


Don’t stare into the abyss: understanding your model.

Dr Neil Burns – neil.burns@sruc.ac.uk

How the session will work

Mix of presentation are R coding

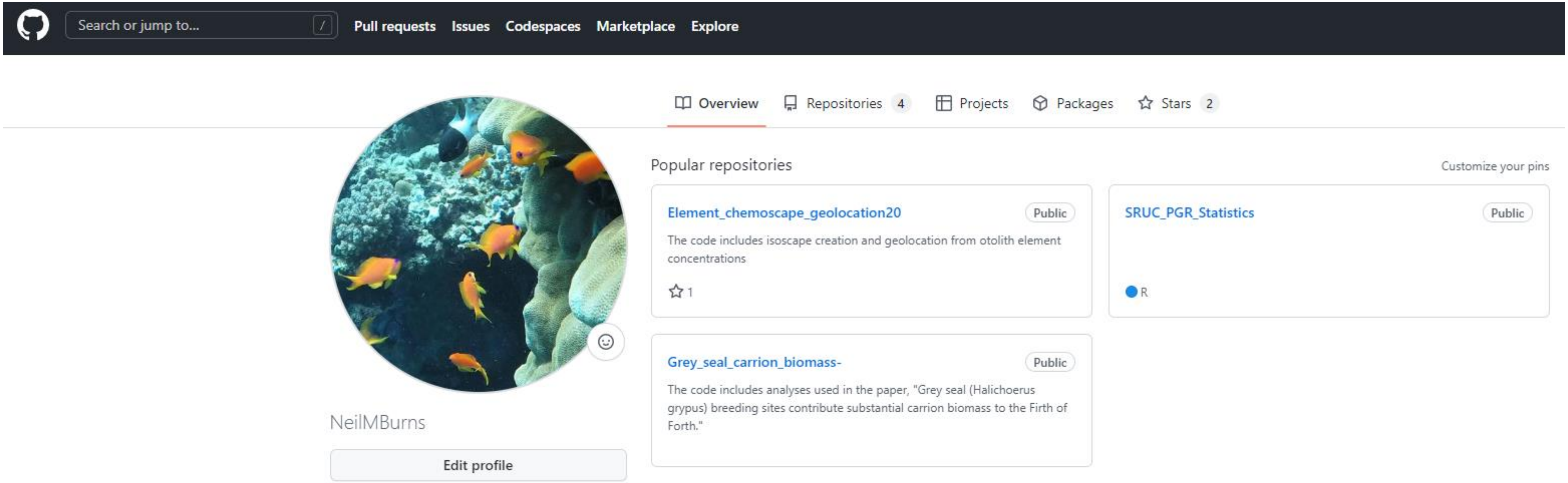
Flit between PowerPoint and R:

- Presentation and code available at my github

https://github.com/NeilMBurns

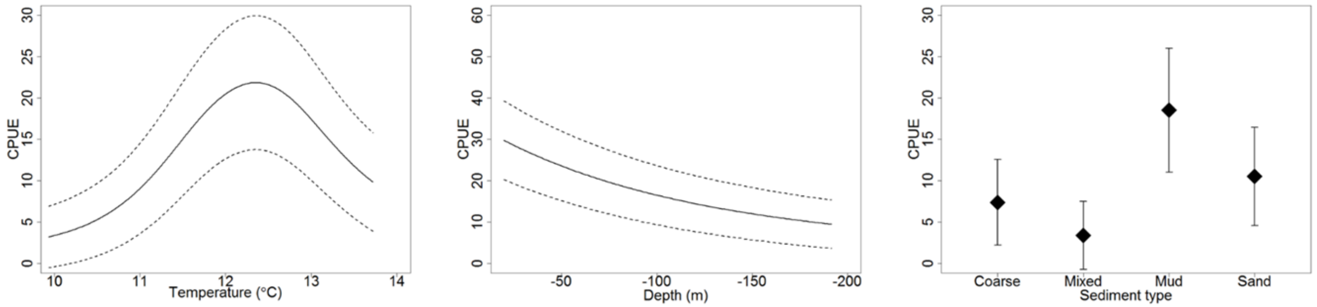
Section headings in R will be highlighted like:

```
########################################
#####        1.  some sort of title       #####
########################################
```



