CODEX PLANETARIUS

Measuring Biodiversity Loss in *Codex Planetarius*

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About *Codex Planetarius*

Codex Planetarius is a proposed system of minimum environmental performance standards for producing globally traded food. It is modeled on the *Codex Alimentarius*, a set of minimum mandatory health and safety standards for globally traded food. The goal of *Codex Planetarius* is to measure and manage the key environmental impacts of food production, acknowledging that while some resources may be renewable, they may be consumed at a faster rate than the planet can renew them.

The global production of food has had the largest impact of any human activity on the planet. Continuing increases in population and per capita income, accompanied by dietary shifts, are putting even more pressure on the planet and its ability to regenerate renewable resources. We need to reduce food production's key impacts.

The impacts of food production are not spread evenly among producers. Data across commodities suggest that the bottom 10-20% of producers account for 60-80% of the impacts associated globally with producing any commodity, even though they produce only 5-10% of the product. We need to focus on the bottom.

Once approved, *Codex Planetarius* will provide governments and trade authorities with a baseline for environmental performance in the global trade of food and soft commodities. It won't replace what governments already do. Rather, it will help build consensus about key impacts, how to measure them, and what minimum acceptable performance should be for global trade. We need a common escalator of continuous improvement.

These papers are part of a multiyear proof of concept to answer questions and explore issues, launch an informed discussion, and help create a pathway to assess the overall viability of *Codex Planetarius*. We believe *Codex Planetarius* would improve food production and reduce its environmental impact on the planet.

This proof-of-concept research and analysis is funded by the Gordon and Betty Moore Foundation and led by World Wildlife Fund in collaboration with a number of global organizations and experts.

For more information, visit www.codexplanetarius.org

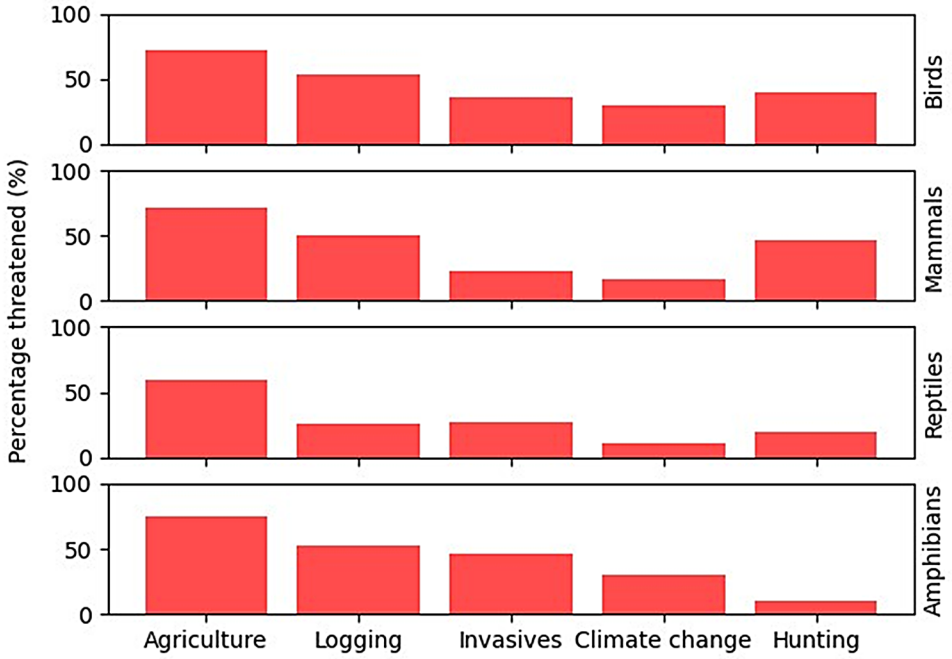
Summary

While the ability of the world's farmers to feed more than 8 billion people is an extraordinary achievement, the way in which that food is currently produced poses an existential threat to much life on earth. Identifying ways of mitigating these impacts while still feeding the world depends in part on a robust framework for tracking the harms done to biodiversity by the production, trade, and consumption of agricultural commodities. We begin this essay by discussing the need for a single metric, focused on a clearly specified dimension of biodiversity loss, which is representative, scalable and critically, comparable across space. We then examine the state of the literature and of efforts thus far to meet this need. Finally, we introduce LIFE – a metric that we believe meets the proposed requirements – and describe both its potential implementation in practical terms as well as its limitations.

The Overwhelming Importance of Farming for Biodiversity

At global scale over the past 65 years food production has more than managed to keep pace with rising human populations. This is remarkable, and has been essential, but the consequences for wild biodiversity have been greater than those of any other human activity. Agriculture – cropland and pasture combined - already occupies around one-half of all suitable land (Ramankutty et al. 2008; Ellis 2011; Foley et al. 2011), and clearance for new farmland is the pre-eminent driver of tropical deforestation (Pendrill et al. 2022) as well as conversion of more open biomes such as the Cerrado (Chaves et al. 2023). BirdLife International's most recent assessment of threats to globally threatened birds shows that 73% of them are threatened by agriculture (Lees et al. 2022). Looked at more widely, IUCN Red List data reveals that farming threatens one-half to three-quarters of all threatened and near-threatened mammals, reptiles, amphibians and birds (IUCN 2023; Tilman & Williams ND; Fig. 1, below). Hunting, which is mainly for food, is the second most important threat to mammals and the greatest threat to IUCN-assessed fish species (Maxwell et al. 2016; IUCN 2023). These impacts look set to increase. For example, the fraction of the world's assessed marine fishery stocks which are overfished continues to grow (FAO 2024a). On land, cropland expansion is accelerating (Cassman et al. 2020; Potapov et al. 2022), and business-as-usual projections indicate that the area under arable production will increase almost everywhere, but especially so in sub-Saharan Africa, where a combination of rapidly rising domestic demand, increasing demand for exports and near-stagnant yield growth means that over a dozen countries have been estimated to need more than four times as much cropland in 2060 as they had in 2010 (Tilman et al. 2017).

