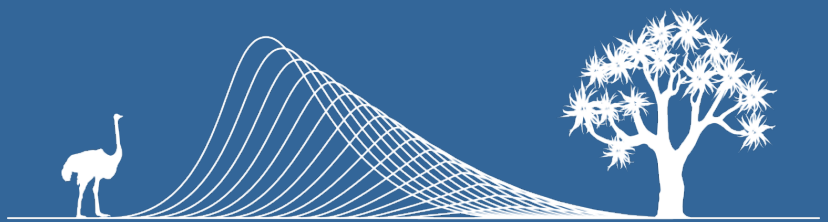
SEEC Toolbox seminars

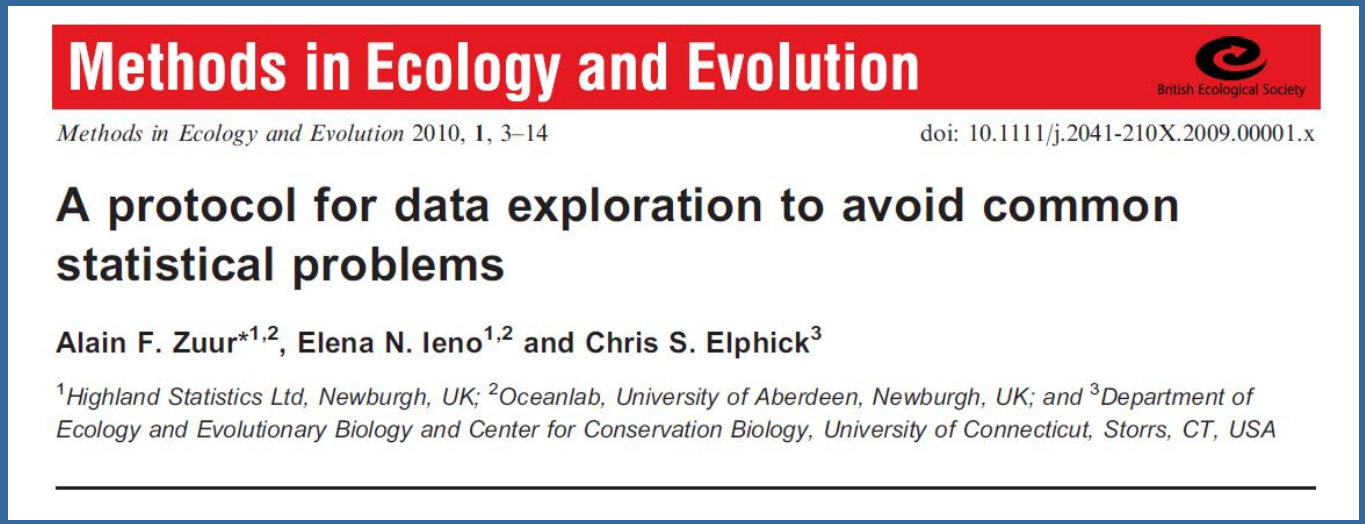
Data Exploration

Greg Distiller

29th November



Motivation



Methods in Ecology and Evolution

British Ecological Society

Methods in Ecology and Evolution 2010, **1**, 3–14 doi: 10.1111/j.2041-210X.2009.00001.x

A protocol for data exploration to avoid common statistical problems

Alain F. Zuur*[1,2], Elena N. Ieno[1,2] and Chris S. Elphick[3]

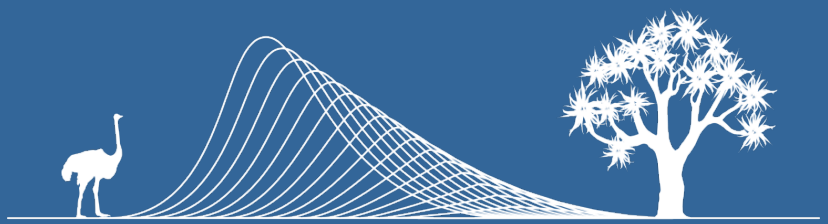
[1]*Highland Statistics Ltd, Newburgh, UK;* [2]*Oceanlab, University of Aberdeen, Newburgh, UK; and* [3]*Department of Ecology and Evolutionary Biology and Center for Conservation Biology, University of Connecticut, Storrs, CT, USA*

- The availability of sophisticated statistical tools has grown. But "rubbish in - rubbish out".
- "... even the well-known assumptions continue to be violated frequently".

Motivation

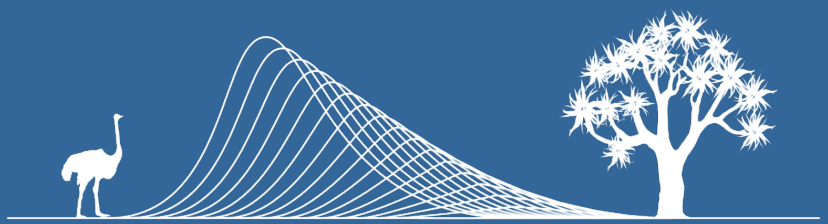
Examples of statistical pitfalls:

- Collinearity $\rightarrow$ Type II errors
- Zero inflation in GLMs may bias parameter estimates
- Spatio / temporal autocorrelation $\rightarrow$ Type I errors
- Linearity
- Ability to model interactions



