



Main Manuscript for

## **High plant diversity and slow assembly of old-growth grasslands**

Ashish N. Nerlekar<sup>1\*</sup> and Joseph W. Veldman<sup>1†</sup>

<sup>1</sup>Department of Ecology and Conservation Biology, Texas A&M University, College Station, TX 77843-2258, U.S.A. \*e-mail: ashishnerlekar@tamu.edu (corresponding author) †e-mail: veldman@tamu.edu

\* Ashish N. Nerlekar

**Email:** ashishnerlekar@tamu.edu

### **Classification**

Biological Sciences: Ecology

### **Keywords**

biodiversity, disturbance, forest, grassland, land-use change, meta-analysis, restoration, savanna, succession

### **Author Contributions**

A.N.N and J.W.V. conceived the study, conducted the literature review, and wrote the manuscript. A.N.N. performed the statistical analyses.

### **This PDF file includes:**

Main Text

1    **Abstract**

2    Earth's ancient grasslands and savannas—hereafter *old-growth grasslands*—have long  
3    been viewed by scientists and environmental policymakers as early successional plant  
4    communities of low conservation value. Challenging this view, emerging research  
5    suggests that old-growth grasslands support substantial biodiversity and are slow to  
6    recover if destroyed by human land uses (e.g., tillage agriculture, plantation forestry). But  
7    despite growing interest in grassland conservation, there has been no global test of  
8    whether old-growth grasslands support greater plant species diversity than *secondary*  
9    *grasslands* (i.e., herbaceous communities that assemble after destruction of old-growth  
10   grasslands). Our synthesis of 31 studies, including 92 timepoints on six continents, found  
11   that secondary grasslands supported 37% fewer plant species than old-growth grasslands  
12   (log response ratio = -0.46), and that secondary grasslands typically require at least a  
13   century, and more often millennia (projected mean 1400 yr), to recover their former  
14   richness. Young (< 29 yr) secondary grasslands were composed of weedy species, and  
15   even as their richness increased over decades to centuries, secondary grasslands were still  
16   missing characteristic old-growth grassland species (e.g., long-lived perennials). In light  
17   of these results, the view that all grasslands are weedy communities, trapped by fire and  
18   large herbivores in a state of arrested succession, is untenable. Moving forward, we  
19   suggest that ecologists should explicitly consider grassland assembly time and  
20   endogenous disturbance regimes in studies of plant community structure and function.  
21   We encourage environmental policymakers to prioritize old-growth grassland

22 conservation and work to elevate the status of old-growth grasslands, alongside old-  
23 growth forests, in the public consciousness.

24

## 25 **Significance Statement**

26 The idea that grasslands can be ancient, particularly in climates that also support forests,  
27 is not widely recognized. Consequently, scientists and conservation planners often  
28 misinterpret old-growth grasslands to be low-diversity, successional vegetation, from  
29 which little is lost through conversion to tillage agriculture or tree plantations. We used a  
30 global analysis of herbaceous plant communities to show that after old-growth grasslands  
31 are destroyed, the recovery of plant diversity requires hundreds to thousands of years.

32 Such slow rates of recovery underscore the need to replace outdated models of forest  
33 succession with models that emphasize the importance of fire, herbivory, and long  
34 periods of time to grassland biodiversity. This study offers evidence that old-growth  
35 grasslands, like old-growth forests, should be prioritized for conservation.

## 36 **Main Text: Introduction**

37 Grasslands (broadly defined, including savannas and open-canopy grassy woodlands)  
38 occupy 28% of the terrestrial biosphere (1), house a significant proportion of global  
39 biodiversity (2), and support the livelihoods of at least a billion people via multitude of  
40 ecosystem services (e.g. provisioning of water and carbon storage; 3). Given the global  
41 importance of grasslands, it is critical that we accurately conceptualize grassland  
42 ecological dynamics to advance our understanding of plant community responses to  
43 environmental change. Hindering such advances, the idea of climate-determined

44 succession (4), one of the dominant ecological paradigms of the past century,  
45 underemphasizes two ubiquitous aspects of grassland ecology and evolution: fires and  
46 large herbivores (5).

47 Fire and herbivores shaped the ecology and evolution of Earth's grasslands for  
48 millions of years before the existence of humans (6). Through consumption of  
49 aboveground plant biomass, these two agents of endogenous disturbance (7, 8) maintain  
50 grasslands in places where the climate and soils are suitable for the development of  
51 forests (9). When interpreted through the lens of climatic determinism, with a focus on  
52 trees rather than herbaceous plant community dynamics, frequent fire and herbivory can  
53 appear to reset, or arrest, ecological succession (10, 11). This successional narrative has  
54 contributed to a crisis in grassland conservation: around the world disturbance-dependent  
55 grasslands are widely misclassified as degraded forests (12, 13), overlooked for their  
56 conservation value (14), targeted for agricultural conversion (15), and viewed as  
57 opportunities for carbon sequestration through tree planting and fire exclusion (i.e.,  
58 afforestation and woody encroachment) (16, 17).

59 The old-growth grassland concept (18)—modelled on parallel ideas in forest ecology  
60 and conservation (19)—is a direct challenge to the narrative that most of earth's  
61 grasslands are successional communities that ought to become forests (11; 20). Of  
62 primary importance, the concept posits that old-growth grasslands are ecologically  
63 distinct from recently formed (secondary) grasslands (18). It is also important to note that  
64 fire and megafaunal herbivory—the endogenous disturbances that maintain old-growth  
65 grassland diversity (8)—are detrimental to many old-growth forests (e.g., 21). Further,

66 readily visible indicators of old-growth forests, such as trees with large girths, are  
67 inapplicable to old-growth grasslands, where signs of antiquity are often underground  
68 (18). Indeed, old-growth grasslands are characterized by slow-growing, long-lived  
69 herbaceous plants, with a suite of traits, including underground storage organs, bud  
70 banks, and rhizomes, which enable resprouting and clonal growth after fire and herbivory  
71 (22, 23).

72 Although old-growth grasslands include some of the most biodiverse terrestrial  
73 ecosystems, there has been no global-scale test of whether old-growth grasslands are, in  
74 fact, more species-rich than secondary grasslands. Several examples suggest that high  
75 species richness is characteristic of old-growth grasslands. The savannas of the South  
76 American Cerrado support 4800 endemic plant and vertebrate species (24). The Shola  
77 grasslands of India, home to endangered Asian elephants and Bengal tigers, are rich with  
78 herbaceous plants (278 species) (25). The world record for local-scale plant species  
79 richness (89 vascular species/  $m^2$ ) is held by a montane grassland in Argentina (26). At  
80 the 100 to 1000- $m^2$  scales, fire-dependent grasslands of the North American Coastal Plain  
81 can be as rich in vascular plant species as tropical forests (14). While illustrative of the  
82 potential diversity of grassland plant communities, these examples do not tell us how  
83 quickly old-growth grassland plant diversity recovers after intensive land-use change,  
84 such as agriculture or afforestation.

85 To test the relevance of the old-growth grassland concept to our understanding of  
86 global patterns of herbaceous plant diversity, we conducted a meta-analysis of 31 pairs of  
87 old-growth grasslands and secondary grasslands on six continents (Fig. 1). Because the

88 application of the term ‘old growth’ to grasslands is recent, we included studies that used  
89 a variety of synonymous adjectives, including: ancient, intact, native, natural, pristine,  
90 reference, remnant, semi-natural, and undisturbed (*SI Appendix*, Fig. S1). For our  
91 analysis, we compared species richness between pairs of old-growth and secondary  
92 grasslands using a random effects model of the log response ratio [ $\ln RR$ , calculated as  
93  $\log_e(\text{secondary grassland richness}/\text{old-growth grassland richness})$ ] (27). To determine the  
94 rate at which secondary grasslands recover the species richness of old-growth grasslands,  
95 we conducted a mixed-effects linear meta-regression (27) of 92 secondary grassland ages  
96 (range 1 to 251 years) extracted from the 31 studies. As is standard in meta-analyses (27),  
97 we weighted each study by the inverse of the associated variance and evaluated the  
98 robustness of our findings through assessments for publication bias and sensitivity (see  
99 Methods).

100 Following the core meta-analysis, we used data from a subset of studies to better  
101 understand how variation in species richness and grassland age relate to plant community  
102 composition. We first assessed the relationship between total species richness in  
103 secondary grasslands and the recovery of old-growth grassland community composition  
104 ( $n = 10$  studies). We then assessed the relationship between grassland age and the number  
105 of weedy species (including ruderals and exotics;  $n = 11$  studies with 29 timepoints). In  
106 combination, we expect these analyses of grassland species richness, assembly time, and  
107 community composition to validate patterns that many grassland ecologists have  
108 recognized in specific ecosystems around the world (e.g., 28, 29). Through global meta-  
109 analysis, we hope to expand recognition of the high species diversity and slow assembly

110 of old-growth grasslands more broadly among ecologists, environmental policymakers,  
111 and the public.

112 **Results**

113 Our results showed that secondary grasslands support 63% of the species richness of  
114 old-growth grasslands (95% CI: 53%, 76%; global weighted mean  $\ln RR$ : -0.46, 95% CI: -  
115 0.64, -0.28; Fig. 2). For individual studies,  $\ln RR$  ranged from -1.8 to 0.4, with only 2 of  
116 31 studies reporting secondary grasslands to be richer than old-growth grasslands (Fig.  
117 2). The weighted mean  $\ln RR$  was associated with a high level of between-study  
118 heterogeneity ( $Q = 230$ ,  $I^2 = 90\%$ ,  $P < 0.0001$ ), which is typical of ecological meta-  
119 analyses (30). Post-hoc assessments suggested that our estimate of the global weighted  
120 mean (i.e.,  $\ln RR = -0.46$ ) is robust (*SI Appendix*, Table S1, *SI Appendix*, Fig. S2-S5).  
121 Tests for publication bias (26) were negative (*SI Appendix*, Table S2, *SI Appendix*, Fig.  
122 S6-S7).

123 Secondary grassland age was weakly, but positively, related to the recovery of plant  
124 species richness (Fig. 3,  $P = 0.0001$ ,  $R^2 = 0.041$ ). The upper bound of the 95% confidence  
125 interval for the meta-regression model yielded a minimum global recovery time (to  $\ln RR$   
126 = 0) for plant species richness of ~160 years. Extrapolation of the regression equation,  
127 which should be interpreted cautiously, projected a mean time of ~1400 years for  
128 richness to recover. At the last time point for which we have data (i.e., 251 years, which  
129 is the oldest value permitting interpolation), the regression equation predicted secondary  
130 grasslands to recover 84% of the richness of old-growth grasslands ( $\ln RR = -0.17$ ).

131 Even as richness increased with time, the communities of plants recolonizing  
132 secondary grasslands remained distinct from those of old-growth grasslands. Based on  
133 regression of the subset of ten studies that reported community similarity indices (Fig.  
134 4A), we projected that recovery of species richness (i.e., to  $\ln RR = 0$ ) would equate to just  
135 43% (95% CI: 31%, 56%) compositional similarity between old-growth and secondary  
136 grasslands. These persistent differences in community composition can be explained in  
137 part by a preponderance of weedy species in secondary grasslands. Regression of 29  
138 timepoints from 11 sites indicated that in the initial 29 to 130 yr of recovery (range based  
139 on lower 95% CI and mean regression equation for  $\ln RR = 0$ ; Fig. 4B) secondary  
140 grasslands supported more weedy species than did old-growth grasslands.

141 **Discussion**

142 By demonstrating that secondary grasslands support just 63%, and are missing 37%, of  
143 the herbaceous plant species richness of old-growth grasslands (Fig. 2), this meta-analysis  
144 provides support for the applicability of the old-growth grassland concept at the global  
145 scale (18). Evidence of the slow assembly of old-growth grasslands (Fig. 3) underscores  
146 recent calls to move away from the view of most grasslands as a successional stage (11),  
147 toward recognition that endogenous disturbances can sustain species-diverse grasslands  
148 for very long periods of time in climatic zones that can also support forests (5, 9, 10, 17,  
149 22). Compared to old-growth forests, which are widely recognized and intensively  
150 studied (31, 32), we still know relatively little about old-growth grasslands. We hope that  
151 these results will motivate future studies, analogous to research on secondary forests (31),  
152 to better understand the recovery rates of secondary grasslands with different land-use

153 histories (*SI Appendix*, Fig. S8), and to compare grasslands of the tropics to those of  
154 temperate latitudes (*SI Appendix*, Fig. S9) (22).

155 In our analysis, we focused on one aspect of plant diversity—species richness—a  
156 community metric available from the modest number of 31 grassland studies that  
157 included both old-growth and secondary grasslands. Because species richness figures  
158 prominently in the application of community ecology to questions of global change [e.g.,  
159 (33)], we suggest that recognizing old-growth grasslands as distinct from secondary  
160 grasslands will improve our understanding of the relationships among plant diversity,  
161 community assembly time, and ecosystem functioning (18, 34). Doing so would pull  
162 together disparate, but clearly related, lines of research, such as those framed around  
163 agricultural legacies (29), fire exclusion (17), declines of native megafauna (35), woody  
164 encroachment (36), and nutrient pollution (37), to help clarify the distinct ecological  
165 consequences of human activities for old-growth versus secondary grasslands.

166 Our results show that old-growth grasslands, once destroyed, require at least a century,  
167 and more typically millennia, to recover their plant species richness (Fig. 3); full recovery  
168 of plant community composition will take even longer (Fig. 4A). To be clear, the  
169 recovery of species richness is not the same as the recovery of community composition;  
170 two communities can have the same number of species, while the identity of those  
171 species can be quite different (38). For the subset of sites that provided compositional  
172 data, recovery of species richness equated to just 43% similarity in community  
173 composition between secondary and old-growth grasslands (Fig. 4A). Thus, our estimate  
174 of the time required for secondary grasslands to attain the richness of old-growth

175 grasslands (160 to 1400 yr; Fig. 3) is certainly less than the time required for secondary  
176 grasslands to recover the community composition (i.e., the full suite of species and  
177 abundances) of old-growth grasslands. This echoes research on secondary tropical  
178 forests, where tree species richness typically rebounds within 50 yr, but recovery of the  
179 composition of old-growth forests requires many centuries or longer (39).

