FRB
FONDATION POUR LA RECHERCHE SUR LA BIODIVERSITÉ

CESAB
CENTRE DE SYNTHÈSE ET D'ANALYSE SUR LA BIODIVERSITÉ

Biodiversity knowledge synthesis: an introduction to meta-analyses and systematic reviews

Risks of bias

October 2024 - Montpellier

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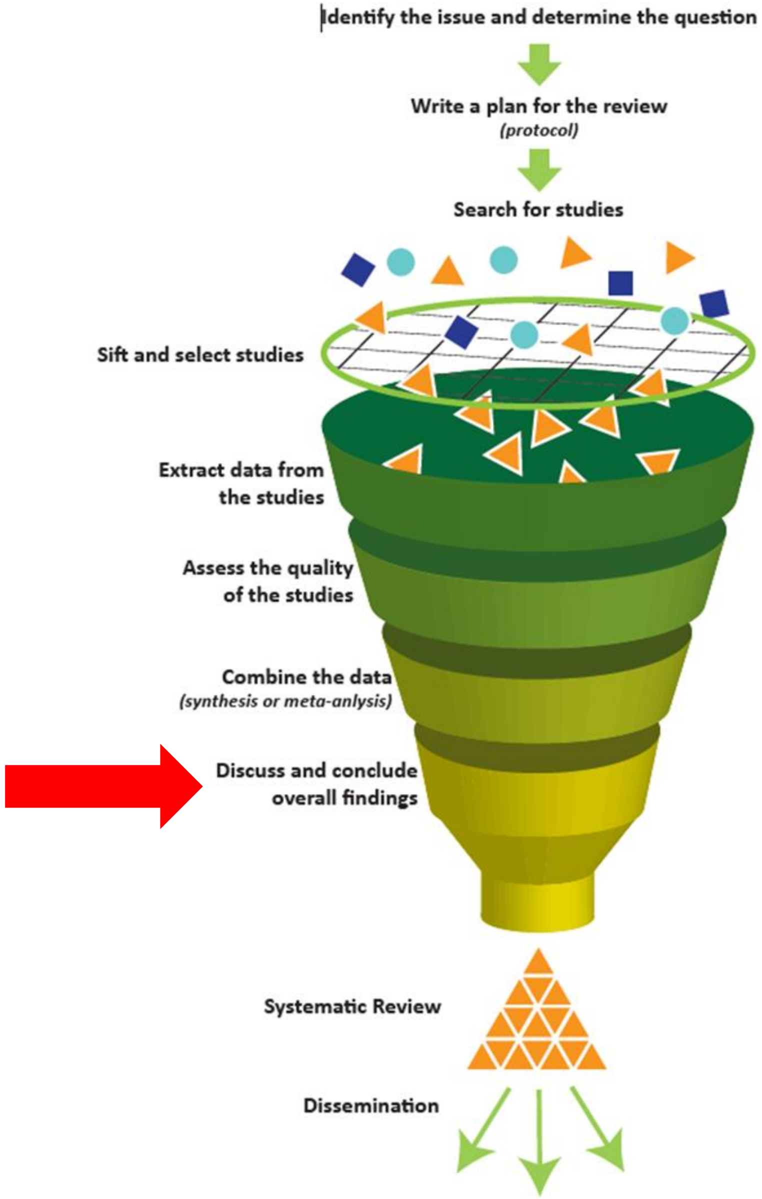
Risks of bias in meta-analyses

Meta-analysis = combine the results of primary studies to determine an overall effect
(+ analysis of heterogeneity)

assumes that the primary studies collected are a representative sample of all available studies



Jessica Kaufman, Cochrane Consumers & Communication Review Group, Centre for Health Communication and Participation, La Trobe University, 2011.

Risks of bias in meta-analyses

… but studies showing a statistically significant effect are more likely to be

published → publication bias

published rapidly → time-lag bias

published in English → language bias

published more than one time → multiple publication bias

cited → citation bias

… so they are more likely to be included in the meta-analysis

Risks of bias in meta-analyses

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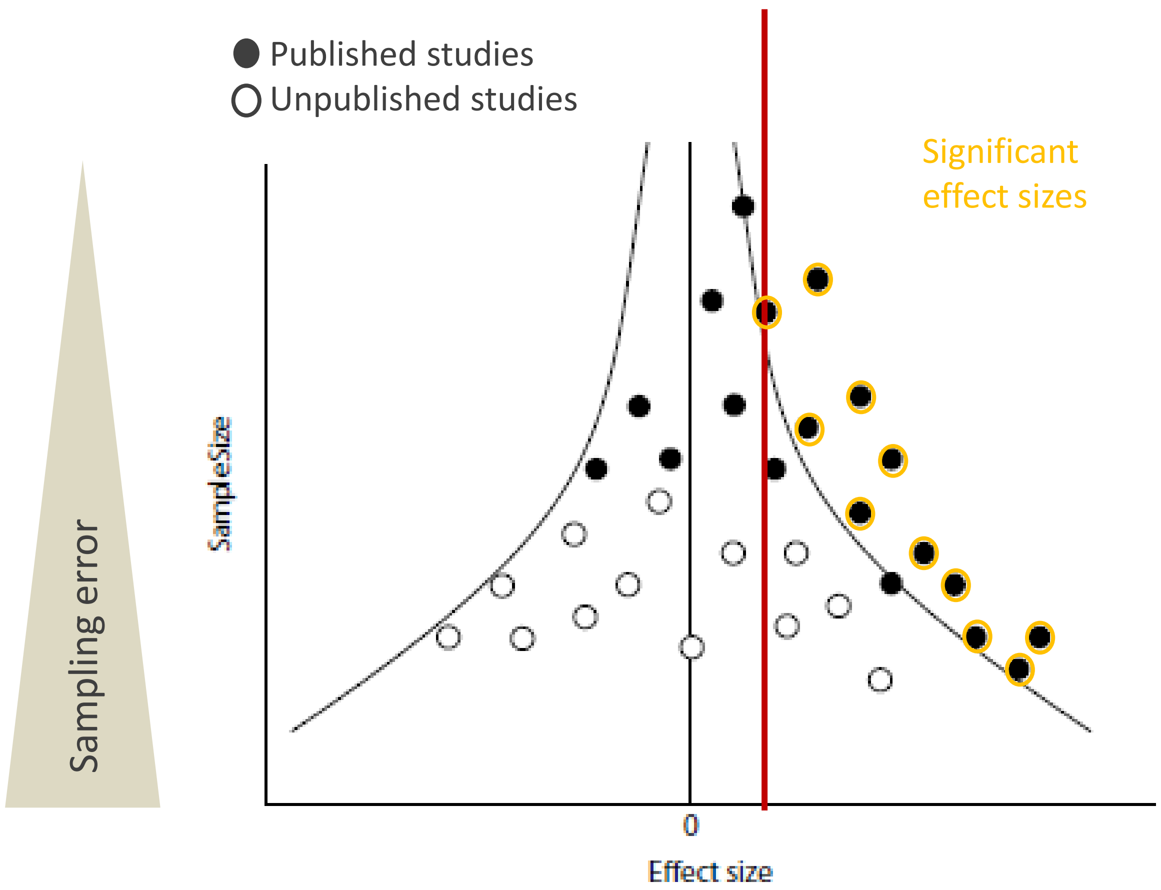
Publication bias: visual detection

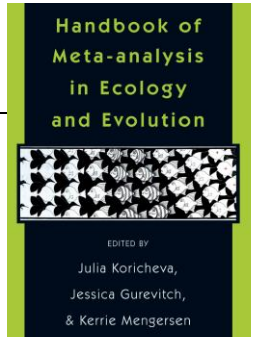
Funnel plots



14

Publication and Related Biases

Michael D. Jennions, Christopher J. Lortie, Michael S. Rosenberg, and Hannah R. Rothstein



Publication bias: visual detection

14

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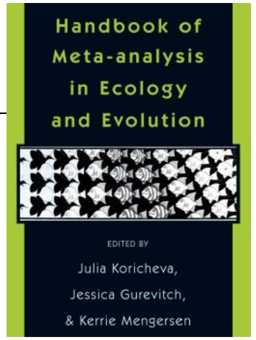

