Handling missing observations with multiple imputation

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Thierry Onkelinx, Koen Devos & Paul Quataert
Research Institute for Nature and Forest, Brussels, Belgium

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Introduction

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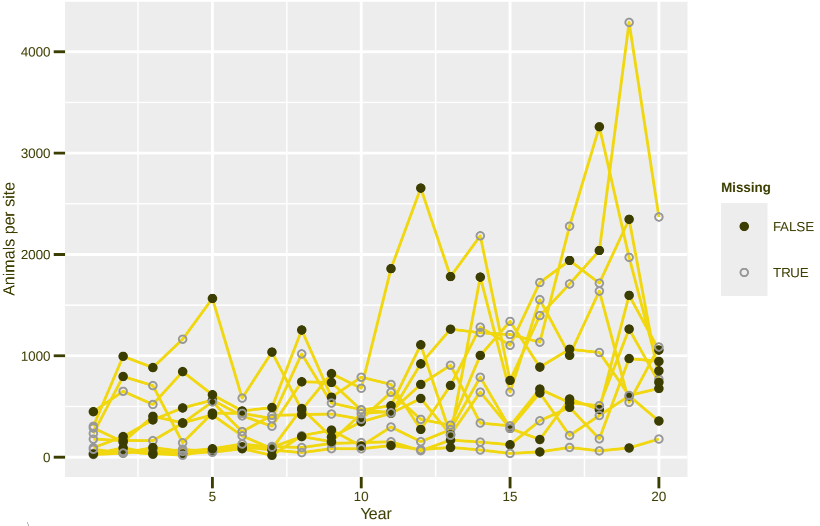
Handling missing observations

The best solution to handle missing data is to have none.
– Sir Ronald Aylmer Fisher

- In practice we can only try to minimise the missingness
- An increase in missingness will lead to a decrease in power
- Analysis can handle missing data (e.g. average number of animals)
  - No need for imputation
- Analysis cannot handle missing data (e.g. population totals)
  - Imputation is required

Number of animals per site



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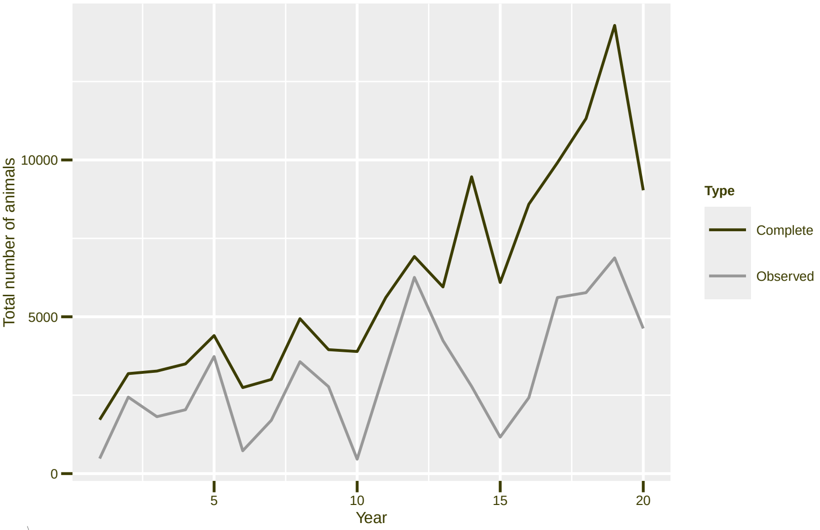
Population totals



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Some imputation methods

- Popular in ecology for analysis of population trends
  - Underhill index, 118 citations (Underhill & Prys-Jones, 1994)
  - TRIM, 310 citations (Pannekoek & Van Strien, 2005)
  - birdSTATs, Access shell around TRIM (Meij, 2013)
  - All are **single** imputation methods
- Popular in medical and social science
  - **Multiple** imputation, 9625 citations (Rubin, 1987)
  - Only emerging in field of ecology

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Single imputation versus multiple imputation

The similarities

- Replace missing values with imputed values
- Imputed values are based on a model
  - The model can be very basic
    - A constant
    - The overal mean
  - The model can be elaborate
    - Use available covariates (e.g. year, season, site, climate, ...)
    - Use correlation structures (e.g. temporal, spatial, ...)
    - Use a relevant distribution (e.g. Poisson, negative binomial, ...)
    - Use zero-inflation
- Final analysis on the augmented dataset

The differences

- Single imputation replaces missing values **only once**
  - It uses the best available single value: the predicted value of the model
  - Single imputation ignores *model uncertainty* and *natural variability*
- Multiple imputation replaces missing values **several times**
  - It uses each time a different random value
  - Based on
    - The distribution of predicted values of the model
    - The noise of the model
  - Multiple imputation takes both *model uncertainty* and *natural variability* into account

