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## **Decline effects are rare in ecology: Comment**

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15 Recently, Costello and Fox (2022) tested, with a large dataset, the hypothesis of whether  
16 there is a widespread decline effect in the discipline of ecology. In other words, the  
17 magnitude of the reported ecological effect sizes declines over time (Leimu and Koricheva  
18 2004). Contrary to early results from much smaller datasets (Jennions and Møller 2002, Barto  
19 and Rillig 2012), Costello and Fox (2022), using 466 ecological meta-analyses with >  
20 100,000 effect sizes, concluded that there was no systematic decline effect across the field of  
21 ecology – only ~5% of ecological meta-analyses showed statistical evidence of a decline  
22 effect. This conclusion seems to be “good news” and has important field-wide implications.  
23 For example, the temporal stability of the cumulative evidence can alleviate the concerns  
24 about policy-making for conservation and environmental management (Koricheva and  
25 Kulinskaya 2019).

26

27 However, we point out that for their test, Costello and Fox (2022) employed a procedure akin  
28 to vote-counting, which is not a preferred method for assessing cumulative evidence in any  
29 discipline (Freemantle and Geddes 1998, Combs et al. 2011, Harrison 2011, Gurevitch et al.  
30 2018). Therefore, we have re-analysed their large dataset using a second-order meta-analysis  
31 or meta-meta-analysis, which uses a meta-analytic model to statistically synthesize results  
32 across different meta-analyses (Fanelli et al. 2017, Nakagawa et al. 2019), and came to a  
33 different conclusion. In the Comment, we first report our results by comparing them with  
34 those of Costello and Fox (2022). Second, we explain the limitations of the vote-counting  
35 method in identifying the decline effect. Finally, to facilitate testing of the decline effect, we  
36 provide recommendations on how to conduct and report the decline effect test in ecological  
37 meta-analyses (all the code can be found in  
38 [https://github.com/Yefeng0920/decline\\_effect\\_Ecology](https://github.com/Yefeng0920/decline_effect_Ecology)).

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## 40 **DECLINE EFFECTS ARE PERSISTANT AND NOT NEGLIGIBLE IN ECOLOGY**

41 As mentioned by Costello and Fox (2022), many methods are available for the identification  
42 of the decline effect in a given meta-analysis. From among these, they chose two formal  
43 statistical methods. The first is a correlation-based approach, which they acknowledge has  
44 many limitations but is still used in order to be comparable to previous results (Jennions and  
45 Møller 2002). In contrast, Costello and Fox (2022) preferred the second approach – the  
46 regression-based approach, which consists of two steps. First, they regressed effect size  
47 estimates on publication year ( $year_i$ ) for each meta-analysis (i.e., univariate meta-regression  
48 with  $year_i$  as a predictor; Nakagawa and Santos 2012, Koricheva and Kulinskaya 2019),  
49 where  $p$ -value of  $year_i$ 's slope ( $\beta_{year}$ )  $< 0.05$  indicates that the examined meta-analysis  
50 shows the statistical evidence of a decline effect. Second, they used a vote-counting-like  
51 method to compute the percentage of  $p$ -value  $< 0.05$  for  $\beta_{year}$  that were obtained from the  
52 first step. Under the binomial distribution, they tested the percentage of the  $p$ -values against  
53 the null hypothesis and concluded that the decline effects were rare at the nominal level of  
54 0.05 in the field of ecology (details see Costello and Fox 2022).

