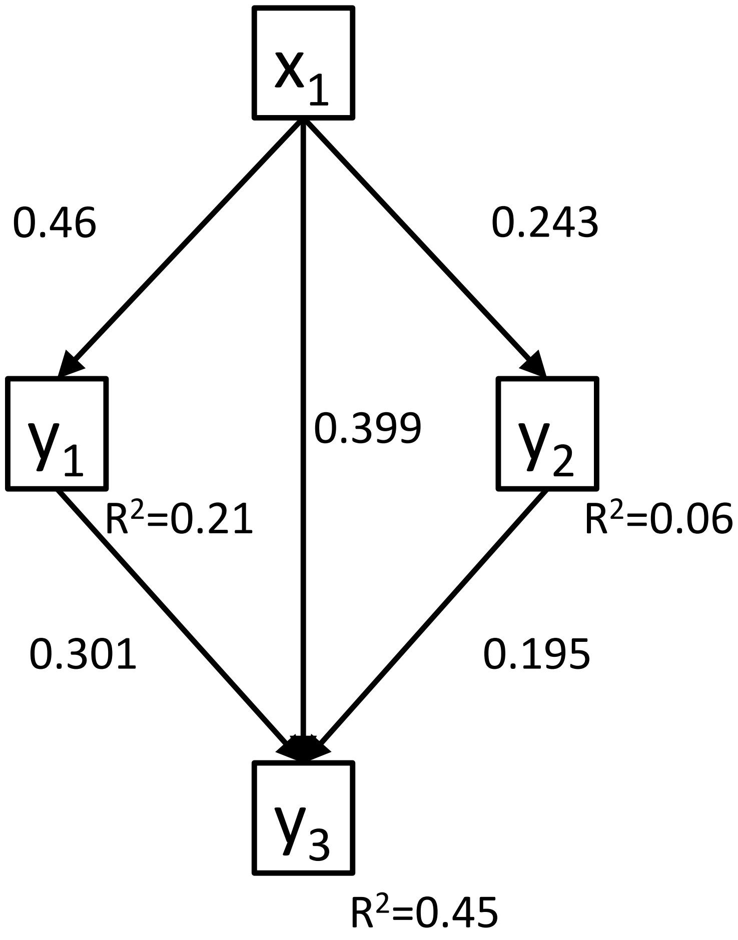
```
          Df     AIC     BIC  Chisq Chisq diff Df diff Pr(>Chisq)
mod.2.fit  1 -310.38 -290.39  0.014
mod.1.fit  2 -294.67 -277.17 17.729     17.715       1  2.566e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Interpreting results

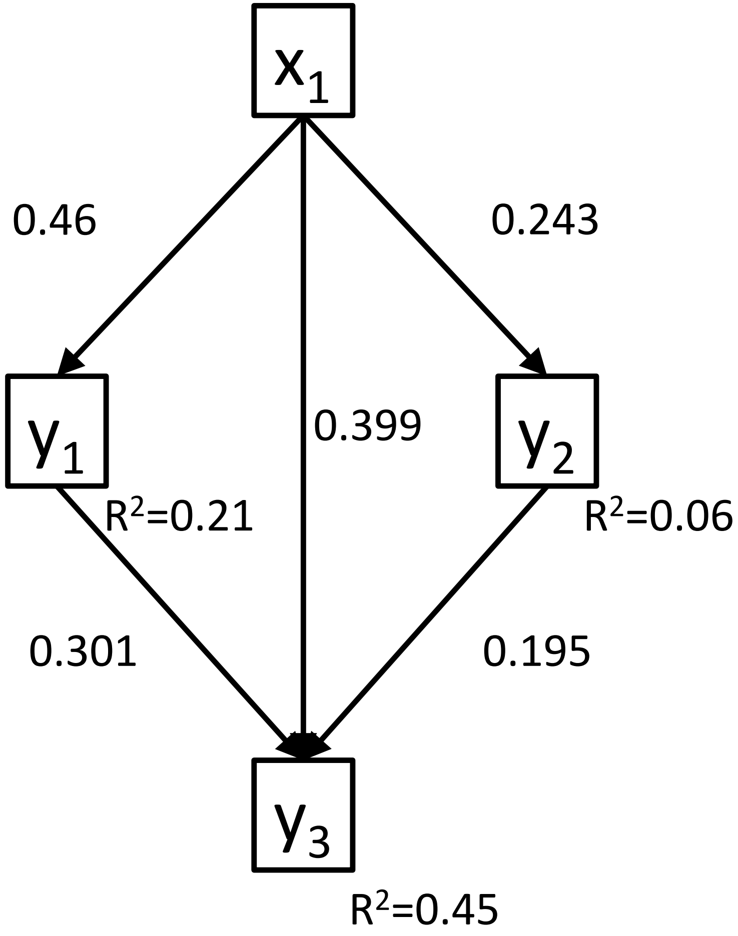
For interpreting the model is best to work with standardize estimates

```
standardizedsolution(mod.2.fit,type="std.all")
lavInspect(mod.2.fit,what="rsquare")
```

	lhs	op	rhs	est.std	se	z	pvalue	ci.lower	ci.upper
1	y1	~	x1	0.460	0.079	5.848	0.000	0.306	0.614
2	y2	~	x1	0.243	0.098	2.492	0.013	0.052	0.435
3	y3	~	y1	0.301	0.086	3.508	0.000	0.133	0.470
4	y3	~	y2	0.195	0.080	2.442	0.015	0.039	0.352
5	y3	~	x1	0.399	0.083	4.776	0.000	0.235	0.562
6	y1	~~	y1	0.789	0.072	10.911	0.000	0.647	0.930
7	y2	~~	y2	0.941	0.048	19.779	0.000	0.848	1.034
8	y3	~~	y3	0.550	0.072	7.610	0.000	0.409	0.692
9	x1	~~	x1	1.000	0.000	NA	NA	1.000	1.000



Calculate the effects



Direct, indirect and total effects can be calculated

