Comparing mean species abundance and the biodiversity intactness index to guide robust biodiversity investment decisions

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Author contributions

Benjamin Stimpson: conceptualisation, methodology, formal analysis, writing. **Joseph Bull**: conceptualisation, methodology, writing – review & editing, supervision. **EJ Milner-Gulland**: conceptualisation, methodology, writing – review & editing, supervision.

Data availability statement

Data and code used in this study is available at:
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Abstract

1. Mean species abundance (MSA) and the biodiversity intactness index (BII) are two leading biodiversity metrics used to quantify how species composition differs between a control site and an impacted site. Both are proposed for global biodiversity monitoring, are used by companies to create corporate biodiversity impact accounts, and are being considered by financial institutions seeking to integrate biodiversity into investment decisions. Understanding the extent to which MSA and BII are interchangeable is therefore essential for assessing whether valid comparisons can be made across companies reporting different metrics. At a market level, comparability determines whether investments are steered towards similar sets of companies: if metrics are poorly comparable, they may create confused or conflicting incentives for reducing biodiversity impact.

2. We assess the comparability of the metrics by: (*i*) deriving mathematical conditions under which they are equal; (*ii*) examining their parameter sensitivity using simulated communities; and (*iii*) applying them to the same real dataset.

3. We find that comparability increases with higher species evenness and total abundance in control communities, but decreases with increasing species richness. Rank correlation between the metrics is strongest at sites where species richness increases, total abundance declines, and evenness remains high or decreases slightly between control and impacted sites. Conversely, correlation is weakest when richness declines from high to intermediate levels and total abundance increases, with no consistent direction of change in evenness. Across biogeographic realms, the metrics generally show strong rank correlation.

4. Overall, across real and simulated data, we find that MSA and BII produce broadly comparable rankings of sites, but the magnitudes of the metrics often differ substantially for any given site. On this basis, companies, financial institutions, and standard-setters can use either metric, but direct numerical comparison between them is rarely appropriate, requiring the consistent use of one metric. To support metric selection, we outline the contexts and business–biodiversity framings in which each metric is most suitable.

1. Introduction

Biodiversity metrics are a vital part of a monitoring system for a nature positive economy, and to guide contributions to global goals. A very wide range of metrics is available for biodiversity monitoring (Burgess et al., 2024). Within the Convention on Biological Diversity's Global Biodiversity Framework, metrics are needed for measurement and disclosure of corporate impacts on biodiversity, for example under Target 15 (Kunming-Montreal Global Biodiversity Framework, 2022).

Within biodiversity finance, a key process is the comparison between two investable assets, e.g. between two companies in the same sector. Target 15 envisages a world in which companies are disclosing their nature-related risks, impacts, and opportunities. Investors can then use this information in investment decisions, causing capital to flow towards nature positive companies and away from those that are nature-negative (Irvine-Broque & Dempsey, 2023; TNFD, 2025a), thereby creating a market incentive for reducing biodiversity impact. Given the lack of mandatory standardisation for corporate disclosure of biodiversity metrics, however, businesses are free to use a variety of metrics to disclose their impact on biodiversity. For example, under the Nature Positive Initiative (Nature Positive Initiative, 2024), which has a close institutional relationship to the Taskforce for Nature-related Financial Disclosures (TNFD), participating businesses are obliged to report, among other information, on changes in ecosystem condition associated with their activities. But businesses have broad scope, following the UN System of Environmental-Economic Accounting (UN-SEEA) Ecosystem Accounting guidance (UN, 2021), to select the exact metric or metrics they intend to disclose. This presents a practical question for biodiversity finance: whether a valid comparison can be made between a company disclosing one metric for a given aspect of biodiversity and another company disclosing a different metric for that same aspect.

If company disclosures are not available, investors can use metrics embedded in tools to model this information, based on related data (Hickman et al., 2025; Stimpson et al., 2025). Tools are specific combinations of a metric and the methodology and data used to compute it (Stimpson et al., 2025): i.e. tool 1 is made up of metric A and method X, applied to dataset C; while tool 2 might use the same metric A and dataset C but calculate outcomes using method Y, etc. Recent evidence has shown that currently available tools provide widely varying rankings of investable companies (Hickman et al., 2025). This variation creates mixed stock price signals on which companies are leaders and laggards in terms of biodiversity impact, which may weaken the incentive to reduce biodiversity impact (Berg et al., 2022). It is not clear, at present, to what extent variation between tools is a function of the comparability of the metrics used, or the methods. This is especially important given that many ecologists would argue for the use of multiple metrics to capture the complexity of biodiversity (Purvis, 2020; Stenseke et al., 2025). This presents a second, policy-level, question associated with metric comparability: if both a clear market signal for reduced biodiversity impact and the use of multiple biodiversity metrics is desirable, to what extent do different metrics for the same aspect of biodiversity agree and therefore lead to similar investment decisions?

Previous analysis of metric comparability has generally been at the level of the tool (Durand et al., 2024; Hickman et al., 2025). Caution on conclusions from analysis at this level is warranted, however, given demonstrations that correlations between metrics are often higher when tools use the same method and data source (Stevenson et al., 2024). A recent study from Kuipers and colleagues (2025) held the methods used to create metrics constant when comparing biodiversity outcomes. They find a significant positive but uncertain relationship between mean species abundance (MSA) and potentially disappeared fraction of species (PDF), concluding that the metrics provide complementary information. This makes sense, given that MSA measures species composition and PDF measures species richness changes, which are related but different measures of biodiversity (Stimpson et al., 2025).

An opportunity to assess the comparability of two metrics for the same aspect of biodiversity is presented by MSA and another leading metric for species composition: the Biodiversity Intactness Index (BII). Both metrics describe changes in species composition between one site and another, considering both the identity of species and the abundance of each species in an area. Generally, as these metrics are deployed to assess the effect of human activity, one site is defined as the *control site* and the other as the *impacted site*. The control site may be a baseline, a previous state of the site that is defined as desirable, or a reference, such as a pristine example of the site's type elsewhere in the world (Gonzalez et al., 2023). The impacted site may be subject to either or both positive and negative anthropogenic impacts. Both metrics, then, capture the compositional intactness of a local ecological community.

These metrics frequently appear next to each other both in the scientific literature (Burgess et al., 2024) and within the various tools listed in the TNFD catalogue (TNFD, 2025b). Often, the two metrics are described as conceptually very similar (van Vuuren et al., 2025), including by the creators of the MSA metric (Alkemade et al., 2009; Schipper et al., 2020). Indeed, the two metrics are sometimes presented as broadly interchangeable metrics for the compositional aspect of ecological integrity (e.g. Burgess et al. 2024, Nicholson et al., 2021). In practice too, financial institutions are beginning to take up either (or both) BII or MSA for use in risk assessment and financial decision-making (Responsible Investor, 2025), facilitated by an increasing number of tools using each metric (TNFD, 2025b).