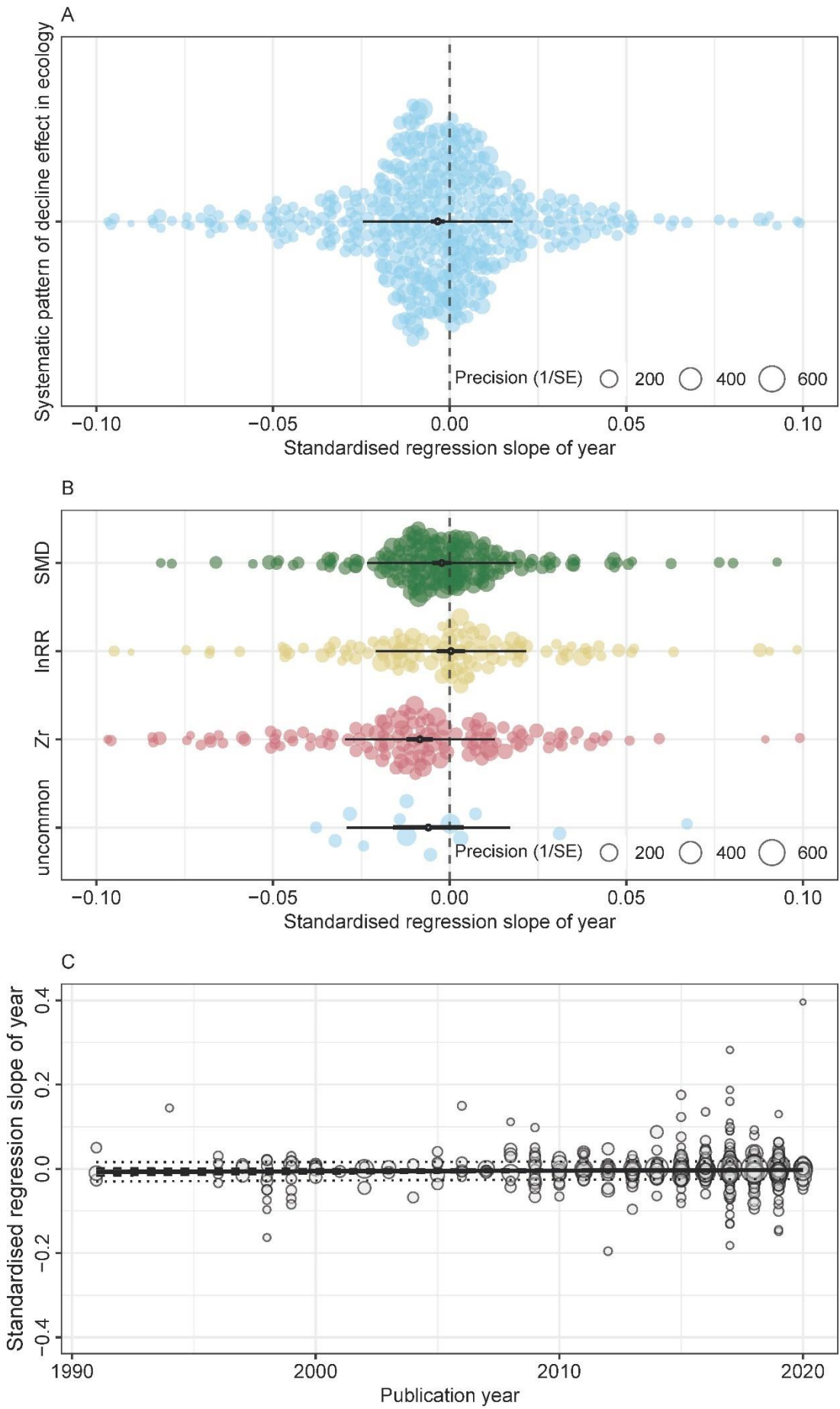
55

56 Rather than using the percentage of statistically significant  $\beta_{year}$  obtained from the first step,  
57 our approach treated slope  $\beta_{year}$  as a standardised effect size measure, which has been used  
58 in ecology (De Frenne et al. 2013, Morrissey 2016) and other disciplines (see Nieminen et al.  
59 2013 for medical sciences; Peterson and Brown 2005, Rose and Stanley 2005 for social  
60 sciences). We fitted a meta-analytic model to quantitatively aggregate  $\beta_{year}$  across 466 meta-  
61 analyses, weighting estimates by the inverse square of standard error  $SE[\beta_{year}]$ . Then, we

62 found that there was a statistically significant systematic decline effect in ecology  
63 (overall/pooled  $\beta_{year} = -0.0034$ , 95% confidence interval (CI) =  $-0.0054$  to  $-0.0014$ ;  $p$ -  
64 value = 0.0008; Figure 1; Supplementary Materials).