Figure 1: Agriculture threatens a greater percentage of threatened and Near-Threatened birds (1773 species), mammals (1280 species), reptiles (1468 species) and amphibians (2523 species) than any other human activity (data from IUCN 2023; figure reproduced from Balmford et al. 2025).



The singular importance of the food system in general and farming in particular means that our ability to bend the curve of biodiversity loss will in part depend on quantifying how agriculture's impacts on wild species compare among and within different commodities. As envisaged in *Codex Planetarius*, with such information buyers can identify the most damaging producers and products, producers can compare their impacts with those of others and potentially gain insights into lessening them, and policymakers and regulators can develop incentives targeting the most damaging producers and indeed track the effectiveness of such interventions. Of course devising an appropriate metric presents several substantial challenges – not least the patchiness and coarse resolution of our knowledge about global biodiversity, and of the global food system. For now, however, we want to flag two other fundamental issues.

The first is the complex, multifaceted nature of biodiversity and of its importance to people (Burgess et al. 2024). The term biodiversity embraces all variability among living organisms, including diversity within species, among species, and across ecosystems (United Nations 1992). People also value biodiversity in very many different ways, from the direct and indirect benefits obtained via ecosystem services through to the values derived simply by knowing that individual organisms or species continue to exist (IPBES 2019; Strange et al. 2024; Nature Futures Framework n.d.). This complexity means that the impacts of food production on biodiversity cannot be completely captured in any single metric (Purvis 2020; Wauchope et al. 2024). Nonetheless decision-makers concerned with the yet broader challenge of addressing sustainability as a whole cannot reasonably be expected to track multiple different biodiversity metrics alongside measures of soil loss, water use, greenhouse gas emissions and so on; instead they need one simple yet robust measure. *Codex Planetarius* has therefore committed to adopting a single biodiversity metric. There are parallels here with the Intergovernmental Panel on Climate Change, which in its first assessment report agreed on Global Warming Potential as a singular, albeit contested, metric for describing the combined impacts of diverse greenhouse gases (IPCC 1990, Fuglestvedt et al. 2003). While many biologists argue for a more complex approach for biodiversity (Purvis 2020; Wauchope et al. 2024), proponents of the *Codex Planetarius* have resolved to adopt a single biodiversity metric. We suggest such a metric should focus on species' extinctions, because unlike many other impacts, extinctions are by definition utterly irreversible; and because addressing elevated rates of extinction is the primary motivation of many conservationists, much environmental policy, and most of the concerned general public (Soulé 1985; CBD 2022; Meier et al. 2024; Rossberg et al. 2024).

Our second fundamental consideration is that the *Codex Planetarius* biodiversity metric needs to be fit for purpose. It needs to be clear exactly which elements of biodiversity it addresses, and which it does not. It needs to be biologically representative, drawing on information from many different taxonomic groups; an ability to be disaggregated in order to isolate impacts on species of particular interest may also be desirable. Applying the metric within *Codex Planetarius* will presumably entail comparing the impacts of food production across different places, so it needs to be spatially explicit, and mapped at global scale, with explicit acknowledgement of underlying assumptions and of biases and limitations in data. It must also be readily computable for activities which vary in their areal extent; biodiversity values are scale-dependent (Rosenzweig 1996), so where values have been derived at one spatial resolution it is important that explicit consideration has been given to how far these can be scaled to estimate larger- or smaller-scale impacts without extensive new analysis. And crucially, the biodiversity metric needs to be comparable across space and hence must be on a ratio scale - i.e. a scale with a true zero and with consistent intervals between points. That way a *Codex* user wanting to compare the impact of, say, a tonne of coffee in two parts of the world can know that if one has an average score twice that of the other, there is a two-fold difference in the level of harm to biodiversity. This last consideration is important because many biodiversity metrics (such as those designed to capture the intactness of a biota relative to an undisturbed baseline) are standardised to local values, so are not comparable across space; or involve assigning numerical weights to categorical classifications (such as species threat status) and so are not on a ratio scale.

In the next section we explore some of the main metrics proposed for assessing the biodiversity impacts of food production, keeping these twin considerations of what aspect of biodiversity they measure and their properties as metrics in mind.

