1   **High impact journals in ecology cover proportionally more statistically**

2   **significant findings**

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Abstract

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22 Unbiased scientific reporting is crucial for data and research synthesis. Previous studies

23 suggest that statistically significant results are more likely to be published and more likely to

24 be submitted to high impact journals. However, the most recent research on statistical

25 significance in relation to journal impact factors in ecological research was published more

26 than two decades ago or addressed a small subset of the literature. Here, we extract p-values

27 from all articles published in 11 journals in 2012 and 2014 across a wide range of impact

28 factors with six journals sampled in both years. Our results indicate that the proportion of

29 statistically significant results increases with rising impact factor. Such a trend can have

30 important consequences for syntheses of ecological data and it highlights the importance of

31 covering a wide range of impact factors when identifying published studies for data

32 syntheses. This trend can also lead to a biased understanding of the probability of true effects

33 in ecology and conservation. We caution against the possible downplaying of non-significant

34 results by either journals or authors.

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Introduction

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37 Research synthetizing published data in ecology and biological sciences is growing (Newbold

38 et al., 2015) but the validity of its results depends on unbiased reporting of research, including

39 of statistically non-significant results. Incentives in academia that emphasize citations indices

40 and publications in high impact factor (IF) journals may undermine this requirement. For

41 instance, research suggests that statistically non-significant results are less likely to be

42 published in the case of clinical trial studies (2) and are submitted to lower IF journals in

43 ecology (Koricheva, 2003; Suñé, Suñé & Montoro, 2013). Such a bias in publication can

44 result in overestimating statistical significance and effect size in research synthetizing data to

45 estimate a particular effect or phenomenon. Moreover, statistically non-significant results can

46   be highly significant scientifically. Research on the effect of these behaviours on the overall

47   pattern of reported statistical significance in relation to IF has only been conducted on a small

48   subset of the literature (Koricheva, 2003), on a small range of IF (Jennions & Møller, 2003)

49   or has been published more than two decades ago (Csada, James & Espie, 1996). Here, we

50   update the research on the relationship between significance levels and IF in the ecology and

51   conservation literature within a wide range of IF.

Methods

53   We examined how the proportion of reported significant results, expressed as p-values,

54   changed with increasing IF. We divided the range of IF into three intervals: low (IF<4),

55   medium (4≤IF<8), and high (IF≥8) to ensure that we cover a broad range of IF. We then

56   randomly selected at least two journals for each IF interval for both 2012 and 2014 from

57   journals listed in the Science Citation Index Expanded (http://mjl.clarivate.com/cgi-

58   bin/jrnlst/jloptions.cgi?PC=D) under four subject categories: biodiversity conservation,

59   biology, ecology, and evolutionary biology. We examined 11 journals (table in S1 Table)

60   (lowest IF 0.36 to highest IF 17.95), six journals for both years, whilst we examined three for

61   2014 and two for 2012 alone. We collected all p-values reported in all articles using

62   Examine32 Text Search from Aquila Software. We extracted exact p-values and inexact p-

63   values (e.g. p<0.05). All the inexact p-values were reassigned to six intervals in order to

64   harmonize all the reported values and calculate the proportion of significant results (Table A

65   in S1 Text). Due to the ubiquitous use of 0.05 as the alpha level in ecology, we considered p-

66   values below this level as significant. We calculated the proportion of significant results for

67   exact p-values and all (i.e. exact and inexact) p-values reported in each journal, for each year.

68   We fitted generalized linear mixed effects models (binomial distribution) to the proportion of

69   significant results with IF as fixed effect and journal as random effect. We used R (version

70   3.4.0) and the "lme4" and "arm" packages for model fitting and back-transformation of model

71   coefficients. We tested through a paired t-test the effect of year on the six journals that we

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72   examined for both years. All data collected for this study are available at:

73   https://figshare.com/projects/High_impact_journals_cover_proportionally_more_statistically_

74   significant_findings/28284. The R code of the data analysis is available at:

75   https://github.com/SilviaCeausu/ImpactFactorsAndPvalues/blob/master/ImpactFactorPvaluec