65

66 Importantly, our meta-meta-analysis can produce new insights that the vote-counting method  
67 is unlikely to provide. For example, the estimates of  $\beta_{year}$  were consistent across 466 meta-  
68 analyses with a small amount of heterogeneity among these slopes ( $I^2_{between-MA} = 16\%$ ; cf.  
69 Senior et al. 2016) (Supplementary Materials). This amount of heterogeneity indicates that  
70 the decline effect, albeit small, is persistent across ecological meta-analyses. We also found  
71 that the types of effect sizes used could explain 9.4% of the variation ( $R^2_{marginal} = 0.094$ ;  
72 Nakagawa and Schielzeth 2013); the ‘global’ decline effect was mainly driven by  $Zr$   
73 (Fisher’s r-to-z; pooled  $\beta_{Zr\sim year} = -0.0084$ , 95% CI =  $-0.0121$  to  $-0.0047$ ; Figure 1B).  
74 Apart from lnRR (log response ratio), standardized mean difference (SMD) and uncommon  
75 effect sizes (e.g., odds ratio) tend to decline over time (albeit non-significantly).



77 Figure 1. Orchard plots showing the distribution of regression slopes of year ( $\beta_{year}$ ; solid  
78 circles) obtained from the first step (decline effect tests for all individual meta-analyses) and  
79 meta-analytic aggregation of  $\beta_{year}$  in the second step (mean  $\beta_{year}$ ; open circle). (A) Mean  
80  $\beta_{year}$  over individual  $\beta_{year}$ , which was used to identify the systematic pattern of decline  
81 effect. (B) Mean  $\beta_{year}$  for each effect size metric. (C) The relationship between meta-  
82 analyses' decline effect and the publication year (the test of the “decline in the decline effect  
83 itself”). The size of each point (individual  $\beta_{year}$ ) is proportional to its precision (inverse  
84 standard error [SE] of  $\beta_{year}$ ). Thick error bars represent 95% confidence intervals (CIs) and  
85 thin error bars represent prediction intervals (PIs). 95% CIs that do not cross zero ( $p$ -value <  
86 0.05) indicate a “global” decline effect in ecology. lnRR = log response ratio; standardized  
87 mean difference = SMD,  $Zr$  Fisher's r-to-z, uncommon effect sizes = uncommonly used  
88 ecological effect size metrics (e.g., odds ratio). All plots were made using *orchaRd* package  
89 (Nakagawa et al. 2021).

90

91 Furthermore, Costello and Fox (2022) speculated that the “decline in the decline effect itself”  
92 may explain the contrasting results obtained by early researchers (Jennions and Møller 2002),  
93 who found a ubiquitous decline effect in ecological meta-analyses published before 2002. We  
94 statistically tested this effect by using a univariate meta-regression with the publication year  
95 of meta-analysis papers as a predictor. We found that there has been no statistical evidence of  
96 the decline in the decline effect (i.e., estimates of decline effect are not related to publication  
97 year of meta-analyses) (Figure 1C).