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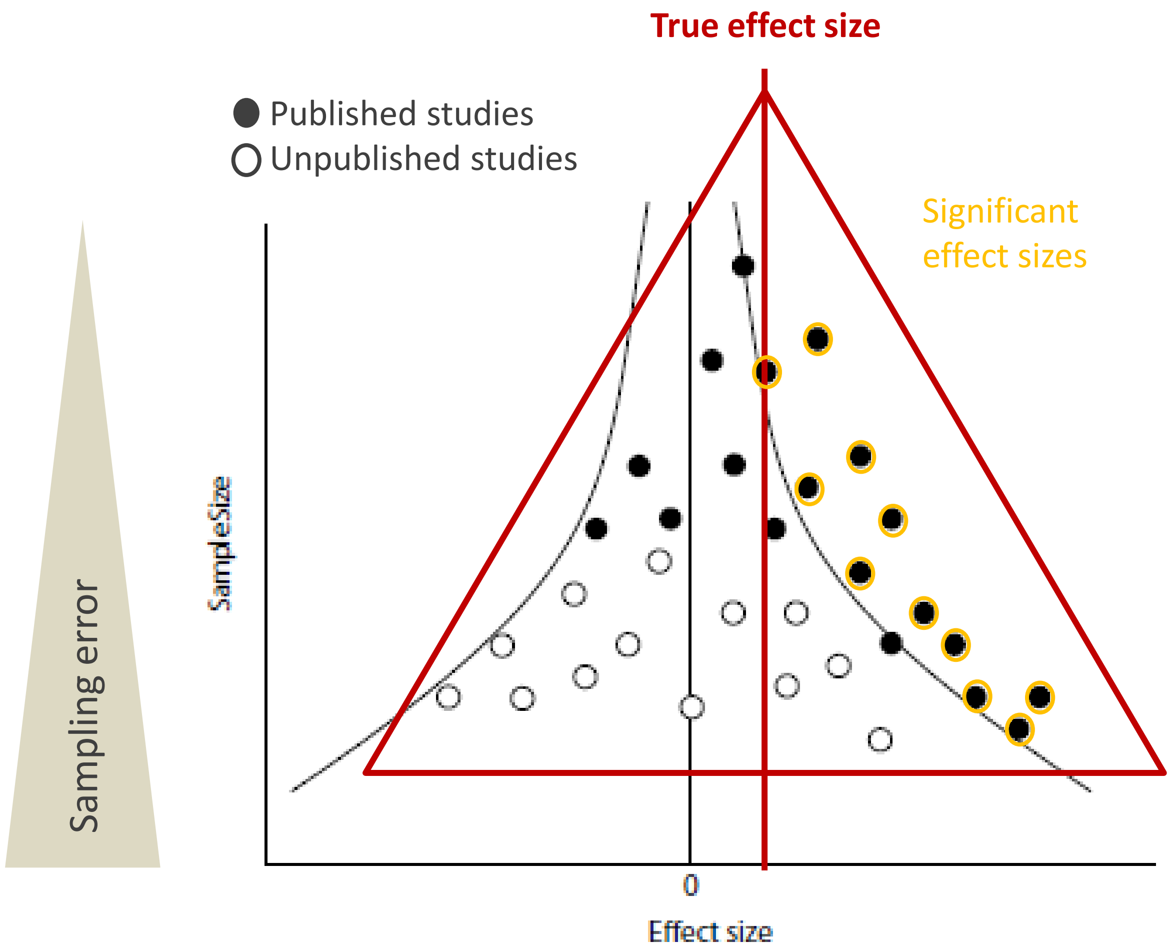
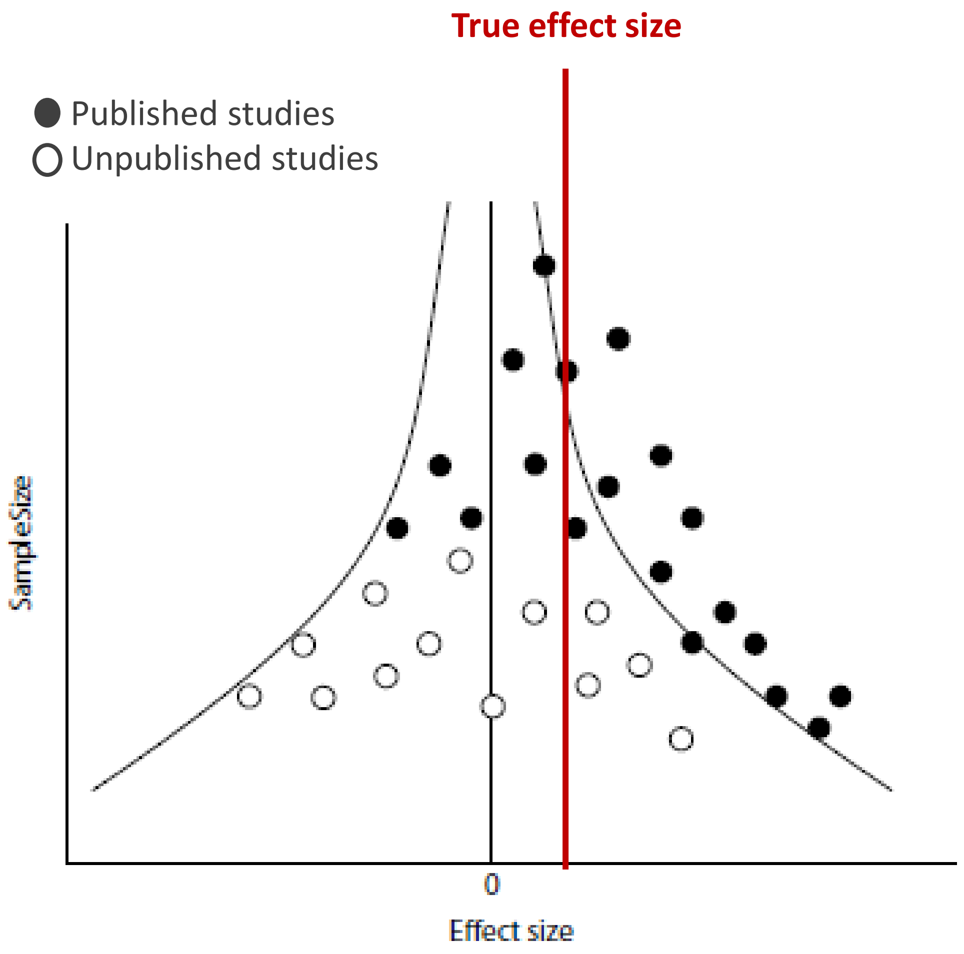


The distribution of all the studies around the true effect is symmetrical

Publication bias: visual detection

Funnel plots

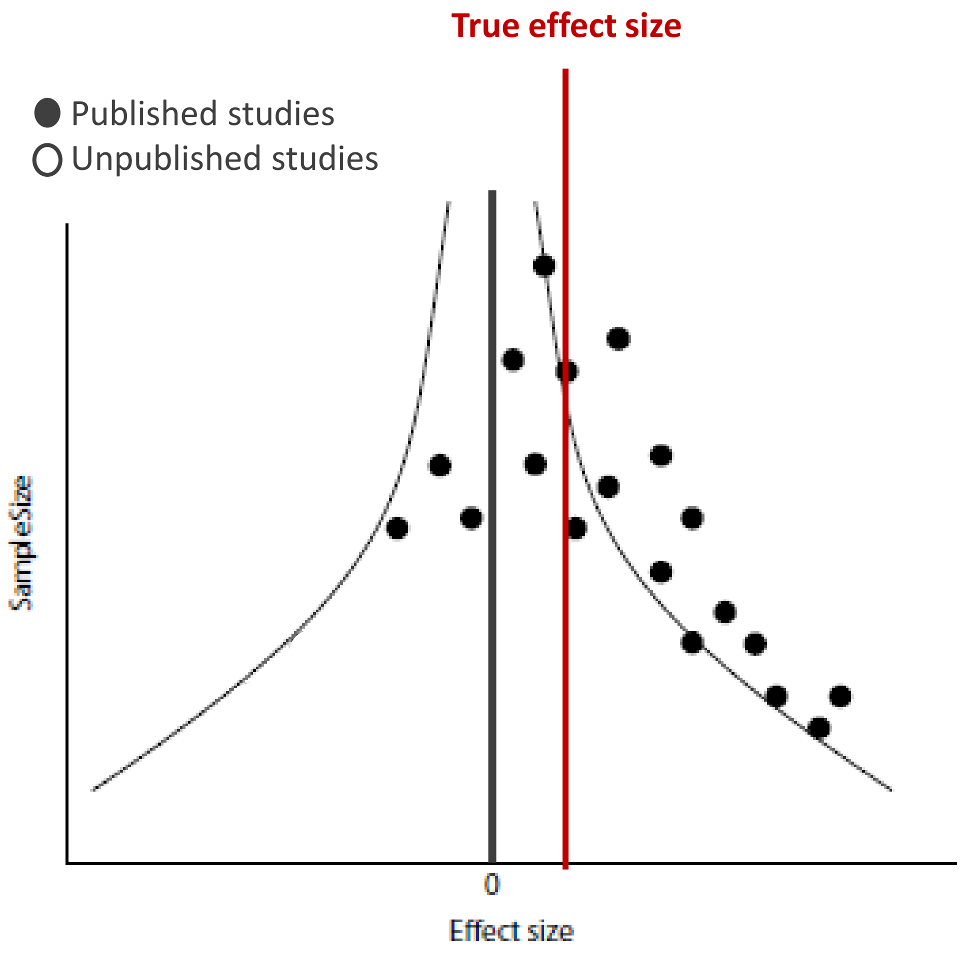


The distribution of all the studies around the true effect is symmetrical

Unpublished studies have **small sample sizes** and non-significant results

Publication bias: visual detection

Funnel plots



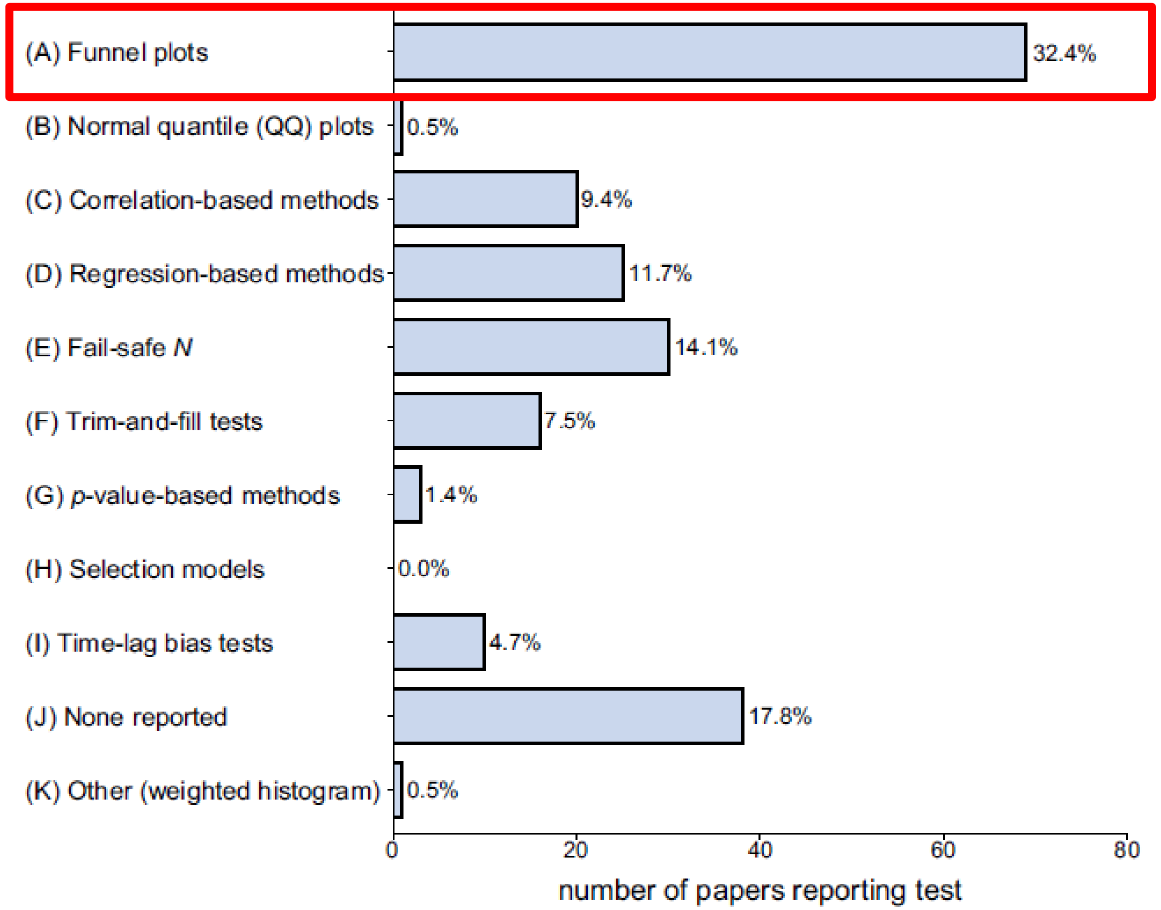
The distribution of all the studies around the true effect is symmetrical

Unpublished studies have **small sample sizes** and non-significant results

→ an **asymmetric distribution** of the effect sizes of published studies (“**small-study effect**”)
→ a relationship between sample size and effect size
→ an overestimation of the true effect

Publication bias: visual detection

Funnel plots



Received: 8 April 2021 | Accepted: 6 September 2021
DOI: 10.1111/2041-210X.13724
REVIEW ARTICLE
Methods in Ecology and Evolution

Methods for testing publication bias in ecological and evolutionary meta-analyses

Shinichi Nakagawa[1] | Malgorzata Lagisz[1] | Michael D. Jennions[2] | Julia Koricheva[3] | Daniel W. A. Noble[2] | Timothy H. Parker[4] | Alfredo Sánchez-Tójar[5] | Yefeng Yang[1] | Rose E. O'Dea[1]

