A tradable metric of local biodiversity impact linked to the Living Planet Index and global species conservation

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Abstract

Difficulties identifying appropriate biodiversity impact metrics remain a major barrier to inclusion of biodiversity considerations in environmentally responsible investment. We propose and analyse a simple science-based local metric: the sum of proportional changes in local species abundances relative to their global species abundances, with a correction for species close to extinction. As we show, this metric quantifies changes in the mean long-term global survival probability of species. It links mathematically to a widely cited global biodiversity indicator, the Living Planet Index, for which we propose an improved formula that directly addresses the known problem of singularities caused by extinctions. We show that, in an ideal market, trade in our metric would lead to near-optimal allocation of resources to species conservation. We further show that the metric is closely related to several other metrics and indices already in use. Barriers to adoption are therefore low. Used in conjunction with metrics addressing ecosystem functioning and services, potential areas of application include biodiversity related financial disclosures and voluntary or legislated no net biodiversity loss policies.

1 Introduction

The rapid recent growth of markets for responsible investments considering Environmental, Social and Governance (ESG) concerns (Diab and Adams, 2021), and the growing attention biodiversity receives in this context (Addison et al., 2019; Nauman, 2020), highlight the need for metrics of biodiversity impacts appropriate for use by businesses and financial institutions (Addison et al., 2019; Smith et al., 2020; TNFD, 2021).

Requirements on such metrics include most of the desiderata identified in the ecosystem management and scientific context, listed, e.g., in the author guidelines of Ecological Indicators, such as simplicity, relevance, scientific justifiability, cost-efficiency, and reliable quantification. The business community, however, emphasises other needs, some summarised in Table 1. These derive from aspects of the business world not encountered as such in traditional conservation, including continuous innovation, risk taking, hierarchical structures of ownership and accountability, transactions under private law, and decision-making in a fluid, complex socioeconomic context. The present work addresses these needs (Table 1).

Important in the business context is also to understand market responses to quantifying biodiversity impacts by a particular metric—in particular whether this may create unintentional, perverse incentives. We study this question here as well.

It is widely acknowledged that a range of different metrics is needed to capture all relevant aspects of biodiversity. Our study focuses on metrics related to what is called the “intrinsic value” of biodiversity (TNFD, 2022), i.e. the view that species should be protected irrespective of their immediate utility to society. This view is widely held on moral grounds (Kantar Public Brussels, 2019). To guide detailed considerations, however, it can be useful to invoke utilitarian arguments supporting it, such as the following: Even when there is no utility to us of a particular species, future generations of our descendants, with needs and priorities inconceivable to us, may yet find this species valuable and suffer from its loss if we do not protect it now.
Table 1: Desiderata for biodiversity metrics voiced by the business community, and how Biodiversity Stewardship Credits (BICs) address these.

| Needs we address | How we achieve this |
|------------------|---------------------|
| Scientific robustness \(^{(TNFD\ 2022)}\) | BICs are mathematically linked to long-term species extinction risk. |
| Can assess both negative and positive impacts \(^{(Bor\ et\ al.,\ 2018)}\) | BICs naturally quantify both positive and negative impacts. |
| Can be used to assess biodiversity risks and opportunities \(^{(TNFD\ 2022)}\) | The close link of BICs to long-term extinction risk facilitates their use in probabilistic risk assessments. By quantifying system state (rather than projections), BICs incentivise innovation where such opportunities arise. |
| Comparable across sectors and providing insights to inform corporate and financial institution decision making, including at aggregated portfolio levels for financial institution \(^{(TNFD\ 2022)}\) | BICs measure biodiversity impact in a single currency based on a simple formula and can be aggregated from site to portfolio level. Decision making based on BICs pricing aligns with conservation objective. |
| Can be used at scale and at different levels \(^{(TNFD\ 2022)}\) | BIC impacts can be estimated at site, product, or corporate level using existing metrics and tools. |
| Can be used for corporate target setting \(^{(TNFD\ 2022)}\) | Corporations can use BICs to set and demonstrably achieve net-zero or net-positive biodiversity targets. |
| Aligned with broader national and global public policy goals for reversing nature loss \(^{(TNFD\ 2022)}\) | BICs are aligned with the global policy objective of reducing extinction rates and with widely used geometric mean abundance indices such as the global Living Planet Index (LPI) \(^{(WWF\ 2020)}\) or UK’s Wild-Bird Indicator \(^{(Defra\ 2021)}\). |
| Suitable for biodiversity credit markets \(^{(World\ Economic\ Forum\ 2022)}\) | BICs are additive, so total BICs do not change through paper transactions. Market forces generated by BICs align with global conservation objectives. |
Considering that the time between speciations of higher organisms is measured in millions of years (Sepkoski, 1998; McPeek and Brown, 2007), any attempt to anticipate how and why a currently extant species might become important to future generations would be preposterous. The argument therefore naturally supports the widely accepted conclusion that we should reduce extinction rates across all biota to near-natural levels (for example, the draft post-2020 Biodiversity Framework states a target: “the rate of extinctions has been reduced at least tenfold”), except for taxa with very high speciation rates. The argument implies that, since the time scales in question are long compared to those between human migration events, the question where on Earth a particular species lives does not affect its conservation value.

Regardless of whether the ‘intrinsic value’ of species is invoked as a metaphor to capture these considerations or as an ethical axiom, quantification of the long-term extinction risk of species is a natural starting point for the construction of a pertinent science-based metric. From this we derive here two closely related metrics, which we call Biodiversity Impact Credits (BIC) and Biodiversity Stewardship Credits (BSC), that quantify impacts on mean long-term species survival probability.

Before we proceed, however, we stress that, as a matter of intergenerational justice, the metrics we propose should be complemented by one or several metrics quantifying Nature’s ability to provide ecosystem services to current generations. We propose a combined use of both types of metrics with the objective to optimise current ecosystem service provision while remaining below or reverting to an upper bound on extinction risk (Rossberg et al., 2017). The Mean Species Abundances metric (MSA, Alkemade et al., 2009) is an example of a well-established metric suitable for quantifying impacts on ecosystem function and services (Mace, 2005). Alternatively, one can use metrics tailored to regional particularities and needs such as the ‘ecosystem credits’ computed using the Biodiversity Assessment Method of New South Wales (NSW Department of Planning and Environment, 2020) or Natural England’s Biodiversity Metric (Natural England, 2021).

Below it will be shown that our BIC and BSC metrics are aligned through approximate mathematical relations to several other widely used and cited metrics already in use for similar purposes: i) BICs quantify impacts on the Living Planet Index (LPI) (WWF, 2020; McRae et al., 2017), one of the most widely cited global biodiversity indicators currently in use (4,710 publications identified by Google Scholar per July 2022); ii) BSCs are strongly correlated with the Species Threat Abatement and Recovery (STAR, 21 publications) metric (Mair et al., 2021), a spatially resolved variant of the IUCN’s Red List Index (Butchart et al., 2007, 2010, 2,490 publications); iii) BICs are approximated by life-cycle impact assessments scores based on the Potentially Disappeared Fraction (PDF) of species (Müller-Wenk, 1998; Goedkoop and Spriensma, 2000, 1,680 publications); and iv) BSCs can be approximated by Range-Size Rarity (RSR; Williams et al., 1996, 885 publications, including name variants), a metric used in conservation ecology to identify sites for protected areas. Thus, BICs and BSCs unify several existing approaches to quantifying biodiversity impact and support the established intuitive motivations of these approaches with a strong theoretical rationale.

In Materials and Methods below we will first establish the theoretical basis for BICs and demonstrate the metric’s linkage to the LPI. In doing so, we derive a solution to a long-standing conceptual problem arising with use and interpretation of the LPI when populations of species entering the LPI approach zero (McRae et al., 2017; Leung et al., 2020). We also briefly describe two models that we use to test and evaluate our metrics. In Theory we derive BICs as a measure of local impact on global species extinction risk. We study the incentive structure generated by BICs in an ideal market, to satisfy ourselves that BICs are well-aligned
with the species conservation objective. Then BSCs are derived as a special case of BICs. Finally, we use simulations to address questions of metric behaviour in light of metacommunity dynamics. From there we progress deriving and describing several methods for calculating BICs and BSCs depending on the scale in question. Metric computation is facilitated by the close mathematical relations between BIC, BSC and other metrics. The Discussion section emphasises practical uses of BSCs and BICs in the business context.

2 Materials and Methods

2.1 Estimating the long-term extinction risk of species

We consider a simple mathematical model that allows us to analytically link the populations sizes of species to their long-term survival. For a given taxonomic or functional group of species (below ‘group of species’ or similar), denote for each species \(i\) in that group by \(N_i\) the global population size of that species. Population sizes can be measured in terms of the number of mature individuals or population biomass, in some cases even by the number of colonies, whichever approximates total reproductive value [Rossberg and Farnsworth 2011] well.

It has been shown on long-term time series data, e.g., for trees [Kalyuzhny et al. 2014; Kessler et al., 2015], fish [Kessler et al. 2015], herbaceous plants [Kessler et al. 2015], and birds [Kalyuzhny et al. 2014] that the populations of most species exhibit random walks on the log(\(N\)) axis with mean-squared increments that are largely independent of \(N\), a phenomenon known as ‘environmental stochasticity’ (caused by variability in both the abiotic environment and the abundances of co-occurring species). For a given population, we denote the mean square of this increment during a time interval of length \(\Delta t\), divided by \(\Delta t\), by \(v_e\). Since the same studies reveal little if any detectable drift towards smaller population sizes or any preferred value, we disregard such drift here.

Next to environmental stochasticity, the discrete nature of life-history events (e.g. birth, germination, death etc.) generates additional variability in population sizes, known as ‘demographic stochasticity’, for which mean-squared increments in \(N\) over a given time interval \(\Delta t\) are proportional to \(N\). We denote the corresponding proportionality constant, divided by \(\Delta t\), by \(v_d\). As a driver of fluctuations in species abundance, demographic stochasticity is widely understood to be negligible compared to environmental stochasticity, except for small populations [Melbourne 2012]. The ratio \(N^* = v_d/v_e\) specifies the population size below which demographic stochasticity dominates over environmental stochasticity.

