LegumeLegacy

LegumeLegacy
SS4 Statistical modelling

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Schweizerische Eidgenossenschaft
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Swiss Confederation

Federal Department of Economic Affairs, Education and Research EAER
State Secretariat for Education, Research and Innovation SERI

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Modelling BEF relationships using Diversity-Interactions models and the `DImodels` R package

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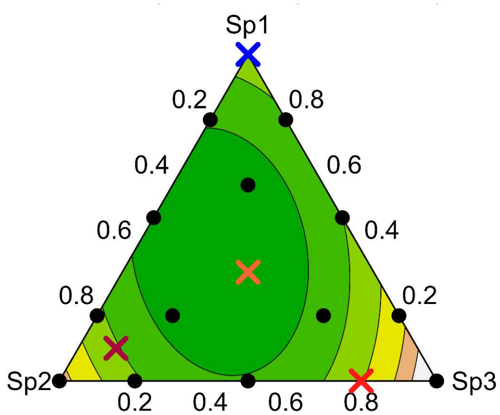
Coláiste na Tríonóide, Baile Átha Cliath
The University of Dublin

With thanks to Laura Byrne, Rafael Moral, James O'Malley and Rishabh Vishwakarma who developed some of the material contained in this presentation.

The plan for this training day?



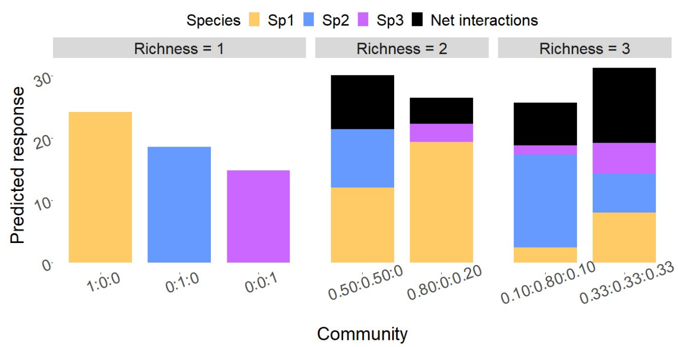
Selecting the best model?

$$y = \sum_{i=1}^{s} \beta_i p_i + \sum_{\substack{i,j=1 \\ i<j}}^{s} \delta_{ij} \left(p_i p_j\right)^{\theta} + \varepsilon$$

$$\varepsilon \sim \text{IID N}(0, \sigma^2)$$

Model interpretation?

Understanding model selection choices?



Model communication?

"All models are wrong, but some are useful"

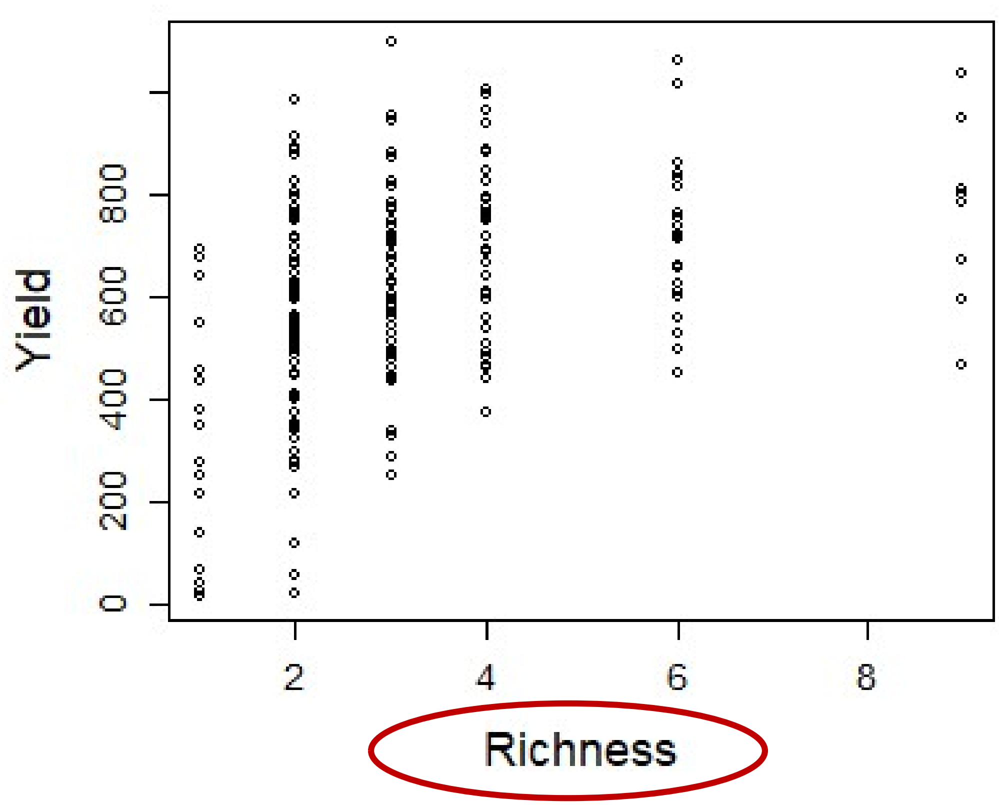
The biodiversity and ecosystem function (BEF) relationship

The biodiversity and ecosystem function (BEF) Relationship

Roscher et al 2004

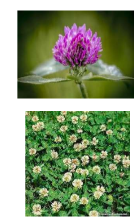
Jena “dominance” experiment

Grasses



Non-legume herbs

Legumes



Roscher C, Schumacher J, Baade J, Wilcke W, Gleixner G, Weisser WW, Schmid B, Schulze ED (2004) The role of biodiversity for element cycling and trophic interactions: an experimental approach in a grassland community. *Basic and Applied Ecology*. 2004 5:107-21.

Diversity-Interactions modelling for BEF data

Ecology, 90(8), 2009, pp. 2032–2038

Diversity–interaction modeling: estimating contributions of species identities and interactions to ecosystem function

L. Kirwan,[1,2,7] J. Connolly,[3] J. A. Finn,[1] C. Brophy,[3,8] A. Lüscher,[4] D. Nyfeler,[4] and M.-T. Sebastià[5,6]

Journal of Ecology 2013, **101**, 344–355 doi: 10.1111/1365-2745.12052

An improved model to predict the effects of changing biodiversity levels on ecosystem function

John Connolly[1]*, Thomas Bell[2], Thomas Bolger[3], Caroline Brophy[4], Timothee Carnus[1,5], John A. Finn[5], Laura Kirwan[6], Forest Isbell[7], Jonathan Levine[8], Andreas Lüscher[9], Valentin Picasso[10], Christiane Roscher[11], Maria Teresa Sebastia[12,13], Matthias Suter[8,9] and Alexandra Weigelt[14]

Received: 9 December 2022 | Accepted: 13 May 2023
DOI: 10.1111/2041-210X.14158

Methods in Ecology and Evolution

APPLICATION

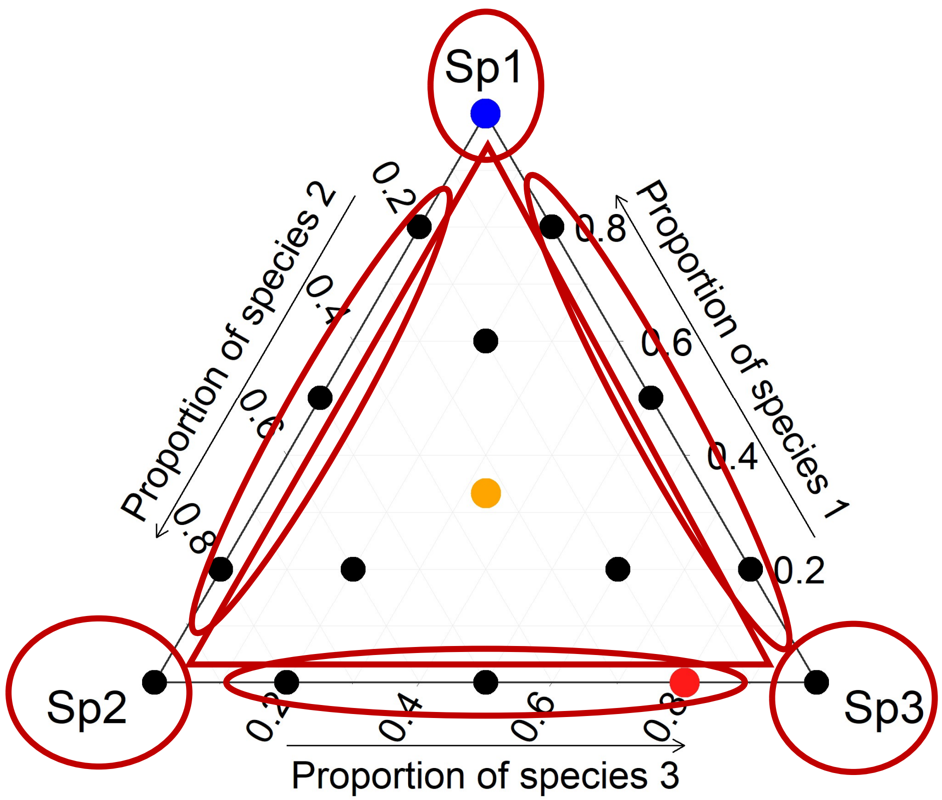
Going beyond richness: Modelling the BEF relationship using species identity, evenness, richness and species interactions via the DImodels R package

Rafael A. Moral[1] | Rishabh Vishwakarma[2] | John Connolly[3] | Laura Byrne[2] | Catherine Hurley[1] | John A. Finn[4] | Caroline Brophy[2]

Species biodiversity?

community	richness	p1	p2	p3	response
1	1	1	0	0	24.855
2	1	0	1	0	19.049
3	1	0	0	1	16.292
4	2	0.8	0.2	0	31.529
5	2	0.2	0.8	0	25.102
6	2	0.8	0	0.2	24.615
⋮	⋮	⋮	⋮	⋮	⋮

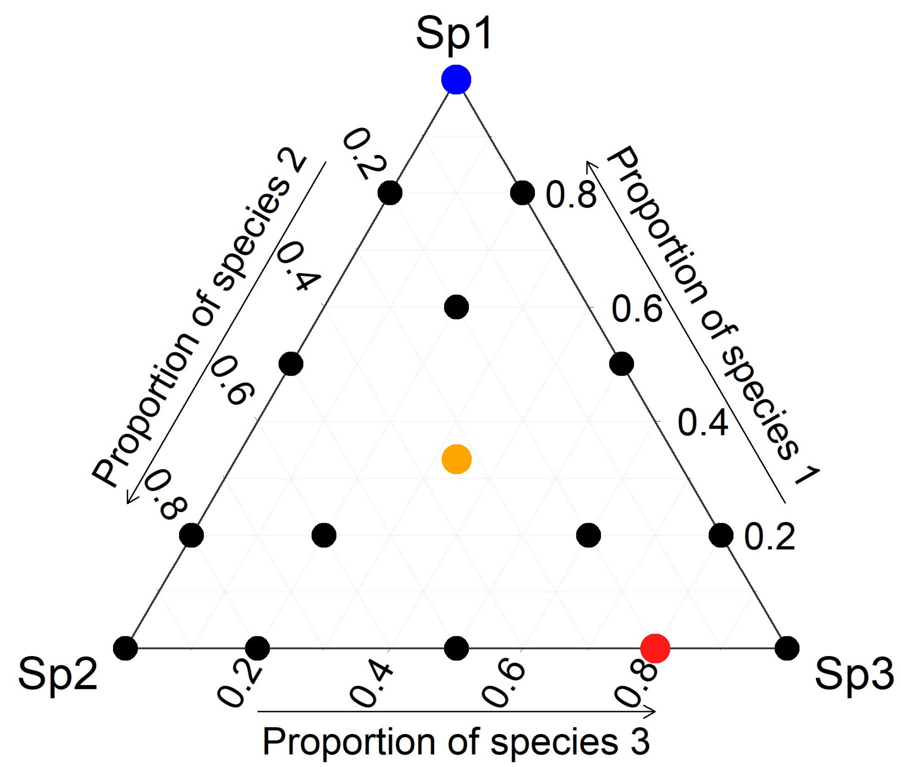
```
install.packages("DImodels")
library(DImodels)
data("sim0")
head(sim0)
```



