1 2	Title: Proactive Policies Could Prevent Biodiversity Habitat Losses to Agricultural Expansion
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20	The projected loss of millions of square kilometres of natural ecosystems to meet future
21	demand for food, animal feed, fibre, and bioenergy crops could massively escalate threats to
22	biodiversity. Preventing this requires a detailed knowledge of how and where such threats are
23	likely to be greatest. We developed a flexible approach to modelling future agricultural
24	expansion based on observed historic changes, and combined this approach with species-
25	specific habitat preferences for 19,859 species of terrestrial vertebrates. We project that
26	87.7% of species will lose habitat to agricultural expansion by 2050, including 1,280 species
27	projected to lose >25% of habitat. Proactive policies targeting how, where, and what food is
28	produced could reduce these threats, with a combination of approaches potentially preventing
29	almost all these losses while contributing to healthier human diets. As international

biodiversity targets are set to be updated in 2020, these results highlight the importance of
proactive efforts to reduce demand for agricultural land to safeguard biodiversity.

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#### 33 Main text

Biodiversity declines are accelerating across the world<sup>1–3</sup>, with one fifth of terrestrial 34 vertebrates threatened with extinction (categorised by the International Union for the 35 Conservation of Nature, IUCN, as Vulnerable, Endangered, or Critically Endangered<sup>4</sup>). 36 Habitat loss, driven by agricultural expansion, is the greatest threat to terrestrial vertebrates<sup>5,6</sup>. 37 If current agricultural trends continue, pressures on biodiversity will increase substantially: 38 projections based on population growth<sup>7</sup> and dietary transitions estimate the need for 2-39 10 million square kilometres of new agricultural land, largely cleared at the expense of 40 natural habitats $^{8-11}$ . In the face of these agricultural trends, conventional conservation 41 approaches, such as site based conservation, may be insufficient to conserve biodiversity<sup>12,13</sup>. 42 Additional proactive approaches that reduce the underlying threats to biodiversity—such as 43 agricultural expansion— will likely be needed to complement existing efforts $^{5,14}$ . 44 45 Responding to the impending biodiversity crisis requires decisions based on high resolution, spatially explicit and species-specific assessments to identify the species and landscapes most 46 at risk from future agricultural expansion. Results from these assessments help plan 47 appropriate conservation responses-such as species- or location-specific legislation-and to 48 assess which proactive changes to food systems have the greatest potential to reduce future 49 threats to biodiversity before they occur. The utility of existing analyses for conservation 50 51 planning and action has been limited by coarse spatial resolutions; a focus on a relatively small suite of species or on generalized biodiversity metrics such as species richness; or using 52 narrative pathways that are neither tied to current agricultural trajectories nor are able to 53

examine how specific changes to food systems might mitigate future biodiversity
declines<sup>5,12,15,16</sup> (see Methods).

We address limitations of existing analyses by developing a model framework that increases 56 the breadth and specificity of analyses, as well as their applicability to conservation efforts 57 (Supplementary Figure 1). We analyse the impacts of agricultural expansion on an 58 59 unprecedented number of species (almost 20,000) while explicitly accounting for differences in how individual species respond to agricultural land-use change, at a high spatial resolution 60 (1.5 x 1.5 km), and by analyzing how proactive food system transitions might mitigate future 61 biodiversity declines. In total, these changes enable us to identify the species and landscapes 62 63 most at risk from agricultural expansion under current trajectories, as well as how proactive agricultural policies could reduce these threats. 64

#### 65 Future patterns of agricultural expansion under Business-As-Usual

We developed a new, flexible, and high-resolution approach to modelling agricultural land 66 cover change. Our approach is built on observed empirical relationships between historical 67 changes in agricultural land cover and known correlates of agricultural land cover change 68 69 (see Methods, Supplementary Figure 2). This differs from the approaches employed by global food system models such as IMAGE, MAgPIE, or GLOBIOM, which are based more on 70 economic theory than on empirically observed patterns and changes. Our projections thus 71 allow the exploration of agricultural futures at high spatial resolutions that are derived from 72 73 observed trends, and can thus incorporate factors which are not accounted for in economic 74 theory (for example strong or weak enforcement of protected areas, or the non-economic factors that determine agricultural expansion) and also be readily updated as new land cover 75 data become available. To achieve this, we developed a flexible, spatially explicit, land 76 allocation model at a resolution of 1.5 x 1.5 km using observed changes in agricultural land 77 cover from 2001-2013 and spatially-explicit data on key determinants of land-cover change: 78

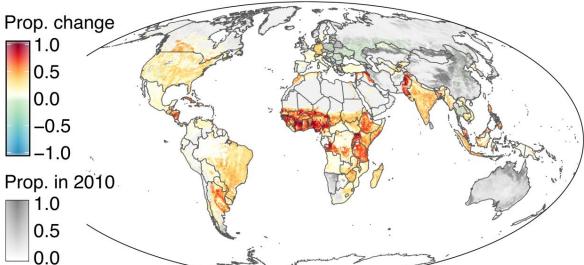
the suitability of an area for agricultural production<sup>1</sup>, current agricultural land cover<sup>17</sup>, previous changes in agricultural land cover<sup>17</sup>, proximity to other agricultural land<sup>17</sup>, market access<sup>1</sup>, and the location of protected areas<sup>1</sup>. Specifically, we used satellite-derived historic land cover data<sup>17</sup> from 2002 to 2007 to fit region-specific multinomial models to estimate the probability that agricultural land cover increased, decreased, or remained the same from 2007 to 2012. Next, we used the same satellite data to fit region-specific generalized linear models to estimate the magnitude of any such change from 2007 to 2012.