180 One reason that richness is thought to recover more rapidly than community  
181 composition is because weedy species are quick to colonize secondary grasslands (e.g.,  
182 40). Consistent with this idea, and based on the 11 studies that reported data on weedy  
183 plants (including, ruderal and non-native species), we found that compared to old-growth  
184 grasslands, young secondary grasslands supported more weedy species. Evidence that  
185 elevated numbers of weedy species persisted for 29 to 130 yr in secondary grasslands  
186 (Fig. 4B) underscores recent calls for grassland experiments to consider compositional  
187 changes over longer periods of time [i.e., >10 yr (41)]. From our analysis, it appears that  
188 while weedy species partially compensated for reduced species richness in secondary  
189 grasslands, certain species characteristic of old-growth grasslands remained missing even  
190 after many decades to centuries (Fig. 3, Fig. 4A, B).

191 Why are certain old-growth grassland species missing in secondary grasslands? A  
192 plausible explanation is that above-ground disturbances (i.e., fire and herbivory), which  
193 select for persistence in old-growth species, are fundamentally different from the  
194 anthropogenic disturbances, like tillage agriculture, that destroy underground organs and  
195 select for secondary grassland species with high colonization ability (18). To explore this  
196 possibility, we revisited the results and discussions of the 31 studies included in the meta-

197 analysis and found that the missing species most frequently described by authors (*SI*  
198 *Appendix*, Dataset 1) were native perennial grasses (typically with C<sub>4</sub> photosynthesis) and  
199 native perennial forbs (often species with underground storage organs). Missing species  
200 were also described as fire-promoting and shade-intolerant, with high capacity to  
201 resprout. Authors further described missing species as being stress-tolerant with poor  
202 colonization ability, producing seeds dispersed by gravity or ants, forming limited seed  
203 banks, and relying on clonal growth or asexual reproduction. In addition, authors noted  
204 missing species that were of conservation concern in specific regions. These included:  
205 medicinally important species in Africa; annual hemiparasites in Asia; composites  
206 (Asteraceae) and legumes (Fabaceae) in North and South America; perennial sedges and  
207 orchids, and threatened IUCN Red-list species in Europe; woody sub-shrubs  
208 (underground trees) in South America, and endemic grasses in Australia (*SI Appendix*,  
209 Dataset 1). These descriptions match the key functional types of old-growth grassland  
210 species that are thought to be most vulnerable to anthropogenic environmental change  
211 (22).

212 In addition to functional traits (e.g., persistence-colonization trade-off; 42, 43), a  
213 multitude of ecological mechanisms likely contribute to the lower richness and slow  
214 recovery of secondary grasslands relative to old-growth grasslands. Indeed, a central  
215 focus of grassland restoration ecology is to identify these mechanisms and overcome the  
216 limitations to old-growth grassland community assembly (44). In some ecosystems,  
217 landscape effects, such as spatial isolation (45) or limited habitat connectivity (46),  
218 restrict the arrival of plant propagules. In others, site-level conditions, such as severely

219 altered soil conditions (47) and species interactions (e.g., priority effects and plant-soil  
220 feedbacks; 48) limit the establishment of old-growth grassland species. Also important,  
221 but often overlooked in grassland restoration studies (49), is the role of vegetation-  
222 disturbance feedbacks (e.g., 50; 51). Plant communities determine the quantity and  
223 quality of biomass available for fire and herbivores to consume, and in turn fire and  
224 herbivores influence grassland community composition via selection on plant traits (52).  
225 Given their differences in species composition (Fig. 4A, B), we should expect pairs of old-  
226 growth and secondary grasslands to also differ in aspects of their disturbance regime,  
227 such as frequency, seasonality, and intensity, even if they experience the same  
228 disturbance type (i.e., fire, grazing, or haying). In sum, altered disturbance regimes,  
229 reinforced by vegetation-disturbance feedbacks (53), should be considered among the  
230 probable mechanisms for reduced species richness and slow compositional recovery of  
231 secondary grassland communities (8).

## 232 Conclusion

233 In light of the high diversity of old-growth grasslands (Fig. 2) and the many  
234 documented challenges to their restoration (8), we encourage environmental  
235 policymakers to give old-growth grasslands equal consideration as old-growth forests  
236 (32) in efforts to conserve earth's biodiversity. We are particularly concerned that recent  
237 research and emerging land-use policies, meant to promote tree-planting for carbon  
238 sequestration, are a threat to undervalued grassland biodiversity and ecosystem services  
239 (16, 17). Fundamental to these afforestation efforts has been the assumption that old-  
240 growth grasslands that occur where climate-vegetation models suggest forest as the

241 potential vegetation must be degraded. Our analysis shows that the reality on the ground  
242 is much more complicated. Indeed, most of the species-rich old-growth grasslands in this  
243 analysis occur in climates that can support forests [Fig. 1; (5)]. We urge conservation  
244 initiatives to safeguard against the conversion of old-growth grasslands for tree planting  
245 or tillage agriculture, to maintain biodiverse grasslands with frequent fires and  
246 megafaunal herbivores, and to emphasize the recovery of grassland plant communities in  
247 efforts to restore Earth's biodiversity.

248 **Materials and Methods**

249 ***Literature search and screening***

250 To identify studies that compared species richness in old-growth grasslands and  
251 secondary grasslands, we conducted a literature search of peer-reviewed journal articles  
252 in the Web of Science database (27, 54). This initial Web of Science search yielded a  
253 total of 8336 articles. We examined the titles of these 8336 articles for relevance and  
254 retained 745 articles. We then screened the abstract (and methods in some cases) of these  
255 745 articles to arrive at a shortlist of 99 articles for detailed examination. We then  
256 examined in detail the full texts of these 99 articles, which resulted in a final set of 31  
257 articles that met our eligibility criteria (described below) for inclusion in the analyses (SI  
258 *Appendix*, Fig. S1) (55).

259 For the initial search, we used the advanced search function in Web of Science to identify  
260 articles published from 1 January 1900 to 14 November 2018 that fit the following topic  
261 search (TS) criteria (i.e., terms found in titles, abstracts, and key words):

262 TS = (savanna\* OR grassland\* OR woodland\* OR pine OR pinus OR eucalypt\* OR  
263 cerrado OR prairie OR veld\* OR steppe) AND TS=(herb\* OR grass\* OR forb\* OR  
264 understor\*) AND TS=(richness OR diversity) AND TS=("old growth" OR secondary  
265 OR succession\* OR remnant\* OR "old field" OR restor\* OR reference OR abandon\*  
266 OR "post agric\*" OR "woody encroach\*" OR mine OR mining OR degrad\* OR  
267 pasture OR plantation OR afforest\*)  
268 We subsequently scrutinized the articles to ensure that they met the following criteria. 1)  
269 Study sites were grasslands, broadly defined to include savannas and open-canopy grassy  
270 woodlands (22). As such, the studies in our analysis encompass herbaceous-dominated  
271 ecosystems with scattered trees that are often called 'forests' or 'woodlands' (12). 2)  
272 Studies included old-growth grasslands (18) that were either clearly described in the  
273 article or that we were able to verify through correspondence with the authors. Because  
274 there is a wide range of synonymous terminology for old-growth grasslands in the  
275 literature, we screened studies to ensure that there were no major human-induced  
276 structural or functional alterations to the historical herbaceous plant communities, and  
277 that current ecosystem management closely resembled historical, endogenous disturbance  
278 regimes (8). As such, we included study sites that supported large herbivores (domestic  
279 livestock and/or native megafauna), were burned with prescribed fire or wildfire, or  
280 where other regular aboveground disturbance (i.e., mowing or haying) served as a  
281 surrogate for fire and herbivory (18). 3) Studies included secondary grasslands (11) on  
282 sites previously occupied by old-growth grasslands that had been destroyed by tillage  
283 agriculture, tree plantations, or other intensive land uses. 4) Studies reported data for  
284 herbaceous plant species richness for both old-growth and secondary grasslands. 5) Study

285 plots were not treated with nutrient additions (e.g., nitrogen or phosphorous fertilizers). 6)  
286 Studies were conducted in a unique location; where multiple papers provided data for the  
287 same study location, we excluded all but the most complete (i.e., best replicated, longest  
288 duration) paper for that location. 7) We only included studies on ‘actively restored’  
289 grasslands (i.e., restoration treatments such as sowing seed mixtures, soil or hay transfer)  
290 if the study included a control treatment of ‘passive restoration’ (i.e., secondary grassland  
291 communities assembling without propagule additions). For such studies, we only  
292 extracted data from the passively restored secondary grasslands and the paired old-growth  
293 grasslands.

294 ***Data extraction***

295 Response variables

296 *Total species richness*: We extracted the mean total species richness per unit area for the  
297 old-growth grasslands and secondary grasslands in each study. For studies that only  
298 presented richness in figures ( $n = 20$ ), we calculated the mean richness using the image  
299 analysis software ImageJ (56). For studies ( $n = 2$ ) that reported median richness but not  
300 mean, we used the median, since these studies had either non-normal data (as verified  
301 from figures) or a large ( $>25$ ) sample size (57). In cases where studies appeared to have  
302 measured richness, but did not report richness, we contacted the authors ( $n = 4$ ).

303 *Weedy species richness*: For each study, we determined whether the authors presented  
304 data on weedy species. We included any group of species that the authors identified using  
305 one, or a combination of, the following terms: ruderals (including annuals, perennials or  
306 both), weedy species, arable weeds, alien species, exotic species, or invasive species.

307 Using the same approaches as for total species richness (described above), we were able  
308 to extract weedy species richness from 11 studies, yielding 29 time points.

309 *Compositional similarity*: 10 out of the 31 studies reported the similarity of old-growth  
310 and secondary grassland plant communities as Jaccard's ( $n = 4$ ), Bray-Curtis ( $n = 3$ ) and  
311 Sorensen's ( $n = 3$ ) indices. For studies that reported dissimilarity we converted the index  
312 to similarity (i.e., 1-dissimilarity). Because these indices range from 0 to 1, we analysed  
313 them without further transformation (58).

314 Predictor and moderator variables

315 *Location*: We used the latitude and longitude of the sites reported in the methods of each  
316 study to map study locations (Fig. 1A) using Q-GIS v 2.10.1 (59).

317

318 *Precipitation and temperature*: We obtained mean annual precipitation and temperature  
319 for each location from the WorldClim2 database (60). In cases where the author-reported  
320 precipitation deviated by more than 100 mm ( $n = 4$  cases) from the WorldClim2  
321 data, we used the author-reported values. We plotted mean annual precipitation versus  
322 mean annual temperature (Fig. 1B) with Minitab (Minitab I.N.C., Pennsylvania State  
323 University, USA).

324

325 *Type of secondary grassland*: We used authors' descriptions of land-use history to  
326 classify secondary grasslands into one or more of the following categories for  
327 supplemental analyses: tree-plantations/woody encroachment; tillage agriculture; soil  
328 excavation; planted pasture; or other (SI Appendix, Table S3, SI Appendix, Fig. S8).

329

330 *Age of secondary grassland*: We determined the assembly time (in years) for each  
331 secondary grassland based on author-reported time since the last grassland-damaging  
332 [i.e., exogenous (8)] disturbance or time since land abandonment. If secondary grasslands  
333 were classified by a range of ages, we used the mean of the range. For open-ended  
334 classes, we approximated the value to get a conservative estimate of age [e.g. for Öster *et*  
335 *al.* (61), we considered the class “<10 years” to be 5 years and “>50 years” to be 55  
336 years]. In the one study with multiple sites of different ages (i.e., Brudvig *et al.* (62), with  
337 sites of age 90 years, 69 years, 58 years) we calculated a weighted mean age (weighted  
338 by sample size). For studies ( $n = 3$ ) that provided a large number ( $>30$ ) of data points  
339 across a range of secondary grassland ages, we extracted a subset of discrete time points  
340 to represented the range. For the two (of the 92 secondary grassland timepoints) that were  
341 sampled after one growing season, we coded their age as one year rather than as a  
342 fraction of a year, to avoid giving them undue weight in our log(time) regression (Fig. 2).

343 ***Statistical analyses***

344 Effect size

345 To compare the differences between old-growth and secondary grassland species  
346 richness, we calculated the log response ratio (lnRR) as the effect size (63). The lnRR has  
347 been widely used in ecology (64) and has several desirable properties. A major advantage  
348 of lnRR over other effect-size metrics is that it does not require variance data for  
349 computation (63). For our calculations,  $\text{lnRR} = \log_e (\bar{Y}_s / \bar{Y}_o)$  where  $\bar{Y}_s$  = species richness  
350 for secondary grasslands,  $\bar{Y}_o$  = species richness for old-growth grasslands. Thus, values of

351     $\ln\text{RR} < 0$  indicated old-growth grasslands have greater richness than secondary  
352    grasslands, whereas  $\ln\text{RR} > 0$  indicated secondary grasslands are richer than old-growth  
353    grasslands, and  $\ln\text{RR} = 0$  indicated both grassland classes are equally rich in species. For  
354    studies that provided more than one data point by time, we calculated the composite  
355    effect size per study (65).

356    Variance and weights

357    We calculated the variance of  $\ln\text{RR}$  ( $V_{\ln\text{RR}}$ ) based upon reported sample sizes (66) using  
358     $V_{\ln\text{RR}} = (N_s + N_o)/(N_s \times N_o)$ , where  $N_s$  is the sample size for secondary grasslands and  $N_o$   
359    is the sample size for old-growth grasslands. By calculating  $V_{\ln\text{RR}}$  in this manner, we  
360    were able to standardize the variance estimates across studies and obtain estimates for  
361    those studies that did not report variance, or that had pseudo-replicated or otherwise  
362    poorly described study designs (67, 68) (*SI Appendix*, Table S1). We weighted the  $\ln\text{RR}$   
363    for each study by the inverse variance, such that studies with higher variance were given  
364    lower weights (27). We used OpenMEE (69) to perform the meta-analysis (Fig. 2),  
365    including tests for heterogeneity, publication bias, and sensitivity. We considered meta-  
366    analysis results to be statistically significant (at  $\alpha = 0.05$ ) if the 95% confidence intervals  
367    (CI) of the overall mean  $\ln\text{RR}$  did not include zero.