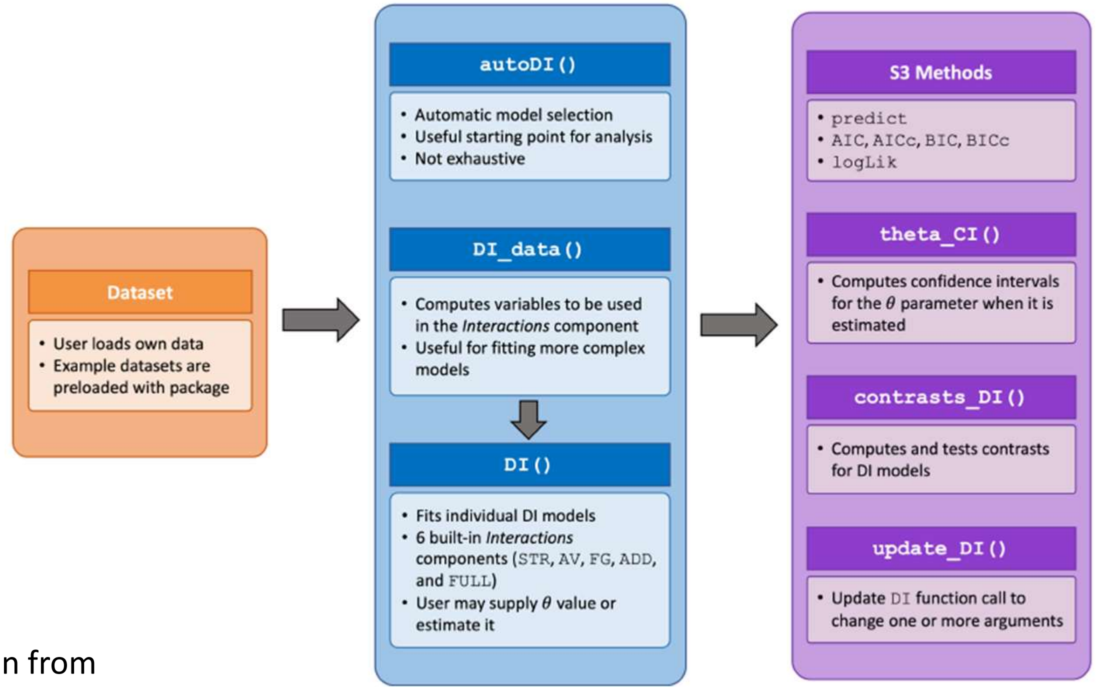
Species biodiversity?

1. Composition – species identity
2. Richness
3. Species proportions

Diversity-Interactions (DI) models can capture all these aspects of species diversity when modelling the BEF relationship



Overview of the DImodels R package



Taken from
Moral et al (2023)
Methods in Ecology and Evolution;
9, 2250-2258.

Additional packages:
`DImodelsVis`
`DImodelsMulti`

Example 1

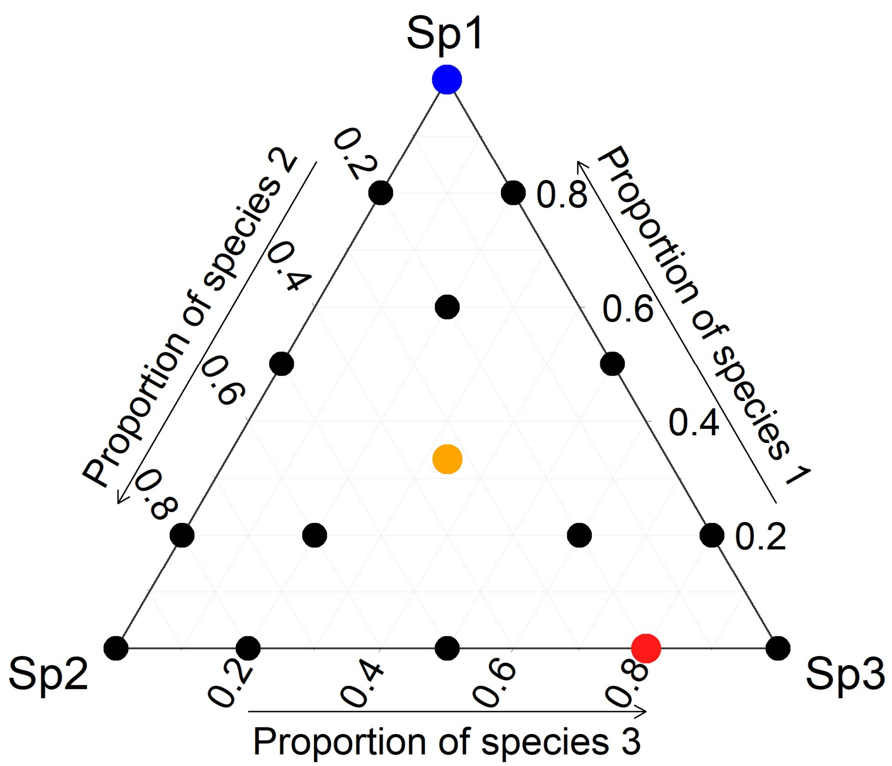
Modelling a 3-species dataset

Moral et al 2023 Methods in Ecology and Evolution; 9, 2250-2258.

Analysing the `sim0` dataset

community	richness	p1	p2	p3	response
1	1	1	0	0	24.855
2	1	0	1	0	19.049
3	1	0	0	1	16.292
4	2	0.8	0.2	0	31.529
5	2	0.2	0.8	0	25.102
6	2	0.8	0	0.2	24.615
⋮	⋮	⋮	⋮	⋮	⋮

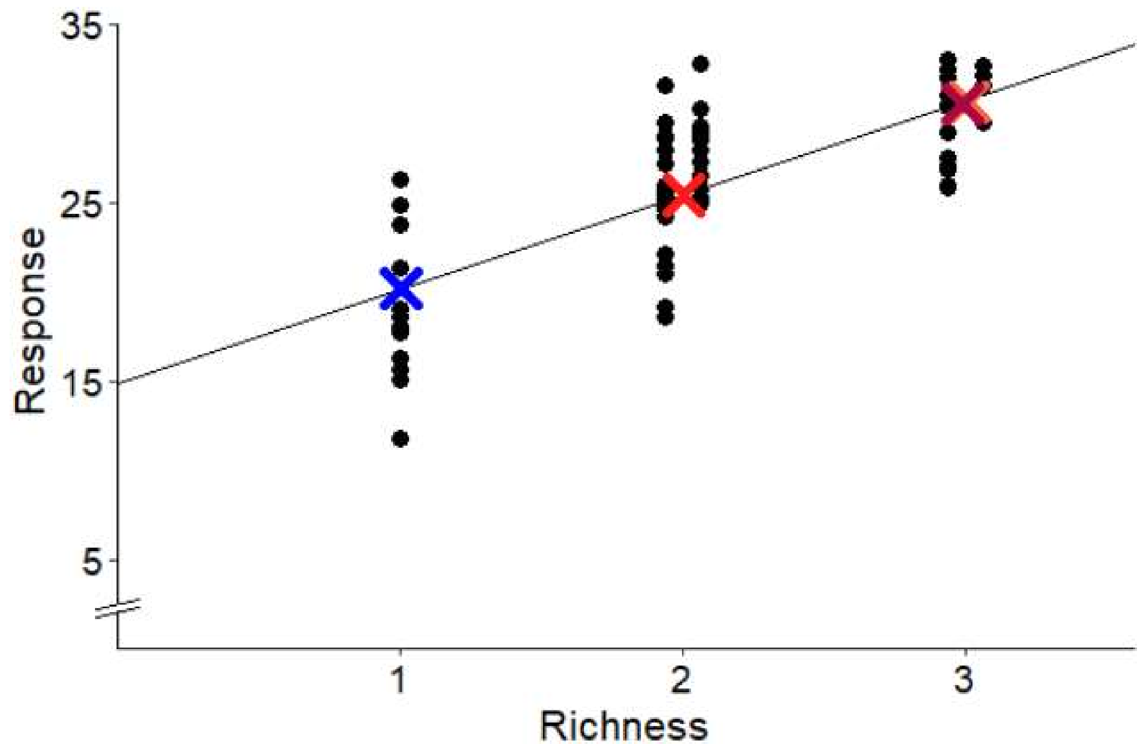
```
install.packages("DImodels")
library(DImodels)
data("sim0")
head(sim0)
```



Analysing the `sim0` dataset: simple linear regression

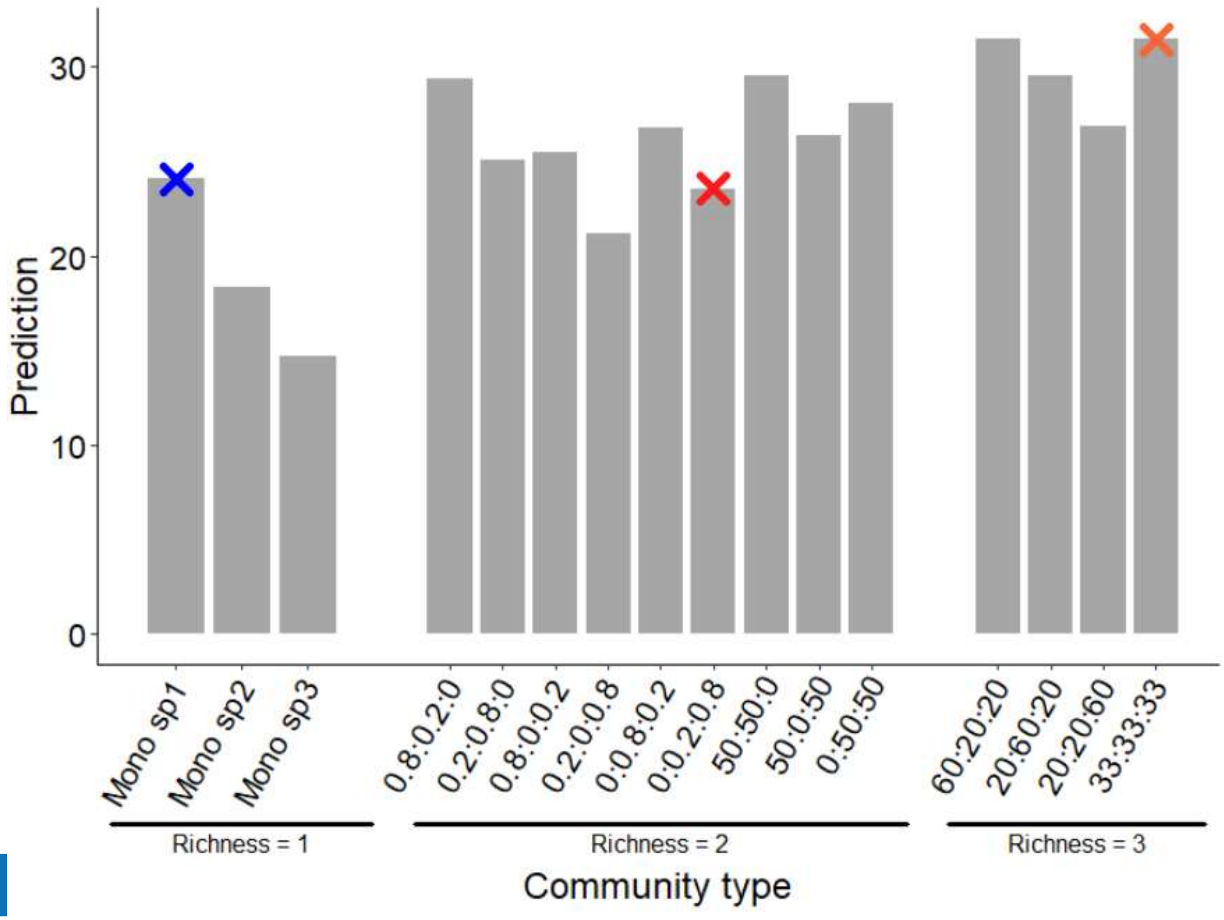
```
m1 <- lm(response ~ richness,
         data = sim0)
summary(m1)
```

	Estimate	Std. Error	P-value
Intercept	14.91	1.3781	p < 0.001
richness	5.25	0.6365	p < 0.001



Analysing the `sim0` dataset: ANOVA model

```
sim0$communityF <- as.factor(sim0$community)
m2 <- lm(response ~ communityF, data = sim0)
summary(m2)
preds <- predict(m2)
preds[1:16]
```