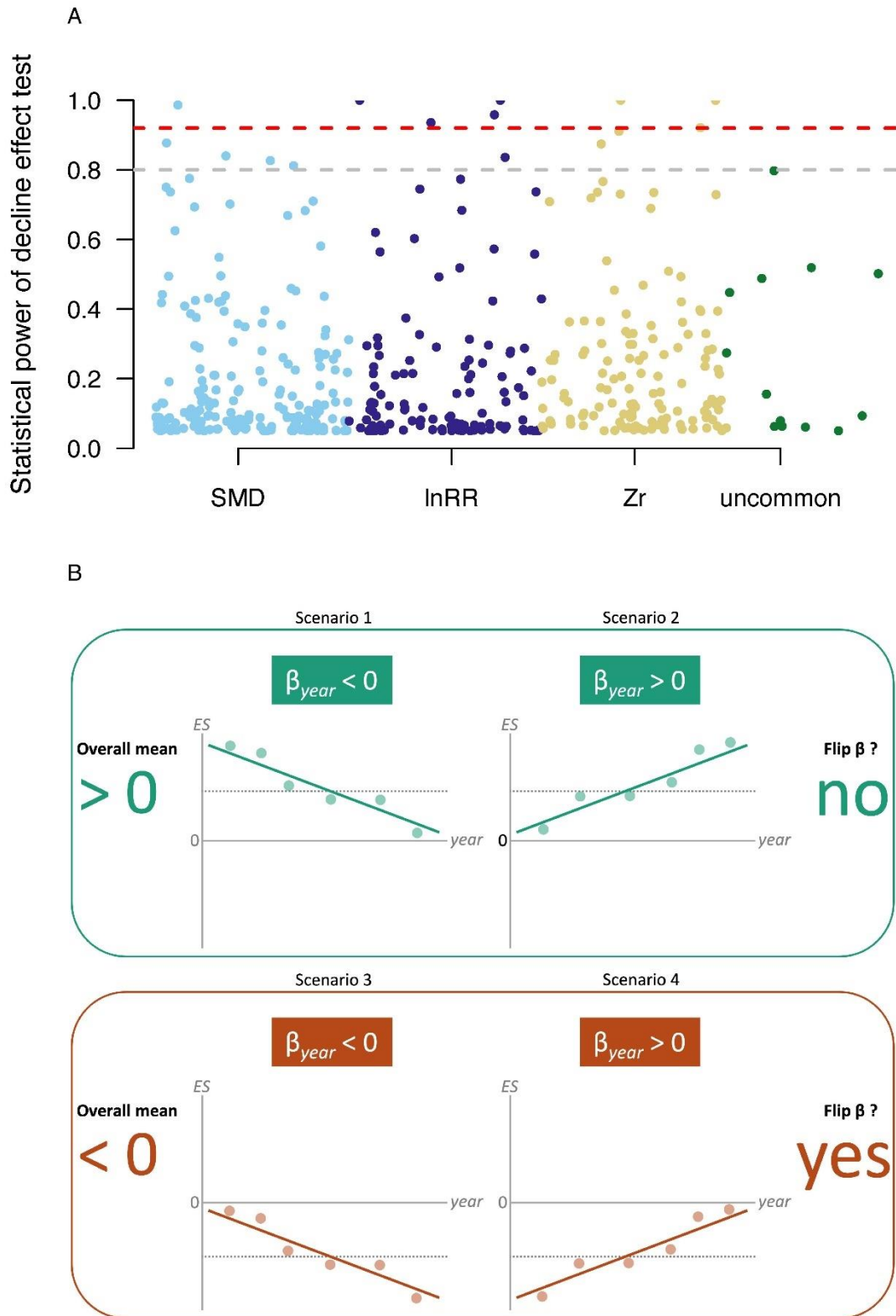
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99 Taken together, we concluded that there is indeed a consistent ‘global’ decline effect in  
100 ecology although the magnitude of the decline effect is small. However, this effect is  
101 certainly not negligible, with the estimates of  $Z_r$  being exaggerated by an average of 0.13  
102 units (equivalent to Cohen’s “small” effect size, Cohen 1988; Supplementary Materials).

103

104 **THE ABSENCE OF EVIDENCE OF THE DECLINE EFFECTS IS NOT THE**  
105 **EVIDENCE OF THE ABSENCE**

106 Costello and Fox (2022) acknowledged that the sample size of the most meta-analyses in  
107 their dataset was very small (< 5 effect sizes). Therefore, we expected that the reason why  
108 they failed to find the systematic decline effect in ecology is that the vote-counting they used  
109 is underpowered, namely reducing the likelihood of detecting a decline effect when it exists  
110 (committing type II errors). Indeed, we found that only ~3% of the meta-analyses had a  
111 statistical power equal or over the nominal power (80%) to detect a decline effect, with a  
112 median power of 17% (0.17, 95% CI = 0.16 to 0.19; Figure 2A). In contrast, the power of our  
113 meta-meta-analytic approach was as high as 92%. In addition to the issue of statistical power,  
114 many researchers have criticized other flaws in the vote-counting method (Harrison 2011,  
115 Nakagawa and Poulin 2012, Koricheva and Gurevitch 2014). For example, it (i) mainly  
116 focuses on statistical significance, whose drawbacks have been highlighted elsewhere  
117 (Nakagawa and Cuthill 2007, Wasserstein and Lazar 2016, Amrhein et al. 2019); (ii) is  
118 incapable of estimating the magnitude and precision of the systematic decline effect; (ii)  
119 cannot adjust for the impact of decline effect on the estimation of effect sizes (bias-adjusted  
120 effect sizes; cf. Kvarven et al. 2020, Nakagawa et al. 2022, Yang et al. 2022). The meta-  
121 meta-analytic approaches can deal with all these issues (see below and Supplementary  
122 Materials).