368    Handling non-independent observations

369    Several studies reported multiple (non-independent) data points ( $n = 18$ ), unbalanced  
370    study designs, or both. We calculated the variance of the composite  $\ln\text{RR}$  for studies with  
371    unequal sample sizes (and thus unequal variances) as  $(1/n)^2 (\sum V_i, i = 1 \text{ to } n + 2 \sum_{i,j} (r_{ij} \sqrt{V_i} \sqrt{V_j}))$ , where  $n$ =number of observations in the study and  $r_{ij}$  = correlation coefficient

373 (covariance) between the pair of effect sizes under consideration (27, 65). If a study had  
374 equal sample sizes (and thus equal variances), the above formula was simplified to:  $(V/n)$   
375  $\times$  Variance Inflation Factor (VIF) (27), where  $VIF = 1 + (n-1) \times r$ . This formula thus  
376 takes into account the non-independence of multiple observations reported by a single  
377 study through the covariance factor. The possible values of 'r' range from 0 to 1  
378 (assuming the correlation is positive), but we cannot know the true value of  $r$  in the  
379 selected studies. To apply  $r = 0$  would be to assume that observations are independent,  
380 and result in an underestimation of the variance. Conversely, to apply  $r = 1$  would assume  
381 perfect (100%) correlation and certainly overestimate the variance (65). We chose to  
382 apply  $r = 0.5$  as a plausible value for our analysis (65), and verified that other plausible  
383 values (i.e.,  $r = 0.25$  and  $0.75$ ), yielded similar results (*SI Appendix*, Table S1, *SI*  
384 *Appendix*, Fig. S2, S3).

385 Between-study heterogeneity

386 We calculated the weighted overall mean effect size (lnRR) for  $n = 31$  studies using a  
387 random effects model, with between-study variance estimated using the restricted  
388 maximum likelihood (REML) approach (70). We also used REML to calculate effects by  
389 sub-groups using moderator variables (as in *SI Appendix*, Fig. S8). To test if there was  
390 significant heterogeneity associated with the effect sizes, we computed the  $Q$  statistic (a  
391 measure of between-study variance), and tested this against a  $\chi^2$  distribution [with  $n-1$   
392 degrees of freedom (dof),  $n$  = number of studies] (27). Because the  $Q$  statistic has low  
393 power and is not intuitive by itself (27, 65), we also report heterogeneity with the  $I^2$

394 statistic [approximately equal to  $100 \times (Q\text{-dof}/Q)$ ], which yields a more intuitive measure  
395 of heterogeneity, from 0 to 100% (65).

396 Sensitivity analyses

397 We performed several sensitivity analyses to verify that the meta-analysis results were  
398 robust. 1) To determine if using the pseudo-replicated (within-study) sample sizes  
399 affected our conclusions, we performed a post-hoc sensitivity analysis by repeating our  
400 meta-analysis without the two studies with highest sample sizes (and consequently  
401 highest weights) (*SI Appendix*, Table S1, *SI Appendix*, Fig. S5). Given the overall result  
402 did not change with exclusion of these highly weighted studies, this analysis supported  
403 our use of study sample sizes to estimate variances (71, 72). 2) To assess the sensitivity  
404 of our results to our assumption of covariance of  $r = 0.5$ , we repeated the analysis using  
405 other plausible covariance values ( $r = 0.25$ ,  $r = 0.75$ ) and verified that results did not  
406 deviate substantially with changes in  $r$  [as in (73); *SI Appendix*, Table S1, *SI Appendix*,  
407 Fig. S2, S3]. 3) Given the high between-study heterogeneity obtained from the weighted  
408 model, and to further assess the sensitivity of the calculated overall mean lnRR to the  
409 weighting of studies, we calculated an unweighted mean lnRR (27) (*SI Appendix*, Fig.  
410 S4).

411 Meta-regression of species richness and time

412 We tested for the effect of secondary grassland age on lnRR using a meta-regression  
413 mixed-effect model that treated each study as a random effect [i.e., REML method; (27)].  
414 To understand the proportion of variance explained by the regression model (27), we  
415 calculated  $R^2$  as  $Q_M/(Q_M + Q_E)$ . We performed the meta-regression using the *metafor*

416 package (70) in R (v 3.6.3) (74). We created all the regression analyses figures using the  
417 *ggplot2* package (75) in R (v 3.6.3) (74).

418 Regression analyses of compositional similarity and weedy species

419 To understand the relationship between the lnRR of total species richness and  
420 compositional similarity of secondary grasslands to old-growth grasslands, we performed  
421 fixed-effect linear regression in the R base package *stats* (v 3.6.3) (74) for the  $n = 10$   
422 studies that reported compositional similarity data. To analyse how lnRR of weedy  
423 species richness changes with secondary grassland age, we constructed a linear mixed-  
424 effect model to predict weedy species lnRR (with secondary grassland age as the fixed  
425 effect and study as the random effect) using the *nlme* package (76) in R (v 3.6.3) (74) for  
426  $n = 11$  studies (and 29 timepoints). For both these analyses, we chose not to weight the  
427 data points (as would be done in meta-regression) given that these studies represent a  
428 relatively small subset of the full meta-analysis dataset.

429 Exploratory models of unexplained variance in lnRR

430 Given the high between-study heterogeneity ( $I^2 = 90\%$ , Fig. 2), we explored whether  
431 unexplained variance in lnRR was attributable to variables that were not part of our core  
432 hypothesis [as in (77)]. We constructed linear mixed-effect models, with study as a  
433 random effect, to predict lnRR based on: continent, latitude, secondary grassland age,  
434 MAP, MAT, type of secondary grassland, and sample area (*SI Appendix*, Table S3).  
435 We generated a starting model using the *nlme* package (76) in R (v 3.6.3) (74). We then  
436 used a step backward selection method, based on Akaike Information Criteria (AIC), to  
437 identify the best model [*MASS* package (78)]. The marginal  $R^2$  value associated with each

438 model was calculated separately by using the *PIECEWISESEM* package (79). To  
439 visualize the relationships between lnRR and the continuous and categorical predictor  
440 variables retained in the top models ( $\Delta\text{AIC} < 2$  compared to the best model; *SI Appendix*,  
441 Table S3), we presented results by secondary grassland type (*SI Appendix*, Fig. S8) and  
442 conducted a meta-regression for latitude (*SI Appendix*, Fig. S9).

443 ***Publication bias***

444 To assess publication bias, we first performed non-parametric correlation tests  
445 (Spearman's rho and Kendall's tau) between the standardized effect sizes and the  
446 composite variance as a substitute (27) (*SI Appendix*, Table S2). A significant positive or  
447 negative correlation would indicate publication bias (27). Second, we performed a  
448 Cumulative Meta-Analysis (CMA) to assess publication bias (*SI Appendix*, Fig. S6) with  
449 publications sorted by year and using a random-effects model (80). The CMA re-  
450 calculates the cumulative effect size after adding studies, one by one (80). In the end, if  
451 the effect sizes do not converge with the calculated effect size, this would suggest bias  
452 (27). Lastly, to assess publication bias, we calculated the Rosenberg's fail-safe number —  
453 i.e., the number of studies with the same weight as the average of the current set of  
454 studies that would be needed to render the results non-significant at  $\alpha=0.05$  (81); results  
455 are considered unbiased if the number is high ( $> 5 \times n + 10$ ) (65). We chose this metric  
456 because it uses a weighted approach, whereas alternative metrics (e.g., Rosenthal's and  
457 Orwin's) use an unweighted approach (27). To test if variation in sampling area affected  
458 lnRR, we conducted a regression between plot size in each study and lnRR (*SI Appendix*,  
459 Fig. S7).

460 **Acknowledgments**

461 We thank D. Boecker, R. Fensham, N. Pilon and C. Rottler for providing data from their  
462 publications. We appreciate the help of J. Gurevitch for clarification on functions and  
463 outputs of the OpenMEE software. A.M. Lawing provided helpful feedback on earlier  
464 versions of the manuscript. A.N.N was supported by the Graduate Excellence Fellowship  
465 and the McMillan-Ward Memorial Graduate Fellowship of Texas A&M University.  
466 J.W.V. was supported by USDA-NIFA Sustainable Agricultural Systems Grant  
467 12726253, USDA-NIFA McIntire-Stennis Project 1016880, and the National Science  
468 Foundation under award number DEB-1931232.

469 **Data availability statement:** All data used for the analyses is provided in *SI Appendix*

470 Dataset 1

471 **References**

- 472 1. E. Dinerstein *et al.*, An ecoregion-based approach to protecting half the terrestrial  
473 realm. *BioScience* 67, 534–545 (2017).
- 474 2. B. P. Murphy, A. N. Andersen, C. L. Parr, The underestimated biodiversity of tropical  
475 grassy biomes. *Phil. Trans. R. Soc. B* 371, 20150319 (2016).
- 476 3. C. L. Parr, C. E. Lehmann, W. J. Bond, W. A. Hoffmann, A. N. Andersen, Tropical  
477 grassy biomes: misunderstood, neglected, and under threat. *Trends Ecol. Evol.* 29,  
478 205–213 (2014).
- 479 4. F. E. Clements, *Plant succession: an analysis of the development of vegetation* (No.  
480 242). (Carnegie Institution, Washington 1916).

481 5. J. G. Pausas, W. J. Bond, Humboldt and the reinvention of nature. *J Ecol.* 107, 1031–  
482 1037 (2019).

483 6. C. A. E. Strömberg, Evolution of grasses and grassland ecosystems. *Annu.*  
484 *Rev. Earth Planet. Sci.* 39, 517–544 (2011).

485 7. S. McIntyre, R. Hobbs, A framework for conceptualizing human effects on  
486 landscapes and its relevance to management and research models. *Conserv. Biol.* 13,  
487 1282–1292 (1999).

488 8. E. Buisson *et al.*, Resilience and restoration of tropical and subtropical grasslands,  
489 savannas, and grassy woodlands. *Biol. Rev.* 94, 590–609 (2019).

490 9. A. C. Staver, S. Archibald, S. A. Levin, The global extent and determinants of  
491 savanna and forest as alternative biome states. *Science* 334, 230–232 (2011).

492 10. J. M. Fill *et al.*, Updating models for restoration and management of fiery  
493 ecosystems. *For. Ecol. Manag.* 356, 54–63 (2015).

494 11. J. W. Veldman, Clarifying the confusion: old-growth savannahs and tropical  
495 ecosystem degradation. *Phil. Trans. R. Soc. B* 371, 20150306 (2016).

496 12. J. Ratnam *et al.*, When is a ‘forest’ a savanna, and why does it matter?. *Glob. Ecol.*  
497 *Biogeogr.* 20, 653–660 (2011).

498 13. D. Kumar *et al.*, Misinterpretation of Asian savannas as degraded forest can mislead  
499 management and conservation policy under climate change. *Biol. Conserv.* 241,  
500 108293 (2020).

501 14. R. F. Noss, *Forgotten Grasslands of the South: Natural History and Conservation*.  
502 (Island Press, Washington, 2012).

503 15. T. D. Searchinger *et al.*, High carbon and biodiversity costs from converting Africa's  
504 wet savannahs to cropland. *Nat. Clim. Chang.* 5, 481 (2015).

505 16. J. W. Veldman *et al.*, Comment on "The global tree restoration potential". *Science*  
506 366, eaay7976 (2019).

507 17. R. C. Abreu *et al.*, The biodiversity cost of carbon sequestration in tropical  
508 savanna. *Sci. Adv.* 3, e1701284 (2017).

509 18. J. W. Veldman *et al.*, Toward an old-growth concept for grasslands, savannas, and  
510 woodlands. *Front. Ecol. Environ.* 13, 154–162 (2015).

511 19. J. M. Feller, D. E. Brown, From old-growth forests to old-growth grasslands:  
512 Managing rangelands for structure and function. *Ariz. L. Rev.* 42, 319–341 (2000).

513 20. L. R. Holdridge, *Life Zone Ecology*. (rev. ed.) (San Jose, Costa Rica, 1967)

514 21. P. M. Brando *et al.*, Abrupt increases in Amazonian tree mortality due to drought–fire  
515 interactions. *Proc. Natl. Acad. Sci. U.S.A.* 111, 6347–6352 (2014).

516 22. W. J. Bond, C. L. Parr, Beyond the forest edge: ecology, diversity and conservation of  
517 the grassy biomes. *Biol. Conserv.* 143, 2395–2404 (2010).

518 23. J. G. Pausas *et al.*, Unearthing belowground bud banks in fire-prone ecosystems. *New  
519 Phytol.* 217, 1435–1448 (2018).

520 24. B. B. Strassburg *et al.*, Moment of truth for the Cerrado hotspot. *Nat. Ecol. Evol.* 1,  
521 0099 (2017).

522 25. M. Sankaran, Diversity patterns in savanna grassland communities: implications for  
523 conservation strategies in a biodiversity hotspot. *Biodivers. Conserv.* 18, 1099–1115  
524 (2009).

525 26. J. B. Wilson, R. K. Peet, J. Dengler, M. Pärtel, Plant species richness: the world  
526 records. *J Veg. Sci.* 23, 796–802 (2012).

527 27. J. Koricheva, J. Gurevitch, K. Mengersen, Eds., *Handbook of Meta-analysis in*  
528 *Ecology and Evolution*. (Princeton University Press, Princeton 2013).

529 28. M. R. Stromberg J. R. Griffin, Long-term patterns in coastal California grasslands in  
530 relation to cultivation, gophers, and grazing. *Ecol. Appl.* 6, 1189–1211 (1996).

531 29. F. Isbell, D. Tilman, P. B. Reich, A. T. Clark, Deficits of biodiversity and  
532 productivity linger a century after agricultural abandonment. *Nat. Ecol. Evol.* 3,  
533 1533–1538 (2019).

534 30. A. M. Senior *et al.*, Heterogeneity in ecological and evolutionary meta-analyses: its  
535 magnitude and implications. *Ecology* 97, 3293–3299 (2016).

536 31. L. Gibson *et al.*, Primary forests are irreplaceable for sustaining tropical biodiversity.  
537 *Nature* 478, 378–381 (2011).

538 32. J. E. Watson *et al.*, The exceptional value of intact forest ecosystems. *Nat. Ecol. Evol.*  
539 2, 599–610 (2018).

540 33. F. I. Isbell, H. W. Polley, B. J. Wilsey, Biodiversity, productivity and the temporal  
541 stability of productivity: patterns and processes. *Ecol. Lett.* 12, 443–451 (2009).

542 34. P. B. Adler *et al.*, Productivity is a poor predictor of plant species richness. *Science*  
543 333, 1750–1753 (2011).

544 35. G. P. Hempson, S. Archibald, W. J. Bond, The consequences of replacing wildlife  
545 with livestock in Africa. *Sci. Rep.* 7, 1–10 (2017).