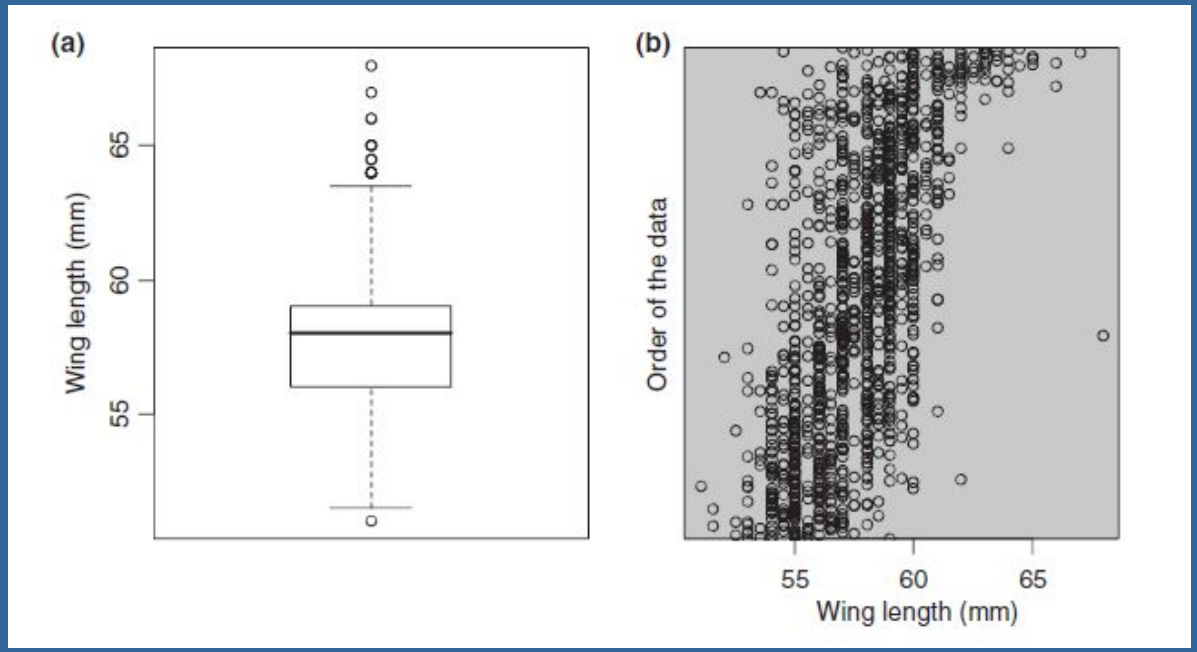
Motivation

- These various pitfalls can be avoided with proper data exploration.
- Exploration is separate from hypothesis testing.
- If a priori knowledge is very thin, exploration can be used as a hypothesis-generating exercise.
- Focus on graphical tools rather than testing.

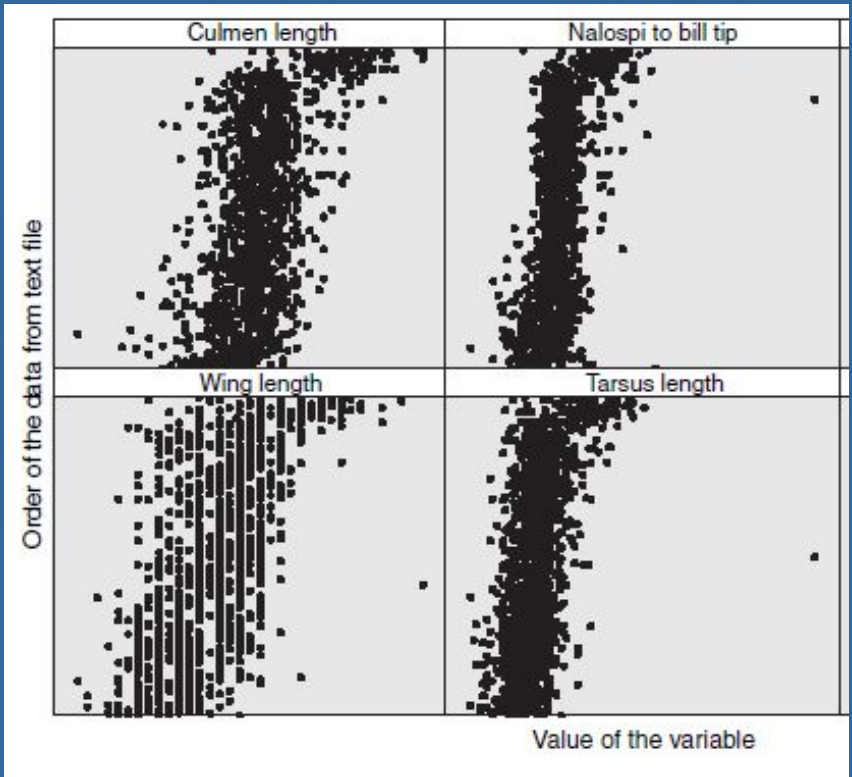


Outliers

- Some techniques can be dominated by outliers.
- They should not be removed as a matter of course!
- Boxplots are typically used.
- Cleveland dotplot (row nos vs observations) provides more information.



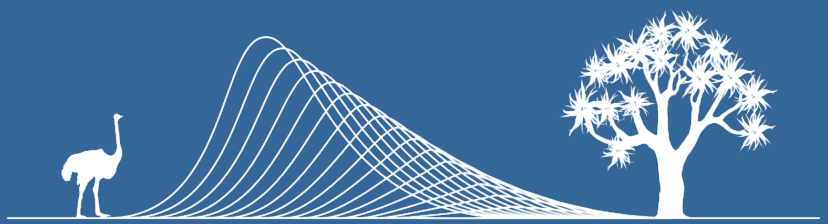
Outliers



- Extreme values by chance?
- Can simulate random observations.
- Can consider dropping if they seem to be measurement errors.

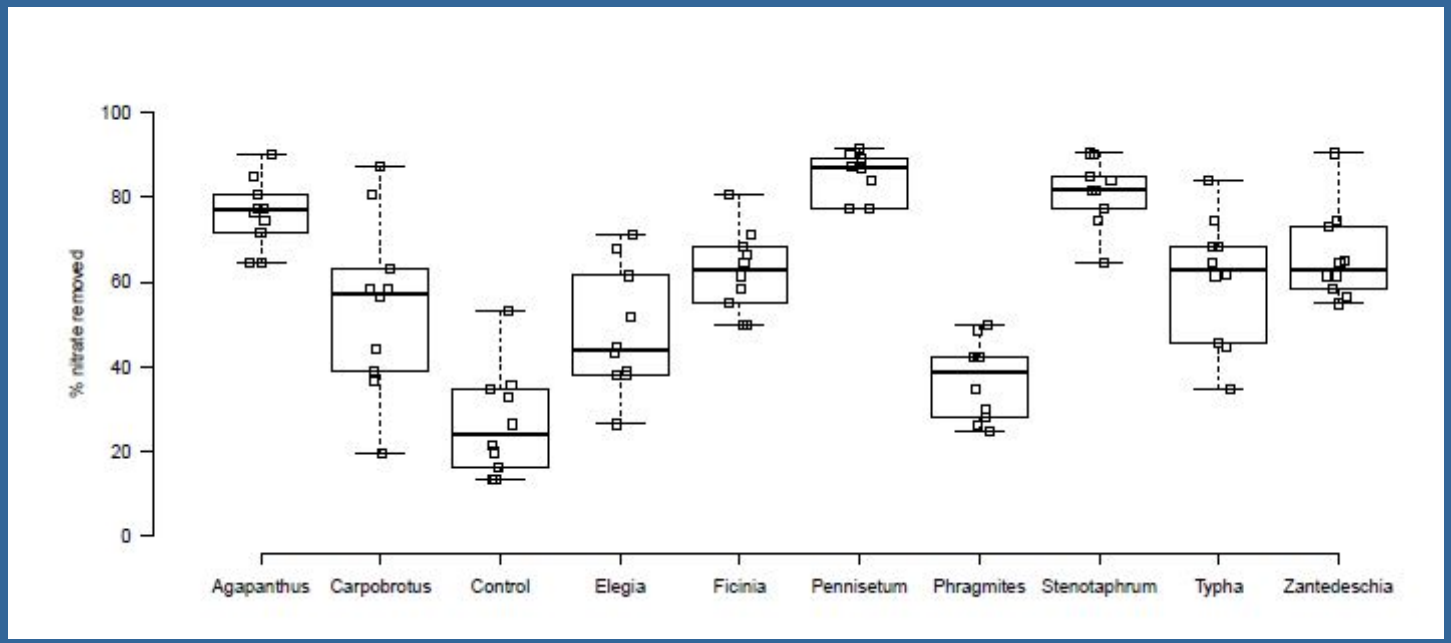
Outliers

- Outliers in X vs Y space.
  - influential observations are usually both!
- Transformations an option but really not ideal (especially for the response).
  - better to choose a more suitable model, or a more suitable metric if not modelling.