Effect size ~ N, SE, variance, precision (1/SE), inverse variance

Most popular method

! Warning: asymmetry may be due to effect sizes heterogeneity

Publication bias: detection tests

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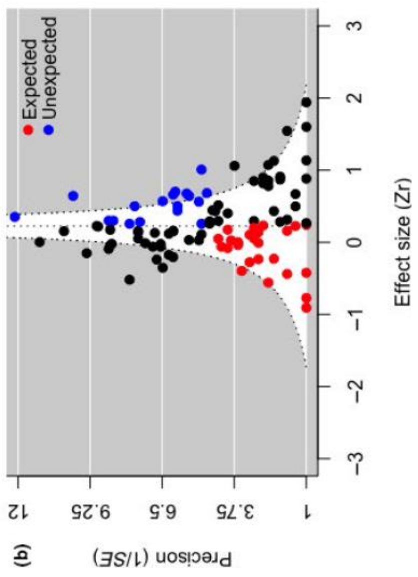
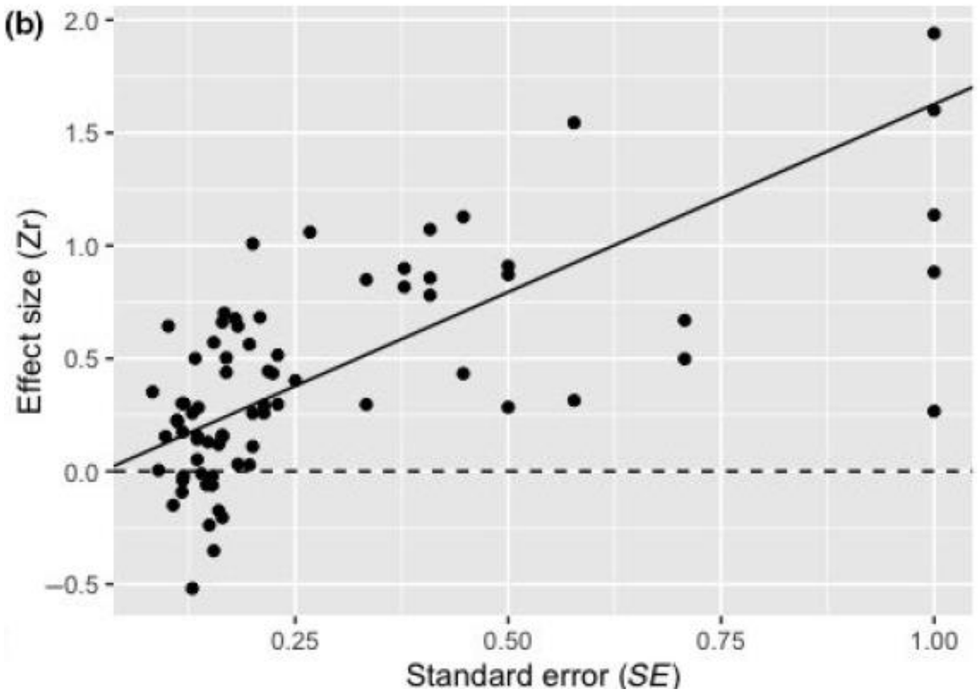
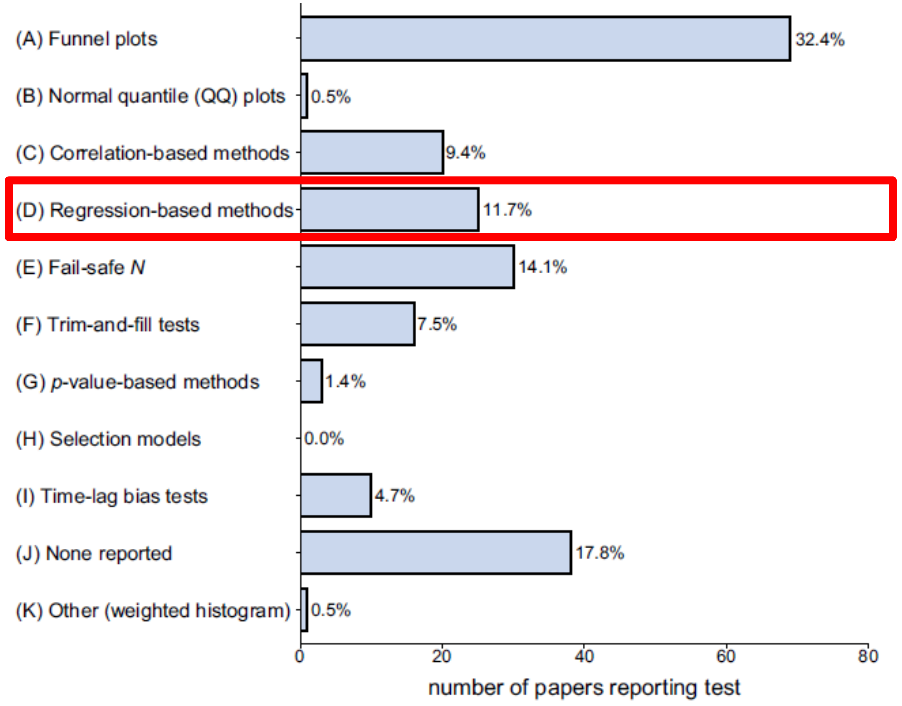
Testing funnel plot asymmetry

Egger's test : regression of effect sizes ~ SE

If the slope is stat. signif. different from 0 → asymmetry stat. signif.







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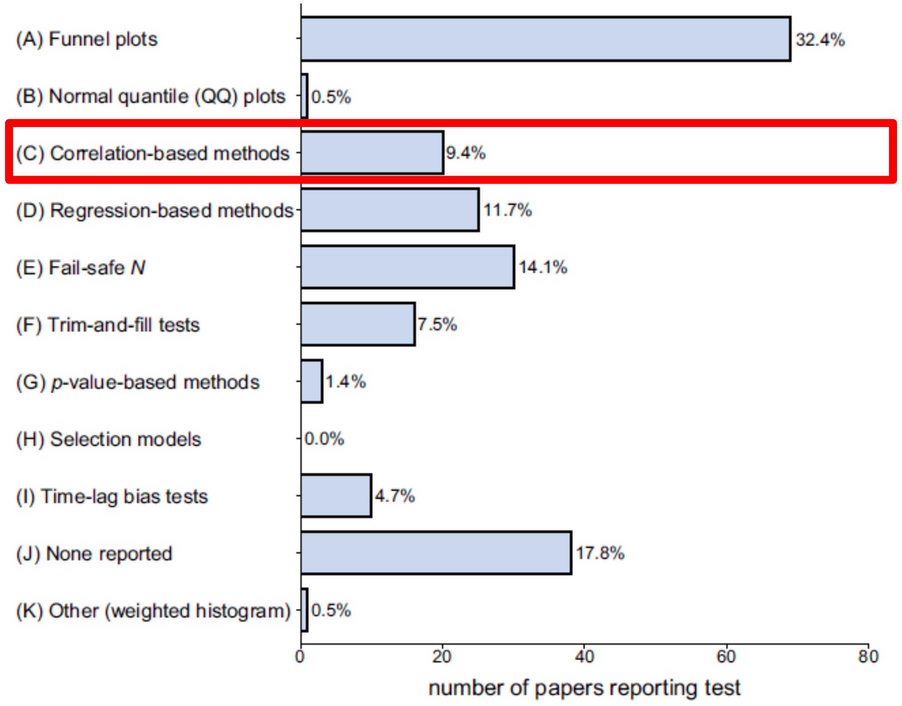
Testing funnel plot asymmetry

Correlation test : non parametric test of the correlation between standardised effect size and variance (or another measure of uncertainty)

Egger’s regression preferred



Publication bias: assessment of the impact

Fail-safe N

= number of unpublished stat. non-significant needed to make the overall effect not significant

If the fail-safe N is high (> $5*N_{studies}+10$) results are considered to be robust to publication bias

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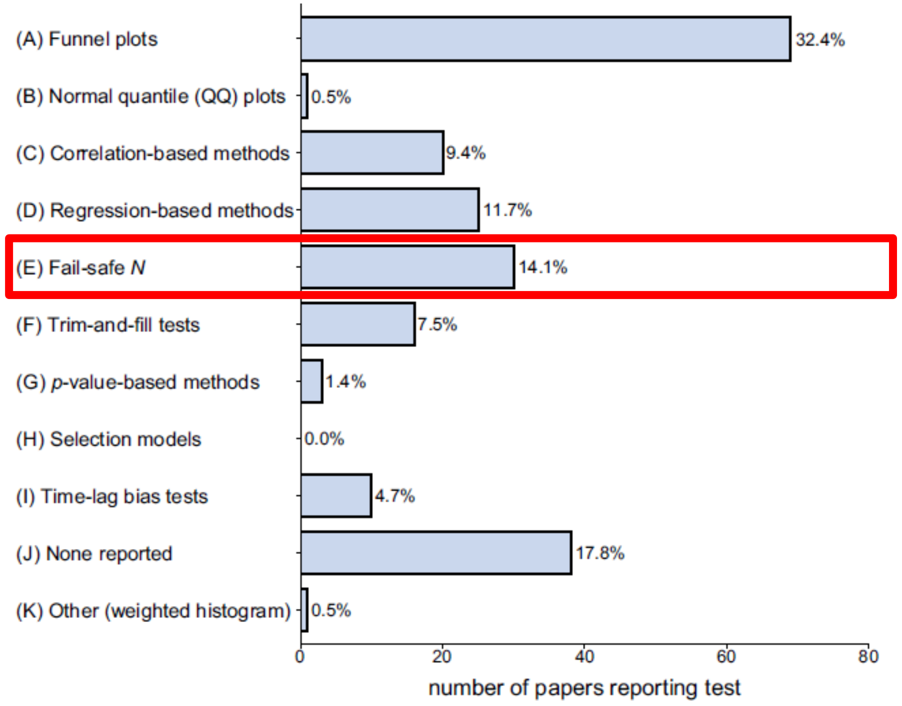