76   odeGitHub2.R.
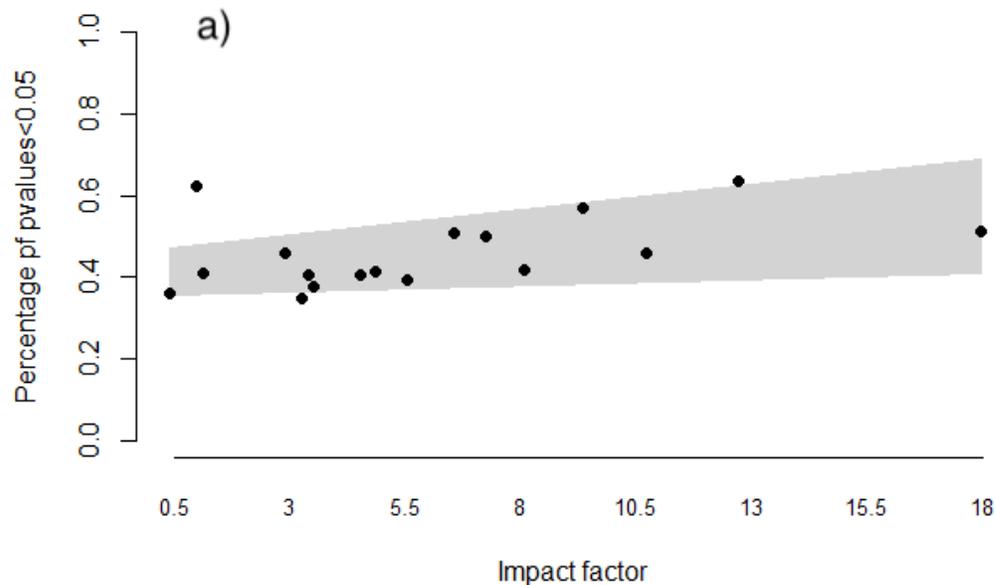
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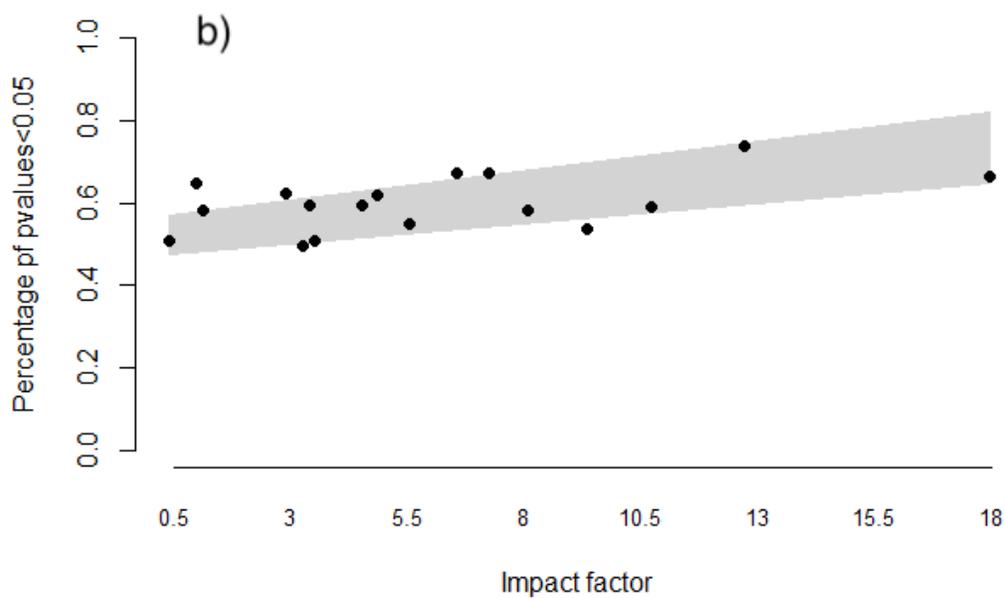
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79   **Figure 1. Proportion of a) exact p-values and b) all p-values below 0.05 reported across**

80   **impact factors (IF).** The grey areas delimitate the 95% confidence intervals. The journals

81   considered and their impact factors are presented in S1 Table.

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Results and discussion

84   The percentage of significant results–out of all published results within a journal– increased

85   with increasing IF (Figure 1). For exact p-values, the percentage of significant results

86   increased on average by 0.7% for each additional IF unit [95% CI: 0.3 - 1.2%]. For all p-

87   values (i.e. exact and inexact), the percentage increased by 1.2% for each additional IF unit

88   [95% CI: 0.9 - 1.5%] (Table S2). In 2012, the percentage of significant results was higher

89   than in 2014 (+3.3%, 95% CI: 0.2 – 6.4%) for the journals examined in both years.

90   Our result concurs with trends noticed in medical research (Jannot et al., 2013) but they

91   contradict results reported for behavioural ecology by (Jennions & Møller, 2003). The latter

92   study concluded that neither p-values nor statistical power varied significantly with IF but the

93   analysis was conducted on a much narrower range of IF (ca. 1 - 5) than our study.