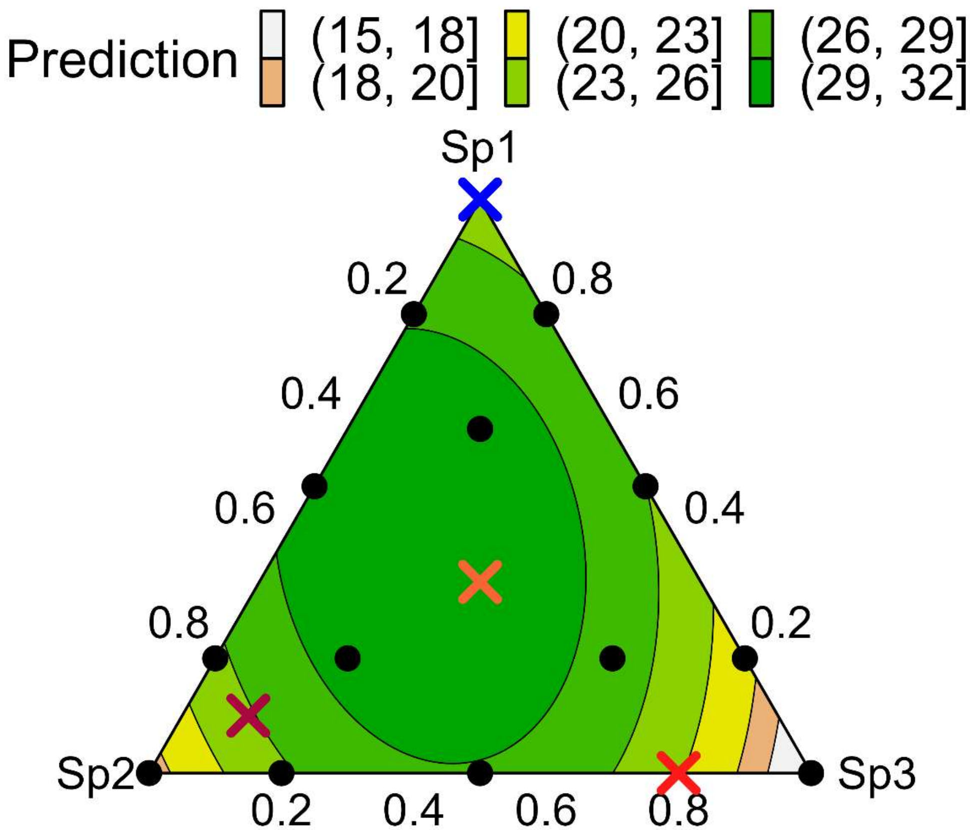


Analysing the `sim0` dataset: Diversity-Interactions model

```
m3 <- DI(y = "response", prop = 3:5,
         DImodel = "FULL", data = sim0)
summary(m3)
```

$$y = \sum_{i=1}^{3} \beta_i p_i + \sum_{\substack{i,j=1 \\ i<j}}^{3} \delta_{ij} p_i p_j + \varepsilon \qquad \varepsilon \sim \text{IID N}(0, \sigma^2)$$

Sown prop	Estimate	Std. Error	P-value
p1	24.17	0.7698	
p2	18.62	0.7698	
p3	14.81	0.7698	
p1*p2	34.83	3.5694	p < 0.001
p1*p3	26.14	3.5694	p < 0.001
p2*p3	47.92	3.5694	p < 0.001



Analysing the `sim0` dataset: Diversity-Interactions model

```
m3 <- DI(y = "response", prop = 3:5,
         DImodel = "FULL", data = sim0)
summary(m3)
```

$$y = \beta_1 p_1 + \beta_2 p_2 + \beta_3 p_3 + \delta_{12} p_1 p_2 + \delta_{23} p_2 p_3 + \delta_{13} p_1 p_3 + \varepsilon$$

$$\varepsilon \sim \text{IID N}(0, \sigma^2)$$

Sown prop	Estimate	Std. Error	P-value
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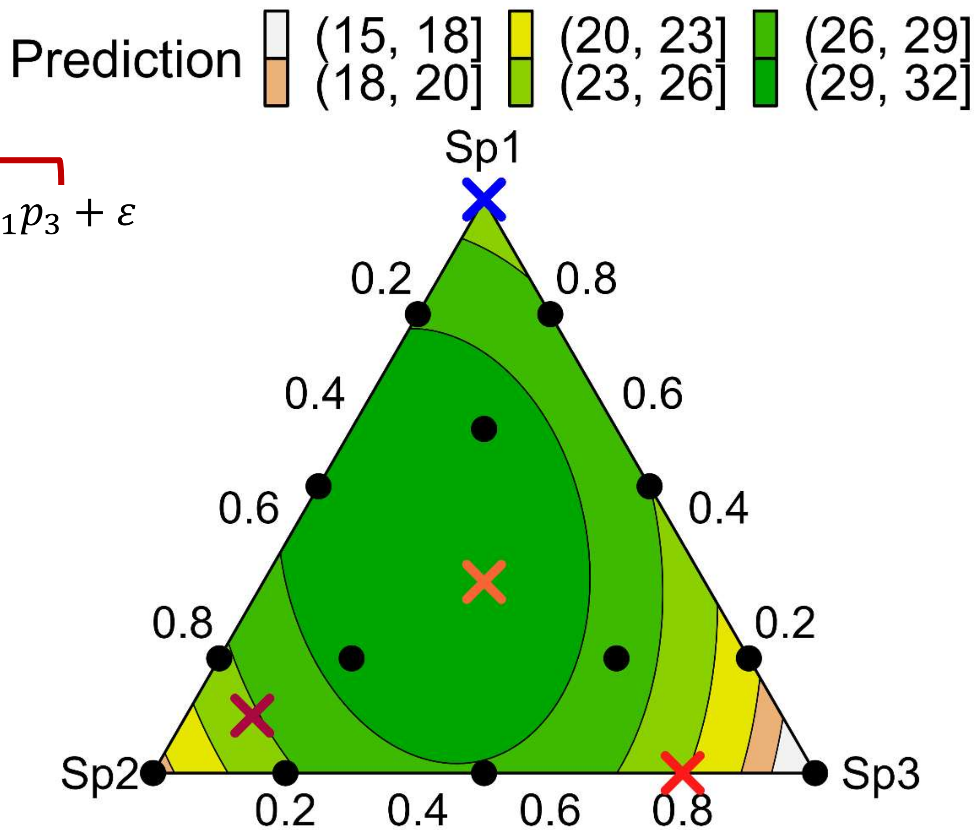
p2*p3	47.92	3.5694	$p < 0.001$



Analysing the `sim0` dataset: Diversity-Interactions model

$$y = \sum_{i=1}^{3} \beta_i p_i + \sum_{\substack{i,j=1 \\ i<j}}^{3} \delta_{ij} p_i p_j + \varepsilon \qquad \varepsilon \sim \text{IID N}(0, \sigma^2)$$

$$y = \beta_1 p_1 + \beta_2 p_2 + \beta_3 p_3 + \delta_{12} p_1 p_2 + \delta_{23} p_2 p_3 + \delta_{13} p_1 p_3 + \varepsilon$$

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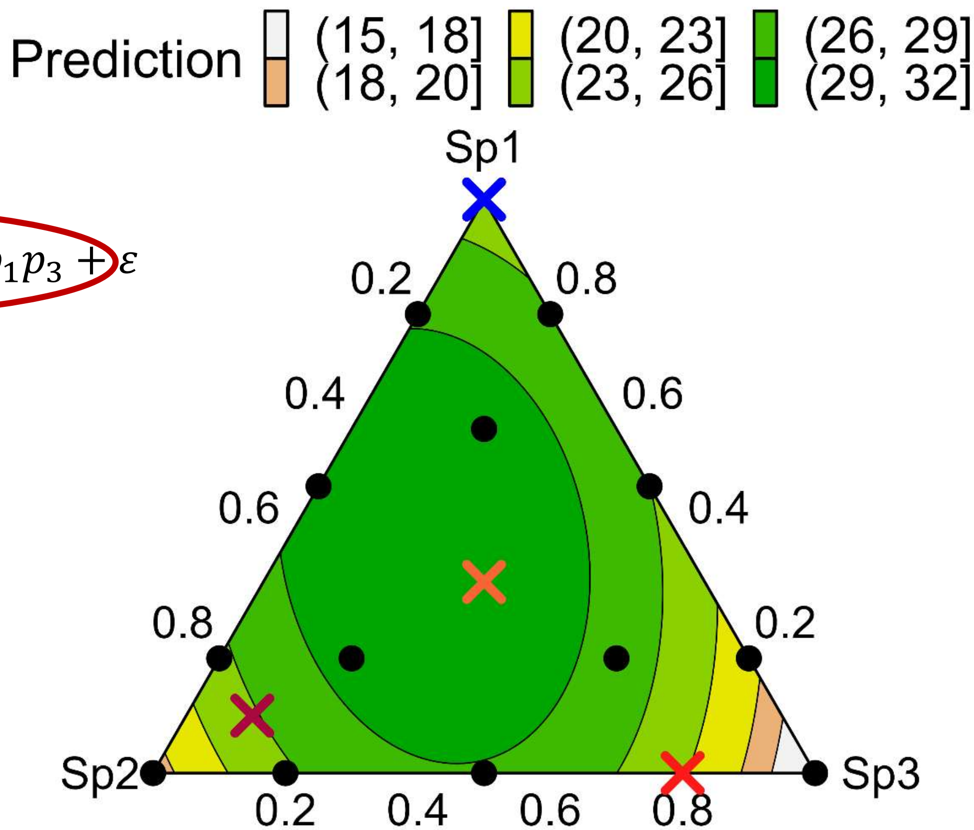
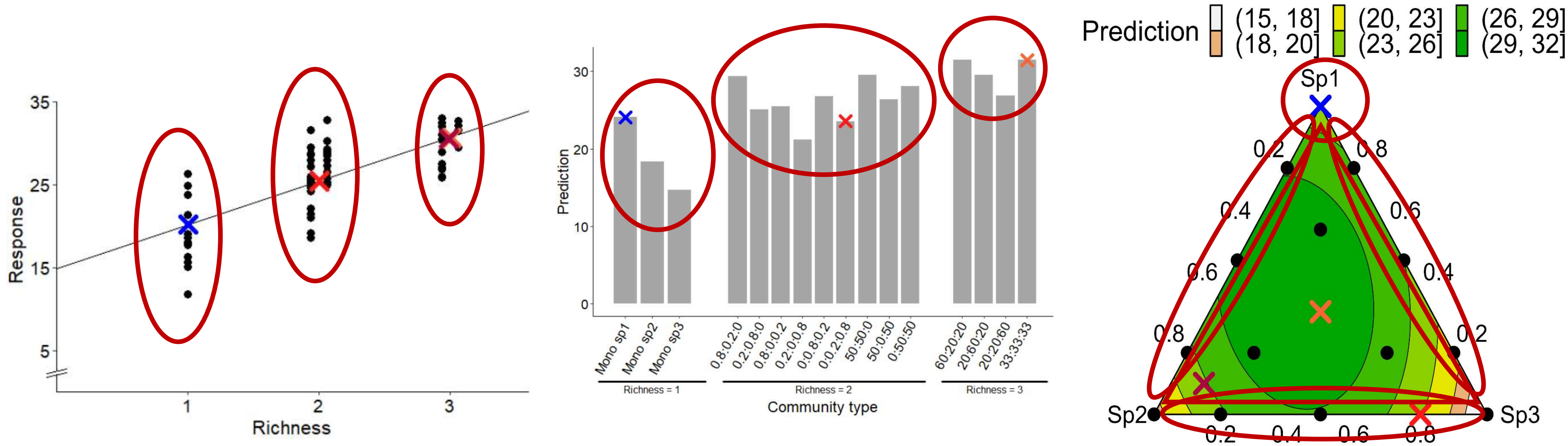


The strength of DI models



Example 2

Modelling a 4-species BEF dataset

Over to you now!

Now, you will work through the tutorial and later we will come back to this presentation.