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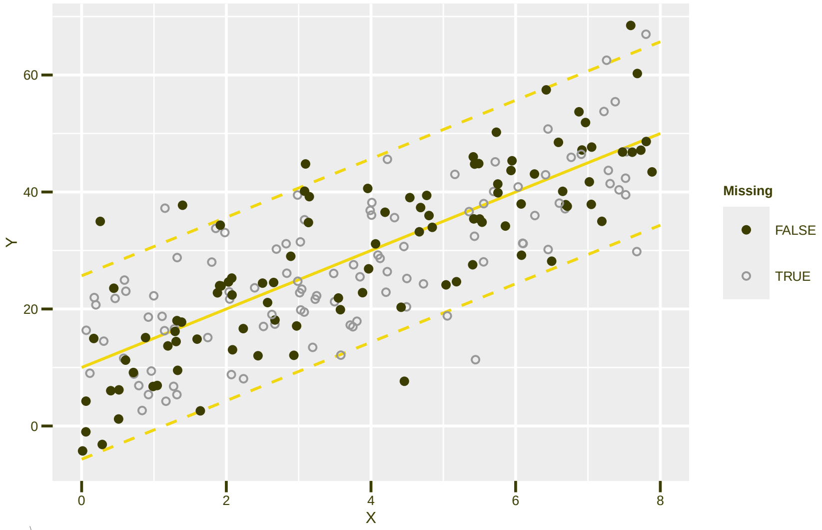
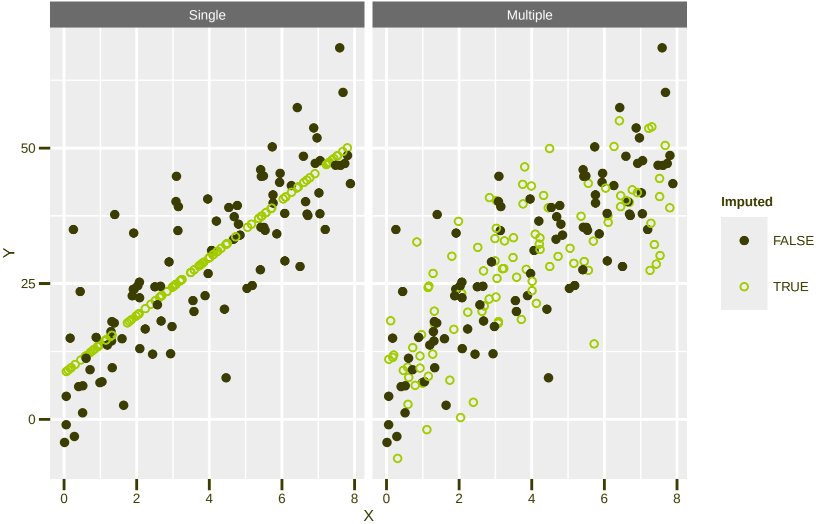
Example dataset



Example of one imputation set



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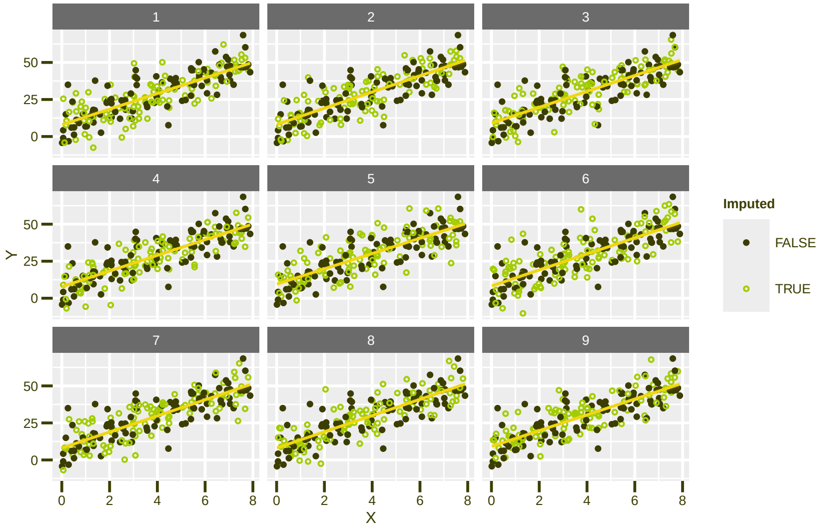
How to handle the randomness in multiple imputation?

- Since the imputed values are random, every imputation set will have different values
- Hence the results of the analysis *after* imputation will be different among imputation sets
- Solution:
  1. Create L imputation sets
  2. Run the analysis on each imputation set
  3. Average the parameter of interest B and its standard error σ_B among imputation sets using the formulas below

$$\overline{B} = \frac{1}{L}\sum_{l=1}^{L}\hat{B}_i$$

$$\overline{\sigma}_B^2 = \frac{1}{L}\sum_{l=1}^{L}\hat{\sigma}_{B_i}^2 + \frac{L+1}{L}\sum_{l=1}^{L}\frac{\hat{B}_i - \overline{B}}{L-1}$$