123

124 Figure 2. Statistical power of decline effect tests in individual meta-analyses (A) and

125 justification of flipping the signs of  $\beta_{year}$  when detecting the systematic pattern of the decline

126 effect (B). (A) The scatter plot of statistical power of decline effect test for all individual meta-



127 analyses from Costello and Fox (2022)'s dataset. The grey dashed line represents the nominal  
128 power level (i.e., 80%), below which the power is insufficient to detect a decline effect. The  
129 red dashed line represents the statistical power of the decline effect test performed using meta-  
130 meta-analysis (92%). (B) Different scenarios of flipping the signs of  $\beta_{year}$ . If a meta-analysis's  
131 mean effect size (overall mean) is positive, a positive  $\beta_{year}$  indicates that the magnitude of the  
132 effect size estimate declines over time (Scenarios 1 & 2). In contrast, for a meta-analysis with  
133 a negative mean effect size, a negative  $\beta_{year}$  indicates that the magnitude of the effect size  
134 estimate declines over time (Scenarios 3 & 4).

135

136 Our meta-meta-analytic approach is a second-order meta-analysis, which uses statistical  
137 models to aggregate evidence from multiple first-order meta-analyses (Gurevitch et al. 2018,  
138 Nakagawa et al. 2019, Oh 2020). The meta-meta-analytic approach can account for (at least in  
139 part) residual sampling variance that the first-order meta-analyses cannot eliminate, thus  
140 obtaining a more precise estimate than that in the first-order meta-analyses (Schmidt and Oh  
141 2013). Researchers from many other disciplines have already used second-order meta-analysis  
142 to detect the 'global' decline effect (Fanelli et al. 2017, Fanshawe et al. 2017, Pietschnig et al.  
143 2019). Here, we point out two important procedures that we suspect Costello and Fox (2022)  
144 may have missed. First, before identifying the decline effect for each meta-analysis, we need  
145 to scale different effect size measures, such that the slopes ( $\beta_{year}$ ) resulting from different  
146 meta-analyses could be directly compared across SMD, lnRR, and  $Zr$  (Schielzeth 2010,  
147 Nakagawa et al. 2017a). Note that we have tested that scaling effect size estimates did not alter  
148 the significance estimates for the meta-regression model slope ( $\beta_{year}$ ) and thus did not change  
149 qualitative conclusions (See Supplementary Materials for a comparison of scaling vs. non-  
150 scaling effects). Second, we need to flip the signs of  $\beta_{year}$  for meta-analyses with negative

151 overall means before conducting a meta-meta-analysis to aggregate them. For a meta-analysis  
152 whose mean/pooled effect size (overall effect) is positive, the sign of  $\beta_{year}$  is expected to be  
153 negative if there is a decline effect. In contrast, for a meta-analysis having a negative overall  
154 mean, the signs of  $\beta_{year}$  is expected to be positive if there is a decline effect (Figure 2B).  
155 Therefore, when using a meta-analytic model to statistically aggregate  $\beta_{year}$  across different  
156 meta-analyses, we need to flip the signs of  $\beta_{year}$  whose associated mean effect sizes are  
157 negative. Otherwise, the meta-meta-analysis would create artefactual heterogeneity among  
158  $\beta_{year}$  slopes and thus reduce the statistical power to identify the systematic pattern of the  
159 decline effect across ecology. We expect more applications of the meta-meta-analyses in  
160 ecology, addressing high-order ecological questions and meta-science questions (the science  
161 of science; also known as meta-research; Fidler et al. 2017, Nakagawa et al. 2019).