Existing Metrics of the Impacts of Food Production on Biodiversity

Given that >500 biodiversity metrics, indicators, indices and layers have been developed (Burgess et al. 2024), this overview of available metrics is not intended to be comprehensive, but rather an attempt to summarise and evaluate some of the metrics most often linked with agricultural commodities. We divide them into three broad groups based on how they go about assessing the impacts of land use on biodiversity. Different approaches also vary widely in how they go on to attribute land use to the food system – in the production layers they draw on, in whether they assign impacts solely to producers or also to consumers, and whether they do so through biophysical accounting or via Multi-Regional Input-Output (MRIO) modelling. However this heterogeneity in how land use is tracked and attributed is common across efforts to measure other food system impacts, and is not dealt with here. Note also that all metrics struggle to capture uncertainty, indeed we are unaware of any that report uncertainty values associated with their primary outcomes. All involve integrating several

types of data, many of which also do not report uncertainty; overall uncertainty is thus challenging to estimate meaningfully outside of sensitivity tests.

1. Metrics of the average relative abundance of species within communities

One approach for tracking the biodiversity impacts of food production focuses on changes in the intactness of biological communities, using data from the literature on the relative abundance of many different species in undisturbed ecosystems versus human-dominated land uses. Mean Species Abundance (MSA) is calculated as the average, across many species, of their abundance (recorded as density, numbers or relative cover) in disturbed situations divided by that in undisturbed situations (Alkemade et al. 2009); values are capped at 1, and species absent from undisturbed ecosystems are excluded. MSA values are derived for different human land uses as well as levels of infrastructure development and exposure to climate change. Reductions in MSA – i.e. declines in the average abundance of species – can then be estimated for each country and attributed via an environmentally-extended MRIO to different economic sectors, including food, and to domestically produced and imported goods (Wilting et al. 2017). A similar but much larger compilation of estimates of the relative abundance of species across contrasting land uses is now available in the PREDICTS database (which underpins, among other metrics, the Biodiversity Intactness Index - Newbold et al. 2016, De Palma et al. 2021).

The MSA approach draws on data from many different taxonomic groups and locations, and importantly considers impacts caused by infrastructure and climate change in addition to land use. However, in the context of *Codex* it does appear to have several limitations. MSA values are averaged across all terrestrial regions where a land use occurs, and so do not capture the substantial geographical variation there is in species' sensitivities to land use (Boakes et al. 2024). Because MSA scores are averages across species assessed under a given land use, they don't reflect differences between locations in their global importance for biodiversity – so if two regions each produce one tonne of coffee in a hectare under the same land use (say, "low-input agriculture"), the associated MSA scores will be identical even though one region may be home to two or indeed ten times more species. Last, MSA deals with impacts on abundance, not on extinctions, and so while it is relevant to stakeholders motivated by changes in the composition of biological communities it is less useful for those concerned primarily with mitigating the extinction crisis.

2. Metrics Derived from Distributions of Threatened Species

Several analyses focus more directly on extinctions by using information on the distributions of species assessed by IUCN's Red List process and the threats to them. A pioneering study by Lenzen et al. (2012) takes country-level distributions and data on the causes of threat to ~8000 threatened animal species, and then uses an MRIO to assign each combined country/species/threat record to a sector and to the producers and consumers of the resulting goods. Moran and Kanemoto (2017) have since revised this analysis, improving its spatial resolution using Extent of Occurrence (EOO) maps of species distribution. Both analyses identify commodities, producers and consumers associated with high levels of threat. However their accuracy is limited by the assumption that all listed threats to a species have equal impact, and affect the species uniformly across its entire range. The equal treatment of species in all threat categories and the exclusion of non-threatened species (which make up the bulk of biodiversity, and which despite not meeting Red List thresholds will often be brought closer to extinction by farming) mean that the relationship between numbers of species-threats (Lenzen et al. 2012) or Biodiversity Footprint scores (Moran et al. 2017) and changes in average species' risk of extinction is also unclear.

A second, broadly similar approach (Irwin et al. 2022), based on the Species Threat Abatement and Reduction (or STAR) metric (Mair et al. 2021) involves assigning the threats to ~5000 threatened and Near Threatened amphibians, birds and mammals to economic sectors in each of 190 countries and regions, according to the proportion each country contains of the species' global Area of Habitat (AOH – that is, the parts of its range where conditions are suitable for it to live; Brooks et al. 2019). Species are assigned linearly ranked weights based on their threat status, with the threats to a species weighted differently based on their scope and severity (following Garnett et al. 2019). The resulting footprint metric has global coverage, and integration with an MRIO enables impacts to be attributed separately to domestic consumption, exports and imports, for each sector in turn. However, the use of subjective weights for different threat categories and for different threats to a species means that the resulting extinction risk scores are not on a ratio scale. Combined with the exclusion of those species not yet considered threatened or Near Threatened, this means that the relation of extinction footprint scores to overall extinction risk is again unclear. Returning to our hypothetical example it is therefore not possible, using this metric, to derive a comparable measure of impact on species extinctions of producing a tonne of coffee in two different places.

One last, recent analysis (Hoang et al. 2023) uses modelled distributions of threatened vertebrate and plant species and the Zonation planning tool (Moilanen et al. 2007) to rank 0.5o gridcells by their Conservation Priority (CP) for addressing threats due to agriculture. It then overlays the ranked CP scores with commodity production maps to estimate the potential for conflict between the production of each commodity and biodiversity conservation. As with other methods in this section,

this procedure helps identify which commodities are likely to impact threatened species, and where. But again there is no consideration of species that are not yet threatened, and the weightings applied to different threat categories and the subsequent ranking of sites means that CP scores are not on a ratio scale, nor related in a direct way to extinction risk.

