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Proactive Conservation to Prevent Habitat Losses to Agricultural Expansion

Authors: David R Williams[1,2]*†, Michael Clark[3]*†, Graeme M. Buchanan[4], G. Francesco Ficetola[5,6], Carlo Rondinini[7], David Tilman[2,8]

Affiliations:

[1] Sustainability Research Institute, School of Earth and Environment, University of Leeds, UK.

[2] Bren School of Environmental Science and Management, University of California Santa Barbara, USA.

[3] Oxford Martin Programme on the Future of Food and Nuffield Department of Population Health, University of Oxford, Oxford, UK

[4] RSPB Centre for Conservation Science, Royal Society for the Protection of Birds, UK.

[5] Department of Environmental Science and Policy, Università degli Studi di Milano, Milano, Italy

[6] University Grenoble Alpes, CNRS, Laboratoire d'Écologie Alpine (LECA), 38000 Grenoble, France

[7] Global Mammal Assessment Programme, Dipartimento di Biologia e Biotecnologie "Charles Darwin,", Sapienza Università di Roma, Rome, Italy

[8] Department of Ecology, Evolution and Behavior, University of Minnesota Twin Cities, Saint Paul, MN, USA

*Correspondence to: d.r.williams@leeds.ac.uk, michael.clark@ndph.ox.ac.uk

† Contributed equally to this work; order was decided with a coin toss at the University of California Santa Barbara

The projected loss of millions of square kilometres of natural ecosystems to meet future demand for food, animal feed, fibre, and bioenergy crops is likely to massively escalate threats to biodiversity. Reducing these threats requires a detailed knowledge of how and where they are likely to be most severe. We developed a geographically explicit model of future agricultural land clearance based on observed historic changes and combine the outputs with species-specific habitat preferences for 19,859 species of terrestrial vertebrates. We project that 87.7% of these species will lose habitat to agricultural expansion by 2050, with 1,280 species projected to lose ≥25% of their habitat. Proactive policies targeting how, where, and what food is produced could reduce these threats, with a combination of approaches potentially preventing almost all these losses while contributing to healthier human diets. As international biodiversity targets are set to be

updated in 2021, these results highlight the importance of proactive efforts to safeguard biodiversity by reducing demand for agricultural land.

Biodiversity declines are accelerating across the world[1–3], with one fifth of terrestrial vertebrates threatened with extinction (categorised by the International Union for the Conservation of Nature, IUCN, as Vulnerable, Endangered, or Critically Endangered[4]). Habitat loss, driven by agricultural expansion, is the greatest threat to terrestrial vertebrates[5,6]. If current agricultural trends continue, pressures on biodiversity will increase substantially: projections based on population growth[7] and dietary transitions estimate the need for 2-10 million square kilometres of new agricultural land, largely cleared at the expense of natural habitats[8–11]. In the face of these trends, conventional conservation approaches, such as site based conservation, may be insufficient to conserve biodiversity[12,13]. Policies to reduce the underlying threats to biodiversity—such as agricultural expansion—through proactive approaches will likely be needed to complement existing efforts[5,14].

Responding to the impending biodiversity crisis requires decisions informed by high resolution, spatially explicit and species-specific assessments on many thousands of species to identify the species and landscapes most at risk. Results from these assessments can be used to help plan appropriate conservation responses—such as species- or location-specific legislation—and to assess which proactive changes to food systems have the greatest potential to reduce future threats to biodiversity before they occur. The utility of most existing analyses for conservation 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 narrative pathways that are neither tied to current agricultural trajectories nor able to examine how specific changes to food systems might mitigate future biodiversity declines[5,12,15,16] (see Methods and Supplementary Information).

We address these limitations by developing an analytical framework that increases both the breadth and specificity of analyses, as well as their applicability to conservation efforts (Supplementary Figure 1). Specifically, we analyse at a high spatial resolution (1.5 x 1.5 km) the impacts of likely agricultural expansion on an unprecedented number of species (almost 20,000), while explicitly accounting for differences in how individual species may be impacted by agricultural land-use change, and by analyzing how proactive food-system transitions might mitigate future biodiversity declines. In total, this approach enables us to identify the species and landscapes most at risk from agricultural expansion under current trajectories, as well as how alternative proactive agricultural policies might reduce these threats.

Projecting agricultural expansion under Business-As-Usual

We developed a flexible and high-resolution approach to modelling agricultural land-cover change. Our approach is built on observed empirical relationships between historical changes in agricultural land cover and known correlates of agricultural land-cover change (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 economic theory and expert opinion than on empirically observed patterns and changes. Our high resolution projections explore agricultural scenarios that are derived from observed relationships and trends, and can thus incorporate factors which are not accounted for in economic 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 data become available. To achieve this, we developed a flexible, spatially explicit, land allocation model at a resolution of 1.5 x 1.5 km based on observed changes in agricultural land cover from 2001-2013 and spatially-explicit data on likely determinants of land-cover change including the suitability of an area for agricultural production[17], current agricultural land cover[18], previous patterns of agricultural land cover change[18], proximity to other agricultural land[18], market access[19], and the location of protected areas[20]. Specifically, we used satellite-derived historic land cover data[18] from 2002 to 2007 to fit region-specific multinomial models to estimate the probability that agricultural land cover in individual cells 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.

We then paired this two-part land allocation model with country-level estimates from 2010 to 2050 of agricultural land demand at five year intervals derived from the EAT-Lancet global food system model[11], that accounts for domestic food demand and international patterns of trade. For each country and time step, we used the land allocation model to first probabilistically select cells to experience a change in agricultural land-cover extent, 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 the probabilistic nature of the model. Spatial patterns of agricultural expansion were consistent across model runs (Supplementary Figures 3, 4) and we therefore report results using the mean of the 25 model iterations.