Kuipers and colleagues (2025) formally defined the MSA of an impacted site as:

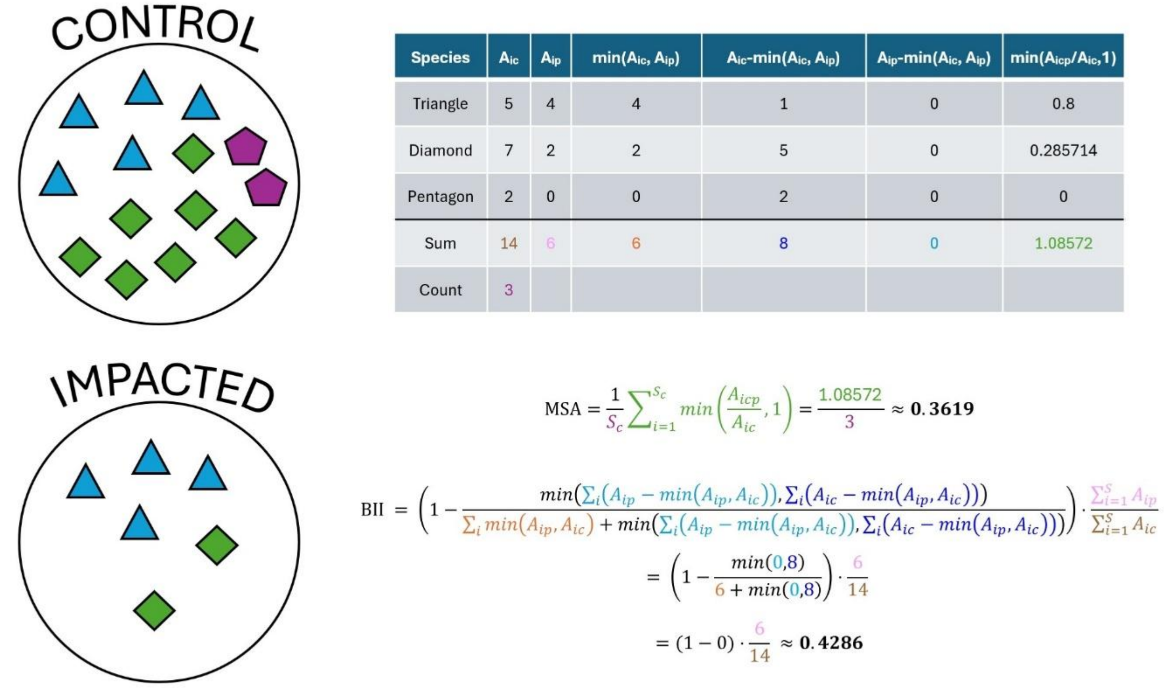
$$\mathrm{MSA} = \frac{1}{S_c}\sum_{i=1}^{S_c} min\left(\frac{A_{icp}}{A_{ic}}, 1\right) \tag{1}$$

Where A_{icp} is the abundance of species i, that is present in both the control site c and in the impacted site p; A_{ic} is the abundance of species i in the control site c; and S_c is the species richness of the control site.

BII's formal definition has changed over time (Newbold et al., 2016; Scholes & Biggs, 2005). From the most recent release of the modelling methodology used to produce publicly available BII layers (De Palma et al., 2024), which uses balanced Bray-Curtis dissimilarity (Baselga, 2013, 2017), the BII of an impacted site can be defined as:

$$\mathrm{BII} \;=\; (1-\frac{min\left(\sum_i\left(A_{ip}-min\left(A_{ip},A_{ic}\right)\right),\sum_i\left(A_{ic}-min\left(A_{ip},A_{ic}\right)\right)\right)}{\sum_i min\left(A_{ip},A_{ic}\right)+min\left(\sum_i\left(A_{ip}-min\left(A_{ip},A_{ic}\right)\right),\sum_i\left(A_{ic}-min\left(A_{ip},A_{ic}\right)\right)\right)})\cdot\frac{\sum_{i=1}^{S}A_{ip}}{\sum_{i=1}^{S}A_{ic}} \tag{2}$$

Where A_{ip} is the abundance of species i in the impacted site p; A_{ic} is the abundance of species i in the control site c; and S is the total species richness across the control and impacted sites ($S = S_c \cup S_p$). Figure 1 describes a worked example of the application of both metrics. Supporting Information (SI) 1 provides a toy that calculates MSA and BII from species abundances.



Species	A_{ic}	A_{ip}	min(A_{ic}, A_{ip})	A_{ic}-min(A_{ic}, A_{ip})	A_{ip}-min(A_{ic}, A_{ip})	min(A_{icp}/A_{ic},1)
Triangle	5	4	4	1	0	0.8
Diamond	7	2	2	5	0	0.285714
Pentagon	2	0	0	2	0	0
Sum	14	6	6	8	0	1.08572
Count	3					

$$\mathrm{MSA} = \frac{1}{S_c}\sum_{i=1}^{S_c} min\left(\frac{A_{icp}}{A_{ic}}, 1\right) = \frac{1.08572}{3} \approx \mathbf{0.3619}$$

$$\begin{aligned}\mathrm{BII} &= \left(1 - \frac{min(\sum_i(A_{ip} - min(A_{ip}, A_{ic})), \sum_i(A_{ic} - min(A_{ip}, A_{ic})))}{\sum_i min(A_{ip}, A_{ic}) + min(\sum_i(A_{ip} - min(A_{ip}, A_{ic})), \sum_i(A_{ic} - min(A_{ip}, A_{ic})))}\right) \cdot \frac{\sum_{i=1}^{S} A_{ip}}{\sum_{i=1}^{S} A_{ic}} \\ &= \left(1 - \frac{min(0,8)}{6 + min(0,8)}\right) \cdot \frac{6}{14} \\ &= (1 - 0) \cdot \frac{6}{14} \approx \mathbf{0.4286}\end{aligned}$$

Figure 1. A demonstration of calculating mean species abundance (MSA) and the biodiversity intactness index (BII) in a scenario in which a company's activity has degraded a site. The abundances of species in the 'Control' site (left, top) appear in column A_{ic}; of those in the 'Impacted' site (left, bottom) in column A_{ip}. Subsidiary calculations are computed in the table (right, top) with results colour matched to their substitution locations in the MSA and BII equations (right, bottom). The final result for each metric appears in bold. This scenario and four further applications appear in Supplementary Material 2 (Invasion; Balanced turnover; Unbalanced turnover, decreasing total abundance; Unbalanced turnover, increasing total abundance).