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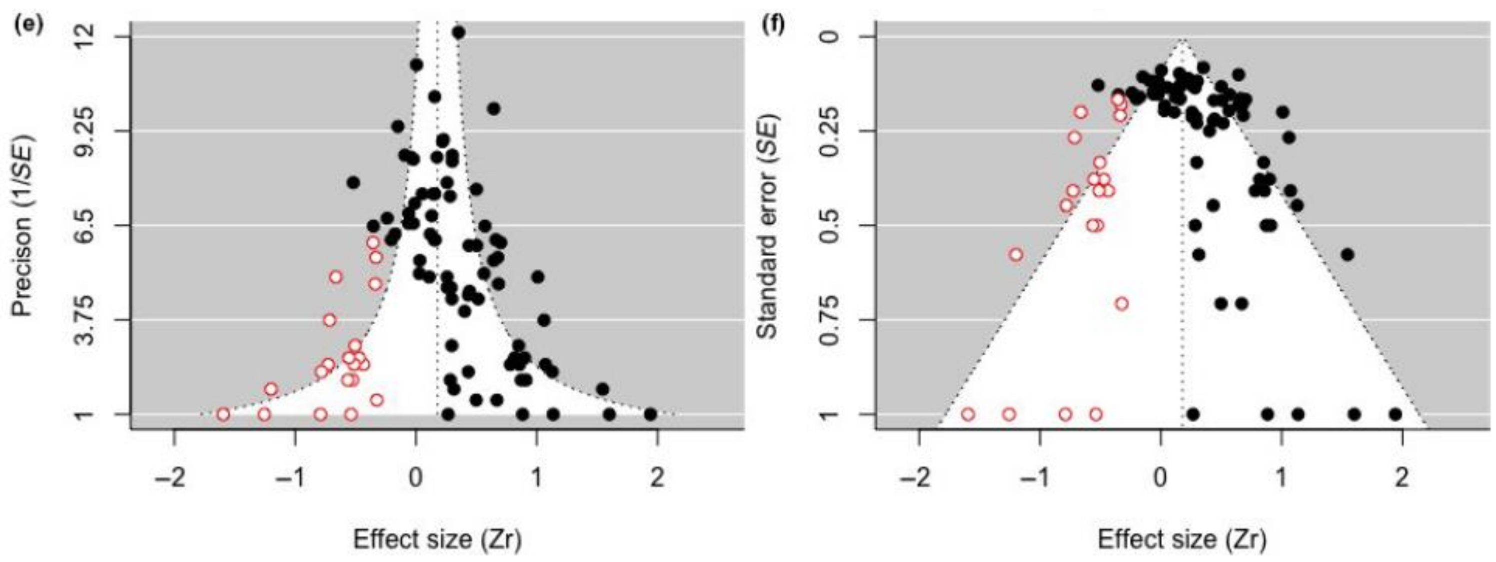
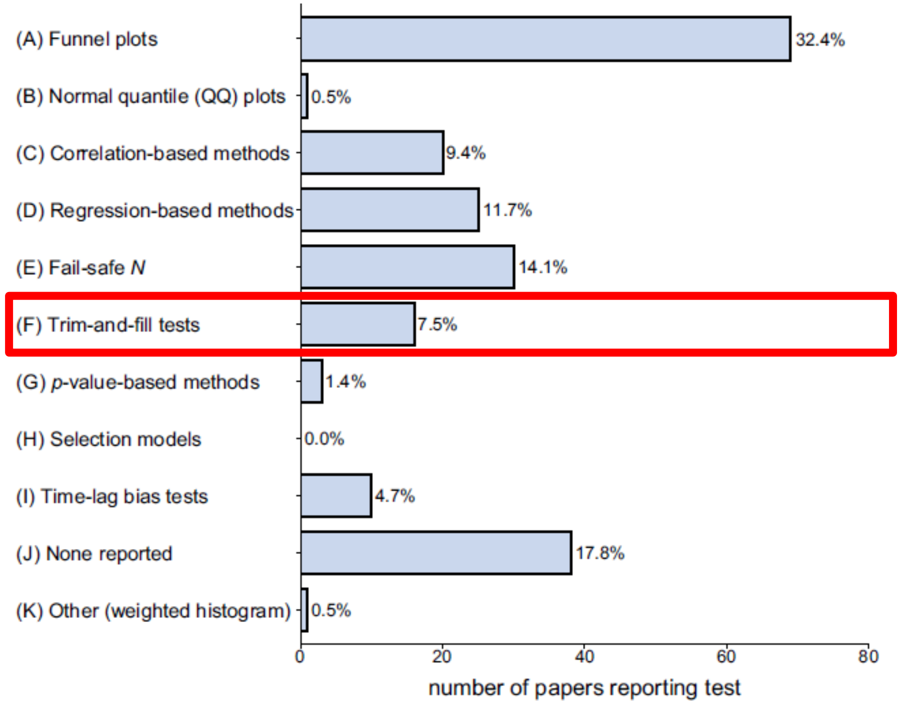
Trim-and-fill

Visualisation of potentially missing effect sizes and re-estimation of the overall effect





Publication bias: modelling

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Methods in Ecology and Evolution BRITISH ECOLOGICAL SOCIETY

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Proposal of a **new method (multilevel meta-regression)** for detecting and correcting publication bias. The method takes into account the **heterogeneity** and **dependency** of effect sizes.

Publication bias: modelling

Nakagawa *et al. Environmental Evidence* (2023) 12:8
https://doi.org/10.1186/s13750-023-00301-6

Environmental Evidence

METHODOLOGY **Open Access**

Quantitative evidence synthesis: a practical guide on meta-analysis, meta-regression, and publication bias tests for environmental sciences

Shinichi Nakagawa[1,2*], Yefeng Yang[1*], Erin L. Macartney[1], Rebecca Spake[3] and Malgorzata Lagisz[1]

https://itchyshin.github.io/Meta-analysis_tutorial/#checking-for-publication-bias-and-robustness

- **Detecting small study effect**

The most well-known form of publication bias is the **small study effect**, where effect size values from a "small" studies, with low replication and therefore large uncertainty and low precision, show different, often larger, treatment effects than large studies. A straightforward way to detect small study effect is to add the uncertainty of effect size as a moderator, such that the relationship between effect size and its uncertainty can be quantified. We propose to formulate Egger's regression (which is a classic method to detect the symmetry of a funnel plot) in the framework multilevel model to detect the small-study effect for dependent effect sizes:

to detect

$$z_i = \beta_0 + \beta_1 \sqrt{\frac{1}{\tilde{n}_i}} + \mu_{j[i]} + e_i + m_i, (16)$$

to correct

$$z_i = \beta_0 + \beta_1 (\frac{1}{\tilde{n}_i}) + \mu_{j[i]} + e_i + m_i, (17)$$

β_0 = publication-bias-corrected overall effect

Accounting for heterogeneity when detecting publication bias

$$z_i = \beta_0 + \beta_1 \sqrt{\frac{1}{\tilde{n}_i}} + \sum \beta_h x_{h[i]} + \mu_{j[i]} + e_i + m_i$$

Risks of bias in meta-analyses

… but studies showing a statistically significant effect are more likely to be

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Time-lag bias

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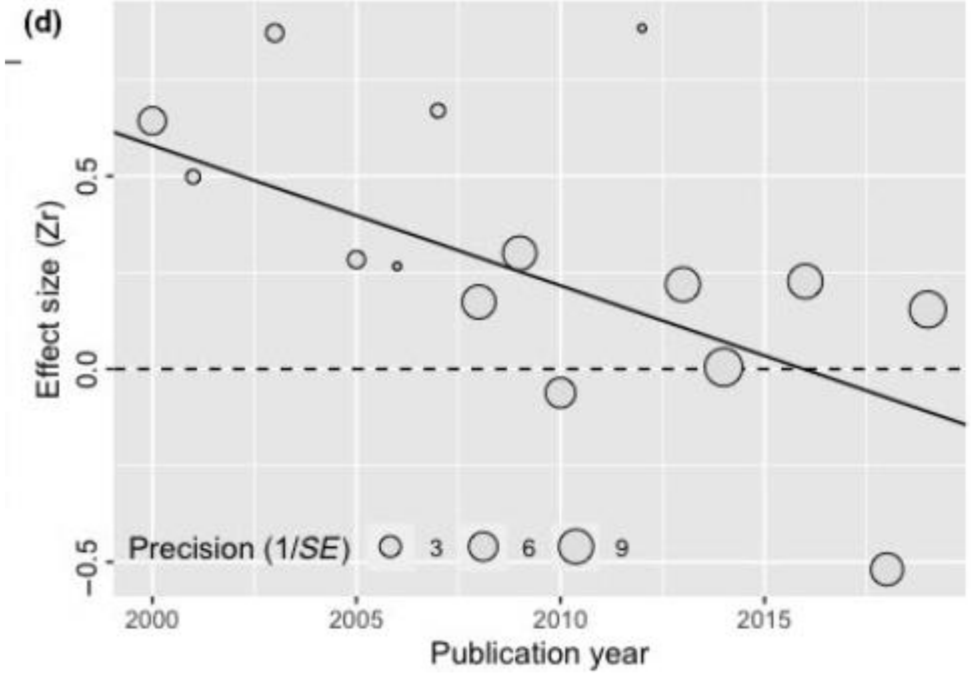
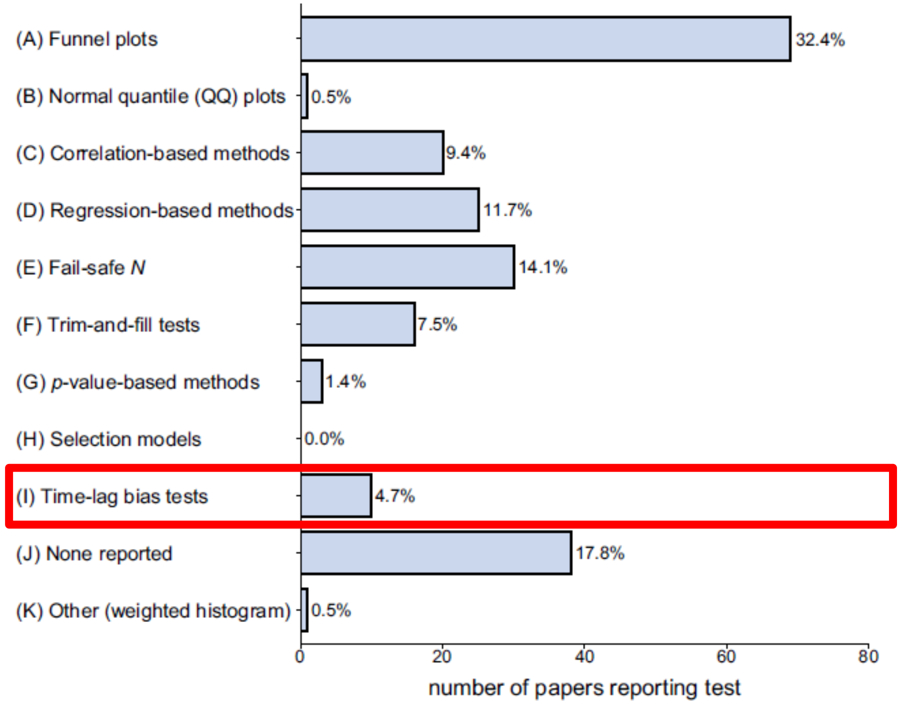
Correlation between effect size and publication year