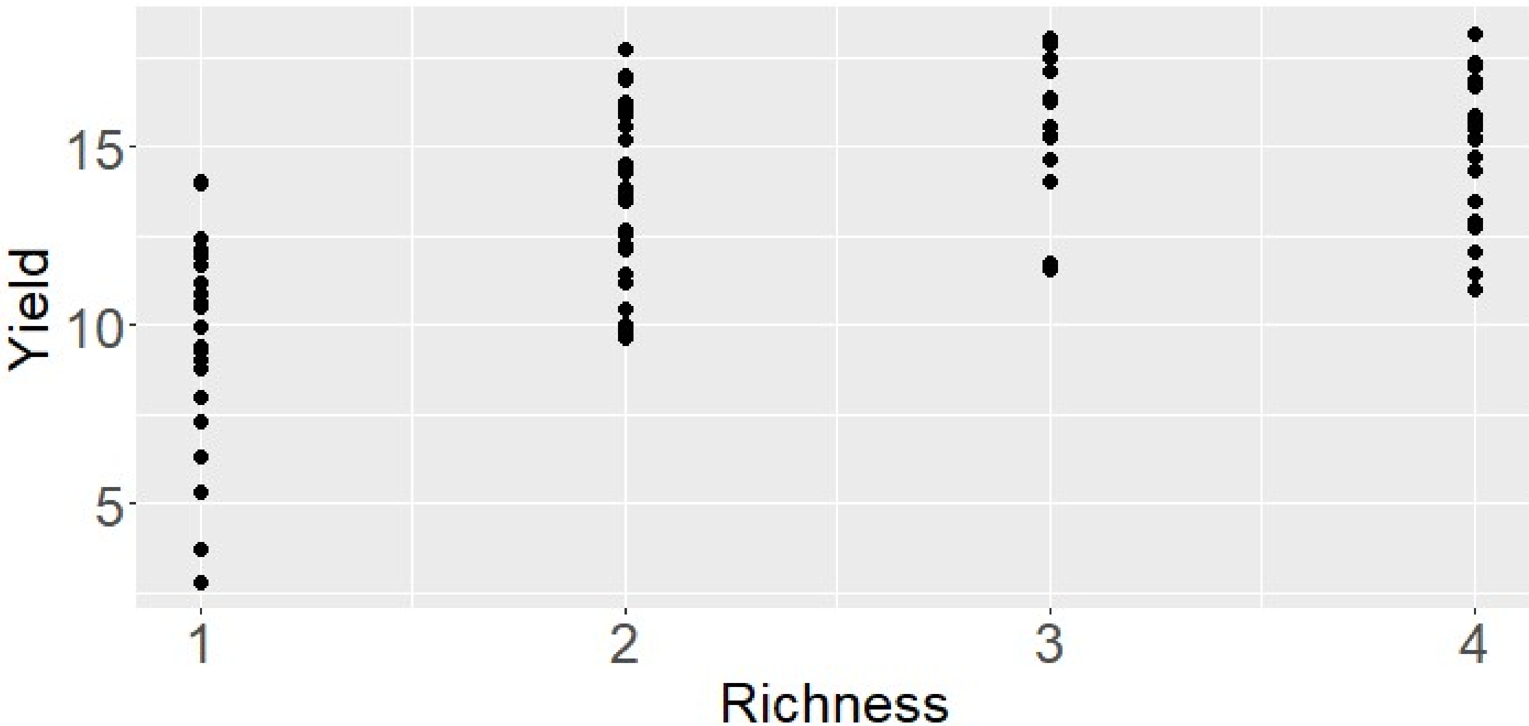
Simulated dataset

- Filename: Dataset_4species_simulated.csv
- Simulated assuming a biodiversity and ecosystem function (BEF) experiment
- Four grassland species (species 1 and 2 grasses, species 3 and 4 legumes), let's call them G1, G2, L1 and L2.
- Species diversity and nitrogen fertiliser treatments manipulated across plots
- Total of 100 plots (50 at low and 50 at regular N)
- Yield of each plot over a growing season was recorded

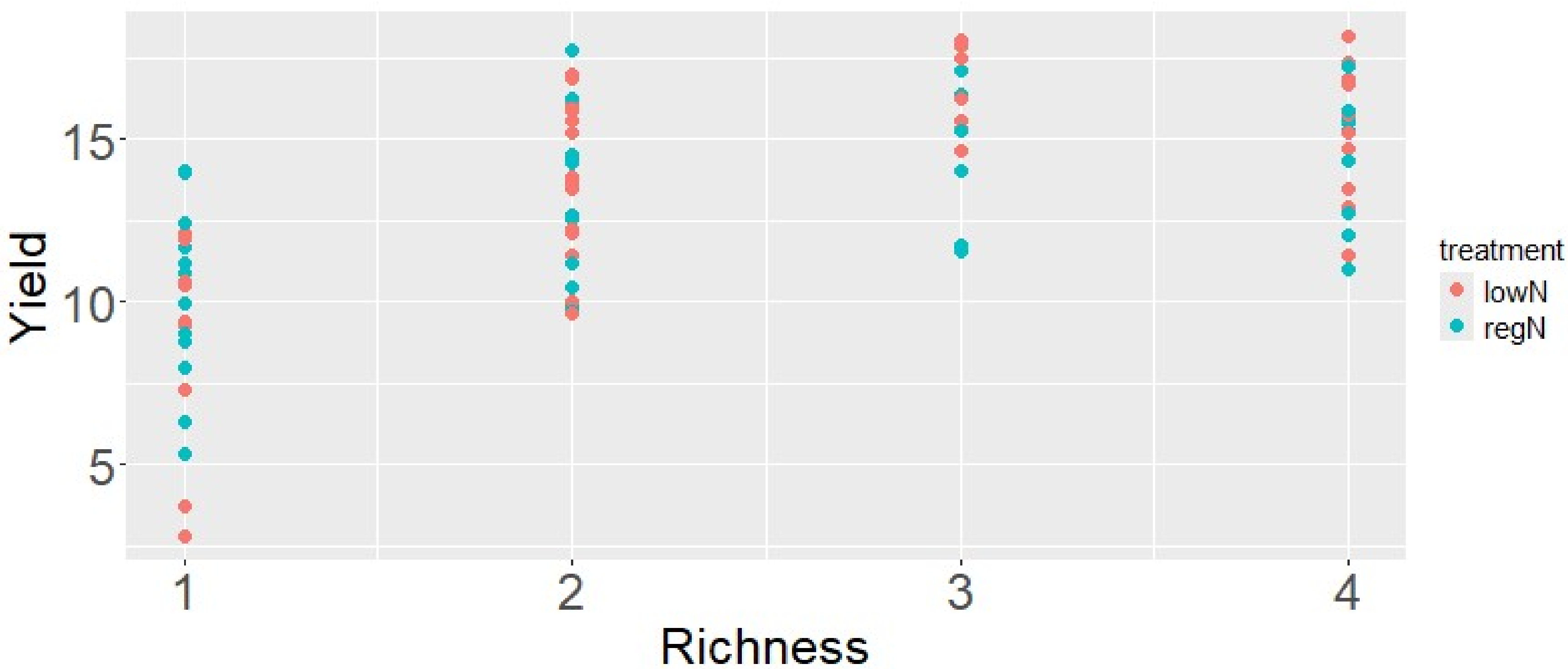
Example 2 continued
Modelling a 4-species BEF dataset

Explore the data graphically

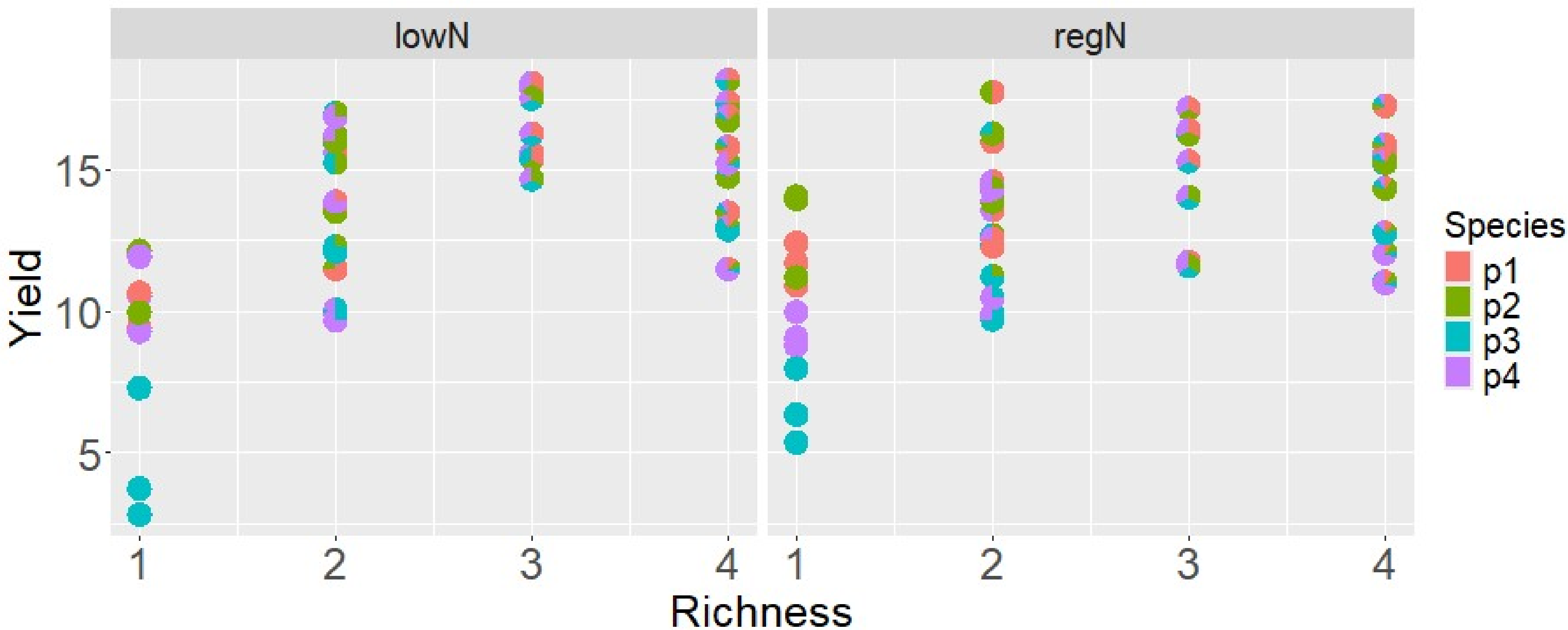
Explore the data



Explore the data



Explore the data

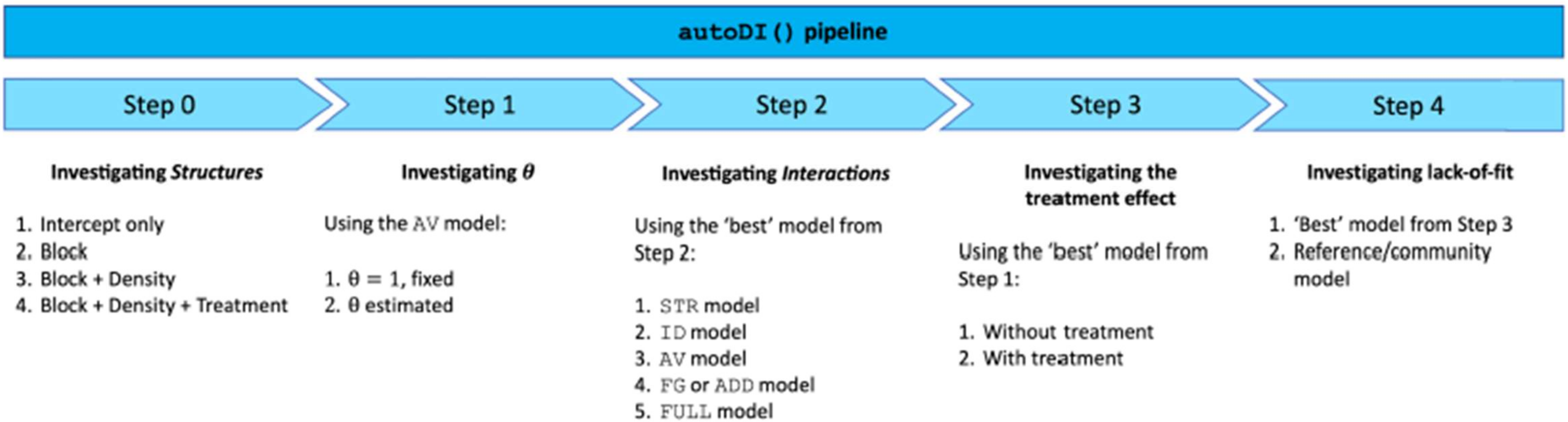


Example 2 continued

Modelling a 4-species BEF dataset

Initial model selection using `autoDI`

Using `autoDI` for model selection



Taken from
Moral et al (2023)
Methods in Ecology and Evolution; 9, 2250-2258.

Using `autoDI` for model selection

```
------------------------------------------------------------------------------------

Sequential analysis: Investigating only non-diversity experimental design structures


            model Resid. Df Resid. SSq Resid. MSq Df    SSq      F Pr(>F)
1 Intercept only        99   1029.603     10.400
2           treat       98   1023.218     10.441  1 6.3847 0.6115 0.4361

------------------------------------------------------------------------------------
```

For a scientific presentation, don't give R output like this!

Models fitted?

Using `autoDI` for model selection

```
------------------------------------------------------------------------------------------------------
Step 1: Investigating whether theta is equal to 1 or not for the AV model, including all available structures

Theta estimate: 1.0017

Selection using F tests

           Description
DI Model 1 Average interactions 'AV' DImodel with treatment
DI Model 2 Average interactions 'AV' DImodel with treatment, estimating theta


           DI_model    treat estimate_theta Resid. Df Resid. SSq Resid. MSq Df    SSq     F Pr(>F)
DI Model 1       AV 'treatF'          FALSE        94   219.8445     2.3388
DI Model 2       AV 'treatF'           TRUE        93   219.8431     2.3639  1 0.0015 6e-04 0.9802

The test concludes that theta is not significantly different from 1.

------------------------------------------------------------------------------------------------------
```

Models fitted?