Under Business-As-Usual (i.e. based on current trajectories), we projected a total increase in in global cropland of 26% or 3.35 million km^2 from 2010 to 2050. We projected particularly large increases in agricultural land throughout Sub-Saharan Africa (particularly tropical West Africa, the Rift Valley, and in the southern Sahel), South and Southeast Asia (particularly Bangladesh, 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 southern Brazil) (Fig. 1, Supplementary Figure 5). These increases were driven by the EAT-Lancet model projecting income-dependent transitions towards diets that contain more 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 yields that are projected to increase slowly, particularly in Sub-Saharan Africa (Supplementary Figure 8). In North America, we model projected increases in agricultural land in south-central Canada and throughout the U.S. but centered in the south-east, due largely to the EAT-Lancet model projecting increased demand for international exports. However, a combination of lower projected population increases than in Sub-Saharan Africa, South and Southeast Asia and Latin America, and higher crop yields led to smaller projected increases in agricultural land compared to these regions (Fig. 1, 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 Eastern Belarus) due to small dietary changes projected by the EAT-Lancet model, combined with low or negative rates of population growth and high or increasing crop yields (Fig. 1, Supplementary Figures 5-8).

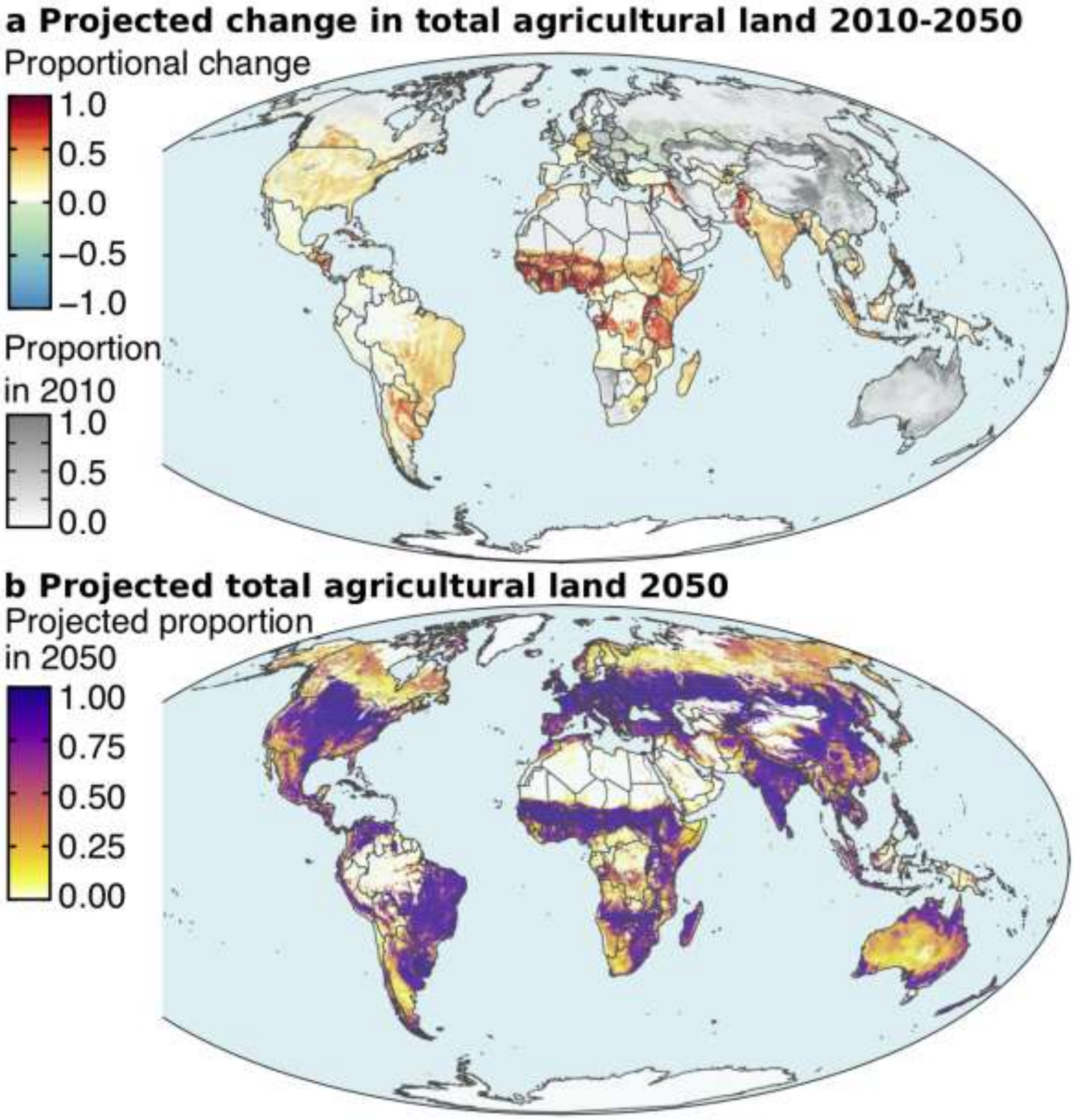


Figure 1. Projected extent of agricultural land in 2050 under Business-As-Usual

a *Projected change in the proportion of agricultural land (cropland plus pastureland, in colour) in each 1.5 x 1.5 km cell 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 each cell in 2050. Map produced using Natural Earth data v2.0 (www.naturalearthdata.com).*

Habitat losses under Business-As-Usual

We next estimated changes in habitat area[21] from 2010 levels for each of 4,003 amphibian, 10,895 bird, and 4,961 mammal species. To do so, we overlaid our projections of future agricultural cover with maps of 2010 habitat for each species[22–24], using species-specific assessments of whether each species can survive and reproduce in agricultural land[4] to calculate changes in total area of habitat for each species (see Methods). We acknowledge that, because a species' population density will vary across its available habitat due to differences in climate, land cover, land-use intensity or abundances of other species[16,25], habitat loss may not linearly equate to population change.