3. Metrics Derived by Estimating Local Extirpations of Species

A final and quite large group of papers attempts to quantify numbers of extinctions by estimating how species richness changes as natural habitats are converted for human land use. Most (e.g. Chaudhary et al. 2015, 2016; Chaudhary & Kastner 2016; Chaudhary & Brooks 2019; Scherer et al. 2023; Cabernard et al. 2024) use the framework of the countryside Species-Area Relationship (cSAR; Pereira & Daly 2006), which estimates what proportion of an area's species will become extinct (over a potentially protracted, so-called relaxation period) as natural land covers are replaced by anthropogenic ones. cSAR calculations typically focus on WWF Ecoregions (Olson et al. 2001), and then are combined with a variety of trade and consumption models to attribute resulting extinctions to different sectors and commodities, including food.

Using the cSAR to estimate global extinctions due to land-use change requires specifying two important properties – the affinity and vulnerability - of each taxonomic group in each ecoregion. The affinity of species in a group to each anthropogenic land use reflects their average relative ability to persist in it, compared to natural habitat. Affinity scores have variously been estimated from the literature (Chaudhary et al. 2015, 2016; Chaudhary & Kastner 2016) or IUCN habitat preference data (Chaudhary & Brooks 2019), and in a recent analysis (Scherer et al. 2023) have been further modified to reflect species' ability to disperse across fragmented landscapes (an important consideration which is not reflected in other metrics). Average affinity scores for taxonomic groups are then used to estimate the proportion of those species originally present in the ecoregion which are likely to survive in each land use, and in the ecoregion as a whole, and hence the proportion lost.

Translating these local extirpations into global extinctions is harder. Applying the cSAR formulation just to those species endemic to an ecoregion underestimates global extinctions, because it ignores the loss of any more widely-distributed species which are extirpated from all ecoregions where they occurred. Similar logic means that if ecoregions were subdivided (thereby creating fewer single-ecoregion endemics), estimates of global extinctions would (quite wrongly) decrease. Hence there have been several attempts to develop so-called vulnerability (or Global Extinction Probability, GEP) scores, reflecting the importance of each ecoregion for the global persistence of all its species. The formulae used incorporate IUCN threat levels for each species and the proportion of species' AOHs falling within the ecoregion (Chaudhary et al. 2015, 2016; Chaudhary & Kastner 2016), and more recently the probability of each species occurrence in the ecoregion (Kuipers et al. 2019; Verones et al. 2022; Scherer et al. 2023). A single vulnerability or GEP score for a group of species in an ecoregion is then multiplied by the cSAR-derived number of local extinctions from land-use change to estimate global extinctions.

cSAR methods are grounded in Life Cycle Analysis literature, and widely cited. Importantly, they often draw on information from a very wide range of taxa and include non-threatened as well as threatened species. However they appear to have several limitations. Early values for affinity scores were based on extensive extrapolation from limited observations (see critique by Chaudhary & Brooks 2019). Newer methods for estimating both affinity and vulnerability scores involve combining multiple factors and assigning simple but essentially arbitrary weights – e.g. to species' IUCN threat status – to which the eventual results are highly sensitive (Kuipers et al. 2019). Hence extinction estimates are again not on a ratio scale, meaning our imaginary *Codex* coffee enthusiast could have no confidence that a two-fold difference in the metric indicates a two-fold difference in extinction risk. There are additional concerns around scalability, and disaggregation. It is not clear how results derived from the cSAR at ecoregion scale can be interpreted at smaller or larger scales. And because cSAR methods apply uniform affinity and vulnerability scores to all of a given taxon's species in an ecoregion, it seems the method cannot identify which species found there are most heavily impacted by land use.

One other approach, which bears some similarity to cSAR methods, overlays EOO maps for terrestrial vertebrates to estimate species richness in undisturbed biomes in specified regions, and then multiplies these by biome-specific values (derived from the PREDICTS database) for the proportion of species likely to persist under human land uses (Boakes et al. 2024). The resulting figures for losses of local species richness, and similarly-derived estimates for the loss of rarity-weighted richness, are then attributed to different land uses, producers and consumers. However, as with the cSAR methods, the use of biome-wide averages for proportional species persistence would seem to mask important geographical and taxonomic variation in species' sensitivities to land use; and the link between the estimated loss of local richness and global extinctions is unclear.

Although inevitably incomplete, this review of biodiversity metrics which have been linked to food production indicates that despite much work and many useful results, we still lack mapped surfaces which simultaneously capture impacts on non-threatened as well as threatened species, are readily scalable, have the potential to be disaggregated, and are on a ratio scale. Interestingly one very recent study (Chapman et al. 2025), which intersects crop surfaces with a 10km x 10km map

of vertebrate species richness and then estimates what it terms Biodiversity Pressure as the sum of the richness scores for all cells where a crop is grown, does meet all of these criteria. However, like many of the longer-established metrics we have reviewed, the values generated by this metric do not relate analytically to extinction risk, and their meaning in the real world is unclear.

For the rest of this essay we describe the derivation and potential use of one final extinction risk metric we have developed to address these concerns, called LIFE.