Using `autoDI` for model selection

```
---------------------------------------------------------------------------------------------
Step 2: Investigating the interactions

Since 'Ftest' was specified as selection criterion and functional groups were specified, dropping the ADD model as it is not n
ested within the FG model.
Selection using F tests

            Description
DI Model 1 Structural 'STR' DImodel with treatment
DI Model 2 Species identity 'ID' DImodel with treatment
DI Model 3 Average interactions 'AV' DImodel with treatment
DI Model 4 Functional group effects 'FG' DImodel with treatment
DI Model 5 Separate pairwise interactions 'FULL' DImodel with treatment


           DI_model    treat estimate_theta Resid. Df Resid. SSq Resid. MSq Df      SSq        F  Pr(>F)
DI Model 1      STR 'treatF'          FALSE        98  1023.2180    10.4410
DI Model 2       ID 'treatF'          FALSE        95   739.1527     7.7806  3 284.0653  45.5645 <0.0001
DI Model 3       AV 'treatF'          FALSE        94   219.8445     2.3388  1 519.3082 249.8937 <0.0001
DI Model 4       FG 'treatF'          FALSE        92   190.8205     2.0741  2   29.024   6.9833  0.0015
DI Model 5     FULL 'treatF'          FALSE        89   184.9523     2.0781  3   5.8682   0.9413  0.4243

Selected model: Functional group effects 'FG' DImodel with treatment

---------------------------------------------------------------------------------------------
```

Models fitted?

Using autoDI for model selection

```
--------------------------------------------------------------------------------------------------
Step 3: Investigating the treatment effect

Selection using F tests

           Description
DI Model 1 Functional group effects 'FG' DImodel
DI Model 2 Functional group effects 'FG' DImodel with treatment


           DI_model     treat estimate_theta Resid. Df Resid. SSq Resid. MSq Df    SSq      F Pr(>F)
DI Model 1       FG      none          FALSE        93   197.2052     2.1205
DI Model 2       FG 'treatF'           FALSE        92   190.8205     2.0741  1 6.3847 3.0783 0.0827

Selected model: Functional group effects 'FG' DImodel


--------------------------------------------------------------------------------------------------
```

Models fitted?

Using `autoDI` for model selection

```
--------------------------------------------------------------------------------
Step 4: Comparing the final selected model with the reference (community) model
'community' is a factor with 31 levels, one for each unique set of proportions.


               model Resid. Df Resid. SSq Resid. MSq Df     SSq      F Pr(>F)
DI Model 1  Selected        93   197.2052     2.1205
DI Model 2 Reference        69   150.9661     2.1879 24 46.2392 0.8806 0.6251

--------------------------------------------------------------------------------
autoDI is limited in terms of model selection. Exercise caution when choosing your final model.
--------------------------------------------------------------------------------
```

Models fitted?

Where are we at after using `autoDI`?

- Theta set to 1
- FG model for species interactions
  - Grass-legume, grass-grass, legume-legume,
- No effect of N fertiliser

Term	Estimate	Std. Error	P-value
p1_ID	10.9	0.483	<0.001
p2_ID	12.0	0.483	<0.001
p3_ID	6.2	0.483	<0.001
p4_ID	9.5	0.483	<0.001
FG_bfg_GL	20.8	1.427	<0.001
FG_wfg_G	17.6	2.871	<0.001
FG_wfg_L	9.0	2.871	0.002

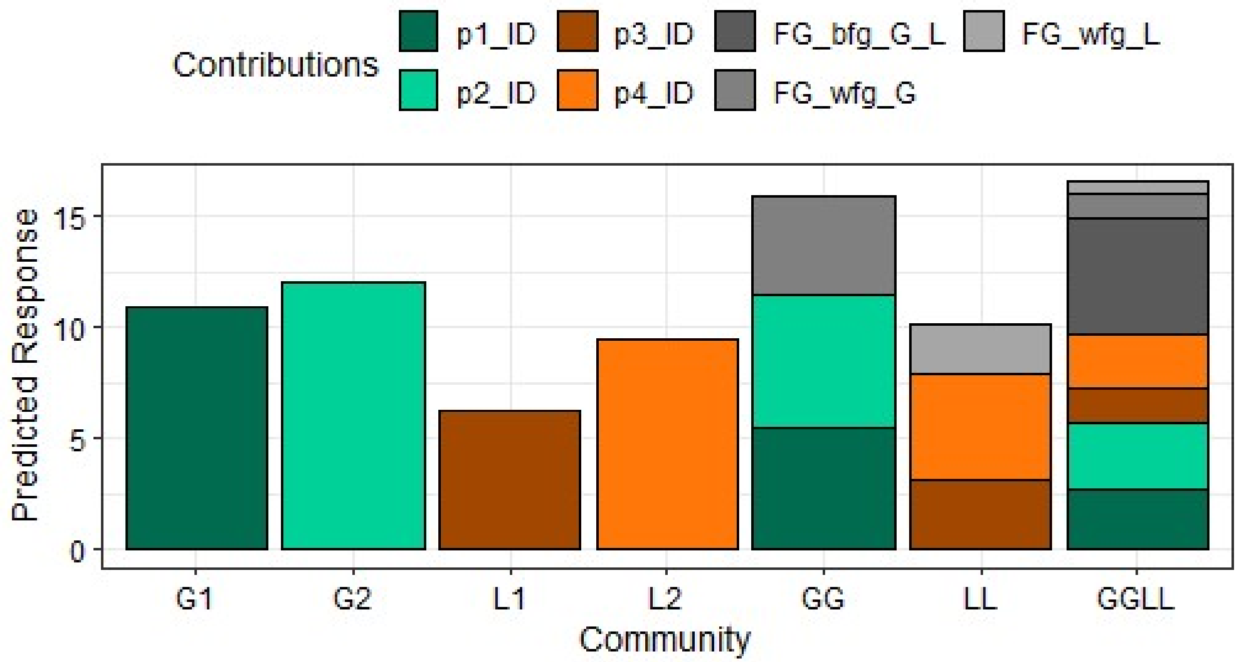
$$y = \sum_{i=1}^{4} \beta_i p_i + \delta_{GL} \sum_{\substack{i \in \{1,2\} \\ j \in \{3,4\}}} p_i p_j + \delta_{GG}(p_1 p_2) + \delta_{LL}(p_3 p_4) + \varepsilon \qquad \varepsilon \sim \text{IID N}(0, \sigma^2)$$

Matrix notation?

$$y = \beta_1 p_1 + \beta_2 p_2 + \beta_3 p_3 + \beta_4 p_4 + \delta_{GL}(p_1 p_3 + p_1 p_4 + p_2 p_3 + p_2 p_4) + \delta_{GG}(p_1 p_2) + \delta_{LL}(p_3 p_4) + \varepsilon$$

Where are we at after using `autoDI`?

- Theta set to 1
- FG model for species interactions
    - Grass-grass, legume-legume, grass-legume
- No effect of treatment

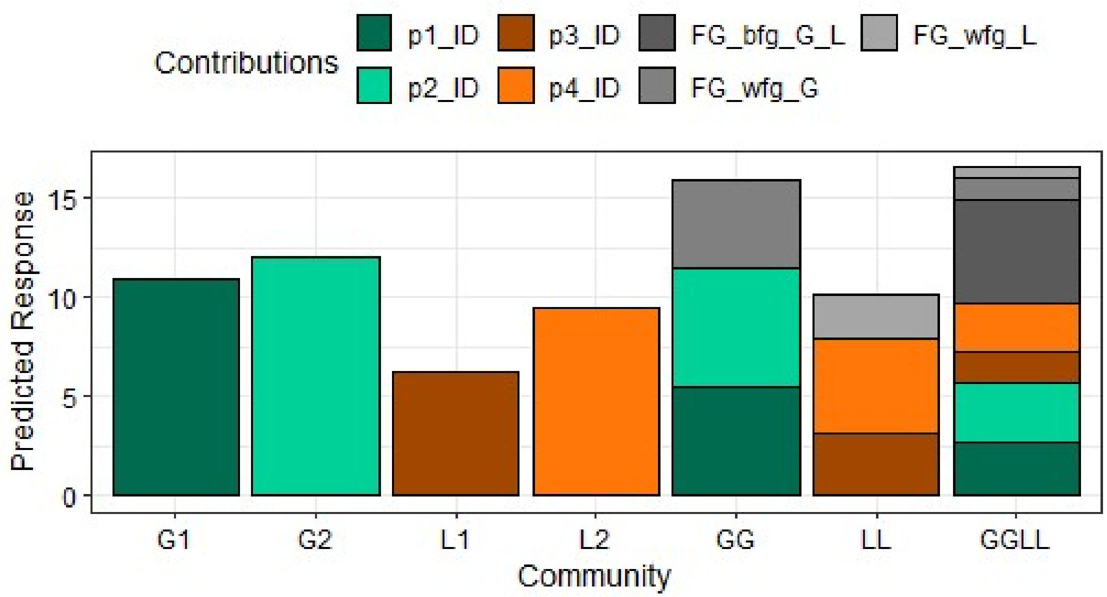


Mixtures are equi-proportional here

Where are we at after using `autoDI`?

Term	Estimate	Std. Error	P-value
p1_ID	10.9	0.483	<0.001
p2_ID	12.0	0.483	<0.001
p3_ID	6.2	0.483	<0.001
p4_ID	9.5	0.483	<0.001
FG_bfg_GL	20.8	1.427	<0.001
FG_wfg_GG	17.6	2.871	<0.001
FG_wfg_LL	9.0	2.871	0.002

Predicted yield for G1?
For G1 = 0.5, G2 = 0.5?
Do these change by N level?



Where are we at after using `autoDI`?

- Theta set to 1
- FG model for species interactions
  - Grass-grass, legume-legume, grass-legume
- No effect of treatment

```
--------------------------------------------------------------------------------
autoDI is limited in terms of model selection. Exercise caution when choosing your final model.
--------------------------------------------------------------------------------
```

What are the limitations of autoDI?

What else do we need to consider?

Example 2 continued
Modelling a 4-species BEF dataset

Deep model selection investigation

Does nitrogen affect the BEF relationship?

So far, the nitrogen treatment has only been tested as an additive factor:

$$y = \sum_{i=1}^{4} \beta_i p_i + \delta_{GL} \sum_{\substack{i \in \{1,2\} \\ j \in \{3,4\}}} p_i p_j + \delta_{GG}(p_1 p_2) + \delta_{LL}(p_3 p_4) + \alpha X_{rN} + \varepsilon$$

X_{rN} is a dummy variable equal to 1 for regular N and 0 for low N

How else might nitrogen be modelled?