Homogeneity of variance

- Important assumption in regression type models (incl. ANOVA) and MV techniques like discriminant analysis.
- Regression-type models $\rightarrow$ verify with residuals.
- Can use conditional boxplots.



Source: Milandri S.G. et al (2012)

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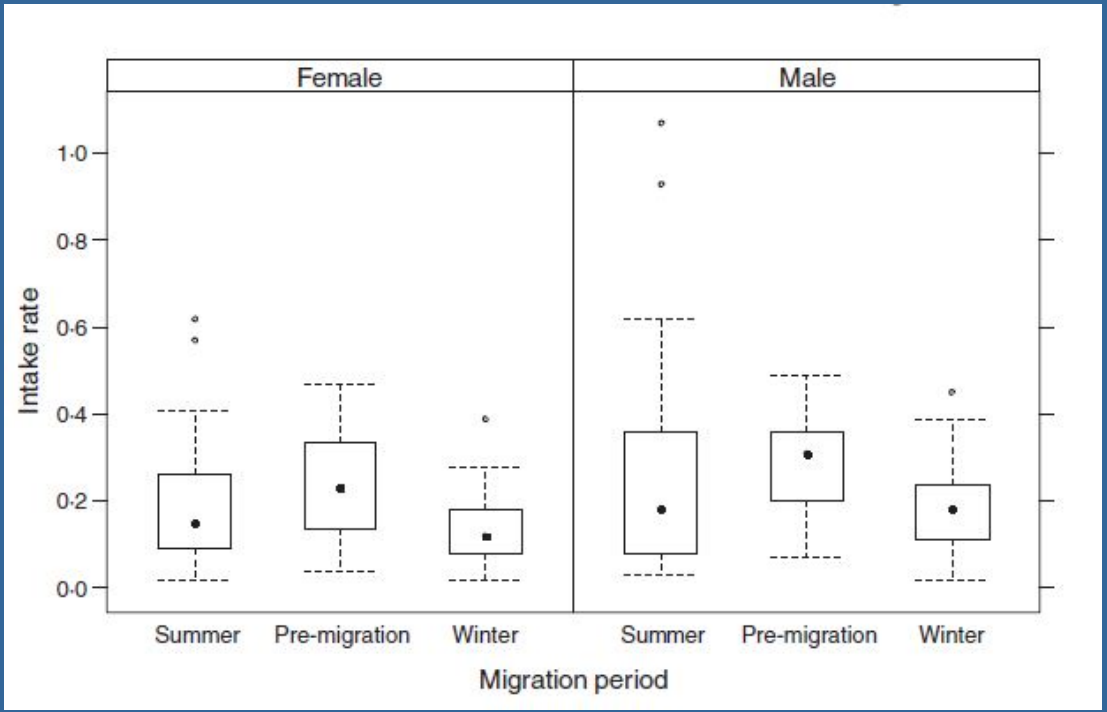
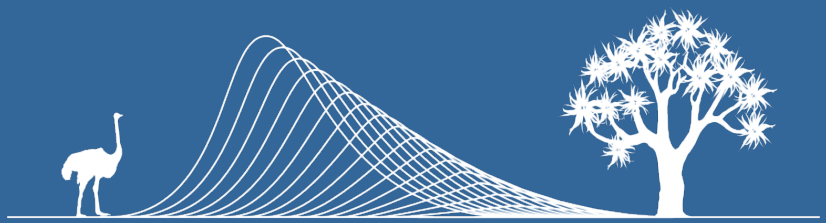


Normality

- Is normality required? What must be normal?



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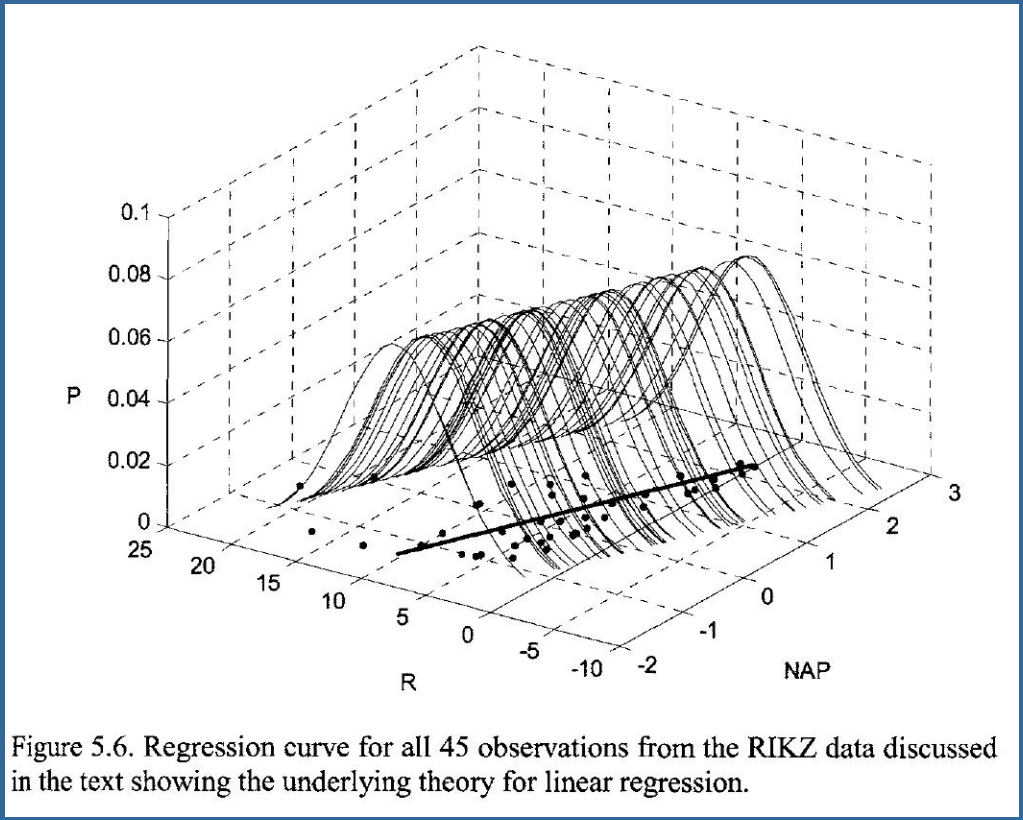

Figure 5.6. Regression curve for all 45 observations from the RIKZ data discussed in the text showing the underlying theory for linear regression.