Research Interests

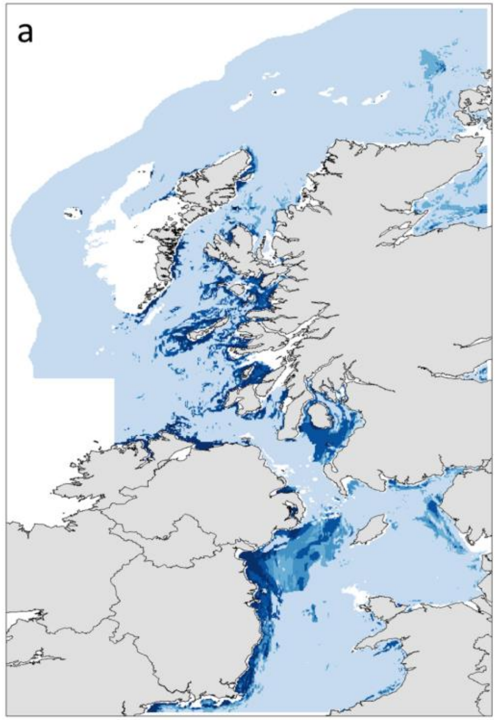
Population ecology and ecosystem health

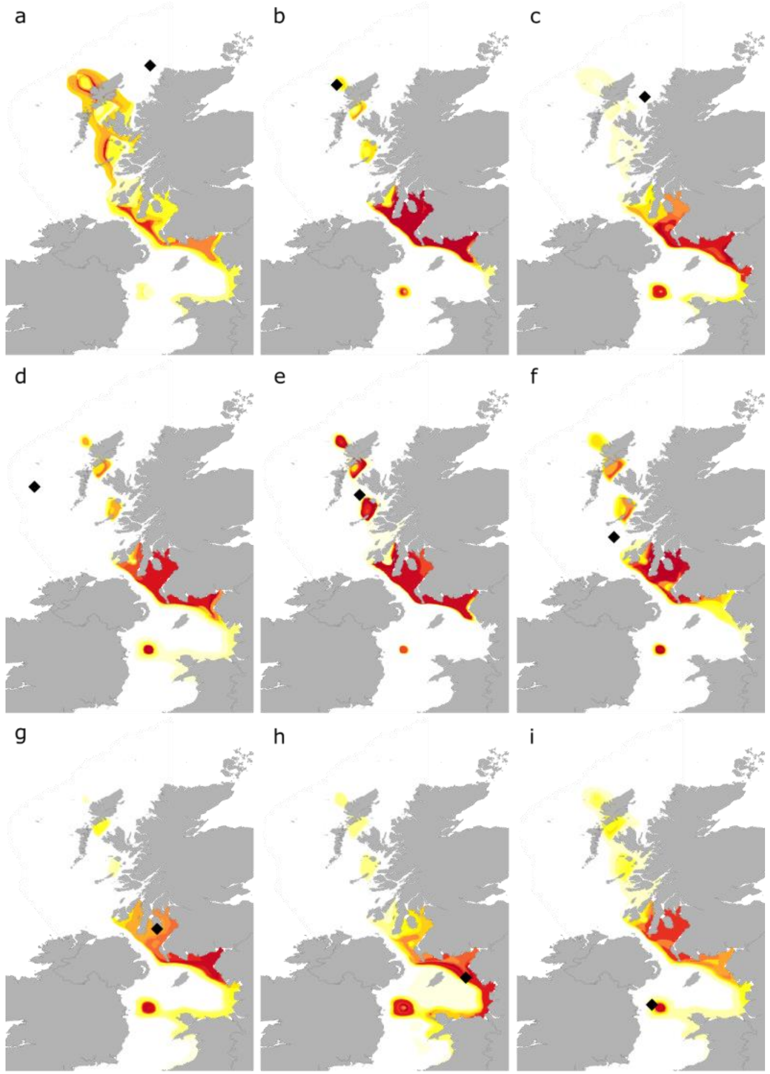


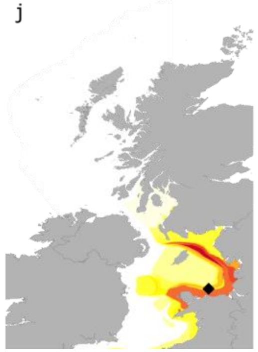
RESEARCH ARTICLE

A method to improve fishing selectivity through age targeted fishing using life stage distribution modelling

Neil M. Burns[1,2]*, David M. Bailey[1], Peter J. Wright[2]





