Biological Conservation 315 (2026) 111663

Contents lists available at ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/biocon

Informing conservation problems and actions using an indicator of extinction risk: A detailed assessment of applying the LIFE metric

Alison Eyres [a,b,*], Andy Arnell [c], Thomas S. Ball [a,b], Richard J. Cuthbert [d], Michael Dales [b,e], Alejandro Guizar-Coutiño [f,g], Jody Holland [a,b], Emilio Luz-Ricca [a,b], Anil Madhavapeddy [b,e], Leila Pain [d], Tom Swinfield [a,b], Thomas B. White [f,g], Andrew Balmford [a,b]

[a] *Department of Zoology, University of Cambridge, Cambridge, UK*
[b] *Conservation Research Institute, University of Cambridge, Cambridge, UK*
[c] *Food and Agriculture Organization of the United Nations, Rome, Italy*
[d] *World Land Trust, Blyth House, Halesworth, Suffolk, UK*
[e] *Department of Computer Science & Technology, University of Cambridge, Cambridge, UK*
[f] *Leverhulme Centre for Nature Recovery & Department of Biology, University of Oxford, Oxford, UK*
[g] *The Biodiversity Consultancy, Cambridge, UK*

ARTICLE INFO

Keywords:
Extinction
Biodiversity metrics
Habitat loss
Metrics
Land cover

ABSTRACT

Extinction is a critical issue, with land-use change the main threat to many terrestrial species. Understanding and tackling this requires global, comparable, and scalable metrics that link land-cover change to extinction risk and are useable across diverse conservation contexts. Here, we demonstrate the flexibility of the new Land-cover change Impacts on Future Extinctions (LIFE) metric through five distinct case studies. First, we explore the near real-time quantification of biodiversity harms in tropical hotspots by integrating LIFE with forest loss data. Second, we couple LIFE with crop distribution and trade data to assess variation in extinction impacts mediated by food consumption – specifically of apples in the UK. Third, we test LIFE's suitability for use in biodiversity compensation through a hypothetical scenario in Sumatra. Fourth, we use LIFE to prioritize competing conservation investments by comparing benefits of area-based projects in Honduras. Finally, we combine LIFE with counterfactual methods to evaluate the effectiveness of a long-term conservation project in Sierra Leone. Together, these examples show that LIFE offers actionable insights into a geographically and thematically wide range of conservation challenges, from land-use planning to sustainable consumption. Like all global metrics, LIFE's broad applicability relies on assumptions and simplifications. It should be used cautiously, and alongside local knowledge and ground-truthing, especially for restoration, offsetting, or fine-scale analysis, and in poorly studied areas. By providing an accompanying "How-to" guide, we aim to ensure LIFE can be used widely to inform understanding of the extinction crisis and support tangible actions to halt it.

1. Introduction

Human activity is driving significant declines in biodiversity, increasing species' extinction risk, and undermining ecosystem functioning and resilience (Brondizio et al., 2019; Díaz et al., 2019). To track and mitigate these losses we need robust metrics linking extinctions to land-cover change - our most significant influence on wild terrestrial species (Jaureguiberry et al., 2022). Here we explore the scope, flexibility, and constraints of using one recently developed extinction-focused metric in a suite of applications critical to addressing the extinction crisis. These range from near real-time tracking of the likely consequences of unfolding threats, through to quantifying the effects of efforts to avoid habitat loss on species extinction risk.

Several global extinction metrics exist, largely reflecting consensus on key risk factors: range size, population size and trends, and threat severity. These global extinction metrics broadly fall into two categories, according to their purpose. The first category of metrics monitor species status over time or space, such as the IUCN Red List Index (Butchart et al., 2004), or the newly developed Biodiversity Impact Credits metric (BIC, Rossberg et al., 2024). The second category of metrics, like the

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[*] Corresponding author at: Department of Zoology, University of Cambridge, Cambridge, UK.
E-mail address: alison.eyres@gmail.com (A. Eyres).

https://doi.org/10.1016/j.biocon.2025.111663
Received 30 June 2025; Received in revised form 2 December 2025; Accepted 5 December 2025

Species Threat Abatement and Restoration metric (STAR, Mair et al., 2021; Turner et al., 2024), isolate the effects of specific drivers of change to predict impacts, identify effective actions, and prioritize conservation efforts. To help users estimate potential extinctions resulting from changes such as specific land-cover conversions, several extinction metrics offer ready-to-use mapped surfaces that show the impact of such changes (e.g. the LIFE metric; Eyres et al., 2025).

To meaningfully address the extinction crisis, global extinction metrics must be broadly applicable across diverse conservation contexts, geographies, and user groups, allowing the consequences of different actions to be compared in a common currency, regardless of computing resources or technical expertise. Achieving this requires a set of specific qualities. A global extinction metric must be representative of geographic, taxonomic, and habitat diversity (Jones et al., 2011); allow aggregation and disaggregation (into scores for individual or groups of species); and enable direct comparisons between locations or between gains and losses by being interpretable on a ratio scale (such that a two-fold difference in metric scores across actions or locations corresponds to a two-fold difference in estimated effects on extinctions). Finally, in order to enable real-world impact, metrics must be accessible and actionable. Part of this depends on the metric in turn being scalable – so that a layer of impact on extinction calculated at one resolution can be reliably used for assessing larger or smaller-scale actions, without requiring extensive further analysis or computation at these new scales (Green et al., 2019). Existing metrics describing the impacts of land-use change on proxies of extinction risk meet many of these criteria, but not all; see Table S1 for an assessment of existing extinction risk metrics.

The newly developed LIFE metric (Eyres et al., 2025) which does fulfil the above mentioned criteria, estimates the spatially explicit change in species' extinctions associated with land-cover change by integrating species distributions, predicted species-specific responses to land-cover change, and the non-linear effects of past and present habitat loss on extinction probability of ~30 K terrestrial vertebrates. LIFE scores are directly comparable across locations, and by default LIFE is split into two pseudo-opposite layers; LIFE-convert and LIFE-restore. These quantify, respectively, the impact of converting natural habitats to arable land and restoring agricultural lands to their natural states, though the framework also accommodates the calculation of other land-cover transitions which have since been produced (Eyres et al., 2025). Like all global metrics, LIFE is based on some simplifications and assumptions and is only as reliable as the underlying data. Addressing these limitations is the basis of ongoing work, for example, by integrating the impacts of different land-use intensity, habitat quality, and fragmentation and striving to include more taxa.

This paper explores the utility of LIFE as a practical tool for guiding a wide range of conservation questions and actions by applying it to five use cases. First, we quantify biodiversity harm at a global scale by integrating LIFE with high-resolution data on tropical forest loss. Second, we link biodiversity decline to agriculture, a key driver of loss, by combining LIFE with crop distribution and trade data in order to assess variation in the impacts of apple consumption in the UK. Third, we examine the hypothetical case of a company attempting to mitigate its impacts in Sumatra, demonstrating LIFE's potential to guide biodiversity compensation efforts. Fourth, we show how LIFE can inform prioritization of conservation actions by evaluating proposed area-based investments for an international NGO. Finally, we use LIFE to quantify the impact of conservation interventions in Sierra Leone, measuring avoided extinctions using state-of-the-art counterfactual methods. Our findings demonstrate the metric's versatility and limitations and suggest it has value for informing diverse conservation actions. In addition to evaluating the flexibility and limitations of the LIFE metric across a representative range of conservation issues we hope this work inspires new and diverse applications. To support this, we've developed accompanying general "How-to" guide designed to help others apply the metric to their own conservation questions (supplementary materials).