Food-LIFE

Derivation

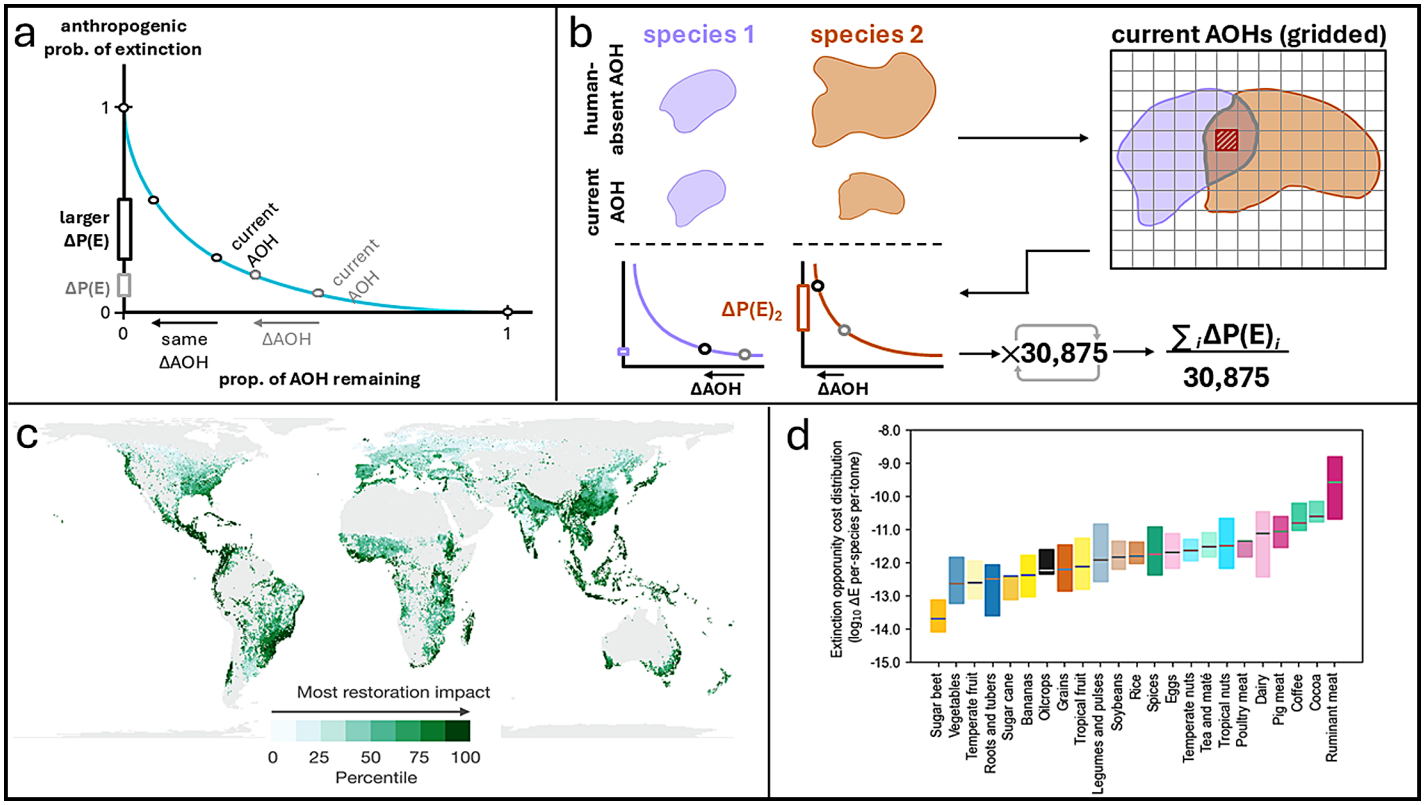
The Land-cover change Impacts on Future Extinctions (or LIFE) metric (Eyres et al. 2025) estimates the spatial distribution of the impact of marginal changes in human land use on the average species' probability of global extinction. The central premise in LIFE is that a species' risk of anthropogenic extinction (i.e. over and above background extinction rate) responds nonlinearly as its population size falls below the long-run average that would be expected in the absence of people (Durán et al. 2020). The exact form of this relationship is not yet known (Ball et al. preprint 2025a), but for now LIFE assumes (as do Thomas et al. 2004; Phalan et al. 2011; Strassburg et al. 2012, 2019; Armsworth et al. 2020; Durán et al. 2020) that, echoing widely observed species-area relationships, this curve follows a simple power-law function with an exponent of 0.25 and a 100-year relaxation period over which species respond to human-induced changes in their population size (Fig. 2a, pg 7). As a proxy for these changes LIFE uses changes in species' AOHs.

The LIFE pipeline begins by building current and absent-human AOH maps for almost all (in practice 30,875) of the world's known terrestrial vertebrate species by combining their global ranges with information on their habitat and elevational preferences (both from IUCN 2023) and maps of current land cover (Jung et al. 2020) as well as projected land cover in the absence of human impacts (Hengl et al. 2018; for further details see Eyres et al. 2025). This allows estimation of the proportion of a species' long-run AOH it currently occupies, hence its risk of extinction from current human land-use, and from that the impact of it losing (or gaining) one further unit of suitable habitat (Fig. 2b, pg 7). This procedure is repeated for all mapped species (whether or not they occur in the area of interest), with the resulting LIFE score for each 1 arc-minute gridcell representing the mean change in extinction risk across all mapped species as a result of converting (or restoring) its natural land cover, expressed per km2 of land under transition (see Eyres et al. 2025 for further details).