546 36. Z. Ratajczak, J. B. Nippert, S. L. Collins, Woody encroachment decreases diversity  
547 across North American grasslands and savannas. *Ecology* 93, 697–703 (2012).

548 37. Hautier *et al.*, Eutrophication weakens stabilizing effects of diversity in natural  
549 grasslands. *Nature* 508, 521–525 (2014).

550 38. H. Hillebrand *et al.*, Biodiversity change is uncoupled from species richness trends:  
551 consequences for conservation and monitoring. *J Appl. Ecol.* 55, 169–184 (2018).

552 39. D. M. Rozendaal *et al.*, Biodiversity recovery of Neotropical secondary forests. *Sci.*  
553 *Adv.* 5, eaau3114 (2019).

554 40. E. Ruprecht, Successfully recovered grassland: a promising example from Romanian  
555 old-fields. *Restor. Ecol.* 14, 473–480 (2006).

556 41. K. J. Komatsu *et al.*, Global change effects on plant communities are magnified by  
557 time and the number of global change factors imposed. *Proc. Natl. Acad. Sci. U. S.*  
558 *A* .116, 17867–17873 (2019).

559 42. L. K. Kirkman, K. L. Coffey, R. J. Mitchell, E. B. Moser, Ground cover recovery  
560 patterns and life-history traits: implications for restoration obstacles and opportunities  
561 in a species-rich savanna. *J Ecol.* 92, 409–421 (2004).

562 43. N. P. Zaloumis, W. J. Bond, Grassland restoration after afforestation: No direction  
563 home?. *Austral Ecol.* 36, 357–366 (2011).

564 44. L. A. Brudvig *et al.*, Interpreting variation to advance predictive restoration science. *J*  
565 *Appl. Ecol.* 54, 1018–1027 (2017).

566 45. K. Helsen, M. Hermy, O. Honnay, Spatial isolation slows down directional plant  
567 functional group assembly in restored semi-natural grasslands. *J Appl. Ecol.* 50, 404–  
568 413 (2013).

569 46. E. I. Damschen *et al.*, Ongoing accumulation of plant diversity through habitat

570 connectivity in an 18-year experiment. *Science* 365, 1478–1480 (2019).

571 47. A. Bradshaw, Restoration of mined lands—using natural processes. *Ecol. Eng.* 8,

572 255–269 (1997).

573 48. E. Grman, K. N. Suding, Within-year soil legacies contribute to strong priority effects

574 of exotics on native California grassland communities. *Restor. Ecol.* 18, 664–670

575 (2010).

576 49. L. M. Martin, K. A. Moloney, B. J. Wilsey, An assessment of grassland restoration

577 success using species diversity components. *J Appl. Ecol.* 42, 327–336 (2005).

578 50. S. D. Fuhlendorf *et al.*, The combined influence of grazing, fire, and herbaceous

579 productivity on tree–grass interactions. In *Western North American Juniperus*

580 *Communities* (pp. 219–238). (Springer, New York, NY, 2008).

581 51. W. J. Platt, Pyrogenic fuels produced by savanna trees can engineer humid

582 savannas. *Ecol. Monogr.* 86, 352–372 (2016).

583 52. S. Archibald, G. H. Hempson, C. Lehmann, A unified framework for plant life-

584 history strategies shaped by fire and herbivory. *New Phytol.* 224, 1490–1503 (2019).

585 53. G. P. Hempson, S. Archibald, J. E. Donaldson, C. E. Lehmann, Alternate grassy

586 ecosystem states are determined by palatability–flammability trade-offs. *Trends Ecol.*

587 *Evol.* 34, 286–290 (2019).

588 54. A. S. Pullin, G. B. Stewart, Guidelines for systematic review in conservation and

589 environmental management. *Conserv. Biol.* 20, 1647–1656 (2006).

590 55. D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, Preferred reporting items for  
591 systematic reviews and meta-analyses: the PRISMA statement. *Ann. Intern.*  
592 *Med.* 151, 264–269 (2009).

593 56. M. D. Abràmoff, P. J. Magalhães, S. J. Ram, Image Processing with ImageJ.  
594 *Biophotonics Intern.* 11, 36–42 (2004).

595 57. C. J. Weir *et al.*, Dealing with missing standard deviation and mean values in meta-  
596 analysis of continuous outcomes: a systematic review. *BMC Med. Res. Methodol.* 18,  
597 25 (2018).

598 58. A. E. Magurran, *Measuring Biological Diversity*. (Oxford: Blackwell, 2004).

599 59. QGIS Development Team. QGIS Geographic Information System-version 2.10.1.  
600 Open Source Geospatial Foundation Project. <http://qgis.osgeo.org> (2010).

601 60. S. E. Fick, R. J. Hijmans, WorldClim 2: new 1-km spatial resolution climate surfaces  
602 for global land areas. *Int. J. Climatol.* 37, 4302–4315 (2017).

603 61. M. Öster, K. Ask, S. A. Cousins, O. Eriksson, Dispersal and establishment limitation  
604 reduces the potential for successful restoration of semi-natural grassland communities  
605 on former arable fields. *J Appl. Ecol.* 46, 1266–1274 (2009).

606 62. L. A. Brudvig *et al.*, Land-use history and contemporary management inform an  
607 ecological reference model for longleaf pine woodland understory plant  
608 communities. *PLoS One* 9, e86604 (2014).

609 63. L. V. Hedges, J. Gurevitch, P. S. Curtis, The meta-analysis of response ratios in  
610 experimental ecology. *Ecology* 80, 1150–1156 (1999).

611 64. J. Koricheva, J. Gurevitch, Uses and misuses of meta-analysis in plant ecology. *J*  
612 *Ecol.* 102, 828–844 (2014).

613 65. M. Borenstein, L. V. Hedges, J. P. T. Higgins, H. R. Rothstein, *Introduction to meta-*  
614 *analysis*. (New York, John Wiley & Sons Ltd, 2009).

615 66. L. V. Hedges, I. Olkin, *Statistical methods for meta-analysis*. (Academic Press, San  
616 Diego, 1985).

617 67. R. Spake, C. P. Doncaster, Use of meta-analysis in forest biodiversity research: Key  
618 challenges and considerations. *For. Ecol. Manage.* 400, 429–437 (2017).

619 68. G. M. Davies, A. Gray, Don't let spurious accusations of pseudoreplication limit our  
620 ability to learn from natural experiments (and other messy kinds of ecological  
621 monitoring). *Ecol. Evol.* 5, 5295–5304 (2015).

622 69. B. C. Wallace *et al.*, OpenMEE: Intuitive, open-source software for meta-analysis in  
623 ecology and evolutionary biology. *Methods Ecol. Evol.* 8, 941–947 (2017).

624 70. W. Viechtbauer, Conducting meta-analyses in R with the metafor package. *J Stat.*  
625 *Softw.* 36, 1–48 (2010).

626 71. M. S. Mayerhofer, G. Kernaghan, K. A. Harper, The effects of fungal root endophytes  
627 on plant growth: A meta-analysis. *Mycorrhiza* 23, 119–128 (2013).

628 72. C. P. Doncaster, R. Spake, Correction for bias in meta-analysis of little-replicated  
629 studies. *Methods Ecol. Evol.* 9, 634–644 (2018).

630 73. L. C. Garcia, M. D. Eubanks, Overcompensation for insect herbivory: a review and  
631 meta-analysis of the evidence. *Ecology* 100, e02585 (2019).

632 74. R Development Core Team. R: A language and environment for statistical computing.  
633 (version 3.6.3, 2020)

634 75. H. Wickham, *ggplot2: Elegant Graphics for Data Analysis*. (Springer-Verlag, New Y  
635 ork, 2016).

636 76. J. Pinheiro, D. Bates, S. DebRoy, D. Sarkar, R Core Team. *nlme: Linear and*  
637 *Nonlinear Mixed Effects Models*. R package version 3.1-140, <https://CRAN.R-project.org/package=nlme> (2019).

638 77. M. C. Brustolin, I. Nagelkerken, G. Fonseca, Large-scale distribution patterns of  
639 mangrove nematodes: A global meta-analysis. *Ecol. Evol.* 8, 4734–4742 (2018).

640 78. W. N. Venables, B. D. Ripley, *Modern Applied Statistics with S. Fourth Edition*.  
641 (Springer, New York, 2002).

642 79. J. S. Lefcheck, piecewiseSEM: Piecewise structural equation modelling in r for  
643 ecology, evolution, and systematics. *Methods Ecol. Evol.* 7, 573–579 (2016).

644 80. R. Leimu, J. Körner, Cumulative meta-analysis: a new tool for detection of  
645 temporal trends and publication bias in ecology. *Proc. R. Soc. Lond. B Biol. Sci.* 271,  
646 1961–1966 (2004).

647 81. M. S. Rosenberg, The file-drawer problem revisited: a general weighted method for  
648 calculating fail-safe numbers in meta-analysis. *Evolution* 59, 464–468 (2005).

649

650

651 **Figure Captions:**

652 **Figure 1.** Geographic and climatic distribution of paired old-growth grassland and  
653 secondary grassland study sites. (A) Locations of the 31 studies included in the meta-  
654 analysis. (B) Bi-variate plot of mean annual precipitation and mean annual temperature  
655 for each study location.

656

657 **Figure 2.** Global comparison of species richness in old-growth grasslands and secondary  
658 grasslands. The 31 plant community studies (left column) are listed alphabetically by  
659 continent and author, and are marked by the type of aboveground disturbance that  
660 currently maintains old-growth grasslands at each site. For each study, boxes and solid  
661 lines display the natural logarithm of the response ratio [ $\log_e$  (secondary grassland  
662 richness/old-growth grassland richness)] and 95% confidence intervals, respectively. Box  
663 sizes are proportional to the weight of the study (see methods). Response ratios less than  
664 zero indicate that old-growth grasslands are more species-rich than secondary grasslands,  
665 whereas values greater than zero indicate secondary grasslands are richer. Displayed as a  
666 red diamond and red vertical line, the global weighted mean response ratio (-0.46,  $I^2 =$   
667 90%,  $P = 0.0001$ ) equates to secondary grasslands supporting 63% of the richness of (or  
668 37% fewer species than) old-growth grasslands (ends of the diamond indicate the 95%  
669 CI: -0.64 to -0.28, equivalent to 53% and 76%). See *SI Appendix*, Dataset 1 for full study  
670 citations.

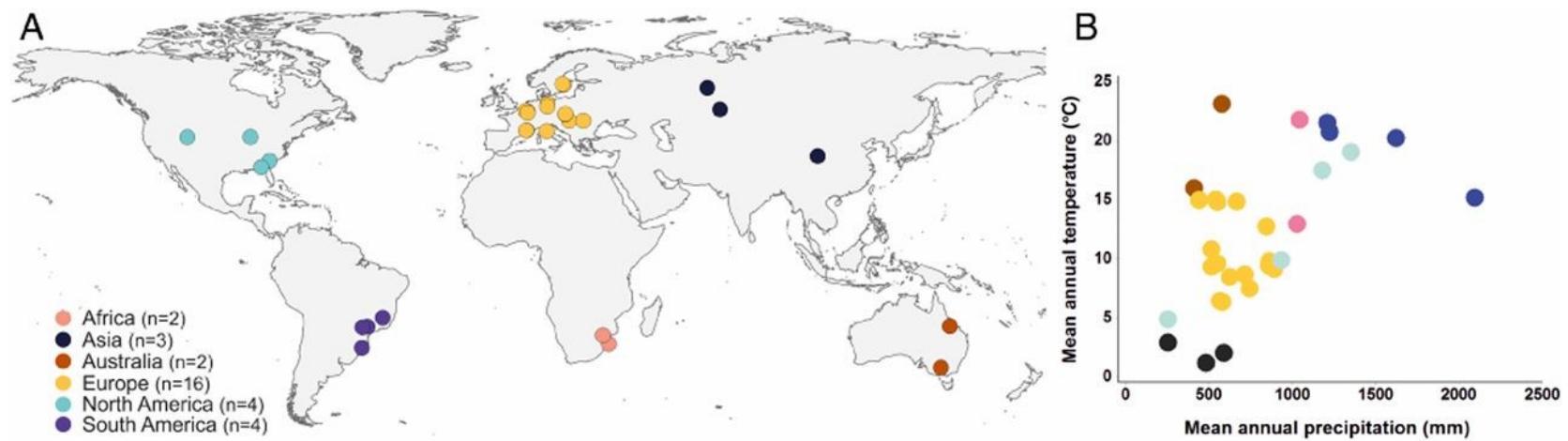
671

672 **Figure 3.** Relationship between secondary grassland age and the recovery of old-growth  
673 grassland species richness. Black circles represent secondary grassland age ( $n = 92$ ,  
674 range: 1 to 251 years, extracted from  $n = 31$  studies) and are scaled in proportion to their  
675 weight (see Methods; note age is represented on a  $\log_{10}$  scale). The meta-regression  
676 model accounts for this weight and the random effect of each study location. The  
677 regression equation,  $\ln\text{RR} = 0.2279 [\log_{10}(\text{secondary grassland age})] - 0.7201$  ( $R^2 =$   
678 0.041,  $P = 0.0001$ ), is displayed as a solid black line; grey shading indicates the 95%  
679 confidence interval. The horizontal dashed line indicates the response ratio at which  
680 secondary and old-growth grassland species richness is equal ( $\ln\text{RR} = 0$ ). Response ratios  
681 less than zero indicate secondary grasslands that have fewer species compared to old-  
682 growth grasslands.