In Box 1 we show for populations driven by environmental and demographic stochasticity that the quantity

\[
\mathcal{L}_{\text{reg}} = \sum_i S \log (1 + N_i/N_i^*)
\]

is, for a given group of \(S\) species, approximately proportional to the expected number of surviving species after a long time \(T\). (We write \(\log(\cdot)\) for natural logarithms.) Larger values of \(\mathcal{L}_{\text{reg}}\) imply that fewer species will go extinct. Next, we establish a relation between this result and the LPI.
Box 1 A simple model for species survival probability

We model the change in the population size of a species over a time interval $\Delta t$ as

$$N(t + \Delta t) = \exp \left[ \xi(t) \sqrt{\nu_t \Delta t} \right] N(t) + \xi'(t) \sqrt{\nu_t \Delta t} N(t), \quad (1)$$

where $\xi(t)$ and $\xi'(t)$ denote independent standard normal random numbers. Parameters $\nu_t$ and $\nu_d$ represent the strengths of environmental and demographic stochasticity, respectively. Formally taking the limit $\Delta t \to 0$, standard procedures lead to an approximation of this process by the Itô stochastic differential equation

$$dN = \frac{\nu_v}{2} N dt + \sqrt{\nu_d N + \nu_v N^2} dW_t, \quad (2)$$

where $W_t$ represents a Wiener process (Brownian motion). The first term on the right-hand-side describes drift to larger values. It goes back to the fact that the expectation value of the log-normal distribution $\exp[\xi(t) \sqrt{\nu_t \Delta t}]$ in Eq. (1) is $\exp(\nu_t \Delta t/2)$. If one were to formulate this process in terms of $\log(N)$ rather then $N$, this term would disappear. However, demographic stochasticity would then generate another drift term. To eliminate drift altogether, we express population sizes in terms of $\log(N)$ instead. To eliminate drift altogether, we express population sizes in terms of $\log(N)$ instead. To eliminate drift altogether, we express population sizes in terms of $\log(N)$ instead. To eliminate drift altogether, we express population sizes in terms of $\log(N)$ instead. To eliminate drift altogether, we express population sizes in terms of $\log(N)$ instead.

For $x$ approaching zero from above, the factor $1 - e^{-x}$ reduces the magnitude of fluctuations in $x$, slowing down the random walk. As a result, $x$ can get trapped in the region of low $x$, and the vicinity of 0 acts similar to an absorbing boundary (Pechenik and Levine 1999; Dornic et al., 2005). This effect is reinforced by the breakdown of the diffusion approximation underlying Eqs. (2) and (3) for small $x$ (Kessler et al., 1998). In reality $N$ and so $x$ reach zero eventually, implying global extinction of that species. We therefore approximate the dynamics of $x$ by simple Brownian motion with an absorbing boundary at $x = 0$ (Pande et al., 2021).

Now consider the probability that a species starting from $x = x_0$ will still exist after a time $T$, i.e., the probability for $x$ to never reach zero before $T$. Textbook methods evaluate this to $\text{erf}(x_0/\sqrt{2Tv_0})$ (Gardiner 1990), where $\text{erf}$ denotes the error function (Abramowitz and Stegun, 1972). For $T$ not too near in the future ($T \gg v_0^{-1}x_0^2$), this simplifies to

$$\text{(probability of survival until } T\text{)} = \sqrt{\frac{2}{\pi Tv_0} x_0}. \quad (4)$$

That is, for any sufficiently large, fixed observation time $T$, the current value of $x_0 = x = \log(1 + N/N^*)$ is directly proportional to the probability of species survival. In Supplementary Information (A) we demonstrate validity of Eq. (4) for a model with discrete population sizes $N$.

Data suggest that $v_d$ does not usually vary strongly within taxonomic groups (Kaluzhny et al., 2014; Kessler et al., 2015). When this is so, $\sum_i \log(1 + N_i/N^*_i)$ is, for a given group of $S$ species, proportional to the expected number of species surviving after a long time $T$.

Above model invokes what is known as an $R$ vortex, one of four mechanisms leading to extinction (Carlson et al., 2019). Corresponding results for other types of extinction vortices are likely to have a similar structure but use different values for $N^*_i$.

2.2 The Living Planet Index

The global Living Planet Index (LPI) is designed to track average “species population trends” (WWF, 2020) for a given taxonomic or functional group of species. In defining the LPI, one needs to distinguish the quantity it aims to represent conceptually and how it is being computed in practice.

2.2.1 Definition of the Living Planet Index

Conceptually, LPI represents the geometric mean of all numbers $x_1, \ldots, x_n$ defined as $\sqrt[n]{x_1 \cdot \ldots \cdot x_n}$. For a given taxonomic or functional group of species, one needs to distinguish the quantity it aims to represent conceptually and how it is being computed in practice.
Figure 1: Comparison of the global Living Planet Index for two methods to estimate global abundances trends of species from limited local abundance data. Shaded areas indicate confidence intervals. The ‘Standard’ method represents the global abundance trends by the trend of the geometric mean of local abundances, the ‘Modified’ method, described in Sec. 2.2.2, estimates the trend from the sum of the available local population time series.

Mathematically, if $S$ is the total number of species in the group and $N_i$ the global population size of the $i$-th species in this group, one can compute

$$LPI = \exp\left(\frac{\mathcal{L} - \mathcal{L}_0}{S}\right),$$

(6)

where

$$\mathcal{L} = \sum_i^S \log N_i$$

(7)

is the sum of logarithmic population sizes and $\mathcal{L}_0$ the value of $\mathcal{L}$ in the baseline year.

### 2.2.2 Computation of the Living Planet Index

The global LPI for vertebrate species is regularly published by the WWF [WWF 2020]. The baseline year is 1970. Its value is estimated from a large database of population time series using a methodology developed by the Zoological Society of London [Collen et al. 2009]. The current methodology compensates for incomplete and uneven temporal, taxonomic and geographic coverage by the database [McRae et al. 2017]. It also takes into account that many time series in the database refer to local or regional rather than global populations.
To address the last issue, the methodology estimates the trend in the global abundance of a recorded species by the trend in the geometric mean of all population time series available for that species. One might therefore argue that the published LPI does not actually estimate changes in the geometric mean of global population sizes, but the geometric mean of the sizes of local populations, which is different, especially in cases of local species extinctions. However, we found that the following modification of the methodology, which avoids this issue, changes global LPI estimates only little.

Specifically, we used the following alternative method to estimate the global population trend of each species entering the empirical LPI. After the smoothing and interpolation of all population time series data for a given species following the established methodology (McRae et al., 2017), we standardised all these time series to attain the same maximum value. This was done to account for ignorance of the absolute population size that each time series effectively represents. For each pair of subsequent years \( y, y + 1 \), we then first determined the set of those time series for that species that were available in both years (time series are considered available over the time interval over which data have been recorded). Then we computed for both \( y \) and \( y + 1 \) the sums over all these population times series and from the ratio of these two sums the estimated change in log\(_{10}\) global abundance from \( y \) to \( y + 1 \). These estimated increments in log\(_{10}\) global abundance were then averaged over species and regions following the established methodology to compute yearly changes in log\(_{10}\) LPI (McRae et al., 2017).

As we show in Fig. 1, the impact of this conceptual refinement of methodology on calculated LPI time series is minimal. One can therefore safely interpret the published global LPI as estimating trends in global population sizes of species, as given by Equations (7) and (6). Our analysis relies on this interpretation.

2.2.3 Regularisation of the Living Planet Index and its link to extinction risk

If one of the \( S \) species entering the LPI goes extinct (\( N_i = 0 \)) at some time after the baseline year, the quantify \( \mathcal{L} \) defined by Eq. (7) attains a value of negative infinity for that year and LPI becomes zero by Eq. (6), irrespective of all other species. Practical calculations of the LPI avoid this mathematical singularity by introducing ad hoc rules to handle rare or extinct species or populations (Collen et al., 2009). A barrier to a conceptually satisfactory resolution of this issue has been that the interpretation of geometric mean abundance metrics in terms of ecological first principles has remained incomplete.

Here we propose to resolve this issue by making use of the intuitive interpretation of \( \mathcal{L}_{\text{reg}} \), defined by Eq. (5), as quantifying long-term species survival. Using \( \mathcal{L}_{\text{reg}} \) in place of \( \mathcal{L} \) and correspondingly defining the regularised Living Planet Index as

\[
\text{LPI}_{\text{reg}} = \exp \left( \frac{\mathcal{L}_{\text{reg}} - \mathcal{L}_{\text{reg},0}}{S} \right),
\]

with \( \mathcal{L}_{\text{reg},0} \) denoting the value of \( \mathcal{L}_{\text{reg}} \) at the baseline year, the singularities occurring when species go extinct disappear. Instead, the corresponding entry in the sum in Eq. (5) becomes zero [since log\((1 + N_i/N_i^*) = 0 \) when \( N_i = 0 \)]. Consistent with intuition, an extinct species is thus treated the same way as a non-existent species in calculating its contribution to the regularised LPI, except that extinctions should not affect the value of \( S \) entering Eq. (8).
Otherwise, when all species populations $N_i$ are much larger than the corresponding $N^*_i$, LPI and LPI$_{reg}$ are nearly identical. Both are then strictly increasing functions of mean long-term species survival probability in our approximation.

### 2.3 Metacommunity modelling using the LVMCM

To study the implications of metacommunity structure and dynamics for the use of BICs, we employed the Lotka-Volterra Metacommunity Model (LVMCM, O’Sullivan et al. 2019, 2021a,b). The model describes species-rich metacommunities as spatial networks of Lotka-Volterra competition models, each understood to represent a distinct ‘patch’ in space, coupled by dispersal. Competition between species leads to biotic filtering, which controls community composition in addition to abiotic filtering modelled by varying intrinsic growth rates between species and patches. Metacommunities are assembled to saturation, i.e., by iteratively introducing new random species at low abundance until each such addition generates one extinction on average. Previous work has shown that, as they saturate, these metacommunities self-organise to reproduce a wide range of well-documented macroecological patterns (O’Sullivan et al., 2019, 2021a).