Under Business-As-Usual trajectories, we projected that 87.7% of species (17,409 species) would lose some habitat by 2050, 6.3% to have no change in habitat area, and 6.0% to have an increase in habitat area due to their survival in agricultural land, with 72.9% of these (877 species) being birds. If natural habitats are allowed to regrow in abandoned agricultural land, these numbers, once habitats have re-established, are projected to be 76.1%, 6.1%, and 17.8%, respectively, with considerable benefits for some species (Supplementary Data 1). Given the long time required for complete recovery after agricultural abandonment[26] we report results assuming that habitats do not recover in the timeframe considered, although our overall conclusions do not differ if we alter this assumption (Supplementary Data 1).

We projected a mean loss of 5.8±0.1% of 2010 habitat across all 19,859 species in the analysis (range: 100% loss to 78.2% increase); across species losing habitat, this value was 6.7±0.9%, but with considerable variation between regions and species (Fig. 2). Projected mean habitat losses were greatest in Sub-Saharan Africa (14.4±0.3%% across all species) with particularly large losses for amphibians in Equatorial West Africa (where five ecoregions had projected mean losses of over 25%, and 10 ecoregions with mean losses over 20%, Supplementary Table 1) and for mammals in East Africa (eight ecoregions had projected mean losses over 18%, Supplementary Table 1). Large mean habitat losses were also projected in the Atlantic Forest in Brazil, in Eastern Argentina, across Central America and the Caribbean, and in parts of South and Southeast Asia (Fig. 2, Supplementary Table 1).