Example of 20 imputation sets



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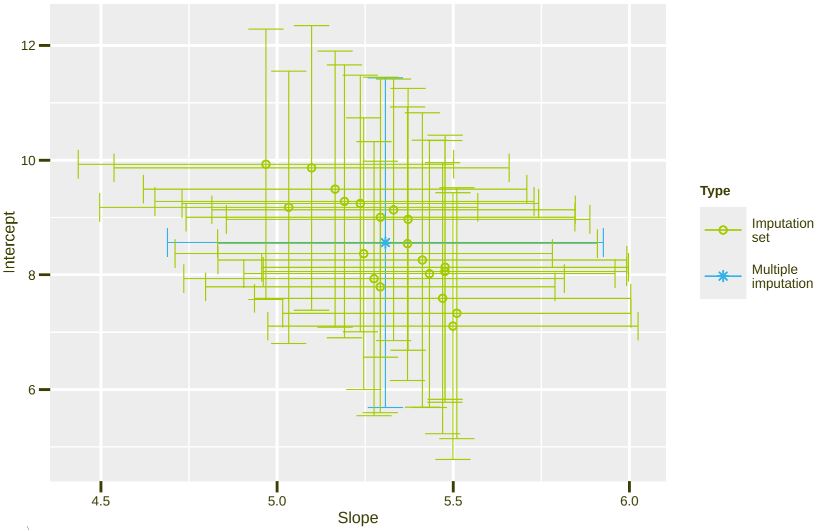
Analysis of 20 imputation sets



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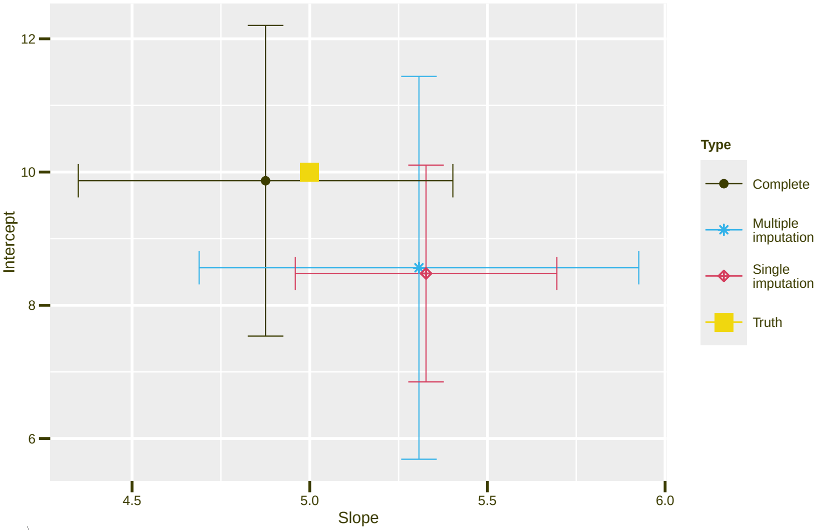
Comparison of results



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Advice on imputation

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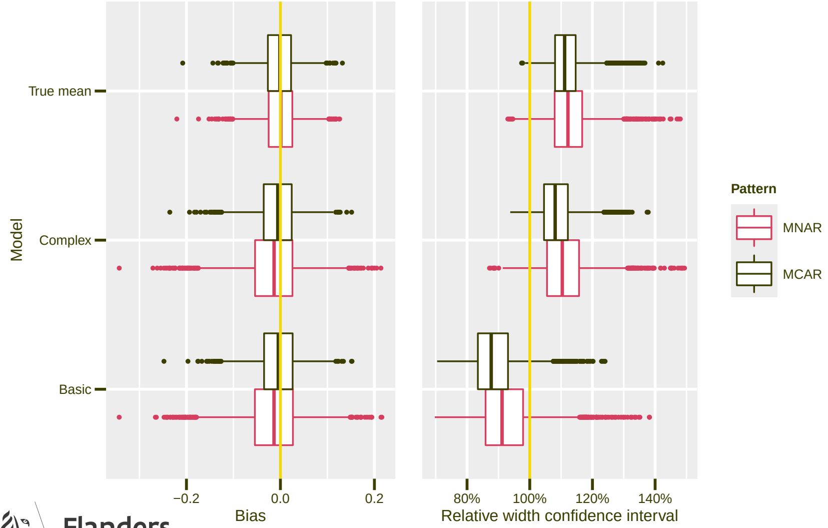
General recommendations

- Forget single imputation
  - Use **multiple** imputation
- Use a reasonable complex model
  - Too simple: model will smooth too much
  - Too complex: unstable or unreliable model
  - Use the relevant distribution!
- Number of imputations (Graham *et al.*, 2007)
  - Aim for $L = 100$ when computational effort is reasonable
  - $L = 3$ can be sufficient (<10% missing and <5% power falloff)
- Proportion of missingness
  - Multiple imputation is robust, even with 50% to 75% missing data
- Type of missingness
  - Missing not at random (MNAR) can introduce biased results

Effect of imputation model and type of missingness (Onkelinx *et al.*, in press)



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Available R packages

- R (R Core Team, 2013) is free and open source software for statistical computing
- Some packages for multiple imputation

Package	Counts	Mixed model	GUI	Missing covariate	Reference
multimput	X	X			Onkelinx *et al.* (2016)
Amelia			X	X	Honaker *et al.* (2011)
mice	X			X	van Buuren & Groothuis-Oudshoorn (2011)

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