Effects on y_1:

Direct = 0.46
Indirect = NA
Total = 0.46

Effects on y_2:

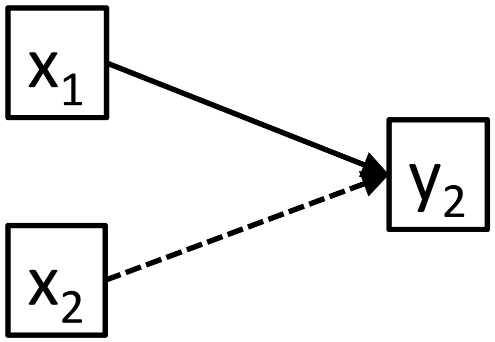
Direct = 0.243
Indirect = NA
Total = 0.243

Effects on y_3:

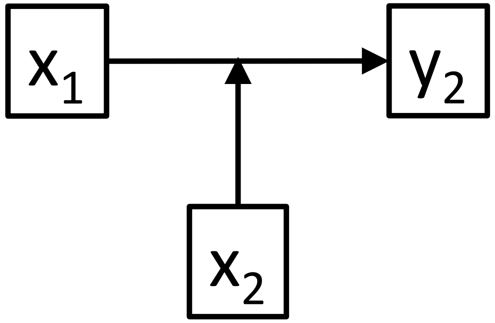
Direct = 0.301 + 0.399 + 0.195 = 0.895
Indirect = 0.46 * 0.301 + 0.243 * 0.195 = 0.186
Total = 0.895 + 0.186 = 1.081

Extras in *lavaan*

It is possible to work with factors (dummy variables)



It is possible to work with interactions



It is possible to work with non-linear (polynomial) relations

Where to look for nice info

lavaan

https://www.usgs.gov/centers/wetland-and-aquatic-research-center/science/quantitative-analysis-using-structural-equation?qt-science_center_objects=0#qt-science_center_objects

https://lavaan.ugent.be/tutorial/cfa.html

piecewiseSEM

https://jonlefcheck.net/teaching/

https://jslefche.github.io/sem_book/index.html

Acknowledgements

UNIVERSITÄT BERN

USGS
science for a changing world

biodiversity exploratories
functional biodiversity research

And all colleagues from the labs