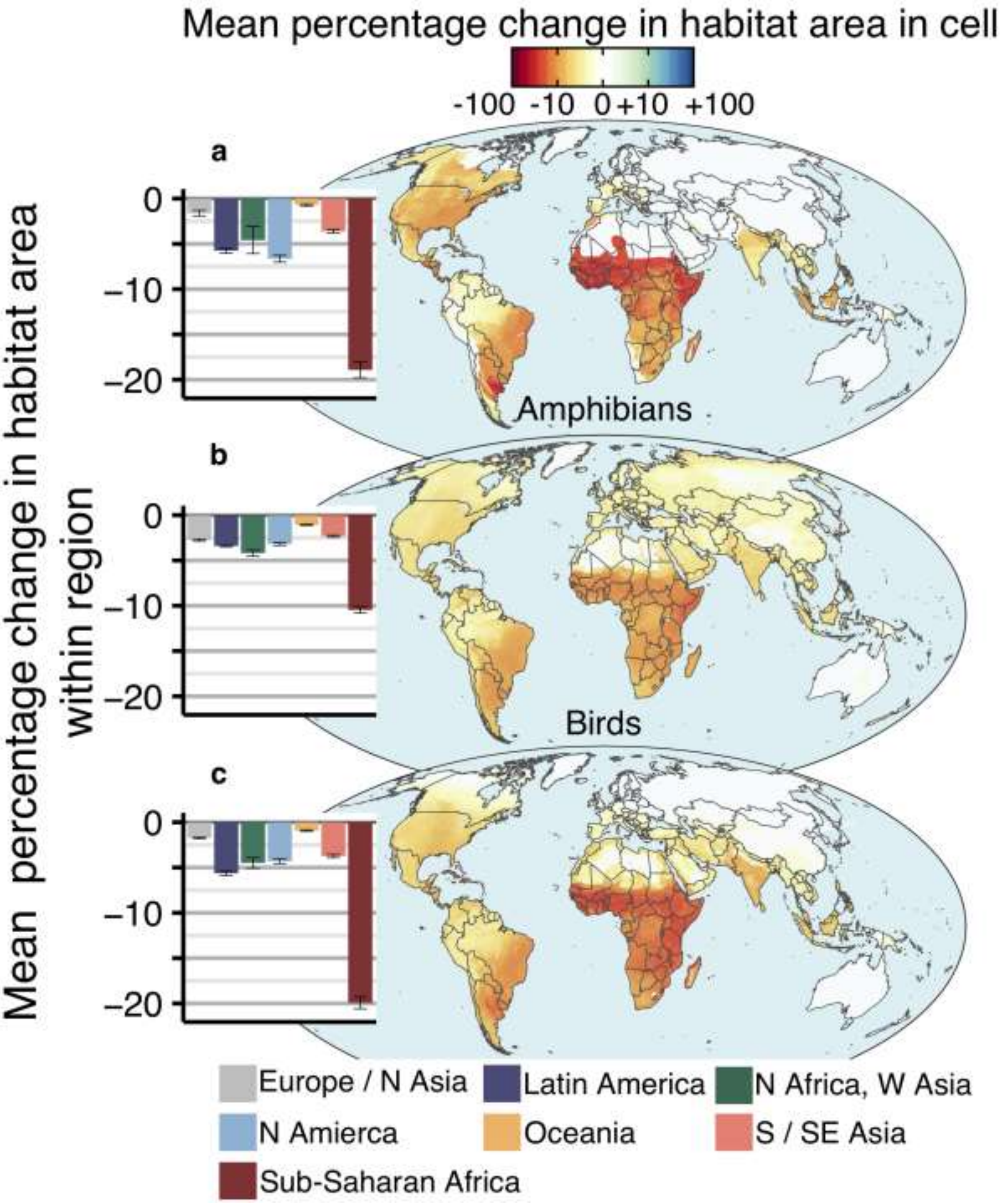


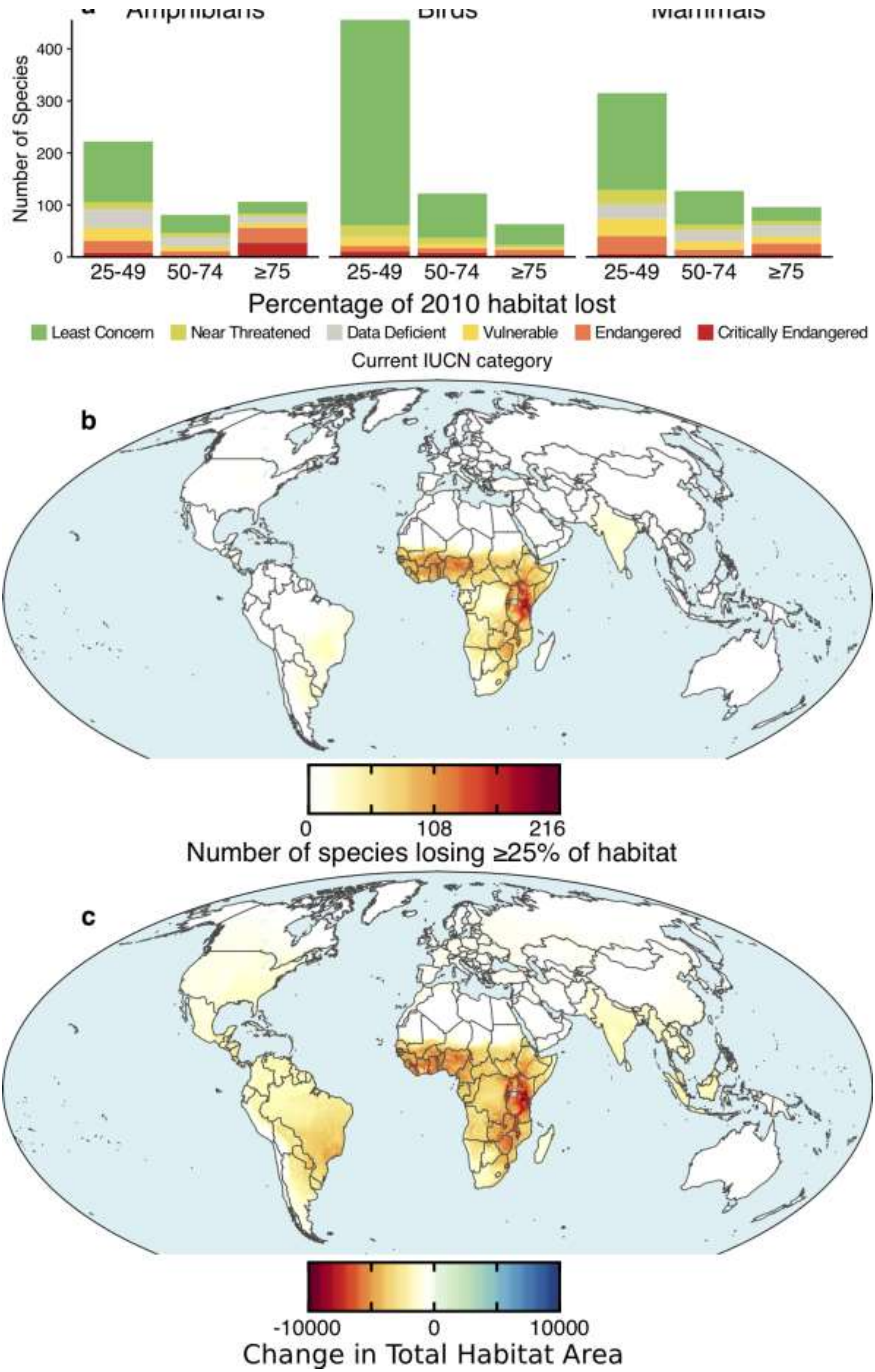
Figure 2. Projected changes in habitat area in 2010-2050 under Business-As-Usual conditions *for* ***a*** *amphibians* ***b*** *birds* ***c*** *mammals. Maps show the mean change in habitat area*

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. Map produced using Natural Earth data v2.0 (www.naturalearthdata.com).

Mean values conceal the severity of projected habitat losses for many species. By 2050, 1,280 species were projected to lose at least 25% of their remaining habitat area (Fig. 3a) and will likely be at increased risk of global extinction. Of these species, 980 are not currently classified as globally threatened according to the IUCN and so may not be a primary focus of current 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 heavily impacted species are currently listed as globally threatened with extinction (34%, 52%, and 55%, respectively), strongly suggesting that agricultural expansion could lead to the regional or global extinction of many species in the coming decades. This highlights the need 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.

Overall biodiversity impact will be greatest where high rates of habitat loss coincide with large numbers of species (Supplementary Figure 9). Loss of total habitat area—the mean 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 Africa, particularly the Rift Valley and throughout tropical Western Africa (Fig. 3b, c). In Sub-Saharan Africa 22.5% of species (941 species: 179 amphibians, 406 birds, and 356 mammals) were projected to lose at least 25% of their remaining habitat, with 44 out of 52 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 remaining Atlantic Forest, with 246 species, including 99 amphibians, projected to lose at least 25% of their habitat (Fig. 3b). Our results highlight the disproportionate share of local, 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 ≥25% of their remaining 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 Sub-Saharan Africa and birds and amphibians in Latin America[5].