162

## 163 **CONCLUSIONS AND RECOMMENDATIONS**

164 The decline effect can lead to undesirable consequences, such as inflated effect size  
165 estimates, temporally ~~instable~~unstable evidence being used in ecological policy-making, and  
166 even undermining the society's and scientists' faith in the use of meta-analytic approaches  
167 (Koricheva and Kulinskaya 2019). Such a decline effect has been empirically identified in  
168 specific and general areas of ecology (Jennions and Møller 2002, Crystal - Ornelas and  
169 Lockwood 2020, Van Klink et al. 2020, Clements et al. 2022). Here, with a much larger  
170 dataset compiled by Costello and Fox (2022) and a powerful approach (i.e., meta-meta-  
171 analysis), we confirmed previous findings: there is a systematic, non-random, and slow, yet  
172 non-negligible, decline effect in ecology (i.e., “global” decline effect; Figure 1A). More  
173 importantly, such a “global” decline effect is likely consistent across different subfields of  
174 ecology (i.e., different meta-analyses). Our finding sets a “strong prior” expectation that the

175 decline effects are common in ecology. Therefore, the decline effect test should be treated as  
176 a routine and mandatory part of ecological meta-analyses (Nakagawa et al. 2017b, Koricheva  
177 and Kulinskaya 2019). However, the decline effect test has rarely been performed in the  
178 current practices of ecological meta-analyses – two independent surveys both showed that  
179 only ~5% of ecological meta-analyses performed the decline effect test (Koricheva and  
180 Gurevitch 2014, Nakagawa et al. 2022). The main reason for this low-test rate may be due to  
181 the decline effect test being often underpowered (of high Type II error rates), as we have  
182 shown. Therefore, we finish with recommendations that could mitigate the issues of low  
183 statistical power when testing the decline effect in ecological meta-analyses.

184

185 A straightforward and effective way to determine if a decline effect exists is to include the  
186 publication year ( $year_i$ ) as a moderator variable in a meta-regression (Nakagawa and Santos  
187 2012, Koricheva and Kulinskaya 2019). The model slope  $\beta_{year}$  provides an intuitive metric  
188 to identify if the magnitude of effect sizes declines over time. To maximize the statistical  
189 power and control for false positive (Type I error rates), we need to account for other forms  
190 of publication bias (e.g., small-study effect) as well as heterogeneity by including important  
191 moderator variables (i.e., multilevel multi-moderator meta-regression; Rodgers and  
192 Pustejovsky 2021, Nakagawa et al. 2022). Such a multilevel multi-moderator meta-regression  
193 can provide a more accurate estimate of the decline effect. Existing software is readily  
194 available, and examples of using *rma.mv()* function in *metafor* package are provided in the  
195 Supplementary Materials (Viechtbauer 2010). Importantly, given the strong expectation of  
196 the decline effect yet limited statistical power to detect it, we need to shift our interpretations  
197 from the focus of dichotomous categories ( $p$ -value < 0.05 meaning decline effect *vs.*  $p$ -value  
198 > 0.05 meaning no decline effect) toward reporting an accurate estimate of the magnitude,

199 precision, and directionality of the temporal changes in effect sizes which are obtained from  
200 the multilevel multi-moderator meta-regression. This is aligned with the statistical philosophy  
201 in ecological/biological sciences emphasizing the effect size estimates and their ‘biological’  
202 or ‘practical’ significance rather than statistical significance (Nakagawa and Cuthill 2007,  
203 Cumming 2014). We believe that our recommendations can assist in the timely detection of  
204 the temporal instability of meta-analytic evidence and make effective allocation of research  
205 resources and efforts.

206

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## 213 **CONFLICT OF INTEREST**

214 The authors declare no conflict of interest.

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## 216 **OPEN RESEARCH**

217 Code is available at Github: [https://github.com/Yefeng0920/decline\\_effect\\_Ecology](https://github.com/Yefeng0920/decline_effect_Ecology)