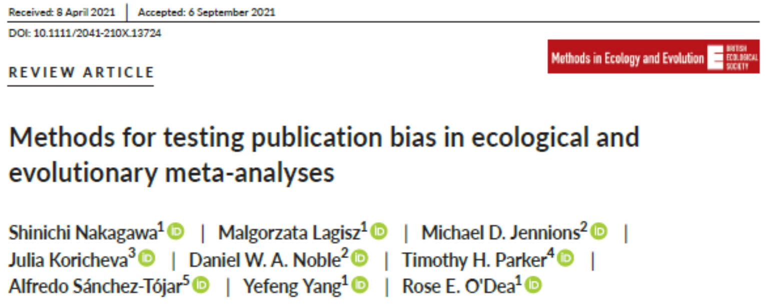




Not recommended,

does not consider precision

Time-lag bias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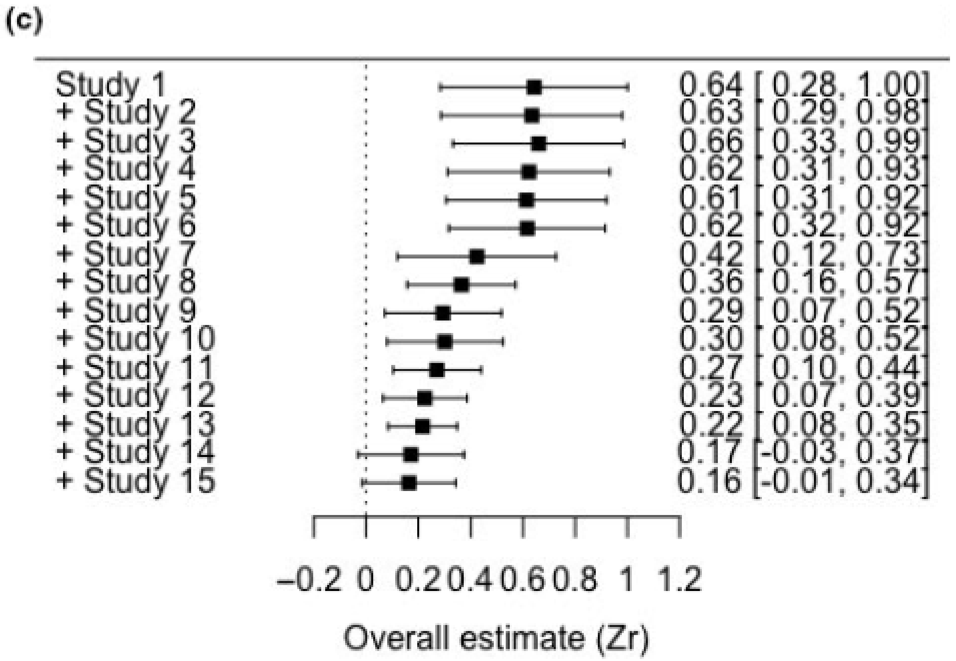
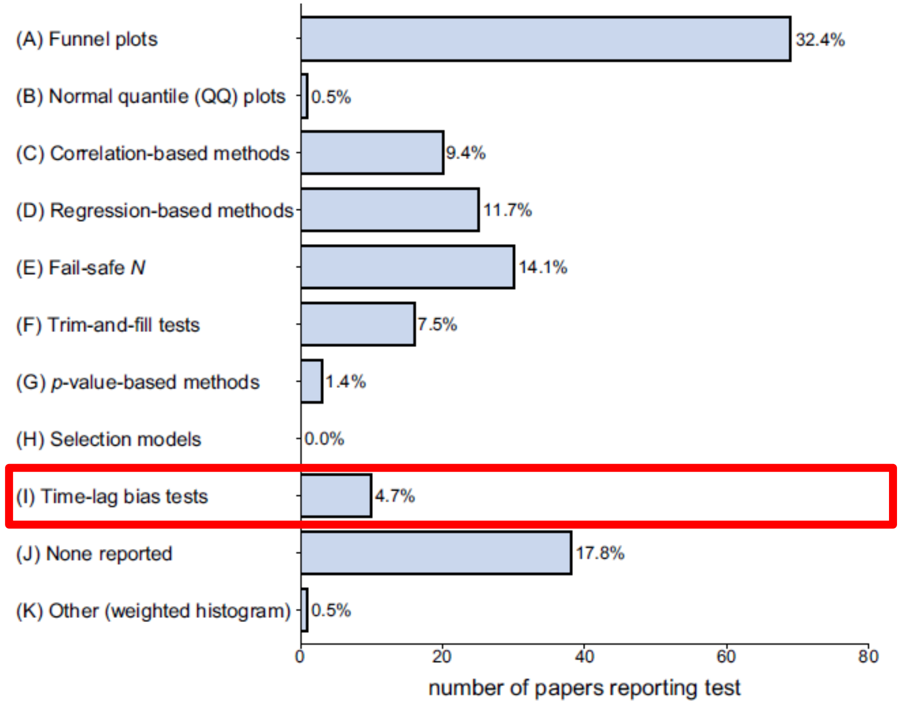
Cumulative meta-analysis

The larger the number of studies, the more we converge on the true effect





Time-lag bias: modelling

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https://itchyshin.github.io/Meta-analysis_tutorial/#checking-for-publication-bias-and-robustness

- **Detecting decline effect**

The decline effect, also known as time-lag bias, is another prominent form of publication bias, where effect sizes tend to get closer to zero over time. Testing for a decline effect is important because the temporal changes in evidence of a given field poses a threat to environmental policy-making, management, and practices. Decline effects can be tested by a meta-regression with publication year (centered to ease interpretation: $c(year_{j[i]})$) as a moderator:

$$z_i = \beta_0 + \beta_1 c(year_{j[i]}) + \mu_{j[i]} + e_i + m_i, (18)$$

Accounting for heterogeneity when detecting publication bias

In our main text, We introduce Equation 19 to simultaneously detect two forms of publication bias while accounting for heterogeneity to increase power and reduce Type I error rate:

$$z_i = \beta_0 + \beta_1 \sqrt{\frac{1}{\tilde{n}_i}} + \beta_2 c(year_{j[i]}) + \sum \beta_h x_{h[i]} + \mu_{j[i]} + e_i + m_i, (19)$$

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Language bias

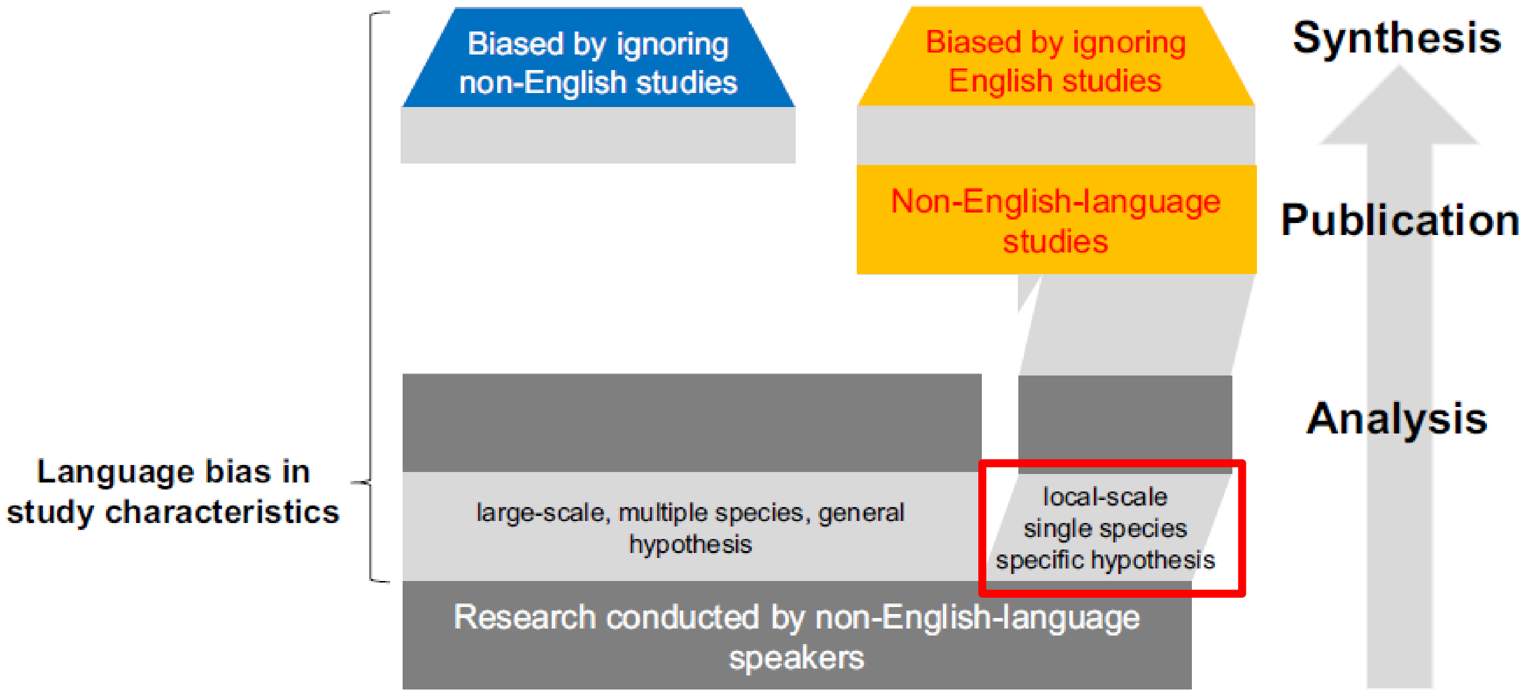
Received: 11 February 2020 | Revised: 20 April 2020 | Accepted: 23 April 2020
DOI: 10.1002/ece3.6368

ORIGINAL RESEARCH

Ecology and Evolution WILEY

Ignoring non-English-language studies may bias ecological meta-analyses

Ko Konno[1] | Munemitsu Akasaka[2,3] | Chieko Koshida[4] | Naoki Katayama[5] | Noriyuki Osada[6] | Rebecca Spake[7] | Tatsuya Amano[3,8,9]



Studies on a local scale, focusing on one species or testing specific hypotheses are more likely to be published in a non-English language
→ Language bias linked to the characteristics of the study

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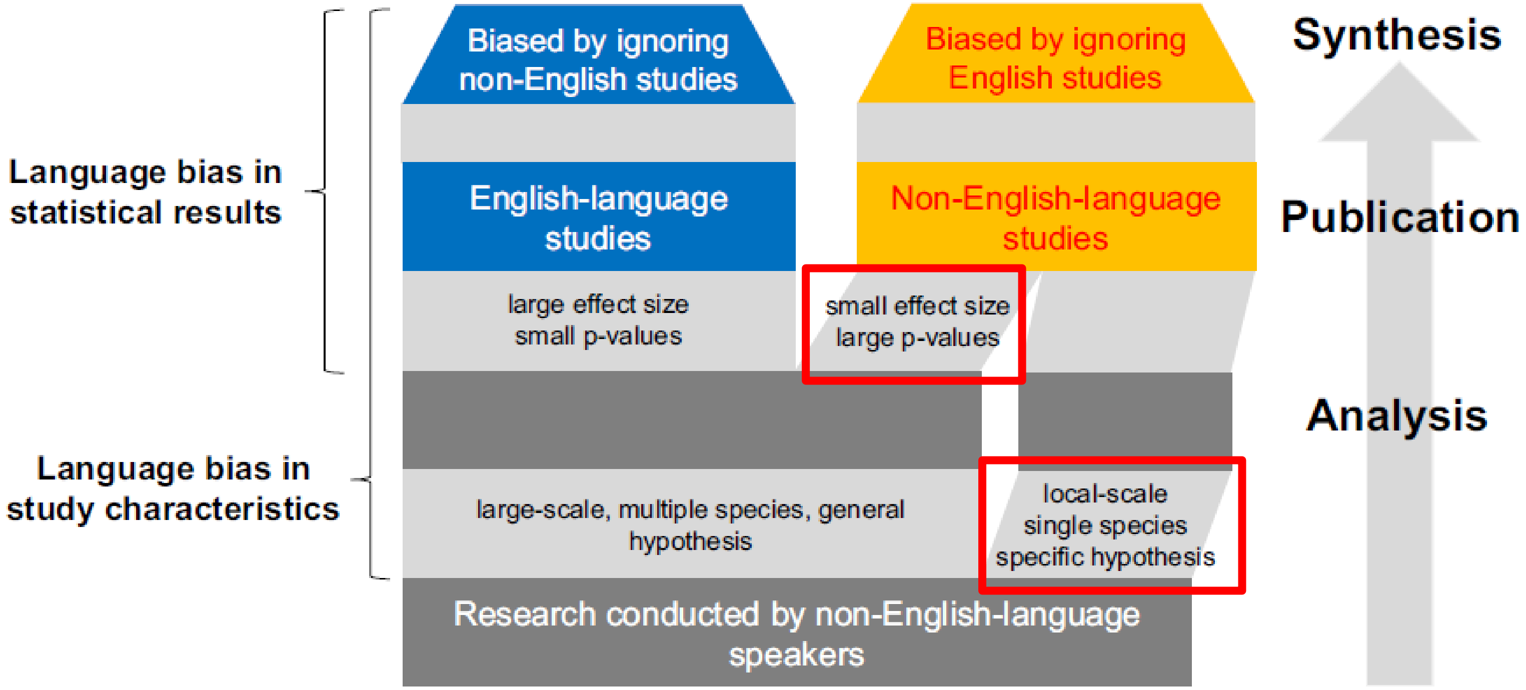
Studies showing a statistically significant effect are more likely to be published in journals with a higher impact factor, in English
→ Language bias linked to the statistical results of the study