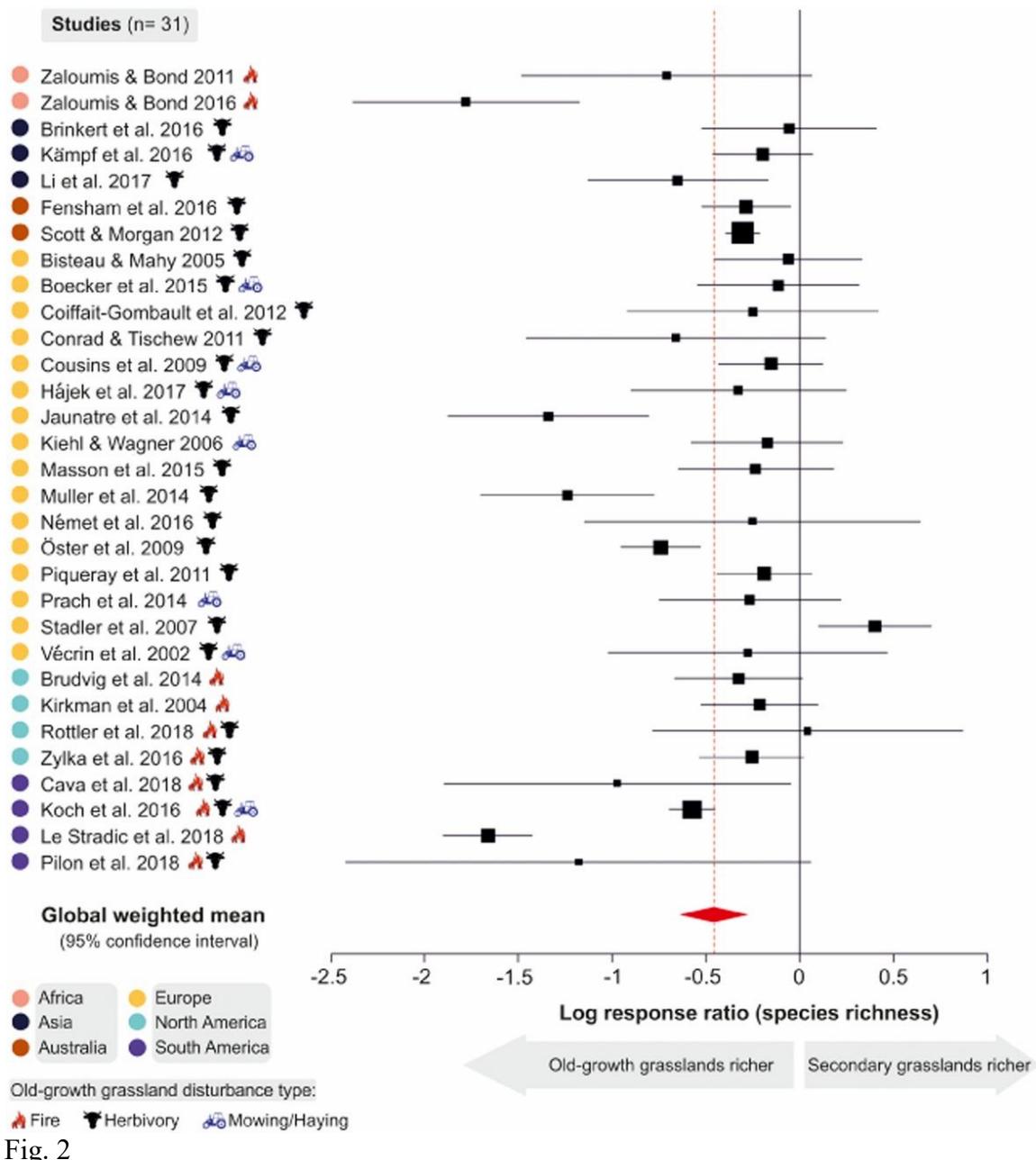
683

684 **Figure 4.** Indicators of plant community composition in relation to secondary grassland  
685 species richness and age. (A) Relationship between the log response ratio ( $\ln\text{RR}$ ) of total  
686 species richness and the compositional similarity between secondary and old-growth  
687 grassland communities. Data are from  $n = 10$  studies that reported similarity indices. The  
688 regression equation,  $\text{similarity} = 0.2681(\ln\text{RR}) + 0.4332$  ( $R^2 = 0.536$ ,  $P = 0.016$ ), is  
689 displayed as a solid black line; grey shading indicates the 95% confidence interval. The  
690 horizontal dashed line ( $\text{similarity} = 0.5$ ) indicates the level at which secondary grasslands  
691 are 50% similar to old-growth grasslands in species composition. At  $\ln\text{RR} = 0$ , secondary  
692 and old-growth grasslands are equal in total species richness. (B) Relationship between  
693 the  $\ln\text{RR}$  of weedy species richness and age of secondary grasslands. The mixed-effect

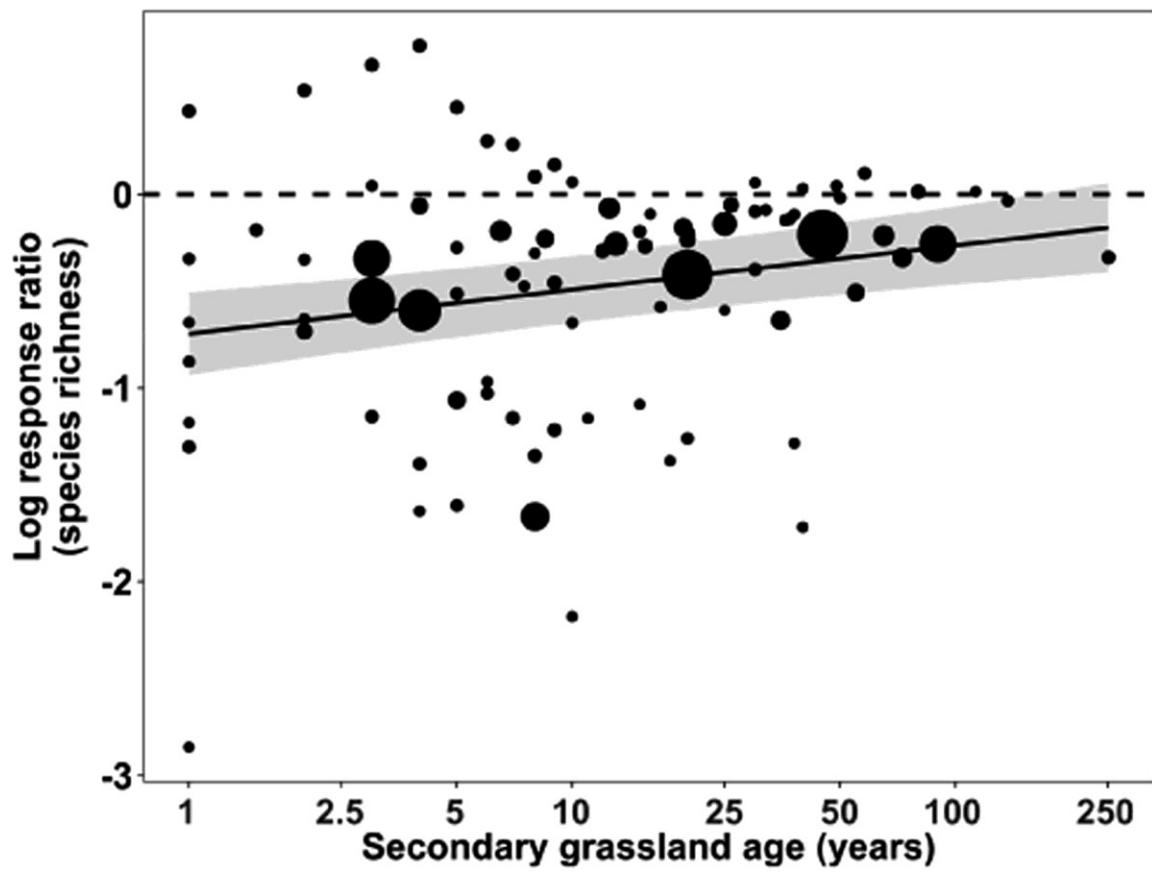
694 regression model is based on the  $n = 11$  studies (random effect) that reported weedy  
695 species richness for  $n = 29$  timepoints (age as fixed effect). The regression equation,  
696  $\ln\text{RR} = -0.8597 [\log_{10}(\text{secondary grassland age})] + 1.8164$  ( $R^2 = 0.274$ ,  $P < 0.0001$ ), is  
697 displayed as a solid black line; grey shading indicates the 95% confidence interval. At  
698  $\ln\text{RR} = 0$ , secondary and old-growth grasslands are equal in weedy species richness.



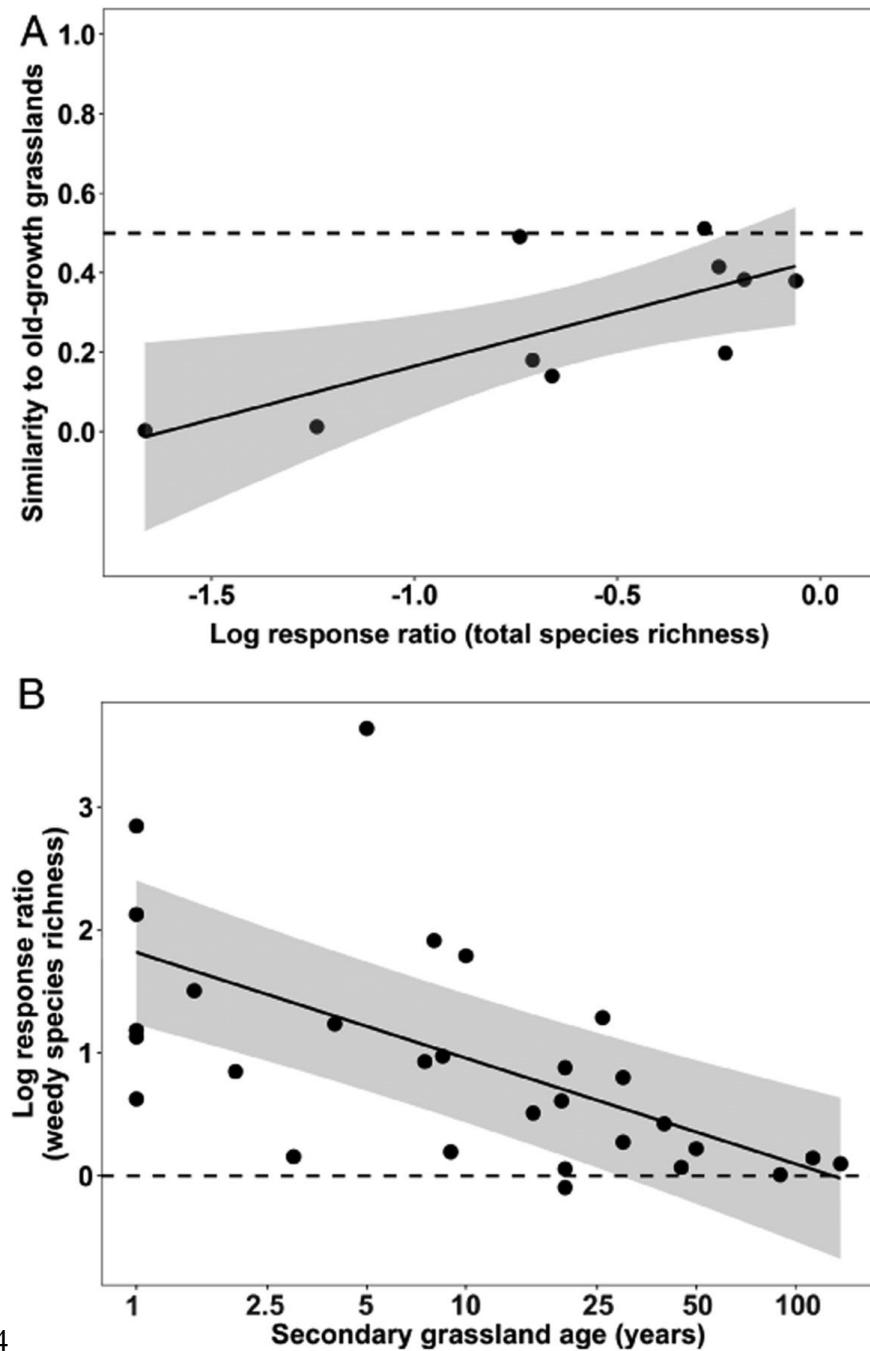
699 Fig. 1



700 Fig. 2



701 Fig. 3



702 Fig. 4



Supplementary Information for

**High plant diversity and slow assembly of old-growth grasslands.**

Ashish N. Nerlekar<sup>1\*</sup> and Joseph W. Veldman<sup>1†</sup>

<sup>1</sup>Department of Ecology and Conservation Biology, Texas A&M University, College Station, TX 77843-2258, U.S.A. \*e-mail: ashishnerlekar@tamu.edu (corresponding author) †e-mail: veldman@tamu.edu

\* Ashish N. Nerlekar (email: ashishnerlekar@tamu.edu)

**This PDF file includes:**

Tables S1 to S3  
Figures S1 to S9  
Legend for Dataset S1

**Other supplementary materials for this manuscript include the following:**

Dataset S1

## SUPPLEMENTARY INFORMATION (TABLES)

**Table S1.** Sensitivity analyses for the global meta-analysis comparing species richness of old-growth and secondary grasslands. Compared to the global meta-analysis ( $r = 0.5$ ,  $\ln\text{RR} = -0.46$ , Fig. 2), models with plausible covariances that were lower ( $r = 0.25$ ) and higher ( $r = 0.75$ ) yielded very similar results ( $\ln\text{RR} = -0.46$  and  $-0.45$ , respectively). An unweighted model ( $\ln\text{RR} = -0.48$ ) and a weighted model that excluded the two highest-weighted studies ( $\ln\text{RR} = -0.46$ ) confirmed that the global meta-analysis results were not driven by weighting. Columns in the table report:  $\ln\text{RR}$ , the associated confidence intervals (CI), p-values for the heterogeneity test ( $P$ ), the between-study heterogeneity ( $I^2$ ), and the number of studies included in the model ( $n$ ).

