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11 **Projecting impacts of global climate and land-use scenarios on plant biodiversity using**  
12 **compositional-turnover modelling**

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14  
15 **Running head:** Impact of global change on plant biodiversity  
16

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37

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41

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43 **Abstract**

44 Nations have committed to ambitious conservation targets in response to accelerating rates of  
45 global biodiversity loss. Anticipating future impacts is essential to inform policy decisions for  
46 achieving these targets, but predictions need to be of sufficiently high spatial resolution to  
47 forecast the local effects of global change. As part of the intercomparison of biodiversity and  
48 ecosystem services models of the IPBES, we present a fine-resolution assessment of trends in  
49 the persistence of global plant biodiversity. We coupled generalised dissimilarity models,  
50 fitted to >52 million records of >254 thousand plant species, with the species-area  
51 relationship, to estimate the effect of land-use and climate change on global biodiversity  
52 persistence. We estimated that the number of plant species committed to extinction over the  
53 long term has increased by 60% globally between 1900 and 2015 (from ~10,000 to ~16,000).  
54 This number is projected to decrease slightly by 2050 under the most optimistic scenario of  
55 land-use change, and to substantially increase (to ~18,000) under the most pessimistic  
56 scenario. This means that, in the absence of climate change, scenarios of sustainable socio-  
57 economic development can potentially bring extinction risk back to pre-2000 levels.  
58 Alarmingly, under all scenarios, the additional impact from climate change might largely  
59 surpass that of land-use change. In this case, the estimated number of species committed to  
60 extinction increases by 3.7-4.5 times compared to land-use-only projections. African regions  
61 (especially central and southern) are expected to suffer some of the highest impacts into the  
62 future, while biodiversity decline in Southeast Asia (which has previously been among the  
63 highest globally) is projected to slow down. Our results suggest that environmentally  
64 sustainable land-use planning alone might not be sufficient to prevent potentially dramatic  
65 biodiversity loss, unless a stabilisation of climate to pre-industrial times is observed.

66 **Introduction**

67 Human impact on biodiversity has been pervasive since prehistoric times (De Vos, Joppa,  
68 Gittleman, Stephens, & Pimm, 2015). Human activities have caused the loss of thousands of  
69 vertebrate species, with hundreds of extinctions in the past 500 years alone (Ceballos,  
70 Ehrlich, & Dirzo, 2017; Johnson et al., 2017). Information on the prehistoric and historic  
71 decline of groups other than vertebrates is much more scattered, but those invertebrate and  
72 plant taxa for which current status has been assessed indicate a similar or higher level of  
73 endangerment to that of vertebrates (Dirzo et al., 2014; IUCN, 2018). Biodiversity loss is a  
74 challenge for sustainable development, because it affects the contribution and regulation of  
75 services on which humanity relies (Cardinale et al., 2012; Díaz et al., 2018; Mace, 2014).  
76 Yet, alarmingly, the current rate of biodiversity loss is higher than that recorded in the past  
77 and is predicted to further accelerate in the near future (Johnson et al., 2017). This is  
78 associated with emerging threats such as climate change (Scheffers et al., 2016), coupled with  
79 the intensification of threats which are already operating at unsustainable levels, such as  
80 habitat loss and the overexploitation of natural resources (Di Marco, Venter, Possingham, &  
81 Watson, 2018; Maxwell, Fuller, Brooks, & Watson, 2016).

82 In response to accelerating rates of global biodiversity loss nations have committed to  
83 ambitious conservation targets (Butchart et al., 2010; Di Marco, Watson, Venter, &  
84 Possingham, 2016; Tittensor et al., 2014), both through dedicated agreements such as the  
85 Convention on Biological Diversity (CBD, 2010), and as part of a broader commitment to the  
86 UN 2030 Agenda for Sustainable Development (United Nations General Assembly, 2015).  
87 Halting global biodiversity decline requires conservation interventions to focus on those areas  
88 (and those taxa) that are threatened from human impact, hence anticipating where future  
89 impacts may occur is essential for preventing future declines (T. M. Brooks et al., 2006).  
90 Scenario analysis is a powerful way to explore the potential magnitude and location of future

91 biodiversity impacts from socio-economic development, and to help establish which policies  
92 and interventions may lead to unsustainable environmental outcomes (Harfoot et al., 2014;  
93 Lead et al., 2010; Rosa et al., 2017) However, forecasting biodiversity trends is a complex  
94 challenge which requires considering how a representative set of biodiversity indicators  
95 respond to a pre-defined set of scenarios. Recently, the Expert Group on Scenarios and  
96 Models of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem  
97 Services (IPBES) carried out an intercomparison of biodiversity and ecosystem services  
98 models, using harmonized scenarios of land-use and climate change (Hyejin Kim et al.,  
99 2018). In this model intercomparison, a standardised set of land-use and climate change  
100 projections were used to project outcomes for a variety of biodiversity and ecosystem-service  
101 indicators. As part of this exercise, we performed a high-resolution (1 km), multi-extent  
102 (local to global) analysis of the expected changes in plant biodiversity persistence through  
103 space and time, using an innovative approach based on compositional turnover modelling  
104 (Hoskins et al., 2019).

105 Our approach shares a feature with other approaches (e.g. Pereira & Daily 2006)  
106 based on the species-area relationship (SAR), in that it translates a proportional loss of habitat  
107 into an expected loss of species. However, unlike other approaches which typically estimate  
108 habitat loss in relation to large discrete regions, our method views any given location (grid  
109 cell) as sitting within a continuum of spatial turnover in biological composition. The  
110 proportional loss of habitat for species originally associated with a given grid cell is therefore  
111 estimated as a function of the habitat condition in all other cells predicted to be “ecologically  
112 similar” to it (Allnutt et al., 2008; Ferrier, Manion, Elith, & Richardson, 2007; Ferrier et al.,  
113 2004).

114 There are inherent differences between our approach and species-level approaches,  
115 where the change in distribution of individual species is estimated in response to changing

116 environmental conditions (Visconti et al., 2016). Under those approaches, a smaller number  
117 of species is considered – those for which global distribution ranges are available, typically  
118 vertebrates (Di Marco et al., 2017) – and the risk of extinction is estimated individually for  
119 each of these species. However there are also similarities with our method, as both types of  
120 approaches are able to estimate global extinction risk from the change in  $\gamma$ -diversity, and both  
121 are capable of accounting for the combined effect that land-use change and climate change  
122 exert on biodiversity.

123         Land-use change and climate change are the two major drivers of terrestrial  
124 biodiversity loss which operate in response to socio-economic development (Pereira et al.,  
125 2010; Visconti et al., 2016; Newbold 2018). Considering the combined effect of these two  
126 drivers is essential to estimating biodiversity trends, as looking only at one or the other might  
127 lead to substantial underestimations of biodiversity decline (Titeux et al., 2016). In particular,  
128 climate change is expected to exacerbate the impact that land-use change has on biodiversity  
129 by reducing the availability of areas with suitable climatic conditions for species, among  
130 those not yet converted to human uses (Mantyka-Pringle et al., 2015; Mantyka-Pringle,  
131 Martin, & Rhodes, 2012). However, the correspondence between levels of land-use change  
132 and levels of climate change can be complex, as a given socio-economic pathway might be  
133 associated with multiple land-use configurations, each associated to different emission levels.  
134 Following Kim et al. (2018), we adopted a pre-defined set of land-use and climate change  
135 scenarios, by associating land-use projections from the shared socio-economic pathways  
136 (SSPs; O'Neill et al. 2014, 2017) with climate change projections from the representative  
137 concentration pathways (RCPs; van Vuuren et al. 2011a). Three SSP-RCP scenarios were  
138 evaluated (see Methods for further details): SSP1-RCP2.6 ‘Sustainability’, where  
139 environmentally sustainable development leads to limited greenhouse gas emissions; SSP3-  
140 RCP6.0 ‘Regional rivalry’, with global deterioration in environmental conditions (i.e. habitat

141 degradation) and increased emissions; SSP5-RCP8.5 ‘Fossil-fuelled development’, where  
142 high-tech development leads to limited environmental impacts locally but high emissions  
143 globally.

144 Our goal is to provide fine-resolution estimates of global change in the proportion of  
145 vascular-plant species expected to persist over the long term. We focus our analyses on  
146 vascular plants because this group sustains life on Earth more than any other biological  
147 group, representing the largest part (~80%) of terrestrial biomass (Bar-On, Phillips, & Milo,  
148 2018), and because of the ready availability of location records for ~70% of the estimated  
149 plant species in the world. We report trends in the expected long-term persistence of vascular  
150 plant biodiversity over the course of 170 years, from 1900 to 2070, assessing the impact of  
151 past land-use change, and that projected from three future scenarios of socio-economic  
152 development. We also assess how the impact of land-use change on biodiversity might be  
153 exacerbated by climate change in each scenario. We report the temporal trends in local,  
154 regional, and global proportions of plant species expected to persist in the long term, and  
155 estimate the associated number of species committed to extinction (i.e. those expected to  
156 disappear from their entire range in the long term). The main interest of our results lies in the  
157 comparison of species persistence predicted under alternative socio-economic scenarios,  
158 more than the absolute value of any individual scenario. Given the consistent application of  
159 our methodology, any level of uncertainty associated with our estimates (see Methods) is  
160 likely to operate in the same way across all scenarios, allowing for a direct comparison of  
161 estimates obtained under different land-use and climate change projections.