2. Conceptual and methodological basis of LIFE

LIFE uses changes in each species' Area of Habitat (AOH) – defined as the habitat available to it and calculated as the intersection between its range and its environmental preferences – as a proxy for human-induced changes in extinction risk (Brooks et al., 2019). Specifically, LIFE estimates the change in extinction probability resulting from present-day land cover change manifested over the next 100 years for ~30,000 terrestrial vertebrates assessed on the IUCN Red List. At present, LIFE is applied only to terrestrial vertebrates due to the lack of comprehensive global data on plants and invertebrates (see required data in Table S2), though the approach could in principle be extended as such data become available. It uses a power law to model how extinction risk varies with each species' current area of habitat (AOH) relative to its potential AOH in the absence of human land use (Fig. 1A.) AOHs were estimated by refining IUCN range polygons according to species' habitat and elevation preferences, in conjunction with a current global habitat distribution map (Jung et al., 2020) and potential natural vegetation (PNV) for AOH in the absence of human impacts (Hengl et al., 2020). For detailed methods, justification and sensitivity to assumptions see caption for Fig. 1A, supplementary table S2 and Eyres et al. (2025). For each species, LIFE then calculates the change in its probability of extinction (relative to that in the absence of human influences) that occurs following an additional change in land-cover, via impacts on AOH (Fig. 1B). The LIFE score is generated for a given pixel by summing the effect of marginal changes in land-cover for all species present (Fig. 1C). The final LIFE maps are the result of this calculation for each 1 arc minute resolution (~1.8 km × 1.8 km at the equator) across the globe. The changes in extinction risk are normalised to the amount of 'changing' land within each pixel, so they are expressed in units of LIFE score per km^2 of land-use change. From a practical perspective the LIFE score values can be interpreted as the contribution to the risk of extinction that is likely to occur (or be avoided) given an area of land use change.

LIFE maps were initially published describing two key land-cover changes; the conversion of natural habitats to cropland (LIFE-convert), and the restoration of all agricultural (crop and pasture) land to potential natural habitat (LIFE-restore). Direct tests show that the metric is scalable: when divided or summed as appropriate the published surfaces yield reliable estimates of the impacts of land-cover change across areas ranging from approximately 0.5 km^2 to 1000 km^2 (Eyres et al., 2025). The LIFE-restore layer has subsequently been used in (Ball et al., 2025), which slightly modified the layer to align with spatial agricultural data from the Global Agro-Ecological Zones (GAEZ) project (FAO and IIASA, 2025) to estimate the opportunity-cost impact of continuing to use land for food production and therefore forgoing reductions in species extinction risks from restoration. To illustrate potential applications the following case studies make further use of these LIFE layers with one key modification. To standardise the LIFE metric, we divide all LIFE/km^2 values by the total number of species included in the analysis (n = 30,875). This ensures the metric is agnostic to the number of species considered and remains comparable even if additional species are included. The resulting value reflects the per-species contribution to the change in extinction probability over the next century due to land conversion or restoration and is referred to subsequently as the change in extinction risk.

3. Case study 1. Measuring harm to biodiversity: linking LIFE with near-real time forest alerts

Ongoing advances in remote sensing allow us to detect deforestation with high certainty at increasingly finer spatial temporal resolution. However, simple areal measures of changes in forest extent or biomass hide substantial variation in biodiversity impacts. To examine how LIFE can be used to detect damage to biodiversity we intersected the LIFE-convert layer with data from Global Forest Watch (Berger et al., 2022). This dataset combines deforestation alerts across the tropics (30°

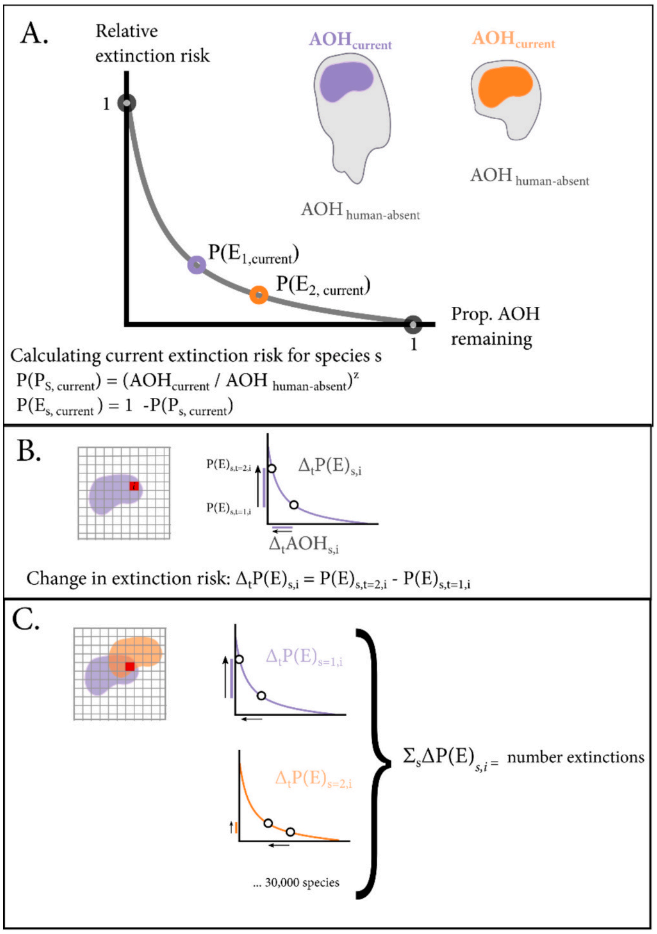

Fig. 1. Overview of the key steps and associated assumptions of the LIFE metric calculation, shown for conversion of natural habitats (LIFE-convert) to arable using two example species depicted in purple and orange. LIFE-restore is calculated following the same procedure but by restoring non-natural habitats to potential natural vegetation. A) By combining species range data from the IUCN with maps of elevation and habitat types a species' proportion of current AOH (coloured) is calculated relative to its AOH in the absence of humans (grey). This proportion is converted to the probability of persistence P(P) of each of two species (in purple and orange), relative to that in the absence of humans using a power-law function. Human absent habitat is inferred using the Potential Natural Vegetation (PNV) in a region (Hengl et al., 2020), and current AOH by using the distribution of current habitats (Jung et al., 2020). Note that probability of extinction is subsequently calculated as 1- P(P). B) For any given pixel in which a species is found we then calculate the marginal impact on probability of extinction (ΔP(E)) of converting the next unit of habitat. This is shown here for pixel i, in red. C) This process is repeated for all species present in the pixel. Note that due to the power-law, ΔP(E) is greater for a given relative loss of AOH (ΔAOH) for those species which have already lost proportionally more of their AOH (in this case, the species in purple). The total LIFE score associated with converting all natural habitat in the pixel is then obtained by applying steps A and B to >30,000 terrestrial vertebrate species and summing the impact across all species in a pixel. These per pixel LIFE values are then expressed as the expected number of extinctions per km^2 (Δ E/km^2) by dividing the summed LIFE scores by area of land-use change in the pixel. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

N and 30° S latitude) from three systems (GLAD-L, GLAD-S2 and RADD) into a single integrated alert layer, providing near-real-time detection of possible deforestation at 30m^2 (GLAD-L) and 10m^2 (GLAD-S2, RADD) resolution. We focused on alert data, as opposed than annual loss estimates (e.g. Hansen et al. (2013)), because the frequent reporting intervals are more relevant for informing conservation interventions. To reduce the potential for false positives, we used only the highest-confidence alerts- those detected by at least two alert systems at the same location (rule set-1; Reiche et al., 2024) – while acknowledging that there will be a time-lag between forest loss and the confirmation of a high confidence alert. Alerts were summarised monthly over the 48 full months between January 2021 and December 2023 and intersected with the LIFE -convert layer to obtain an estimate of forest loss and associated extinctions through time. To assess temporal and spatial impacts we aggregated forest loss and LIFE scores monthly by country, focussing on five countries with high forest loss or biodiversity loss in this period. For these analyses we assumed that each high-confidence alert represented a deforestation event with a persistent impact (i.e. not reversed). Full details of data and methods can be found in the supplement (Supplementary methods & Table S3).