Crossing N with all other model terms

```
DI(y = "response", prop = c("p1", "p2", "p3", "p4"),
   FG = c("G","G","L","L"), DImodel = "FG",
   extra_formula = ~ p1:treatF + p2:treatF + p3:treatF + p4:treatF
   + bfg_G_L:treatF + wfg_G:treatF + wfg_L:treatF,
   data = data1)
```

Crossing N with all other model terms

Sown prop	lowN est	regN est
p1_ID	9.99	11.77
p2_ID	11.33	12.68
p3_ID	5.62	6.85
p4_ID	9.65	9.31
FG_bfg_GL	26.98	14.64
FG_wfg_GG	14.65	20.59
FG_wfg_LL	10.38	7.72

```
Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
p1_ID                  11.7747     0.5873  20.050  < 2e-16 ***
p2_ID                  12.6753     0.5873  21.583  < 2e-16 ***
p3_ID                   6.8511     0.5873  11.666  < 2e-16 ***
p4_ID                   9.3053     0.5873  15.845  < 2e-16 ***
FG_bfg_G_L             14.6371     1.7352   8.436 6.93e-13 ***
FG_wfg_G               20.5948     3.4923   5.897 7.08e-08 ***
FG_wfg_L                7.7236     3.4923   2.212   0.0296 *
`p1:treatFlowN`        -1.7875     0.8305  -2.152   0.0342 *
`treatFlowN:p2`        -1.3482     0.8305  -1.623   0.1082
`treatFlowN:p3`        -1.2286     0.8305  -1.479   0.1427
`treatFlowN:p4`         0.3427     0.8305   0.413   0.6809
`treatFlowN:bfg_G_L`   12.3432     2.4539   5.030 2.65e-06 ***
`treatFlowN:wfg_G`     -5.9494     4.9388  -1.205   0.2316
`treatFlowN:wfg_L`      2.6524     4.9388   0.537   0.5926
```

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Model selection

- Reduce the nitrogen interaction terms in the model, removing one non-significant term at a time
- Final model: N crossed with p1, p2 and the grass-legume interaction term

```
Coefficients:

p1_ID
p2_ID
p3_ID
p4_ID
FG_bfg_G_L
FG_wfg_G
FG_wfg_L
`p1:treatFlowN`
`treatFlowN:p2`
~~`treatFlowN:p3`~~
~~`treatFlowN:p4`~~
`treatFlowN:bfg_G_L`
~~`treatFlowN:wfg_G`~~
~~`treatFlowN:wfg_L`~~
```

Example 2 continued

Modelling a 4-species BEF dataset

Final model equation, different parameterisations and diagnostics

Final model coefficient estimates

```
Coefficients:
                      Estimate Std. Error t value Pr(>|t|)    
p1_ID                  11.9830     0.5592  21.427  < 2e-16 ***
p2_ID                  12.8836     0.5592  23.038  < 2e-16 ***
p3_ID                   6.2368     0.4158  15.001  < 2e-16 ***
p4_ID                   9.4766     0.4158  22.794  < 2e-16 ***
FG_bfg_G_L             14.9219     1.5792   9.449 4.00e-15 ***
FG_wfg_G               17.6201     2.4723   7.127 2.46e-10 ***
FG_wfg_L                9.0498     2.4723   3.660 0.000424 ***
`p1:treatFlowN`        -2.2042     0.7481  -2.947 0.004091 ** 
`treatFlowN:p2`        -1.7648     0.7481  -2.359 0.020475 *  
`treatFlowN:bfg_G_L`   11.7736     1.9848   5.932 5.48e-08 ***
```

Term	Low N Est	Reg N Est
p1	**9.78**	**11.98**
p2	**11.12**	**12.88**
p3	6.23	6.23
p4	9.48	9.48
FG_bfg_GL	**26.70**	**14.92**
FG_wfg_G	17.62	17.62
FG_wfg_L	9.05	9.05

Different parameterisations?

Final model coefficient estimates

```
Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
p3                   6.2368     0.4158  15.001  < 2e-16 ***
p4                   9.4766     0.4158  22.794  < 2e-16 ***
wfg_G               17.6201     2.4723   7.127 2.46e-10 ***
wfg_L                9.0498     2.4723   3.660 0.000424 ***
p1:treatFlowN        9.7788     0.5592  17.486  < 2e-16 ***
p1:treatFregN       11.9830     0.5592  21.427  < 2e-16 ***
treatFlowN:p2       11.1188     0.5592  19.882  < 2e-16 ***
treatFregN:p2       12.8836     0.5592  23.038  < 2e-16 ***
treatFlowN:bfg_G_L  26.6955     1.5792  16.905  < 2e-16 ***
treatFregN:bfg_G_L  14.9219     1.5792   9.449 4.00e-15 ***
```

Term	Low N Est	Reg N Est
p1	**9.78**	**11.98**
p2	**11.12**	**12.88**
p3	6.23	6.23
p4	9.48	9.48
FG_bfg_GL	**26.70**	**14.92**
FG_wfg_G	17.62	17.62
FG_wfg_L	9.05	9.05

Others?