Amphibians
Birds
Mammals
Number of Species
400
300
200
100
0
25-49
50-74
≥75
Percentage of 2010 habitat lost
Least Concern
Near Threatened
Data Deficient
Vulnerable
Endangered
Critically Endangered
Current IUCN category
b
0
108
216
Number of species losing ≥25% of habitat
c
-10000
0
10000
Change in Total Habitat Area

Fig. 3. ***Severity of projected habitat losses from 2010-2050 a*** *Number of species projected to lose ≥25% of their 2010 habitat by 2050, split by current IUCN status* ***b*** *Global distribution of species projected to lose ≥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. See Supplementary Figure 10 for projected total habitat loss for individual taxa. Map produced using Natural Earth data v2.0 (www.naturalearthdata.com).*

We projected small decreases in agricultural land in parts of Europe, Central and Northern Asia, China, Australia, and New Zealand (Fig 1a). If these lands are allowed to revert to a natural state— a process which may take many decades[27]—then there is the possibility for small increases in habitat area in these regions. However, these potential increases for some species were far outweighed by projected losses in habitat area for others. Allowing for habitat recovery or restoration after agricultural abandonment has a minor impact to the overall projections of widespread habitat loss across all species examined (Supplementary Data 1).

Proactive food-system changes to reduce biodiversity threats

The projected severity of agricultural land-cover change on habitat area means that proactive policies to reduce future demand for agricultural land will likely be required to mitigate widespread biodiversity declines. To investigate the potential of such proactive approaches, we developed a scenario that implemented four changes to food systems: closing crop yield gaps globally; a global transition to healthier diets; halving food loss and waste; and global agricultural land-use planning to avoid competition between food production and habitat protection. In addition, to identify the relative impacts of specific changes to the food system, we investigated the impacts of each approach individually. We used previously published scenarios for yield increases, diets and food waste[5,11], and used projected habitat losses in the

Business-As-Usual scenario to identify the countries that could most benefit 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 and Supplementary Information for details). Under the "combined approach" scenario, employing all four approaches, we projected that global cropland would, by 2050, actually decline by nearly 3.4 million square kilometres relative to 2010, and by 6.7 million square kilometres relative to Business-As-Usual (Supplementary Table 2, Supplementary Figure 11).

We also projected that under the combined approach 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 in 2050 without major habitat losses. The greatest benefits compared to Business-As-Usual were in Sub-Saharan Africa, where we projected a mean loss of global habitat of 1.0±0.04% under the combined approach compared with a mean loss of 14.4±0.3% under Business-As-Usual (Fig. 4, Supplementary Figures 12-14). If natural habitats are allowed to regrow in abandoned agricultural land, then we projected mean habitat would increase in every region (Supplementary Figures 15-16; Supplementary Data 1).

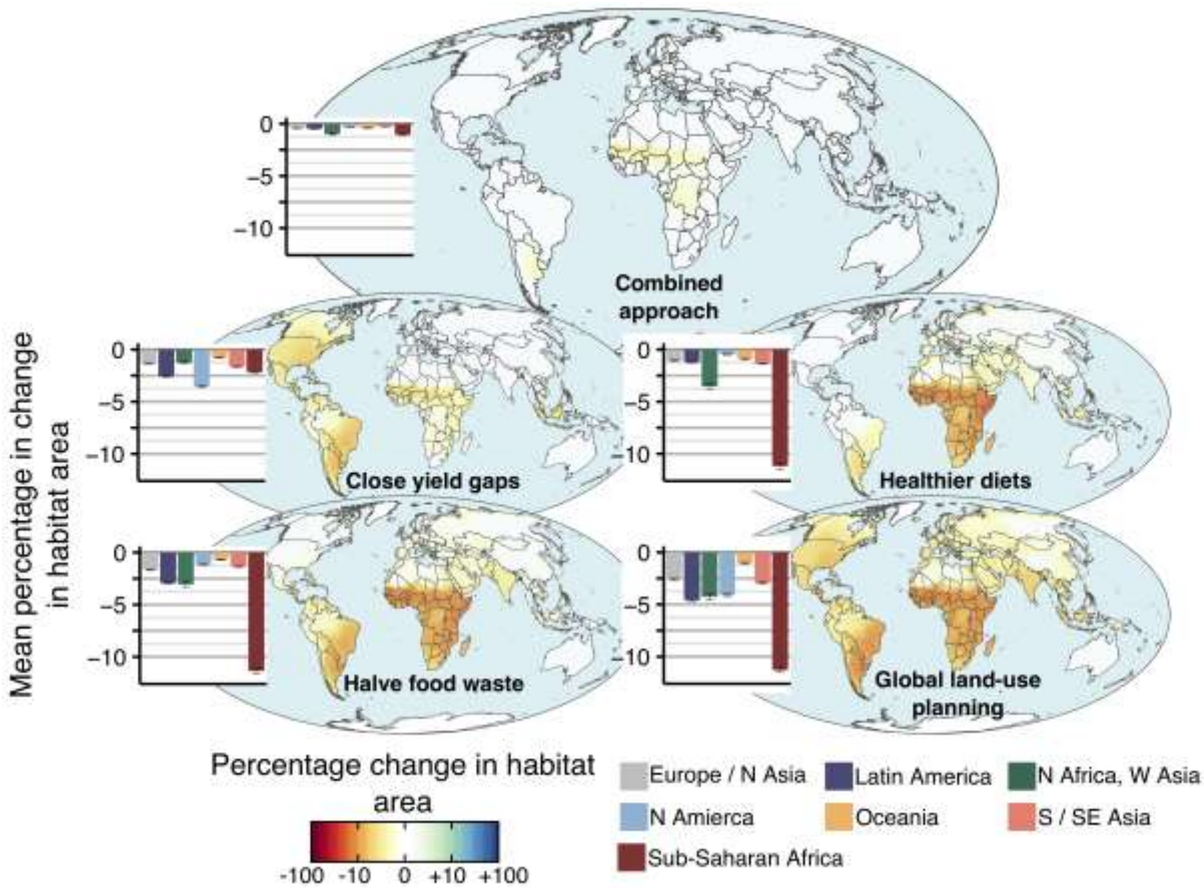


Figure 4. Projected changes in mean habitat area from 2010-2050 under alternative scenarios. *Maps show the mean change for all species of all taxa in a cell, with values on a log10 scale. Insets show the mean change in habitat area for all species within a region. The lower four panels show the results from scenarios using single approaches, the top panel ("Combined approach") show the combination of all four approaches. See Supplementary Data 2 for which countries are included in each region. Patterns for total habitat change are similar (Supplementary Figure 13). Map produced using Natural Earth data v2.0 (www.naturalearthdata.com).*

Perhaps more importantly, habitat losses were far less severe for the species most heavily impacted under Business-As-Usual. Globally, only 33 species were projected to lose more than 25% of their habitat, compared to 1,280 under Business-As-Usual. Thus, our analyses demonstrate that addressing the underlying drivers of agricultural expansion has the potential to greatly benefit the most at-risk species, and thereby reduce extinction risks. However, the majority of species (81.6%) were still projected to lose small amounts of habitat, suggesting that conventional conservation measures will continue to be vital to protect biodiversity.