Here, we demonstrate conditions when MSA and BII are strictly equal and how varying conditions affects the correlation between the two metrics. We do this by: first, finding mathematical conditions of equality; second, exploring the parameter sensitivity of the two metrics in simulated datasets; finally, by applying the metrics to the same real dataset. We then reflect on what our results suggest for the use of BII and MSA by companies and investors and explore the different framings of corporate interactions with nature under which each metric is more useful for biodiversity accounting.

2. Methods

To identify the conditions under which BII and MSA are equal, we performed a formal mathematical analysis of both metrics using the above formulations (SI3). To identify when BII and MSA are similar, we construct an empirical dataset and simulated dataset. The empirical dataset is a combination of two databases of species composition under land use stress, compared to a natural vegetation site: PREDICTS (Contu et al., 2022; Hudson et al., 2023) and that from Kuipers et al. (Kuipers et al., 2023). We used a modification of the processing workflow from Kuipers and colleagues (2025) to bring together studies that occurred within 5km of each other and that record impacts across the same land use categories, producing 1100 and 98 pairs of sites, respectively (Figure 2). We did so, following Kuipers et al., in order to give more representative estimations of real ecosystems, on the assumption that the close proximity studies are sampling the same ecosystem. Biogeographical information comes from the ecoregion dataset from Dinerstein et al. (2017).

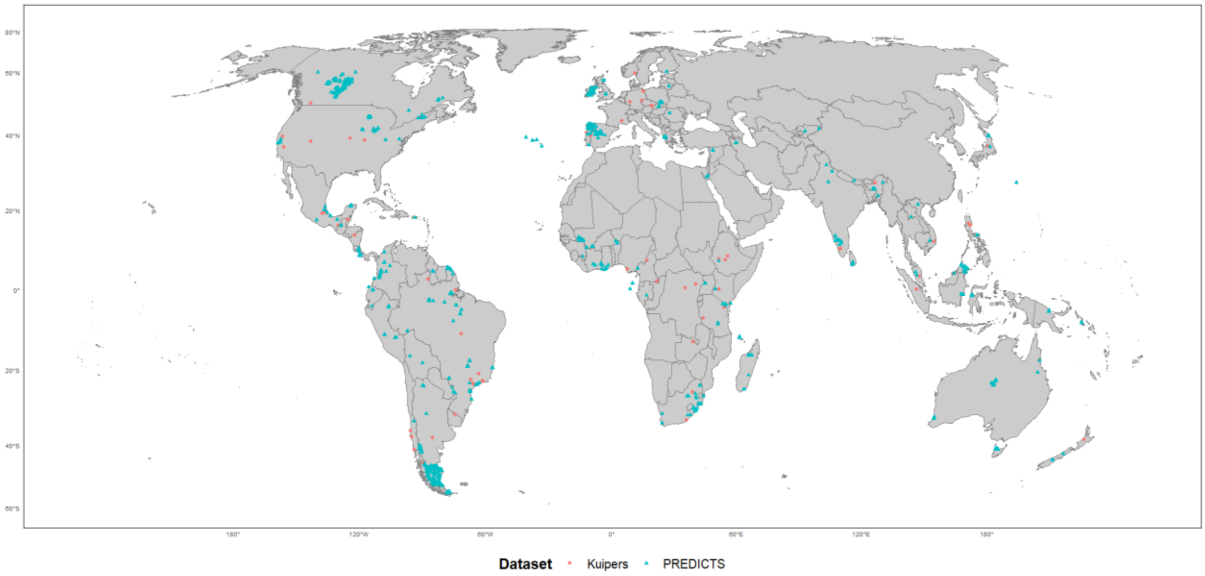


Figure 2. Locations of sites in PREDICTS (n = 1100) and Kuipers et al., 2023 (n = 102). Dataset removed four sites sourced from Kuipers et al., 2023., leaving 98 metric pairs for analysis. Equal Earth projection.

To construct simulated communities, a species' relative abundance in a community was drawn from a gamma distribution, defined by the species richness (S) of the community and the shape parameter (α), used as a proxy for evenness. A species' relative abundance was then normalised by the total abundance of the community (N). The code to generate these simulated data was written in R (R Core Team, 2024). We used ChatGPT5 to assist in writing portions of this code, which were reviewed, tested, and edited by the authors.

From the empirical dataset, we extracted the maximum and minimum values of species richness (0, 473) and total abundance (0, 87740) to help define ecologically realistic ranges of parameter values to construct simulated communities (Table 1). For simplicity, we round the maximum values of species richness to 500 and total abundance to 100,000. From the results of mathematical analysis, presented below, we know that BII and MSA will be equal (BII = MSA = 0) when all species are extinct in the impacted site. Hence, we raised the minimum for S and N to an appropriate small value. We approximated the large range in species evenness of the empirical dataset with a large range of the gamma shape parameter.

Table 1. Parameter ranges used to produce simulated communities

Parameter	Range	Increment
Species Richness (S)	5 then [25, 500]	25
Total abundance (N)	50 then [5000, 100000]	5000
Species Evenness (α)	[0.5, 5]	0.5

This simulation process produced 1,103,550 communities. MSA and BII metrics were then calculated pairwise between communities, excluding self-comparison due to equality of BII and MSA in this condition, producing 19,443,690 metric pairs.

To investigate the level of agreement between the two metrics on how ecological communities differ between control and impacted sites, as defined by changes in ecological parameters, we assigned each community's ecological parameter to a tercile bucket (high, middle, low). Each community pair was then assigned a 'move category' for each parameter (e.g. high species evenness to middle species evenness, low total abundance to high total abundance, etc). Move categories for each parameter were then combined to give 729 profiles of change.

Due to the non-normal and heteroscedastic nature of both the simulated and real data and presence of tied ranks, we used Kendall rank correlation tests in analysis. This was implemented in R using the *kendallknight* package (R Core Team, 2024; Sepulveda et al., 2025), which accounts for ties using the tau-b approach. We interpreted correlation strength by the following thresholds: -0.05 to 0.05 as negligible; (-)0.05 to (-)0.25 as weak; (-)0.25 to (-)0.5 as moderate; (-)0.5 to (-)0.7 as strong; and >0.7 and <-0.7 as very strong (Wicklin, 2023). We report related p-values for each test in SI4.

3. Results

3.1 Under what conditions are the two metrics equal?

From mathematical analysis of the two metric definitions (SI3), we find that the two metrics are equal to each other in two specific ecological scenarios:

1. No new species appears in the impacted site ($S = S_c$),

    and...