86 We then paired this two-part land allocation model with country-level estimates of agricultural land demand at five year intervals from 2010 to 2050 derived from the EAT-87 Lancet global food system model<sup>11</sup> that accounts for domestic food demand and international 88 patterns of trade. For each country and each time step, the land allocation model was first 89 used to probabilistically select cells to experience a change in agricultural land cover extent, 90 91 and then second to estimate the magnitude of this change. This process was repeated until a country's estimated agricultural land demand was met, and replicated 25 times to account for 92 the probabilistic nature of the land allocation model. Because spatial patterns of agricultural 93 expansion were consistent across model runs (see Supplementary Figures 3, 4 for variation 94 across model iterations), we report results using the mean of the 25 model iterations. 95

Under Business-As-Usual (i.e. based on current trajectories), we projected a total increase in 96 in global cropland of 26% or 3.35 million km<sup>2</sup>. We projected particularly large increases in 97 agricultural land throughout Sub-Saharan Africa (particularly tropical West Africa, the Rift 98 Valley, and in the southern Sahel), South and Southeast Asia (particularly Bangladesh, 99 100 Pakistan and southern Malaysia), and to a lesser extent Central and South America (large increases in northern Argentina, and much of Central America, smaller increases across 101 southern Brazil) (Fig. 1, Supplementary Figure 5). These increases were driven by the EAT-102 Lancet model projecting income-dependent transitions towards diets that contain more 103

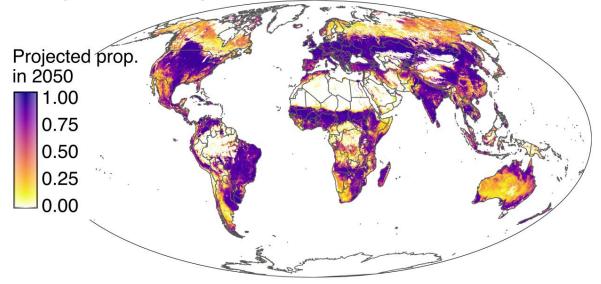
104 calories and larger quantities of animal-based foods (Supplementary Figure 6), combining with high levels of projected population growth (Supplementary Figure 7) and low crop 105 yields that are only projected to increase slowly (Supplementary Figure 8). In North America, 106 our allocation model projected increases in agricultural land in south-central Canada and 107 throughout the U.S. (but centered in the south-east). This was due to the EAT-Lancet model 108 projecting increased demand for international exports, but a combination of lower projected 109 population increases than in Sub-Saharan Africa, South and Southeast Asia and Latin 110 America and higher crop yields led to smaller projected increases in agricultural land (Fig. 1, 111 112 Supplementary Figure 5). In contrast, we projected reductions in agricultural land demand across eastern Europe and central and northern Asia (especially in Southern Russia and 113 Eastern Belarus) due to small dietary changes projected by the EAT-Lancet model, combined 114 with low or negative rates of population growth and high or increasing crop yields (Fig. 1, 115 Supplementary Figures 5-8). 116

Our approach offers an empirically derived complement to integrated assessment models 117 such as GLOBIOM<sup>18</sup>, MAgPIE<sup>19</sup> and and IMAGE<sup>20</sup>. Despite the difference in modelling 118 approaches, our projections are in broad agreement with those based on Shared 119 Socioeconomic Pathways, with the exception of projected agricultural expansion in North 120 America, which is not seen under all of the Pathways (19). This difference results from 121 increased crop demand from the EAT-Lancet projections we used(11) and are in agreement 122 with analyses based on other non-SSP projections(20). However, our projections are at a 123 higher resolution than most existing efforts, while the modular and adaptable nature of the 124 land allocation model means it can be updated as new data becomes available, and can be 125 paired with any estimate of future agricultural land demand at local to global scales (see 126 Supplementary Figure 1 for model construction). 127



# a Projected change in total agricultural land 2010-2050

b Projected total agricultural land 2050



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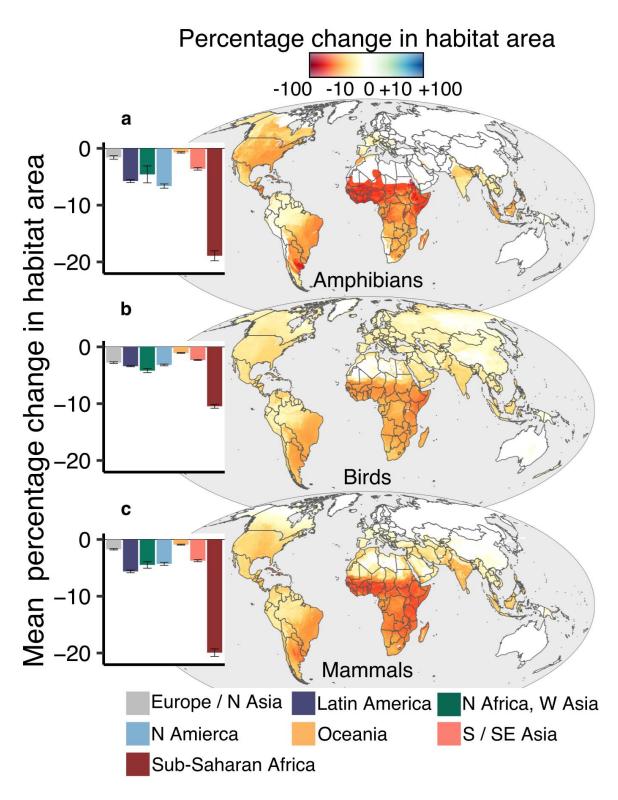
Figure 1. Projected extent of agricultural land in 2050 under Business-As-Usual a Projected change in the proportion of agricultural land (cropland plus pastureland, in colour) in cells from 2010-2050, overlaid on proportions of agricultural land in 2010 for cells not projected to experience a change in extent (in greyscale). Note the offset scale to highlight areas with small decreases in the proportion of agricultural land. **b** Projected proportion of agricultural land in cells in 2050.