162

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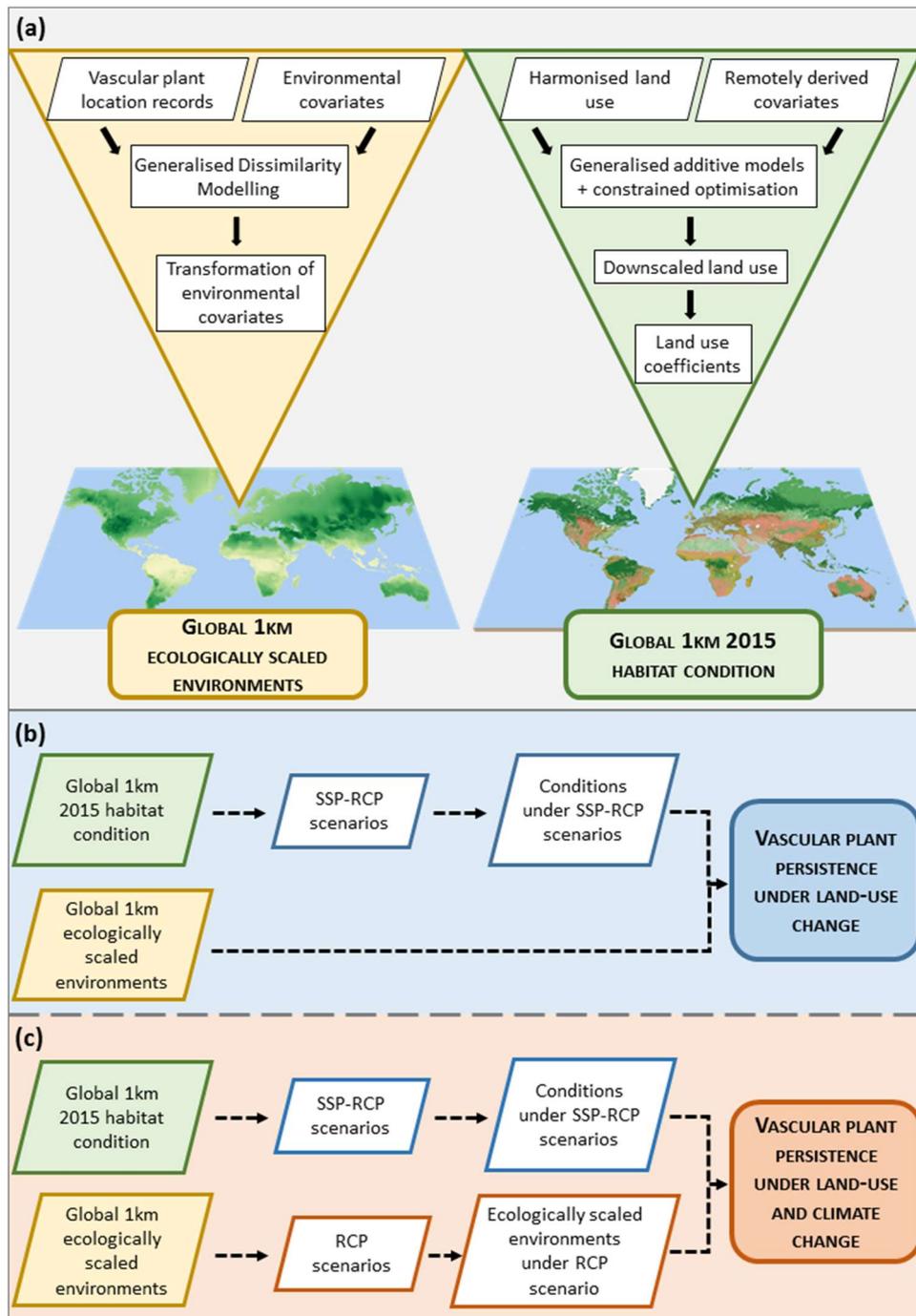
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165 **Materials and Methods**

166

167 **Modelling compositional turnover in vascular plant communities**

168 We combined models of the spatial turnover in species composition of vascular plant  
169 communities with estimates of habitats condition to generate projections of plant biodiversity  
170 persistence under scenarios of land-use and climate change (Fig. 1).



171

172 **Fig. 1** Conceptual framework of the methodology adopted to generate global-scale scenarios  
173 of the persistence of vascular plant biodiversity. Once the ecologically scaled environments

174 and the habitat condition surface are generated (a), they are used to estimate plant persistence  
175 under scenarios of land-use change (b), or scenarios of land-use and climate change (c).  
176

177 Underpinning our analyses are global models of compositional turnover in vascular  
178 plant communities. These models were developed using generalised dissimilarity modelling  
179 (GDM), a statistical technique for predicting the dissimilarity in species composition between  
180 pairs of sites as a function of environmental differences between, and spatial separation of,  
181 those sites (Ferrier et al., 2007, 2004). GDM effectively scales the relationship between  
182 spatial turnover in community composition and environmental gradients to generate  
183 “ecologically scaled environments”, thereby providing continuous predictions of  $\beta$ -diversity  
184 patterns across the modelling domain. This prediction of ecological similarity is based on  
185 fine-scaled modelling of spatial turnover in community composition (we employed a spatial  
186 resolution of 30 arc-seconds globally,  $\sim 1 \text{ km}^2$  at the equator). Our approach allows us to  
187 factor the fine-scaled patterns in  $\beta$ -diversity into the prediction of changes in the total species  
188 diversity (i.e.  $\gamma$ -diversity) of any spatial region of interest (be it a country, a continent, or the  
189 globe). Because these  $\beta$ -diversity patterns are modelled as a function of abiotic environmental  
190 predictors, including climate, our approach can also account for the effects of climate change  
191 in projecting potential biodiversity impacts of alternative scenarios of socio-economic  
192 development.

193 In the current study, we used a specially modified form of GDM, as implemented in  
194 the Biogeographic Infrastructure for Large-scaled Biodiversity Indicators (BILBI; Hoskins et  
195 al., 2019). This approach corrects for biases introduced into predictions when models are  
196 fitted to incomplete survey inventories. This is achieved by replacing the response variable  
197 normally employed in GDM fitting (i.e. compositional dissimilarity) with the probability that  
198 a pair of species records drawn randomly from two sites represent two different species rather  
199 than the same species. This modelled probability is then back-transformed to the common 0-1

200 measure of dissimilarity in ecological communities (similar to the Sørensen index) for  
201 prediction and analysis. In doing so, incompleteness in survey inventories is less likely to  
202 yield inflated estimates of turnover (see below), which is often a risk when modelling  
203 compositional dissimilarities.

204         A total of >52 million records of 254,145 plant species, derived from the Global  
205 Biodiversity Information Facility (GBIF; <https://www.gbif.org>), were used to fit GDM  
206 models (see Hoskins et al., 2019 for full details of model fitting). This is equivalent to ~70%  
207 of the estimated number of extant vascular plant species in the world (Chapman, 2009).  
208 While GBIF data present inherent limitations, especially in terms of the variation in sampling  
209 intensity for different parts of the globe, the innovative type of GDM modelling employed in  
210 our study reduces the bias determined by incomplete sampling (Hoskins et al., 2019; Ware et  
211 al., 2018). In fact, comparing “observation pairs” (as opposed to site pairs) in the BILBI  
212 modelling infrastructure ensured that variation in sampling intensity was effectively  
213 accounted for during model fitting, because the probability that two observations in two sites  
214 refer to the same species is independent of the number of other species observed (Hoskins et  
215 al., 2019). Furthermore, by focusing on modelling spatial patterns in a collective property of  
216 biodiversity – i.e. compositional turnover – rather than modelling distributions of individual  
217 species, the BILBI infrastructure is expected to achieve relatively robust extrapolation of  
218 patterns across poorly-sampled regions, even where the particular species occurring in these  
219 regions are unknown or unrecorded.

220

### 221 **Generating habitat condition surfaces from land use**

222 We generated global maps of habitat condition by multiplying spatially continuous estimates  
223 of land-use coverage with coefficients representing the proportional species richness expected  
224 to be retained in each land-use class, relative to the richness under a pristine environment

225 (Fig. 1). We used version 2 of the land-use harmonisation dataset (LUH2; Hurtt et al. 2016),  
226 which reports the proportional coverage of 12 land-use classes within each 15 minute grid  
227 cell of the globe (approximately 25 km at the equator). In order to derive a continuous surface  
228 matching the fine-scale resolution at which we fit models of compositional turnover, we  
229 downscaled the present-day (year 2015) LUH2 surface to 30 arc-seconds, following the  
230 approach employed by Hoskins et al. (2016) to downscale the previous version of that dataset  
231 (LUH1).

232         The downscaling approach uses a combination of Generalised Additive Models  
233 (GAMs) and constrained optimisation to derive fine-grained estimates of spatial data from  
234 regularly gridded coarse-grained information. The results are the estimated proportions of the  
235 12 land-use classes in the LUH2 dataset within each fine-grained grid cell, where all classes  
236 are balanced so that their sum equals 1. The method we used to downscale the 12 land-use  
237 classes in LUH2 follows that described in Hoskins et al. (2016), with three main differences.  
238 Firstly, in each iteration of the analysis, an initial GAM was fitted to only time-varying  
239 predictors while the remaining static variables were fitted in a subsequent GAM, for which  
240 the effects of the time-varying predictors were fixed as a model offset; this approach  
241 maximises the influence of time-varying predictors in the models. Secondly, compared to  
242 predictors used in Hoskins et al. (2016), we used an updated set of remote sensing input  
243 variables, in particular the MODIS vegetation continuous fields data for the year 2015  
244 (DiMiceli et al., 2011), and the 2014 gridded population (European Commission & Columbia  
245 University, 2015) and 2015 urban extent (Pesaresi et al., 2015) data from the global human  
246 settlement dataset. Finally, to tackle the computational complexity resulting from an  
247 increased number of land-use classes in the LUH2 dataset ( $n=12$ ) compared to LUH1 ( $n=5$ ),  
248 the optimisation was carried out in a hierarchical manner (Fig. S1). Initially, five aggregated  
249 land-uses were created from the GAM predictions: cropping, forest, non-forest, grazing and

250 urban. Subsequently, each land-use group underwent one or two sequential optimisations, to  
251 arrive at the final 12 downscaled classes.

252         Once the present-day land-use classes were downscaled, we created a map of habitat  
253 condition; this was achieved by multiplying, for each grid cell, the percentage coverage of  
254 each land-use class by a coefficient representing the proportional species richness expected to  
255 be retained in that class within the forested or non-forested areas classified in LUH2 (Table  
256 S1). This is the same approach reported in Kim et al. (2018), following previous works (Hill  
257 et al., 2018; Newbold et al., 2016) based on the PREDICTS database (Hudson et al., 2017).  
258 Past (starting from 1900) and future (up to 2070) trends in habitat condition were generated  
259 by multiplying the present-day downscaled habitat condition surface by the projected  
260 (backcast or forecast) change in coarse-grained (15 arc-minutes) habitat condition values.  
261 This was necessary given the lack of suitable remote-sensing predictors to downscale land-  
262 use classes for the entire study period. The assumption in this case is that each 30 second  
263 pixel within a 15 minutes cell has undergone the same proportional change in habitat  
264 condition through time. While this information is less refined than the present-day estimate of  
265 habitat condition, it is expected to have limited impact on the regional and global trends  
266 reported in our results (see next section), given these trends derive from an aggregation  
267 performed across several million grid cells. In those cases where the habitat condition of a 30  
268 second pixel was projected to exceed the maximum value of 1 (i.e. intact landscape), the  
269 excess value was reallocated to other pixels within the same 15 minutes cell. The final results  
270 are past and future projections of habitat condition values at a resolution of 30 arc-seconds.  
271 This approach assumes that differences in condition from land-use change over time (at a  
272 single location) are of a similar magnitude to differences observed between land uses at a  
273 single point in time (across different locations), as assessed by the PREDICTS model (Hill et  
274 al., 2018; Newbold et al., 2016).