Source: Zuur et al. Analysing Ecological Data

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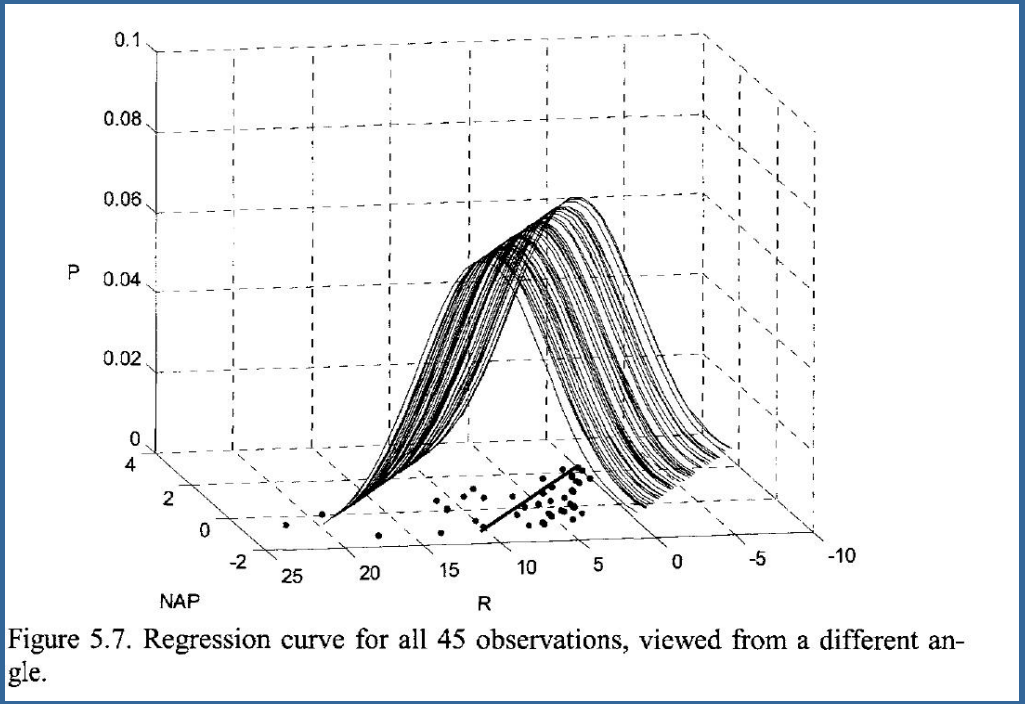

Figure 5.7. Regression curve for all 45 observations, viewed from a different angle.

Source: Zuur et al. Analysing Ecological Data

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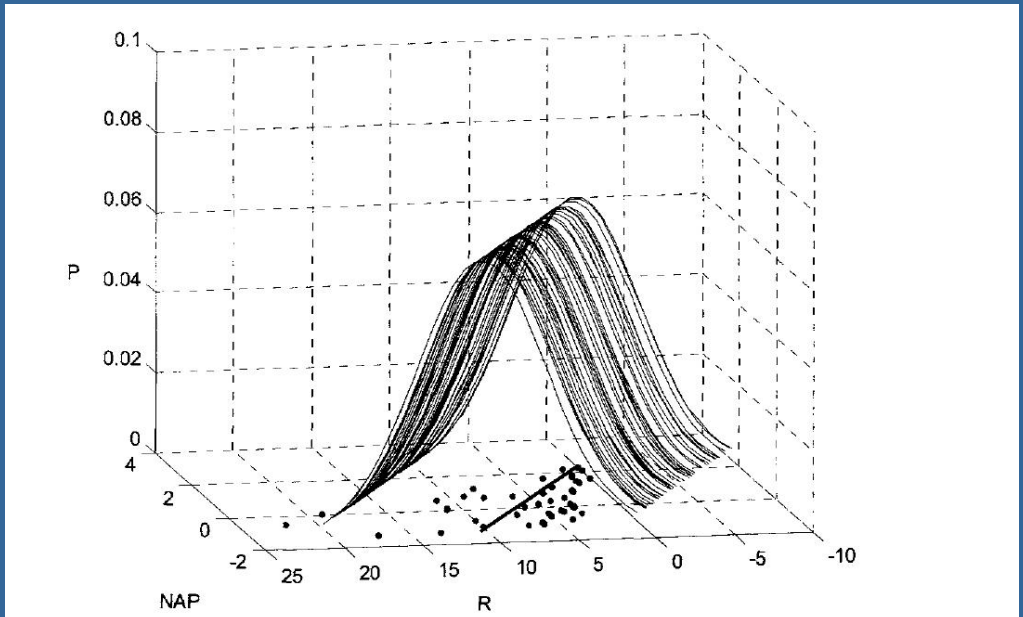