Our analyses show that within the tropics, over this period Brazil, the Democratic Republic of the Congo (DRC), Peru, Indonesia, and Papua New Guinea experienced significant forest loss. Brazil showed the greatest absolute levels of forest loss (Fig. 2A, 82.1 % of total) with the other four countries experiencing much lower absolute losses. However, our analyses demonstrate that forest loss has a greater per km^2 impact on extinction in some countries than others (Fig. 2A and Fig. 2B). The impact in terms of extinction risk arising in Peru, Indonesia and Papua New Guinea are disproportionately large compared to the extent of forest loss in these regions (Fig. 2B). For example, despite Papua New Guinea accounting for less than 1 % of forest loss, more than 5 % of the resulting impacts of extinction risk occurred here. Combining LIFE with deforestation rates highlights the variety in biodiversity impacts behind forest loss.

Both total extent of forest loss and its impacts on biodiversity across these five countries show upward trends through time (Fig. 2C and D, respectively). There is considerable inter-annual variation in both forest loss and its impacts, with peaks between August and October each year. Across years, forest loss and its impact on species extinctions broadly follow similar trends, but the contributions of different countries vary through time and across measures. These varying contributions reflect differences in the number of species present in areas experiencing forest loss, as well as the relative extinction risk of those species, which in turn depends on their current area of habitat and the extent of past habitat loss.

LIFE provides deeper insight here than simple species richness. As shown in Eyres et al. (2025), regions the spatial variation in LIFE is predicted by three key components: species richness, degree of endemism of the species present and the extent to which they have already lost suitable habitat anywhere in their ranges. By integrating these factors, LIFE identifies areas of high conservation concern that would not necessarily be detected through species richness alone, where the loss of a widespread species is weighted equally to that of a narrowly endemic or threatened species. Similar insights could, in principle, be obtained using the extinction-based metrics such as cSAR; however, unlike LIFE, cSAR analyses are not easily scalable. Precomputed outputs are not yet available at fine spatial or temporal resolutions, and implementation requires bespoke, computationally intensive workflows. As a result, cSAR is generally applied at coarser resolutions (typically >10 km^2), making it impractical for the high-resolution, time-resolved analysis undertaken here. Last, for direct comparisons between locations, or between gains and losses, metrics such as STAR are unsuitable: while they indicate where to prioritize action (e.g., restoration or threat abatement), they do not quantify the impact of ongoing habitat loss.

The ease of use of the LIFE metric and its relatively fine spatial scale means that deforestation can be readily converted into expected extinction impact without complex additional analysis. This allows a transition from retrospective annual loss mapping to proactive alerts that identify areas where deforestation poses disproportionate risks to biodiversity, facilitating timely and targeted mitigation efforts. This type of analysis -linking land-use change to biodiversity harm- can be conducted for any region, habitat, or timeframe where data are available. It

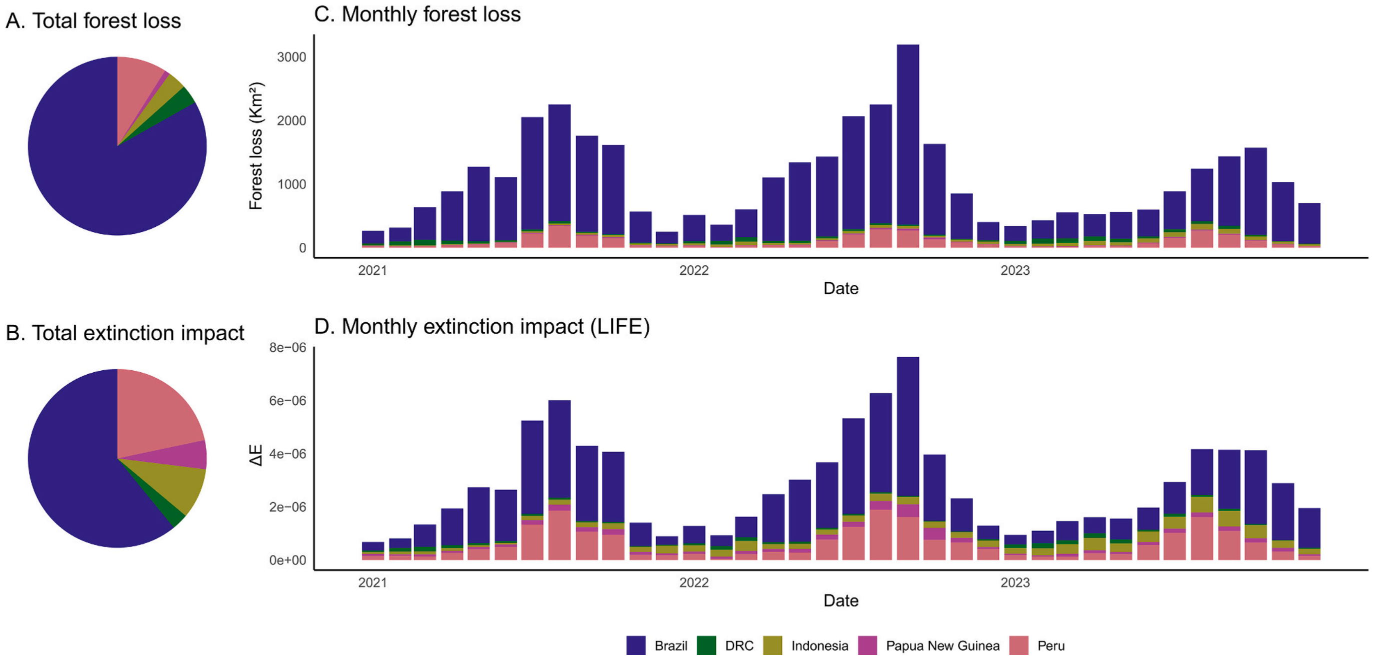

Fig. 2. Tropical forest loss and associated impacts on extinction (as assessed by standardised summed changes in LIFE scores) between 2021 and 2023 for five countries suffering significant tropical forest loss, as inferred from integrated deforestation alerts. Contribution of each country to overall forest loss (A) and resulting change in extinctions of terrestrial vertebrates (B) across the four years examined. These patterns can also be examined through time: monthly forest loss by country (km^2) (C) and monthly extinction impact (ΔE) (D). Forest loss (C) shows the area of forest cleared each month. Monthly extinction impact (D) shows the contribution to species extinction risk attributable specifically to deforestation occurring in that month. These impacts are ongoing unless the forest is subsequently restored.

can also be tailored to specific drivers of habitat loss, such as fires, illegal pasture conversion or road development. However, note that the impact of wildfires may not be the same as conversion to arable land in part because although the immediate impacts of wildfire can be dramatic, they are often temporary with many ecosystems recovering quickly. Finally this framework is not limited to measuring the impacts after they occur, LIFE could be combined with predicted changes in forest distribution in order to ascertain which regions might be most impacted by climate change (Roebroek et al., 2025) or fires (Di Giuseppe et al., 2025). Guidelines for conducting such analyses are provided in the supplementary material (How-to guide, Example 1). Additionally, code and pseudocode is also available for the analysis.

4. Case study 2. Linking biodiversity loss to drivers: apple consumption in the UK

To explore the potential for linking LIFE with agriculture and the global food system—the biggest driver of land-use change—we used it to assess the average extinction risk impacts of apple consumption in the United Kingdom, averaged over the years 2019 to 2023, and how these vary depending on source country. Where and how food is produced can strongly influence biodiversity impacts (Ball et al., 2025), and apples are a useful case study because they are widely consumed and produced in the UK, yet much of the supply comes from other countries with very different land-use and conservation contexts.