For the detailed model structure, see O’Sullivan et al. (2021b). In the present study we simulated metacommunities with 100 patches randomly distributed over a 10 $\times$ 10 square, with dispersal length 0.5, and set the niche width parameter of O’Sullivan et al. (2021b) to 0.2. Intraspecific competition strength was 1 for all species, and any species suppressed any given other species with probability 0.3, in which case the corresponding interaction strength was sampled from a beta distribution with shape parameters $\alpha = \beta = 2$. The resulting metacommunities contained about 320 species and sustained at each patch around 50 species with biomass larger than a hundredth of the single-species carrying capacity.

### 2.4 Population modelling using GLOBIO-Species

We used GLOBIO-Species (de Jonge, 2021) to demonstrate calculation and projection of BICs on large spatial scales. We based our calculations on the 2015 land-use and cover map of Jung et al. (2020), which we resampled to a spatial resolution of 10 arc-seconds ($\approx$ 300 m) using the majority rule in order to match the resolution used in GLOBIO-Species. To evaluate a restoration scenario, we changed all arable land, pastureland, plantations, rural gardens and subtropical/tropical heavily degraded former forest within a (hypothetical) restoration area in Madagascar to the potential natural vegetation (Hengl et al., 2018) occurring at that cell (scenario ‘Restored to PNV’). We then used GLOBIO-Species to calculate, per scenario (i.e., baseline and ‘Restored to PNV’), for each grid cell the population size of each of the 130 mammal species endemic to Madagascar. From this we computed BIC as explained below.

In GLOBIO-Species, the total potential population size is computed by multiplying the density of a species (based on the TetraDENSITY database; Santini et al. 2018) with the range size of a species (IUCN 2021) excluding cells that consist of unsuitable natural land cover or are outside of species’ elevation preferences (IUCN 2021). The population size of a species for each scenario is then derived by including the impacts of land use, infrastructure and habitat fragmentation on the distribution and abundance of the species within the area encompassing the total initial population size (see www.globio.info for more information).
3 Theory

We now propose our biodiversity impact metric BIC and report some of its key characteristics, especially in the context of a biodiversity credit market.

3.1 Quantifying local biodiversity impact

Since $\mathcal{L}_{\text{reg}}$ is proportional to the expected number of surviving species in our approximation, we can quantify the impact of any human intervention on long-term species extinction risk by the resulting change $\Delta \mathcal{L}_{\text{reg}}$ in this metric. If the changes in population sizes $\Delta N_i$ resulting from this impact are small compared to total population sizes $N_i$, as will often be the case, $\Delta \mathcal{L}_{\text{reg}}$ is well approximated to linear order in $\Delta N_i$, i.e., as

$$
\Delta \mathcal{L}_{\text{reg}} \approx \sum_i S \frac{\partial \mathcal{L}_{\text{reg}}}{\partial N_i} \Delta N_i = \sum_i \frac{\Delta N_i}{N_i^{\ast} + N_i}.
$$

From Eq. (9) it is clear that $\Delta \mathcal{L}_{\text{reg}}$ weights impacts on globally rare species higher than impacts on common species, thus plausibly providing an appropriate measure of pressure on ($\Delta \mathcal{L}_{\text{reg}} < 0$), or relief to ($\Delta \mathcal{L}_{\text{reg}} > 0$) global biodiversity.

3.2 The Biodiversity Impact Credit metric

In view of above result, we define the Biodiversity Impact Credits associated with an area or site $\alpha$ as

$$
\text{BIC}_\alpha = \sum_i \frac{\Delta n_{\alpha,i}}{N_i^{\ast} + N_i},
$$

with $N_i$ denoting the current global abundance and $\Delta n_{\alpha,i}$ denoting the difference between the current local abundances and a baseline abundance documented at some time in the past. While sometimes we refer to $\alpha$ as ‘land’ held by an organisation, it could equally be an area of aquatic habitat. The $\Delta n_{\alpha,i}$ do not need to be small compared to $N_i$ and can be negative.

For values of $N_i$ larger than about 100-1000, $N_i^{\ast}$ is generally sufficiently small to be disregarded in the evaluation of Eq. (10) [Melbourne 2012; Kalyuzhny et al. 2014]. The $N_i^{\ast}$ thus play the role of regularisation constants relevant only for species close to global extinction. Where required, $N^\ast$ values can be computed as $N^\ast = v_d/v_e$, with $v_d$ and $v_e$ estimated from population time series data as used in calculations of the global LPI [Kalyuzhny et al. 2014; Kessler et al. 2015], life-history data [Sæther et al. 2004; 2013; Engen et al. 2009], or combinations thereof [Lande et al. 2003; Sæther et al. 2009]. Note, however, that the value of $v_e$ may depend on extent and location of species ranges [Lande et al. 1999]. Considering that species close to extinction tend to have comparatively narrow ranges [Mace et al. 2008], we recommend in such cases to determine a value of $v_e$ that correspond to the location and range of the near-extinct species in question.

We designed BICs for use in a biodiversity credit markets. In order to avoid undesired artefacts in such markets, we propose a set of rules for the setting of baseline abundances:
1. Tradable gains can be claimed only against empirically determined published baseline abundances.

2. When publishing baseline abundances to determine BICs for a site, values for all species within the group considered must be published at the same time. For species that are empirically absent from a site, baseline abundance is zero.

3. Baseline abundances can be amended when more accurate data become available but not to get a ‘fresh start’ after a population decline.

In particular, these rules forbid that market participants claim BICs for past gains that have since been reversed.

Two desirable properties of BICs follow directly from Eq. (10): First, BICs are additive, that is, the BICs of a combination of non-overlapping areas is simply the sum of their BICs. Additivity is a crucial property for a tradable credit metric. If violated, credits can appear or disappear by simply merging or splitting the areas of sites in paper transactions without actual ecological change—an undesirable outcome.

We note that quantification of biodiversity gain (or loss) in terms of the exact effects local populations gains (or losses) $\Delta n_{\alpha,i}$ have on $L_{\text{reg}}, i.e.

$$
\Delta L_{\text{reg}} = \sum_i S \log \left[ 1 + \frac{N_i}{N_i^*} \right] - \log \left[ 1 + \frac{(N_i - \Delta n_{\alpha,i})/N_i^*}{} \right] = \sum_i S \log \left[ \frac{N_i^* + N_i}{N_i^* + N_i - \Delta n_{\alpha,i}} \right],
$$

(11)

is not additive in this sense. This is why, in the context of marketisation, the approximate measure of impact on extinction risk BIC is preferable over the exact measure $\Delta L_{\text{reg}}$.

Second, BICs represent a strictly finite resources. The total population sizes $N_i$ of each species $i$ can never be smaller than the sum of population increments over all sites $\sum_{\alpha} \Delta n_{\alpha,i}$. The sum of all BIC

$$
\sum_{\alpha} \text{BIC}_\alpha = \sum_{\alpha} \sum_i S \frac{\Delta n_{\alpha,i}}{N_i^* + N_i} = \sum_i \frac{S \sum_{\alpha} \Delta n_{\alpha,i}}{N_i^* + N_i}
$$

(12)

is therefore always less than $S$. It approaches $S$ in the hypothetical case of large increments $\sum_{\alpha} \Delta n_{\alpha,i}$. Numerical BIC values can thus be interpreted by comparison to global species richness $S$ implying that BICs have units of ‘species’.

3.3 Incentive structure generated by BICs

What would the overall effect of trade in BICs be? Could it create perverse incentives running contrary to the original objective of reducing extinction rates? We study these questions in the following, assuming a perfect market.

Let $p$ be the market price of one BIC and $C_\alpha = C_\alpha(n_{\alpha,1}, \ldots, n_{\alpha,S})$ the net present value of the costs of sustaining local population sizes $n_{\alpha,1}, \ldots, n_{\alpha,S} \geq 0$ in areas of land held by market participant $\alpha$, including costs related to lost opportunities for other uses, minus the net present value of the resulting ecosystem services. Denote by $n_{\alpha,i,0}$ the baseline abundances for species $i$ over all sites held by market participant
α, so that $Δn_{α,i} = n_{α,i} - n_{α,i,0}$ are the increments entering Eq. (10). The total value of that area is then $V_α = -C_α(n_{α,1}, \ldots, n_{α,S}) + pBIC_α$, plus value unrelated to $n_{α,1}, \ldots, n_{α,S}$.

In a perfect market, market participant $α$ will take measures to maximise $V_α$, at which point

$$0 = \frac{∂V_α}{∂n_{α,i}} = -\frac{∂C_α}{∂n_{α,i}} + \frac{p}{N_i^* + N_i} - \frac{pΔn_{α,i}}{(N_i^* + N_i)^2} \quad (\text{or} \quad n_{α,i} = 0) \quad (13)$$

for all species $1 ≤ i ≤ S$. The last term in Eq. (13) results because $n_{α,i}$ contributes to total population size $N_i$(so $∂N_i/∂n_{α,i} = 1$). The $n_{α,i} = 0$ case arises when there are no net benefits at all in sustaining species $i$. In such a case one typically finds that even small populations of $n_{α,i} > 0$ do not add value, implying that $∂C_α/∂n_{α,i} > p/(N_i^* + N_i) + p n_{α,i,0}/(N_i^* + N_i)^2$ at $n_{α,i} = 0$, which in turn implies that $∂C_α/∂n_{α,i} > p/(N_i^* + N_i)$.