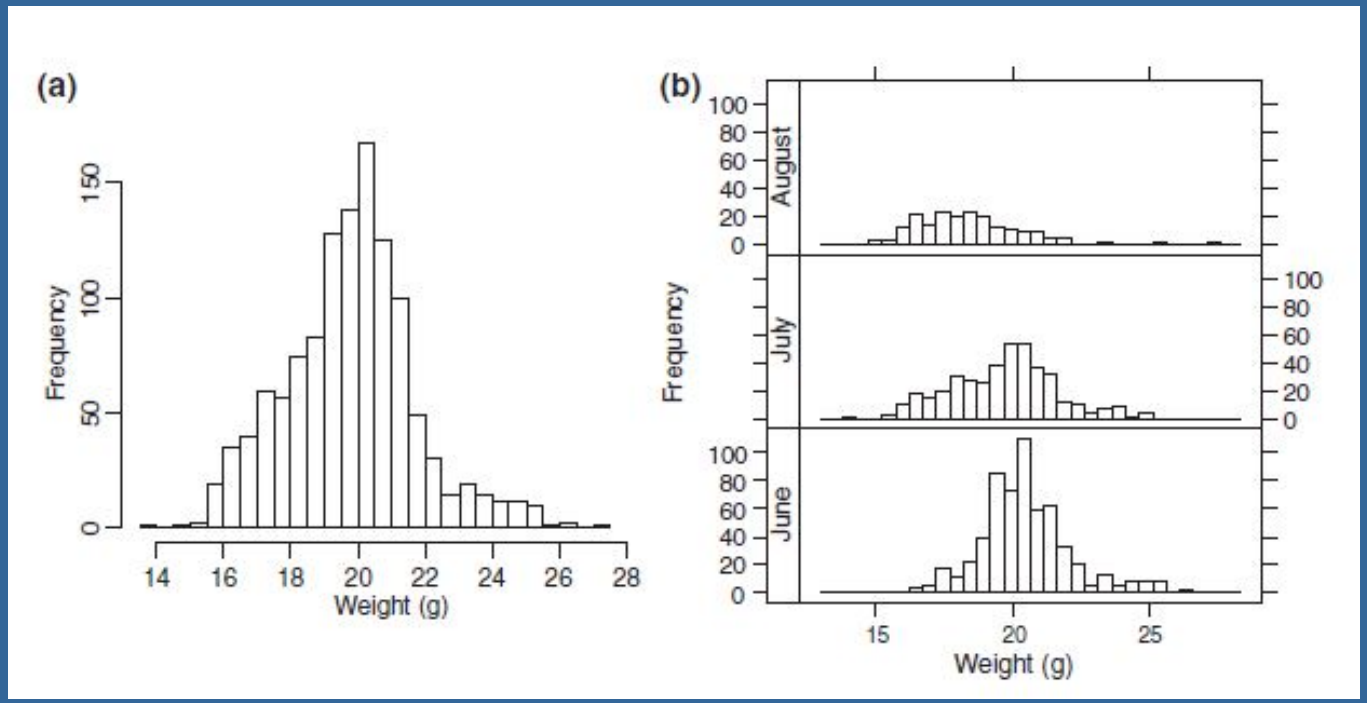
Figure 5.7. Regression curve for all 45 observations, viewed from a different angle.

Source: Zuur et al. Analysing Ecological Data

- Implies normality of the residuals.

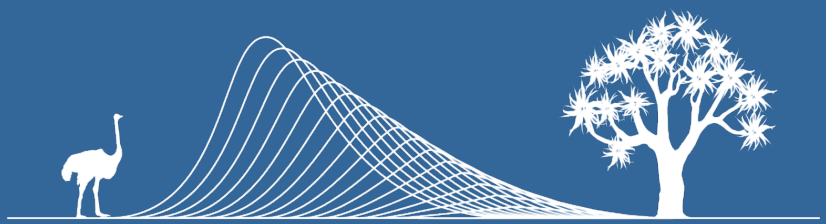
Normality

- There can be more to it than meets the eye:



Excess Zeros

- Poisson GLM often used to model count data.



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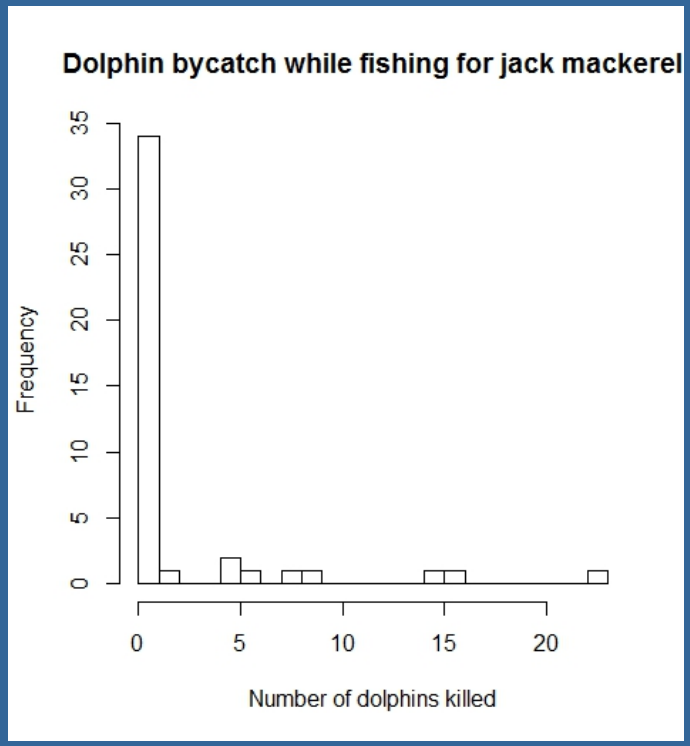


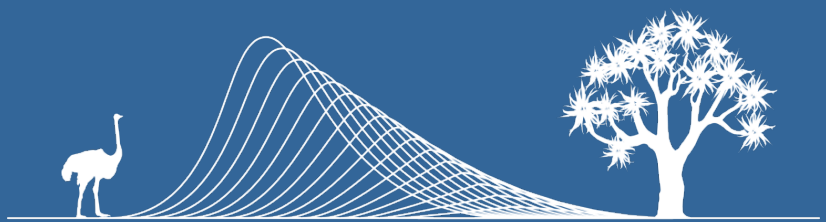
Source: Abraham, E. R., & Thompson, F. N. (2011)

- Zero-inflated models (ZIPs, ZINBs, Hurdle models . . .)

Excess Zeros

MV setting:

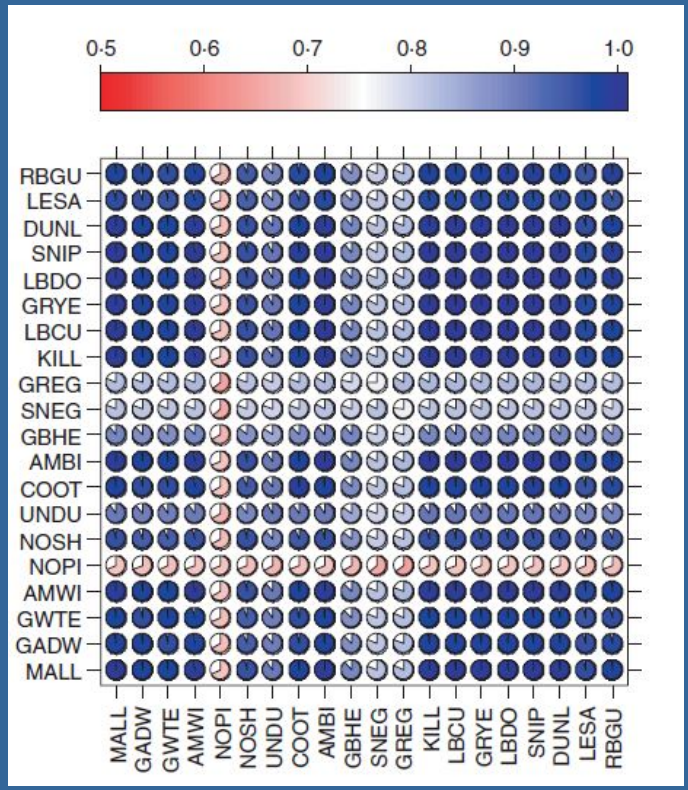
- is there useful information in joint zeros?