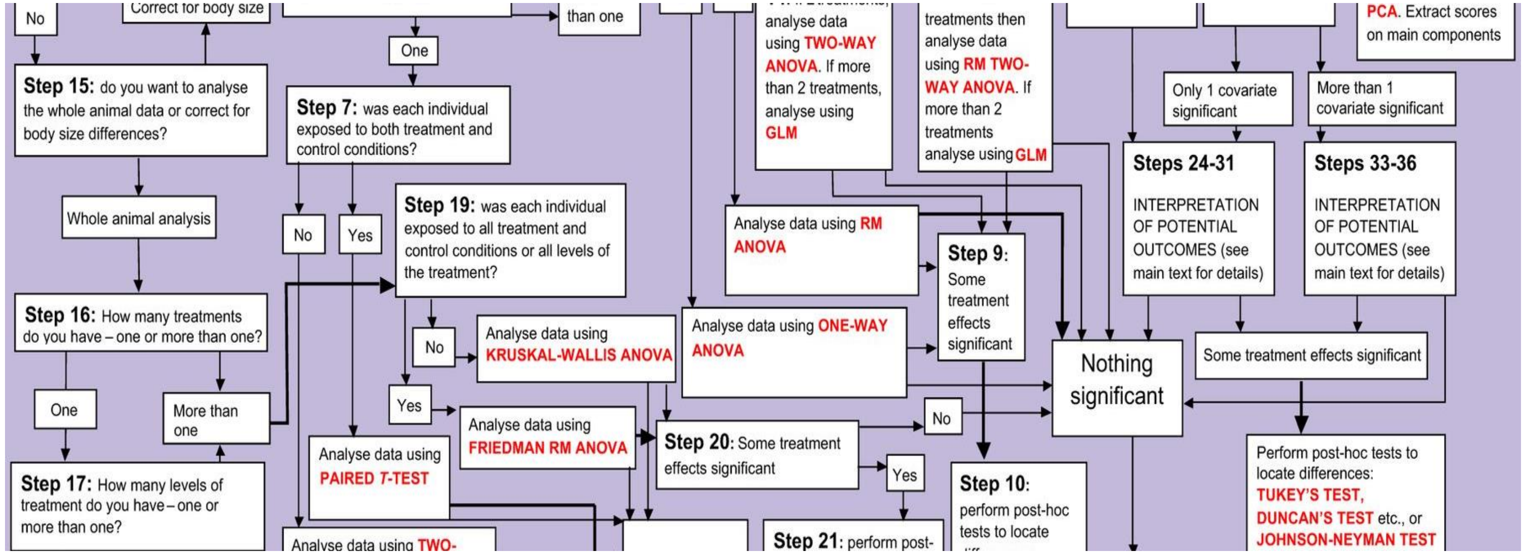


COMMUNICATIONS BIOLOGY

Otolith chemoscape analysis in whiting links fishing grounds to nursery areas

Neil M. Burns, Charlotte R. Hopkins, David M. Bailey and Peter J. Wright *2020*

Why use someone else's robot?



Linear models (lm)
Generalised Linear Models (glm)
Generalised Additive Models (gam)
Mixed effects versions of (lmm, glmm, gamm)

Statistical modelling
using glms

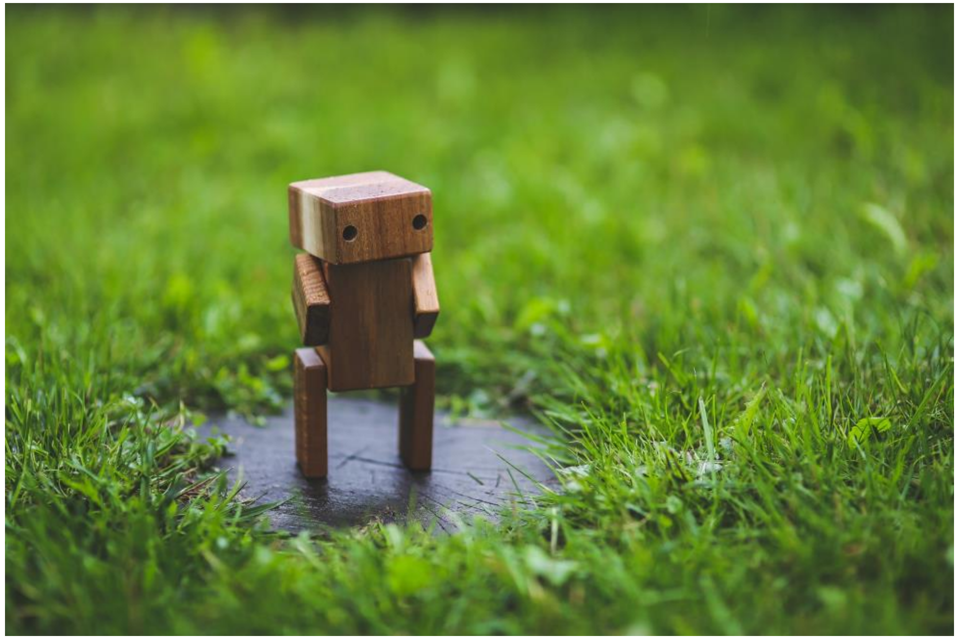
Why R?

Building useful robots and making inferences

Build the model from the knowledge of your data then use information theory to select models (and make inferences).

A. Model selection
   - Picking the best of a bad bunch.

B. Model validation
   - So how rubbish is it?



By using AIC we are selecting the most "cost" effective model. With cost being measured in degrees of freedom.

AIC balance between over and underfitting by estimating out-of-sample deviance without needing to do cross-validation (the gold standard)

A - Model selection

Using AIC (log-likelihood ratio tests are also useful for those who like a p-value)

<u>Selection recipe</u>

- Start with the most complex model and work "back" towards the most simple
- Use AIC to choose (3 rules)
    1. Simple models are best
    2. Small AIC is best
    3. If these rules contradict (ie the more complex model has smaller AIC) then AIC should be different by more then 2

"I used backwards stepwise model selection to …"

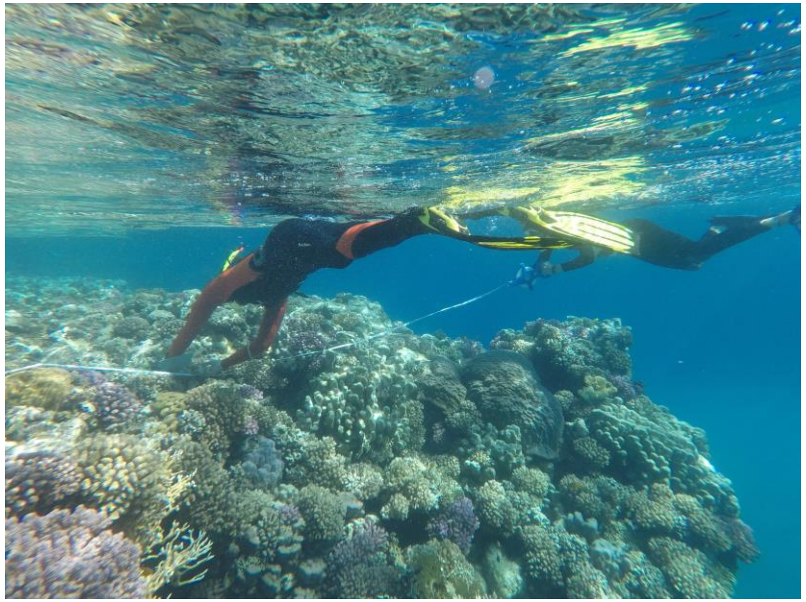
Final interpretation – a word about staring into the abyss