Studies on a local scale, focusing on one species or testing specific hypotheses are more likely to be published in a non-English language
→ Language bias linked to the characteristics of the study

Language bias

Meta-analysis	Levene's test for homogeneity of variance *F (df)*	*p*	Two-sample Kolmogorov–Smirnov test for normality *D*	*p*	Two-sample *t* test for effect-size differences between languages *t (df)*	*p*
Rice-field meta-analysis	0.13 (1, 56)	.72	0.44	.06	2.18 (56)	**.03**
Leaf life span meta-analysis	4.55 (1, 132)	**.03**	0.27	.08	−2.40 (38.42)	**.02**
Plant forestry meta-analysis	1.68 (1, 63)	.20	0.29	.12	−0.19 (63)	.85
Sapling forestry meta-analysis	6.07 (1, 39)	**.02**	0.36	.17	−2.03 (21.62)	.05

Note: Statistically significant results are in bold. Welch two-sample *t* test was used where the assumption of homogeneity of variance was not met.

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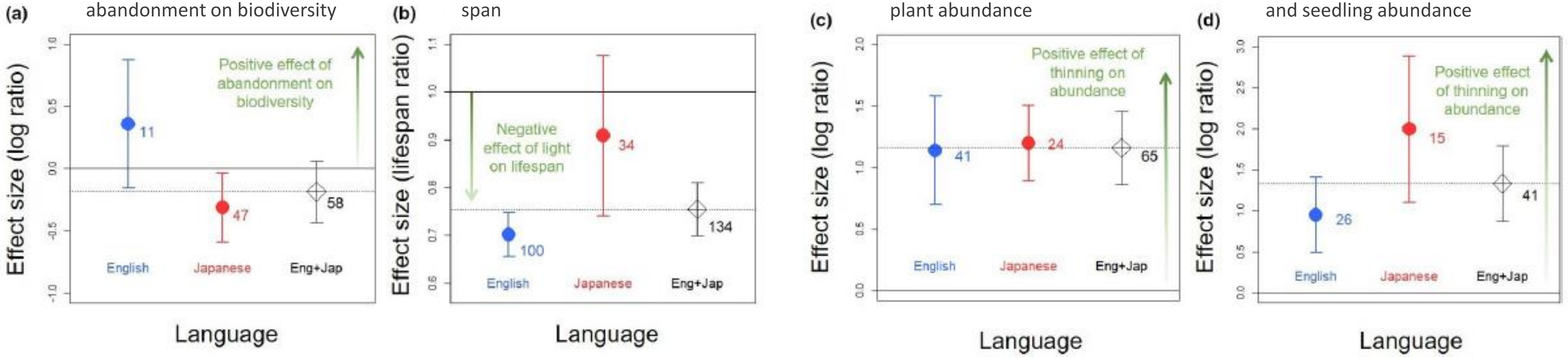
Effects of rice-field abandonment on biodiversity

Effect of light on plants' leaf life span

Effect of thinning on groundlayer plant abundance

Effect of thinning on sapling and seedling abundance

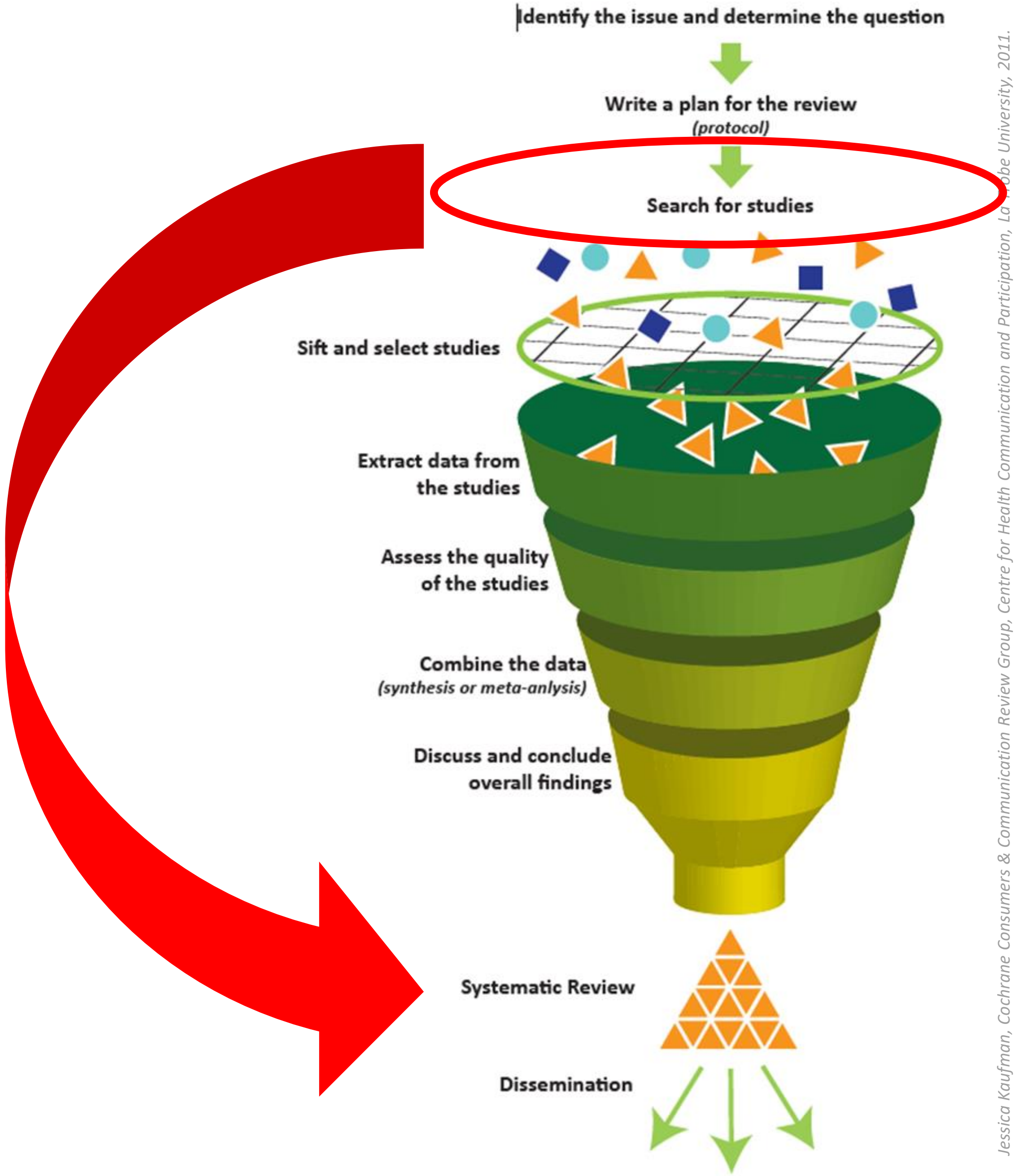


Conclusion risks of bias

- **Importance of literature search!**

→ search for grey literature
→ include literature published in non-English languages

- Publication bias tests should always be **interpreted with caution**, as there is no method for checking the real number of missing studies



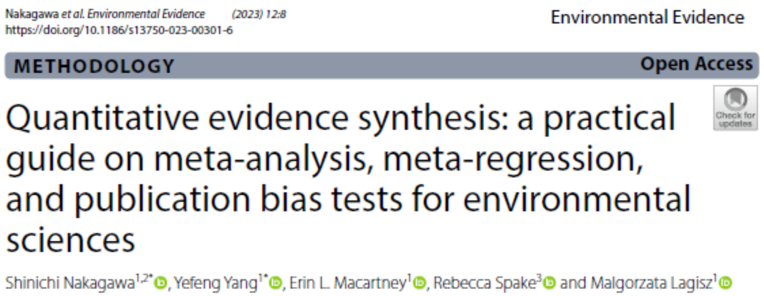
Jessica Kaufman, Cochrane Consumers & Communication Review Group, Centre for Health Communication and Participation, La Trobe University, 2011.

Sensitivity analysis

Explores the robustness of meta-analytic results by running a different set of analyses from the original analysis, and comparing the results

→ Robustness to influential studies

“leave-one-out” analysis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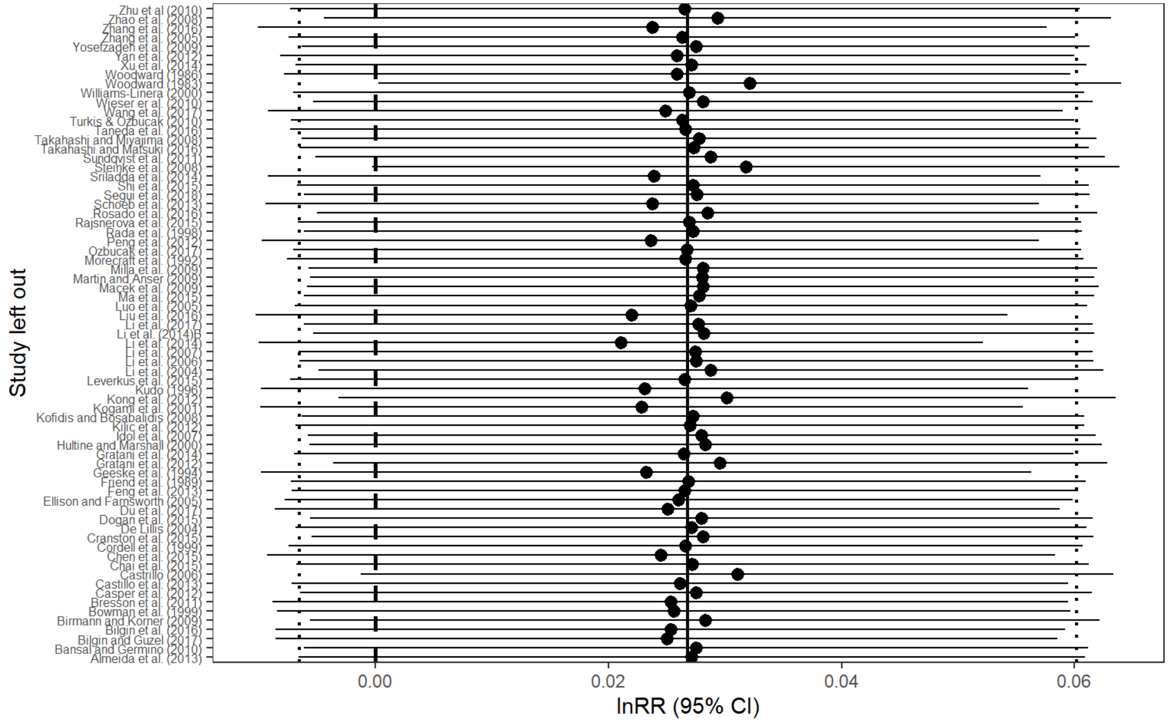