275

## 276 **Projecting biodiversity persistence under land-use and climate change**

277 The fitted GDMs were used to estimate the proportional retention of vascular plant species,  
278 as a function of changes in land use and climate (Fig. 1), employing the SAR-based approach  
279 described by Allnutt et al. (2008). This approach scales the availability of remaining habitat  
280 across all grid cells with a similar ecological environment to a given cell of interest, relative  
281 to the area of this environment which would be present in an intact landscape. Calculations  
282 were undertaken using the global biodiversity modelling infrastructure BILBI (Hoskins et al.,  
283 2019), with separate models run for each biome-realm combination of the globe (Olson et al.,  
284 2001) with the exclusion of Antarctica. There are two types of sampling employed in this  
285 study. For each biome within a biogeographic realm, model predictions covering the whole  
286 realm were used to make comparisons between a systematic sample of 4% of grid cells (i.e.  
287 one pixel sampled for every 5 by 5 km area) to an evenly stratified 1% sample of all cells in  
288 the realm, allowing for species ranges to cross the biome boundary in order to estimate  
289 similarity beyond the biome boundaries. This strategy was adopted to make the analysis  
290 computationally tractable while maintaining adequate representativeness of the dissimilarity  
291 estimates, given the total number of possible pairwise comparisons for  $>220 \times 10^6$  grid cells at  
292 a resolution of 30 arc-seconds. The same sample points were used for all calculations, to  
293 ensure consistency in the derivation of biodiversity trends.

294 The denominator for all analyses was calculated as the potential area of similar  
295 ecological environments remaining relative to a given cell  $i$ , under the present climate and  
296 assuming an intact landscape (i.e. the habitat condition  $h_j$  of all cells  $j$  is assumed to equal 1):

297

$$298 \quad A_{i_{baseline}} = \sum_{j=1}^{j=n} S_{i_{present}j_{present}} \quad [1],$$

299

300 where  $A_{i_{baseline}}$  is the potential area of similar ecological environments to cell  $i$ , calculated as  
 301 the summed pairwise similarity ( $s_{ij}$ ) to all other cells  $j$ . Within the present climate, the actual  
 302 area of similar ecological environments ( $A_{i_{test}}$ ) is then measured in relation to the habitat  
 303 condition observed under a given scenario ( $h_{j_{scen}}$ ):

$$305 \quad A_{i_{test}} = \sum_{j=1}^{j=n} s_{i_{present}j_{present}} h_{j_{scen}} \quad [2].$$

306  
 307 Following Allnutt et al. (2008), we used the SAR formulation (taking the widely-used power  
 308 of 0.25) to translate the fraction  $A_{i_{test}}/A_{i_{baseline}}$  into the proportion of species expected to  
 309 persist in the long term under the scenario ( $p_{j_{scen}}$ ):

$$311 \quad p_{i_{test}} = \left[ \frac{\sum_{j=1}^{j=n} s_{i_{present}j_{present}} h_{j_{scen}}}{\sum_{j=1}^{j=n} s_{i_{present}j_{present}}} \right]^{0.25} \quad [3].$$

312  
 313 This formulation was then modified to consider the effects of changing climate, by replacing  
 314 the compositional similarity  $s_{ij}$  employed in the numerator to be that predicted between cell  $i$   
 315 under present climatic conditions and cell  $j$  under the future climate scenario of interest:

$$317 \quad p_{i_{test}} = \left[ \frac{\sum_{j=1}^{j=n} s_{i_{present}j_{future}} h_{j_{scen}}}{\sum_{j=1}^{j=n} s_{i_{present}j_{present}}} \right]^{0.25} \quad [4].$$

318  
 319 This calculation assumes that a space-for-time substitution is appropriate, i.e. the spatial  
 320 variation in species composition observed under current climate can be used to predict

321 variation in composition through time under changing climate. Blois et al. (2013)  
 322 demonstrated that such an assumption is reasonable when modelling compositional similarity  
 323 of plant communities, with 72% accuracy in the space-for-time predictions compared to time-  
 324 for-time predictions (validated on Late Quaternary pollen records). Fitzpatrick et al. (2011)  
 325 also showed that GDMs present an advantage over species distribution models, when  
 326 projecting the impact of climate change under non-analogue climate conditions. In practice,  
 327 the projected turnover of species from this comparison will be limited by dispersal in and out  
 328 of the area, and will be affected by local adaptation.

329         The proportion of species originally associated with a specified region of interest (e.g.  
 330 Central Africa) and expected to persist over the long term can finally be calculated as a  
 331 weighted geometric mean of the values for all individual cells in that region (Allnutt et al.,  
 332 2008; Ferrier et al., 2004):

333

$$334 \quad p_{region} = \exp\left(\frac{\sum_{i=1}^m w_i \ln(p_i)}{\sum_{i=1}^m w_i}\right) \quad [5],$$

335

336 where  $m$  is the total number of cells in the region of interest, and the weights employed are:

337

$$338 \quad w_i = \frac{1}{\sum_{j=1}^n s_{i_{present}j_{present}}} \quad [6],$$

339 where  $n$  is total number of grid cells. This composite index was derived as a geometric mean,  
 340 rather than an arithmetic mean, in keeping with recommendations (Buckland, Studeny,  
 341 Magurran, Illian, & Newson, 2011) regarding the appropriateness of this approach when  
 342 aggregating relative, or proportional, measures of change across multiple elements of  
 343 biodiversity.

344 It is important to clarify that this method, as for any other SAR-based approach  
345 (Chaudhary & Mooers, 2018; Pereira & Daily, 2006), does not estimate the proportion of  
346 species that will go extinct within a specified time frame. Rather, the approach estimates the  
347 proportion of species which are expected to persist or become extinct over the long term, as a  
348 consequence of the climate and land-use conditions observed or predicted at a specified time  
349 point. For example, an estimate of 95% species persistence in year 2050 means that 5% of the  
350 species originally found in the region are ‘committed to extinction’ over the longer term (i.e.  
351 beyond 2050), given the environmental conditions predicted for 2050. A number of empirical  
352 evaluations of the ability of SAR-based approaches to predict long-term extinction levels  
353 have yielded promising results (Thomas M. Brooks et al., 2002; Pimm & Askins, 1995), even  
354 if further work is needed to develop a better understanding of the rate at which such  
355 extinctions manifest across different biological groups and environments.

356

### 357 **Defining scenarios of land-use and climate change**

358 Under the IPBES model intercomparison exercise, different integrated assessment models  
359 (IAMs) have been applied to derive a quantitative representation of the land use trends  
360 represented by each SSP storylines, as described in Popp et al. (2017). Each IAM contains a  
361 land-use module that parametrises biogeo-chemical, biophysical, and socio-economic  
362 processes and allocates amounts of land uses to each individual 0.25 degrees grid cell. The  
363 quantitative land-use projections from each of the IAMs were then harmonized using the  
364 LUH2 methodology, as part of a Land Use Model Intercomparison Project (Lawrence et al.,  
365 2016), resulting in a consistent set of land-use classes in each grid cell, across scenarios and  
366 through time.

367 Following Kim et al. (2018), we focussed our scenario analyses on three SSP  
368 storylines: SSP1 ‘Sustainability’, SSP3 ‘Regional rivalry’, and SSP5 ‘Fossil-fueled

369 development'. These alternative scenarios are associated with different degrees of projected  
370 environmental pressure (O'Neill et al., 2017): scenario SSP1 projects a global improvement  
371 in environmental conditions, due to less resource-intensive lifestyles and more resource-  
372 efficient technologies (van Vuuren et al., 2017); scenario SSP3 projects a global deterioration  
373 in environmental conditions, due to a regionalised focus on energy and food production, the  
374 lack of international cooperation, and the intensification of materials consumption (Fujimori  
375 et al., 2017); scenario SSP5 depicts a high technological pathway to sustainable development,  
376 with resource-demanding lifestyles supported by high exploitation of fossil fuel resources at  
377 the expenses of global greenhouse-gas emissions, while local-scale environmental impacts  
378 are mitigated by technological solutions (Kriegler et al., 2017).

379         Each of the selected scenarios can be associated with varying degrees of global  
380 climate change. We adopted the following land-use and climate change associations: SSP1-  
381 RCP2.6 (lowest climatic impact), SSP3-RCP6.0 (intermediate climatic impact), SSP5-  
382 RCP8.5 (highest climatic impact). We first evaluated the trend in biodiversity persistence  
383 associated with land-use change for the period 1900-2070. We then evaluated the potential  
384 additional impact of climate change, by considering biodiversity persistence under RCP-  
385 derived climate scenarios associated with the land-use scenarios for the year 2050. While the  
386 land-use-only scenarios can be considered 'optimistic' from a climatic adaptation  
387 perspective, with plant communities expected to respond to changes in land use but not  
388 climate (i.e. high climatic resilience), the land-use and climate change scenarios can be  
389 considered 'pessimistic', with plant communities considered unable to locally adapt to  
390 changing climatic conditions (i.e. low climatic resilience). Importantly, while the impact of  
391 land-use change is considered from the past to the future, the impact of climate change is  
392 considered only for the future. The inherent difficulty in measuring the impact of past climate  
393 change is the lack of data at a sufficiently resolved temporal resolution for the period 1900-

394 2015. In fact, while LUH2 land-use data are available on a yearly basis in the past and the  
395 future, Worldclim climatic data (used for the models intercomparison) are provided as  
396 average conditions registered (or predicted) during 2-3 decades in the present or the future.  
397 We thus associated the ‘current’ Worldclim dataset (representing the period 1960 to 1990) to  
398 the ‘present’ year from LUH2 (i.e. 2015), and the 2050 Worldclim dataset (representing the  
399 period 2040-2060) to the year 2050 in LUH2.

400         We report the past-to-future change in the persistence of plant communities relative to  
401 a baseline of continuous native vegetation, as the proportion of originally present species  
402 expected to persist in the long term anywhere within their distribution range. In addition to  
403 the SSP-RCP scenarios of future persistence, we also report a spline interpolation of past  
404 trends into the future (for comparison). Following the SAR-based approach described above,  
405 we aggregate the grid cell results to report both global-scale and regional-scale trends in  
406 vascular plant persistence over time. At the global scale, we also report the absolute number  
407 of species committed to extinction at any time point, by combining the proportion of species  
408 expected to disappear (i.e.  $1 - P_{region}$ , from Eq. 5) with an estimate of the global number of  
409 extant vascular plant species ( $n = 368,050$ ; Chapman 2009). We applied the same global  
410 estimate of plant species number across all assessed years, to make the results comparable  
411 through time, using present-day estimate of plant species numbers. As already mentioned, our  
412 approach estimates the proportion of species expected to go extinct over the long term as a  
413 consequence of the conditions observed at a given time point, and this interpretation also  
414 applies to the estimate of the absolute number of species committed to extinction.