2. No species increases in abundance in the impacted site ($A_{ip} \leq A_{ic}$ for all species i),

    and, either...

3a. All species have equal proportional reduction (k) in abundance ($A_{ip} = kA_{ic}$ for all species i),

    or...

3b. All species have even abundances (a) in the control site ($A_{ic} = a$ for all species i).

Condition 3a captures two special cases of equality: complete extirpation (k = 0) and no change (k = 1). In both cases, BII and MSA are equal: both 0 and 1, in the respective conditions.

3.2 Under what conditions do the two metrics agree?

3.2.1 Overall relationship

There was a statistically significant and very strong positive correlation between BII and MSA (Kendall correlation coefficient $\tau = 0.721$). However, direct inspection of the relationship shows that the magnitude of each metric, for any given pair of sites, can differ markedly and the overall relationships are nonlinear and heteroscedastic (Figure 3A). The striated nature of Figure 3 is a result of the stepped approach to exploring parameter variation we used.

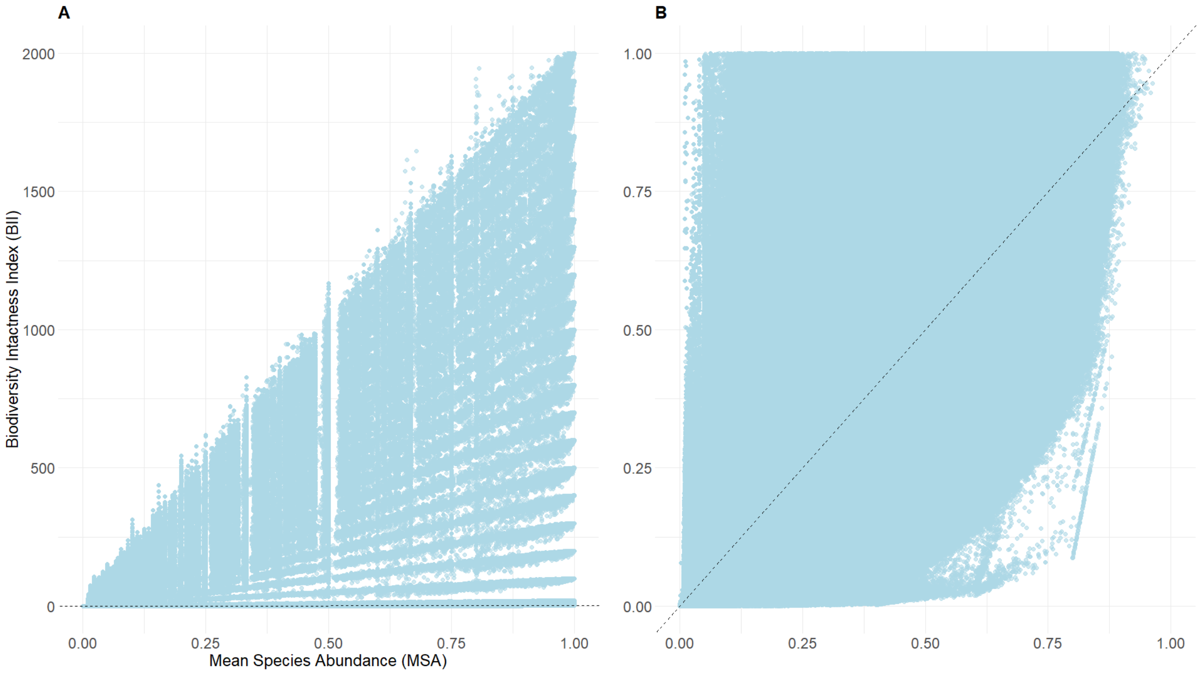


Figure 3. Relationship between MSA and BII for 19,443,690 simulated impacted-control site pairs, ranging in species richness (S = 5 then [50, 250] by 25), total abundance (N = 50 then [5000, 100000] by 5000), and species evenness (Gamma shape parameter (α) = [0.5, 5] by 0.5). Dotted line represents a 1:1 relationship between MSA and BII. A) Full dataset; B) Dataset with both metrics < 1.

Limiting both metrics to below 1, the direction and strength of correlation continue to hold ($\tau = 0.724$; Figure 3B), also remaining statistically significant. In this region, the non-linear relationship between the metrics is particularly apparent, however, with the relationship becoming curved at the lower edge. This curved shape is due to the constrained nature of MSA: as a mean proportional measure of native species' abundances, it occupies a narrower range of values. BII, on the other hand, has a multiplicative formulation that allows it to a span a larger portion of metric space, for a given value of MSA.

3.2.2 Parameters in control sites

As species evenness and total abundance in the control site increase, there is an increasingly strong rank correlation between MSA and BII, while increasing species richness in the control site reduces the strength of correlation (Figure 4). The effect of increasing species evenness is because, in more balanced communities, BII's abundance weighting of species more closely approximates the equal weighting species have in MSA, leading to similar ordering of sites. From condition 3b, we expect that both rank and magnitude correlations converge to 1 at complete evenness in the control site. At high levels of total abundance in the control site, holding other parameters equal, species tend to reduce in abundance in the impacted site because abundance is biologically bounded by carrying capacity at the upper level. If all species reduce in abundance, MSA simplifies to the average abundance gradient for each species, while BII reduces to the total abundance gradient. Hence, both metrics are responding to the same underlying feature of the community, the remaining abundance in the impacted site, leading to correlated rank outputs. Conversely, as species richness increases, MSA becomes less sensitive to the behaviour of any given species. By contrast, BII remains highly sensitive to changes in abundance of more common species, pushing rankings of sites apart. At lower levels of richness, these effects more closely align, giving rise to very strong rank correlation across sites. Hence, both for producers and users of these metrics, knowledge of the state of the control site is important for interpreting comparability.