The impacts of individual approaches varied regionally. Closing yield gaps was projected to have the largest overall benefits (Fig. 4) and was particularly effective in North Africa, West Asia, and Sub-Saharan Africa, where large yield gaps remain[28,29]. When the only change from Business-As-Usual practices was closing yield gaps, 33 species in these regions were projected to lose more than 25% of their habitat, compared to 953 under Business-As-Usual. Projected benefits were considerably lower in other regions, where yield gaps are smaller, but still reduced the number of such species from 361 to 103. The magnitude of these projected benefits supports, and is supported by, recent analyses investigating the land-saving potential of closing yield gaps across the world[30,31] However, increasing yields often has negative consequences for species within agricultural lands[16,32,33]. As such, while all scenarios could see declines in the suitability of croplands by 2050, this effect may be exacerbated by closing yield gaps. For most species, these losses are likely to be outweighed by the land-saving benefits of yield increases[32] but the benefits of closing yield gaps may be reduced for some species that rely heavily on agricultural lands.

Transitioning to healthier diets and reducing food waste were projected to have considerable benefits—while not completely eliminating habitat losses—particularly in wealthier regions with high per capita consumption of both calories and animal-based foods, and in regions such as South America with high consumption of animal-based foods (Fig. 4). In contrast, projected benefits from international land-use planning were far smaller, with 1,026 species being still projected to lose at least 25% of their 2010 habitat. The biggest benefits of land-use planning were in Sub-Saharan Africa, where all the countries with reduced agricultural land demand under this scenario were located. Even here, however, there were still 646 species projected to lose ≥25% of 2010 habitat, compared to 942 under Business-As-Usual, 673 under healthy diets, and 695 under halved food waste.

Analyzing the potential benefits of individual changes to the food system reveals that combining different approaches could have synergistic benefits. For example, a country projected to see a 20% fall in food demand under the halved food waste scenario and a 50% increase in yields under the close yield gaps scenario would see 20% and 33% reductions in land demand under each scenario respectively, compared to Business-As-Usual. However, combining these two approaches reduces the area required to just 53% of Business-As-Usual demand. This results in the avoided habitat loss under the combined approach being greater than the sum of the avoided loss under the four constituent scenarios (Fig. 4).

Maintaining biodiversity in a world with 10 billion people

Our projections suggest that, under Business-As-Usual, agricultural expansion will drive widespread and severe biodiversity declines, but that these could be avoided with concerted, proactive efforts to address food consumption and production as ultimate drivers of biodiversity loss. Our approach and results are immediately relevant to international efforts for the development of new strategic goals and targets for 2030 and 2050 under the auspices of the Convention on Biological Diversity in 2021. We identify the policy approaches with the greatest potential to combat the underlying drivers of future biodiversity declines in different countries and highlight, at spatial scales relevant to conservation action, the species and landscapes most at risk. These results can support proactive planning of both on-the-ground conservation schemes and changes to the wider food system to mitigate threats.

Our approach offers an empirically derived complement to integrated assessment models such as GLOBIOM[36], MAgPIE[37] and and IMAGE[38]. Despite the difference in approaches, our projections are in broad agreement with those based on Shared Socioeconomic Pathways

(SSPs), with the exception of projected agricultural expansion in North America, which is not seen under all the Pathways[39]. This difference results from increased crop demand projected by the EAT-Lancet projections[11] and are in agreement with analyses based on other non-SSP projections[40]. Our projections are at a higher resolution than most existing efforts, while the modular and adaptable nature of the land allocation model means it can be easily updated as new data become available, and can be paired with any estimate of future agricultural land demand at local to global scales (Supplementary Figure 1). There are likely to be non-linearities in future agricultural expansion, for example, the construction of a new road or the degazetting of a protected area could lead 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 these changes into projections by adjusting the value of explanatory variables (in these cases travel time and the presence of a protected area) and recalculating the probability of future agricultural expansion. Thus, we hope that our approach can help provide a dynamic and responsive tool for decision makers to investigate the potential impacts of different policies.

In reality, threats to biodiversity could be considerably greater than those we project: other projections of future agricultural land demand are higher than those we use[5], and we do not include the impacts of anthropogenic climate change, habitat fragmentation, over-exploitation, invasive species or pollution[5,6,41–43]. Climate change is likely to drive widespread changes in biodiversity by altering the location of suitable habitats and environments, and may have synergistic effects with habitat loss and fragmentation from agricultural expansion[43]. In addition, its effect on agricultural yields[44] and the relative suitability of different regions for various crops[45] could have indirect impacts on biodiversity by altering patterns of agricultural expansion. Uncertainty in how climatic changes will affect agriculture[46] and species[47] precludes quantitatively assessing these impacts, but we note that the scenarios we discuss could also help reduce the impacts of climate change and other threats. Reducing demand for new cropland can reduce greenhouse gas emissions from land-use change, reduce habitat fragmentation, and lessen the opportunity costs of protected areas for local people[48], while land-use planning could help preserve unfragmented habitats or allow habitat restoration.