Now, consider the problem of minimising the global costs of sustaining $L_{reg}$ at a given level by appropriately choosing the population sizes $n_{α,i} ≥ 0$ sustained by each land holder $α$. Solutions of such a constrained non-linear optimisation problem satisfy the Karush–Kuhn–Tucker conditions (Chiang and Wainwright, 2005). These are derived from a Lagrangian, which here becomes

$$\sum_α C_α - \sum_{α,i} µ_{α,i}n_{α,i} - λL_{reg}, \quad (14)$$

where $µ_{α,i}$ and $λ$ are the Karush-Kuhn-Tucker multipliers. The resulting Karush–Kuhn–Tucker conditions are that

$$-\frac{∂C_α}{∂n_{α,i}} - µ_{α,i} + \frac{λ}{N_i^* + N_i} = 0 \quad (15)$$

for all $α$ and $i$, where either $µ_{α,i} = 0$ and $n_{α,i} ≥ 0$ or $µ_{α,i} > 0$ and $n_{α,i} = 0$. Comparison of Eqs. (13) and (15) and of the considerations for $n_{α,i} = 0$ shows that with $p = λ$ the two conditions are identical, except for the term $pΔn_{α,i}/(N_i^* + N_i)^2$ in Eq. (13). However, this term makes a sizeable contribution compared to the term $p/(N_i^* + N_i)$ only when $α$ has changed the abundance of a species $i$ by an amount that is comparable to or larger than the current global abundance $N_i$ (so $Δn_{α,i}$ and $N_i$ are of comparable size). Absent such dominant market participants, an ideal BIC market leads to near optimal allocation of resources to sustain $L_{reg}$, and so $LPI_{reg}$, at a given level. Larger $LPI_{reg}$ correspond to higher BIC prices $p$.

To study the case of dominant market participants, we first consider the case of negative $Δn_{α,i}$. In this case, Eq. (13) can be read as implying that the marginal cost $∂C_α/∂n_{α,i}$ that $α$ is willing to incur to maintain the abundance of species $i$ is by a factor $1 + |Δn_{α,i}|/(N_i^* + N_i)$ larger than the price of the resulting BICs. This additional conservation effort will not usually be detrimental.

The opposite case, positive $Δn_{α,i}$ that are of similar magnitude as $N_i$, can arise only when a large fraction of the population of species $i$ is held by $α$. To address such situations we now show that, firstly, even when a species is dominantly held by a single market participant, BICs still incentivise protecting this species and growing its populations and, secondly, BICs disincentivise dominance.

Consider first a market participant $α$ whose land is home to the entire global population of some species $i$. Suppressing the indices $i$ and $α$, assume that this market participant has grown this population from an
Figure 2: Accumulation of BICs when rebuilding a species as a dominant market participant. The solid line gives the BICs associated with this species, Eq. (16). As illustrated by the dashed lines, BICs gained by increasing the species’ population by a single individual are largest when it is closest to its baseline population $n_0$. However, to achieve full BIC, the species’ population must be lifted well above $N^* + n_0$.

associated BICs = \frac{\Delta n}{N^* + n_0 + \Delta n}.

A population gain of $\Delta n = N^* + n_0$, for example, earns this market participant BICs worth 0.5 species (Fig. 2). For a species that was originally close to extinction, so that $n_0$ is of similar magnitude as $N^*$, maintaining the population at this or even higher levels can be well worth while, even when, by Eq. (13), the effective value of BICs for this species is for $\alpha$ discounted by a factor $1 - \Delta n/(N^* + n_0 + \Delta n) = (N^* + n_0)/(N^* + n_0 + \Delta n)$. Importantly, market incentives to rebuild the species’ population are highest for the initial gains (Fig. 2).

To see that BICs disincentivise market dominance, note that market participants that achieved a smaller population gain of a species $i$ on their land benefit more from increasing this population further than those who have achieved larger gains. The reason is that increasing a population not only generates further BIC gains through the numerator in Eq. (10), but also penalises the value of previous gains by increasing global species abundance in the denominator, and this penalty is larger for those who have achieved larger previous gains. This disincentivises dominant holdings of population gains. We therefore expect that market misalignment due to the difference between conditions Eq. (13) and (15) will be harmless in most cases,
implying near-optimal resource allocation as explained above.

3.4 Consideration of off-site impacts

For most business activities, impacts on biodiversity are not constrained to sites the businesses hold. Often, these off-site impacts will be spread out widely, e.g., along complex supply chains or because they result from widely dispersing pollutants. It can be impractical for a business to fully avoid the resulting non-local impacts on species populations.

In order not to endanger, despite this, attainment of the societal goal of reducing species extinction risk, a business (or a similar organization) may choose to compensate the non-local increase in mean long-term species extinction risk resulting from its activity by generating BICs at sites it holds or by purchasing BICs that other organizations generate for this purpose.

Specifically, denote by $\Delta N_{\text{off},i}$ the diffuse off-site changes in species abundances generated by the activity of a business compared to the baseline, and define

$$BIC_{\text{off}} = \sum_i S N_i \Delta N_{\text{off},i} / (N_i^* + N_i),$$

where $N_i$ again denoting current species abundances. Since the $\Delta N_{\text{off},i}$ will usually be negative, so will $BIC_{\text{off}}$. However, we can show that when

$$BIC_\alpha + BIC_{\text{off}} > 0$$

the resulting change in $L_{\text{reg}}$ is always positive. This result holds for both small and large $BIC_\alpha$ and $BIC_{\text{off}}$ without invoking any approximation. Since a positive change $\Delta L_{\text{reg}}$ implies a positive overall impact on mean long-term species survival, one can identify Eq. (18) as a condition for a business to be biodiversity positive with respect to protection of species.

The proof of above result starts with the analogue of Eq. (11), taking both on-site and off-site changes in abundances into account, and then makes use of the fact that $\log(1+x) \leq x$ for any $x > -1$ (so that $-\log(1+x) \geq -x$) and of Eq. (18) to demonstrate an increase in $L_{\text{reg}}$: 
\[ \Delta \mathcal{L}_{\text{reg}} = \sum_{i} S \log \left[ 1 + \frac{N_i}{N_i^*} \right] - \log \left[ 1 + \frac{(N_i - \Delta n_{\alpha,i} - \Delta N_{\text{off},i})/N_i^*}{1 + \Delta n_{\alpha,i} + \Delta N_{\text{off},i}/N_i^*} \right] \]

\[ = \sum_{i} \log \left[ 1 + \frac{N_i}{N_i^*} \right] - \log \left( 1 + \frac{(\Delta n_{\alpha,i} + \Delta N_{\text{off},i})/N_i^*}{1 + N_i/N_i^*} \right) \]

\[ = \sum_{i} - \log \left[ 1 - \frac{1}{1 + N_i/N_i^*} \right] \]

\[ \geq \sum_{i} \frac{\Delta n_{\alpha,i} + \Delta N_{\text{off},i}}{N_i^* + N_i} \]

\[ = \sum_{i} \frac{\Delta n_{\alpha,i}}{N_i^* + N_i} + \sum_{i} \frac{\Delta N_{\text{off},i}}{N_i^* + N_i} \]

\[ = \text{BIC}_\alpha + \text{BIC}_{\text{off}} > 0 \quad (19) \]

### 3.5 The Biodiversity Stewardship Credit metric

A special case of the BIC metric arises when the baseline abundances of all species are zero. Such a situation might occur, e.g. when rewilding barren or intensively used agricultural land. From the abstract standpoint that all land and water on Earth was originally lifeless, one can argue that zero is the natural value for all baseline abundances, and that the current holders of any site are entitled to credits for sustaining, to the present day, the biodiversity on this site pass on to them by their predecessors. The credits are then awarded not for changes in biodiversity but for exercising stewardship over existing biodiversity. We therefore call the variant of BICs where the baseline abundances are set to zero Biodiversity Stewardship Credits (BSC).

The explicit formula for this metric is

\[ \text{BSC}_\alpha = \sum_{i} n_{\alpha,i}/N_i^* + \sum_{i} N_i^* + N_i \quad (20) \]

with \( n_{\alpha,i} \) denoting the sustained abundance of species \( i \) at site \( \alpha \).

BSCs share with BICs all the properties derived above. While BSCs have the advantage over BICs of being conceptually simpler, BSCs are not immediately suitable for a trade in biodiversity impacts. Global BSCs are overabundant, and trading them off against negative impacts could theoretically bring Earth back to its lifeless primordial state.

BSCs have their own role to play when biodiversity stewardship itself is of interest rather than the balancing of impacts. Organisations can, for example, include accounts of the total BSCs they hold in yearly reports to demonstrate their biodiversity credentials.
A second important role for BSC arises because BICs can often be approximated by the change in BSCs between baseline year and present:

\[ \text{BIC} \approx \Delta \text{BSC}. \]  

To quantify the accuracy of this approximation, we compute the error in Eq. (21) for the contribution from a single species \( i \) in comparison with this species’ contribution to current BSC\( _\alpha \). Denoting by \( N_{i,0} \) the species’ global abundance in the baseline year, we obtain

\[
\left| \left( \frac{n_{\alpha,i}}{N_i + N_{t}} - \frac{n_{\alpha,i,0}}{N_{i,0} + N_{t}} \right) - \frac{\Delta n_{\alpha,i}}{N_{t}} \right| = \frac{n_{\alpha,i,0} |N_i - N_{i,0}|}{n_{\alpha,i} (N^*_i + N_{i,0})},
\]

This relative error is small compared to one, e.g., when the species’ local baseline abundance \( n_{\alpha,i,0} \) was not much larger than its current abundance \( n_{\alpha,i} \) and the absolute change in the species’ global population size \( |N_i - N_{i,0}| \) is small compared to the global baseline abundance \( N_{i,0} \). While these conditions will often be satisfied, they break down, e.g., when a site holder rebuilds a species’ population from the verge of extinction. In such cases care should be taken to use BICs rather than BSCs to avoid undesirable artefacts. Thus, while site holders can often track changes in their BSCs to estimate their BICs, they should keep records of baseline abundances \( n_{\alpha,i,0} \) so BICs can accurately be computed using Eq. (10) if required.

### 3.6 BIC and BSC density

Since BICs and BSCs are additive across sites one can define a corresponding \textit{BIC density} and \textit{BSC density} by dividing BICs and BSCs, respectively, by site area, thus making metric values more comparable across sites of different size. Below we will provide some empirical values of this density in units of species km\(^{-2}\).