Model	Purpose of Sensitivity Test	$\ln\text{RR}$	95% CI	$P$	$I^2$	$n$
<b>Weighted mean <math>\ln\text{RR}</math>, random effects model (<math>r = 0.5</math>)</b>	Global meta-analysis (Fig. 2)	-0.458	-0.637, -0.278	< 0.0001	90%	31
<b>Weighted mean <math>\ln\text{RR}</math>, random effects model (<math>r = 0.25</math>)</b>	To determine the effect of low plausible covariance estimate on results ( <i>SI Appendix</i> , Fig. S2)	-0.463	-0.643, -0.284	< 0.0001	91%	31
<b>Weighted mean <math>\ln\text{RR}</math>, random effects model (<math>r = 0.75</math>)</b>	To determine the effect of high plausible covariance estimate ( <i>SI Appendix</i> , Fig. S3)	-0.450	-0.629, -0.272	< 0.0001	89%	31
<b>Unweighted mean <math>\ln\text{RR}</math></b>	To determine the effect of weighting on the global meta-analysis results ( <i>SI Appendix</i> , Fig. S4)	-0.484	-0.662, -0.305	< 0.0001	61%	31
<b>Weighted mean <math>\ln\text{RR}</math>, random effects model (<math>r = 0.5</math>), two highest-weighted studies excluded</b>	To determine whether results were heavily influenced by the two highest-weighted studies ( <i>SI Appendix</i> , Fig. S5)	-0.461	-0.656, -0.266	< 0.0001	85%	29

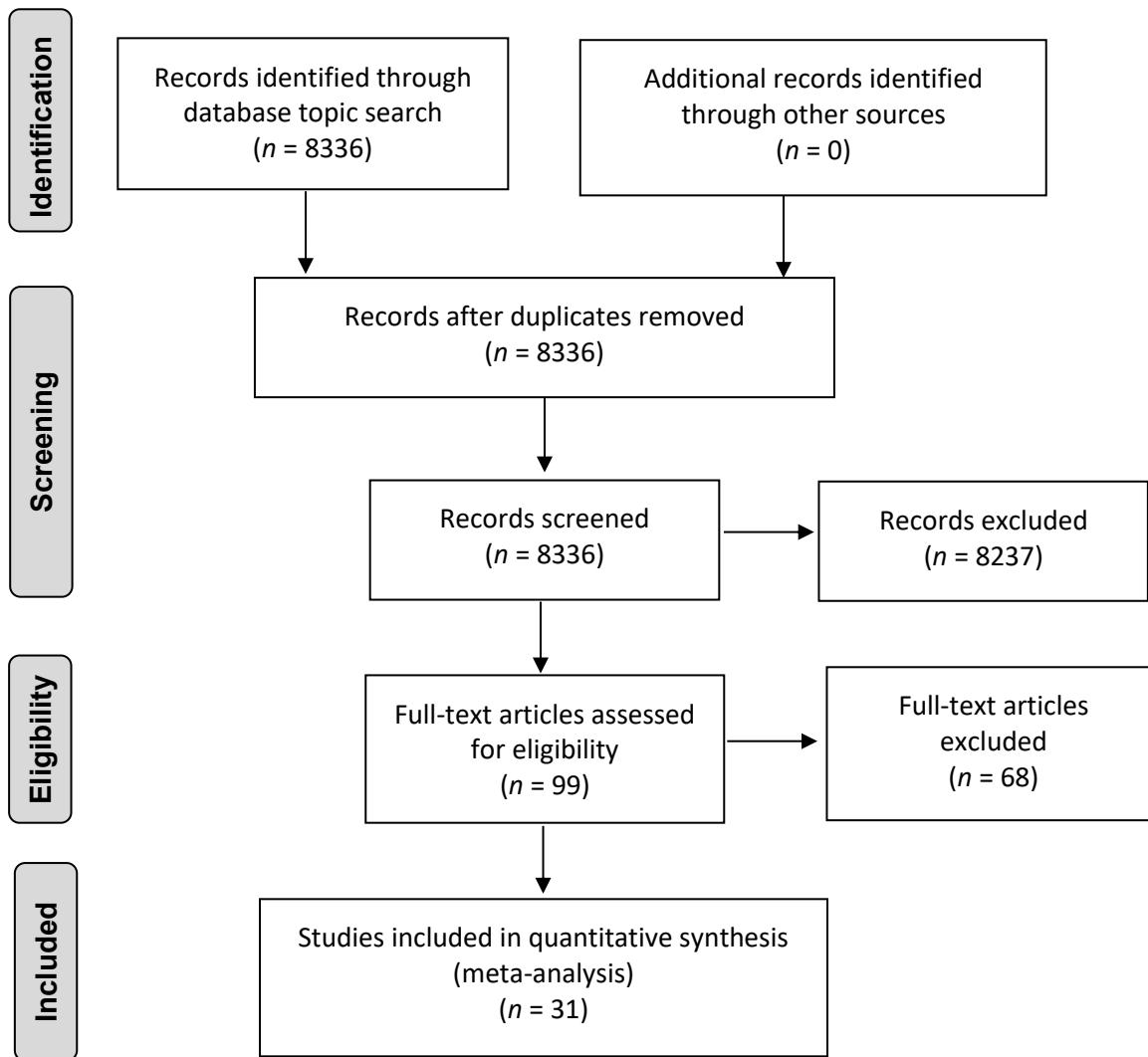
**Table S2.** Tests for bias. We performed three tests to assess publication bias (27, 80, 81), and one test for the influence of sample plot size on lnRR, all of which were negative. The rows describe the tests, associated statistics, test interpretations, and the result of the tests.

TEST DESCRIPTION	TEST STATISTICS	INTERPRETATION	RESULT
Correlation between standardized effect sizes and standard errors (27)	Spearman's rho = -0.176, $P= 0.343$ ; Kendall's tau = -0.1185, $P= 0.349$	Correlations were not significant	Negative
Cumulative meta-analysis (80) ( <i>SI Appendix</i> , Fig. S6)	NA	Over time (publication year), effect size became more negative, and converged with global mean lnRR	Negative
Rosenberg's fail safe number (81)	Fail-safe number: 2165	Fail-safe number was greater than the minimum cut-off of 165 (i.e., $5 \times n + 10$ ; where $n$ = number of studies)	Negative
Relationship between plot size and lnRR ( <i>SI Appendix</i> , Fig. S7)	Slope: -0.00076, $R^2 = 0.0021$ , $P = 0.806$	Variation in sample area among studies did not influence global mean lnRR	Negative

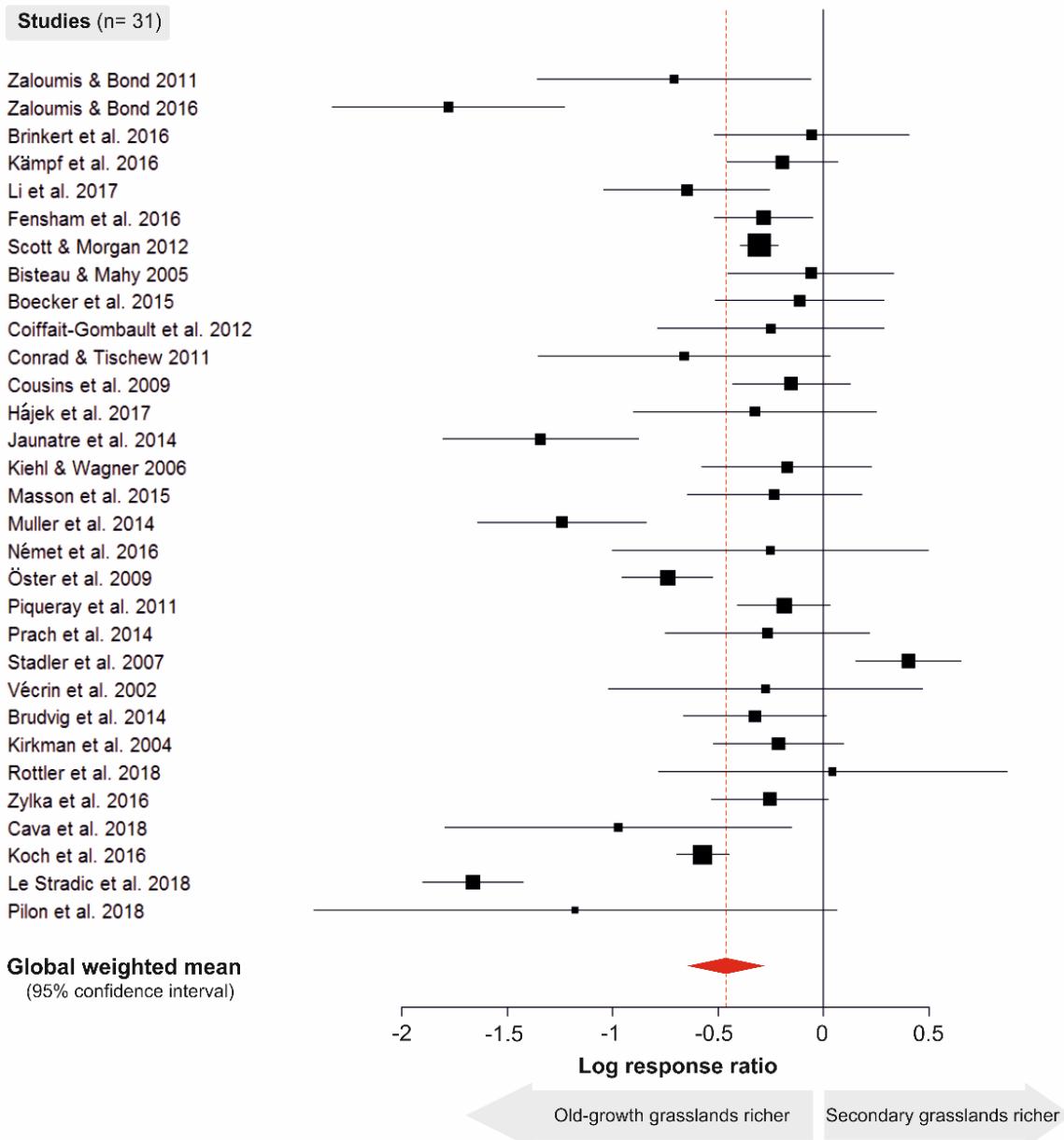
**Table S3.** Models to identify potential sources of unexplained variation in Log response ratio. We began by defining a linear mixed effect model of lnRR values, from  $n = 92$  time points, with seven predictor variables as fixed effects, and study sites ( $n = 31$ ) as random effects. We then used a step-backward selection method based on Akaike Information Criteria (AIC) to identify the best model. We calculated the  $\Delta\text{AIC}$  for each model in relation to the best model. For predictor variables that appeared in models with  $\Delta\text{AIC} < 2$  (in bold), and were not part of the core hypotheses (i.e., secondary grassland type and latitude, as opposed to secondary grassland age, Fig. 3), we produced supplemental figures to visualize their relationships with lnRR (SI Appendix, Fig. S8, S9). Abbreviations are as follows: MAP, Mean annual precipitation; MAT, Mean annual temperature; SG\_type, type of secondary grassland; plot\_area, size of the sampling unit in each study; Latitude, site location in degrees north or south of the equator; and log\_time, base 10 logarithm of secondary grassland age.

Model	Parameters	AIC	$\Delta\text{AIC}$	$R^2$
<b>LnRR ~ Continent + Latitude + MAP + MAT + log_time + SG_type + plot_area</b>	7	85.61	7.38	0.399
<b>LnRR ~ Continent + Latitude + MAP + log_time + SG_type + plot_area</b>	6	83.65	5.42	0.399
<b>LnRR ~ Continent + Latitude + MAP + log_time + SG_type</b>	5	81.71	3.48	0.398
<b>LnRR ~ Continent + Latitude + log_time + SG_type</b>	4	80.34	2.11	0.379
<b>LnRR ~ Latitude + log_time + SG_type</b>	3	<b>78.85</b>	<b>0.62</b>	<b>0.356</b>
<b>LnRR ~ Latitude + log_time</b>	2	<b>78.23</b>	<b>0</b>	<b>0.322</b>
<b>LnRR ~ log_time</b>	1	85.48	7.25	0.14

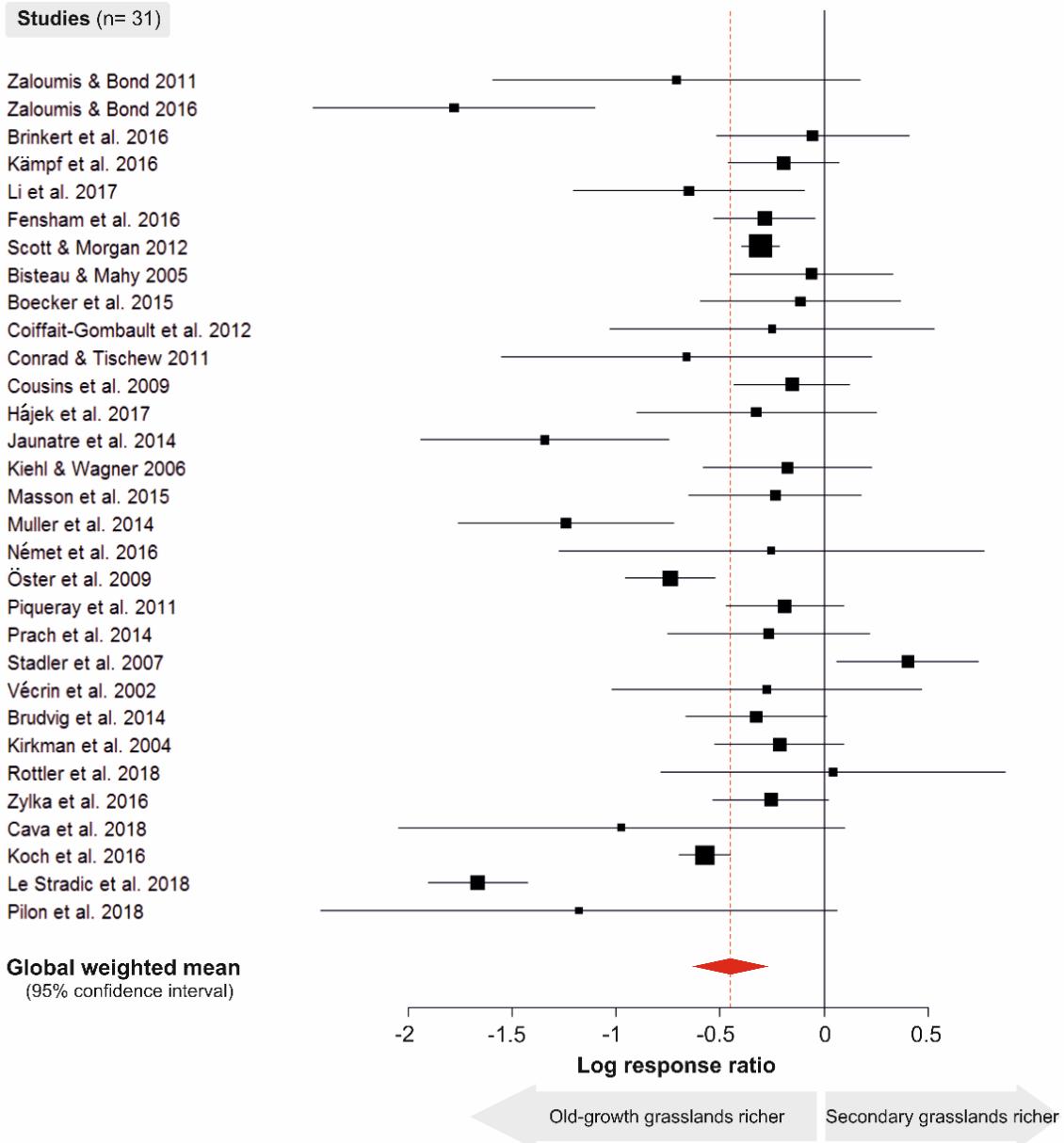
## SUPPLEMENTARY INFORMATION (FIGURES)