94   Our result can arise if statistical significance influences submission or editorial decisions.

95   Analysing the output of doctoral dissertations in ecology, Koricheva (Koricheva, 2003) found

96   that the proportion of non-significant results in a study was negatively associated with IF,

97   although the rejection rates for non-significant results were not higher for higher IF journals.

98   In an article that examined clinical trials, Suñé et al (Suñé, Suñé & Montoro, 2013) found that

99   non-significant studies are less likely to be published and, if published, more time passes

100   between conducting the research and publication. However, the IF of the publishing journal

101   was not different for significant versus non-significant results (Suñé, Suñé & Montoro, 2013).

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102   These studies suggest that authors invest less effort into the publication of their non-

103   significant results and submit them to lower IF journals.

104   Our outcome can also be an effect of higher impact journals selecting studies with higher

105   sample or effect sizes, or requesting stricter statistical reporting and shorter articles. In studies

106   of the relationships between IF, and sample and effects sizes results are mixed. For meta-

107   analyses in ecology Lortie et al (Lortie et al., 2013) did not find a relationship between IF and

108   effect size. Analyzing studies collected for four meta-analyses, Murtaugh found a positive

109   correlation between effect strength and IF in two of the four datasets (Murtaugh, 2002), and

110   Barto and Rilig (Barto & Rillig, 2012) found that high IF journal published the strongest

111   effects, although in the absence of correlations with data quality. Regarding statistical

112   reporting, Tressoldi et al (Tressoldi et al., 2013) suggest that higher IF journal do not

113   necessarily display better standards. Our data also show no indication that higher IF journals

114   publish more precise p-values then lower IF journals (figure in S1 Figure). The heterogeneity

115   of article length requirements across journals did not allow us to test whether article length

116   requirements play a role in our result (table in S1 Table). Moreover, we did not analyse

117   supplementary materials, which might include additional non-significant results considered

118   secondary by authors.

119   The large confidence intervals in our results suggest that other factors also have an influence

120   on publication. For example, the difference in percentage of significant results between years

121   suggests changes in the prominence of different research topics. However, we cannot exclude

122   an undervaluation of non-significant results, either by authors or by journals. This pattern may

123   make significant results more visible if they are published in higher IF journals than non-

124   significant findings, and may create an inaccurate perception of the probability of true effects

125   in ecology. This could lead to wasted efforts on approaches or interventions that could in

126   reality be far less effective than we assume (Meli et al., 2017). Publication biases could also

127   negatively impact our understanding of biodiversity change and its drivers if a higher

128 proportion of non-significant results remain unpublished compared with significant ones,

129 especially at a time when growing synthesis efforts are trying to shed light on important

130 biodiversity and ecology questions (Vellend et al., 2013; Dornelas et al., 2014; Newbold et

131 al., 2015). Moreover, statistically non-significant results can give rise to new theories or

132 amendments to old ones, as it is the case of the emerging debate on the importance of

133 isolation in fragmented landscapes (Collinge, 2000; Fahrig, 2013). Therefore, we advise

134 careful consideration of submission and publication decisions to ensure solid foundations for

135 our scientific understanding.

Acknowledgments

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Supporting information

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181 **Data collected for this study are available at:**

182 https://figshare.com/projects/High_impact_journals_cover_proportionally_more_statistically_

183 significant_findings/28284.

184 **R code of the data analysis is available at:**

185 https://github.com/SilviaCeausu/ImpactFactorsAndPvalues/blob/master/ImpactFactorPvaluec

186 odeGitHub2.R.

187 **S1 File. Data collection protocol (separate document)**

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200   **S1 Table. Information regarding the journals included in the analysis.** Journal title,

201   publication year, the impact factor in the respective year, length limits for the main article

202   type of the journal, total number of articles published by each journal during the respective

203   year, total number of exact and inexact p-values identified. NL - no length limit specified in

204   the author guidelines.

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Journal Name	Year	Impact factor	Length limits	Number of total published articles	Number of exact p-values	Number of inexact p-values
Agriculture Ecosystems & Environment	2012	2.859	NL	268	1980	4050
	2014	3.402		269	2260	4050
Biochemical Systematics And Ecology	2014	0.967	NL	261	393	1132
Ecology Letters	2012	17.949	5000 words	167	1263	1177
	2014	10.689		157	1041	787
Global Change Biology	2014	8.044	8000	317	2589	4853
Global Ecology and Biogeography	2012	7.223	10 printed pages, ~ 5000 words	111	418	1599
	2014	6.531		133	660	1193
Journal of Animal Ecology	2012	4.841	8500 words	150	1308	892
	2014	4.504		137	1726	1304
Journal of Ecology	2014	5.521	12 typeset pages; ~ 9500 words	155	2435	2829
Journal of Evolutionary Biology	2012	3.479	6-10 printed pages	237	4184	2418
	2014	3.232		256	4412	2828
PLOS Biology	2012	12.69	NL	153	689	520
	2014	9.343		223	560	702
Northeastern Naturalist	2012	0.362	NL	51	347	216
Wildlife Biology	2012	1.102	40000 characters	43	232	147