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 1.929914   0.417166   4.626 1.14e-05 ***
perc_cov    0.116220   0.007622  15.248  < 2e-16 ***
---
```

```
Coefficients:
                      Estimate Std. Error t value Pr(>|t|)    
(Intercept)            5.49784    0.60079   9.151 1.17e-14 ***
perc_cov               0.10071    0.01005  10.026  < 2e-16 ***
cor_colBrown          -1.61468    1.00986  -1.599  0.11320    
cor_colGreen           3.69075    1.38125   2.672  0.00889 ** 
perc_cov:cor_colBrown  0.01524    0.02008   0.759  0.44973    
perc_cov:cor_colGreen -0.08092    0.02581  -3.135  0.00229 ** 
---
```

= 42

Example 1 – Sharks and coral



Abundance of sharks (y_1) ~

It's a whole number (or maybe not)

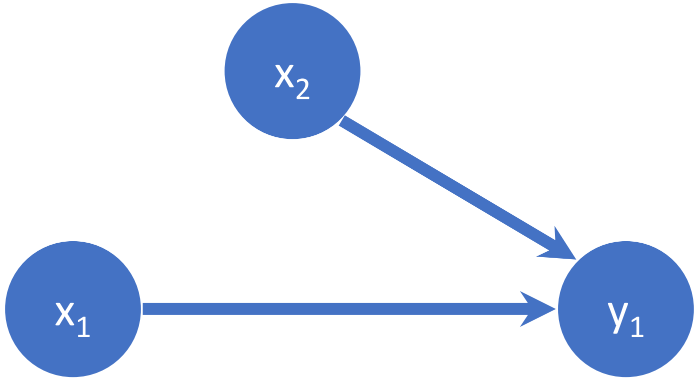
They are big and there are not loads of them so probably less than 60

Coral percentage cover (x_1)

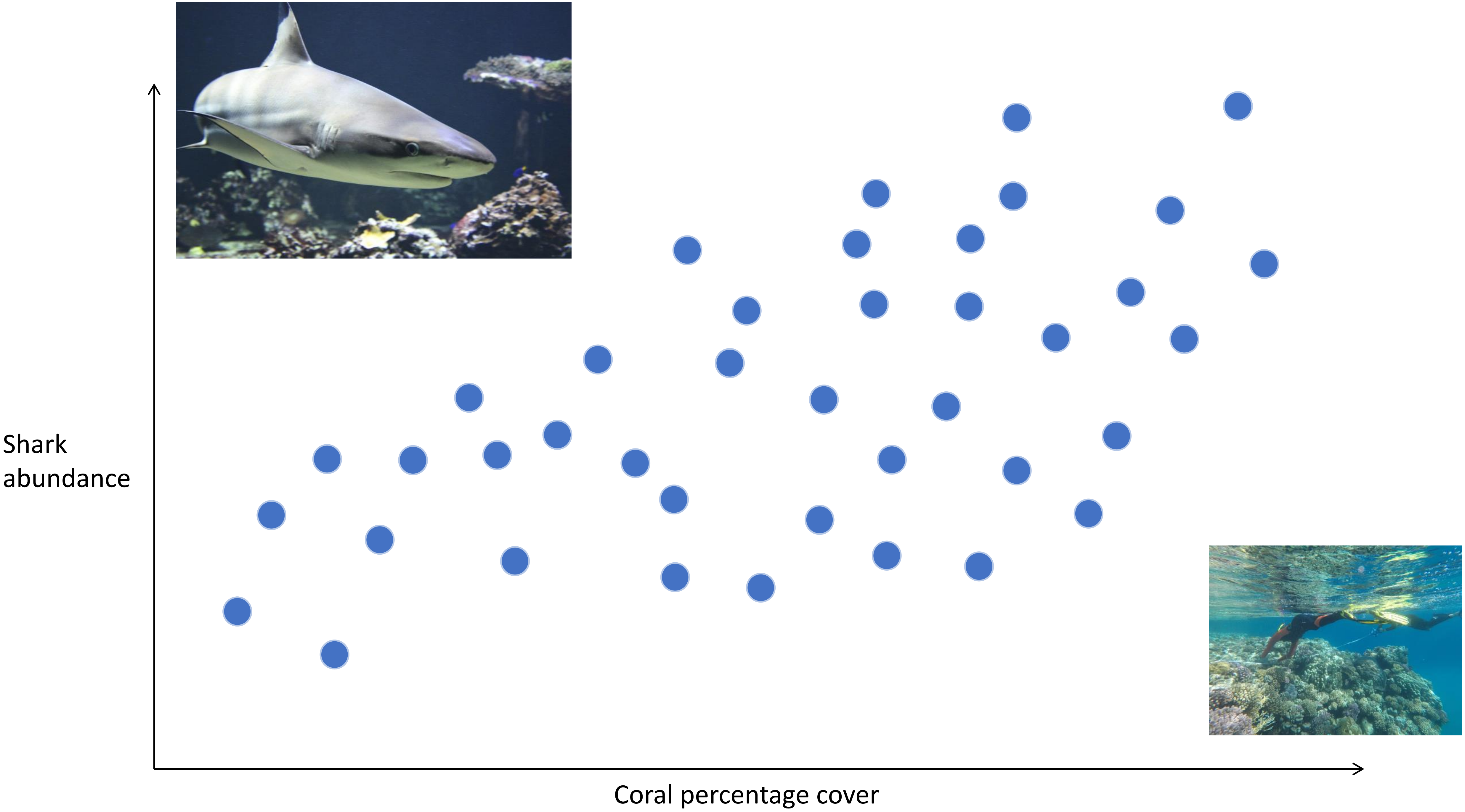
0 to 100%

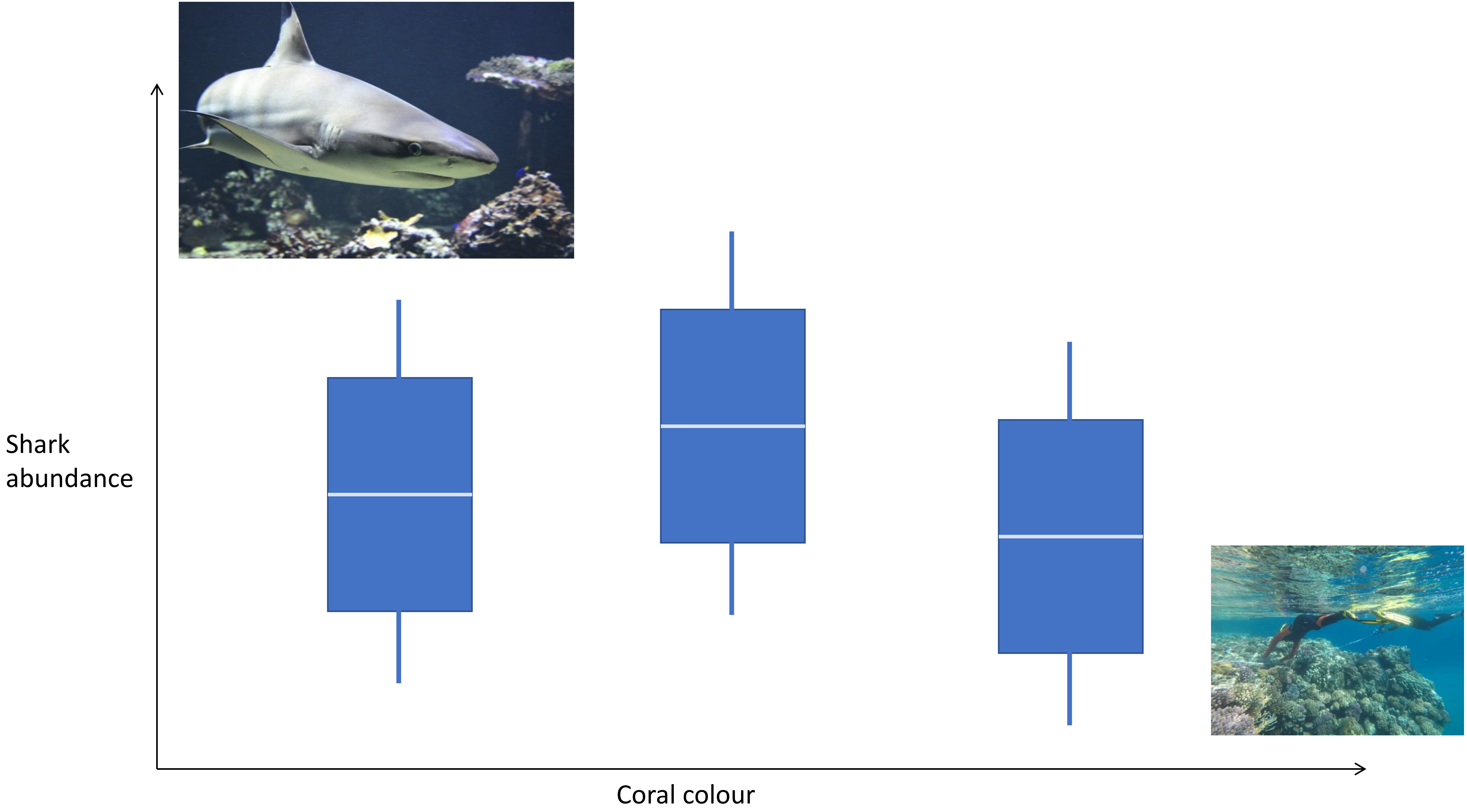
Coral colour (x_2)

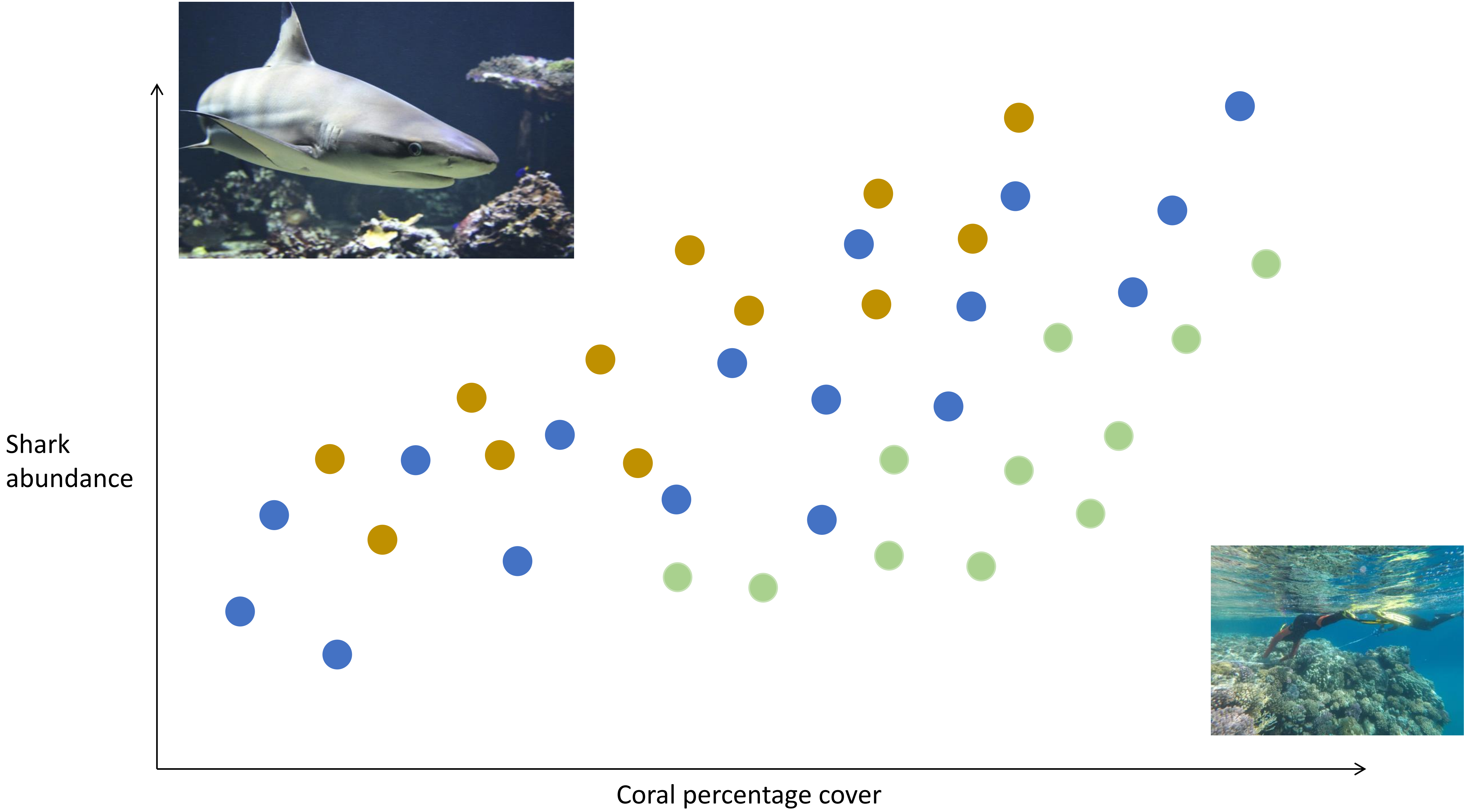
Blue, Brown & green



Directed Acyclic Graph (DAG)


Shark abundance
Coral percentage cover


Shark
abundance
Coral colour


Shark
abundance
Coral percentage cover

Back to R – Worked example