### 3.7 Local vs regional impacts on species populations

Both BICs and BSCs are defined in terms of the local population sizes of species at sites, disregarding the effects local changes in these populations might have at regional level. Such regional responses might take time to unfold (Tilman et al., 1994; Jackson and Sax, 2010; Essl et al., 2015) and can be difficult to predict. This might raise concerns that the long-term ecological reverberations of local impacts are yet to unfold after they registered in BICs or BSCs, and so be missed by these metrics.

Indeed, we demonstrated such complex, far-reaching long-term effects of perturbations in recent simulation of the LVMCM (O’Sullivan et al., 2021b). Remarkably, however, these simulations also reveal that, at least in the case of complete eradication of all species on a site (as when building a warehouse on a meadow), the average long-term change in the total population of each species across the metacommunity is nearly identical to the size of the local population removed by the intervention (Fig. 3). This suggests that quantification of biodiversity impacts in terms of local, short-term changes in population sizes provides a good estimate of the expectation value of the long-term impact, even when ecological complexity makes the actual long-term impacts less predictable.
Figure 3: **Long-term, regional-scale impacts of localised perturbations in simulated meta-communities.** In each simulation, we removed a single patch from a model metacommunity and compared the initial population biomasses of each species in that patch with the resulting long-term impact on the regional biomass of that species. While there is variation in the long-term biomass change, in some cases larger than removed biomass, on average biomass removed is a good predictor of long-term regional biomass loss. Axes are equally scaled. The grey dotted line represents a linear regression (O’Sullivan et al., 2021b).
Accruement of BICs during local site rewilding. Each line corresponds to a different simulation of ‘rewilding’ a single site as detailed in the text. After verifying that the precise value of $B^*$ has little effect on metric values, we set $B^*$ to one $10^{th}$ of the local single-species carrying capacity. Note the logarithmic time axis. Accruement tends to be fast but can be followed by ongoing slow fluctuations.

### 3.8 Rewilding

The perhaps simplest approach to gaining BICs is to permit the natural rewilding of a barren area. We used LVMCM simulations to get a first idea of how BICs in such areas increase over time as rewilding progresses. For this, we first kept all biomass at zero in a given site in our metacommunity model and allowed the surrounding metacommunity to relax to a new equilibrium or steady state. Then we allowed recolonisation of the barren site to occur, recording the associated BICs, where we used as the ‘global’ abundances of species their metacommunity-level population biomasses. As shown in Fig. 4, BICs rapidly accumulate over the first 10 unit times. Since the intrinsic growth rates of local populations in absence of competitors are $O(1)$ in our model, these results suggest that BICs tend to recover on a similar time scale as community biomass. The fluctuations in BICs on longer time scales seen in Fig. 4 are due to intrinsically driven community turnover (O’Sullivan et al., 2021) and can similarly be expected on real sites where community turnover occurs.
4 Calculating BICs and BSCs

BICs and BSCs can be determined by a variety of methods. We discuss both direct approaches based on survey data and indirect approaches where closely related other metrics are converted into BICs through appropriate approximations (summarised in Fig. 5). The latter methods provide more than just useful shortcuts to computing BICs. They also highlight unifying threads running through various approaches of quantifying biodiversity impacts, and, given the fact that BICs are directly derived from a measure of extinction risk, lend additional scientific rigour to established tools.

The choice of method/approximation will depend on the spatial resolution required, the accuracy sought and the type and quality of the available data. When simplified methods yield inconsistent results, it is likely that one of the underlying simplifying assumptions linking them to BICs has been violated in an essential way. Since these assumptions are spelled out in the derivations below, researchers can seek to refine existing tools where these assumptions are violated to align better with the objective of quantifying impact on extinction risk.

4.1 Direct determination of BICs and BSCs

4.1.1 From bespoke survey data and global population estimates

Direct computation of BICs and BSCs from survey data is most suitable for small sites with good data availability. As a pilot test on commercial property, we obtained permission from the owner of a grouse moor estate in Yorkshire, UK, to determine BSCs on their estate. Grouse moors are managed to provide optimal growth conditions for populations of game birds for recreational shooting. For an in-depth discussion of this practice, see, e.g. Grouse Moor Management Review Group (2019). Many grouse moors are run as businesses, and BSCs might provide opportunities and incentives to create additional value through biodiversity protection.

A commercial biodiversity survey provider (Ecology Services Ltd) was commissioned to conduct bird surveys on a representative area (1.7 km$^2$ size) within the estate. One-hour surveys were conducted on four days in the spring of 2022 (9, 21 April and 13, 26 May). To conduct the surveys, the area was divided into 5 sections along clearly visible boundaries and consecutively for each section the birds present in it at one moment were counted by observation from an adjacent road.

BSCs were determined for each day, inserting observed population sizes as $n_i$ in the BSC definition, Eq. (20). Chicks were included where visible, but did not affect the counts in a relevant way. For the global population sizes $N_i$ in Eq. (20) we used the central estimates of Callaghan et al. (2021) (see also Robinson et al., 2022; Callaghan et al., 2022). The globally rarest observed species was the stock dove (Columba oenas) with an estimated global abundance of 5 million individuals. For comparison, typical estimates for the regularisation constants $N^* = v_d/v_e$ for birds are in the range of 2.6–60 individuals (Sæther et al., 2004; Engen et al., 2009; Sæther et al., 2013), i.e., much smaller. We therefore disregarded the regularisation constants here and, by the same reasoning, in all subsequent calculations.

Averaging over the four days, we calculated a bird BSC density of $1.82 \pm 0.37 \times 10^{-6}$ species km$^{-2}$. Just 14 species contributed over 99% to this score – a pattern reflecting the known high skews of local and
Figure 5: Alternative approximate determinations of BICs. All formulas provide approximately the same value in units of ‘species’. Notation and approximations are discussed in Section 4. Annotations of arrows indicate the simplifying assumptions invoked. Where these assumptions are inadequate corresponding approximations should be omitted.
Figure 6:  **Prediction of BIC generation through hypothetical habitat restoration in Madagascar.** Using the GLOBIO-Species model, we simulated restoration, within the area indicated by the dashed rectangle, of anthropogenic land use, indicated by red areas in (a) and (b), to potential natural vegetation. Comparing predicted populations densities of native mammals before (panel a) and after restoration (panel b) we computed the resulting BIC-density (panel c) and total BICs gained.

global species abundance distributions [Enquist et al., 2019; Callaghan et al., 2021] and expected to be typical for BSCs. Here, the metric was dominated by black-headed gull (*Chroicocephalus ridibundus*), which contributed 33%, willow ptarmigan (*Lagopus lagopus*) contributing 23%, and Eurasian curlew (*Numenius arquata*) contributing 18%. While Eurasian curlew is listed as Near Threatened on the IUCN Red List (REF), the reason is not a low population (∼26 million) but a rather high rate of population decline. The next largest contributions came from European golden plover (*Pluvialis apricaria*, 7%) and stock dove (5%). The latter was represented by only 4 of a total of 705 observations (0.6%) but contributed disproportionately due to its low global abundance. This finding might indicate a potential to increase BSCs at the site by creating conditions somewhat more suitable for this comparatively rare species.

4.1.2 **Using the GLOBIO-Species global population model**

As an alternative to direct surveys, BSCs and BICs can be computed from model-based predictions of population sizes. We illustrate this here by a prediction of BIC gains resulting from hypothetical habitat restoration in Madagascar using the GLOBIO-Species model.

We delineated a hypothetical 32,400 km² restoration area (dashed rectangle in Fig. 6) and assumed that all anthropogenic land use types except for urban areas would be restored to potential natural vegetation [Hengl et al., 2018]. We then used GLOBIO-Species to calculate the BIC metric based on the distributions and population sizes of the 130 Malagasy mammals before and after restoration. That is, for each species $i$ we computed the quantities $\Delta n_i$ and $N_i$ entering Eq. (10) directly from the model (assuming $N_i^* \ll N_i$).
Non-native mammals were excluded, as we would expect their contributions to be negligible in view of large global population sizes $N_i$.

The density of BICs gained was positive throughout the restoration area (Fig. 6), reflecting that restoration was predicted to increase the populations of all 57 mammals native to this area. In most of the area BIC density was relatively low (but comparable to the BSC density computed above) because of small population increases compared to total population size. The highest BIC density was found along the eastern edge of the restoration area, where most of the Malagasy mammals occur.

The model predicts an overall BIC gain of 7.2 species. As for the grouse moor, this score was dominated by just a few species. Leading were the contributions from the Betsileo short-tailed rat ($Brachyuromys betsileoensis$), contributing 0.91 species and the lesser long-tailed shrew tenrec ($Microgale longicaudata$) with 0.81 species.

### 4.2 Indirect computation from established metrics

#### 4.2.1 From Range Size Rarity

For practical reasons, conservation ecologists often work with presence/absence data of species at lattice elements, disregarding population density. A biodiversity metric often computed from such data is Range Size Rarity (Howard, 1991; Williams et al., 1994), also known, e.g., as ‘endemism richness’ (Kier et al., 2009) and ‘Rarity Score’ (Possingham et al., 2000).

Denote by $C_i$ the index set of the lattice elements occupied by species $i$ and by $S_e$ the set of (the indices of) the species present at lattice element $e$, so that $i \in S_e$ if and only if $e \in C_i$. We shall write $|\cdot|$ to denote the number of elements of a set. For example, $|C_i|$ is the number of lattice elements in which species $i$ is present—a measure of range size. Range Size Rarity (RSR) at a given lattice element $e$ is then defined as the sum of the inverse range sizes of all extant species (Williams et al., 1994):

$$RSR_e = \sum_{i \in S_e} \frac{1}{|C_i|}. \quad (23)$$

RSR has been interpreted as a measure of local species richness where species are weighted by inverse range size, a measure of endemism (Williams et al., 1994). Kier and Barthlott (2001) propose further approximations to simplify computation of this metric.