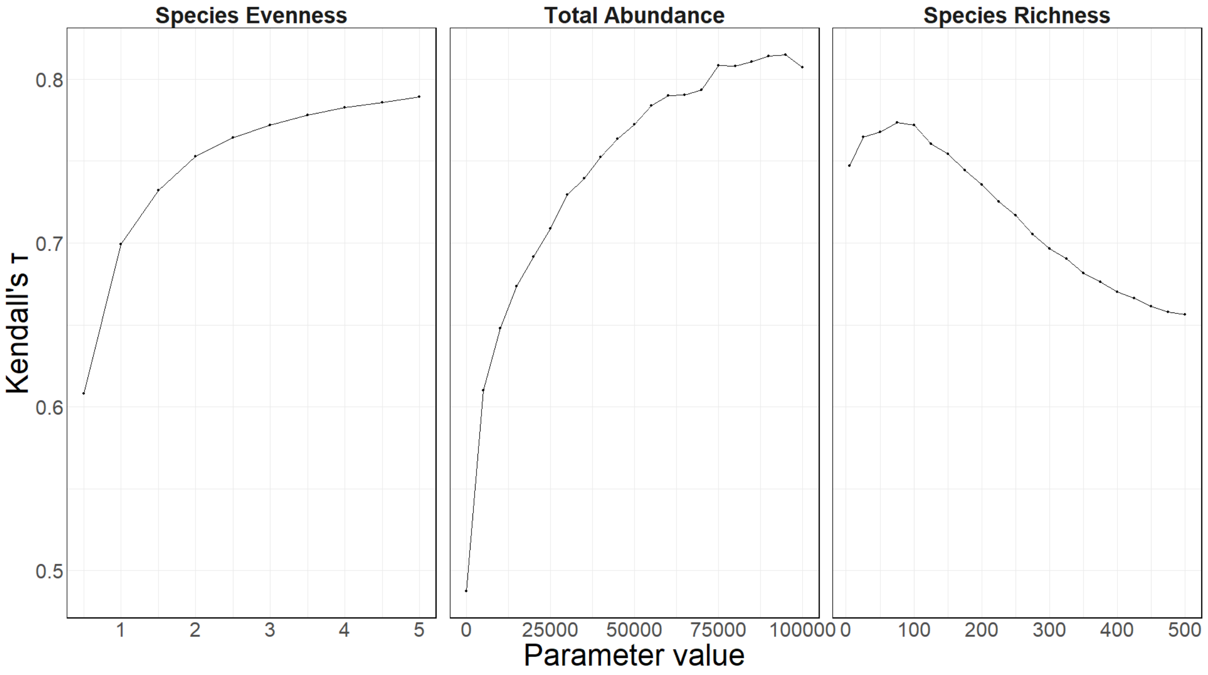


Figure 4. MSA-BII Kendall correlations between BII and MSA at varying values of ecological parameters (species evenness, total abundance, and species richness) in the control site.

3.2.3 Agreement on changes between sites

Observing the correlations of the metrics when describing ecological change, we found that MSA and BII produce most similar rankings when calculated for impacted sites that increase in species richness, reduce in total abundance (particularly from mid to low levels), and maintain a high level of evenness, or reduce slightly, in comparison to their control site (Figure 5, green highlighted segments). Similarity in rankings is a result of BII closely approximating MSA's focus on the loss of abundance of species present in the control site. This behaviour is a function of the interaction between the Bray-Curtis dissimilarity function and the negative total abundance gradient, which results in any newly arrived species having no effect on BII (SI2, Scenarios 3 and

4). Hence, both metrics are responding to the same underlying feature, the loss of abundance of species present in the control site, and produce similar ranks of sites.

Rankings of sites by the metrics are least similar when applied to sites that reduce in richness from high to middle levels while increasing in total abundance. These sites do not have a clear tendency for direction of change in species evenness (Figure 5, red highlighted segments). This is because MSA and BII are being pushed in opposite directions by different features of this type of change. MSA is strongly reduced by the extinction of species present in the control site, while BII is increased by the total abundance in the impacted site. This effect pushes the ranking of sites by the two metrics apart.

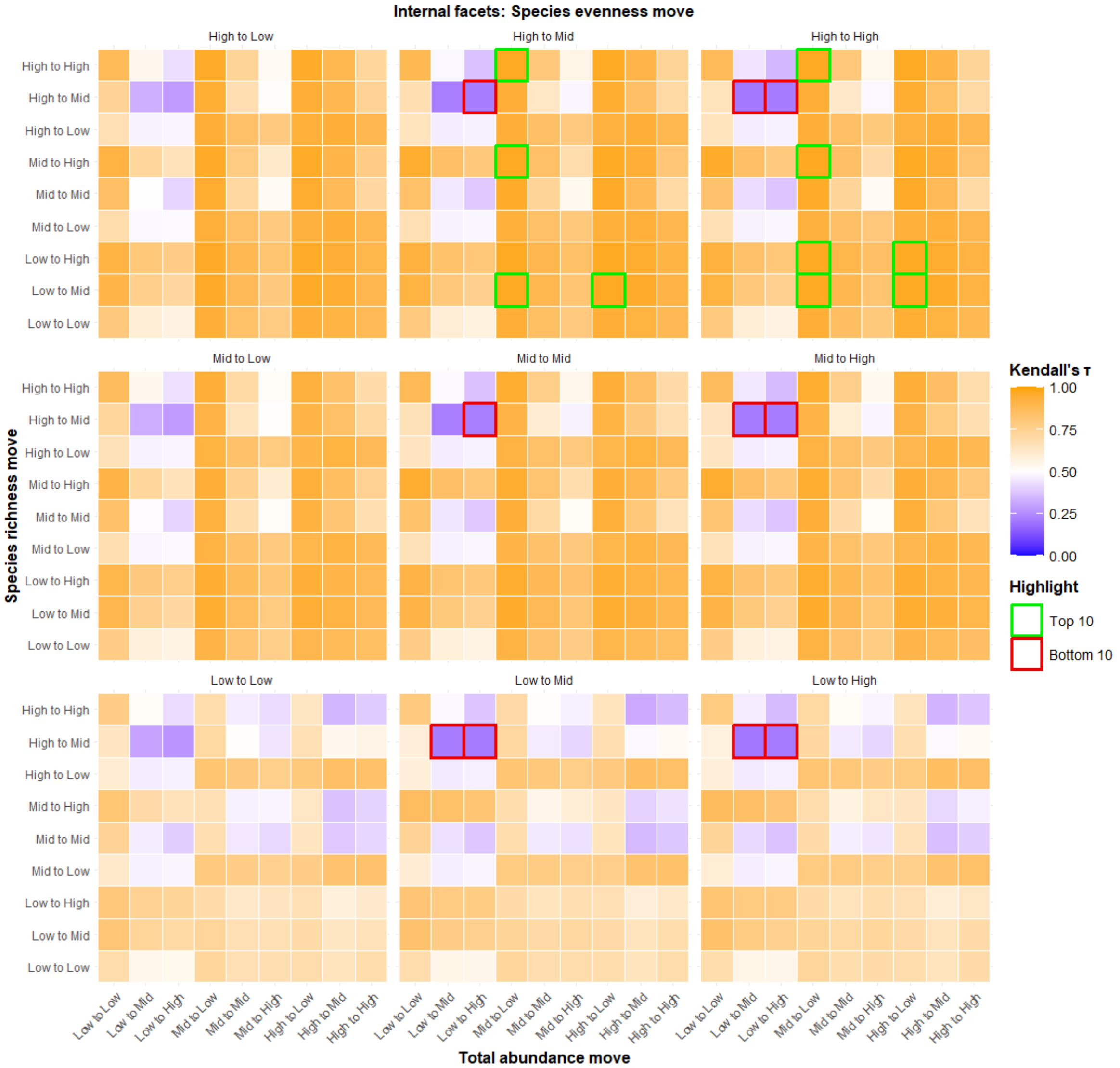


Figure 5. MSA-BII Kendall correlations in community pairs with combinations of changes in ecological parameters between control and impacted sites, categorised into High-Medium-Low change. The green highlighted segments are the changes for which BII and MSA are most

strongly correlated; the red highlighted segments, the least. In all cases the control site value is listed first.