We first estimated the provenance of apples consumed in the UK by combining a trade matrix from Schwarzmueller and Kastner (2022) and consumption values from FAO (2025). In practice, this meant estimating the mass of apples consumed in the UK that originated from different countries. The trade matrix from Schwarzmueller and Kastner (2022) provides information on the proportion of apples imported from each country. By multiplying these proportions by the total mass of apples consumed in the UK (Supply Utilisation Accounts, FAO, 2025), we derived the mass of apples sourced from each country (including those sourced domestically). Following Ball et al. (2025), we estimated source country-specific impacts associated with the continued use of agriculture land for apple production, in terms of the forgone opportunity to reduce extinction risk. This was calculated using a modified LIFE-restore layer which quantifies the reduction in extinction risk that would occur if agricultural land were restored to natural habitat rather than maintained in production. As discussed earlier this layer had been slightly modified in Ball et al. (2025) to align with spatial agricultural data from the Global Agro-Ecological Zones (GAEZ) project (FAO and IIASA, 2025; at 9.3 km resolution), ensuring its resolution was compatible with the subnational apple production data used in subsequent steps (Monfreda et al., 2008). The median opportunity cost associated with the annual production of 1 kg of apples was calculated for each source country by intersecting the modified LIFE-restore layer (Ball et al., 2025) with spatial data on the distribution of apple production for the year 2000 (Monfreda et al., 2008). Although these production data are relatively old, they are the most up to date publicly available information on apple production at subnational resolution. As apple yields have changed substantially since 2000, we chose to combine the 2000 spatial distribution of production with more recent national yield data (average 2019–2023; FAO, 2025), assuming that the distribution of production has remained broadly consistent. This approach provides a contemporary picture of apple-related impacts. To assess the influence of yield changes over time, we also conducted the analysis using 2000 yield data; results are provided in the supplement. The biodiversity impact in each country attributable to UK apple consumption was then calculated as the product of the quantity of UK consumption from that country and the median opportunity cost to extinctions of producing one kilogram in that country. Full details of data and methods can be found in the supplement (Supplementary methods & Table S3).

Although most apples consumed in the UK are grown domestically (>45 % by mass), the extinction costs of UK apple consumption are largely driven by imports (Fig. 3). The UK generally imports apples to meet demand during the off-season for domestic production, sourcing them from the EU as well as further afield (Fig. 3A). The average impact of consuming one kilogram of apples varies significantly by origin, with much higher extinction opportunity costs associated with apples from

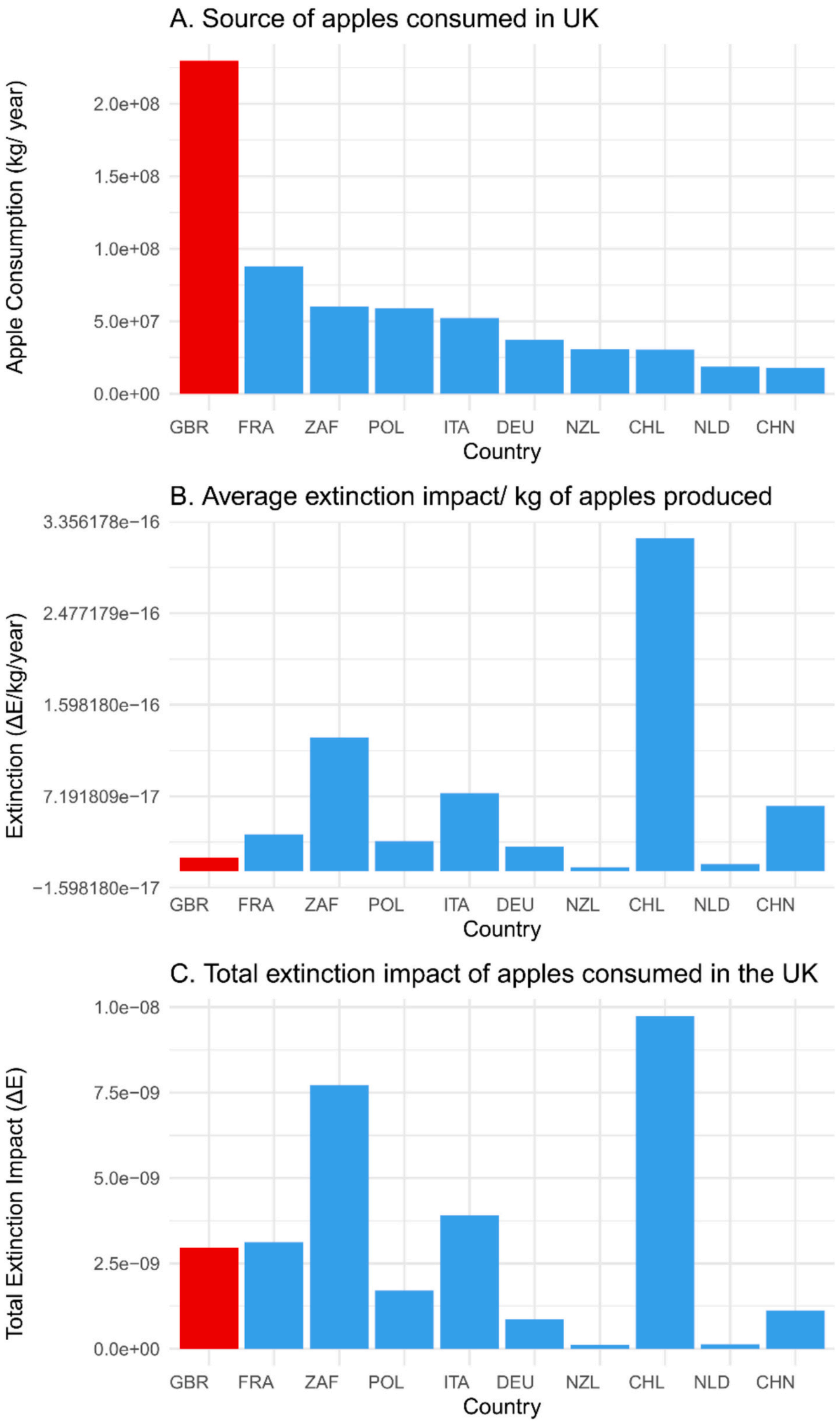

Fig. 3. Extinction opportunity cost of UK apple consumption. Values reflect an average across the years 2019–2023. A.) The top 10 countries supplying apples to the UK by mass (kg) in a year, including domestic production; GBR = United Kingdom, FRA = France, ZAF = South Africa, POL = Poland, ITA = Italy, DEU = Germany, NZL = New Zealand, CHL = Chile, NLD = Netherlands and CHN = China. B.) The median extinction impact /kg of apples consumed (ΔE/kg/year). C.) The total extinction cost of UK apple consumption (ΔE), shown by country. Domestic production in red, imported apples in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Chile and South Africa compared to domestic production or imports from the EU (Fig. 3B). Apple production in Chile is associated with the highest per kilogram extinction cost, despite having very high apple yields (FAO, 2025). Most notably it is higher than the impact for apples produced in South Africa. Although LIFE scores in South Africa are on average higher than those in Chile (which is to be expected based on patterns of species richness and endemism), apple production in Chile is located in areas associated with high LIFE-restore scores. The per-kilogram extinction cost of UK apple production is relatively low, with only the Netherlands and New Zealand having lower values. Although the Netherlands and the UK have similar average LIFE values, both in general and in apple producing regions, the Netherlands has higher apple yields (>10 % higher, FAO, 2025). Apple production in New Zealand is associated with relatively low extinction costs, with apple yields typically double those of the UK (FAO, 2025). Although some regions of New Zealand have higher LIFE per km^2 scores those of the UK – driven by the occurrence of highly endemic species- the two countries have on average similar values, this can be explained in part by New Zealand being relatively species poor (at least in terms of terrestrial vertebrates). The impact of New Zealand apple production may well be disproportionately larger if the extinction risk of plant species or invertebrate species was considered. Similarly, apple production in South Africa and Chile may have greater impacts if it overlaps with areas of high plant biodiversity in those countries. Qualitatively our results were consistent across years (Fig. S1).