Range-Size Rarity and variants thereof (Guerin and Lowe, 2015) are often considered in conservation ecology, especially in the selection of protected areas for species conservation. In the simplest case, one would place protected areas in the subset of lattice elements with the highest Range-Size Rarity, with the size of this subset depending on conservation effort.

To derive the approximate relation between Range Size Rarity and BSCs, we assume Earth’s surface to be covered by a lattice of $E$ non-overlapping surface elements of equal area $\Delta A$ and, to the degree possible, approximate square shape. We denote by $n_{i,e}$ the number of individuals of species $i$ in lattice element $e$ and by $\Delta n_{i,e}$ changes in these numbers. Summing over all lattice elements, $N_i = \sum_e E \ n_{i,e}$. 

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To emulate presence/absence (rather than abundance) data in our analysis, assume that each species \( i \) has, wherever it is present, a constant density \( \rho_i \). That is, either \( n_{i,e} = \rho_i \Delta A \) or \( n_{i,e} = 0 \). In this approximation, \( N_i = \rho_i |C_i| \Delta A \).

For the following demonstration of the close relation between RSR, BICs and BSCs, we consider, for simplicity, only the case where the approximation of BIC \( \alpha \) as \( \Delta \text{BSC}_\alpha \), Eq. (21), holds. In particular, we assume that changes in global abundances are relatively small. To compute BICs using RSR, Eq. (10), we further assume that the site \( \alpha \) is given by one or more lattice elements and write \( e \in \alpha \) to express that an element \( e \) is contained in \( \alpha \). We introduce indicator variables \( x_{i,e} \) such that \( x_{i,e} = 1 \) if the impact leads to extirpation of species \( i \) in element \( e \) and \( x_{i,e} = 0 \) otherwise, so that \( \Delta n_{i,e} = -\rho_i x_{i,e} \Delta A \). Above assumption that changes in the \( N_i \) are small implies that most \( x_{i,e} \) are zero. Disregarding the regularisation constants \( N_i^* \), we can then write

\[
\text{BIC}_\alpha \approx -\sum_i \frac{\Delta n_{\alpha,i}}{N_i} \approx -\sum_i \sum_{e \in \alpha} \frac{\rho_i x_{i,e} \Delta A}{\rho_i |C_i| \Delta A} = -\sum_{e \in \alpha} \sum_i \frac{\rho_i x_{i,e} |C_i|}{\rho_i |C_i| \Delta A} = -\sum_{e \in \alpha} \sum_i \frac{x_{i,e}}{|C_i|}.
\]

(24)

Analogously,

\[
\text{BIC}_{\text{off}} \approx -\sum_{e \notin \alpha} \sum_i \frac{x_{i,e}}{|C_i|}.
\]

(25)

The crucial observation at this step is that each species’ density \( \rho_i \) and the size of lattice elements \( \Delta A \) cancel out.

As a simple example, consider the case where site \( \alpha \) becomes uninhabitable to all species in the group of interest (e.g. due to conversion of natural land to intensively farmed land). All species present at \( \alpha \) disappear from that site, implying that \( x_{i,e} = 1 \) for all \( e \in \alpha \) and all species \( i \in S_e \), and otherwise \( x_{i,e} = 0 \). Then we get from Eqs. (24), applying Eq. (23),

\[
\text{BIC}_\alpha \approx -\sum_{e \in \alpha} \sum_{i \in S_e} \frac{1}{|C_i|} = -\sum_{e \in \alpha} \text{RSR}_e.
\]

(26)

The simple case of rewilding can be handled analogously. In more complicated situations, however, more detailed calculations as demonstrated in Sec. 4.1.2 are recommended.

The interpretation of BICs as a predictor of species survival implies that selection of protected areas based on Range-Size Rarity is the strategy that minimises mean long-term species extinction risks if range maps are the only data available. This result substantiates intuitive arguments conservation ecologists have invoked since Howard (1991) to justify use of Range-Size Rarity in conservation decisions.

A simple way to understand Eq. (26) is to notice the analogy between BSCs and RSR: while BSCs are given by the sum of the proportions that the focal area contributes to the global populations of species, RSR are defined as the sum of the proportions that the area contributes to the total ranges of species. In the approximation that species are evenly distributed over ranges, the BSCs of a lattice element equal its RSR.

It follows that the global distribution of RSR shown in Fig. 7 provides a good representation of the global distribution of BSCs. Considering the logarithmic colour scale used, it becomes clear that globally BSC are concentrated in a few geographically constrained biodiversity hotspots, typically at low latitudes.
Figure 7: Comparison of Range-Size Rarity (RSR) and Species Threat Abatement and Recovery (STAR\(_T\)) metrics for amphibians, birds and mammals. Spearman’s rank correlation of the two global data sets is 0.80. Logarithmic major axis regression yields \(\text{STAR}_{T,e} \propto (\text{RSR}_e)^{1.51}\). The STAR\(_T\) data was published by [Mair et al. (2021)](https://www.iucnredlist.org/resources/other-spatial-downloads), the RSR data was provided by IUCN. See SI for the detailed method of data analysis and comparison.

4.2.2 From the STAR metric

The Species Threat Abatement and Recovery (STAR) metric (Mair et al., 2021) is a weighted variant of Range-Size Rarity. The threat-related STAR (summed over all threats), for example, is given by

\[
\text{STAR}_{T,e} = \sum_{i \in C_i} \frac{W_i}{|C_i|},
\]

with the weighing factors \(W_i\) quantifying the IUCN Red-List category of species \(i\) by an integer ranging from 0 (Least Concern) to 4 (Critically Endangered).

IUCN’s threat-level categories are determined not only based on population size, but also also on other factors affecting the likelihood of future population declines, such as past or current population decline or the fragmentation of populations [Mace et al. 2008]. Population size itself enters the STAR\(_T\) metric twice. As an important determinant of threat level \(W_i\) and in the form of range size \(|C_i|\). Indeed, \(W_i\) and logarithmic range size are correlated (see Extended Data Figure 4b in Mair et al. 2021). Because \(|C_i|\)-values vary over many orders of magnitude, most of the variation in STAR\(_T\) is due to \(|C_i|\) rather than \(W_i\). As a result, the global patterns of variation in STAR\(_T\) and RSR, and so in BSC, are very similar (Fig. 7).

Unfortunately, the published global data sets of RSR and STAR\(_T\) available to us have been generated using incompatible methodologies. We therefore could not determine a valid statistical relationship that would permit numerical conversion between the two metrics, but hope that future work will close this gap.

An immediate implication of the formal similarity of RSR and STAR is that wherever STAR can be computed RSR can be computed to a similar accuracy. Since STAR assigns weight 0 to species of Least Concern, data deficiency in this category could in principle lead to additional uncertainty in RSR. In general, however, these species will have large ranges and so make relatively small contribution to RSR, limiting the
resulting uncertainty. In fact, the IBAT tool (www.ibat-alliance.org) used to compute STAR can output RSR values as well.

4.2.3 From Range Size Rarity and the Potentially Disappeared Fraction of species

As explained above, the off-site biodiversity impacts of business activity can be spread out widely across the world. Even when impacts at any given location are small, the accumulated global impact may be large. This is the kind of problem often considered in life-cycle assessments. In this context, the concept of the Potentially Disappeared Fraction of species (PDF) has been introduced to quantify diffuse impacts of products on the environment (Müller-Wenk, 1998; Goedkoop and Spriensma, 2000). The metric is defined as the proportion of locally extant species that get extirpated (i.e. ‘disappear’) as a result of exposure to a pressure such as environmental pollution. The local ‘disappearance’ of species quantified by PDF is considered reversible once the pressure has ceased.

Denote by PDF$_e$ the potentially disappeared fraction of species at lattice element $e$. Now, recall that if a species $i$ locally disappears (i.e. is extirpated), then $x_{i,e}$ in Eq. (24) is one, and otherwise it is zero. We therefore have on average

$$PDF_e = \frac{1}{|S_e|} \sum_{i \in S_e} x_{i,e}. \quad (28)$$

PDF and RSR together can be used to approximate $BIC_{off}$. This approximation depends on the assumption that disappearance of species at a site where it is present is uncorrelated with its inverse range size, that is, that we can approximate the mean of $x_{i,e} |C_i|^{-1}$ at $e$ over all species $i$ by the product of the means of the two factors. With $|S_e|$ denoting local species richness, we can then write

$$\sum_{i \in S_e} x_{i,e} |C_i|^{-1} \approx \frac{\sum_{i \in S_e} x_{i,e} \sum_{i \in S_e} |C_i|^{-1}}{|S_e|}. \quad (29)$$

This assumption is justified, e.g., when, as recent results suggest (O’Sullivan et al., 2019, 2022), population and range sizes of species are to a large part controlled by complex ecological interaction networks rather than by the species’ own traits, and so effectively random.

Equations (29), (28) and (23) allow us to evaluate Eq. (25) as

$$BIC_{off} \approx -\sum_{e \notin \alpha} \sum_{i} \frac{x_{i,e}}{|C_i|} = -\sum_{e \notin \alpha} \sum_{i} \frac{x_{i,e}}{|C_i|} \approx -\sum_{e \notin \alpha} \frac{\sum_{i \in S_e} x_{i,e}}{|S_e|} \frac{1}{|C_i|} \approx -\sum_{e \notin \alpha} PDF_e RSR_e. \quad (30)$$

4.2.4 From species density and PDF

Range-Size Rarity is closely related to species density (Kier and Barthlott, 2001). To see this, we compute the sum of RSR$_e$ over a hypothetical large area in which all species are endemic. We denote the set of lattice elements forming this area by $\Omega$ and the set of endemic species by $S_\Omega$. Then
\[
\sum_{e \in \Omega} \text{RSR}_e = \sum_{e \in \Omega} \sum_{i \in S_e} \frac{1}{|C_i|} = \sum_{i \in S_\Omega} \sum_{e \in C_i} \frac{1}{|C_i|} = \sum_{i \in S_\Omega} \sum_{e \in C_i} 1 = \sum_{i \in S_\Omega} 1 = |S_\Omega|.
\]

Dividing both the first and the last expression by the size of the area \( A = |\Omega| \Delta A \), we see that species density \( |S_\Omega|/A \) equals the average of RSR\(_e\) over \( \Omega \) in units of \( \Delta A \). In particular, the global sum of Range Size Rarity equals global species richness \( S \). Even when the ranges of a few species extend beyond the area considered, Eq. (31) holds to a good approximation. Similar arguments apply to BSCs. On large scales, BSC density, \( \text{RSR}/\Delta A \), and species density therefore become largely indistinguishable.