Excess Zeros

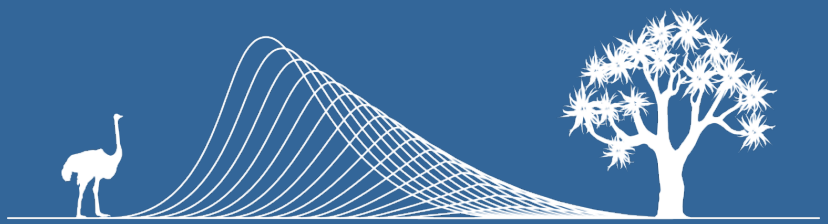
MV setting:

- is there useful information in joint zeros?
- corrgram can be used to assess prevalence of "joint absences":



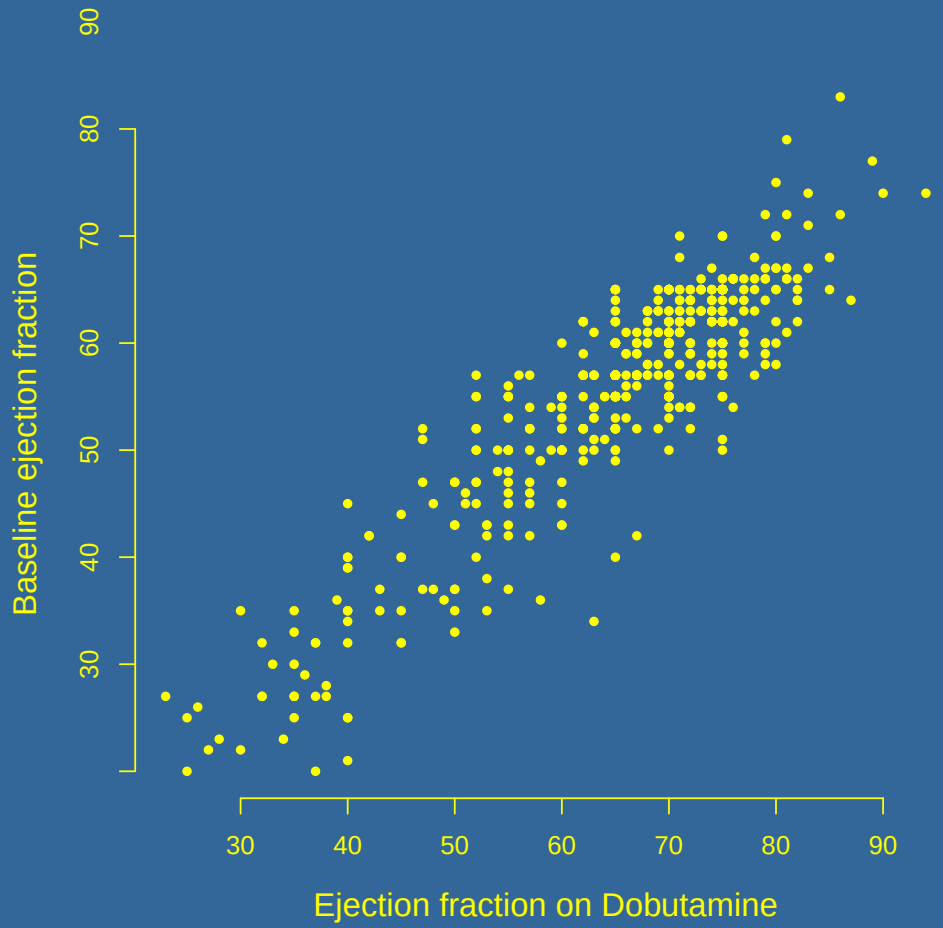
Collinearity

- NB when objective is to understand what covariates drive a system.
- Common examples: morphological measurements, water depth and distance to the shore ...
- Can lead to a confusing set of results.



Collinearity

Source: Krivokapich J et al (1999)



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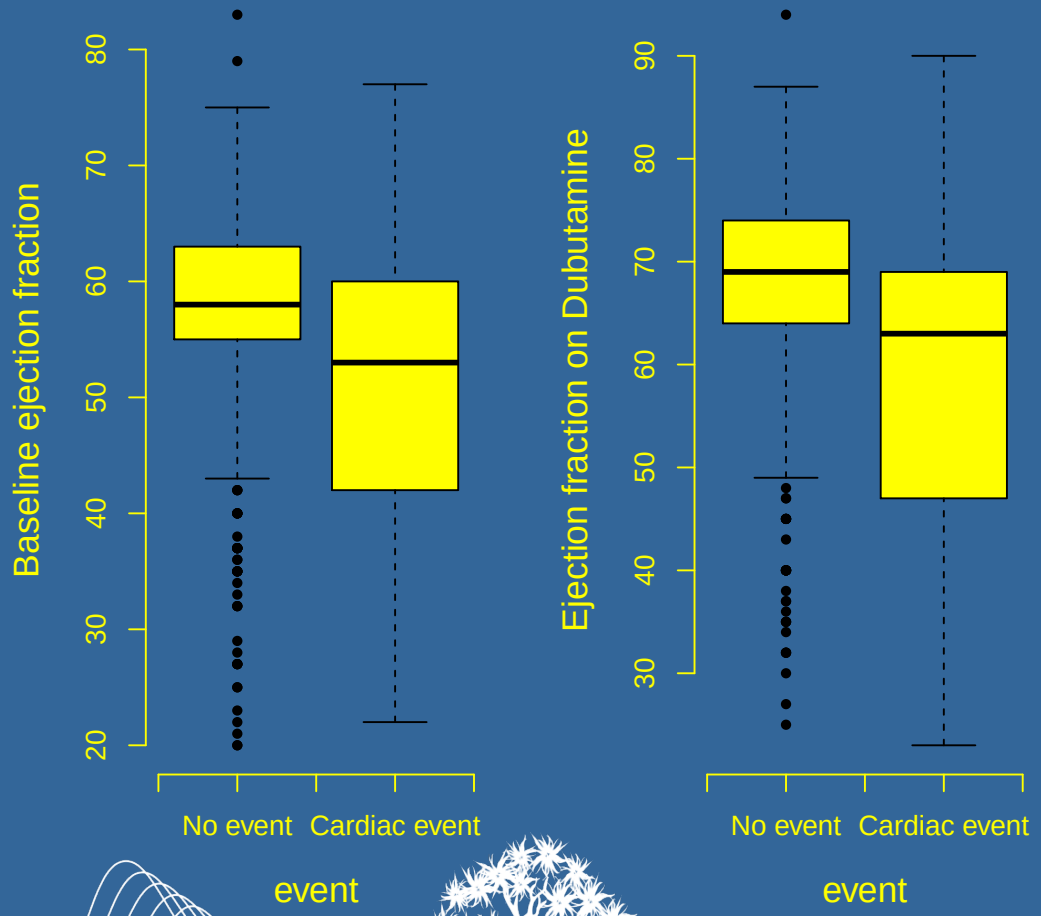
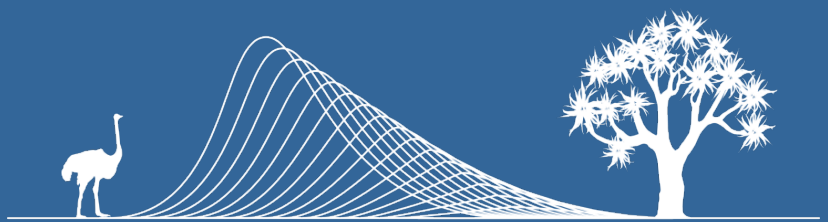