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## LITERATURE CITED

- Amrhein, V., S. Greenland, and B. McShane. 2019. Scientists rise up against statistical significance. *Nature* **567**:305-307.
- Barto, E. K., and M. C. Rillig. 2012. Dissemination biases in ecology: effect sizes matter more than quality. *Oikos* **121**:228-235.
- Clements, J. C., J. Sundin, T. D. Clark, and F. Jutfelt. 2022. Meta-analysis reveals an extreme “decline effect” in the impacts of ocean acidification on fish behavior. *PLoS biology* **20**:e3001511.
- Cohen, J. 1988. *Statistical power analysis for the behavioral sciences*. 2nd edition. Lawrence Erlbaum., Hillsdale, New Jersey.
- Combs, J. G., J. Ketchen, David J, T. R. Crook, and P. L. Roth. 2011. Assessing cumulative evidence within ‘macro’ research: Why meta - analysis should be preferred over vote counting. *Journal of Management Studies* **48**:178-197.
- Costello, L., and J. W. Fox. 2022. Decline effects are rare in ecology. *Ecology*:e3680.
- Crystal - Ornelas, R., and J. L. Lockwood. 2020. Cumulative meta - analysis identifies declining but negative impacts of invasive species on richness after 20 yr. *Ecology* **101**:e03082.
- Cumming, G. 2014. The new statistics: Why and how. *Psychological science* **25**:7-29.
- De Frenne, P., B. J. Graae, F. Rodríguez - Sánchez, A. Kolb, O. Chabrerie, G. Decocq, H. De Kort, A. De Schrijver, M. Diekmann, and O. Eriksson. 2013. Latitudinal gradients as natural laboratories to infer species' responses to temperature. *Journal of Ecology* **101**:784-795.
- Fanelli, D., R. Costas, and J. P. Ioannidis. 2017. Meta-assessment of bias in science. *Proceedings of the National Academy of Sciences* **114**:3714-3719.
- Fanshawe, T. R., L. F. Shaw, and G. T. Spence. 2017. A large - scale assessment of temporal trends in meta - analyses using systematic review reports from the Cochrane Library. *Research Synthesis Methods* **8**:404-415.
- Fidler, F., Y. E. Chee, B. C. Wintle, M. A. Burgman, M. A. McCarthy, and A. Gordon. 2017. Metaresearch for evaluating reproducibility in ecology and evolution. *BioScience* **67**:282-289.
- Freemantle, N., and J. Geddes. 1998. Understanding and interpreting systematic reviews and meta-analyses. Part 2: meta-analyses. *Evidence-Based Mental Health* **1**:102-104.
- Gurevitch, J., J. Koricheva, S. Nakagawa, and G. Stewart. 2018. Meta-analysis and the science of research synthesis. *Nature* **555**:175-182.
- Harrison, F. 2011. Getting started with meta - analysis. *Methods in Ecology and Evolution* **2**:1-10.
- Jennions, M. D., and A. P. Møller. 2002. Relationships fade with time: a meta-analysis of temporal trends in publication in ecology and evolution. *Proceedings of the Royal Society of London. Series B: Biological Sciences* **269**:43-48.
- Koricheva, J., and J. Gurevitch. 2014. Uses and misuses of meta - analysis in plant ecology. *Journal of Ecology* **102**:828-844.
- Koricheva, J., and E. Kulinskaya. 2019. Temporal instability of evidence base: a threat to policy making? *Trends in ecology & evolution* **34**:895-902.
- Kvarven, A., E. Strømland, and M. Johannesson. 2020. Comparing meta-analyses and preregistered multiple-laboratory replication projects. *Nature Human Behaviour* **4**:423-434.