For pollutants that spread globally before they decay, we may assume that PDF\(_e\) is constant or at least uncorrelated with RSR\(_e\). Disregarding the exclusion of the (usually small) site \( \alpha \) in Eq. (30), we can then replace PDF\(_e\) by its global average PDF to obtain, using Eq. (31),

\[
\text{BIC}_{\text{off}} \approx - \sum_e E \text{PDF}_e \text{RSR}_e \approx - \sum_e \text{PDF} \text{RSR}_e = - \text{PDF} \sum_e \text{RSR}_e = - S \text{PDF}.
\]

When PDF\(_e\) and species density are correlated, e.g., on continental scale, expressions such as the right-hand-side of Eq. (32) should be evaluated for each continent separately and then added up.

An alternative formulation of Eq. (32) expresses species richness \( S \) in terms of global species density \( \text{SD} = S/(E \Delta A) \), recalling that \( E \) is the total number of lattice elements covering Earth’s surface:

\[
\text{BIC}_{\text{off}} \approx - S \text{PDF} = - \text{SD} E \Delta A \sum_e \frac{E \text{PDF}_e}{E} = - \text{SD} \sum_e \text{PDF}_e \Delta A.
\]

In practical calculations care must be taken to average and sum only over land surfaces, only over water surfaces, or consistently over both.

4.2.5 Relations to the work of Kuipers et al. (2019) and Verones et al. (2022)

It is worth noting the similarity between the sum on the right-hand side of Eq. (30) and Equation (2) of Verones et al. (2022), which formalises a corresponding verbal prescription by Kuipers et al. (2019). Both differ in three rather minor points from our Eq. (30): (i) in place of RSR an early variant of STAR\(_T\), containing weighting by Red-List Categories is used, (ii) this variant metric (called ‘Global Extinction Probability’, although it was not derived as a probability) is normalised such that its sum over the globe is 1, and (iii) rather than summing over lattice elements, the sum is over a partition of Earth’s land surface into ecological coherent regions (ecoregions). Kuipers et al. (2019) interpreted this sum as “translating fractions of regional species extinctions into global species extinctions”, arguing for this interpretation by considering situations where all species are lost from one or several ecoregions (i.e. PDF = 1 in these regions).

This interpretation is correct without the weighting by Red-List Categories (i.e. when using RSR) and when these ecoregions contain only endemic species (in which case RSR reduces to regional species richness). For the more common situation with non-endemic species and PDF values between 0 and 1 (which then refer
to local rather than regional extirpations), our interpretation as a measure of impact on the risk of future extinctions (rather than a measure of current extinctions) appears appropriate in view of its mathematical derivation above. This refined interpretation notwithstanding, the work by Kuipers et al. (2019) and Verones et al. (2022) has demonstrated the strong intuitive appeal of Eq. (30) and related results presented above.

4.2.6 From PDF-based metrics in species×year units

PDF-based footprinting tools such as ReCiPe 2016 (Huijbregts et al., 2019), which have their roots in life-cycle impact assessment, allow users to compute a measure of the ecosystem damage (ED) resulting from a single unit of business activity. Such a unit may be the production, sale and use of a single product, emission of one unit of pollutant, or one year of business activity. Since the environmental impact of one such unit will eventually, if slowly, decline as pollutants decay and mineralise and ecosystems recover, ecosystem damage is not measured as static global mean PDF value but in terms of the integral of a dynamically declining impacts over time. As a result, units of impact generally contain a factor ‘year’.

ED, for example, is computed by a formula analogous to the right-hand-side of Eq. (33), where in place of PDF one finds a sum of impacts along different pathways (e.g. different pollutants) in units of PDF×year. Hence, while the right-hand-side of Eq. (33) has units of species, ED is expressed in units of species×year.

The simplest way to convert time-integrated metrics into metrics of static impact is to multiply them with the rate \( r \) at which units of business activity are produced (\( r = 1 \text{ year}^{-1} \) when the unit is all activity over one year), which yields the long-term impact that would result if the business activity would progress indefinitely at a constant rate. We can then approximate BIC\(_{\text{off}}\) in terms of ED as

\[
BIC_{\text{off}} \approx -SD \sum_{e} PDF_e \Delta A = ED r. \tag{34}
\]

More detailed calculations would take the time scales of accumulation and decline of various pressures on biodiversity into account, e.g., according to the models underlying ReCiPe 2016.

5 Discussion

5.1 BICs in a nutshell

The use of BICs by business is based on two simple messages: (1) When \( BIC_\alpha + BIC_{\text{off}} > 0 \) the mean long-term survival probability of species increases as a result of the business’s activities. Businesses that are biodiversity positive in the sense that \( BIC_\alpha + BIC_{\text{off}} > 0 \) contribute to overcoming the global extinction crises rather than being part of the problem. (2) The value of LPI (as fundamentally defined; not necessarily empirical estimates from population time series) increases as a result of the business’s activities by a proportion

\[
\frac{\Delta LPI}{LPI} \approx \frac{BIC_\alpha + BIC_{\text{off}}}{S}, \tag{35}
\]
where $S$ is the total number of species in the group considered. Biodiversity positive businesses in the sense above therefore increase the value of this widely cited measure of biodiversity loss.

5.2 Offsetting or not?

Businesses have a wide range of options for positioning themselves in the debate on how exactly to achieve ‘nature positive’ outcomes [zu Ermgassen et al., 2022]. These include: achieving positive on-site biodiversity impact on their own or after adding bought-in credits; achieving this objective after inclusion of off-site impacts; precautionary approaches that apply a multiplier to negative impacts before adding the positives [Bull et al., 2020]; reporting on negative and positive impacts without computing a net impact; emphasising systemic change to address externalities [Science Based Targets Network, 2021]; or decoupling the discourse on positive impacts entirely from the consideration of negatives [World Economic Forum, 2022]. The metrics proposed here are applicable in any of these contexts and we do not advocate for any particular position.

However, a clarification of terminology is in place. The term ‘biodiversity offset’ tends to be associated with traditional schemes focused on on-site impacts, emphasising ecosystem function and services and like-for-like compensation [Bull et al., 2013]. Zu Ermgassen et al. (2022) argued for moving away from such schemes, based on the recognition that “footprinting assessments across companies’ entire value chains are showing that direct operational impacts are a relatively small part of total biodiversity impacts for many large organisations”. The objective of ‘nature-positive’ outcomes should instead draw attention to wider impacts and societal objectives. We note, though, that the ‘net’ in any conceptualisation of ‘Nature Positive’ involving “net gain in biodiversity” [Milner-Gulland, 2022] implies some form of arithmetics combining positives and negatives, whether one calls this ‘offsetting’ or not. Rather than attempting to coin new terms, we here follow Bull et al. (2022) in sticking to the term ‘offset’ even if applied in the context of the Nature Positive agenda. We argue below that, this terminology notwithstanding, the offsetting of BICs can overcome several of the issues associated with traditional offsetting schemes. This might encourage businesses to quantitatively compare their positive and negative impacts, provide materiality to biodiversity credits [World Economic Forum, 2022], and improve resource allocation to species conservation by stimulating entrepreneurial thinking to find cost efficient ways of achieving this in the context of other needs such as ecosystem services.

5.3 Choice of groups of species to cover

A question we did hitherto not address is that of the choice of the group of $S$ species entering an implementation of BICs or BSCs. For established related metrics such as PDF-based metrics, LPI, or STAR, this choice appears to have been made based on the availability of suitable data. Since data requirements differ between metrics, so do the taxa or functional groups they cover.

We will not recommend a specific choice for BICs and BSCs at this stage. Amongst the desiderata that this choice should consider are (i) availability of data or technology to determine the metrics or approximate variants, (ii) alignment with relevant established variants, (iii) inclusion of vulnerable taxa, such as Cycads or Amphibians.
One might consider computing and trading BICs separately for two or more distinct groups of species, especially when there are concerns that some groups require more protection than others. On the other hand, businesses are unlikely to be able to consider biodiversity constraints imposed by very many metrics, and best results might be achieved if BICs are reported and traded for a single but encompassing species group.

Relevant in this context is that RSR and species richness are known to be correlated across taxonomic and functional groups, especially on larger scales and when these groups are not too narrowly defined (Warren and Gaston 1992; Kier et al. 2009; Qian and Kissling 2010; Castagneyrol and Jactel 2012). As this correlation is causally explained by interactions between groups (Castagneyrol and Jactel 2012; Rossberg 2013; Zhang et al. 2018) there can be a degree of equivalence of metrics covering different groups of species. It might therefore be possible to convert, to some extent, between metrics defined over different groups.

5.4 A worked example

Let’s consider an example. In a recent self-assessment using the ReCiPe 2016 tool, University of Oxford reported to be generating an ecosystem damage (ED) of 1.6 species × year in the academic year 2019-20 (Bull et al. 2022). As this quantifies the summed impact for one year of activity, we can estimate the corresponding steady-state impact by setting \( r = \text{year}^{-1} \) in Eq. (34), giving an estimated offsite impact of \( \text{BIC}_{\text{off}} \approx -1.6 \text{ species} \).