3.3 In what biogeographic realms do the two metrics agree?

Across the entire dataset, MSA and BII display a strong positive rank correlation (Fig. 6A; $\tau = 0.627$, $p < 2.2e\text{-}16$). In sites at which both metrics agree that general degradation has occurred (MSA and BII both less than 1), rank correlation remains strongly positive (Fig. 6B; $\tau = 0.620$, $p < 2.2e\text{-}16$). However, BII and MSA can strongly disagree in terms of magnitude at particular sites: for example, the two obvious outliers in Fig. 6A (1, BII = 231, MSA = 0.5; 2, BII = 175.3, MSA = 0.75) or a site producing a value of 0.007 in MSA and 0.69 in BII (Fig. 6B, 3). The divergence in magnitude of MSA and BII at these sites is related to the metrics' different sensitivities to turnover, total abundance, and novel species. In the former two pairs of sites, dozens of new species of carabid beetles were found in post-impact rotational arable and pasture land, respectively, often with very large abundances (Vanbergen et al., 2005). The few species that were native in the primary vegetation control site reduced to a very small abundance, were not found, or were extirpated. In datapoint 3 in Fig 6B, all species of ant native to a Brazilian savanna ecosystem were reduced to zero, or near zero, reducing MSA strongly in the impacted site. However, a single, highly abundant new species was present in the impacted site, which had scattered tree cover, driving BII up (Frizzo & Vasconcelos, 2013).

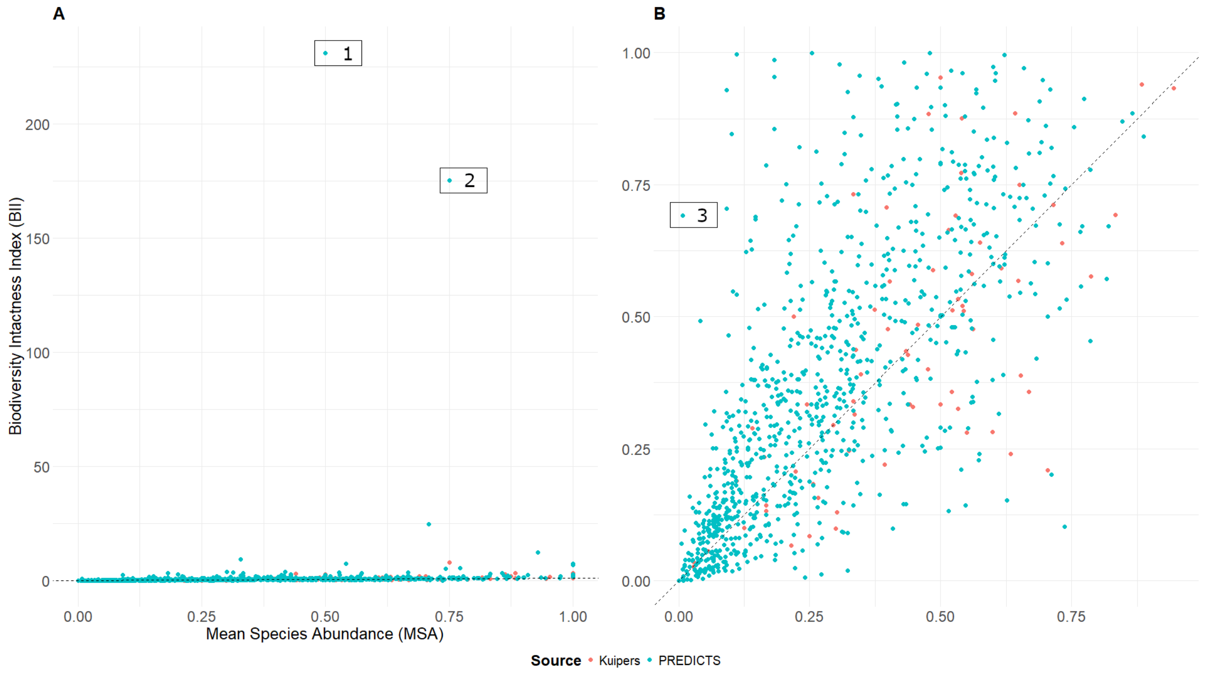


Figure 6. Relationship between MSA and BII for 1202 pairs of sites in PREDICTS (blue) and

Kuipers et al., 2023 (red). A shows the relationship across all metrics; B shows the relationship across sites for which MSA and BII are both less than 1 (n = 1039). The dotted line represents a 1:1 relationship between the metrics. 1 and 2 mark particular outliers in the overall dataset, driven by large numbers of introduced insects in these sites. 3 marks a point that illustrates that, although correlation is strongly positive overall, BII and MSA can be very different at individual sites.

The two metrics display strong statistically significant positive rank correlation at sites across all biogeographic realms (Table 2), apart from in the Indomalayan realm, which shows moderate correlation across the full dataset, and the Nearctic realm, which displays very strong correlation across the main and filtered datasets. Coupled with direct observation of the relationship, the conclusion that the metrics produce comparable rankings of sites but differ in magnitude at individual sites holds across biogeographic realms (Figures 7 and 8). The low number of observations in each move category precludes more specific testing of our simulated predictions. Future research could develop realm-specific parameter ranges and simulation approaches to confirm our findings.