Iterating this process for all cells then allows production of spatially mapped layers describing the impact of different land-cover transitions, such as converting remaining natural habitat to cropland or restoring current farmland to natural land covers (Fig. 2c, pg 7). Because these maps are based on IUCN habitat preference data they incorporate the ability of many species to persist or indeed expand their AOHs into farmed land. Statistical analyses of the very substantial geographical variation in LIFE values confirm (as expected) that these co-vary with a cell's species richness, the degree of endemism of the species present and the level of habitat loss they have experienced to date; where any of these three factors are greater, changing the extent of natural habitats has more impact on the average species risk of extinction (Eyres et al. 2025). Simulations also show that LIFE scores generated for 1 arc-minute cells (3.4km2 at the equator) are quite scalable: despite the non-linearity of the assumed extinction risk-AOH curve, impacts from 0.5 to at least 1000km2 in extent (and up to 30,000km2 in some regions, such as western Europe) can be estimated reasonably reliably simply by adding or dividing marginal scores for the constituent gridcells (for details of this analysis see Eyres et al. 2025).

As with recent efforts to quantify the climate change impacts of growing food (Searchinger et al. 2018, Balmford et al. 2018; Wirsenius et al. 2025), LIFE can be used to estimate the extinction impact of farming by taking an opportunity-cost approach – essentially viewing LIFE's cropland and pasture restoration layer as a description of the impact of being unable to restore natural habitats because of continuing food production. By intersecting the LIFE restoration layer with maps of where given agricultural commodities are produced and at what annual yield (FAO 2024b), Food-LIFE estimates the impact on global mean per-species extinction risk of the land used to produce a flow of one tonne of that commodity annually, for each cell where that production occurs (for detailed methods see Ball et al. 2025b). For feed-based livestock production, trade data (taken from FAO 2024b, following methods of Schwarzmueller & Kastner 2022) is used to incorporate the impacts of feed production, which is then added to those from pasture use. Results for all cells where a commodity is produced (Fig. 2d, pg 7) reveal that differences in where products are grown and at what yields lead to very marked variation both across and within major commodities in their impacts on species' risks of extinction. Aggregating data by countries or regions and linking it

Figure 2: Agriculture threatens a greater percentage of threatened and Near-Threatened birds (1773 species), mammals (1280 species), reptiles (1468 species) and amphibians (2523 species) than any other human activity (data from IUCN 2023; figure reproduced from Balmford et al. 2025).



with data on production and trade allows estimation of the footprints associated with annual flows of each commodity, of food items made from multiple commodities, and even those of individual consumers' diets (Ball et al. 2025, Madhavapeddy 2025). Its broad applicability means that this version of LIFE has been incorporated into an official statistic of the UK as a metric within the Global Environmental Impacts of Consumption (GEIC) indicator (JNCC 2024).

Like all other metrics we've looked at here, Food-LIFE has limitations (Eyres et al. 2025; Ball et al. 2025). It captures only those impacts mediated through changes in habitat area, and not other effects of the food system such as climate change, pollution or the degradation or fragmentation (rather than complete loss) of habitat. Like other metrics it does not capture the effects of local changes in a species' abundance on its populations elsewhere, or on the populations of other species, and like many metrics it uses information only for terrestrial vertebrates, and is limited by the accuracy and resolution of species' distribution, habitat preference, land cover and food production and trade data. Critically, the relationship at the centre of the LIFE method between a species' risk of extinction and loss of its habitat is currently only poorly characterised, and will vary across species. And Food-LIFE does not address the effects of capture fisheries or wild meat harvesting, or the impacts of agriculture on ecosystem services or on the local (rather than global) abundance of organisms - which (as in the case of pollinators or soil microbes) can be very important to the long-run sustainability of food production. On this point in particular a good case could be made for supplementing a global extinction metric with a metric characterising changes in local population sizes of agriculturally significant organisms or other aspects of biodiversity that underpin nature's contributions to people.

But in its favour, Food-LIFE generates a direct measure of the extinction impacts of producing different commodities in different places, on a ratio scale (so that a doubling of the value indicates a doubling of mean extinction risk; Eyres et al. 2025). Food-LIFE extinction risk estimates are also reasonably scalable, so that impacts of small or indeed large-scale production can be obtained from existing data layers (Eyres et al. 2025), and they can be broken down to look at impacts on individual species (Durán et al. 2020; Eyres et al. 2025). Impact estimates based on national or regional yield data can be refined if users can provide finer-resolution information on provenance. Moreover Food-LIFE estimates can be readily contextualised, as they are directly comparable with other land use-mediated anthropogenic impacts and indeed with background rates of extinction (Balmford et al. in prep). Given its potential usefulness, in the final section of this essay we set out, briefly, how one might apply Food-LIFE as part of a *Codex Planetarius* impact-tracking system.