```
#########################################
#####          2. Understanding our data     #####
#########################################
```

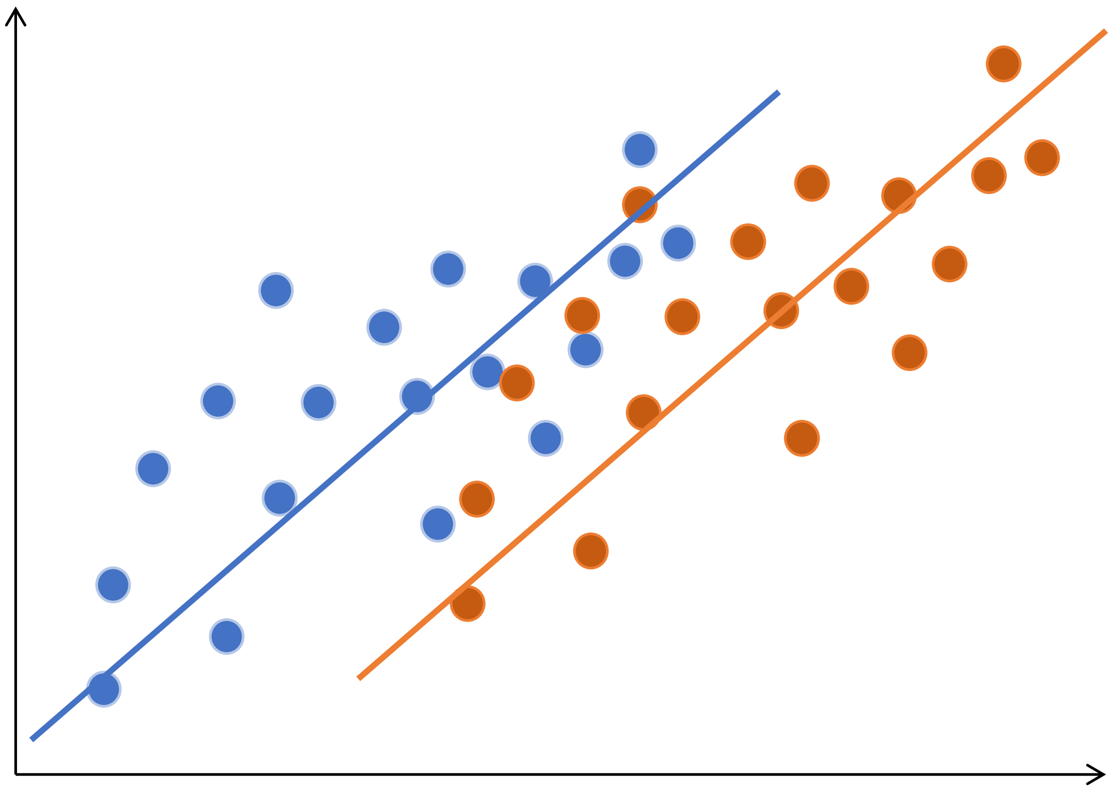
```
#########################################
#####          3. Models and inference        #####
#########################################
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)    
(Intercept) 1.913513   0.048185   39.71   <2e-16 ***
perc_cov    0.012233   0.000753   16.25   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Coefficients:
                       Estimate Std. Error z value Pr(>|z|)    
(Intercept)           3.5978497  0.0331302 108.597  < 2e-16 ***
perc_cov              0.0196547  0.0004554  43.159  < 2e-16 ***
cor_colBrown         -3.2761745  0.1571768 -20.844  < 2e-16 ***
cor_colGreen         -0.8946106  0.0577938 -15.479  < 2e-16 ***
perc_cov:cor_colBrown 0.0014695  0.0021828   0.673  0.50081    
perc_cov:cor_colGreen 0.0027831  0.0008577   3.245  0.00118 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Counterfactuals – One continuous variable under a set of conditions (factor/treatment)