Table 2. Tests of correlation between MSA and BII by realm

	Full data		Metrics < 1	
Realm	Kendall's τ	Magnitude	Kendall's τ	Magnitude
Afrotropic	0.536	Strong	0.556	Strong
Australasia & Oceania	0.504	Strong	0.545	Strong
Indomalayan	0.426	Moderate	0.514	Strong
Nearctic	0.727	Very Strong	0.720	Very Strong
Neotropic	0.676	Strong	0.642	Strong
Palearctic	0.634	Strong	0.644	Strong

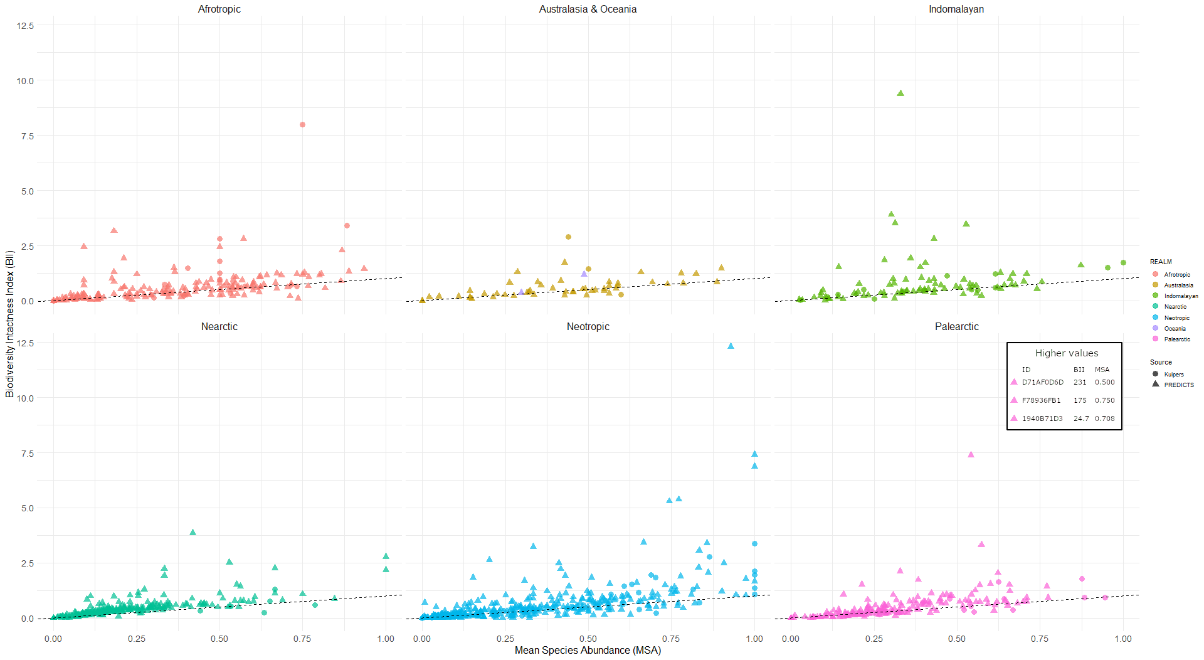


Figure 7. Relationships between MSA and BII by biogeographic realm across full dataset. The dotted line in all case is a 1:1 relationship between the two metrics.

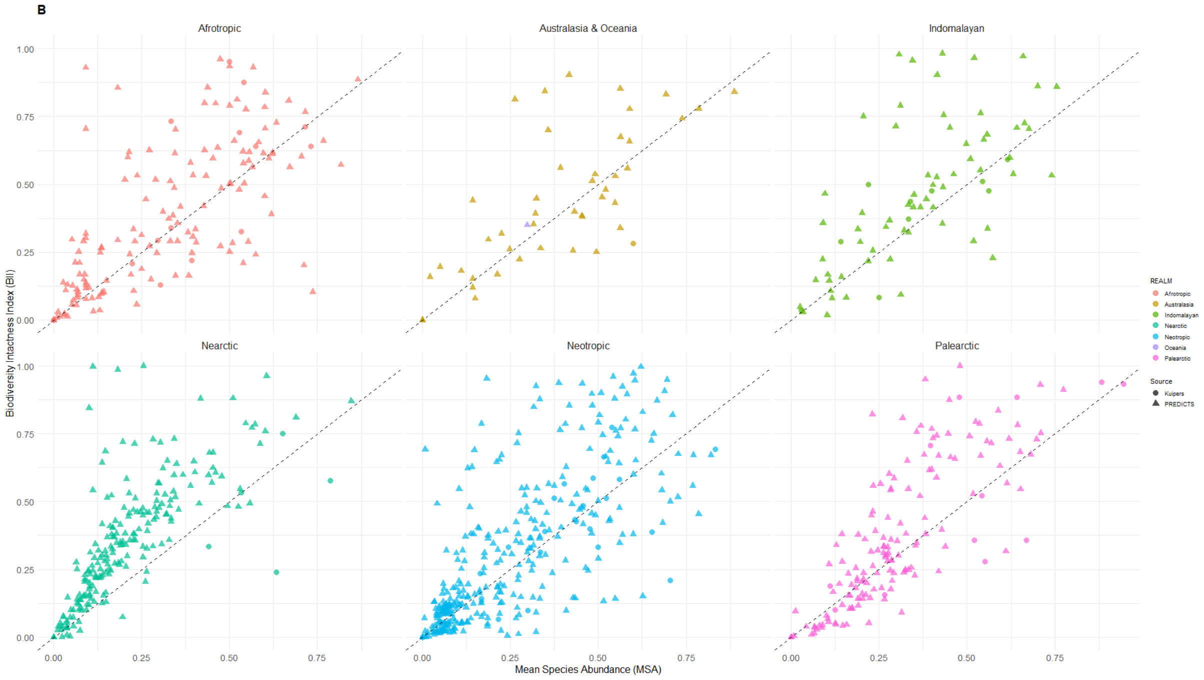


Figure 8. Relationships between MSA and BII by biogeographic realm when MSA and BII are both less than 1. The dotted line in all case is a 1:1 relationship between the two metrics.

4. Discussion

Here, we have shown that two leading metrics for the change in species composition between an impacted and control site, BII and MSA, are equal when no new species appear in the impacted site, no species increases in abundance in the impacted site, and all species either have the same proportional loss in abundance or even abundances in the control site. From simulations with varying levels of species richness, species evenness, and total richness in the control and impacted sites, we have shown that agreement between MSA and BII on the ranks of sites increases with increasing species richness and total abundance in the control site but decreases with increasing richness in the impacted site. Further, we showed that BII and MSA tend to most strongly agree on site ranking when species richness increases, total abundance reduces (particularly from mid to low levels), and evenness remains high, or reduces slightly, between an impacted and control site. Conversely, we found that the ranks of sites under each metric are least similar when applied to sites that reduce in richness from high to middling levels and increase in total abundance, with no clear tendency for change in species evenness. Finally, we have shown that BII and MSA generally agree on the rankings of sites from around the globe, using an empirical dataset. We noted, however, that differences in magnitude can be large at any given site.

Overall, we conclude from these findings that MSA and BII are generally comparable but are not interchangeable – apart from under very specific ecological conditions. This suggests that the ranking of companies identified for investment on the basis of their impacts on nature as calculated using MSA or BII will not be very different, meaning that a reasonably strong market signal can emerge with the use of both metrics in the market (Stimpson et al., 2025). However, we also conclude that the frequently large difference between the metrics at individual sites means an individual investor cannot make a reliable comparison between an investee company reporting biodiversity impact accounts with BII and another reporting using MSA.