- Leimu, R., and J. Koricheva. 2004. Cumulative meta-analysis: a new tool for detection of temporal trends and publication bias in ecology. *Proceedings of the Royal Society of London. Series B: Biological Sciences* **271**:1961-1966.
- Morrissey, M. B. 2016. Meta - analysis of magnitudes, differences and variation in evolutionary parameters. *Journal of Evolutionary Biology* **29**:1882-1904.
- Nakagawa, S., and I. C. Cuthill. 2007. Effect size, confidence interval and statistical significance: a practical guide for biologists. *Biological reviews* **82**:591-605.
- Nakagawa, S., P. C. Johnson, and H. Schielzeth. 2017a. The coefficient of determination  $R^2$  and intra-class correlation coefficient from generalized linear mixed-effects models revisited and expanded. *Journal of the Royal Society Interface* **14**:20170213.
- Nakagawa, S., M. Lagisz, M. D. Jennions, J. Koricheva, D. Noble, T. H. Parker, A. Sánchez-Tójar, Y. Yang, and R. E. O'Dea. 2022. Methods for testing publication bias in ecological and evolutionary meta-analyses. *Methods in Ecology and Evolution* **13**:4-21.
- Nakagawa, S., M. Lagisz, R. E. O'Dea, J. Rutkowska, Y. Yang, D. W. Noble, and A. M. Senior. 2021. The orchard plot: Cultivating a forest plot for use in ecology, evolution, and beyond. *Research Synthesis Methods* **12**:4-12.
- Nakagawa, S., D. W. Noble, A. M. Senior, and M. Lagisz. 2017b. Meta-evaluation of meta-analysis: ten appraisal questions for biologists. *BMC biology* **15**:1-14.
- Nakagawa, S., and R. Poulin. 2012. Meta-analytic insights into evolutionary ecology: an introduction and synthesis. *Evolutionary Ecology* **26**:1085-1099.
- Nakagawa, S., G. Samarasinghe, N. R. Haddaway, M. J. Westgate, R. E. O'Dea, D. W. Noble, and M. Lagisz. 2019. Research weaving: visualizing the future of research synthesis. *Trends in ecology & evolution* **34**:224-238.
- Nakagawa, S., and E. S. Santos. 2012. Methodological issues and advances in biological meta-analysis. *Evolutionary Ecology* **26**:1253-1274.
- Nakagawa, S., and H. Schielzeth. 2013. A general and simple method for obtaining  $R^2$  from generalized linear mixed - effects models. *Methods in Ecology and Evolution* **4**:133-142.
- Nieminen, P., H. Lehtiniemi, K. Vähäkangas, A. Huusko, and A. Rautio. 2013. Standardised regression coefficient as an effect size index in summarising findings in epidemiological studies. *Epidemiology, Biostatistics and Public Health* **10**:e8854.
- Oh, I.-S. 2020. Beyond meta-analysis: Secondary uses of meta-analytic data. *Annual Review of Organizational Psychology and Organizational Behavior* **7**:125-153.
- Peterson, R. A., and S. P. Brown. 2005. On the use of beta coefficients in meta-analysis. *Journal of Applied Psychology* **90**:175.
- Pietschnig, J., M. Siegel, J. S. N. Eder, and G. Gittler. 2019. Effect declines are systematic, strong, and ubiquitous: A meta-meta-analysis of the decline effect in intelligence research. *Frontiers in Psychology* **10**:2874.
- Rodgers, M. A., and J. E. Pustejovsky. 2021. Evaluating meta-analytic methods to detect selective reporting in the presence of dependent effect sizes. *Psychological methods* **26**:141.
- Rose, A. K., and T. D. Stanley. 2005. A meta - analysis of the effect of common currencies on international trade. *Journal of economic surveys* **19**:347-365.
- Schielzeth, H. 2010. Simple means to improve the interpretability of regression coefficients. *Methods in Ecology and Evolution* **1**:103-113.

- Schmidt, F. L., and I.-S. Oh. 2013. Methods for second order meta-analysis and illustrative applications. *Organizational Behavior and Human Decision Processes* **121**:204-218.
- Senior, A. M., C. E. Grueber, T. Kamiya, M. Lagisz, K. O'dwyer, E. S. Santos, and S. Nakagawa. 2016. Heterogeneity in ecological and evolutionary meta - analyses: its magnitude and implications. *Ecology* **97**:3293-3299.
- Van Klink, R., D. E. Bowler, K. B. Gongalsky, A. B. Swengel, A. Gentile, and J. M. Chase. 2020. Meta-analysis reveals declines in terrestrial but increases in freshwater insect abundances. *Science* **368**:417-420.
- Viechtbauer, W. 2010. Conducting meta-analyses in R with the metafor package. *Journal of statistical software* **36**:1-48.
- Wasserstein, R. L., and N. A. Lazar. 2016. The ASA statement on p-values: context, process, and purpose. *The American Statistician* **70**:129-133.
- Yang, Y., H. Hillebrand, M. Lagisz, I. Cleasby, and S. Nakagawa. 2022. Low statistical power and overestimated anthropogenic impacts, exacerbated by publication bias, dominate field studies in global change biology. *Global Change Biology* **28**:969-989.