#### 135 Linking Business-As-Usual agricultural expansion to habitat losses

We next estimated changes in habitat area<sup>21</sup> for each of 4,003 amphibian, 10,895 bird, and 136 4,961 mammal species. To do so, we overlaid our projections of future agricultural cover 137 with maps of current habitat for each species $^{22-24}$ , using species-specific assessments of 138 whether each species can survive and reproduce in agricultural land<sup>4</sup> to calculate changes in 139 total area of habitat for each species (see Methods). We acknowledge that, because a species' 140 population density will vary across its available habitat due to differences in climate, land 141 cover, or land-use intensity<sup>16,25</sup>, habitat loss may not linearly equate to population change. 142 In the Business-As-Usual scenario, we projected that 87.7% of species (17,409 species) 143 would lose some habitat by 2050, 6.3% to have no change in habitat area, and 6.0% to have 144 an increase in habitat area due to their survival in agricultural land, with 72.9% of these (877 145 species) being birds. If natural habitats are allowed to regrow in abandoned agricultural land, 146 these numbers are projected to be 76.1%, 6.1%, and 17.8%, respectively, with considerable 147 benefits for some species (Supplementary Data 1). Henceforth, we report results assuming 148 149 that habitats do not recover in abandoned agricultural land within the time period we analysed, although our overall conclusions do not differ if we alter this assumption 150 (Supplementary Data 1). We projected a mean loss of 5.8±0.1% of habitat across all 19,859 151 species in the analysis (range: 100% loss to 78.2% increase); across species losing habitat, 152 this value was  $6.7\pm0.9\%$ , but with considerable variation between regions and species 153 (Fig. 2). Projected mean habitat losses were greatest in Sub-Saharan Africa (14.4±0.3%% 154 across all species) with particularly large losses for amphibians in Equatorial West Africa 155 156 (where five ecoregions had projected mean losses of over 25%, and 10 ecoregions with mean losses over 20%, Supplementary Table 4) and for mammals in East Africa (eight ecoregions 157 had projected mean losses over 18%, Supplementary Table 4). Large mean habitat losses 158 were also projected in the Atlantic Forest in Brazil, in Eastern Argentina, across Central 159

- America and the Caribbean, and in parts of South and Southeast Asia (Fig. 2, Supplementary
- 161 Table 4).

162



163 Figure 2. Projected changes in habitat area in 2010-2050 under Business-As-Usual

164 *conditions* for **A** amphibians **B** birds **C** mammals. Maps show the mean change in habitat

area for all species within a cell, with values on a log10 scale. Insets show the mean change
in habitat area for all species within a region. See Supplementary Data 2 for which countries
are included in each region.

Mean values conceal the severity of projected habitat losses for many species. By 2050, 168 1,280 species were projected to lose at least 25% of their habitat area (Fig. 3a) and will likely 169 be at increased risk of global extinction. Of these species, 980 are not currently classified as 170 globally threatened according to the IUCN and so may not be a primary focus of current 171 172 conservation efforts. More alarmingly, 347 species were projected to lose at least 50% of their remaining habitat; 96 at least 75%; and 33 at least 90%. A high proportion of these 173 heavily impacted species are currently listed as globally threatened with extinction (34%, 174 52%, and 55%, respectively), strongly suggesting that agricultural expansion could lead to 175 regional or global extinction of many species in the coming decades. This highlights the need 176 177 for analyses that project how and where future threats to biodiversity are likely to emerge, allowing conservationists and policy-makers to act proactively to mitigate against threats. 178 Overall biodiversity impact will be greatest where high rates of habitat loss coincide with 179 large numbers of species (Supplementary Figure 9). Loss of total habitat area—the mean 180 181 habitat loss within a cell multiplied by the number of species present—as well as the number of species losing at least 25% of their habitat were projected to be highest in Sub-Saharan 182 Africa, particularly the Rift Valley and throughout tropical Western Africa (Fig. 3b, c). In 183 Sub-Saharan Africa 22.5% of species (941 species: 179 amphibians, 406 birds, and 356 184 mammals) were projected to lose at least 25% of their remaining habitat, with 44 out of 52 185 186 Sub-Saharan African countries containing at least 25 such species (Supplementary Data 7). Projected habitat losses were also high in Latin America, particularly southeast Brazil and the 187 remaining Atlantic Forest, with 246 species, including 99 amphibians, projected to lose at 188 189 least 25% of their habitat (Fig. 3b). Our results highlight the disproportionate share of local,

- 190 regional, or even global extinctions that Sub-Saharan Africa and Latin America are projected
- to account for, containing 93% of the species projected to lose  $\geq 25\%$  of their remaining
- 192 habitat. These continent-wide patterns of habitat loss could radically transform ecosystems
- that hold a large proportion of the world's biodiversity, particularly of large mammals (in
- 194 Sub-Saharan Africa) and birds and amphibians (in Latin America)<sup>1</sup>.

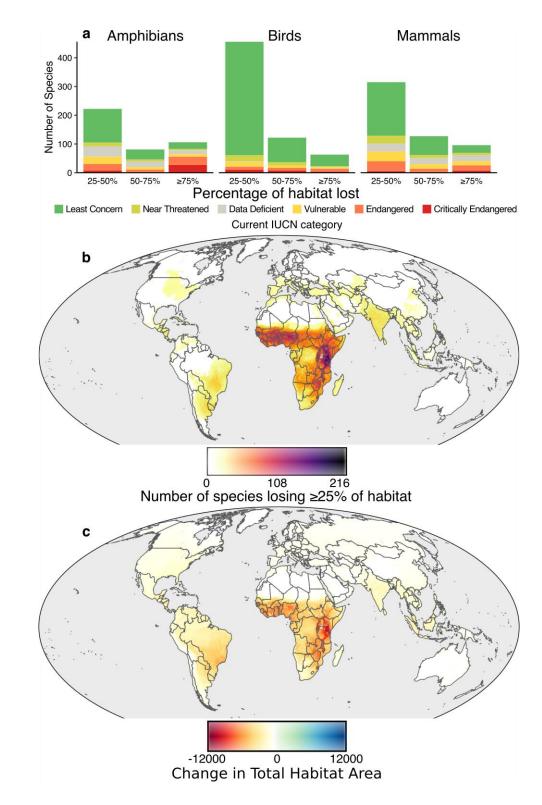




Fig. 3. Severity of projected habitat losses from 2010-2050 A Number of species projected to lose  $\geq 25\%$  of their 2010 habitat by 2050, split by current IUCN status **B** Global distribution of species projected to lose  $\geq 25\%$  of their 2010 habitat by 2050 **C** Projected changes in total habitat (mean habitat loss in a cell multiplied by the number of species present) by 2050.