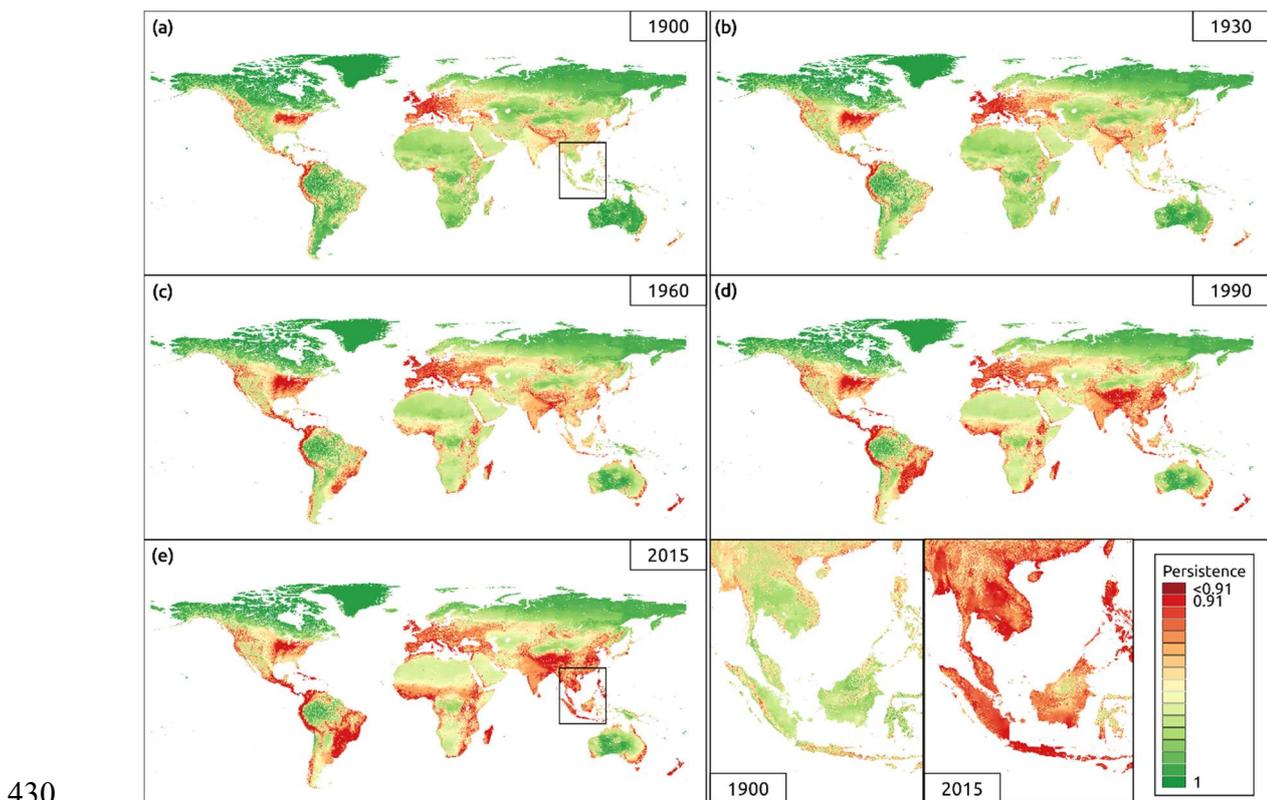
415

416

417

418 **Results**

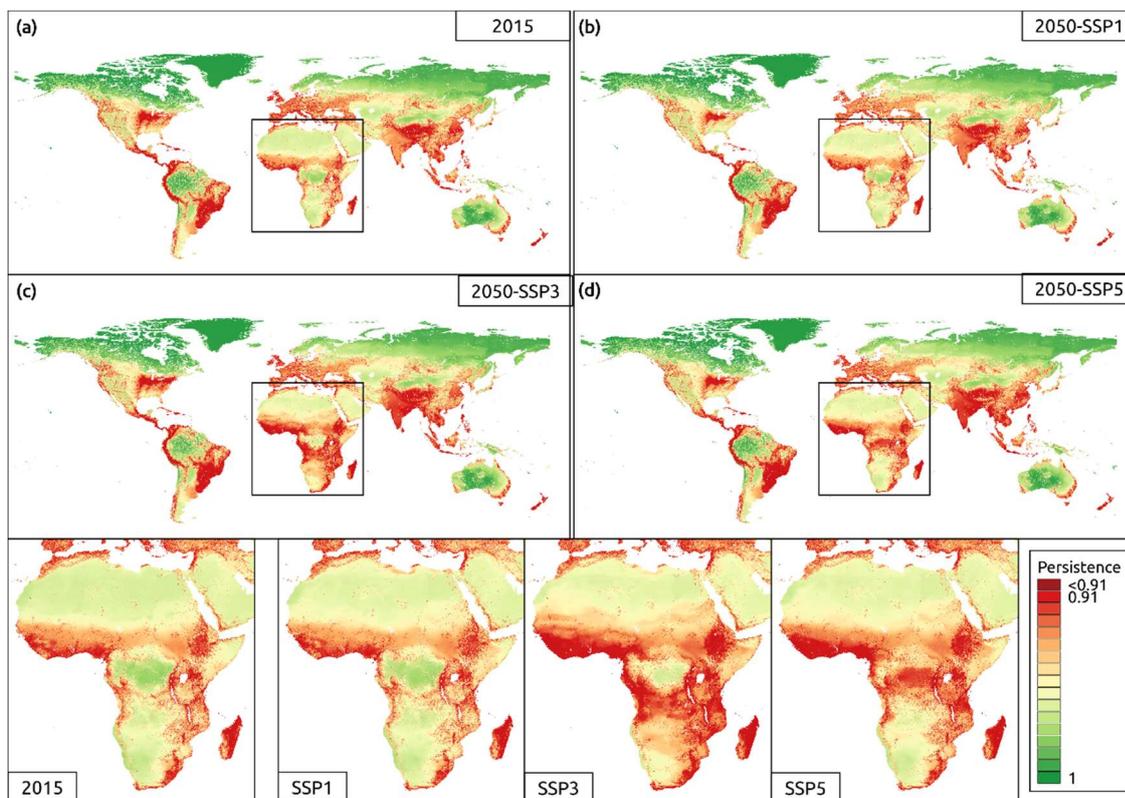
419 The estimated proportion of vascular plant species expected to persist over the long term has  
420 declined globally in the past century, from 97.27% in 1900 to 95.69% in 2015. This  
421 represents an increase in the number of projected species extinctions from 10,022 to 15,873  
422 over the course of the 20th century. Plant communities that suffered the highest reduction in  
423 persistence are found in tropical and subtropical areas (Fig. 2, Fig. S2), including Brazil, Sub-  
424 Saharan Africa, Central and Southeast Asia. Communities found at high latitudes, those in the  
425 Amazon, those around the Tibetan plateau, and those in central Australia have the highest  
426 proportion of species expected to persist in the long term. Communities found in Europe have  
427 suffered from low persistence values since the beginning of the study period. Significant  
428 recent declines (post-1990) have occurred in Africa, on the Guinean coast, and in Southeast  
429 Asia.



431 **Fig. 2** Past impact of land-use change on the persistence of vascular plant biodiversity, from  
432 1900 to present day. Maps represent the proportion of species originally associated with a  
433 given grid cell that are expected to persist anywhere within their range (over the long term).

434 Inset maps for Southeast Asia are represented at the bottom-right of the figure. The colour  
435 legend is the same for all panels.  
436

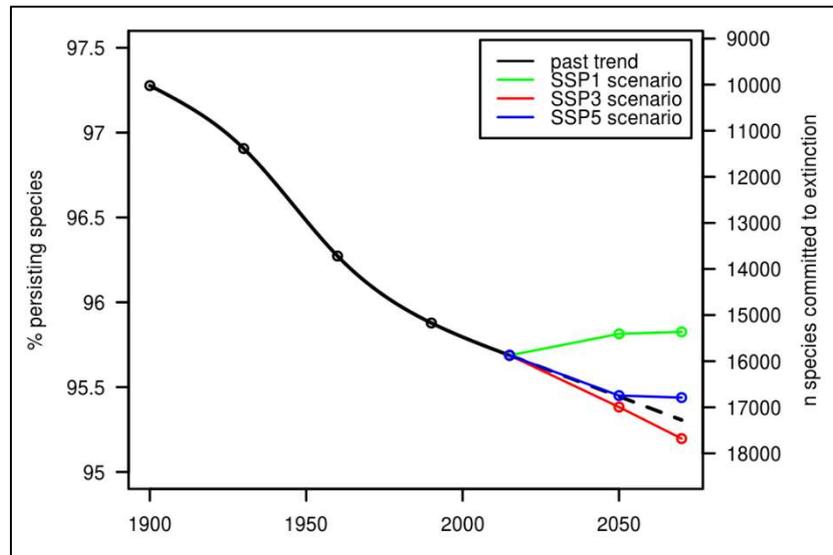
437 The rate of biodiversity decline observed in the past is projected to slow into the  
438 future under scenario SSP1 of sustainability, when accounting only for the impact of land-use  
439 change (Fig. 3, Fig. S3). Under this scenario, biodiversity persistence is expected to remain  
440 stable in most of Africa, Central and Southeast Asia, and South America, and to increase in  
441 Europe, Central America, and North America. The situation is inverted when looking at  
442 scenario SSP3 of regional rivalry, where the declining trend in species persistence is  
443 projected to continue globally. Under this scenario, plant biodiversity declines are expected to  
444 be especially high across Sub-Saharan Africa. Scenario SSP5 of fossil-fuelled development  
445 also shows continuing global declines, albeit not as dramatic as in scenario SSP3. Once again  
446 Sub-Saharan Africa exhibits the highest projected decline, but compared to SSP3 such  
447 decline is confined to the Central African region.



448  
449 **Fig. 3** Future impact of land-use change on the persistence of plant biodiversity in year 2050,  
450 under (b) an environmentally sustainable scenario (SSP1), (c) a scenario with intensification

451 of natural resources use (SSP3), and (d) a scenario of high-tech fossil-fuelled development  
452 (SSP5). Present-day persistence is reported as a reference (a). Inset maps for Africa are  
453 represented at the bottom of the figure. The colour legend is the same for all panels.  
454

455           When looking at the global trend in persistence of plant communities between 1900  
456 and 2070 (Fig. 4), the steepest decline was observed in the period 1930-1960 while declines  
457 slowed between 1990 and 2015. Scenario SSP1 shows improvements for the years 2050 and  
458 2070 compared to the present-day conditions, with a reduction in the number of species  
459 committed to extinction. The trend projected under scenario SSP5 exhibits a decline similar  
460 to what would be observed from a simple interpolation of past trends to year 2050; however,  
461 the trend improves during 2050-2070, with a higher persistence estimate to that expected  
462 from interpolation of past values. Scenario SSP3 has the most negative projections globally,  
463 which exceeds the decline projected under other SSP scenarios and also that interpolated  
464 from past trends. This scenario indicates an acceleration in global plant extinction rates  
465 compared to the current trajectory. Overall, the estimated number of species committed to  
466 extinction (which has increased by ~60% between 1900 and 2015) is projected to decrease to  
467 15,364 in 2070 under the most optimistic scenario SSP1 (i.e. 3% lower than in 2015). Instead,  
468 the number is projected to substantially increase under the most pessimistic scenario SSP3,  
469 with 17,680 species committed to extinction (+11.3% compared to 2015, +76% compared to  
470 1900).