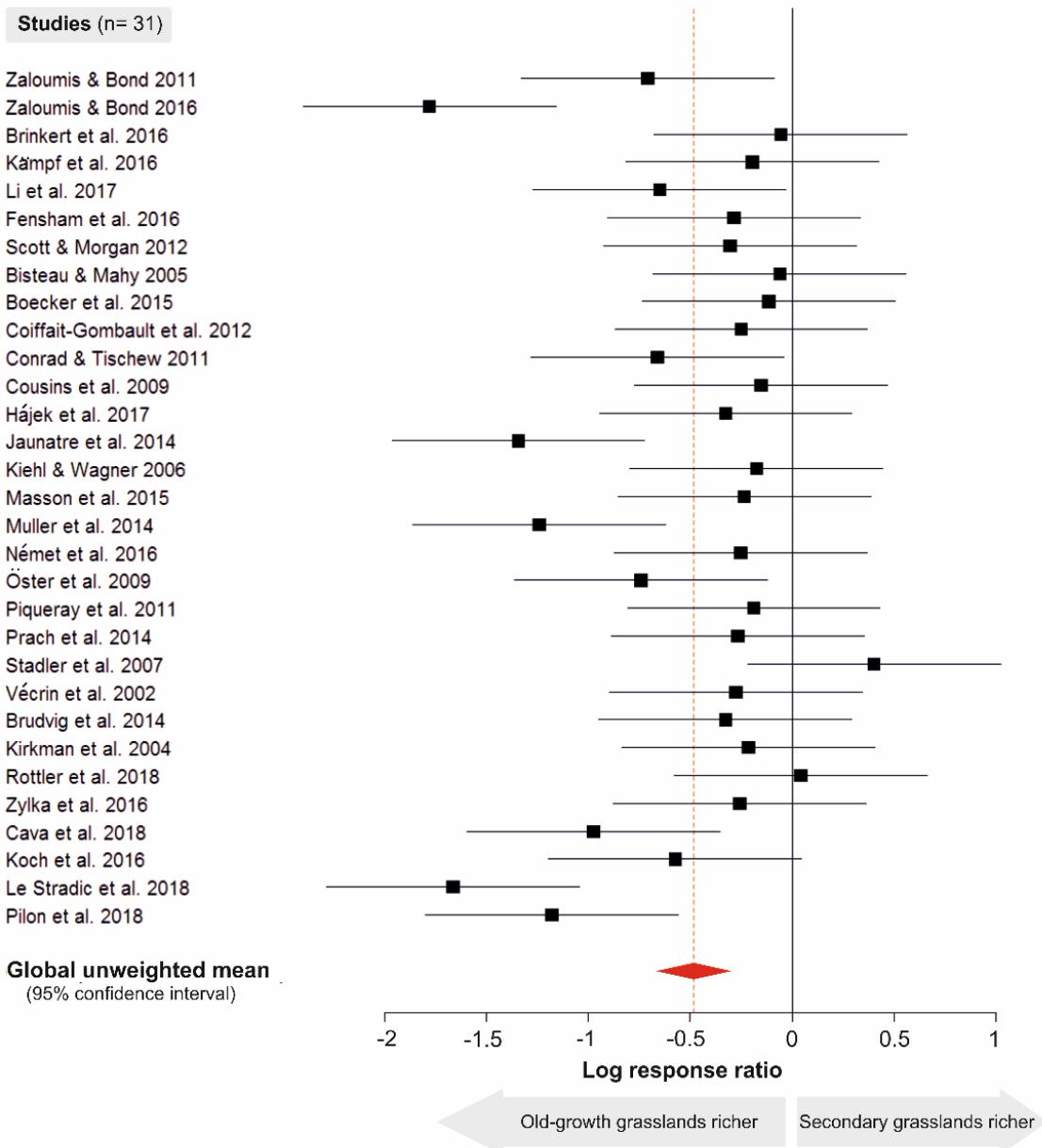
**Figure S1.** Flowchart of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) for step-wise selection of studies (55). Identification: The Web of Science topic search yielded a total of 8336 articles (we were unable to identify additional records in recent review articles). Screening: We examined the titles of the 8336 articles to eliminate those that were obviously irrelevant (for ambiguous titles, we further screened the abstract and methods), which resulted in 99 articles for the final screening: Lastly, we read the full texts of the 99 articles and determined that 31 articles met the eligibility criteria (see Methods) to be included in the analysis.



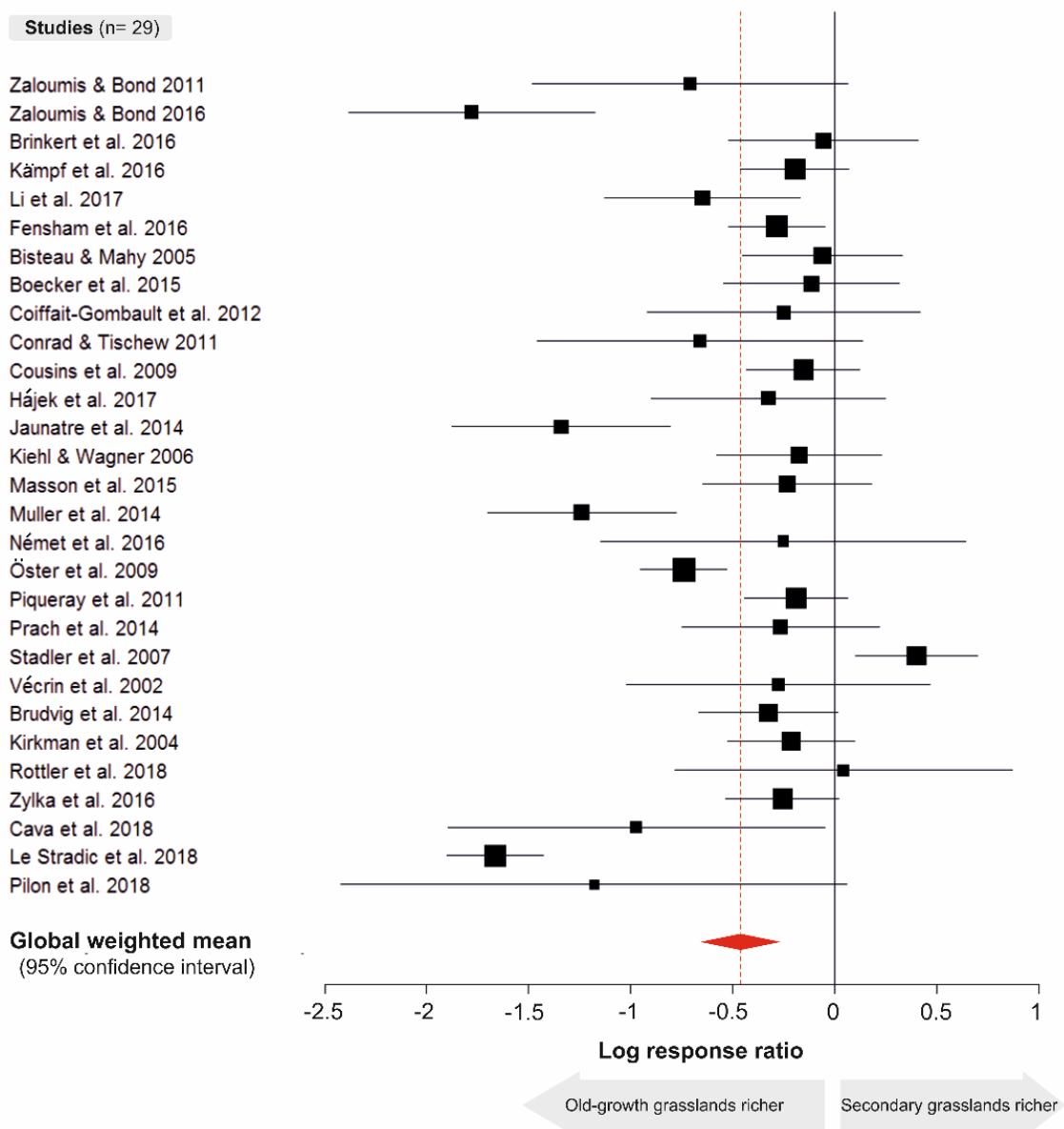
**Figure S2.** Sensitivity analysis using a plausible covariance of  $r = 0.25$ . Studies ( $n = 31$ ) are listed alphabetically by continent and author. Boxes and error bars display the natural logarithm of the response ratio (lnRR) and 95% confidence intervals, respectively. Box sizes are proportional to the weight of the study. Log response ratios less than zero indicate that old-growth grasslands are more species-rich than secondary grasslands, whereas values greater than zero indicates secondary grasslands are richer. Displayed as a red diamond and red vertical line, the global weighted mean ( $\text{lnRR} = -0.46$ ,  $I^2 = 91\%$ ,  $P < 0.0001$ ) equates to secondary grasslands supporting 63% of the species richness of old-growth grasslands (SI Appendix, Table S1).



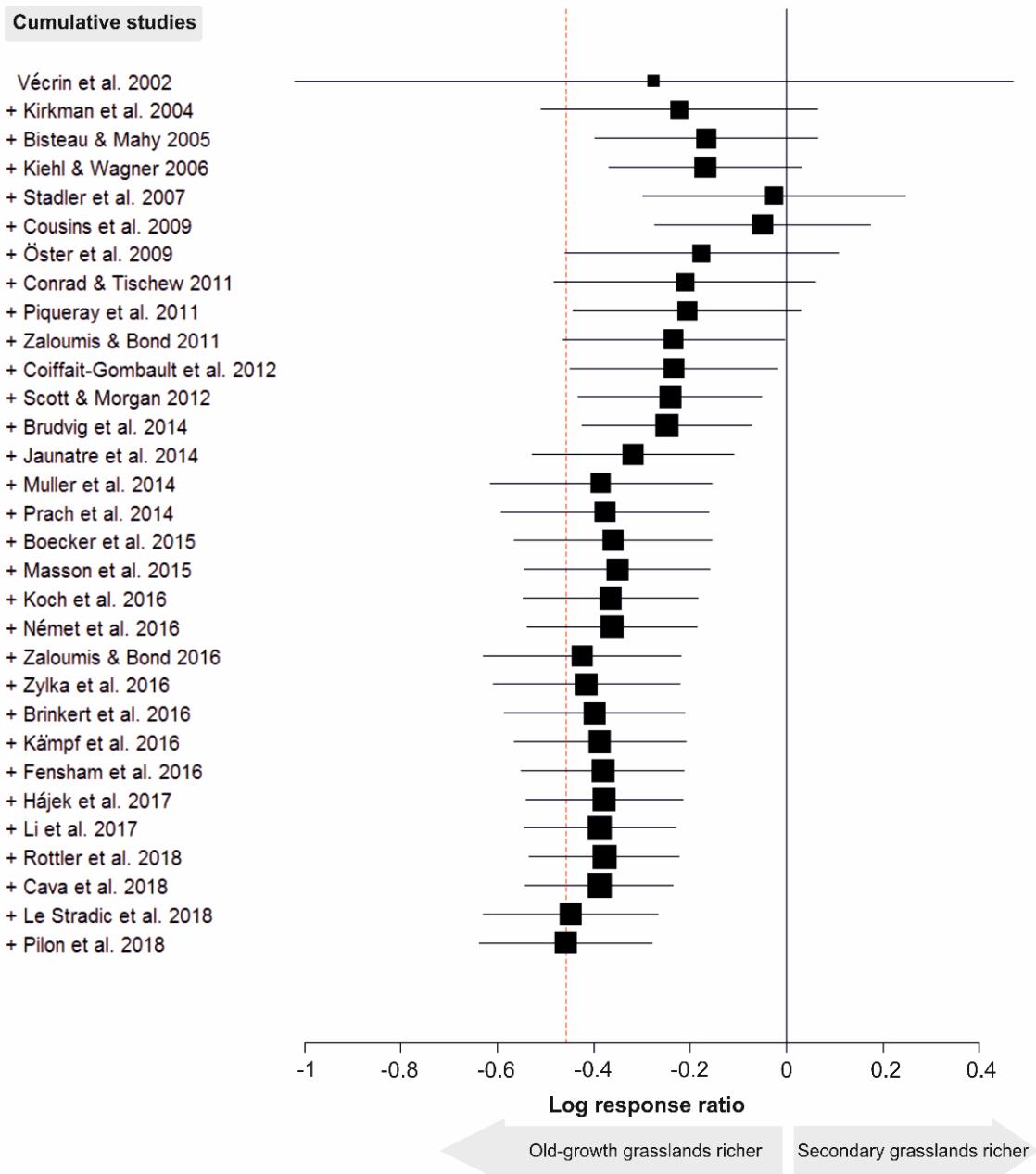
**Figure S3.** Sensitivity analysis using a plausible covariance of  $r = 0.75$ . Studies ( $n = 31$ ) are listed alphabetically by continent and author. Boxes and error bars display the natural logarithm of the response ratio (lnRR) and 95% confidence intervals, respectively. Box sizes are proportional to the weight of the study. Log response ratios less than zero indicate that old-growth grasslands are more species-rich than secondary grasslands, whereas values greater than zero indicate secondary grasslands are richer. Displayed as a red diamond and red vertical line, the global weighted mean ( $\text{lnRR} = -0.45$ ,  $I^2 = 89\%$ ,  $P < 0.0001$ ) equates to secondary grasslands supporting 64% of the species richness of old-growth grasslands (SI Appendix, Table S1).