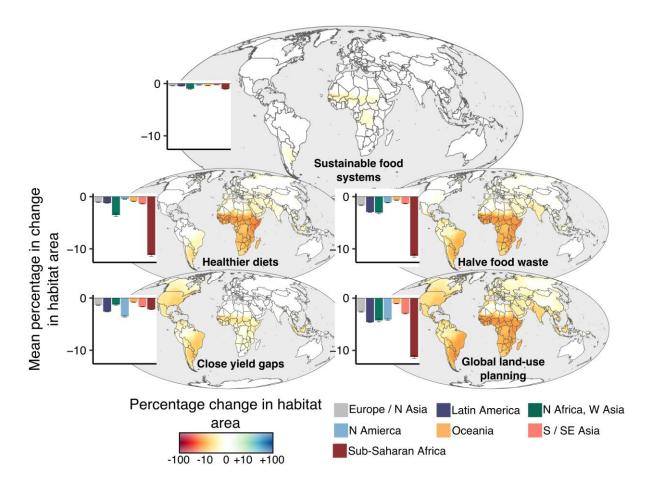
We projected small decreases in agricultural land in parts of Europe, Central and Northern 200 Asia, China, Australia, and New Zealand (Fig 1a). If these lands are allowed to revert to a 201 natural state— a process which may take decades or over a century<sup>26</sup>—then there is the 202 possibility for small increases in habitat area in these regions. However, these potential 203 increases for some species were far outweighed by projected losses in habitat area for others, 204 and allowing for recovery after habitat regrowth and restoration has a minor impact to the 205 206 overall projections of widespread habitat loss across all species examined (Supplementary Data 1). 207

# 208 **Proactive changes to food systems to reduce threats to biodiversity**

The projected severity of agricultural land cover change on habitat area means that proactive 209 210 policies to reduce future demand for agricultural land will likely be required to mitigate widespread biodiversity declines. To investigate the potential of such a proactive approach, 211 we developed a "Sustainable Food Systems" scenario that implemented four changes to food 212 systems: a global transition to healthier diets; halving food loss and waste; closing crop yield 213 gaps; and global agricultural land-use planning to avoid competition between food production 214 and habitat protection. In addition, to identify the relative impacts of specific changes to the 215 food system, we investigated the impacts of each approach individually. We used previously 216 published scenarios for diets, food waste, and yield increases<sup>5,11</sup>, and used projected habitat 217 losses in the Business-As-Usual scenario to identify the countries that could most benefit 218 219 from global agricultural land-use planning. In each case, we assumed each approach was steadily adopted, such that the complete transition was only achieved in 2050 (see Methods 220 for details). 221

Under the Sustainable Food Systems scenario, we projected that all regions would see mean
habitat losses of 1% or less by 2050 (Fig. 4): that is, with global coordination and rapid
action, it should be possible to provide healthy diets for the global population without major

habitat losses. The greatest benefits compared to Business-As-Usual were in Sub-Saharan
Africa, where we projected a mean loss of habitat of 1.0±0.04% under Sustainable Food
Systems compared with a mean loss of 14.4±0.3% under Business-As-Usual (Fig. 4,
Supplementary Figures 10, 11). If natural habitats are allowed to regrow in abandoned
agricultural land, then we projected mean habitat increases in every region (Supplementary
Data 1).



231



scenarios. Maps show the mean change for all species of all taxa in a cell, with values on a

234 log10 scale. Insets show the mean change in habitat area for all species within a region. The

- 235 lower four panels show the results from scenarios using single approaches, the top panel
- 236 ("Sustainable food systems") show the combination of all four approaches. See

Supplementary Data 2 for which countries are included in each region. Patterns for total
habitat are similar (Supplementary Figure 12).

Perhaps more importantly, habitat losses were far less severe for the species most heavily 239 impacted under business-as-usual. Globally, only 33 species were projected to lose more than 240 25% of their habitat, compared to 1,280 under Business-As-Usual. Thus, our analyses 241 demonstrate that addressing the underlying drivers of agricultural expansion has the potential 242 to greatly benefit the most at-risk species, thereby reducing extinction risks. However, the 243 majority of species (81.6%) were still projected to lose small amounts of habitat, suggesting 244 that conventional conservation measures will continue to be vital to protect biodiversity. 245 The impacts of individual approaches varied regionally. Closing yield gaps was projected to 246 have the largest overall benefits (Fig. 4) and was particularly effective in North Africa, West 247 Asia, and Sub-Saharan Africa where large yield gaps remain<sup>27,28</sup>. Under this scenario only 33 248 species in these regions were projected to lose more than 25% of their habitat, compared to 249 953 under Business-As-Usual. Projected benefits were considerably lower in other regions, 250 where yield gaps are smaller, but still reduced the number of such species from 361 to 103. 251 The magnitude of these projected benefits supports, and is supported by, recent analyses 252 investigating the land-saving potential of closing yield gaps across the world  $\frac{1.2}{1.2}$  Transitioning 253 to healthier diets and reducing food waste had considerable benefits-while not completely 254 eliminating habitat losses—particularly in wealthier regions with high per capita consumption 255 of both calories and animal-based foods, and in regions such as South America with high 256 consumption of animal-based foods (Fig. 4). In contrast, projected benefits from international 257 258 land-use planning were far smaller, with 1,026 species being still projected to lose at least 25% of their habitat. The biggest benefits were projected in Sub-Saharan Africa, where all the 259 countries with reduced agricultural land demand under this scenario were located, but even 260 here there were 646 such species (compared to 942 under Business-As-Usual, 673 under 261

healthy diets, and 695 under halved food waste). By analyzing the potential benefit of 262 individual food system changes, we found that combining different approaches had 263 synergistic benefits. For example, a country projected to see a 20% fall in food demand under 264 the halved food waste scenario and a 50% increase yields under the close yield gaps scenario 265 would see 20% and 33% reductions in land demand under each scenario respectively, 266 compared to Business-As-Usual. However, when combined, the area required falls even 267 268 further, to just 53% of Business-As-Usual demand. This results in the avoided habitat loss under Sustainable Food Systems being greater than the sum of the avoided loss under the four 269 270 constituent scenarios (Fig. 4).