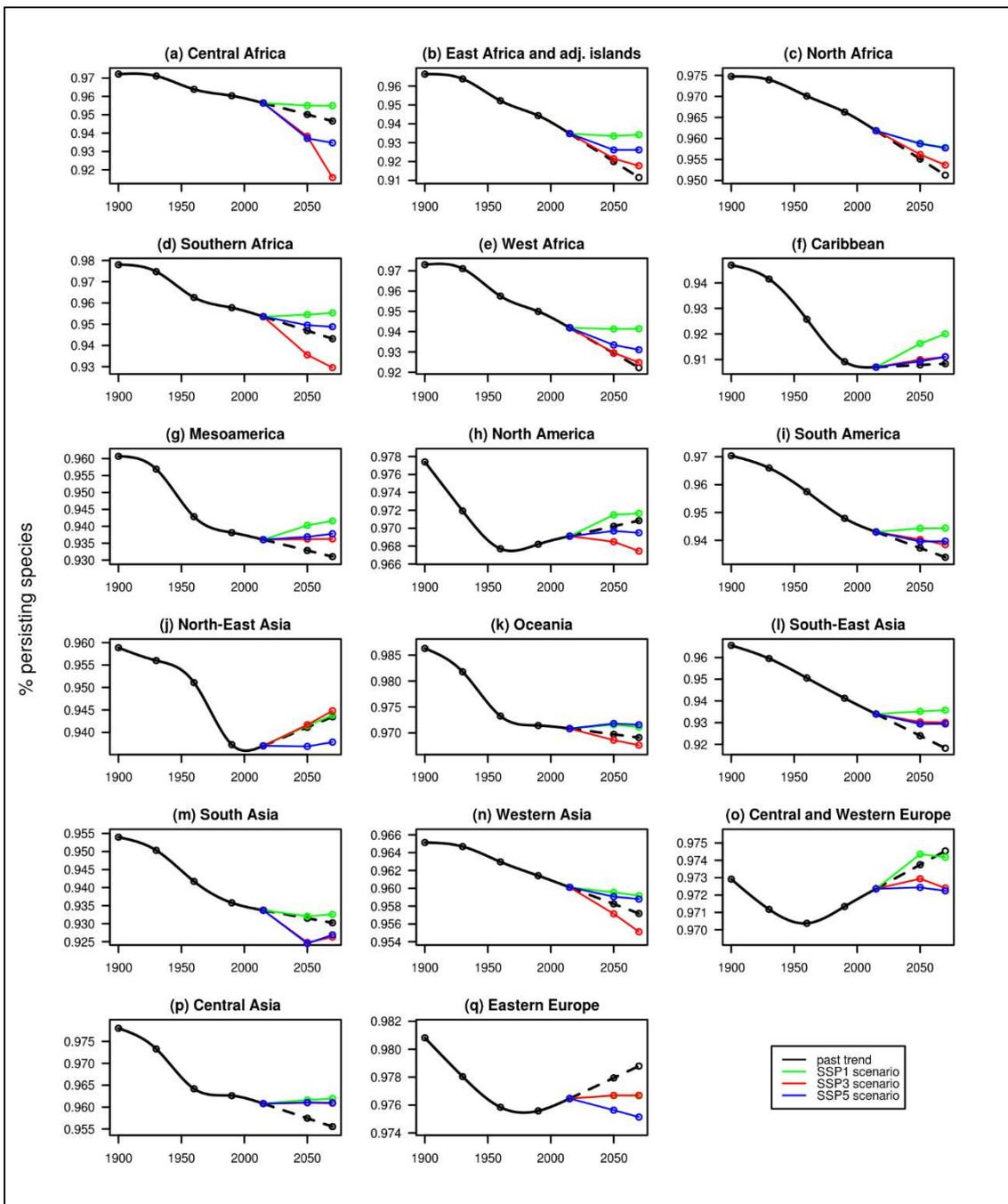


471

472 **Fig. 4** Trends in the global persistence of plant biodiversity in response to land-use change,  
 473 over the course of 170 years (1900 to 2070). The plot reports the percentage of species  
 474 expected to persist (left y-axis) and the number of projected species extinctions (right y-axis).  
 475 Future projections, for years 2050 and 2070, represent three alternative scenarios of land-use  
 476 change as described in the main text: environmental sustainability (SSP1), regional rivalry  
 477 (SSP3), fossil-fuelled development (SSP5). An interpolation of past trends (dashed line) is  
 478 also projected for comparison.  
 479

480 The estimates of regionally aggregated persistence values exhibit contrasting patterns  
 481 between the past and the future (Fig. 5). All African regions show continuing decline under  
 482 the most intensive scenarios, SSP3 and SSP5, with Central Africa showing the most alarming  
 483 future projections, which exceed the rate of past biodiversity decline. All scenarios show  
 484 improving trends of species persistence in Central and South America. North America shows  
 485 a stable trend under scenario SSP5 and a declining trend under scenario SSP3, which  
 486 contrasts with the expectation of improved biodiversity trends both under scenario SSP1 and  
 487 under an interpolation of past trends. Central and South East Asia show optimistic  
 488 projections, relative to the declining rates observed in the past. North-East Asia and Eastern  
 489 Europe are the only two regions where scenario SSP5 shows a higher projected decline than  
 490 scenario SSP3, with a steeper decline than that expected from interpolation of past values; in  
 491 all other regions, scenario SSP3 is associated with the highest projected decline. Scenario  
 492 SSP1 almost invariably shows the most optimistic biodiversity projections, and an

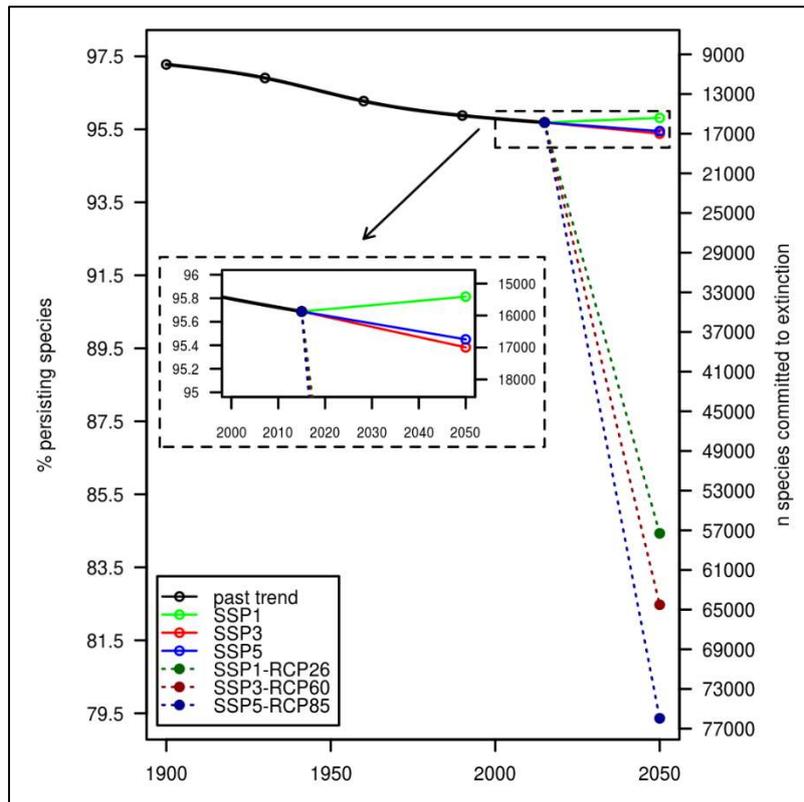
493 improvement in biodiversity persistence, both in relation to the present-day estimates and in  
 494 relation to past trends, with the only regional exception being Eastern Europe. Some regions  
 495 show stable or positive trends even under the most pessimistic scenario of land use (SSP3):  
 496 Caribbean, North-East Asia, Central and Western Europe, Eastern Europe, and Central Asia.  
 497 In all these regions, an overall increase in the coverage of natural vegetation is projected to  
 498 occur at the expenses of non-natural land uses.



499

500 **Fig. 5** Trends in the regional persistence of plant biodiversity in response to land-use change,  
501 over the course of 170 years (1900 to 2070). The plot reports the percentage of species  
502 expected to persist in each region. Future projections, for years 2050 and 2070, represent  
503 three alternative scenarios of land-use change as described in the main text: environmental  
504 sustainability (SSP1), regional rivalry (SSP3), fossil-fuelled development (SSP5). An  
505 interpolation of past trends (dashed line) is also projected for comparison. Note that the scale  
506 of y-axis is different between plots (to improve readability and to highlight intra-regional  
507 differences between scenarios).  
508

509           Climate change has the potential to dramatically exacerbate the impact of land-use  
510 change on global biodiversity persistence (Fig. 6), in the absence of climatic adaptation. We  
511 found a much higher decline in future biodiversity persistence under all scenarios, when the  
512 impact of climate change was combined with that of land-use change. In these cases, scenario  
513 SSP5-RCP8.5 of fossil fuel development, which is associated with the highest level of  
514 greenhouse-gas emissions, caused the steepest decline in projected species persistence,  
515 surpassing both scenario SSP3-RCP6.0 (intermediate emissions) and SSP1-RCP2.6 (low  
516 emissions). The number of projected species extinctions under these climatic projections is  
517 between 57,308 (under SSP1-RCP2.6) and 75,961 (under SSP5-RCP8.5), which is 3.7-4.5  
518 times higher than the number of extinctions predicted under land-use change alone. While  
519 these results represent a low-resilience case, where plant communities are considered unable  
520 to locally adapt to new climatic conditions, they point to the potentially magnifying impact  
521 that climate change has on plant extinction risk globally.