Counterfactual variable

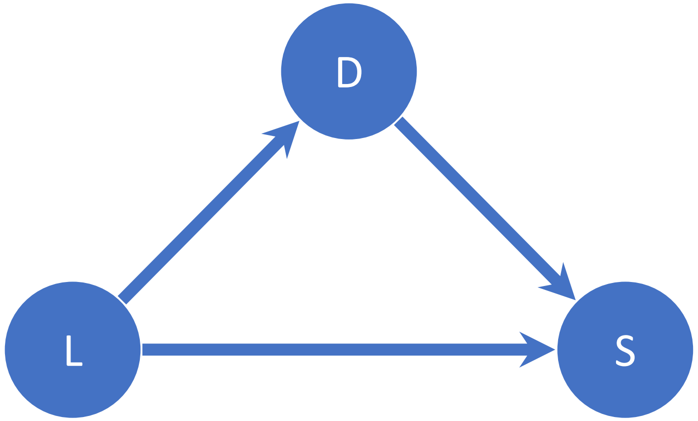


Manipulated variable under condition A & B

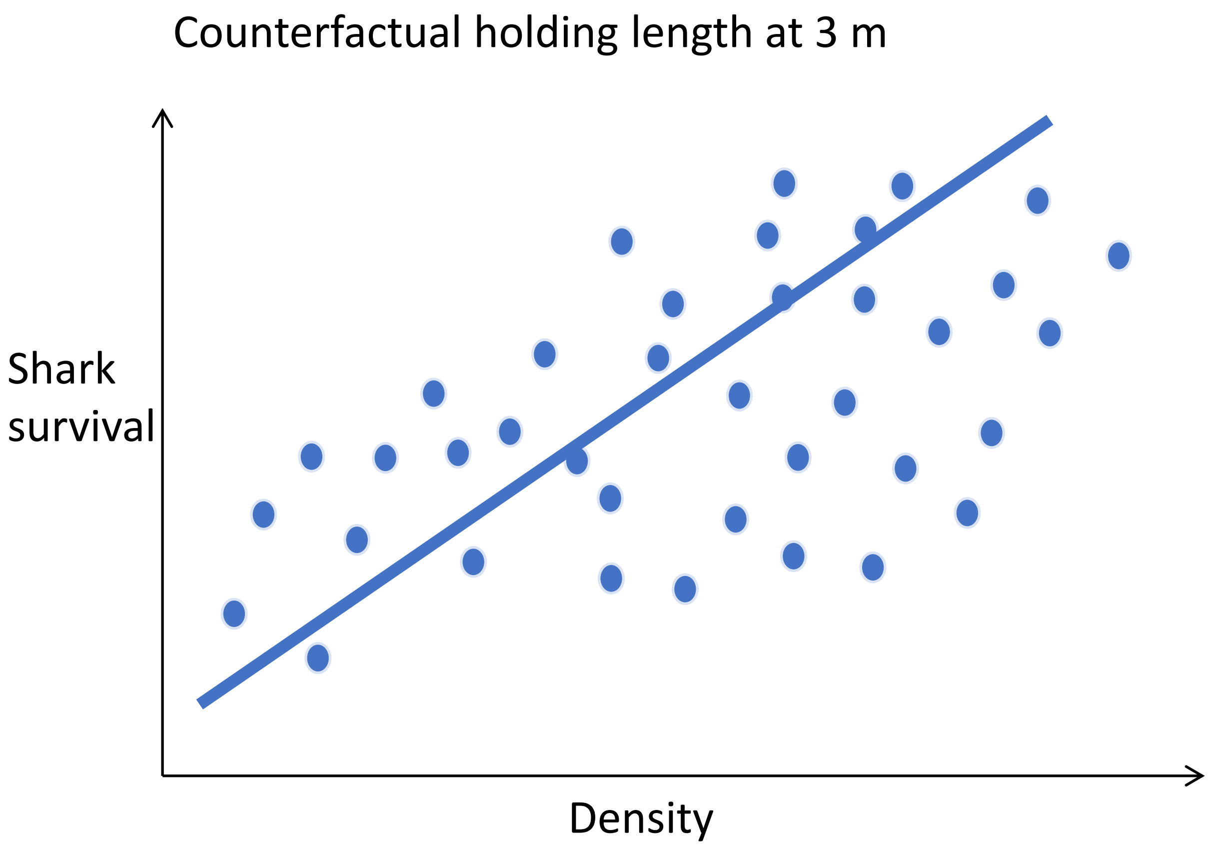

```
#################################################
### Use prediction to understand the model   ####
#################################################
```