# 271 Conclusions: Maintaining biodiversity in a world with 10 billion people

Our projections suggest that under business as usual agricultural expansion will continue to 272 drive widespread and severe biodiversity declines, but that these could be avoided with 273 concerted efforts to address food consumption and production as ultimate drivers of 274 biodiversity loss. Our approach and results are immediately relevant to international efforts 275 for the development of new strategic goals and targets for 2030 and 2050 under the auspices 276 of the Convention on Biological Diversity. We identify which policy approaches have the 277 greatest potential to combat the underlying drivers of future biodiversity declines in different 278 countries and highlight, at spatial scales relevant to conservation action, the species and 279 landscapes most at risk. These results can support proactive planning of both changes to the 280 wider food system, and on-the-ground conservation schemes to mitigate threats. 281

Our approach offers an empirically derived complement to integrated assessment models such as GLOBIOM <sup>18</sup>, MAgPIE<sup>19</sup> and and IMAGE<sup>20</sup>. Despite the difference in modelling approaches, our projections are in broad agreement with those based on Shared Socioeconomic Pathways, with the exception of projected agricultural expansion in North America, which is not seen under all of the Pathways(*19*). This difference results from

increased crop demand from the EAT-Lancet projections we used(11) and are in agreement 287 with analyses based on other non-SSP projections (20). Our projections are at a higher 288 289 resolution than most existing efforts, while the modular and adaptable nature of the land allocation model means it can be updated as new data becomes available, and can be paired 290 with any estimate of future agricultural land demand at local to global scales (see 291 Supplementary Figure 1 for model construction). The adaptable and updateable nature of our 292 293 approach offers particular improvements when accounting for non-linearities in agricultural expansion. For example, a new road being built or the removal of a protected area could lead 294 295 to rapid agricultural expansion in a region that neither our approach nor integrated assessment models highlight as vulnerable. Our approach, however, allows for the rapid inclusion of 296 these changes into projections by adjusting the value of explanatory variables (in these cases 297 travel time and the presence of a protected area) and recalculating the probability of future 298 agricultural expansion. Thus, we hope that our approach can help provide a dynamic and 299 responsive tool for decision makers to investigate the potential impacts of different policies. 300 Future human activities will likely have even greater impacts on biodiversity than those 301 projected by our scenarios. Anthropogenic climate change is likely to drive widespread 302 changes in ecosystems both directly, through impacts on species' potential distributions<sup>1</sup> and 303 indirectly, by affecting agricultural yields<sup>1</sup> and the relative suitability of different regions<sup>1</sup>. 304 Uncertainty in how changing precipitation and temperature regimes might affect farmer 305 profitability, and thus the future location of agricultural lands, preclude a quantitative 306 assessment of the impact of climate change on biodiversity. Likewise, increasing agricultural 307 yields-the proactive approach estimated to have the largest potential benefits for reducing 308 global habitat loss—may also have negative consequences not accounted for in this analysis. 309 Increasing crop yields-even if sustainably-often has negative biodiversity consequences 310 for species which exist in or near agricultural lands. As such, all scenarios will likely see a 311

decline in habitat suitability (and thus biodiversity) on cropland, an effect that is likely to be 312 exacerbated if yield gaps are closed. Other human impacts, such as the habitat fragmentation 313 that accompanies land clearing; over-hunting; invasive species; and pollution also threaten 314 biodiversity<sup>5,6,31,32</sup>. However, the proactive changes to the global food system that we discuss 315 could also help reduce these threats. For example, reducing demand for new cropland would 316 reduce habitat fragmentation, reduce greenhouse gas emissions from land-use change, and 317 lessen the opportunity costs of protected areas for local people<sup>33</sup>, thus increasing protection 318 from hunting. 319

Here, we demonstrate the potential benefits of actions covered under our 'sustainable food 320 system' to conservation, but such recommendations remain a long way from specific policy 321 recommendations. Actions will require locally appropriate policies, taking into account 322 individual countries' socio-economic and governance environments, the cultural acceptance 323 of different strategies, and on-the-ground capacity to implement strategies. Past successes can 324 provide insights into how to ensure that strategies are both effective and maintain fair and 325 equitable access to food, for example, through increasing crop yields<sup>34–36</sup>, shifting to healthier 326 dietary patterns<sup>37–39</sup>, reducing food and crop waste<sup>40,41</sup>, and implementing landscape-scale 327 land-use planning<sup>42</sup>. Previous efforts to increase sustainability can also be used to avoid 328 unintended consequences, such as when increases in agricultural yields promote local 329 agricultural expansion<sup>43</sup>. 330

Completely achieving the sustainable food systems we investigated may not be feasible in all situations, but there will likely be benefits of even the partial implementation of these approaches. As we approach the updating of the Convention on Biological Diversity's targets for global biodiversity conservation, now in 2021, and the halfway point of the SDGs in 2022, our results strongly suggest there are synergies between biodiversity conservation and sustainable development. The approaches we investigated will also be key to meeting other SDGs: in particular raising reducing food waste, and shifting to healthier diets supports Goals ("No hunger"), 3 ("Good health"), and 12 (Sustainable consumption), but also economic and social development (Goal8, "Good jobs and economic growth") and climate action (Goal 13, "Climate action"), bringing further benefits to people, biodiversity, and the wider environment **REFs**. These efforts to change how we produce and consume food will be a challenge, but one which cannot be avoided if we are to safeguard species for future generations.