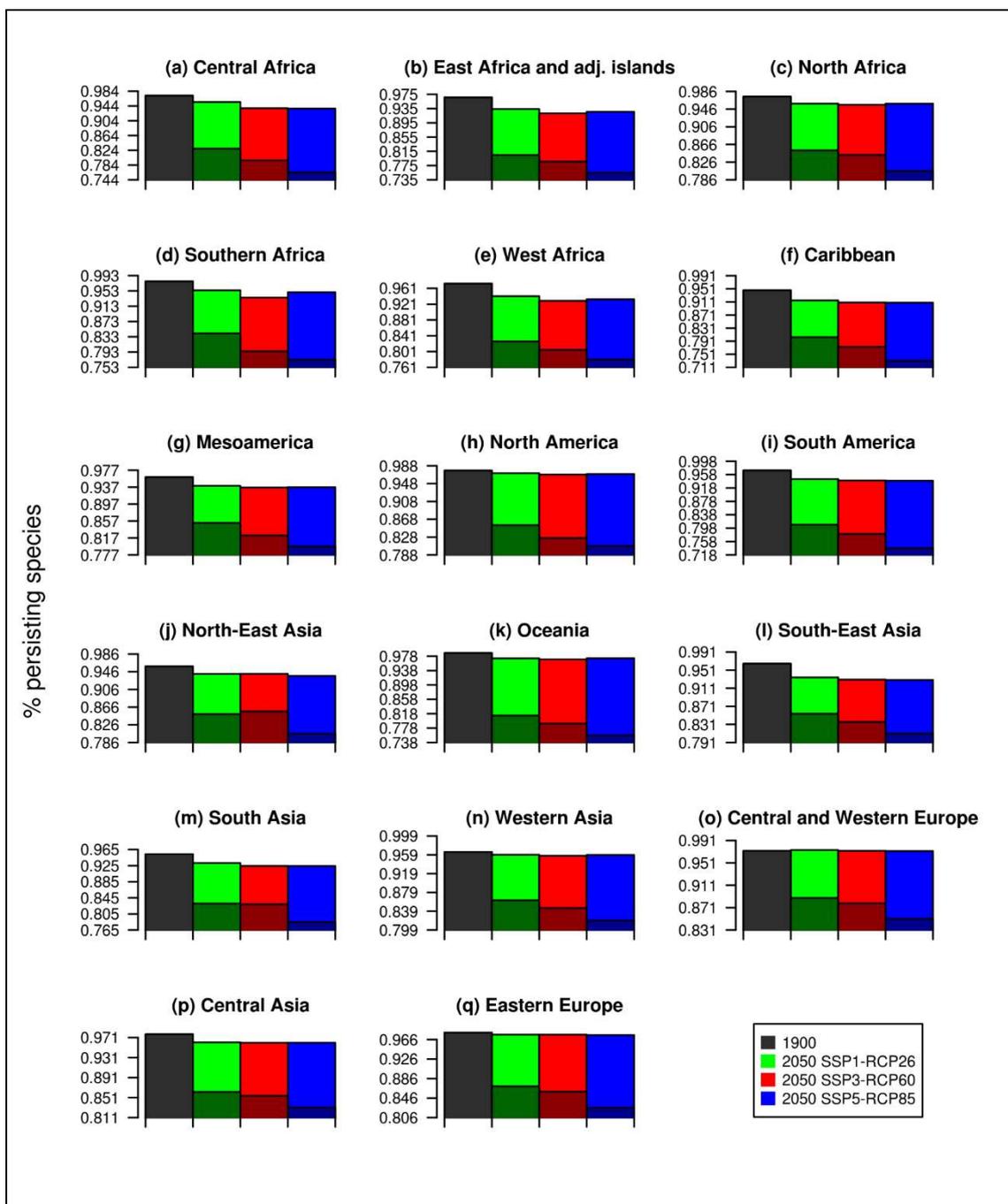


522

523 **Fig. 6** Trends in the global persistence of plant biodiversity in response to land-use and  
 524 climate change. The plot reports the percentage of species expected to persist (left y-axis) and  
 525 the number of projected species extinctions (right y-axis). Future projections represent two  
 526 versions of the three socio-economic scenarios described in Fig. 4, one version accounts only  
 527 for the impact of land-use change on biodiversity (solid coloured lines), while the other  
 528 version also accounts for the impact of climate change (dashed coloured lines). The inset  
 529 reports a larger plot of future trends under land-use only scenarios.  
 530

531 The effect of climate change is expected to be ubiquitous, with impacts across all  
 532 regions (Fig. 7). Even regions where land-use change is not expected to generate further loss  
 533 in biodiversity persistence, such as Western Asia and Europe, are predicted to experience  
 534 biodiversity declines from the impact of climate change. Similar to the global results,  
 535 scenario SSP5-RCP8.5 shows the highest drop in persistence for regional plant biodiversity.  
 536 This confirms the contrasting patterns exhibited under scenario SSP5 in relation to SSP3,  
 537 with or without considering climate change effects. When considering only the impact of  
 538 land-use change, scenario SSP5 is associated with a slightly more optimistic biodiversity  
 539 trend compared to scenario SSP3. However, when including the potential impact of climate

540 change, scenario SSP5-RCP8.5 is by far the worst for plant biodiversity, with an extra 11,454  
 541 projected extinctions compared to SSP3-RCP6.0 in year 2050. Scenario SSP1-RCP2.6  
 542 remains the most optimistic at a regional scale, confirming global results, with the exception  
 543 of two Asian regions (North-East and South) where it showed similar biodiversity impacts to  
 544 scenario SSP3-RCP6.0.  
 545



546

547 **Fig. 7** Combined effect of land-use change and climate change on the persistence of vascular  
548 plant biodiversity within each IPBES region in year 2050. The bars report the estimated  
549 persistence of plant biodiversity in response to land-use change, and in response to the  
550 combination of land-use and climate change impact. In each plot the dark-grey bars report the  
551 persistence value in year 1900 (as a reference), while coloured bars report the persistence  
552 values under different scenarios. For each scenario, the persistence under land-use change is  
553 represented by the bright coloured part of the bar, while the persistence under climate and  
554 land-use change is reported by the dark coloured part of the bar.  
555

556

557

## 558 **Discussion**

559 Our study shows that vascular plant biodiversity has undergone a global decline over the past  
560 century, with thousands of species potentially committed to extinction, and this decline will  
561 likely accelerate in the future unless both land-use change and climate change are minimised.  
562 Scenarios in which future socio-economic development relies on intensive use of resources  
563 are projected to lead to biodiversity loss at rates that are similar (SSP5) or worse (SSP3) than  
564 those observed over the past century. On the other hand, scenarios of sustainable  
565 development based on a green economy with reduced consumptions (SSP1) offer the  
566 potential to revert land-use-driven decline of plant biodiversity to pre-2000 levels if  
567 considered in isolation of climate change. This suggests that achieving socio-economic  
568 development goals and biodiversity conservation goals is possible, in principle, if further  
569 conversion of natural habitats is averted and if climate change is prevented. Alarming,ly,  
570 however, the impact of climate change might largely surpass that of land-use change under  
571 all scenarios, suggesting substantial global declines in plant biodiversity. The risk is that  
572 climate change will become the predominant driver of biodiversity decline in coming years,  
573 with impacts that far exceed those observed from land-use-driven habitat loss over the past  
574 century.

575           The synergistic effect that land-use and climate change exert on biodiversity can be  
576 dramatic (Mantyka-Pringle et al., 2015; Visconti et al., 2016). As such, the evaluation of  
577 environmental impacts from socio-economic development must account for both the local  
578 effects of land-use change and the global effects of climate change, or risk underestimating  
579 the response of biodiversity to one or both of these pressures (Titeux et al., 2016). Pursuing  
580 resource-intensive development, where local-scale impacts are mitigated through the use of  
581 technological solutions (as in SSP5; Kriegler et al., 2017), might be largely insufficient to  
582 avert plant biodiversity decline under rapid climate change (as in RCP8.5). Adopting  
583 technological innovation and societal change to reduce resources use and associated  
584 emissions, as in SSP1 (van Vuuren et al., 2017), leads to global improvement in habitat  
585 conditions and overall to the most optimistic biodiversity response. However this might be  
586 insufficient to prevent climate-driven biodiversity decline even under the lowest radiative  
587 forcing pathway (RCP 2.6), as this is still associated with an ~2 °C increase in global mean  
588 temperature by 2050 (van Vuuren, Stehfest, et al., 2011). While each SSP scenario can  
589 potentially result in different levels of climatic emission, the specific SSP-RCP associations  
590 selected as part of the model intercomparison exercise allowed us to represent a broad range  
591 of potential biodiversity impacts (HyeJin Kim et al., 2018).

592           Regional trends in plant species persistence tend to follow the global trend overall, but  
593 there are regions where land-use projections are more optimistic than elsewhere. Within  
594 several regions of Asia, especially South-East, the historically steep declines in biodiversity  
595 are expected to slow or even reverse. The unique biodiversity of this region has faced  
596 multiple significant threats in the recent past (Sodhi, Koh, Brook, & Ng, 2004), and future  
597 projections show that, with concerted effort under multiple possible scenarios, it is possible to  
598 reduce the biodiversity impact from land-use change (one of the major operating threats). In  
599 parallel, Central and Western Europe showed a recent improvement in plant biodiversity

600 persistence driven by land use, despite an overall global decline. This is related to the  
601 reduction in the extent of agricultural production (both crops and livestock) and the  
602 progressive abandonment of rural areas in the second half of the 20th century (Navarro &  
603 Pereira, 2012), which led to (passive and active) habitat restoration with broad benefits to  
604 biodiversity (Chapron et al., 2014). This positive regional trend is projected to further  
605 increase (SSP1) or at least stabilise (SSP3 and SSP5) in the future, in contrast to the global-  
606 scale trend.

607         Other regions show an opposite condition, with future declines expected to exceed  
608 global-scale trends and largely surpass past declines. In particular, biodiversity declines are  
609 projected to accelerate in the central (SSP3 and SSP5) and southern (SSP3) part of Africa,  
610 which place these regions at the forefront of global risk for plant biodiversity. Some of the  
611 highest levels of forest plant endemism in Africa are found in the central part of the continent  
612 (Sosef et al., 2017), while the southern part has some of the highest concentrations of rare  
613 plant species in the world (Cowling & Hilton Taylor, 1994); both Central and Southern  
614 Africa have long been recognised as global biodiversity hotspots (Myers, Mittermeier,  
615 Mittermeier, da Fonseca, & Kent, 2000). Land-use change predicted in these regions, under  
616 resource-intensive development scenarios, could drive enormous losses for global plant  
617 biodiversity. Our estimates of the proportion of species expected to persist in the long term is  
618 independent of the total number of species living in a region. At a global scale we were able  
619 to associate such proportion to an absolute number of species, but this was not possible at a  
620 regional scale due to lack of regional richness estimates. Combining biome-level estimates of  
621 species richness with estimates of persistence probability (derived independently for each  
622 biome-realm) would probably further highlight biomes with high predicted biodiversity loss  
623 and high richness.