Collinearity

```
> m1 <- glm(event ~ baseef + dobef, family = binomial)
> summary(m1)

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  1.66404    0.56674   2.936 0.003323 **
baseef       0.02878    0.02605   1.105 0.269212
dobef       -0.07770    0.02333  -3.331 0.000865 ***
```

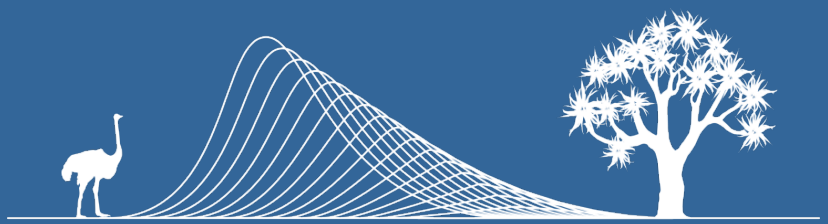


Collinearity

- There are some diagnostic tools:
  - VIF

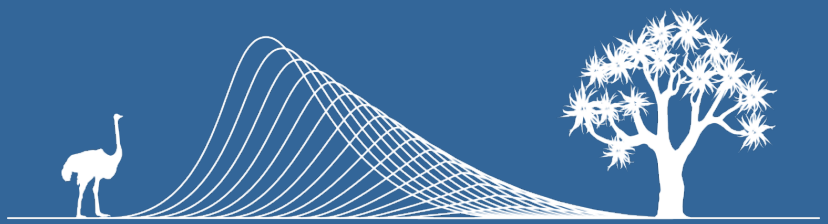
$$\frac{1}{1 - R_j^2}$$

  - scatterplots: plot covariates against any temporal / spatial variables.
- High or even moderate collinearity is problematic when the signal is weak.



Nature of the Relationship

- Use scatterplots of the response variable vs each covariate.
- Note that the absence of two-way relationships does not necessarily mean that there are no relationships.



Nature of the Relationship

Source: Gary Witt. Using data from climate science to teach introductory statistics. Journal of Statistics Education, 21(1), 2013.

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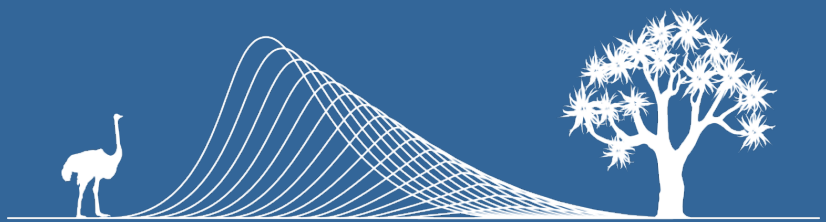
Nature of the Relationship

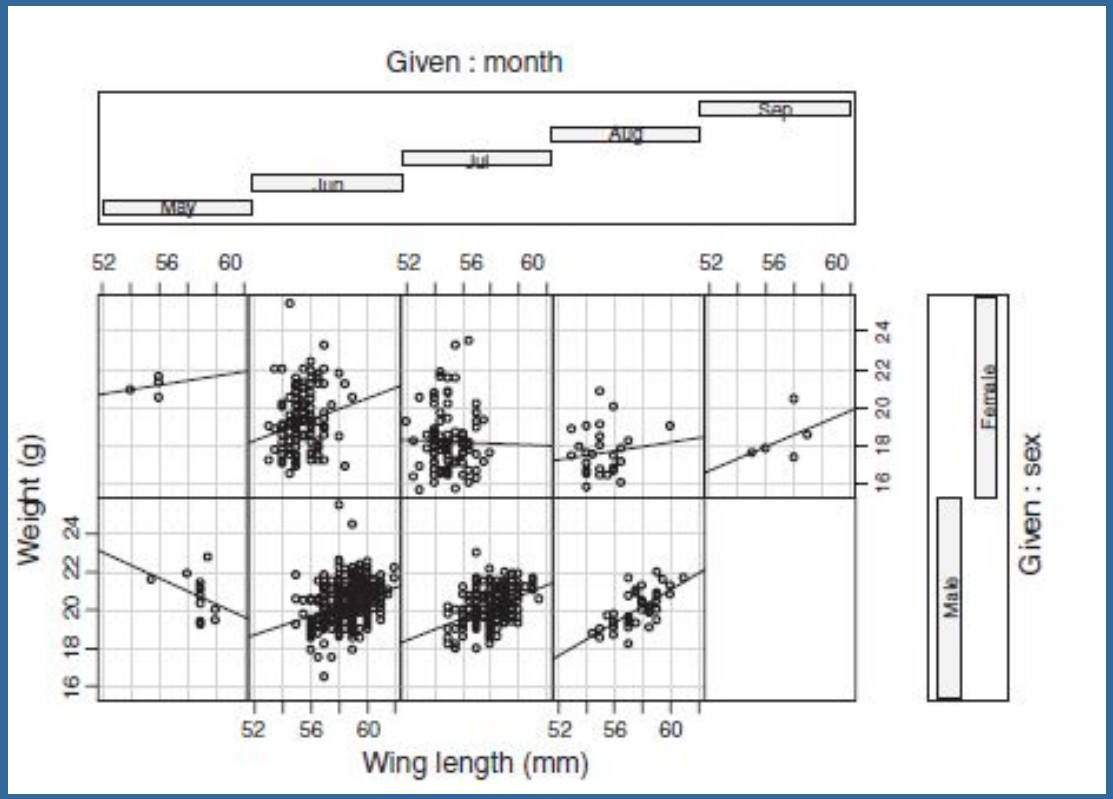
```
> m1 <- lm(ice ~ year, data = dat)
> m2 <- lm(ice ~ year + I(year^2), data = dat)
> anova(m1,m2)
Analysis of Variance Table

Model 1: ice ~ year
Model 2: ice ~ year + I(year^2)
  Res.Df    RSS Df Sum of Sq      F    Pr(>F)
1     32 10.529
2     31  6.822  1    3.7072 16.846 0.0002731 ***
```



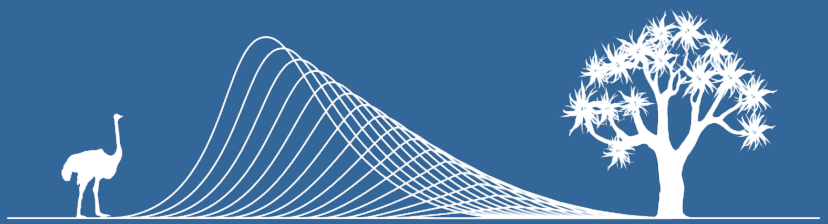
Including interactions

- A coplot is a useful plot to visualise potential interactions.
- Can reveal data sparsity.