### 344 Methods

To project impacts of future agricultural land-cover change on biodiversity, we linked a land 345 346 demand model, a land allocation model, and a biodiversity model in a flexible framework (Supplementary Figure 1). This approach to be readily adapted, for example to different 347 future scenarios or different spatial scales, or to incorporate new data as it becomes available. 348 Collectively, this approach enables us to project changes in land cover and their impact on 349 habitat availability for individual species at a resolution of 1.5 x 1.5km for every 5 years from 350 2010 to 2050. Our analysis includes nearly 20,000 species of birds, mammals, and 351 amphibians, and 152 nations that occupy >99% of Earth's ice-free land and contain >99% of 352 current agricultural land (see Supplementary Data 2). Full details of model specification, 353 datasets used, and sensitivity analyses are in Supplementary Information. 354

355 Land Demand Model

# 356 Projections of agricultural land demand under Business-As-Usual

357 We used income-dependent projections of country-specific agricultural production under

- 358 Business-As-Usual conditions (i.e. continuing historic trajectories) from EAT-Lancet
- 359 Commission<sup>11</sup>, pairing them with the United Nation's medium-fertility population
- $_{360}$  projection<sup>65,66</sup> and previously published yield projections<sup>1</sup>. We did not use the population

projections used in EAT-Lancet because they are derived from Shared Socioeconomic 361 Pathway (SSP) scenarios<sup>64</sup> and so are not updated to account for recent population trends. As 362 such, SSP 2-the pathway most similar to current Business-As-Usual trajectories-projects 363 approximately 570 million fewer people worldwide than current UN medium variant 364 population projections<sup>1</sup>. Additionally, we did not use the yield scenarios from the EAT-365 Lancet projections because they assume increases in future crop yields at faster-than-historic 366 trajectories<sup>11</sup>, which is not been supported by historic data<sup>1</sup>. We instead used published crop 367 yield forecasts that project crop yields increase along historic linear trajectories, but cannot 368 surpass current country-specific maximum potential yields  $\frac{1-3}{2}$ . 369 We projected cropland demand for each country in each 5-year time period from 2010 to 370 2050. To do so, we divided projections of demand for national food production (derived from 371 combining EAT-Lancet projections with UN population projections) by crop yield 372 projections. EAT-Lancet estimates of current cropland are based on FAO data<sup>1</sup>, while the 373 Land Allocation Model is based on MODIS satellite data  $\frac{1}{2}$ . We therefore harmonised EAT-374 Lancet projections with satellite data by: (1) calculating proportional change in cropland in 375 each 5-year time period (here called a "5-year target") from 2010-2050; (2) estimating the 376 total cropland in each country in 2010 based on MODIS data; (3) multiplying this satellite-377 derived estimate by the projected change in proportional demand; and (4) capping country-378 specific land-demand projections at FAO estimates of potential arable land in each country<sup>55</sup>. 379 This ensures continuity between datasets but could lead to under-projecting agricultural 380 381 expansion in countries where cropland is under-detected by satellite data (e.g. very small areas are farmed, or farming is largely under dense tree cover). 382 We assumed the area of pastureland remained constant for each country, following recent 383

<sup>384</sup> patterns<sup>55</sup>, reallocating pastureland within a country if cropland expanded into existing

385 pastureland. See Supplementary Information for more details.

#### 386 Projections of agricultural land demand under alternative future scenarios

To investigate the impact of proactive policies that could reduce future cropland demand we repeated the Business-As-Usual analysis with five alternative scenarios:

- 389 (1) Healthy diets: Diets transition from current diets to healthier composition and caloric
   390 quantity<sup>11</sup>.
- 391 (2) Halved food waste: Food loss and waste throughout entire food supply chains is
   392 reduced from current rates<sup>67</sup> by 25% in 2030 and halved by 2050.
- 393 (3) Close yield gaps: Yields increase linearly from current yields to 80% of the estimated
   394 maximum potential by 2050. This upper bound was chosen as increasing yields above
   395 80% often decreases economic profits<sup>68</sup>.
- (4) International land-use planning: Agricultural production shifts from the 25
  countries projected to have the greatest mean losses of suitable habitat across all
  species to countries where less than 10% of species are threatened with extinction and
  less than 10% of species would qualify as being threatened with extinction under
  IUCN Criteria B2<sup>1</sup> under Business-As-Usual in 2050. The shift in agricultural
  production is gradual, such that an additional 10% of total food demand is imported
  by 2030 and by 20% in 2050.
- The goal of this scenario is to estimate the impact on biodiversity of land use planning
- 404 across international borders, avoiding expansion in the most at-risk countries. We
- 405 recognize this scenario could be antagonistic to food security and sovereignty,
- 406 especially in countries where agriculture is a large source of employment and/or407 income.
- 408 (5) **Sustainable food systems:** All four approaches were adopted simultaneously.

By 2050, each scenario individually—with the exception of international land-use planning—
is estimated to reduce global demand for cropland by at least 2.5 million square kilometres,
while simultaneous adoption of all four scenarios would reduce global land demand by
~7.5 million square kilometres. International land-use planning had smaller impacts, reducing
global demand by 220,000 square kilometres. See Supplementary Information for more
explanation on the alternative land demand scenarios.