Other metrics can, and have been linked with agricultural data to assess the impacts of food production (Irwin et al., 2022; Schwarzmueller and Kastner, 2022). However they suffer from several limitations. Many of these metrics including PDF, cSAR and STAR often incorporate categorical threat weightings meaning they are not on a ratio scale, prohibiting meaningful comparisons between regions. Some other approaches, such as the Biodiversity Impact Credits (BIC), have the potential to provide more detailed insights but require extensive population-level data, which prohibits application at global scales (i.e. not scalable).

Altogether, our findings suggest that the UK could reduce the impact of its apple consumption by increasing the relative contribution of domestic production and in particular by decreasing reliance on imports from high-impact regions (both nationally and sub-nationally) when fewer domestically grown apples are available. More generally this overall framework could also be used to help evaluate the consequences of policies promoting lower-yield domestic agriculture, and to track how food-related biodiversity impacts change over time as a consequence of developments such as post-Brexit trade shifts (Kren and Lawless, 2024) and the emergence of major new markets like China (Lu et al., 2015; Tian and Cheng, 2024). From a business perspective, this could be used to assess the impacts of supply chains and the relative benefits of different sourcing and mitigation strategies. This framework could also be used predictively, for example to assess the impact of continued agricultural expansion under BAU and compare different policy proposals (Williams et al., 2020). Finally, while our analysis focusses on net extinction outcomes, a small number of species benefit from agriculture. The LIFE metric can be disaggregated to examine specific subsets of species (see Case Study 4), allowing, for example, an exploration of the potential benefits of maintaining UK orchards—a priority habitat that benefits several target species. Guidance on how to incorporate LIFE with agricultural data to answer such questions can be found in supplementary material (How-to guide, Example 2). Additionally, code and pseudocode is also available for the analysis.

5. Case study 3. Informing compensation strategies: mitigating the damage of a hypothetical development in Sumatra

To investigate whether the LIFE metric can help quantify biodiversity impacts from land conversion and inform possible biodiversity compensation strategies, we use a hypothetical scenario where a company has converted forest to agricultural land for coffee production. The company wants to use the LIFE metric to assess its impact and then select the most suitable restoration site to compensate for biodiversity loss by restoring biodiversity to a 'pre-impact' baseline, choosing from several candidate areas that differ in their geographical and ecological similarity to the impact site. We explore the possible use and concerns of using the metric in the calculation of NNL claims.

For the proposed impact site, we used maps of current habitat distribution (Jung et al., 2020) and coffee production (Tang et al., 2024) to identify a 1 km^2 site potentially at risk of agricultural expansion within currently forested areas but in close proximity to existing coffee-production lands in the state of Aceh, north of Sumatra. The site was chosen at random from pixels which are currently forested and are adjacent to existing coffee production; we then extracted the associated value (per km^2) from the LIFE-convert layer. Three potential offset pixels for restoration were selected to illustrate how the LIFE metric can be used to compare potential restoration sites; this was not an attempt to optimise offset placement, however the approach described could be extended toward spatial optimisation frameworks (discussed below). The offset sites were chosen from pixels that are currently agricultural land but were historically forested (Hengl et al., 2020), all within the state of Aceh. To ensure we sampled from across the suitable geographic space, we divided the eligible pixels into three distance-based categories relative to the impact site (near, intermediate, and far) and randomly selected one pixel from each category. For each selected pixel, we extracted the corresponding value (per km^2) from the LIFE-restore layer (Fig. 4A). For each offset pixel we then looked at the area of land that would be required to fully compensate the increase in extinction risk caused by the 1 km^2 impact site if the LIFE metric was used as the sole metric for loss and gain calculations. To account for the fact that restoration is often highly uncertain, with large time lags and incomplete recovery, we applied three multipliers to our restoration values based on (Jones et al., 2018). We used rates of recovery of 1 %, 2.9 % and 10 % per year, and calculated the number of km^2 to be restored at each potential offset location in order to completely compensate the impact at the impact site within 10 years. Full details of data and methods can be found in the supplement (Supplementary methods & Table S3). Additionally, code and pseudocode is also available for the analysis.

These analyses show that the area required for restoration in order to fully compensate the increase in extinction risk at the impact site varies (Fig. 4B). At Site 2, larger areas of habitat would have to be restored to offset predicted impacts on global extinction risk than in Sites 1 and 3. The area required for restoration also differs by assumed recovery rate (Fig. 4B). For example, if the fastest recovery rate is used, 1.9 km^2 would need to be restored at Site 1, but this increases to 19 km^2 at the most conservative recovery rate (Fig. 4B). This uncertainty around recovery timelines underscores the importance of taking a precautionary approach when planning restoration, especially since published recovery rates may be overly optimistic due to publication bias (Marchand et al., 2021).

The varying areas required at each offset site reflect differences in species' potential habitat, with restoration at some locations contributing more to reducing global extinction risk. However, this issue raises concerns about equivalency—a core principle in biodiversity offsetting (Bull et al., 2013). Relying solely on the aggregated LIFE metric for NNL claims will obscure gains and losses of particular species or habitats, potentially overlooking local biodiversity values allowing trades of extinction risk of one species for the increase in another. Without further detail, the metric may be trading small gains of extinction risk in many species, to larger reductions for one species. Depending on their nature, these compensatory trades between species could be seen as contentious and not meet equivalency standards of many offsetting frameworks. These risks posed by these non-equivalent trades are especially high if impacts on species of conservation or socio-economic importance (e.g. legally protected species, culturally important species, migratory

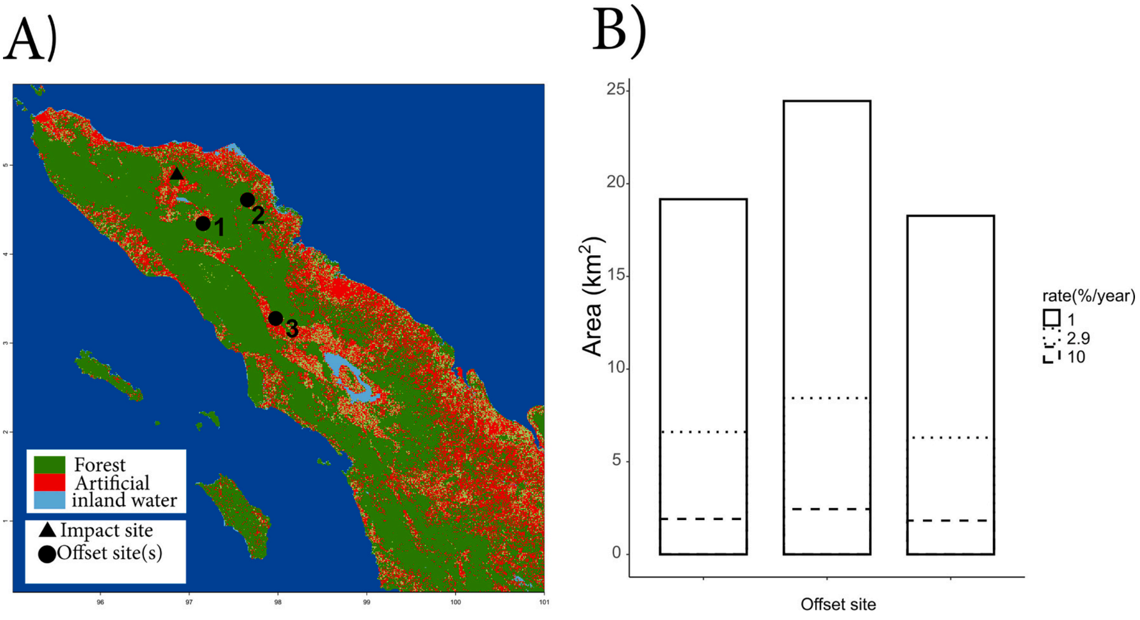

Fig. 4. Using LIFE to inform compensation of harmful impacts. A) Location of a hypothetical impact caused by a company establishing new farmland in a forested area in Sumatra (triangle) and three potential locations at increasing distance from the impact that are being considered for restoration to offset the negative impacts on extinctions (numbered circles). Restoration sites are on land which is currently used for farming but which was historically forested. B) Area of land which would need to be restored at each of three sites in order to completely offset the impact site. This is shown for three rates of recovery across 10 years (assuming restoration is linear through time).

species) are hidden.