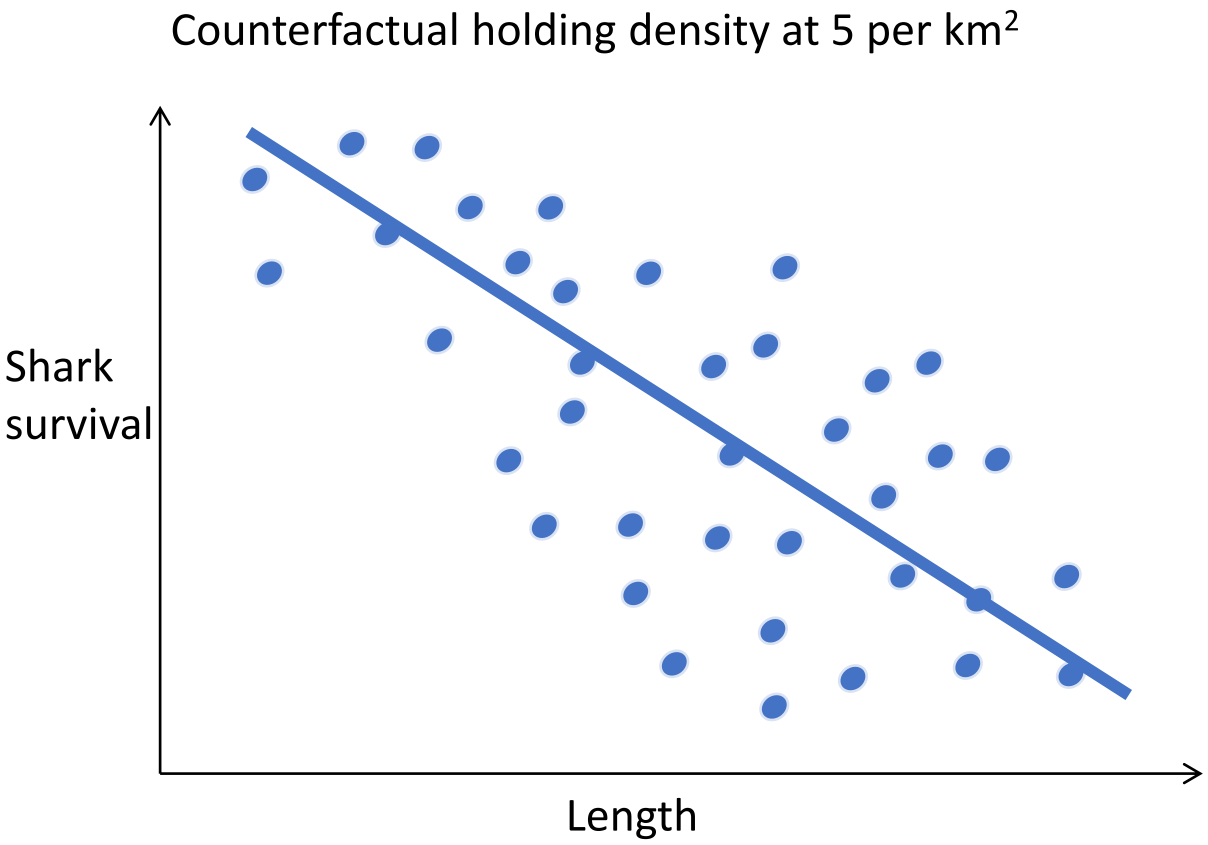
Example 2 – Shark survival

L= shark length
D = shark density
S = survival



Method to deal with multiple continuous variable counterfactual






```
##################################################
######### 4. Example 3. Shark survival   #########
##################################################
```

Summary

- Graph and understand your data (this is critical)
- Most models will be too complex to understand by gazing at coefficient tables
- Use counterfactuals to understand the model (with care)
- Its nice and symmetrical!

PGR next session?

- You direct focus
- Suggestions
  - Continuation of this session
    - GLMs
    - GLMM?
    - GAM?
  - Multivariate modelling
  - Spatial data analysis
  - Writing with impact