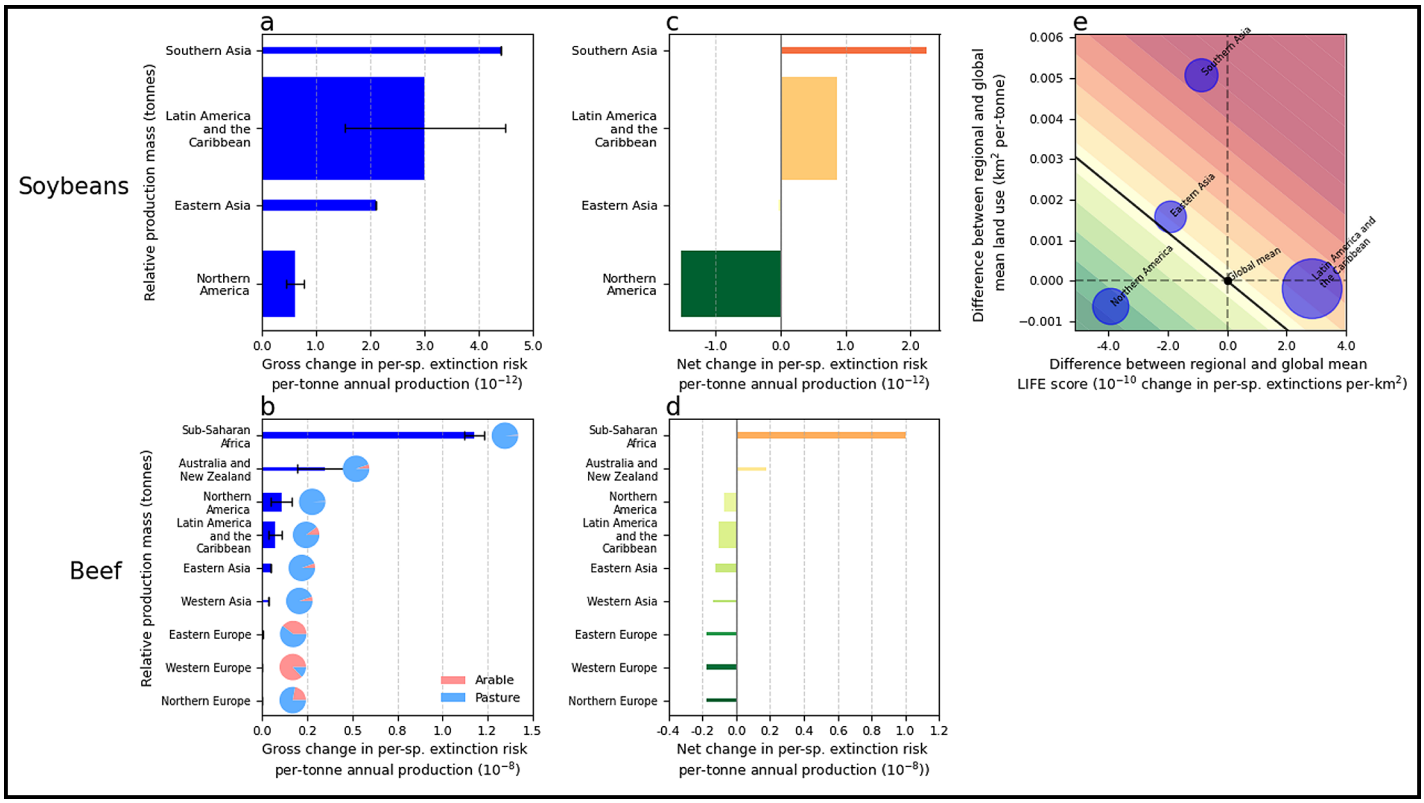
Potential Application in *Codex Planetarius*

We suggest Food-LIFE could be readily deployed in *Codex* in two complementary ways. First, it can be used to estimate the gross impact on the average species' risk of extinction of producing a tonne annually of any food commodity, anywhere in world – essentially breaking down the global-level bars in Figure 2d (pg 7). This means that Food-LIFE can provide the hypothetical *Codex* user with meaningful, ratio-scale estimates of the average impacts on global extinctions risk of producing one tonne per year of a commodity in every country of interest (and indeed at finer scales if the user has better-resolved production data). Figure 3 (panels a and b, pg 9) illustrates such an analysis for two highly traded food commodities. For soybeans (panel a), this shows that impacts per tonne are especially high in Southern Asia, but also in Latin America and the Caribbean, which produce almost as much as all other regions combined; impacts per tonne are substantially less in the next most important producer, Northern America. The same analysis for beef (panel b) reveals very strikingly that global average impacts per tonne are almost three orders of magnitude greater than for soybeans, and are especially high in sub-Saharan Africa, but also in Australia and New Zealand. The beef impacts combine those of pasture and of feed production, with the former responsible for a greater share of footprint of beef production in every region except Western Europe, where there is much greater use of feed (a proportion of which is sourced from high biodiversity regions elsewhere). For simplicity these results are summarised by the main producer regions, but it is analytically straightforward to produce data by country or for separate subnational regions.

Of course producing a commodity in one place on average lowers the incentive to produce it elsewhere, so as well as considering gross impact, it would be useful for an impact-tracking mechanism to report impact compared with other production areas. This in effect describes the consequence, at global scale, of this supply option versus others; such information can then help buyers source lower-impact products, and enable industry, governments and NGOs to identify where to target support for improved production practices. Hence a second way of reporting Food-LIFE results within *Codex* would be to calculate the net impact of production in a focal location by deducting from its gross impact the mean global impact of producing the commodity. Applied to soybeans (Fig. 3c, pg 9) we see very substantial differences between regions, with Latin American production having considerably worse-than-average impacts (i.e. causing net positive damage) and North American production better-than-average (i.e. net negative) impacts. This result underscores serious concerns raised about the marked shift in China towards sourcing much more of the soy it uses for animal feed from Brazil rather the United States as a consequence of the recent turmoil in trade tariffs (Antonelli et al. 2025; Li et al. 2025). Applied to beef (Fig. 3d, pg 9) the especially high impact of African beef stands out, but so too does that of Australian and New Zealand production, highlighting the likely net damage to biodiversity caused by the UK moving, post-Brexit, towards buying more of its ruminant meat from there rather than Europe (Spencer 2025).