Claims of No Net Loss or Net Gain need to be well supported by robust data on species and habitat recovery, as if not robust they can be seen as legitimizing the loss of biodiversity without these targets being achieved. Due to uncertainties in the restoration outcomes, challenges around equivalency, LIFE can be best used to help identify suitable areas for compensation through restoration (and indeed protection – Case Study 5), identifying those areas of highest significance for biodiversity. But demonstrating loss and gain calculations for offsets will require additional local data on species and habitat recovery, detailed consideration of counterfactuals (i.e. supported by ex-post assessments of recovery trajectories in matched areas outside of offsetting zones and accounting for leakage effects), along with well-defined rules for acceptable trades and "red lines". Additional guardrails, such as extinction risk thresholds, geographic restrictions on compensation sites, transparency about species and habitats lost or gained may be required if LIFE is used as part of an offset design. When using LIFE-convert and LIFE-restore layers together, we strongly recommend applying conservative recovery rates to the restore layer to prevent overestimation of potential gains (as outlined in the supplementary material, How-to guide, Example 3). With these considerations in mind, this approach could be extended to be incorporated with more complex spatial optimisation methods for example allowing for optimisation of multicriteria including cost or connectivity (Daigle et al., 2020; Hanson et al., 2025).

While other metrics could in principle be used to compare potential offset sites or claims of No Net Loss, comparing the negative impacts of habitat loss with the potential benefits of restoration - and assessing restoration outcomes across sites - requires metrics that can quantify both losses and gains on a ratio scale. Several metrics which weight species "threat" by categorical values are not on a ratio scale making comparisons problematic. As mentioned above, relying on aggregated metrics for NNL claims risk allowing trades of extinction risk of one species for the increase in another. Metrics that cannot be disaggregated, such as PDF and cSAR, should therefore not be applied in isolation. The LIFE metric can be disaggregated to track the fate of individual species, making it well suited to capture local biodiversity values and ensure that both losses and gains are transparently assessed. For a full exploration of the benefits of desegregation see case study 4 below.

6. Case study 4. Prioritising site-based conservation efforts: a species-level comparison of potential projects

We explore the potential of the LIFE metric to inform prioritisation of site-based conservation actions by applying it to four proposed projects within the context of the World Land Trust's existing portfolio of interventions. The World Land Trust (WLT) is a conservation organization with a mission to protect the world's most threatened habitats and species through supporting in-country conservation partners to bring land into permanent protection. Like all organisations with limited resources, they need to prioritize the projects they support. To see if LIFE might help inform that decision-making, we first intersected polygons of four prospective projects in Central America and 574 conservation projects already within the WLT portfolio with the LIFE-convert layer. This allowed us to place the prospective projects in the context of WLT's existing interventions. For each project polygon, we estimated the extinctions that could be averted under an extreme counterfactual in which all habitat was assumed to be converted to agriculture. We did this by multiplying each pixel level LIFE-convert value by its area and summing across all pixels within the polygon. We then explored the additional species-level insight that can be gained through disaggregating the LIFE metric. Published LIFE layers are produced by summing up individual species values (aggregation). To gain species-level insights, we instead used disaggregated LIFE-convert maps (i.e. per species LIFE maps). For each species-level LIFE map we multiplied values by pixel area to account for map projection skew and then summed across all pixels within the four prospective projects polygons. We then calculated each of these species' contribution to a given project's total LIFE score, allowing us to understand which species might be especially important at each project site. Full details of data and methods can be found in the supplement (Supplementary methods & Table S3). Additionally, code and pseudocode is also available for the analysis.

The four prospective projects showed considerable variation in total

LIFE-convert scores (Fig. 5A; note the log-scale x-axis). Project 1 ranked in the top 60 % of all existing WLT projects by total LIFE score, Project 2 in the top 40 % and Projects 3 and 4 in the top 20 %. While projects 3 and 4 both fall within the top 20 %, full conversion to arable land in Project 4 would result in an extinction risk five times greater than that of Project 3. When examining individual species' contributions, we see that each project's LIFE score is primarily driven by a few species, mostly amphibians and reptiles: the high score for Project 4 is due to five such species, while the score for Project 1 is largely influenced by a single endangered reptile. Unsurprisingly, species with the highest contributions tend to have small ranges, making them disproportionately affected by habitat conversion.

Given this, and the uncertainties surrounding species distributions, at this scale LIFE is best used as a prioritisation scoping tool, with ground-truthing essential to confirm species' presence at a site and, as far as possible, its approximate current AOH (as per Case Study 3 on biodiversity offsets), an approach also advocated for by the STAR metric (Mair et al., 2021). Although the IUCN range data represents one of the most comprehensive and consistent data on species distributions globally, it is not without biases that users of LIFE should be aware of. For example, the ranges are likely less accurate in hard to reach locations and islands (Nori et al., 2023) and have been shown to overestimate species distribution (Cordier et al., 2025). In this case the LIFE assessment allowed WLT to narrow down its investigations to nine species. WLT in due course obtained further evidence of the presence of five of these species in the region. Where better local data are available, updated LIFE layers could be produced. A further improvement would be to include the likely threat of deforestation to each candidate site (the present analyses simply assume all natural habitat would be lost in the absence of a project), something that is explored in case study 5 below.

Despite inherent uncertainties, species-level information is valuable for comparing sites. It enables practitioners, policy makers and funders to better understand why a metric identifies a site as important and provides persuasive evidence for conservation investment by highlighting key threatened species. Such species-specific insights are not possible with metrics that cannot be disaggregated (Table S1). For example, cSAR and PDF report only overall changes in species richness (total numbers or proportions), which prevents examination at the individual species level. Nevertheless, other metrics can still offer complementary perspectives. For instance, the WLT could use STAR-T to identify regions with the greatest potential threats, either to guide avoidance of high-risk areas or to highlight where intervention may generate additional benefits beyond habitat conservation (e.g., tackling hunting).

Finally, site selection for conservation should also integrate other factors such as costs, land ownership and broader social and environmental impacts (Colchester, 2004; Soto-Navarro et al., 2020; White et al., 2022), the assessment of local in-country conservation partners as well as the long-term conservation value of a region, accounting for potential future land-use and habitat change under climate change (Hoffmann et al., 2019). We have outlined how the broad approach here could be applied to other contexts in the How-to guide in the supplement (Example 4).

7. Case study 5. Measuring conservation impact: combining LIFE with counterfactual methods

We investigate the use of the LIFE metric to assess the impact of site based conservation efforts by combining it with counterfactual methods. As a case study, we focus on the Gola Rainforest project – a long-running conservation intervention in an area of tropical forest within eastern Sierra Leone funded by Reducing Emissions from Deforestation and Forest Degradation (REDD+) finance since 2011. We quantified the likely number of avoided extinctions resulting from conservation activities for the period 2011 to 2022 by integrating the LIFE convert layer with a state-of-the-art pixel-matching method to generate a counterfactual scenario of deforestation in absence of conservation. Using the Joint Research Council's Tropical Moist Forest Annual Change Collection as a base layer, matching entailed selecting control pixels (not receiving REDD+ funding) that were similar in key pre-project characteristics, including rates of historic land use change, ecoregion, accessibility, topography, and country (for full details of methods and assumptions see Balmford et al. (2024)). This process aims to remove the effect of observable confounders, allowing us to estimate what would have happened in the absence of the intervention and directly compare this counterfactual with observed project outcomes. By comparing the loss of undisturbed forest through time between project pixels and the counterfactual set, we determined the avoided habitat loss in km^2 for each LIFE pixel overlapping the project area. We then multiplied each pixel's avoided habitat loss by its LIFE-convert score to calculated pixel-level avoided extinctions, which were summed to obtain overall avoidance of extinctions attributable to the Gola REDD+ project (2011–2022). Full details of data and methods can be found in the supplement (Supplementary materials & Table S3). Additionally, code and pseudocode is also available for the analysis.