#### 415 Land Allocation Model

We developed a novel and highly resolute (1.5km x 1.5km) spatial allocation model using 416 observed changes in land cover to project future spatial patterns of agricultural land-cover 417 change. We fitted relationships between empirically observed changes in cropland or 418 pastureland and a set of key explanatory variables and assumed that these fitted relationships 419 remain constant into the future. Thus, we are not simply extrapolating past changes in 420 agricultural land into the future, but rather basing projections on an understanding of the 421 factors that shape how spatial patterns of agricultural land-cover evolves through time. 422 423 By separating projections of agricultural land demand from its spatial allocation, our approach enables investigation of how specific interventions might influence future land-use 424 change and biodiversity loss. Our projections are at a far higher resolution than existing 425 projections of agricultural land-use change, e.g. GLOBIOM (5-30 arc minutes; approximately 426 100-2500 km2 at the equator)<sup>18</sup>, CLUMondo, and MAgPie (30 arc minutes; approximately 427 2500 km2 at the equator)<sup>19,44</sup>. This allows stakeholders to identify areas likely to experience 428 large biodiversity declines at the spatial scales at which conservation actions and policies are 429 implemented. 430

#### 431 Modelling past changes in agricultural land

To understand past drivers of change in agricultural land we applied a two-stage modelling process applied to each 1.5 x 1.5 km terrestrial cell on earth. First, we fitted a multinomial regression to estimate the probability a cell experienced a change in the proportion of agricultural land during a 5-year period. Secondly, we fitted generalized linear models (GLMs) to estimate the magnitude of this change. We fitted separate models for cropland and pastureland because of differences in the relative importance of factors influencing their dynamics.

### 439 Data Inputs

Land-use change is driven by interacting biophysical and socio-economic forces<sup>45</sup>. We

441 reviewed land-use change literature, identifying potential drivers of agricultural expansion

442 and including those where global data was available at appropriate spatial resolutions. We

therefore included in our models: extent and surrounding agricultural land; historic changes

444 in agricultural land; agro-ecological suitability; travel time to large cities (>50,000 people) as

445 a proxy for market access; and the presence of a protected area in a cell<sup>1-7</sup>. See

446 Supplementary Information for more detail and data sources.

We resampled all data to  $1.5 \times 1.5 \text{ km}$  Mollweide projection using the resample() function in the raster package<sup>1</sup> in R<sup>1</sup>. Note that agro-ecological suitability was originally at a coarser resolution<sup>1</sup> (Supplementary Table 2), adding a degree of uncertainty to our projections. All other input data was originally at a higher resolution.

#### 451 Model fitting

We fitted region-specific multinomial regressions to estimate the probability that each cell experienced a change in cropland or pastureland extent and then used GLMs to estimate the magnitude of this change. Because drivers of cropland and pasture expansion differ by region (Supplementary Data 3-6), we fitted separate models for each IUCN region<sup>59</sup> and for
cropland and pastureland.

457 We *a priori* included the same explanatory variables for all models (although see

458 Supplementary Table 2 for differences between cropland and pastureland models) and used

- 459 cell-specific values for each explanatory variable.
- 460 Examining univariate relationships between explanatory and response variables showed non-

461 linear relationships for some variables. We therefore log-transformed travel time and

462 included quadratic effects for all variables except AES and presence/absence of a protected

463 area. We also included country as a fixed effect in the model because differences in country-

specific laws, policies, and demand for agricultural land affect the spatial pattern of cropland

465 expansion. See Supplementary Information for more information on model fitting.

# 466 Probability of Change in Agricultural Extent

Our first response variable was whether the proportion of cropland or pastureland in a cell increased, decreased, or remained constant from 2007 to 2012. To account for uncertainty in MODIS data, we classified cells as having a constant agricultural extent if the proportion of a cell under agricultural land cover changed by less than 0.025 from 2007 to 2012. We then used the R package {nnet}<sup>60</sup> to fit a multinomial regression model to estimate the probability a cell increased, decreased, or did not change in cropland or pastureland extent from 2007 to 2012.

# 474 Magnitude of Change in Agricultural Extent

475 To estimate the magnitude of agricultural cover change in a cell, we fitted separate GLMs to

476 cells that experienced increases in agricultural land and those that experienced decreases.

- 477 This resulted in three GLMs for each IUCN region: cropland increases, cropland decreases,
- 478 and pastureland increases. We did not fit models for pastureland decreases because we

479 assume pastureland extent remains constant in each country. We fitted models using the 480 glm() function in the {stats} package in  $R^{61}$ , with a gamma error distribution and a log-link 481 function to bound estimates between 0 and 1.

#### 482 *Modelling results and accuracy*

483 Model coefficients and accuracies are shown in Supplementary Table 3 and Supplementary

484 Data 3-6. See Supplementary Information for more details on modeling testing, results and485 accuracy.

486 Modelling Accuracy: Probability of Change in Agricultural Extent

487 We assessed model accuracy by classifying cells as having expanded or contracted from

488 2007-2012 based on the cell's most probabilistic modelled outcome. We then compared these

489 classifications with actual changes over 2007-2012.

490 Model accuracy varied across regions, ranging from ~62.5% (Caribbean) to ~95% (North

491 Africa) for cropland and 59% (Oceania) to 77% (South and Southeast Asia) (Supplementary

492 Table 3) for pastureland. This compares with a 33% chance of randomly selecting the correct

493 outcome. The lower accuracy of pastureland predictions is possibly due to MODIS data not

494 differentiating between natural grasslands or savannas and artificial pastures<sup>17</sup>.

# 495 Agricultural Projections: Projecting the location and magnitude of future

# 496 agricultural land cover change

We estimated the probability and magnitude of future agricultural land cover change for
every cell using the coefficients from the fitted models. We extracted land cover data from
MODIS for 2005 (estimated as the mean of 2004-2006) and 2010 (mean of 2009-2011),
using 2010 as a baseline for our projections and calculating the change from 2005 to 2010 as
an independent variable. We used the region-specific multinomial models to estimate the

502 probability that each cell would experience an increase or decrease in cropland, then

estimated the magnitude of these increases or decreases using the GLMs. See Supplementary
Information for more detail on how the location and magnitude of future agricultural land
cover change was projected.

506 Cropland expansion

507 To project future agricultural land cover we then linked these estimated probabilities and 508 magnitudes of land-cover change from the Land Allocation Model with the agricultural land 509 demand estimated from the Land Demand Model (Supplementary Figure 1).

510 For countries with a projected increase in cropland demand, we randomly selected a single

511 cell, based on the probability it would experience an increase in cropland extent (i.e. the

512 output from the region-specific multinomial model), then increased the proportion of

513 cropland in the chosen cell by the cell-specific amount estimated from the expansion GLMs.