Here, we demonstrate the potential conservation benefits of multiple approaches, but our findings are still a long way from specific policy recommendations. Actions will require locally appropriate policies, taking into account individual countries' socio-economic and governance environments, the cultural acceptance of different strategies, and on-the-ground capacity to implement strategies. Past successes can provide insights into how to ensure that strategies are both effective and maintain fair and equitable access to food, for example, through increasing crop yields[49–51], shifting to healthier diets[52–54], reducing food and crop waste[55,56], and implementing landscape-scale land-use planning[57]. Learning from previous efforts to increase sustainability can also be used to avoid unintended consequences, such as when increases in agricultural yields promote local agricultural expansion[58].

Although fully achieving the approaches we investigated may not be feasible in all regions, even the partial implementation of proactive approaches could be environmentally beneficial. As we approach the updating of the Convention on Biological Diversity's targets for global biodiversity conservation in 2021, and the halfway point of the SDGs in 2022, our results strongly suggest there are co-benefits to biodiversity of appropriate agriculture-related development: reducing agricultural land-cover change can reduce anthropogenic climate change and alleviate poverty by increasing farmer incomes; shifting to healthier diets and reducing food waste can reduce hunger and support better health and sustainable consumption. These proactive efforts to change how we produce and consume food will be a major challenge, but one which cannot be avoided if we are to safeguard species for future generations.

Methods

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

Land Demand Model

Projecting agricultural land demand under Business-As-Usual

We combined income-and-trade-dependent projections of country-specific agricultural production under Business-As-Usual conditions (i.e. continuing historic trajectories) from EAT-Lancet Commission[11], with the United Nation's medium-fertility population projection[59,60] and previously published yield projections[5]. We did not use the population projections used in EAT-Lancet because they are derived from Shared Socioeconomic Pathway (SSP) scenarios[61] and so are not updated to account for recent population trends. As such, SSP 2—the pathway most similar to current Business-As-Usual trajectories—projects approximately 570 million fewer people worldwide than current UN medium variant population projections[7]. Additionally, we did not use the yield scenarios from the EAT-Lancet projections because they assume increases in future crop yields at faster-than-historic trajectories[11], something for which there is no empirical support[62]. We instead used published crop yield forecasts that project crop yield increases along historic linear trajectories, but cannot surpass current country-specific maximum potential yields[5,28,29].

We projected cropland demand for each country in each five-year time period from 2010 to 2050. To do so, we divided projections of demand for national food production (derived from combining EAT-Lancet projections with UN population projections) by crop yield projections. EAT-Lancet estimates of current cropland are based on FAO data[17], while the Land Allocation Model is based on MODIS satellite data[18]. We therefore harmonised EAT-Lancet projections with satellite data by: (1) calculating proportional change in cropland in each five-year time period from 2010-2050; (2) estimating the total cropland in each country in 2010 based on MODIS data; (3) multiplying this satellite-derived estimate by the projected change in proportional demand; and (4) capping country-specific land-demand projections at FAO estimates of potential arable land in each country[63]. This ensures continuity between datasets but could lead to under-projecting agricultural 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).

We assumed the area of pastureland remained constant for each country, following recent patterns[63], reallocating pastureland within a country if cropland expanded into existing pastureland. See Supplementary Information for more details.

Agricultural land demand under alternative 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 (see Supplementary Table 3 for assumptions of different scenarios):

(1) **Close yield gaps:** Yields increase linearly from current yields to 80% of the estimated maximum potential[28,29] by 2050. Increasing yields above 80% is rarely achieved over large areas[64].

(2) **Healthier diets:** Diets transition from current diets to healthier composition and caloric quantity[11].

(3) **Halved food waste:** Food loss and waste throughout entire food supply chains is reduced from current rates[65] by 25% by 2030 and 50% by 2050.

(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[66] 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 across international borders, avoiding expansion in the most at-risk countries. We recognize this scenario could be antagonistic to food security and sovereignty, especially in countries where agriculture is a large source of employment and/or income.

(5) **Combined approach:** All four approaches were adopted simultaneously.

We assumed each approach was steadily adopted, such that the complete transition was only achieved in 2050. We estimated that, by 2050, each approach individually—with the exception of international land-use planning—could reduce global demand for cropland by at least 2 million square kilometres, while simultaneous adoption of all four scenarios would reduce global land demand by ~6.7 million square kilometres (Supplementary Table 2, Supplementary Figure 11). International land-use planning had smaller impacts, reducing global demand by 230,000 square kilometres. See Supplementary Information for more explanation on the alternative land demand scenarios.

Land Allocation Model

We developed a novel and highly resolute (1.5 x 1.5km) spatial allocation model using observed relationships between explanatory variables and changes in land cover to project future spatial patterns of agricultural land-cover change. We fitted relationships between empirically observed changes in cropland or pastureland and a set of key explanatory variables and assumed that these fitted relationships remain constant into the future. Thus, we are not simply extrapolating past changes in agricultural land into the future, but rather basing projections on an understanding of the factors that shape how spatial patterns of agricultural land-cover evolve.

By separating projections of agricultural land demand from its spatial allocation, our approach enables the investigation of how specific interventions might influence future land-use change and biodiversity loss. Our projections are at a far higher resolution than existing projections of agricultural land-use change, e.g. GLOBIOM (5-30 arc minutes; approximately 100-2,500 km2 at the equator)[36], CLUMondo, and MAgPie (30 arc minutes; approximately 2,500 km2 at the equator)[37,40]. This allows stakeholders to identify areas likely to experience large biodiversity declines at the spatial scales at which conservation actions and policies are implemented.

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 five-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.