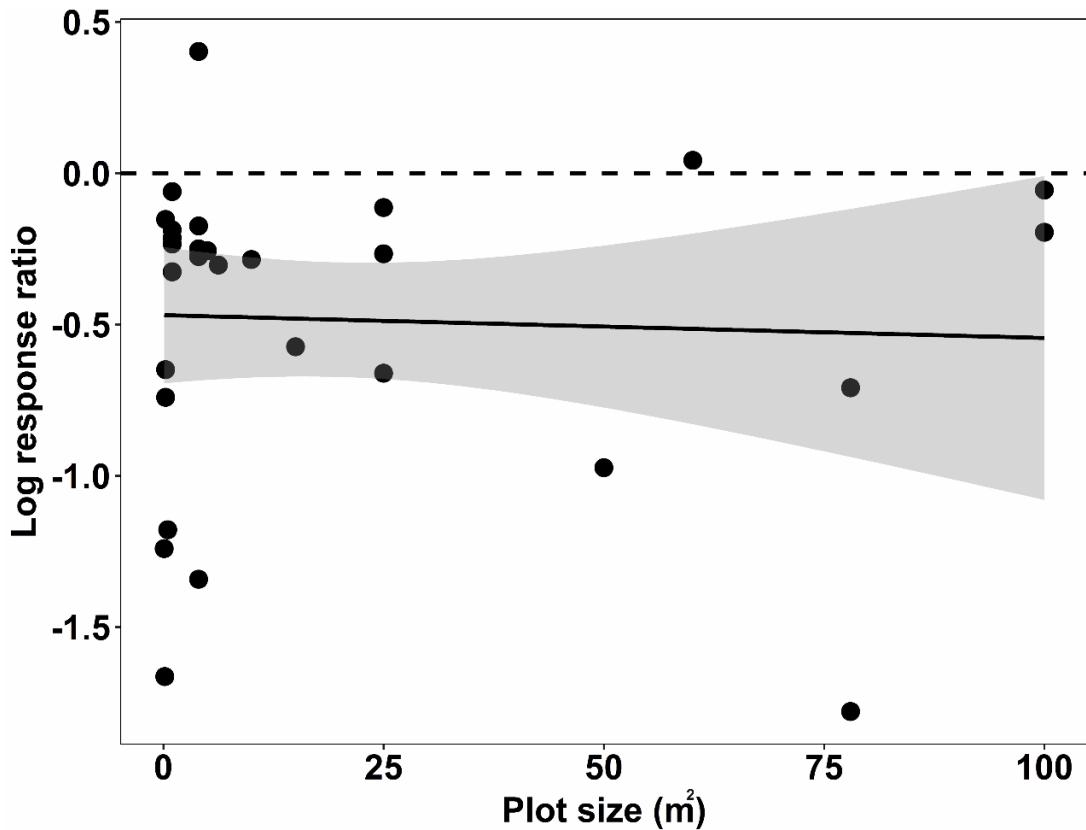
**Figure S4.** Sensitivity analysis with an unweighted mean lnRR. Studies ( $n = 31$ ) are listed alphabetically by continent and author. Boxes and error bars display the natural logarithm of response ratio (lnRR) and 95% confidence intervals, respectively. Box sizes are proportional to the study weights, which are all equal for this unweighted sensitivity analysis. Log response ratios less than zero indicate that old-growth grasslands are more species-rich than secondary grasslands, whereas values greater than zero indicate secondary grasslands are richer. Displayed as a red diamond and red vertical line, the global unweighted mean ( $\text{lnRR} = -0.48$ ,  $I^2 = 61\%$ ,  $P < 0.0001$ ) equates to secondary grasslands supporting 62% of the species richness of old-growth grasslands (SI Appendix, Table S1).



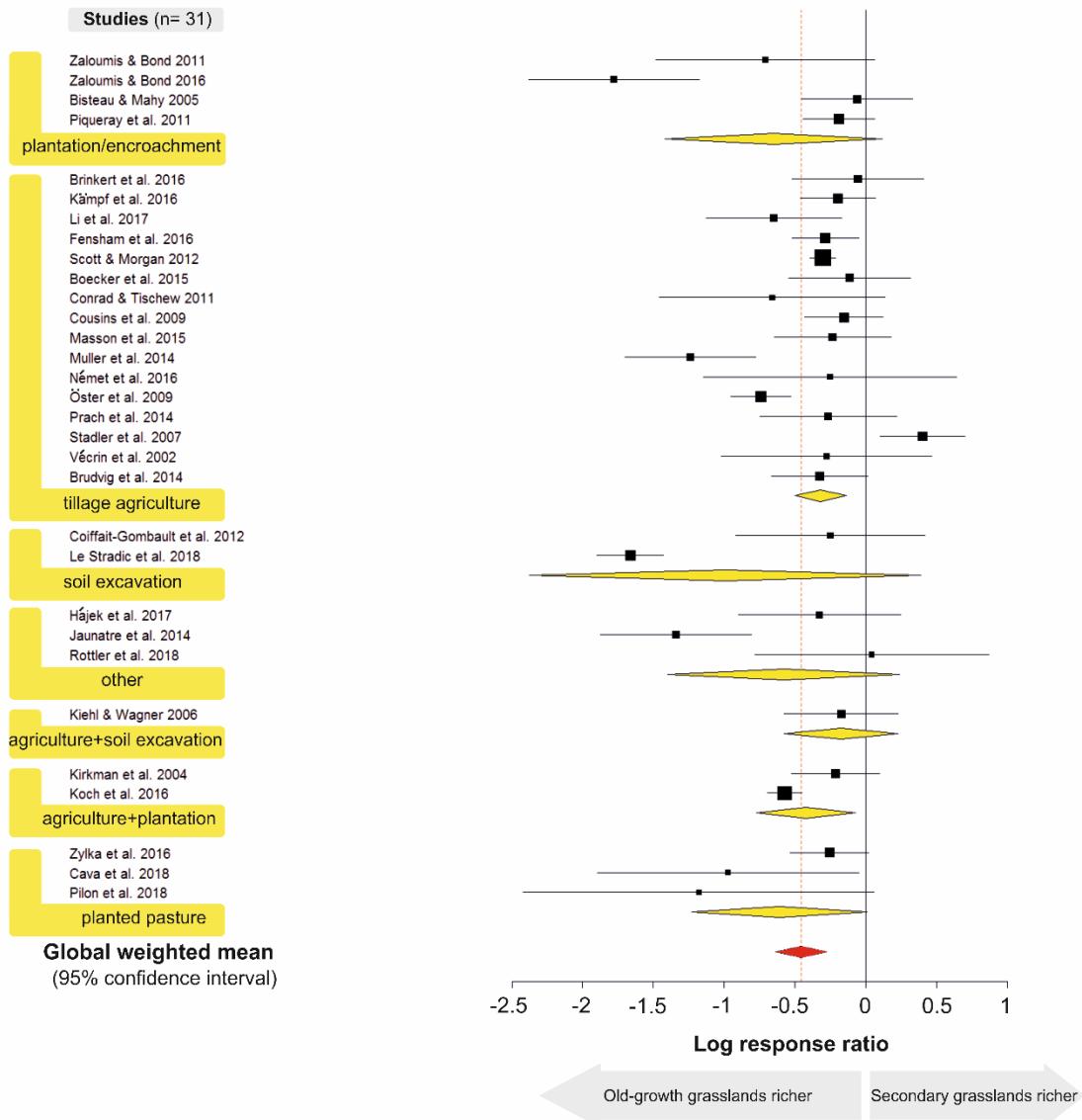
**Figure S5.** Sensitivity analysis with two highest-weighted studies excluded. Studies ( $n = 29$ ) are listed alphabetically by continent and author. Boxes and error bars display the natural logarithm of the response ratio (lnRR) and 95% confidence intervals, respectively. Box sizes are proportional to the weight of the study. Log response ratios less than zero indicates that old-growth grasslands are more species-rich than secondary grasslands, whereas values greater than zero indicate secondary grasslands are richer. Displayed as a red diamond and red vertical line, the global weighted mean ( $\text{lnRR} = -0.46$ ,  $I^2 = 85\%$ ,  $P < 0.0001$ ) equates to secondary grasslands supporting 63% of the species richness of old-growth grasslands (SI Appendix, Table S1)



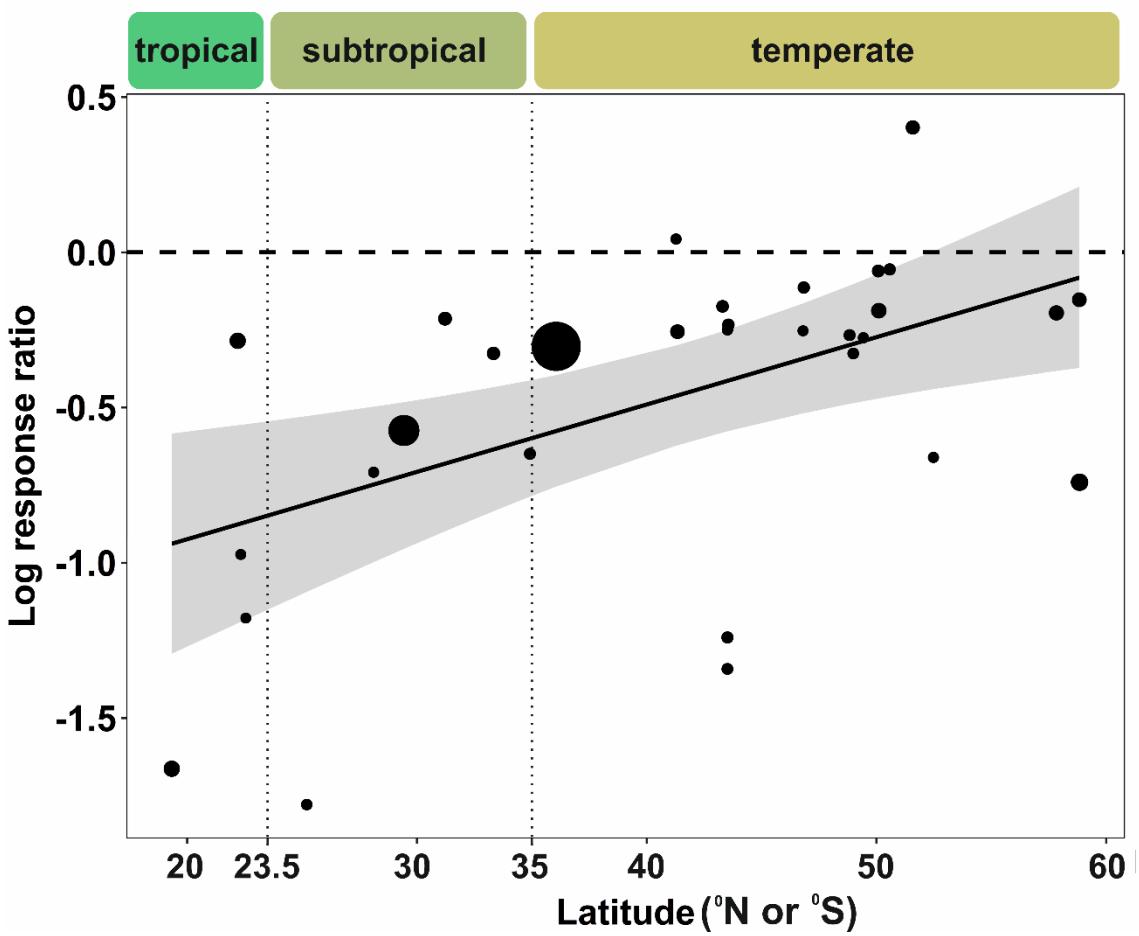
**Figure S6.** Cumulative meta-analysis to assess publication bias. Studies were sorted by publication year (oldest to most recent) and added one by one to the analysis. With each additional study, the effect size was recalculated using a random effects model. Boxes represent iteratively calculated effect-sizes and the bars represent 95% confidence intervals. The red dashed line represents the global mean ( $\ln RR = -0.46$ , Fig. 2). Convergence of the iteratively calculated effect sizes with the global mean effect size indicates there is no publication bias.



**Figure S7.** Relationship between plot size and log response ratio (lnRR) of secondary grassland versus old-growth grassland species richness. Because species-area relationships can differ between ecosystems, we sought to determine if variation in sample area between studies influenced lnRR. We extracted information on plot size (which ranged from 0.009 to 100 m<sup>2</sup>) from each of the  $n = 31$  studies and conducted a linear regression. The regression equation [ $\text{lnRR} = -0.00076(\text{plot size}) - 0.4688$ , ( $R^2 = 0.0021$ ,  $P = 0.806$ )] is displayed as a solid black line; grey shading indicates the 95% confidence interval. Given that the slope is non-significant and the y-intercept (lnRR = 0.47) is very close to the global weighted mean estimates (i.e., lnRR = 0.46, Fig. 2), we conclude that variation in plot size had no influence on overall results (Fig. 2, Fig. 3).



**Figure S8.** Comparison of old-growth grassland versus secondary grassland species richness based on type of secondary grasslands. Studies ( $n = 31$ ) are listed by secondary grassland classification. Boxes and error bars display the natural logarithm of response ratio (lnRR) and 95% confidence intervals (CI), respectively. Box sizes are proportional to the weight of the study. Response ratios less than zero indicate that old-growth grasslands are more species rich than secondary grasslands, whereas values greater than zero indicate secondary grasslands are richer. Yellow diamonds represent the weighted subgroup mean and associated 95% CI. The global weighted mean is displayed as a red diamond and red vertical line. ‘Plantation/encroachment’ refers to tree plantations and woody encroachment; ‘agriculture’ refers to tillage agriculture.



**Figure S9.** Relationship between the log response ratio (lnRR) of species richness and the absolute latitude of studies. Points represent data from  $n = 31$  studies, and are scaled in proportion to their weight (see methods). The regression equation [ $\text{lnRR} = 0.0217(\text{latitude}) - 1.358$ ,  $R^2 = 0.24$ ,  $P = 0.0026$ ], is displayed as a solid black line; grey shading indicates the 95% confidence interval. The horizontal dashed line indicates the response ratio at which secondary and old-growth grassland species richness is equal ( $\text{lnRR} = 0$ ). Response ratios less than zero indicate secondary grasslands that have fewer species compared to old-growth grasslands. The labels tropical ( $n = 4$ ), subtropical ( $n = 6$ ), and temperate ( $n = 21$ ) correspond to latitudes of  $< 23.5^\circ$ ,  $23.5-35^\circ$ , and  $> 35^\circ$ , respectively.

**Dataset S1 (separate file).** Data used for the analyses.