Final model coefficient estimates

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
p1             9.7788     0.5592  17.486  < 2e-16 ***
p2            11.1188     0.5592  19.882  < 2e-16 ***
p3             6.2368     0.4158  15.001  < 2e-16 ***
p4             9.4766     0.4158  22.794  < 2e-16 ***
bfg_G_L       26.6955     1.5792  16.905  < 2e-16 ***
wfg_G         17.6201     2.4723   7.127 2.46e-10 ***
wfg_L          9.0498     2.4723   3.660 0.000424 ***
p1:regN        2.2042     0.7481   2.947 0.004091 ** 
p2:regN        1.7648     0.7481   2.359 0.020475 *  
bfg_G_L:regN -11.7736     1.9848  -5.932 5.48e-08 ***
```

Term	Low N Est	Reg N Est
p1	**9.78**	**11.98**
p2	**11.12**	**12.88**
p3	6.23	6.23
p4	9.48	9.48
FG_bfg_GL	**26.70**	**14.92**
FG_wfg_G	17.62	17.62
FG_wfg_L	9.05	9.05

Which parameterisation do you prefer?

Model equation

Let: p_i = sown proportion of species i

$FG\_bfg\_GL = p_1p_3 + p_1p_4 + p_2p_3 + p_2p_4$

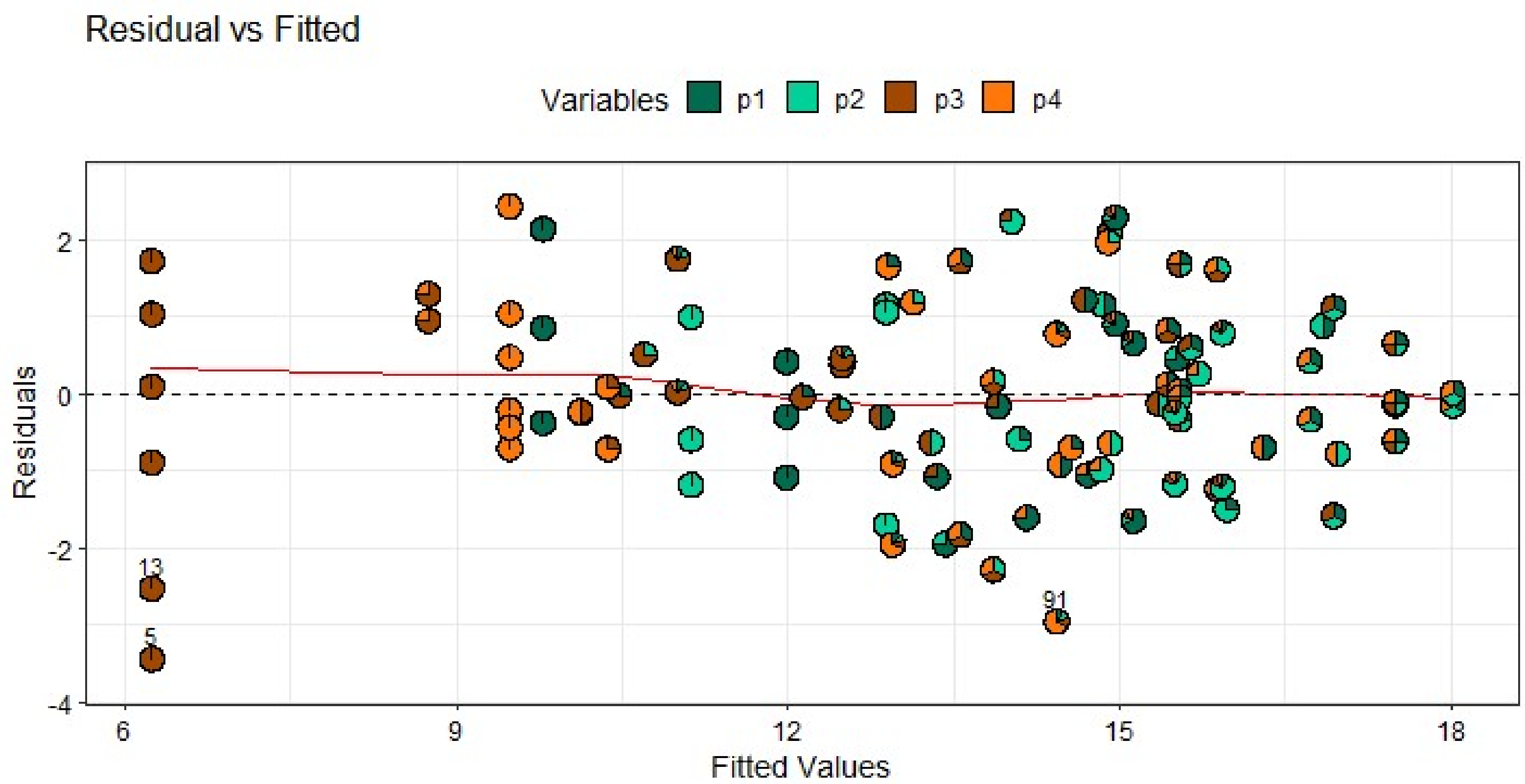
X_{rN} = 1 for regular N and 0 for low N

$$y = \beta_1 p_1 + \beta_2 p_2 + \beta_3 p_3 + \beta_4 p_4 + \delta_{GL}(FG\_bfg\_GL) + \delta_{GG}(p_1p_2) + \delta_{LL}(p_3p_4)$$
$$+\beta_{1rN}p_1X_{rN} + \beta_{2rN}p_2X_{rN} + \delta_{GL\_rN}(FG\_bfg\_GL)X_{rN} + \varepsilon$$

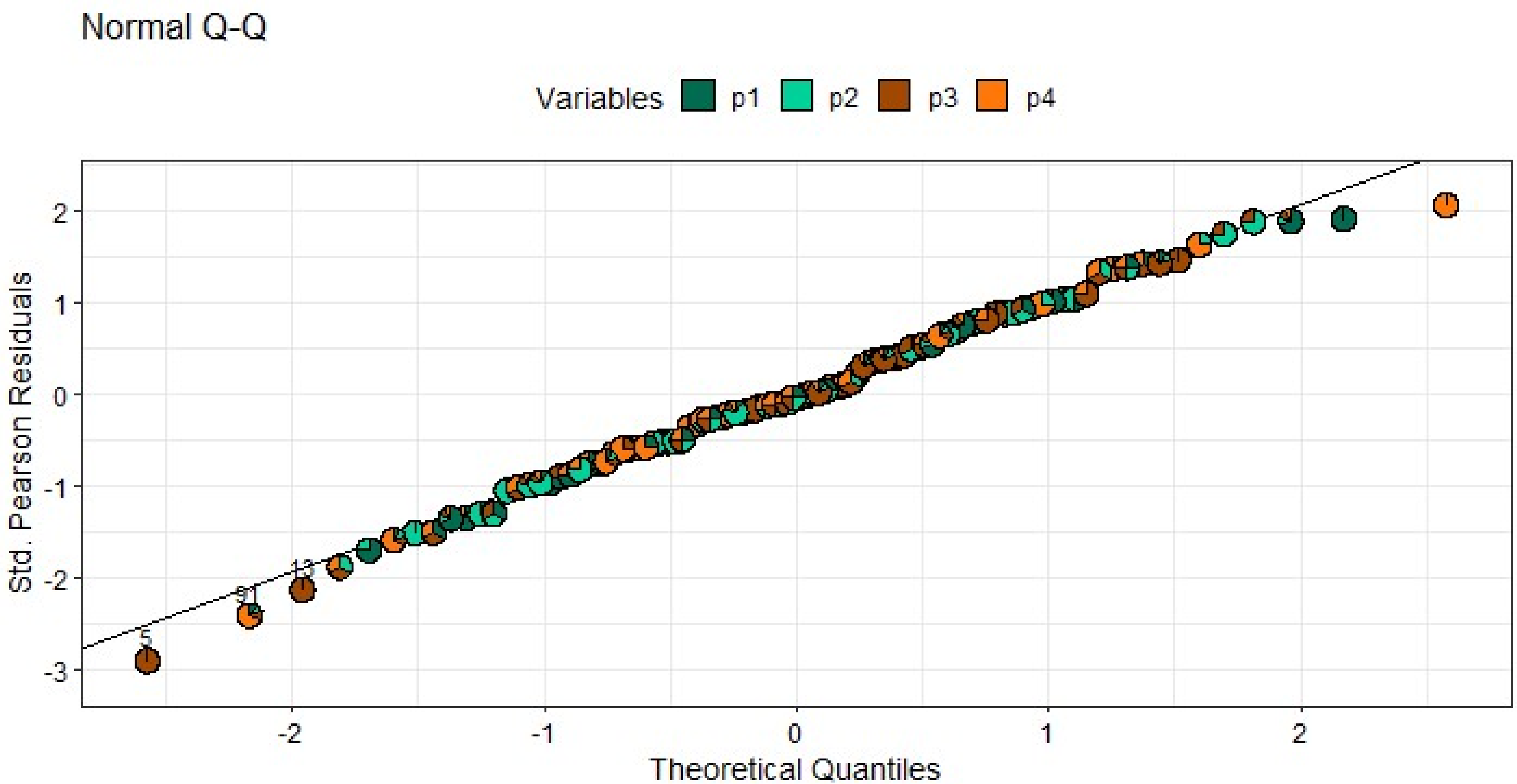
$\varepsilon \sim$ IID N(0, σ^2)

Matrix notation?

Final model diagnostics



Final model diagnostics



Example 2 continued
Modelling a 4-species BEF dataset

Predicting from the final model

Predicting from the model

- Grass 1 monoculture low N

$$\hat{y} = 9.78$$

- Grass 1 monoculture regular N

$$\hat{y} = 9.78 + 2.20 = 11.98$$

- Equi-prop 4-species mix low N

$$\hat{y} = 9.78 \times 0.25 + 11.12 \times 0.25 + 6.24 \times 0.25 + 9.48 \times 0.25$$
$$+26.70 \times 0.25 + 17.62 \times 0.0625 + 9.05 \times 0.0625 = 17.49$$

- Equi-prop 4-species mix regular N

$$\hat{y} = 17.49 + 2.20 \times 0.25 + 1.76 \times 0.25 - 11.77 \times 0.25 = 15.54$$

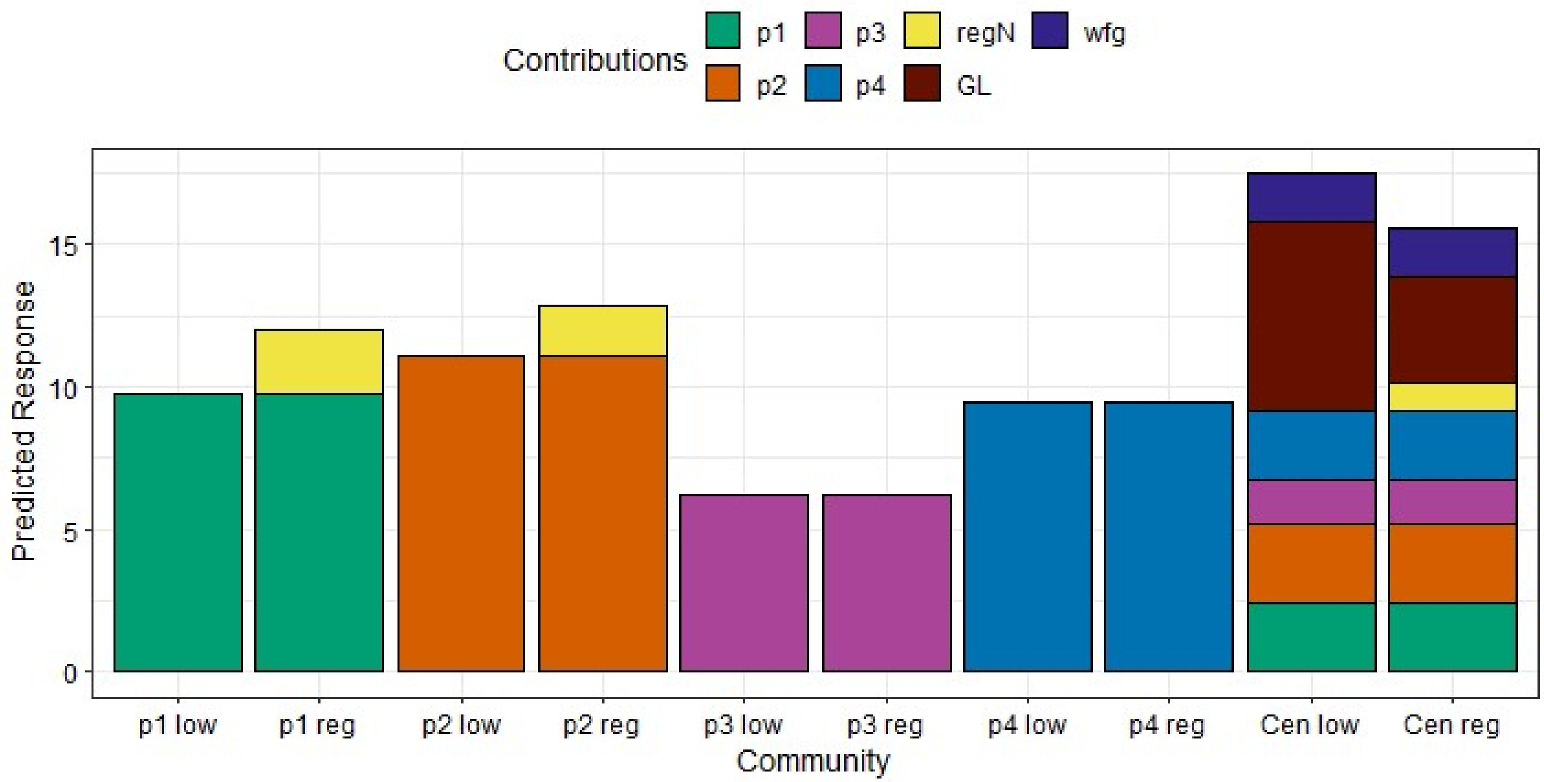
Term	Estimate
p1_ID	9.78
p2_ID	11.12
p3_ID	6.24
p4_ID	9.48
FG_bfg_G_L	26.70
FG_wfg_G	17.62
FG_wfg_L	9.05
p1:regN	2.20
p2:regN	1.76
bfg_G_L:regN	-11.77

Example 2 continued

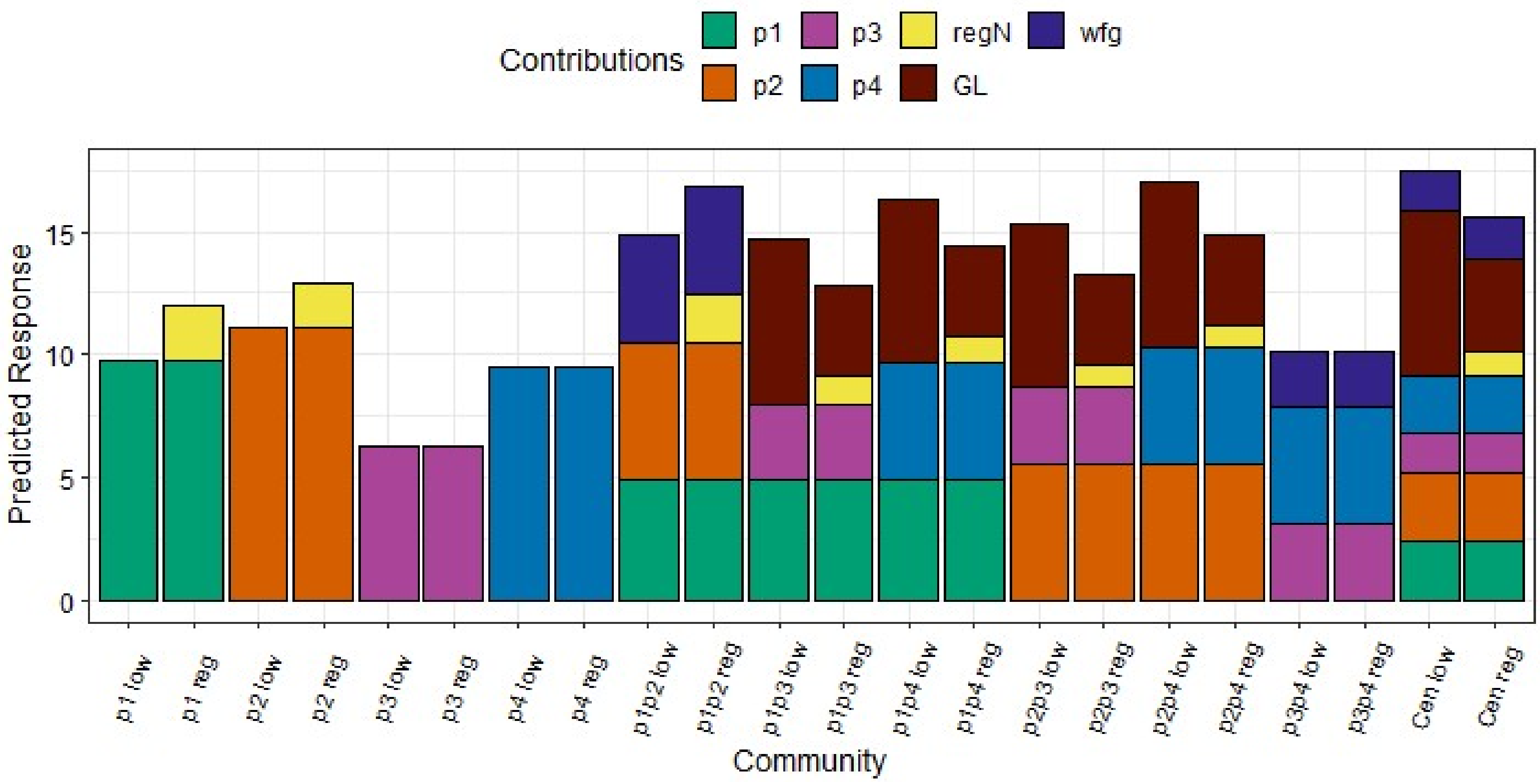
Modelling a 4-species BEF dataset

Final model interpretation

Interpreting the final model

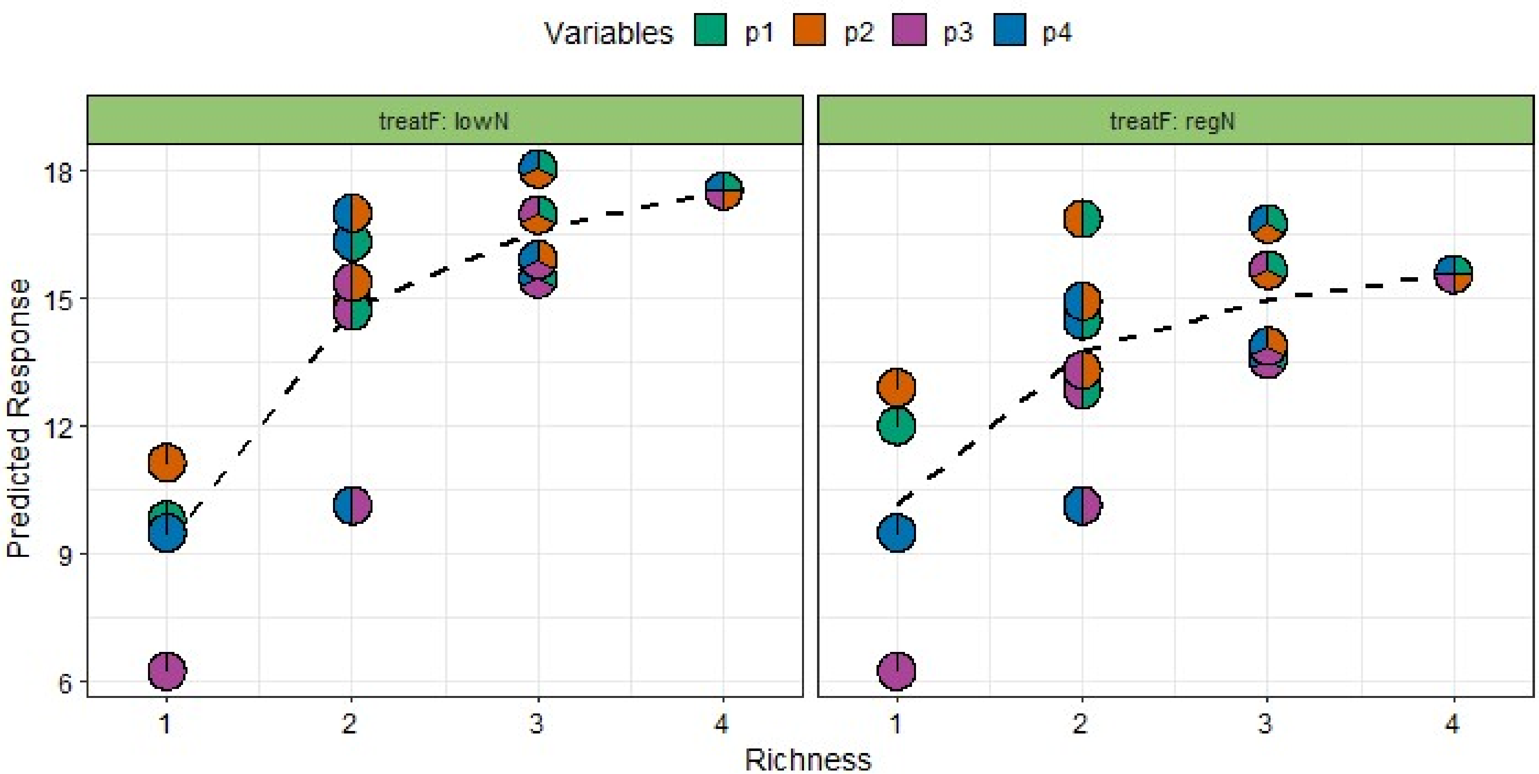


Interpreting the final model

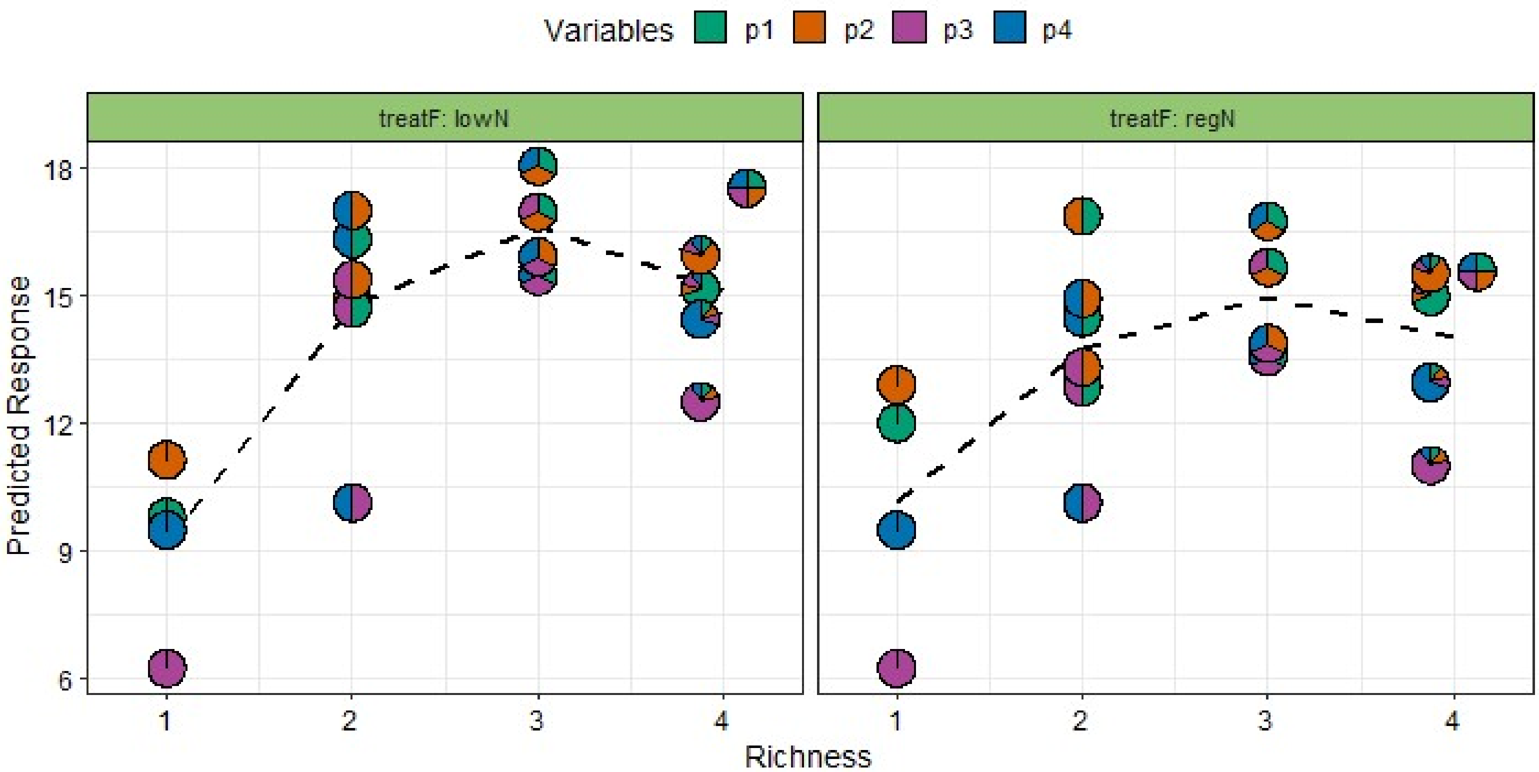


Mixtures are equi-proportional here

Interpreting the final model

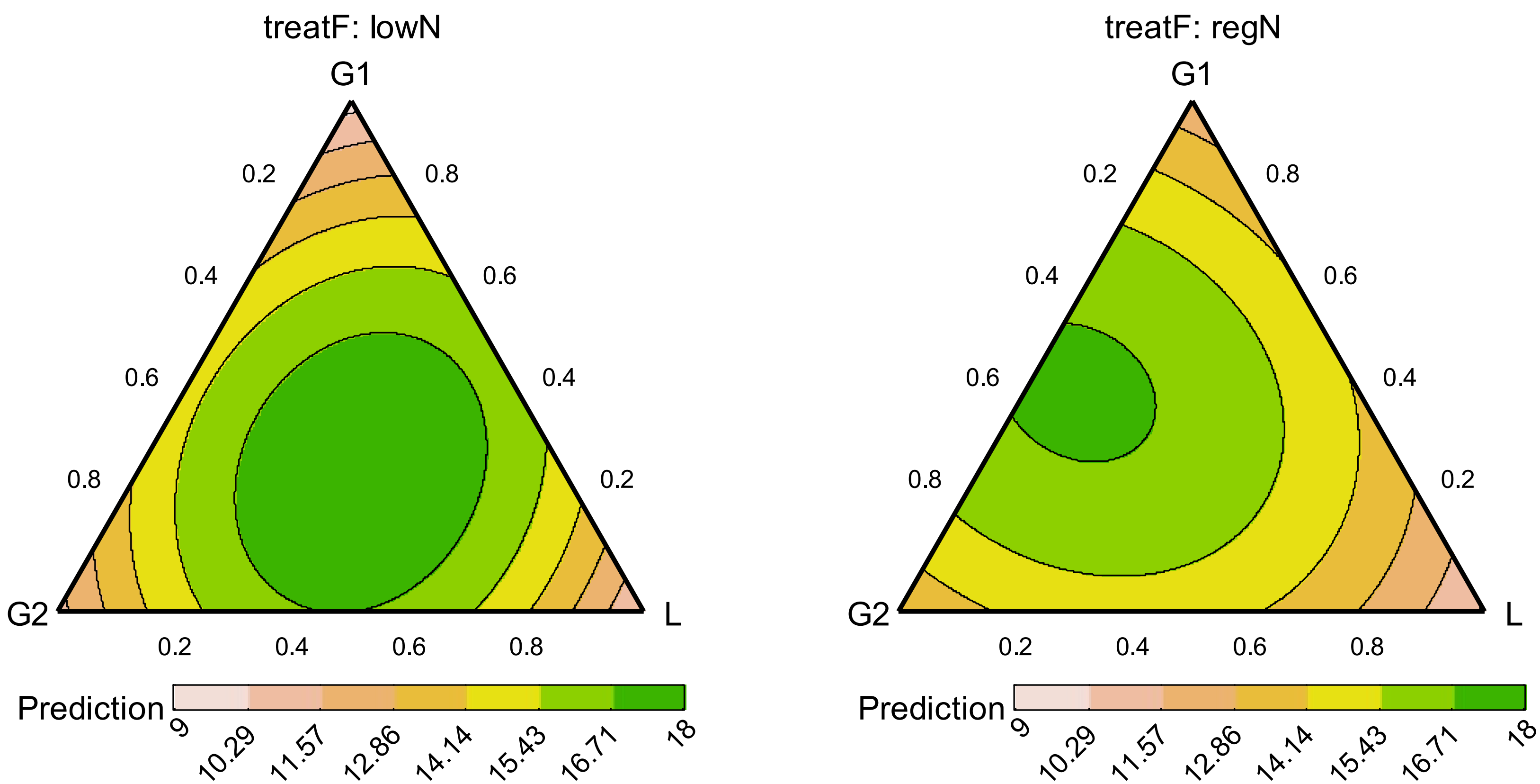


Interpreting the final model



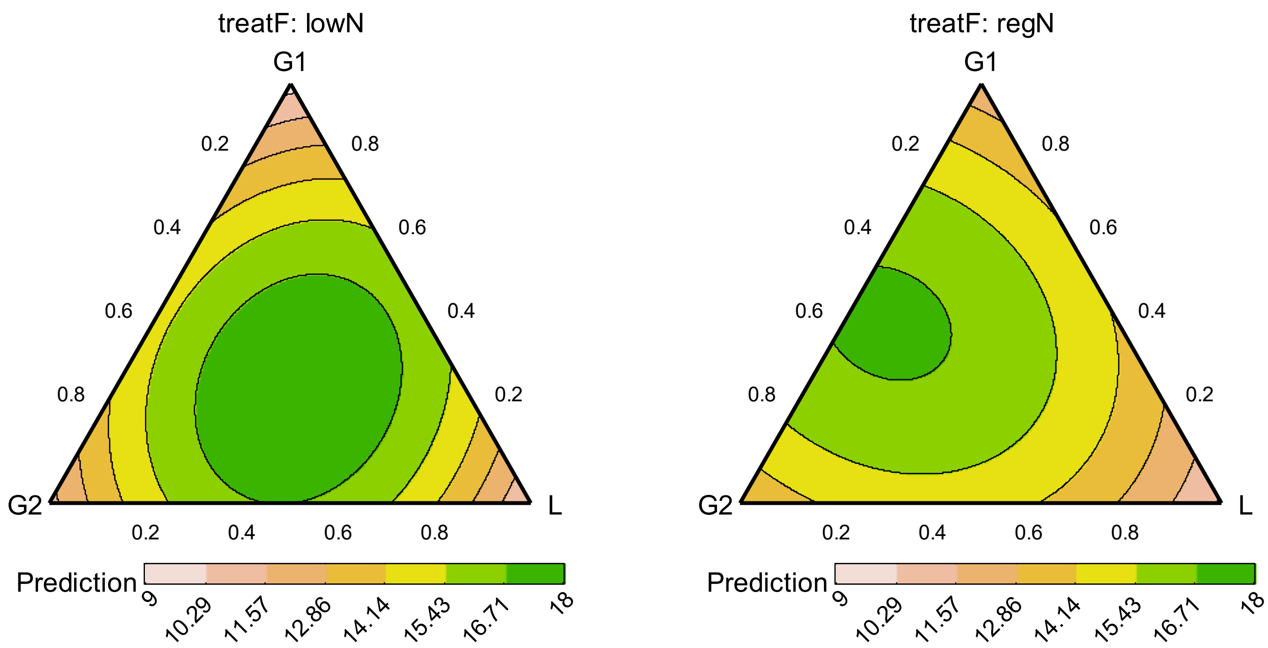
Interpreting the final model

Each prediction assumes L1:L2 in an equal ratio