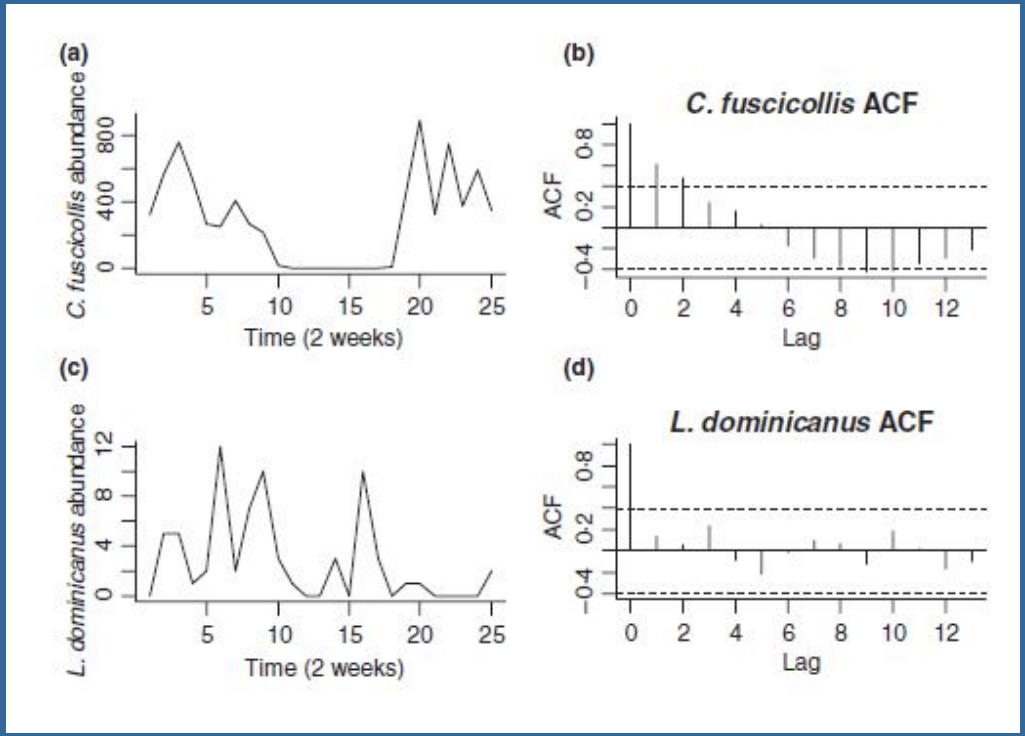
Independence

- A crucial assumption for many techniques.
- Violation increases type I errors.
- Some examples:
  - Data from different locations $\rightarrow$ are birds from locations close to each other more similar than birds from locations further away?
  - Individuals from one family may tend to be similar due to shared genes.
  - Repeated measurements.



Independence

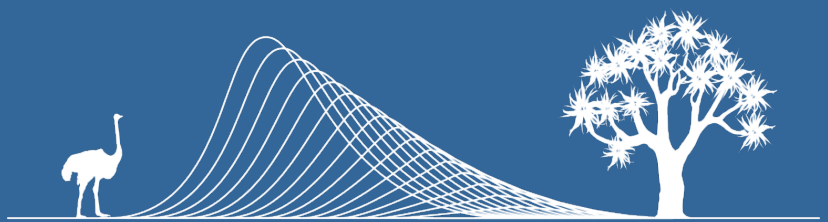
- Plot the response against time or space, any pattern suggests dependence.
- More formally, plot auto-correlation functions (ACF's).



Independence

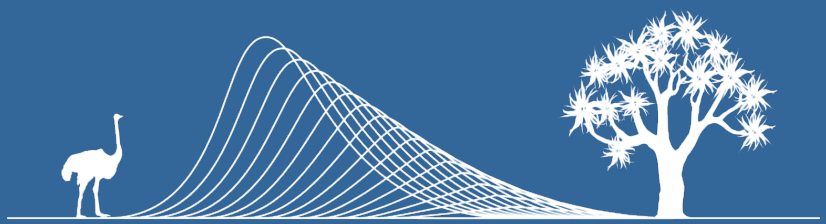
When the data are not independent:

- need a model that can account for the dependence: mixed-effects models, AR models, generalised least squares (modelling the correlation structure).
- can sometimes model the dependence with suitable covariates.
- residuals should display no dependence.



Final thoughts

- Not all steps are relevant for all data sets.
- Some techniques require analysis first (i.e. to produce residuals)
- Transformations are not ideal.



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- Some techniques require analysis first (i.e. to produce residuals)
- Transformations are not ideal.

"...the routine use and transparent reporting of systematic data exploration would improve the quality of ecological research and any applied recommendations that it produces."

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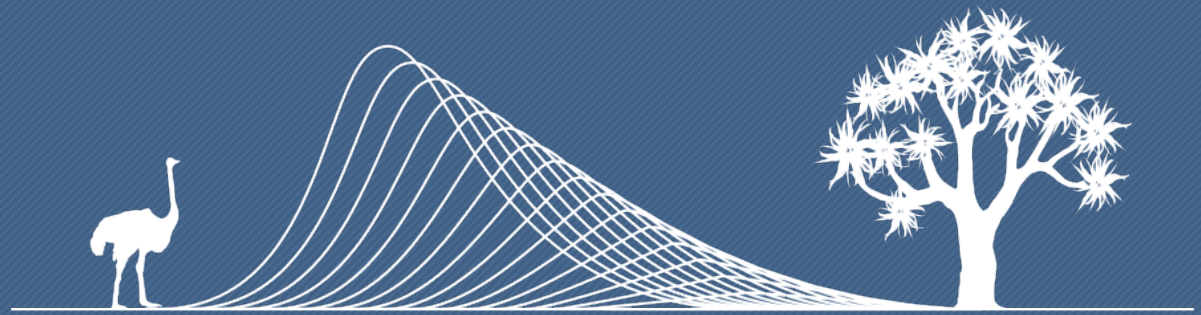

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