One other way in which Food-LIFE results could potentially be reported within *Codex* would provide context for why producers have the impacts they do, and how in principle these might be reduced. The per-species extinction risk score attributable to a tonne of commodity is dependent on the average LIFE score per unit area in the place used to produce it, and its average yield there. Figure 3e (pg 9) illustrates for soybeans how the contributions of these two components can be dissected. For each main producing region, the plot shows its average land use per tonne (the inverse of yield) and its average LIFE score per unit area, both expressed as a difference from the weighted global mean across all producing regions. Coloured bands represent lines of constant extinction risk per tonne, with the solid central line representing the global mean score for soybean. Regions with scores above that central line on average have production impacts above the global mean – some as a result of high land use and some because of high LIFE scores per unit area. Provided it can be achieved equitably, without disproportionately reducing species' populations on farmed land, and without increasing other negative impacts (such as eutrophication, poor animal welfare or runoff of harmful chemicals), all regions could reduce the extinction impact of their production by increasing their yields (Balmford et al. 2025) - or indeed by reducing food loss (which likewise lowers the area required to produce a given amount of the commodity). The impact of such improvements would be greater in regions which combine substantial production with a high average LIFE score or with very low yield (e.g. for soybean, Latin America and the Caribbean, and Southern Asia respectively; Fig. 3e, pg 9). Those regions with high LIFE scores per unit area might also be able to reduce their average impacts over time by directing any expansion of their production into less biodiverse places capable of achieving reasonably high yields.

Figure 3: (a) the gross change in mean per-species extinction risk associated with producing one tonne of soybeans each year. The regions shown are responsible for 97% of global production. The height of each bar is proportional to the total annual production in the region, with bar area therefore proportional to the estimated total impact of production in the region. Error bars represent 95% confidence intervals based on within-country variation in yields.(b) the gross change in mean per-species extinction risk associated with producing one tonne of beef each year, calculated as the sum of both grazed land and feed production (including feed imported from outside the region). The proportional contribution to each region's total impact of arable and grazed land is shown in the pie charts. Selection of regions, height of bars and error bars are as in (a) but note the markedly different x-axis scale. (c), (d) the net change in mean per-species extinction risk associated with producing one tonne of soybeans or beef each year in the same regions, where the zero line is the global weighted mean. (e) the mean land use and mean LIFE score per unit area of soy production in the main producing regions, expressed as differences from their respective global mean values. Coloured bands represent lines of constant change in mean per-species extinction risk per tonne of annual production, with the sloped solid line representing the global mean. Circle area is proportional to the estimated total impact on extinction risk of production in the region.



Prospect

The pilot Food-LIFE analyses presented here could be improved in various ways. The accuracy and resolution of estimates could be enhanced by governments, producers or initiatives such as Trase (https://trase.earth/) with access to higher-quality and finer-scale production, land use, yield and trade data, allowing results to be disaggregated sub-nationally or segregated into different consumer markets or production methods. Assessment could be undertaken annually, to incorporate the impact of changes in the places used to produce particular commodities. Where, for example, expansion occurs into lower-yielding and/or higher-biodiversity areas, average extinction impacts per tonne will increase. Assessing the impacts of farm abandonment is harder, given that land may not revert to natural land cover, and the uncertainties and lags in biodiversity gains if it does. Net impact results could be made more useful for buyers by providing more granular results showing the distribution of impacts of all their potential suppliers. Last there is also a need to address as far as possible the limitations of the LIFE metric flagged above. Work is already underway on several of these issues – including incorporating the effects of differences in agricultural practices, and extending taxonomic coverage to a reasonably large sample of plant species. Fortunately the LIFE pipeline has been designed in a transparent, open-access format (code available at github.com/quantifyearth/LIFE and pre-computed LIFE layers at https://zenodo.org/records/14945383). This should allow these improvements and those that might be developed by other groups to be readily adopted. Other limitations (common, we believe to all the metrics reviewed here) are at present less tractable – in particular, meaningfully estimating uncertainty, and capturing the cascading effects of changes in the abundance of one species on the extinction risks of others.

Considering the challenge for *Codex* of tracking the biodiversity impacts of food production, both the complexity of the living world and our limited documentation of the food system mean that any measure focused on just one element of biodiversity loss will be far from complete and as such will be contested. An extinction-focused metric is in particular likely to perform quite poorly at tracking nature's contributions to people. However, we contend that alternative approaches, involving several, potentially conflicting measures, or collapsing multiple elements of biodiversity into a compound measure, could lead to confusion and risk biodiversity concerns being overlooked. A pragmatic solution would instead seem to be to identify what aspect of biodiversity and its loss is of greatest importance to *Codex* stakeholders and then proceed, with very clear caveats, with a single metric which captures that dimension robustly and with as many desirable traits (such as coverage, scalability, and especially comparability) as possible.

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