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210 **S2 Table. Model coefficients and selection.** We tested the model used for Figure1 (main

211 text) against alternative random effects structures and null models. A model with both random

212 slope and intercept was not possible due to the low number of data points. We compared the

213 models according to theoretic information criteria: Akaikes' Information Criterion (AIC) and

214 Bayesian Information Criterion (BIC). We used the same models for both exact p-values and

215 all p-values. We rounded up all values to three decimal places.

| Model	Coefficients (95% CI)		AIC	BIC
Exact p-values	Intercept	IF		
Final model %significant ~IF + (1|journal)	-0.364 (-0.599, -0.129)	0.032 (0.013, 0.051)	206.30	208.80
Null model - journal %significant ~ 1 + (1 | journal)	-0.187 (-0.412, 0.039)	-	214.75	216.41
Random intercept - journal %significant ~ IF + (IF - 1 | journal)	-0.38 (-0.581, -0.188)	0.069 (-0.118, 0.261)	231.75	234.25
All p-values				
Final model %significant ~ IF + (1 | journal)	0.076 (-0.11, 0.245)	0.055 (0.04, 0.071)	286.27	288.77
Random slope - journal %significant ~IF + (IF - 1 | journal)	0.027 (-0.139, 0.18)	0.121 (0.012, 0.263)	317.52	320.02
Null model - journal %significant ~1 + (1 | journal)	0.383 (0.242, 0.523)	-	339.72	341.38

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220 **S1 Figure. Proportion of exact p-values below 0.05 reported in a) 2012 and b) 2014**