624 Our approach is able to project the local and global risk of species loss for an entire  
625 group of species, reporting the expected change in total species numbers ( $\gamma$ -diversity). This  
626 offers the advantage of estimating not only the local impact of environmental change, but  
627 also how this affects the collective biodiversity of a region (and the globe). Our estimates of  
628 the impact of land-use change on plant biodiversity are in broad agreement with those for  
629 vertebrate biodiversity based on a different SAR-based approach (Chaudhary & Mooers,  
630 2018). In both cases, scenario SSP1 projects an improvement in biodiversity persistence to  
631 year 2050, compared to present day (i.e. a reduction in the number of species committed to  
632 extinction), while SSP3 and SSP5 show higher species decline in year 2050. Our results,  
633 however, suggest a much higher impact under climate and land-use change than under land-  
634 use change alone. This is not surprising given the magnitude of the projected climatic change  
635 (between 2°C and 4°C increase in global mean temperature, depending on the scenario),  
636 relative to the magnitude of projected land-use change (up to 2% increase in global coverage  
637 of non-natural lands under the most pessimistic scenario). Again, this pattern is broadly in  
638 agreement with predictions of the change in local vertebrate species richness (Newbold,  
639 2018), where land-use-only predictions showed overall stable or improving future trends  
640 (under all but the most pessimistic scenario) while climate scenarios showed steep declines.

641 SAR-based estimates of extinction risk typically assume that habitat loss is distributed  
642 randomly relative to the distribution of species in a region, which is often not the case. Our  
643 approach, based on compositional dissimilarity and local habitat conditions, overcomes this  
644 issue allowing extinction to be estimated as a function of the spatial location of habitat loss.  
645 Our estimates however rely heavily on model-based prediction and inference (Ferrier et al.,  
646 2007; Hoskins et al., 2019), in order to deal with the largely incomplete information on the  
647 global distribution of vascular plant species. Some important caveats therefore apply to the  
648 interpretation of our results. First, all our results refer to long-term probability of species

649 persistence and extinction, and we are unable to predict precisely how long it will take for  
650 these impacts to be realised (i.e. for species to disappear). Second, our estimates of climate  
651 change impact imply plant communities do not adapt to changing local conditions. This  
652 caveat applies to biodiversity models in general (not just those based on compositional  
653 dissimilarity), because bioclimatic envelopes are fit to present-day climate conditions where  
654 species are found, even if these conditions are typically a subset of those that can be tolerated  
655 by the species (Bush et al., 2018). As described in the Methods, a conservative interpretation  
656 of our results is that land-use only scenarios assume plant communities to have high local  
657 resilience to changing climate, while land-use and climate scenarios assume low resilience.

658 GDM models were shown to have high concordance with actual patterns of spatial  
659 variation in biological composition in Australia (Ware et al., 2018), reinforcing the test done  
660 by Elith et al. (2006), on six study regions, demonstrating that GDM-based modelling  
661 achieved similar predictive performance to MaxEnt (and higher than most other tested  
662 techniques). GDMs were also shown to produce reliable estimates of the effect of climate  
663 change on North American biodiversity (Blois et al., 2013), allowing to project compositional  
664 turnover in novel climates (Fitzpatrick et al., 2011). Yet further work (based on independent  
665 datasets) is needed to refine and validate global-scale GDM projections, to complement  
666 existing regional tests like the ones described above. Future priorities for the improvement of  
667 SAR-based approaches built on compositional turnover modelling include higher ecological  
668 accuracy in the predictions of climate change impact on biological communities, estimating  
669 species persistence in a way that accounts for the potential of local-scale adaptation.  
670 Additionally, our estimates of biodiversity persistence rely on methods and data to predict the  
671 local biodiversity effect of habitat conditions, and updated estimates of persistence will be  
672 possible as new and more refined data become available. These uncertainties affect our

673 absolute estimates of extinction risk levels, but factors leading to them operate in the same  
674 way across all scenarios, which makes our projections comparable with each other.

675         Anticipating future biodiversity trends under alternative scenarios of socio-economic  
676 development, in the context of past trends, is necessary to inform global environmental  
677 policy. Despite inherent uncertainty in global-scale scenario modelling, our analysis suggests  
678 tens of thousands of plant species might be lost due to global change driven by socio-  
679 economic development. Crucially, our analysis underscores the need to jointly consider the  
680 effects of land-use and climate change in identifying biodiversity impacts. Reconciling  
681 biodiversity conservation goals and socio-economic development goals might be possible  
682 (United Nations General Assembly, 2015), but this will require that further conversion of  
683 natural habitats is prevented and climate conditions are stabilised to pre-industrial levels.

684

685

686

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693 **References**

- 694 Allnutt, T. F., Ferrier, S., Manion, G., Powell, G. V. N., Ricketts, T. H., Fisher, B. L., ...  
695 Rakotondrainibe, F. (2008). A method for quantifying biodiversity loss and its  
696 application to a 50-year record of deforestation across Madagascar. *Conservation*  
697 *Letters*, 1(August), 173–181.
- 698 Bar-On, Y. M., Phillips, R., & Milo, R. (2018). The biomass distribution on Earth.  
699 *Proceedings of the National Academy of Sciences*, doi 10.1073/pnas.1711842115
- 700 Blois, J. L., Williams, J. W., Fitzpatrick, M. C., Jackson, S. T., & Ferrier, S. (2013). Space  
701 can substitute for time in predicting climate-change effects on biodiversity.  
702 *Proceedings of the National Academy of Sciences*, 110(23), 9374–9379.
- 703 Brooks, T. M., Mittermeier, R. A., da Fonseca, G. A. B., Gerlach, J., Hoffmann, M.,  
704 Lamoreux, J. F., ... Rodrigues, A. S. L. (2006). Global Biodiversity Conservation  
705 Priorities. *Science*, 313(5783), 58–61.
- 706 Brooks, T. M., Mittermeier, R. A., Mittermeier, C. G., da Fonseca, G. a. B., Rylands, A. B.,  
707 Konstant, W. R., ... Hilton-Taylor, C. (2002). Habitat Loss and Extinction in the  
708 Hotspots of Biodiversity. *Conservation Biology*, 16(4), 909–923.
- 709 Bush, A., Catullo, R. A., Mokany, K., Thornhill, A. H., Miller, J. T., & Ferrier, S. (2018).  
710 Truncation of thermal tolerance niches among Australian plants. *Global Ecology and*  
711 *Biogeography*, 27(1), 22–31.
- 712 Butchart, S. H. M., Walpole, M., Collen, B., van Strien, A., Scharlemann, J. P. W., Almond,  
713 R. E. a, ... Watson, R. (2010). Global Biodiversity: Indicators of Recent Declines.  
714 *Science*, 328, 1164–1168.

715 Cardinale, B. J., Duffy, J. E., Gonzalez, A., Hooper, D. U., Perrings, C., Venail, P., ...  
716 Naeem, S. (2012). Biodiversity loss and its impact on humanity. *Nature*, 486(7401),  
717 59–67.

718 CBD. (2010). Conference of the Parties 10 Decision X/2. Strategic Plan for Biodiversity  
719 2011-2020.

720 Ceballos, G., Ehrlich, P. R., & Dirzo, R. (2017). Biological annihilation via the ongoing sixth  
721 mass extinction signaled by vertebrate population losses and declines. *Proceedings of*  
722 *the National Academy of Sciences*, doi 10.1073/pnas.1704949114

723 Chapman, A. D. (2009). *Numbers of Living Species in Australia and the World*. Canberra,  
724 Australia.

725 Chapron, G., Kaczensky, P., Linnell, J. D. C., von Arx, M., Huber, D., Andrén, H., ...  
726 Adamec, M. (2014). Recovery of large carnivores in Europe ' s modern human-  
727 dominated landscapes. *Science*, 346(6215), 17–20.

728 Chaudhary, A., & Mooers, A. (2018). Terrestrial Vertebrate Biodiversity Loss under Future  
729 Global Land Use Change Scenarios. *Sustainability*, 10(8), 2764.

730 Cowling, R. M., & Hilton Taylor, C. (1994). Patterns of plant diversity and endemism in  
731 southern Africa: an overview. *Botanical Diversity in Southern Africa*. (Strelitzia, 1,  
732 31–52).

733 De Vos, J. M., Joppa, L. N., Gittleman, J. L., Stephens, P. R., & Pimm, S. L. (2015).  
734 Estimating the normal background rate of species extinction. *Conservation Biology*,  
735 29(2), 452–462.

736 Di Marco, M., Chapman, S., Althor, G., Kearney, S., Besancon, C., Butt, N., ... Watson, J. E.  
737 M. (2017). Changing trends and persisting biases in three decades of conservation  
738 science. *Global Ecology and Conservation*, 10, 32–42.

739 Di Marco, M., Venter, O., Possingham, H. P., & Watson, J. E. M. (2018). Changes in human  
740 footprint drive changes in species extinction risk. *Nature Communications*, 9, 4621.

741 Di Marco, M., Watson, J. E. M., Venter, O., & Possingham, H. (2016). Global biodiversity  
742 targets requires both sufficiency and efficiency. *Conservatio Letters*, 9(6), 395–397.

743 Díaz, S., Pascual, U., Stenseke, M., Martín-López, B., Watson, R. T., Molnár, Z., Shirayama,  
744 Y. (2018). Assessing nature’s contributions to people. *Science*, 359(6373), 270–272.

745 DiMiceli, C. M., Carroll, M. L., Sohlberg, R. A., Huang, C., Hansen, M. C., Townshend, J.  
746 R. G. (2011). Annual global automated MODIS vegetation continuous fields  
747 (MOD44B) at 250 m spatial resolution for data years beginning day 65, 2000–2010,  
748 collection 5 percent tree cover. University of Maryland, College Park, MD, USA.

749 Dirzo, R., Young, H. S., Galetti, M., Ceballos, G., Isaac, N. J. B., & Collen, B. (2014).  
750 Defaunation in the Anthropocene. *Science*, 345(6195), 401–406.

751 Elith, J., Graham, C. H., Anderson, R. P., Dudík, M., Ferrier, S., Guisan, A., ...,  
752 Zimmermann, N. E. (2006) Novel methods improve prediction of species’  
753 distributions from occurrence data. *Ecography*, 29, 129–151.

754 European Commission, J., & Columbia University, C. (2015). GHS Population Grid, derived  
755 from GPW4, Multitemporal (1975, 1990, 2000, 2015). Retrieved from  
756 [http://data.europa.eu/89h/jrc-ghsl-ghs\\_pop\\_gpw4\\_globe\\_r2015a](http://data.europa.eu/89h/jrc-ghsl-ghs_pop_gpw4_globe_r2015a)

757 Ferrier, S., Manion, G., Elith, J., & Richardson, K. (2007). Using generalized dissimilarity  
758 modelling to analyse and predict patterns of beta diversity in regional biodiversity  
759 assessment. *Diversity and Distributions*, 13(3), 252–264.

760 Ferrier, S., Powell, G. V. N., Richardson, K. S., Manion, G., Overton, J. M., Allnutt, F., ...  
761 Daniel, P. (2004). Mapping More of Terrestrial Biodiversity for Global Conservation  
762 Assessment. *BioScience*, 54(12), 1101–1109.

763 Fujimori, S., Hasegawa, T., Masui, T., Takahashi, K., Herran, D. S., Dai, H., ... Kainuma, M.  
764 (2017). SSP3: AIM implementation of Shared Socioeconomic Pathways. *Global*  
765 *Environmental Change*, 42, 268–283.