Data Inputs

Land-cover change is driven by interacting biophysical and socio-economic forces[67]. We reviewed land-cover change literature to identify potential drivers of agricultural expansion and included those for which global data was available at appropriate spatial resolutions. We therefore included in our models: extent of surrounding agricultural land; historic changes in agricultural land; agro-ecological suitability (AES); travel time to large cities (>50,000 people) as a proxy for market access; and the presence of a protected area in a cell[67–73] . See Supplementary Information for more detail and data sources.

We resampled all data to 1.5 x 1.5 km Mollweide projection using the resample() function in the raster package[75] in R[76]. Note that AES was originally at a coarser resolution[17] (Supplementary Table 4), adding a degree of uncertainty to our projections (see Supplementary Information for details). All other input data was originally at a higher resolution.

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 pastureland expansion differ by region (Supplementary Data 3-6), we fitted separate models for each IUCN region[77] and for cropland and pastureland.

We *a priori* included the same explanatory variables for all models (although see Supplementary Table 4 for differences between cropland and pastureland models) and used cell-specific values for each explanatory variable.

Examining univariate relationships between explanatory and response variables showed non-linear relationships for some variables. We therefore log-transformed travel time and included quadratic effects for all variables except AES and presence/absence of a protected 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 expansion. See Supplementary Information for more information on model fitting.

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}[78] 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.

Magnitude of Change in Agricultural Extent

Our second response variable was the magnitude of agricultural land cover change in a cell. We fitted separate GLMs to cells that experienced increases in agricultural land and those that experienced decreases. This resulted in three GLMs for each IUCN region: cropland increases, cropland decreases, and pastureland increases. We did not fit models for pastureland decreases because we assume pastureland extent remains constant in each country. We fitted models using the glm() function in the {stats} package in R[76], with a gamma error distribution and a log-link function to bound estimates between 0 and 1.

Modelling results and accuracy

Model coefficients and accuracies are shown in Supplementary Table 5 and Supplementary Data 3-6. See Supplementary Information for more details on modeling testing, results and accuracy.

Model Accuracy: Probability of Change in Agricultural Extent

We assessed model accuracy by classifying cells as having expanded or contracted from 2007-2012 based on the cell's most probabilistic modelled outcome. We then compared these classifications with actual changes over 2007-2012.

Model accuracy varied across regions, ranging from ~62.5% (Caribbean) to ~95% (North Africa) for cropland and 59% (Oceania) to 77% (South and Southeast Asia) (Supplementary Table 5) for pastureland. This compares with a 33% chance of randomly selecting the correct outcome. The lower accuracy of pastureland predictions is possibly due to MODIS data not differentiating between natural grasslands or savannas and artificial pastures[18].

Projecting 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 explanatory variable. We used the region-specific multinomial models to estimate the 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.

Cropland expansion

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

For countries with a projected increase in cropland demand, we randomly selected a single cell, based on the probability it would experience an increase in cropland extent (i.e. the output from the region-specific multinomial model), then increased the proportion of cropland in the chosen cell by the cell-specific amount estimated from the expansion GLMs. We updated the estimates from both parts of the model (because the area of cropland is a key 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 for cropland was met.

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

Changes in pastureland

Following recent trends in global pastureland[63,79] 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 reallocated 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 overestimating future pastureland extent, we limit pastureland expansion to cells identified as having livestock by Gridded Livestock of the World[80] in 2010. If pastureland extent could not expand adequately to meet the five-year target, we assumed that shortfalls were compensated by livestock intensification[5,81].

Adjusting probabilities and the magnitude of changes

Agriculture cannot expand into all regions and land cover classes, specifically into 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.

Consistency of projections

Because the land allocation model is probabilistic, we repeated it 25 times, calculating the mean and standard deviation of the extent of cropland and pasture in each cell for each five-year time period. The allocation model produced consistent projections (Supplementary Figure 3) and we therefore use the mean value in our analyses. 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.

Potential impacts of climate change on agricultural land

We did not include the potential impact of climate change on AES or agricultural yields in our models. Doing so would be hampered by a lack of consensus of how climate change might affect AES and crop yields, and would rely on a large number of untestable assumptions over farmer and policy responses to environmental change. However, 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. See Supplementary Information for a longer discussion of how climate change might affect future patterns of agricultural land cover change.

Biodiversity Model

Area of habitat in 2010

Maps of suitable habitat (referred to as Area of Habitat, AOH[21]) were produced for 4,003 amphibians, 10,895 birds, and 4,961 mammal species[21–24]. 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[21]. These habitat models reliably predict species distribution over wide geographical and taxonomic extents at the 1 km resolution[23,24]. Supplementary Figure 9 shows the species richness patterns created from the AOH maps.

Species' habitat tolerances

We used IUCN data to define whether species are able to survive in agricultural land[4]. 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.

Current Area of Habitat

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

Biodiversity Projections

We estimated future changes in the 2010 area of suitable habitat for 19,859 species of terrestrial amphibians, birds, and mammals, repeating the process described above for each five-year time period from 2010 to 2050. We assumed species were unable to recolonise areas where agricultural land was abandoned to provide conservative estimates of biodiversity gains from agricultural abandonment. Altering this assumption such that species are able to colonise abandoned agricultural areas (as is often observed in long-term dynamics[82]) has little overall impact on our results: with recolonisation allowed, 17.8% of species were projected to see 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 1). Across all species, mean changes were even smaller, from a mean loss of 5.8% to a mean loss of 5.3% with recolonisation. Species for which agricultural land is suitable could see increases in area of habitat as cropland and pastureland expand, or as pastureland is converted into cropland.

Projecting changes 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.

Data and materials availability:

Data are available at https://doi.org/10.5061/dryad.jq2bvq87m and from the corresponding authors upon reasonable request.

Code availability:

Code used is available at https://doi.org/10.5061/dryad.jq2bvq87m.

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Correspondence and requests for materials should be addressed to DRW or MC

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