We found that the project prevented the loss of approximately 29 km^2 of forest between 2011 and 2022, which corresponds to a total standardised LIFE score of -1.78×10^{-7}, meaning that the extinction risk has decreased by 1.78×10^{-7} as a result. To put this in context the LIFE-restore score for an average 29 km^2 region in the UK is 9×10^{-10}

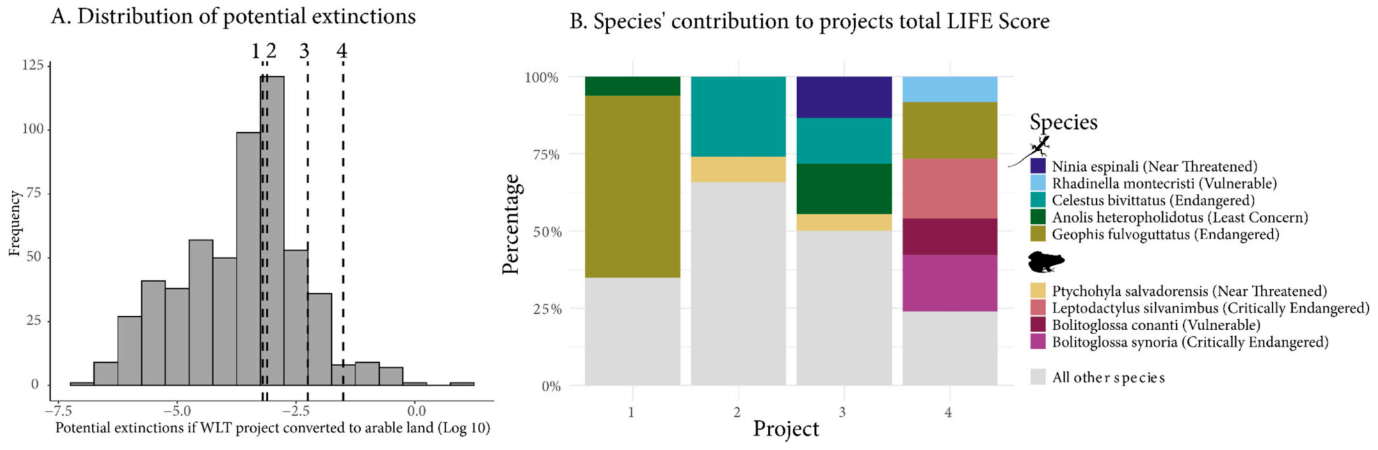

Fig. 5. A.) Potential total extinctions assuming 100 % conversion of natural habitats in existing WLT projects to arable land. Dashed lines show four potential projects in Honduras (1–4). B.) Disaggregation of the four projects' total LIFE score to show individual species contributions. Species with larger percent contributions have the greatest change in extinction risk when impacted by land-use change. Species which contribute >5 % of a projects total LIFE score are coloured individually.

extinctions – the forest saved at Gola is thus, in terms of global extinction risk, roughly 200 times more valuable. Avoided habitat loss was concentrated in accessible areas, particularly along the project boundary and in the southwest, where a road intersects the landscape (Fig. 6A); the LIFE-convert layer on the other hand had highest values in the north and east (Fig. 6B). We estimate that avoided extinctions were distributed as the product of these two layers (Fig. 6C).

In this use case LIFE provides a deeper perspective than simple species richness. The Gola region hosts several narrow-ranged, highly threatened species (e.g. Diana Monkey and the Pygmy hippopotamus), which would not be highlighted by analyses focused solely on species richness, including those based on PDF or cSAR (without rarity weightings). While PDF and cSAR can become more informative when combined with scaling factors that weight species by perceived threat level, the use of categorical weightings means that they are still not on a ratio scale, making it difficult to compare results across regions. STAR is unsuitable for this analysis, as it does not provide information on the impacts of habitat loss, however could be used to examine which areas of the world are potentially under greatest pressure from specific threats e.g. logging. Last, in terms of scalability, again LIFE is quick to use at relatively fine scale as it does not require bespoke analyses.

Our analysis assumes that, without the project, land would have been converted to arable use— the most common transition in the region (Tubbs et al., 2015). This probably underestimates the extinction impact if forest loss is caused by more damaging conversions, such as mining. It is important to note that this characterisation of project performance does not currently account for impermanence whereby deforestation is delayed rather than stopped (Balmford et al., 2024); or leakage—the displacement, of damaging activities to other areas as a result of the intervention (Balmford et al., 2025). Additional work would be needed to incorporate these effects into a more comprehensive assessment. Our framework could in theory be used to assess potential ex-ante impacts of conservation interventions by using long-term estimates of habitat change. However we note this should be done with caution (Delacote et al., 2025). We have outlined how the broad approach applied here could be used to assess the impact of other interventions in the How-to guide in the supplement (Example 5).

8. Discussion

This paper explores the use of the LIFE metric to estimate changes in terrestrial vertebrate extinctions from land-cover change in five conservation contexts. Its flexibility and ease of use suggest broad applicability—from assessing biodiversity impacts of land-use change (e.g., forestry, infrastructure, urban expansion) to evaluating conservation interventions and commodity-driven land-use shifts. LIFE can also be integrated into broader decision-making frameworks alongside other factors, such as financial costs, land tenure, and conservation of ecosystem services or dis-services (Naidoo et al., 2006; White et al., 2022).

As with any global metric, LIFE's strength lies in its generality, but thoughtful application is essential- particularly when assessing changes in biodiversity at individual sites and fine spatial scales. Our case studies highlight key considerations: Case study 2 raises the limitations (shared with many other biodiversity metrics) of the current focus on terrestrial vertebrates, and the consequences for overall biodiversity impacts in regions rich in non-vertebrates (e.g., New Zealand, South Africa); Case studies 3 and 4 emphasize the need for local validation and highlights the need to understand biases in underlying data, and Case study 3 underscores the importance of careful consideration of restoration time lags. While published LIFE maps are best suited to mid-scale analysis, our open-source framework enables tailored applications.

Despite these considerations, our case studies show that LIFE is both practical and broadly applicable for a range of conservation use cases. We have used it here to inform land-use decisions across diverse biomes, from tropical forests to temperate farmlands, and in all regions. Its