766 Harfoot, M., Tittensor, D. P., Newbold, T., Mcinerny, G., Smith, M. J., Scharlemann, J. P.W.  
767 (2014) Integrated assessment models for ecologists: The present and the future.  
768 *Global Ecology and Biogeography*, 23, 124–143.

769 Hill, S. L. L., Gonzalez, R., Sanchez-ortiz, K., Caton, E., Espinoza, F., Tylianakis, J., ...  
770 Purvis, A. (2018). Worldwide impacts of past and projected future land-use change on  
771 local species richness and the Biodiversity Intactness Index. *bioRxiv*,  
772 <http://dx.doi.org/10.1101/311787>.

773 Hoskins, A. J., Bush, A., Gilmore, J., Harwood, T., Hudson, L. N., Ware, C., ... Ferrier, S.  
774 (2016). Downscaling land-use data to provide global 30" estimates of five land-use  
775 classes. *Ecology and Evolution*, 6(9), 3040–3055.

776 Hoskins, A. J., Harwood, T. D., Ware, C., Williams, K. J., Perry, J. J., Ota, N., ... Ferrier, S.  
777 (2019). Supporting global biodiversity assessment through high-resolution  
778 macroecological modelling: Methodological underpinnings of the BILBI framework.  
779 *BioRxiv*. <https://doi.org/10.1101/309377>

780 Hudson, L. N., Newbold, T., Contu, S., Hill, S. L. L., Lysenko, I., De Palma, A., ... Purvis,  
781 A. (2017). The database of the PREDICTS (Projecting Responses of Ecological  
782 Diversity In Changing Terrestrial Systems) project. *Ecology and Evolution*, 7(1),  
783 145–188.

784 Hurtt, G., Chini, L., Sahajpal, R., Frohling, S., Calvin, K., Fujimori, S., ... others. (2016).  
785 Harmonization of global land-use change and management for the period 850--2100.  
786 *Geoscientific Model Development*.

787 IUCN. (2018). The IUCN Red List of Threatened Species. Version 2018-1. Retrieved July 5,  
788 2018, from <http://www.iucnredlist.org>

789 Johnson, C. N., Balmford, A., Brook, B. W., Buettel, J. C., Galetti, M., Guangchun, L., &  
790 Wilmshurst, J. M. (2017). Biodiversity losses and conservation responses in the  
791 Anthropocene. *Science*, 356(6335).

792 Kim, H., Rosa, I. M. D., Alkemade, R., Leadley, P., Hurtt, G., Popp, A., & Van, D. P. (2018).  
793 A protocol for an intercomparison of biodiversity and ecosystem services models  
794 using harmonized land-use and climate scenarios. *Geoscientific Model Development*,  
795 11, 4537–4562

796 Kriegler, E., Bauer, N., Popp, A., Humpenöder, F., Leimbach, M., Strefler, J., ... Edenhofer,  
797 O. (2017). Fossil-fueled development (SSP5): An energy and resource intensive  
798 scenario for the 21st century. *Global Environmental Change*, 42, 297–315.

799 Lawrence, D. M., Hurtt, G. C., Arneth, A., Brovkin, V., Calvin, K. V., Jones, A. D., ...  
800 Shevliakova, E. (2016). The Land Use Model Intercomparison Project (LUMIP)  
801 contribution to CMIP6: Rationale and experimental design. *Geoscientific Model*  
802 *Development*, 9(9), 2973–2998.

803 Mace, G. M. (2014). Whose conservation? Changes in the perception and goals of nature  
804 conservation require a solid scientific basis. *Science*, 245(6204), 1558–1560.

805 Mantyka-Pringle, C. S., Martin, T. G., & Rhodes, J. R. (2012). Interactions between climate  
806 and habitat loss effects on biodiversity: a systematic review and meta-analysis. *Global*  
807 *Change Biology*, 18, 1239-1252

808 Mantyka-Pringle, C. S., Visconti, P., Di Marco, M., Martin, T. G., Rondinini, C., & Rhodes,  
809 J. R. (2015). Climate change modifies risk of global biodiversity loss due to land-  
810 cover change. *Biological Conservation*, 187, 103-111.

811 Maxwell, S. L., Fuller, R. a., Brooks, T. M., & Watson, J. E. M. (2016). The ravages of guns,  
812 nets and bulldozers. *Nature*, 536, 146–145.

813 Myers, N., Mittermeier, R. a, Mittermeier, C. G., da Fonseca, G. a, & Kent, J. (2000).  
814 Biodiversity hotspots for conservation priorities. *Nature*, 403(6772), 853–858.

815 Navarro, L. M., & Pereira, H. M. (2012). Rewilding abandoned landscapes in Europe.  
816 *Ecosystems*, 15, 900–912..

817 Newbold, T. (2018). Future effects of climate and land-use change on terrestrial vertebrate  
818 community diversity under different scenarios. *Proceedings of the Royal Society B*,  
819 doi 10.1098/rspb.2018.0792.

820 Newbold, T., Hudson, L. N., Arnell, A. P., Contu, S., Palma, A. D., Ferrier, S., ... Zhang, H.  
821 (2016). Has land use pushed terrestrial biodiversity beyond the planetary boundary? A  
822 global assessment. *Science*, 353, 288–291.

823 O’Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., ...  
824 Solecki, W. (2017). The roads ahead: Narratives for shared socioeconomic pathways  
825 describing world futures in the 21st century. *Global Environmental Change*, 42, 169–  
826 180.

827 O’Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., ... van Vuuren,  
828 D. P. (2014). A new scenario framework for climate change research: The concept of  
829 shared socioeconomic pathways. *Climatic Change*, 122(3), 387–400.

830 Olson, D. M., Dinerstein, E., Wikramanayake, E. D., Burgess, N. D., Powell, G. V. N.,  
831 Underwood, E. C., ... Morrison, J. C. (2001). Terrestrial ecoregions of the world: a  
832 new map of life on earth. *BioScience*, 51(11), 933–938.

833 Pereira, H. M., & Daily, G. C. (2006). Modelling Biodiversity Dynamics in countryside  
834 Landscapes. *Ecology*, 87(8), 1877–1885.

835 Pereira, H. M., Leadley, P. W., Proença, V., Alkemade, R., Scharlemann, J. P. W.,  
836 Fernandez-Manjarrés, J. F., ... Walpole, M. (2010). Scenarios for global biodiversity  
837 in the 21st century. *Science*, 330(6010), 1496–501.

838 Pesaresi, M., Ehrlich, D., Florczyk, A. J., Freire, S., Julea, A., Kemper, T., ... Syrris, V.  
839 (2015). GHS built-up grid, derived from Landsat, multitemporal (1975, 1990, 2000,  
840 2014). European Commission, Joint Research Centre, JRC Data Catalogue.

841 Pimm, S. L., & Askins, R. A. (1995). Forest losses predict bird extinctions in eastern North  
842 America. *PNAS*, 92, 9343–9347.

843 Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., ... Vuuren, D. P.  
844 va. (2017). Land-use futures in the shared socio-economic pathways. *Global  
845 Environmental Change*, 42, 331–345.

846 Rosa, I. M. D., Pereira, H. M., Ferrier, S., Alkemade, R., Acosta, L. A., Akcakaya, H. R., ...  
847 Van Vuuren, D. (2017). Multiscale scenarios for nature futures. *Nature Ecology and  
848 Evolution*, 1(10), 1416–1419.

849 Scheffers, B. R., DeMeester, L., Bridge, T. C. L., Hoffmann, A. a., Pandolfi, J. M., Corlett, R.  
850 ., ... Watson, J. E. M. (2016). The broad footprint of climate change from genes to  
851 biomes to people. *Science*, 354(6313), aaf7671.

852 Sodhi, N. S., Koh, L. P., Brook, B. W., & Ng, P. K. L. (2004). Southeast Asian biodiversity:  
853 an impending disaster. *Trends in Ecology & Evolution*, 19(12), 654–60.

854 Sosef, M. S. M., Dauby, G., Blach-Overgaard, A., van der Burgt, X., Catarino, L., Damen, T.,  
855 ... Couvreur, T. L. P. (2017). Exploring the floristic diversity of tropical Africa. *BMC  
856 Biology*, 15(1), 15.

857 Titeux, N., Henle, K., Mihoub, J. B., Regos, A., Geijzendorffer, I. R., Cramer, W., ...  
858 Brotons, L. (2016). Biodiversity scenarios neglect future land-use changes. *Global*  
859 *Change Biology*, 22(7), 2505–2515.

860 Tittensor, D. P., Walpole, M., Hill, S. L. L., Boyce, D. G., Britten, G. L., Burgess, N. D., ...  
861 Ye, Y. (2014). A mid-term analysis of progress toward international biodiversity  
862 targets. *Science*, 346, 241–244.

863 United Nations General Assembly. (2015). Transforming our world: the 2030 Agenda for  
864 Sustainable Development.

865 van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., ... Rose,  
866 S. K. (2011). The representative concentration pathways: An overview. *Climatic*  
867 *Change*, 109(1), 5–31.

868 van Vuuren, D. P., Stehfest, E., den Elzen, M. G. J., Kram, T., van Vliet, J., Deetman, S., ...  
869 van Ruijven, B. (2011). RCP2.6: Exploring the possibility to keep global mean  
870 temperature increase below 2°C. *Climatic Change*, 109(1), 95–116.

871 van Vuuren, D. P., Stehfest, E., Gernaat, D. E. H. J., Doelman, J. C., van den Berg, M.,  
872 Harmsen, M., ... Tabeau, A. (2017). Energy, land-use and greenhouse gas emissions  
873 trajectories under a green growth paradigm. *Global Environmental Change*, 42, 237–  
874 250.

875 Visconti, P., Bakkenes, M., Baisero, D., Brooks, T., Butchart, S. H. M., Joppa, L., ...  
876 Rondinini, C. (2016). Projecting Global Biodiversity Indicators under Future  
877 Development Scenarios. *Conservation Letters*, 9(1), 5-13.

878 Ware, C., Williams, K. J., Harding, J., Hawkins, B., Harwood, T., Manion, G., ... Ferrier, S.  
879 (2018). Improving biodiversity surrogates for conservation assessment: A test of

880 methods and the value of targeted biological surveys. *Diversity and Distributions*, doi  
881 10.1111/ddi.12766.

882

883 **Supporting information**

884

885 **Figure S1** Diagram of the hierarchical structure used to solve the 12 class constrained  
886 optimisation problem when creating the new fine-grained land-use dataset.

887

888 **Figure S2** Relative decline in biodiversity persistence over the course of the 20th century.

889

890 **Figure S3** Relative decline in biodiversity persistence projected to year 2050, under  
891 alternative land-use scenarios.

892

893 **Table S1** Coefficient of conversion of land-use categories into habitat condition values.

894