This conclusion implies that reporting standards should not give the freedom to individual companies to choose between MSA and BII, if there is an intention that the disclosures should be used by investors to make investment decisions, as with the TNFD (2025a). Whether MSA or BII should be used in a reporting standard depends on how the standard frames corporate interactions with nature. Broadly construed, there are two major framings. First, ‘impact monitoring’, in which companies are responsible for the extent to which they degrade a site away from some desirable state. Second, ‘stewardship’, in which companies are responsible for the ongoing management of a site and are rewarded for its flourishing.

For the ‘impact monitoring’ framing, intactness is an essential concept, as it is in many global conservation policies (Kunming-Montreal Global Biodiversity Framework, 2022; McNellie et al., 2020). The ‘intact’ state is used as both the baseline for impact measurement and the target for restoration regimes. The intact state can be defined as a previous state of the same site or the current state of a matched proxy site elsewhere in the world (McNellie et al., 2020), with the date or proxy state varying between framings of intactness (Donadio Linares, 2022). The place of intactness as a concept in conservation policy has been defended for its utility (Karr et al., 2022; Watson et al., 2018) but has been criticised as an essentially subjective definition (Marris & Rohwer, 2022; Rohwer & Marris, 2021). For this framing, MSA is a more useful metric than BII as its range between 0 (destroyed) and 1 (intact) aligns with the concept of intactness. The fact that BII can be >1, on the other hand, contradicts the essentially bounded nature of intactness: a BII>1 implies that a site has become more intact than a reference or baseline site that has been *defined* as intact.

Under certain restrictions, however, BII can be made to better match the concept of intactness. Following the format of MSA, BII can be conceptually limited to interpretation only between 0 and 1, and methodologically limited to only include species present in the control site in metric calculation (De Palma et al., 2024; Sánchez-Ortiz et al., 2020). Under these adjustments, the Bray-Curtis dissimilarity component of BII is always equal to 1 (SI2, Scenario 1). Hence, BII becomes an abundance-weighted metric of intactness because the total abundance gradient is controlled by more common species. This contrasts with the equal-weighting of species approach of MSA.

To choose between MSA or an adjusted-BII metric, standard setters should reflect on their reasoning as to why the intact state is desirable. On one hand, the intact state may be held to be inherently valuable or represent a proxy for a complex of ecosystem services. On the other, the functions of the ecosystem may be foregrounded, specifically identifying related ecosystem services as valuable. For the former, MSA’s equal-weighted approach is more useful, as it better accounts for rare species that would be otherwise overlooked (Kondratyeva et al., 2019). The arithmetic approach could be replaced by a geometric or harmonic approach, depending on the importance standard framers want to give to extremely rare and common species (Buckland et al., 2011; Roswell et al., 2021). However, these approaches require adjustments to guard against becoming mathematically undefined on the extirpation of a single species, such as through the addition of an epsilon value to each species’ abundance (Loh et al., 2005). For the latter, the adjusted-BII metric is more useful as it focuses on the common species that contribute the bulk of ecosystem services extracted from a system (Gaston, 2010; Gaston & Fuller, 2008).

Under the ‘stewardship’ framing, the concept of an intact state is not meaningful. Instead, the role of corporate reporting is to demonstrate management of flourishing ecosystems beyond a baseline, with less interest in the identity of the species that make up the ecosystem. This implies that novel ecosystems, comprising species combinations not previously found together, have ecological value (Hobbs et al., 2006, 2009). This framing foregrounds the dynamic nature of ecosystems, both over the long-term and in the increasingly variable short-term, under global environmental change (Van Meerbeek & Haesen, 2025). Crucially, the baseline state or date is not defined as the target state of the system. Under this framing, BII is a more useful metric than MSA, for its ability to account for turnover in species composition. Hence, companies would be rewarded for increasing the BII value that they report. This could be unrestricted, rejecting the concept of alien or non-native species (Van Meerbeek & Haesen, 2025) or restricted to traditionally-conceived native species (De Palma et al., 2024; Sánchez-Ortiz et al., 2020), tracking the shifts in relative abundance and potential increases in total abundance of these species. In the unrestricted version, however, the interaction between the total abundance gradient and the Bray-Curtis dissimilarity function results in newly arrived species having no effect on BII until the total abundance of the impacted site exceeds that of the control site (SI2, Scenarios 3, 4, and 5). Hence, there may be reduced ability to discern the relative success of companies at stewardship in these conditions.

The relative utility of BII and MSA, therefore, depends on the framing adopted, which ought to influence standard setters’ choice of metric. Going further, the differential utility of the two metrics under different framings of nature could influence indicator selection decisions for biodiversity monitoring policies, such as the GBF Monitoring Framework (Affinito et al., 2025). However, this may be a politically more fraught choice than that made by a standard-setter. It may also affect the choice of metric by individual financial institutions. This may lead to conflict between the disclosing company and an investor, if different metrics are chosen. This could be resolved by a shift of focus to disclosure of underlying data by investee companies, rather than of metrics. Of course, this is constrained by the reporting entity having such data to disclose, which is currently rarely true (Hasan et al., 2025). This solution may become more easily achievable in future, however, as more easily accessible sampling technologies emerge (Granqvist et al., 2025; Wägele et al., 2022).

Moreover, at present, metrics are generally pre-packaged with certain methods and data, as tools (Stimpson et al., 2025). This restricts the ways in which metrics can be created and reported. For example, commercially-available BII tools (e.g. Bloomberg, 2023; UNEP & S&P Global Sustainable1, 2023) draw inferences from the PREDICTS database (Hudson et al., 2017). PREDICTS has also been integrated as the land use model in the latest version of GLOBIO, the canonical model producing MSA (GLOBIO4; Schipper et al., 2020). However, despite many GLOBIO-based tools being available to the market, all run on GLOBIO3 (e.g. CDC Biodiversité, 2023; Molinier, 2023; van Rooij & Arets, 2017), an earlier version of the model that relies on a different land-use module (Schipper et al., 2016). Examples such as this may lead to metrics being chosen under the wrong framing, because of preferences for specific methods. To resolve this path-dependency and to allow commercially-available tools to be applied most usefully, we encourage the development of tools that allow for interchangeable use of metrics and methods, including the use of corporate-disclosed primary data. Researchers interested in tool comparability can then assess the effects of varying methods in relation to varying BII and MSA, noting the ecological conditions under which the metrics themselves are more or less comparable.

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