514 We updated the estimates from both parts of the model (because the area of cropland is a key

515 predictor), reduced the country's five-year agricultural land demand target by the amount of

expansion estimated for the cell, and repeated the process until the country's five-year target

517 for cropland was met.

518 For countries projected to see a decrease in cropland, we used the same procedure, but using 519 the probability of cells experiencing a decrease in cropland from the multinomial model, and 520 the estimated magnitude of this decrease from the contraction GLMs.

521 Changes in pastureland

Following recent trends in global pastureland<sup>55,71</sup> and the EAT-Lancet projections, we did not project changes in countries' areas of pastureland. However, we did allow cropland to expand into pastureland. This displaced pastureland was then reallocating within the country using the allocation process described above for crops, but using the region-specific models for pastureland and additionally assuming pastureland cannot expand into cropland. To avoid 527 overestimating future pastureland extent, we limit pastureland expansion to cells identified as 528 having livestock by Gridded Livestock of the World in 2010. If pastureland extent could not 529 expand adequately to meet the five-year target, we assumed that shortfalls were compensated 530 by livestock intensification<sup>5,72</sup>.

531 Adjusting probabilities and the magnitude of changes

Agriculture cannot expand into all regions and land cover classes, specifically regions with very low growing degree days, and urban, rock and ice, barren ground, and water land cover classes. We therefore assumed that agriculture could not expand into certain cells based on their land cover type and climatic conditions, and further capped the potential amount of agricultural land based on the proportion of each cell that is suitable for agriculture. See "Input data for models" and "Adjusting probabilities and the magnitude of changes" in Supplementary Methods for details.

# 539 Consistency of projections

540 Because the land allocation model is probablistic, we repeated it 25 times, calculating the 541 mean and standard deviation of the extent of cropland and pasture in each cell for each five-542 year time period and using the mean value in our analyses.

The allocation model produced consistent projections (Supplementary Figure 3). The median global coefficient of variation (standard deviation / mean) in 2050 was 0.26 for cropland and <0.001 for pastureland (Supplementary Figure 4), indicating variation in agricultural extent was small relative to estimated mean agricultural extent.

#### 547 Potential impacts of climate change on agricultural land

548 We did not include the potential impact of climate change on AES or agricultural yields in

our models. Doing so would rely on a large number of untestable assumptions over farmer

and policy responses to environmental change, and is further hampered by a lack of

consensus of how climate change might affect AES and crop yields. See Supplementary
Information for a longer discussion of how climate change might affect future patterns of
agricultural land cover change.

The flexibility and adaptability of our approach allows for the easy inclusion of climate change impacts in the future. This can be done by adjusting future yield projections based on local conditions and adaptive capabilities, or by adjusting future AES to capture how changing climates might affect the relative suitability of different regions.

# 558 Biodiversity Model

# 559 Current area of habitat

Maps of suitable habitat (referred to as Area of Habitat, AOH<sup>21</sup>) were produced for 4,003 amphibians, 10,895 birds, and 4,961 mammal species<sup>21–24</sup>. These maps were originally developed at 300 x 300m resolution through deductive habitat suitability models integrating species ranges with data on suitable land-cover and elevations<sup>21</sup>. These habitat models reliably predict species distribution over wide geographical and taxonomic extents at the 1km resolution<sup>23,24</sup>. Supplementary Figure 9 shows the species richness patterns created from the AOH maps.

### 567 Species' habitat tolerances

We used IUCN data to define whether species are able to survive in agricultural land<sup>1</sup>. For each species, we recorded if habitats were "suitable" or "marginal" and took the maximum value of all habitats that qualify as either cropland or pastureland. i.e. if a species has "Arable Land" as "marginal" and "Plantations" as "suitable", we defined cropland as "suitable" for the species. See Supplementary Information for a longer description on species habitat tolerances.

#### 574 Current Area of Habitat

We next estimated the global area of suitable habitat for each species in 2010. We first 575 calculated the overlap between each species' suitable habitat and current cropland and 576 pastureland (from MODIS data) and subtracted the area of agricultural land from the habitat 577 maps, adjusting for suitability of cropland or pastureland: we assigned "suitable", "marginal", 578 and "unsuitable" habitats a value of 0, .5, and 1, respectively, and multiplied this value by the 579 overlap between habitat and agriculture in each cell. Thus, the value in each cell indicates the 580 proportion of the cell suitable for a species. We then summed this value to estimate of area of 581 suitable habitat in 2010. See Supplementary Information for more detail on how current area 582 583 of habitat was calculated.

# 584 **Biodiversity Projections**

We estimated future changes in area of suitable habitat for 19,859 species of terrestrial 585 amphibians, birds, and mammals, repeating the process described above for each 5-year time 586 period from 2010 to 2050. We assumed species were unable to recolonise areas where 587 agricultural land was abandoned to provide conservative estimates of biodiversity gains from 588 agricultural abandonment. Altering this assumption such that species are able to colonise 589 abandoned agricultural areas (as is often observed in long-term dynamics<sup>80</sup>) has little overall 590 impact on our results: with recolonisation allowed, 17.8% of species were projected to see 591 592 their area of habitat area increase, compared to 6.1% without recolonisation, and the mean change in habitat area for these species increased from 1.2% to 2.2% (Supplementary Data 593 1). Across all species, mean changes were even smaller, changing from a mean loss of 5.8% 594 to a mean loss of 5.3% with recolonisation. Species for which agricultural land is suitable 595 could see increases in area of habitat as cropland and pastureland expand, or as pastureland is 596 converted into cropland. 597

#### 598 Projecting changes in habitat extent under alternative scenarios

We repeated the process above for each of the five alternative scenarios and calculated both the absolute changes in habitat area, as well as the difference between Business-As-Usual and the alternatives.

#### 602 **References**

Automatic citation updates are disabled. To see the bibliography, click Refresh in the Zotero tab.

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