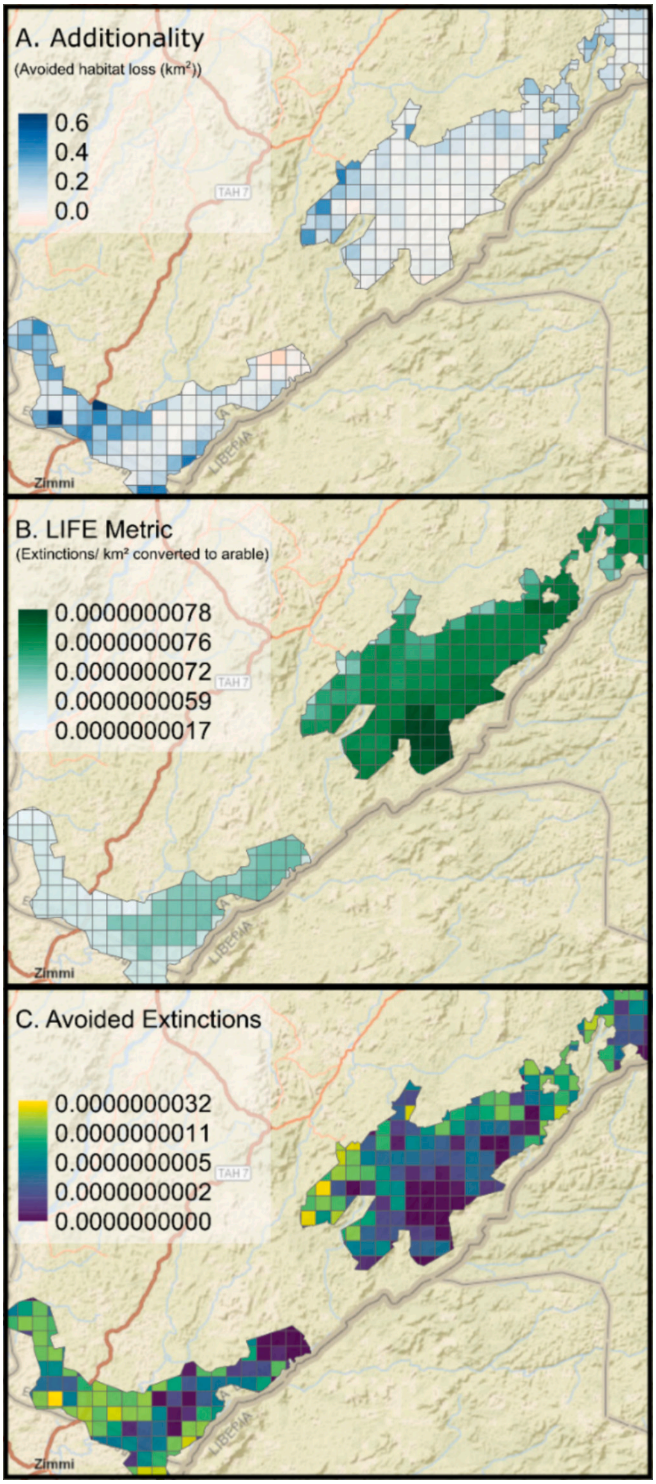

Fig. 6. Estimated avoided loss of natural habitat and associated avoided impact on extinction calculated using the LIFE metric for the Gola Rainforest project in Sierra Leone. Avoided deforestation within the Gola project (A) was calculated for the period 2011 to 2022 by comparing to a counterfactual scenario of deforestation in the absence of conservation. (B) The LIFE-convert layer shows the extinction impact/km^2 converted from natural habitat to arable land. Pixel-level avoided extinction impact (C) are then estimated as the product of additionality (A) and LIFE score (B).

simplicity and accessibility have enabled use by a wide range of stakeholders, including NGOs, consultants, and local practitioners. These applications are illustrated by several examples. In terms of forest loss, LIFE shows that not all land-cover change contributes equally to biodiversity risk. For instance, although only ~1 % of the forest loss in the study period occurred in Papua New Guinea, this accounted for over 5 % of the total biodiversity impact detected by LIFE. This disproportionate effect highlights the importance of moving beyond simple area-based measures of habitat loss and demonstrates LIFE's potential for guiding conservation prioritization toward regions where relatively small changes in land cover translate into significant biodiversity consequences. LIFE also provides a powerful framework for linking consumption to global biodiversity outcomes. For example, applying the metric to food production demonstrates that the biodiversity consequences of apples vary by more than an order of magnitude depending on source country: one kilogram of apples produced in the UK has more than ten times lower impact than the same quantity produced in Chile. Similarly, cross-commodity comparisons show that ruminant meat production has biodiversity impacts up to 100 times higher than legumes and pulses, even after accounting for protein content (Ball et al., 2025). Such analyses emphasize how LIFE can inform both supply-chain decisions and national policies by quantifying the hidden biodiversity costs of commodity trade. Finally, by applying LIFE to the WLT portfolio of projects, we demonstrate that extinction value varies enormously across sites - by more than five orders of magnitude. These examples together highlight the importance of place: any action that alters land cover carries very different consequences depending on where it occurs. It is therefore crucial to make global comparisons on a common scale. At the same time, there are many different pathways to slowing the extinction crisis, and LIFE provides a way to compare how actions such as dietary shifts or sourcing decisions stack up against direct site protection.

A consistent strength highlighted by users is LIFE's simplicity. Its pixel-based, additive values allow for rapid, scalable biodiversity assessments without heavy computing or custom analyses, which is valuable when resources are needed or timely decisions are needed. As LIFE uses AOH as a proxy for population size it may also provide useful, early insights into potential population changes following land cover change that could help flag situations where a species' threat status may warrant closer examination (Ball et al., 2025). A second strength of the LIFE metric is its ability to support both broad-scale assessments and detailed, species-level analysis. This is particularly valuable for conservation prioritisation, enabling organisations like World Land Trust (WLT) to identify regions with the highest potential biodiversity impact globally while also accessing the fine-scale information necessary for making more targeted, site-specific decisions. Finally the relative fine-scale availability of the metric allows meaningful insight below the country level. In this paper we have underscored both the strengths of the LIFE metric and its exceptional generality across a wide array of applications. Although a comprehensive comparison with other metrics is not appropriate here as most cannot be applied consistently across this breadth of scenarios, focused comparisons in specific contexts would provide a fruitful avenue for future work, helping to reveal how alternative approaches differ and what these divergences mean for our understanding of biodiversity outcomes (e.g., sourcing commodities; Molotoks et al. (2024) or offsetting; Durand et al. (2025)).

Importantly, the LIFE metric has been developed at a time when opportunities for meaningful conservation impact are expanding. New datasets and methodological advances - including near-real-time deforestation alerts and supply chain traceability- are creating new options for understanding and mitigating biodiversity impact, alongside continued improvements in biodiversity data, including greater coverage of underrepresented taxa such as plants and invertebrates. We have the ambition to continually update the underlying LIFE layers to reflect advances in the underlying biodiversity and environmental data, including projections of how these may change in the future. Our case studies demonstrate that LIFE can be readily integrated with these tools, enhancing its value for both forward-looking planning and retrospective assessment. More broadly, LIFE highlights the diverse opportunities available for addressing the extinction crisis and provides a framework for comparing and prioritising them.

CRediT authorship contribution statement

Alison Eyres: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Andy Arnell:** Writing – review & editing, Visualization, Software, Methodology, Investigation, Formal analysis. **Thomas S. Ball:** Writing – review & editing, Methodology, Investigation. **Richard J. Cuthbert:** Writing – review & editing, Investigation, Conceptualization. **Michael Dales:** Writing – review & editing, Visualization, Software, Investigation, Data curation. **Alejandro Guizar-Coutiño:** Writing – review & editing, Visualization, Investigation, Formal analysis, Conceptualization. **Jody Holland:** Visualization, Investigation, Formal analysis. **Emilio Luz-Ricca:** Writing – review & editing, Visualization. **Anil Madhavapeddy:** Writing – review & editing, Supervision, Resources, Funding acquisition. **Leila Pain:** Writing – review & editing, Methodology, Investigation, Formal analysis, Conceptualization. **Tom Swinfield:** Writing – review & editing, Funding acquisition. **Thomas B. White:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization. **Andrew Balmford:** Writing – review & editing, Writing – original draft, Supervision, Resources, Funding acquisition.

Funding

A.E., M.D., J.H. and T.S. were supported through grants from the Tezos Foundation and Tarides to the Cambridge Centre for Carbon Credits (grant code NRAG/719). T.S.B. was funded by UK Research and Innovation's BBSRC through the Mandala Consortium (grant no. BB/V004832/1).

Declaration of competing interest

At the time of writing TBW and AGC received income from commercial consultancy services to businesses to understand and mitigate their biodiversity impacts. AB is a Trustee of World Land Trust.

Acknowledgements

The authors thank Diana Bowler, Graeme Buchanan, Margaux Durand, Mike Harfoot, Jake Owen, Laura Sonter, and Catherine Waite for helpful discussions, comments, and collegial support.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2025.111663.

Data availability

Code and data are on github and will be made public upon acceptance

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