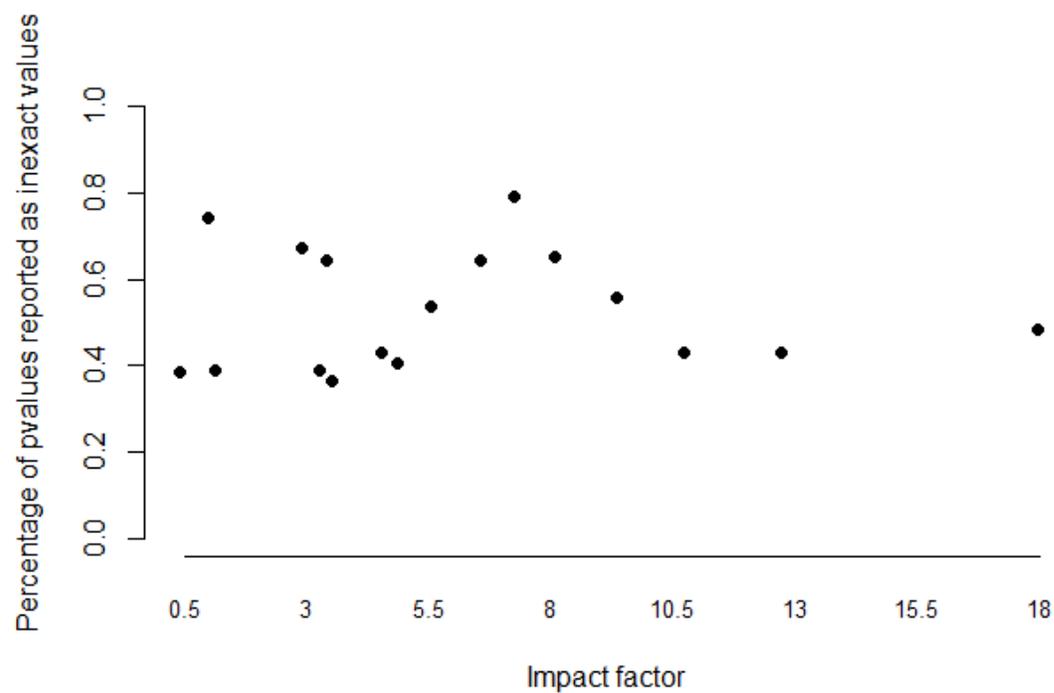221 **across the range of impact factors (IF).**
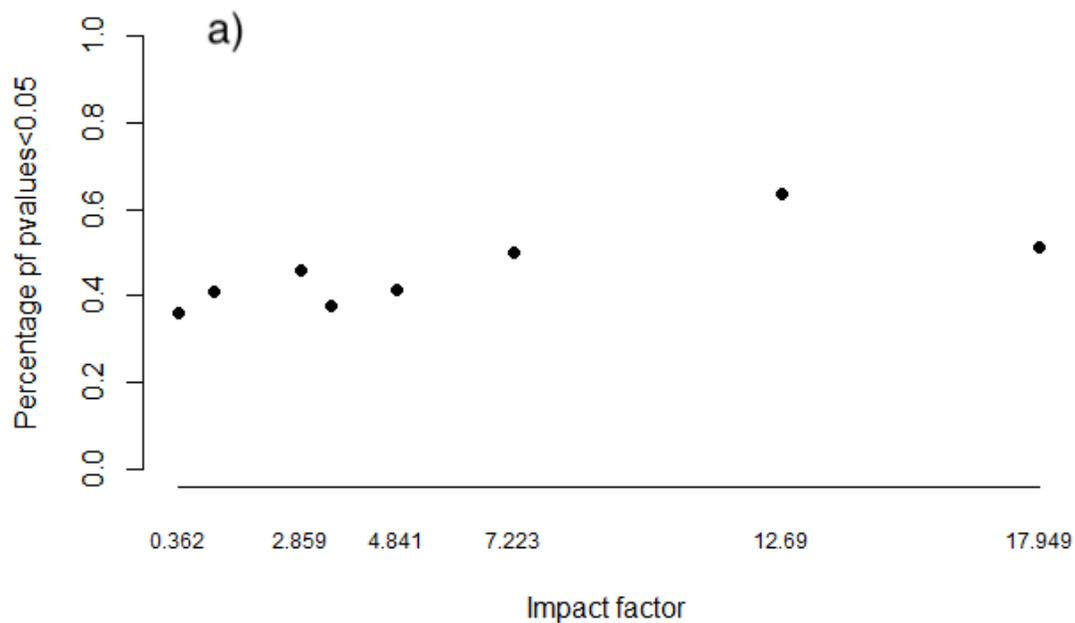
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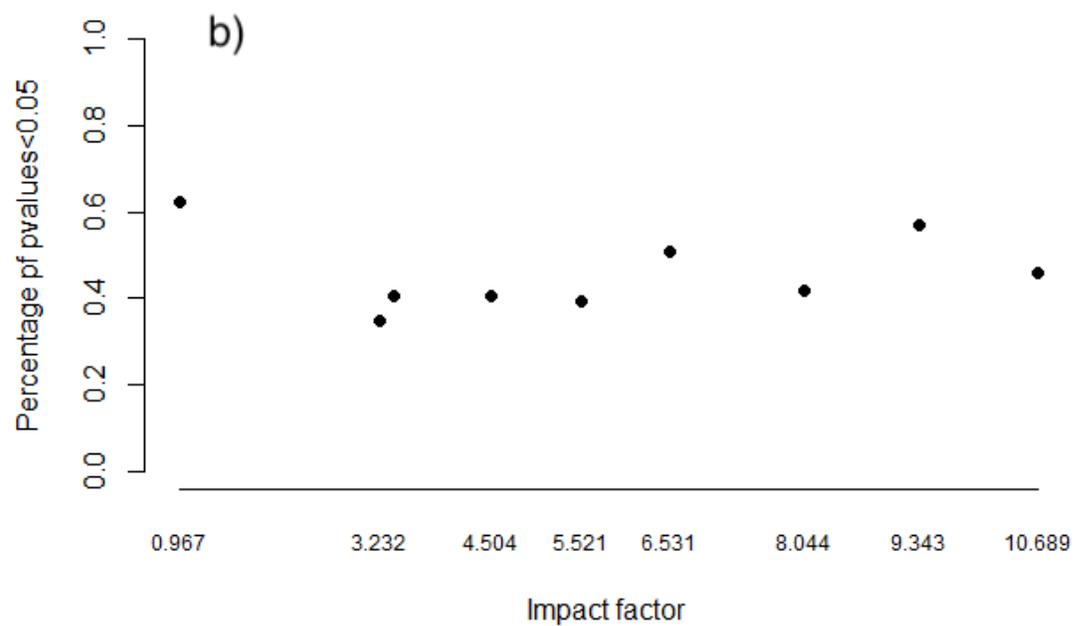
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225 **S2 Figure. Proportion of inexact p-values out of the total reported values across the**

226 **range of impact factors (IF).**

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