To compensate this increase in species extinction risk, University of Oxford could acquire BICs from a conservation NGO such as the Tree Conservation Fund. With funding from University of Oxford, the Fund and its partners would, say, acquire an area of land suitable for the reintroduction of Chinese watermelon trees (Artocarpus nanchuanensis), which are critically endangered with perhaps only 100 individuals remaining in the wild. They might plant 1000 saplings of \( A. nanchuanensis \) in this area. Assume that when the trees mature after about five years over 200 saplings survive, increasing the tree’s mature population on the land held by the fund or its partners by \( \Delta n = 200 \) and bringing the total global mature population to about \( N = 300 \). Assume further a regularisation constant of \( N^* \approx 100 \) for this species. The resulting BICs would then evaluate by Eq. (10) to

\[
\text{BIC} \approx \frac{\Delta n}{N^* + N} \approx \frac{200}{100 + 300} = 0.5 \text{ species},
\]

where we disregarded impacts on other species, as these would likely be dwarfed by the \( A. nanchuanensis \) contribution (except for species dependent on \( A. nanchuanensis \)). The Tree Conservation Fund can provide this contribution to species conservation at an estimated cost of just around USD 250,000 (Tree Conservation Fund, 2021).

Supporting four projects of this kind, University of Oxford might be able to obtain \( \text{BSC}_\alpha = 2 \text{ species} \) at a cost of around USD 1,000,000 after five years, thus having turned from a negative to a positive impact to the long-term survival of species, quantified by BICs as \( \text{BIC}_{\text{off}} + \text{BSC}_\alpha \approx 0.4 \text{ species} \), with some margin of error.
The range of taxa considered by ReCiPe 2016 is very broad, including insects, plants, arachnids and vertebrates amongst others and covering $S = 1.85 \times 10^6$ known species (Goedkoop et al., 2013). For an LPI computed for this large group the resulting proportional increase is, by Eq. (35), $0.4 \text{ species}/S \approx 2 \times 10^{-7}$.

5.5 A dynamic economy of biodiversity

To meet the needs of the business community, the BIC metric has deliberately been designed to be simple and widely applicable and to rely as little as possible on expert input. Rather than incorporating the complexities and uncertainties of ecological and social systems in the metric’s definition, the decision on how best to deal with these is intentionally left to the users of the metric.

There will, for example, always be some uncertainty as to whether restoration measures will generate anticipated gains in BICs. Rather than awarding credits to plans to restore populations and ecosystems and the resulting projected gains, BICs and BSCs are strictly linked to the documented current state. This does not stop business partners from agreeing on restoration plans and making commitments for gains in BIC, the associated uncertainty is just not part of the metric’s definition. Instead, allocation of risks and opportunities amongst business partners should be part of contractual agreements. To stimulate entrepreneurial spirit, an agreement might, for example, permit an organisation growing BICs for a client to sell BICs grown beyond the contractual agreement to third parties, while also leaving it responsible to compensate the client for underachievement. Alternatively, BIC growers might act as service providers, leaving any risks to the commissioning clients, while the latter might hedge these risks by investing into a diverse portfolio of BIC-growing projects.

This flexibility arises because the BIC metric measures a wide variety of positive and negative impacts in the same, convertible currency, thus providing the foundations of a wide BIC market capable of absorbing unexpected gains and losses. Critics might argue that this flexibility constitutes a weakness of the metric: how can rebuilding one species’ population in Malaysia compensate the decline of another species’ population in Guatemala? Doesn’t the metric’s proposed use as a commodity imply that species are substitutable with each other, while in fact the irreplaceability of each species provides the moral underpinning of biodiversity conservation at the species level?

Such arguments, however, are likely due to misunderstandings. A first misunderstanding might be that our scheme aims fundamentally at the maintenance of species populations. This is not the case. The scheme aims to reduce the risk of species extinctions; keeping species populations large is just a means to this end.

A second misunderstanding might be that BICs directly trade off gains in one population against losses in another. This would indeed be inadequate for species conservation, especially if the species experiencing losses is the rarer one of the two. In fact, however, rarer species enter BIC with a higher weight, which intrinsically encourages rebuilding their populations.

Finally, should the above critical argument relate to a situation where both the Malaysian and the Guatemalan species are rare and at similarly high risk of extinction, its fallacy lies in the assumption that sufficient funding to protect these two species and all other species with similar status is available. Extinction rates are high (Ceballos et al., 2015) and global resources for conservation insufficient and inadequately allocated (Deutz et al., 2020; Rodriguez et al., 2022). A choice of how much to invest into each species is required. We invoked a substitutability argument at this point only insofar as we assumed the extinction of
one species to be just as undesirable as that of any other (within the group considered). Resources should therefore be allocated such as to maximise overall expected long-term species survival, even if this means leaving some species at a high risk of extinction.

Intuitively, above example of rebuilding the *A. nanchuanensis* population might strike readers as somewhat artificial and as it barely generates any of the benefits we are used to associate with the restoration of nature. Readers may also wonder how a tree restoration project in China can compensate for damage to the environment done by an institution in England. We believe that such concerns arise from confounding species conservation with the conservation of ecosystems and ecosystem services. Indeed, service provision tends to require complex ecosystems and is often not substitutable over large geographic distances. For species conservation, neither must be an immediate constraint. Yet, linkages between BICs, complex ecosystems, and ecosystem services naturally arise.

For species conservation it currently makes sense to focus investments on those species at highest risk of extinction. BICs provide the market signal to do this where feasible. Coming back to our example: considering the low RSR and BSC density of England (Fig. 7), investments by University of Oxford into species protection abroad can reduce overall extinction risk much more than similar investments to restore habitats in England would. However, after these low-hanging fruit of species conservation have been picked, more intricate schemes where entire ecosystems are rebuilt are likely to become attractive for BIC generation. This shift in species conservation efforts from populations to ecosystems would be reinforced by the property of BICs, discussed above, of disincentivising dominant holdings for population gains.

Linkages to ecosystem services arise when organisations develop “nature-based solutions” that combine generation of BICs with the provision of ecosystem services (e.g. food, clean water, tourism, carbon sequestration, etc.). The market price of BICs and the expected benefits from ecosystem service provision (which depend on local conditions) will signal to these organisations how best to allocate their resources and where the highest potential for effective synergies might lie. Thus, our focus on species protection in the design of BICs does not deny the importance of ecosystem services. We just consider that their clean conceptual separation is conducive to the efficient conservation of both.

By intentionally addressing species conservation only, the approach we propose differs from most traditional biodiversity offsetting schemes and overcomes some of their potential weaknesses, reviewed, e.g., by Bull et al. (2013). Our scheme does not involve like-for-like offsetting and so avoids the question to which extent this is achieved (Madsen et al., 2010). This generates a larger market for potential offsets, reducing transaction costs and leading to more efficient resource allocation. In particular, we expect availability of offsets from biodiversity gains that have already been achieved (Bekessy et al., 2010), thus sidestepping questions related to risk of failure and discount rates.

Two important recommendations, however, apply to our scheme just as much as to traditional offsetting. The first is that offsets should last at least as long as the negative impacts they are meant to compensate (Bull et al., 2013). Businesses practising offsetting should be ready to demonstrate at any time that they hold sufficient positive BICs to compensate their negative impacts, even when the BICs they hold change due to changes in global species abundances $N_i$.

The second is to maintain reversibility of impacts (Godden and Vernon, 2003). On paper it is possible to compensate, in terms of BIC, the deliberate global extinction of one species by rebuilding the populations of several other species close to extinction, and indeed this might increase overall long-term species survival.
Yet, we caution against this based on arguments similar to those invoked in opposition to the death penalty: the irreversibly of the intentional extermination makes it impossible to correct methodological, conceptual, theoretical and implementation errors that may become clear after the scheme’s execution.

Conclusion

We have demonstrated that BICs have properties suitable for use in biodiversity-related disclosures in business and financial contexts. The metric can also support voluntary or legislated nature positive policies. In all cases, we recommend its use in conjunction with metrics for ecosystem services or natural capital. Many of the attractive properties of BICs reflect that this metric is strictly science based, mathematically linked to the LPI and the species conservation objective. Data requirements of BICs are similar to those of existing comparable metrics. Pilot studies are now underway to test marketing of BICs in practice.

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Appendices

A Numerical test of our model for extinction risk

Here we demonstrate that Eq. (4) provides a good estimate of mean species lifetime despite making use of
the diffusion (continuum) approximation and disregarding the decline of the strength of fluctuations near
$x = 0$.

For this we simulated an asexual population with non-overlapping generations as

\[ \lambda(t) \sim \exp\left(\frac{v_e^1/2}{2} \xi(t)\right), \quad (A.1a) \]
\[ N(t + 1) \sim \text{Poisson}(\lambda(t) N(t)), \quad (A.1b) \]

with $\xi(t)$ denoting a standard normal random number and Poisson($\mu$) a Poisson-distributed random number
with mean $\mu$. The model implies $v_d = 1$.

We set $v_e = (0.15)^2$ and evaluated 26 values for the initial population size $N(0) = N_0$, spaced equally
on the log axis from 1 to $10^5$, except for rounding to the nearest integer. For each $N_0$, the probability of
species survival ($N(T) > 0$) until time $T = 10^4$ was estimated from $10^4$ replicates.

As shown in Fig. A.1a, extinction probability increases linearly with $\log(N_0)$ only for large $N_0$. By
contrast, $x_0 = \log(1 + N_0/N^*)$, with $N^* = v_e/v_e = 44.4$, is linearly related to extinction probability for
all $N_0$ considered (because probabilities are $\leq 1$ by definition, the relationship would break down for even
larger $N_0$). The slope of the relation is as predicted by Eq. (4).
Figure A.1: Demonstration that $x_0$ predicts expected species lifetime better than $\log(N_0)$. Points are simulation results for the individual-based model Eq. (A.1) with $v_e = (0.15)^2$ over $T = 10^4$ time steps. The dashed line is the probability of survival as approximated by Eq. (4). Panels (a) and (b) represent the same data on different horizontal scales.
Code availability statement For review purposes, the R code underlying Appendix A has been deposited at [http://axel.rossberg.net/pExt.R](http://axel.rossberg.net/pExt.R). The LVMCM simulation model used to elucidate some properties of the BIC/BSC is available at [http://www.github.com/jacobosullivan/LVMCM_src](http://www.github.com/jacobosullivan/LVMCM_src).

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