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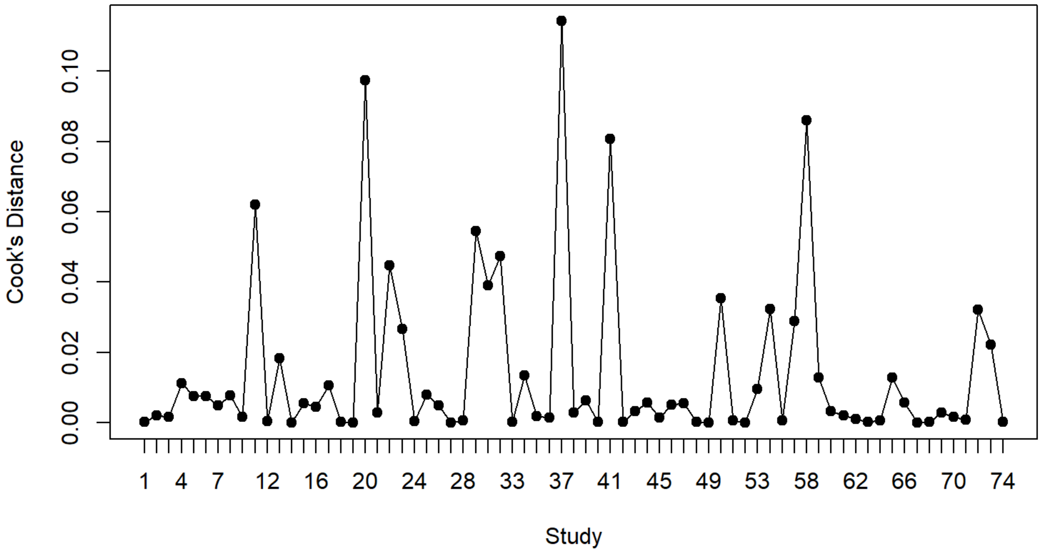

Figure S10 Cook's distance showing how much all of the predicted effects in the model change when one study is deleted.

Sensitivity analysis

Explores the robustness of meta-analytic results by running a different set of analyses from the original analysis, and comparing the results

→ Robustness to influential studies

"leave-one-out" analysis

Cook's distance

→ Robustness to choice of method (effect size metric, imputation method, rho coef. in variance-covariance matrix, …)

TD: publication bias visual detection and test

Data from Midolo et al. 2019

Received: 17 December 2018 | Accepted: 3 April 2019
DOI: 10.1111/gcb.14646

PRIMARY RESEARCH ARTICLE

Global Change Biology WILEY

Global patterns of intraspecific leaf trait responses to elevation

Gabriele Midolo[1] | Pieter De Frenne[2] | Norbert Hölzel[3] | Camilla Wellstein[1]

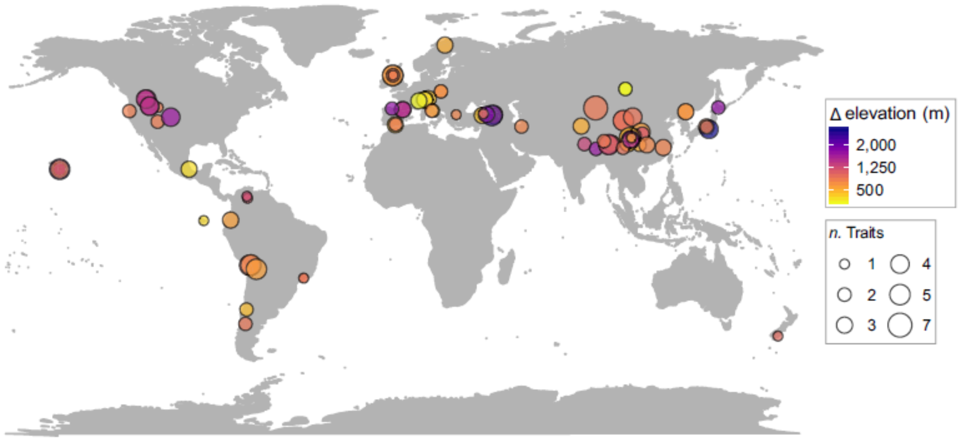

FIGURE 1 Geographical distribution of the 92 elevational gradients included in the meta-analysis. For each gradient, point size depict the number of leaf traits available and the colours depict the larger value of difference in elevation (i.e. the vertical distance between the highest site sampled along the gradient and the lowest site sampled) [Colour figure can be viewed at wileyonlinelibrary.com]

meta-analysis of the intraspecific leaf trait variation along 92 elevational gradients worldwide reported in 71 studies

-> install and load `metafor`; load and look at data (cf. script)

TD: publication bias visual detection and test

Column name	Variable Description
trait	Trait type; use this to subset the dataset for each trait separately in the analysis.
id	row ID.
common_id	common ID value for each gradient and species sharing the same ‘control’ (i.e. the point at the lowest elevation; see below); use this to calculate the variance-covariance matrix (see the R code).
study_id	ID value for each study.
study_name	Author’s name (year).
country	Country where the elevational gradient is located.
gradient_id	Name for each gradient (nested within ‘study_name’).
species	Plant species name.
family	Plant family name.
ele_level	ID value for each elevational level above the lowest site sampled for each single species within a gradient (range from 2 to onwards, where e.g. 2 is the 2nd site sampled above the first sampled at the lowest elevation).
treatment	‘treatment’ is the mean of the trait sampled at a higher elevational level.
control	‘control’ is the mean of the trait sampled at the lowest elevational level (note that often multiple ‘treatments’ are compared to the same ‘control’).
sd_treatment	Standard deviation of the mean ‘treatment’.
sd_control	Standard deviation of the mean ‘control’.
n_individuals	Number of plant individuals sampled; sample size.
pt	Plant functional group (either herbaceous ‘H’ or woody ‘W’).
LONG	Mean longitude estimated for each gradient.
LAT	Mean latitude estimated for each gradient.
ARIDITY_INDEX	Estimated aridity index for each gradient; see ‘Methods’.
SOLAR_RADIATION	Annual mean radiation (W m-2); ‘Bio20’ in CliMond; see ‘Methods’.
MEAN_GROWING_SEASON_TEMPERATURE	Mean Temperature of Warmest Quarter; ‘BIO10’ in WorldClim 2.0; see ‘Methods’.
elevation_treatment	Elevation of the ‘tretment’ (m a.s.l.)
elevation_control	Elevation of the ‘control’ (m a.s.l.)
elevation	= ‘elevation_treatment’ – ‘elevation_control’ (m)
elevation_log	= log (‘elevation’)
yi	Log-response ratio (lnRR) of the ‘treatment’/’control’ calculated via metafor::escalc()
vi	Sampling variance of ‘yi’ calculated via metafor::escalc(). See Hedges et al (1999) for the formula: https://doi.org/10.1890/0012-9658(1999)080[1150:TMAORR]2.0.CO;2

TD: publication bias visual detection and test

-> calculate effect size: log-response ratios (lnRR)

escalc() function metafor

[Measures for quantitative variables, log transformed ratio of means]

TD: publication bias visual detection and test

-> calculate effect size: log-response ratios (lnRR)

escalc() function metafor

[Measures for quantitative variables, log transformed ratio of means]

```
dat_Midolo_2019 <- metafor::escalc(measure = "ROM", # "ROM" means ratio of
means;
       m1i = treatment, # mean value of group 1 (e.g., environmental stressor);
mean value of a trait measured at the higher elevation level;
      m2i = control, # mean value of group 2 (e.g., control); mean of the same
trait measured at the lower elevation level;
      sd1i = sd_treatment, # standard deviation of mean of group 1
      sd2i = sd_control, # standard deviation of group 2
      n1i = n_treatment, # sample size of group 1
      n2i = n_control, # sample size of group 2
      data = dat_Midolo_2019)
```

TD: publication bias visual detection and test

-> check for publication bias for traits "SLA" and "Pmass"

funnel() function metafor

Do you see any potential publication bias for SLA and Pmass?

Try different representation of the funnel plot with different measures of sampling error

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TD: publication bias visual detection and test

-> check for publication bias for traits "SLA" and "Pmass"

funnel() function metafor

Do you see any potential publication bias for SLA and Pmass?

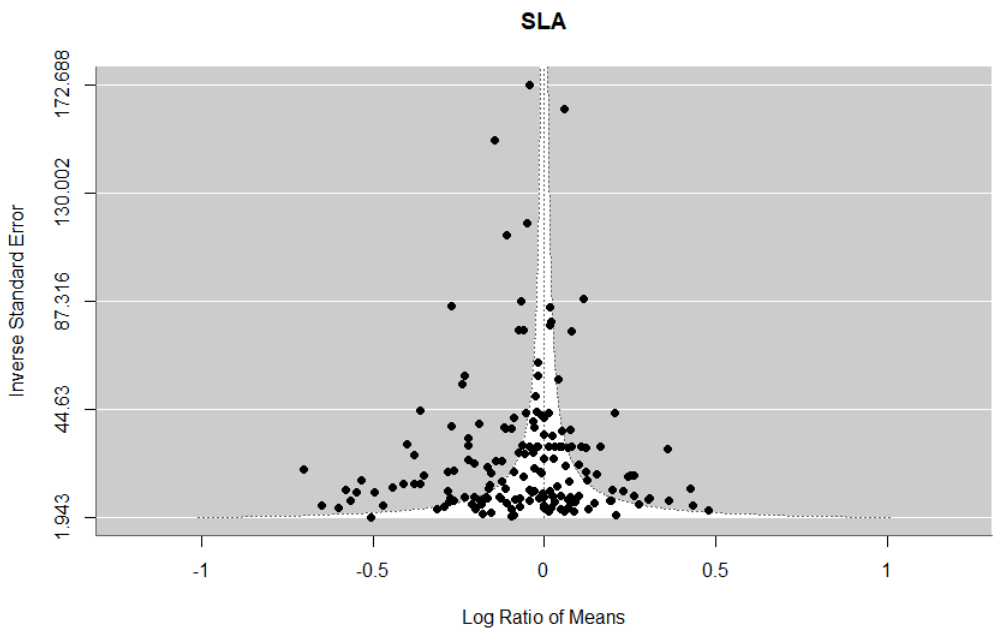
Try different representation of the funnel plot with different measures of sampling error