Interpreting the final model

Each prediction assumes L1:L2 in an equal ratio



Term	Low N Est	Reg N Est
p1	**9.78**	**11.98**
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FG_bfg_GL	**26.70**	**14.92**
FG_wfg_G	17.62	17.62
FG_wfg_L	9.05	9.05

Key messages

- Effect of species diversity?
- Effect of low versus regular N fertiliser?
- Other?

- What have you put in your one-page report?

Final remarks

DImodels website

DI MODELS

Home Training Blog About Archive

Diversity-Interactions Modelling

Resources And Toolkit For Fitting DI Models

Introduction To Diversity-Interactions Models

Welcome to the Diversity-Interactions (DI) models website! Here you will find out all the latest news and research developments related to DI models. You will also find training resources and guides to fitting and interpreting DI models.

What Is A Diversity-Interactions Model?

In biodiversity and ecosystem function (BEF) studies, usually there are a range of communities varying in species diversity.
For example, selecting from a pool of species, the communities may vary in:

- the number of species,
- the identities of the species, and
- the proportions of each species

In a BEF experiment, usually these species diversity variables are manipulated across all experimental units and an ecosystem function is recorded at a later point in time. Models of the BEF relationship assess how species diversity affects an ecosystem function, but should account for all of these variations in species diversity, not just a subset of them. This is what Diversity-Interactions models will do!

DI models jointly assess the effects of species identity, richness, evenness, community composition, and interspecific interactions on an ecosystem function in a regression modelling framework.

The DImodels R package is available to implement the Diversity-Interactions modelling approach. Select Training for advice on how to get started using DI models. Find out all the latest news on our Blog.

References for extending DI models

- Repeated measures and a spatial gradient
  - Kirwan et al (2007) Journal of Ecology 95, 530–539
  - Finn et al (2013) Journal of Applied Ecology 50, 365–375
  - Connolly et al (2018) Journal of Applied Ecology 55, 852-862
- Multivariate responses
  - Dooley et al (2015) Ecology Letters 18, 1242-1251
  - Suter et al (2021) Scientific Reports 11, 1-16
- Dealing with many pairwise interactions
  - Brophy et al (2017) Ecology 98, 1771–1778
- Investigating theta properties
  - Vishwakarma et al (2023) Environmental and Ecological Statistics 30, 555–574.

Packages for fitting and interpreting DI models

`DImodels, DImodelsVis, DImodelsMulti.`