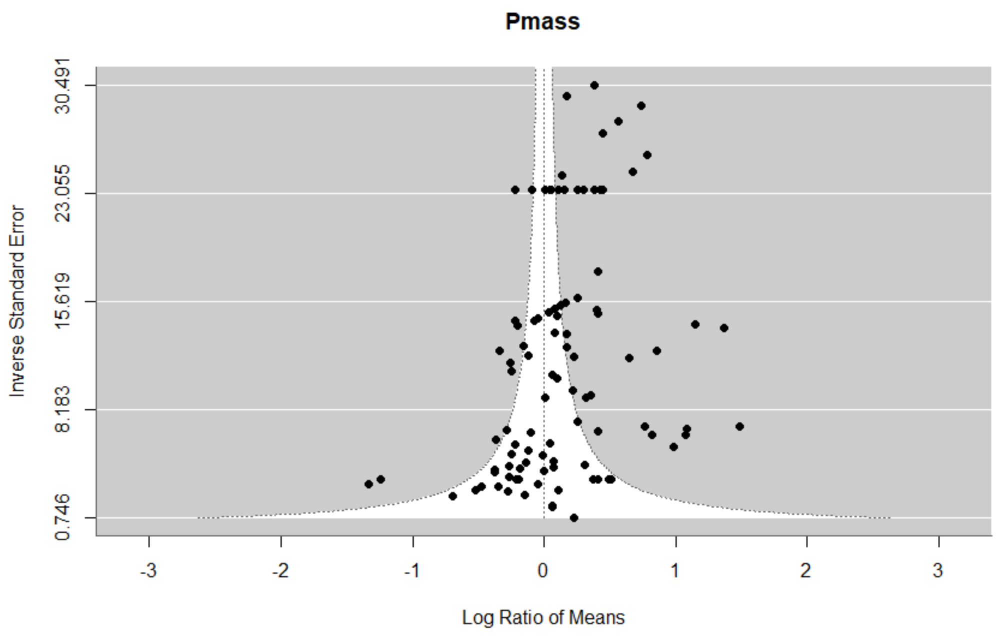
```
metafor::funnel(x = dat_Midolo_2019_SLA$yi,
                vi = dat_Midolo_2019_SLA$vi,
                yaxis = "seinv",
               main = "SLA")

metafor::funnel(x = dat_Midolo_2019_Pmass$yi,
                vi = dat_Midolo_2019_Pmass$vi,
                yaxis = "seinv",
                main = "Pmass")
```

TD: publication bias visual detection and test

-> check for publication bias for traits "SLA" and "Pmass"





Warning! Funnel plots are only visual checks, not reliable for detecting publication bias

Visual asymmetry for Pmass

TD: publication bias visual detection and test

-> test for publication bias for traits "SLA" and "Pmass"

Egger’s test: regtest() function metafor

Do you detect any potential publication bias for SLA and Pmass?

TD: publication bias visual detection and test

-> test for publication bias for traits "SLA" and "Pmass"

Egger's test: regtest() function metafor

Do you detect any potential publication bias for SLA and Pmass?

```
metafor::regtest(x = dat_Midolo_2019_SLA$yi,
                 vi = dat_Midolo_2019_SLA$vi)

metafor::regtest(x = dat_Midolo_2019_Pmass$yi,
                 vi = dat_Midolo_2019_Pmass$vi)
```

TD: publication bias visual detection and test

-> test for publication bias for traits "SLA" and "Pmass"

Egger's test: regtest() function metafor

Do you detect any potential publication bias for SLA and Pmass?

```
> metafor::regtest(x = dat_Midolo_2019_SLA$yi,
+                  vi = dat_Midolo_2019_SLA$vi)

Regression Test for Funnel Plot Asymmetry

Model:     mixed-effects meta-regression model
Predictor: standard error

Test for Funnel Plot Asymmetry: z = -0.4698, p = 0.6385
Limit Estimate (as sei -> 0):   b = -0.0539 (CI: -0.1000, -0.0078)
```

```
> metafor::regtest(x = dat_Midolo_2019_Pmass$yi,
+                  vi = dat_Midolo_2019_Pmass$vi)

Regression Test for Funnel Plot Asymmetry

Model:     mixed-effects meta-regression model
Predictor: standard error

Test for Funnel Plot Asymmetry: z = -3.3213, p = 0.0009
Limit Estimate (as sei -> 0):   b =  0.3272 (CI: 0.1973, 0.4570)
```

Stat. signif. asymmetry detected for Pmass

TD: publication bias visual detection and test

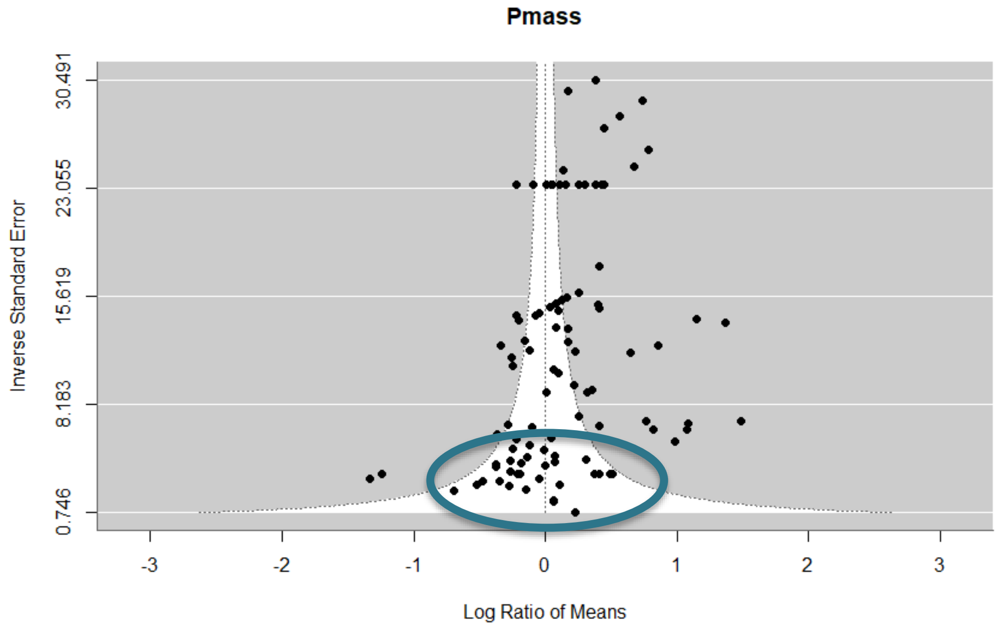
-> Interpret and conclude on the publication bias analysis

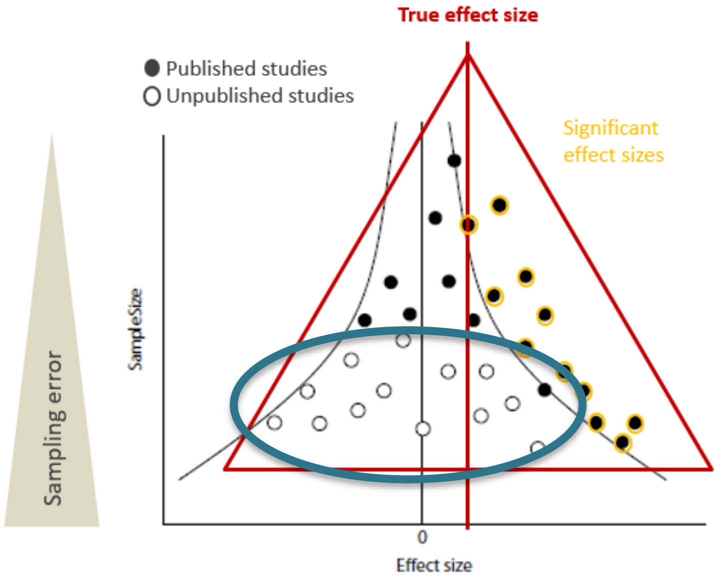
TD: publication bias visual detection and test

-> Interpret and conclude on the publication bias analysis

SLA: no evidence of publication bias

Pmass: presence of non-significant estimates at the left of the funnel suggest that funnel plot asymmetry detected by the Egger's test is not due to publication bias (asymmetry due to effect sizes heterogeneity)





TD: publication bias visual detection and test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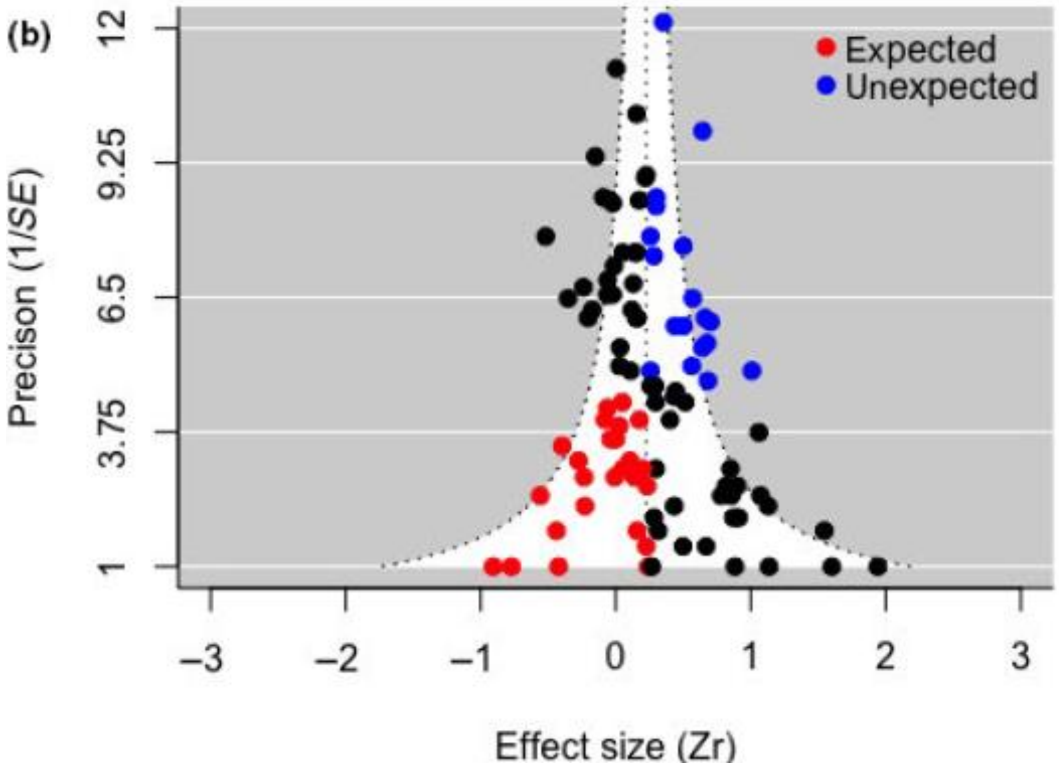
REVIEW ARTICLE
Methods in Ecology and Evolution
Methods for testing publication bias in ecological and evolutionary meta-analyses
Shinichi Nakagawa[1] | Malgorzata Lagisz[1] | Michael D. Jennions[2] | Julia Koricheva[3] | Daniel W. A. Noble[2] | Timothy H. Parker[4] | Alfredo Sánchez-Tójar[5] | Yefeng Yang[1] | Rose E. O'Dea[1]



red dots: ‘expected’ missing data under publication bias

blue dots: ‘unexpected’ missing data