# Making money talk nicely: Biodiversity impact assessment for investors

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**Abstract**

Business activity drives economic prosperity but can also degrade biodiversity, imposing regulatory, reputational, and operational risks. Under Global Biodiversity Framework Target 15, large and transnational companies must disclose nature-related financial risks, prompting investors to adopt emerging biodiversity impact software tools. We compare eight widely used tools via methodological review and analysis of impact ratings for a sample of 500 large publicly traded U.S. companies. We demonstrate that rankings of company impact exhibit low correlation between most tools. These tools rely on non-standardized methodologies and workflows that lack clear theoretical foundation, peer-review and scrutiny. Modelling assumptions often appear disconnected from actual on-ground or supply chain impacts. We conclude that reliance on any single tool may lead to investment decisions that fail to adequately mitigate risk or reflect investor preferences. Reliable nature impact assessment in finance requires more transparent, spatially explicit methodologies, supported by improved corporate disclosures.

**Keywords:** Biodiversity, Finance, Ecology, Nature-related financial risk, Biodiversity impact assessment, Global Biodiversity Framework (GBF), Taskforce on Nature-related Financial Disclosures (TNFD), Corporate Sustainability Reporting Directive (CSRD), European Sustainability Reporting Standards (ESRS), Science Based Targets Network (SBTN)

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# 1 Introduction

Biodiversity is declining at an unprecedented rate[1], signaling a global ecological crisis[2]. The collapse of biodiversity is not just an environmental concern but a profound economic threat because over half of global GDP is moderately or highly dependent on nature and its services[3]. This dependence on nature and the ongoing loss of key ecosystem services could reduce global GDP by 2.3% annually by 2030[4]. Major financial and policy institutions increasingly recognize these risks – for instance, the World Economic Forum's 2025 Global Risks Report ranks biodiversity loss and ecosystem collapse as the second most severe risk for the global economy in the coming decade[5]. Despite the acknowledged risks, approximately US$7 trillion continues to be invested annually in activities that harm nature[6]. The private sector accounts for US$5 trillion of this total, underscoring the importance of effective action from the private sector.

In response to the biodiversity crisis and the recognition of the impacts and dependencies of business on nature, several global frameworks have been introduced to guide businesses to manage their nature-related risks. One of the most prominent is the Taskforce on Nature-related Financial Disclosures (TNFD). The TNFD's first recommendations were released 2023, providing a reporting framework for companies to Locate, Evaluate, Assess, and Prepare (LEAP) for their nature-related risks and opportunities[7]. International goals have also been set that relate to business: the Kunming–Montreal Global Biodiversity Framework (KMGBF), adopted in late 2022 under the UN Convention on Biological Diversity, includes Target 15 which calls for policy and legal measures to encourage all businesses and financial institutions to monitor, assess, and disclose their dependencies and impacts on biodiversity by 2030[8].

The financial sector is uniquely positioned to advance global progress toward Target 15, as capital allocation decisions determine which firms and activities receive funding, and which are constrained. By measuring, understanding, and pricing nature-related risks, investors can make more informed capital allocation decisions, supporting investments that contribute to positive ecological outcomes while limiting exposure to activities that degrade natural systems. However, institutional investors face substantial challenges in the practical implementation of this goal. Notably, the current frameworks, such as the TNFD, stop short of prescribing how to measure impacts on biodiversity[7]. Instead, they offer broad sectoral guidance for financial institutions[9], and outline general approaches for biodiversity footprinting[10], ultimately leaving the selection of tools and metrics to the discretion of financial decision-makers.

With over 212 tools currently listed on the TNFD's website for conducting such assessments[11], selecting an appropriate tool presents significant practical challenges. It is characterized by both epistemic and epistemological uncertainty, which most of the finance and consulting industries are not well equipped to navigate. Robust investment decision-making and constructive influence by investors on corporate behavior are unlikely without a substantial improvement in the availability and accessibility of ecological data, expertise and analytical tools to the business community.

Our research addresses a critical gap in the knowledge required to understand and measure nature-related risk in investment decision-making. We examine and compare the tools currently available to asset managers and institutional investors for assessing firms' impacts on biodiversity. First, we analyze and describe the methodological foundations of widely used nature impact assessment tools applied in finance. Second, we evaluate the consistency of firm-level impact rankings produced by these tools, using companies included in the S&P 500 index as a representative sample. Third, we assess the overall effectiveness of these tools, identifying key opportunities to develop more robust approaches for measuring nature-related impacts. Our findings aim to support more informed and ecologically grounded investment decision-making within the financial sector, with implications for other economic sectors across the globe.

## 2 Results

From more than 212 tools listed in the TNFD tool catalogue, we identified 11 that were potentially suitable for use by a large asset manager. Of these, eight agreed to participate in our analysis.

Each tool employed a distinct methodological approach to assessing firms' biodiversity impacts, but limited documentation and lack of transparency—particularly regarding data sources and modelling assumptions—created considerable uncertainty about how the tools operate in practice. We summarize the core features of each tool in Tab. 1 and classify them into four general methodological approaches used to quantify biodiversity impacts.

The most common approach used by the tools we reviewed applies principles of Life Cycle Assessment (LCA) to estimate the impacts of firms on biodiversity[12]. These tools quantify emissions and resource use associated with company activities using data from three main sources: company-reported disclosures; estimated values derived from publicly available information; and modelled values generated from financial indicators such as revenue or sales, typically through Environmentally Extended Multi-Regional Input–Output (EE-MRIO) analysis.

After modelling environmental pressures, the tools translate these into expected impacts on biodiversity using Life Cycle Impact Assessment (LCIA)[13] methods. LCIA methods link environmental pressures, such as global warming, water use, and land use, to expected reductions in species diversity or abundance. Reductions in diversity are quantified using metrics such as the Potentially Disappeared Fraction of species (PDF)[14, 15], which estimates the proportion of species lost relative to a natural baseline, while reductions in abundance are measured using metrics such as the Mean Species Abundance (MSA)[16], which captures the average decline in species abundance at a given location relative to its intact state.

This general approach is employed by Global Impact Database (GID), GIST Impact (GIST), Iceberg Data Lab's Corporate Biodiversity Footprint (IDL), MSCI's Nature and Biodiversity Solutions (MSCI), and NatureAlpha's BioFootprint Module (NAlpha).

The second type of assessment approach, employed exclusively by Fair Supply (FSupply), focuses on biodiversity impacts embedded in companies' upstream supply chain[17]. FSupply implements this method through its proprietary Integrated Assessment Engine, which combines a multi-regional input-output (MRIO) model with the non-normalized Species Threat Abatement and Restoration (nSTAR) metric[18, 19]. The nSTAR metric quantifies biodiversity impacts by integrating species extinction risk categories, ranging from Near Threatened to Critically Endangered, with the scope and severity of threats identified in the International Union for Conservation of Nature IUCN Red List[20, 21]. These extinction risk values are spatially allocated to countries based on each species' Area of Habitat. They are then linked to industry sectors by mapping IUCN threat classifications to relevant economic activities[18]. This results in an extinction-risk footprint that is both sector- and country-specific, allowing biodiversity impacts to be embedded directly into global supply chain assessments.

The third methodological approach, used by S&P Global Sustainable1 (S&PS1), quantifies biodiversity impacts through its proprietary Ecosystem Footprint metric, which expresses a company's nature impact as the equivalent hectares of pristine, high-value ecosystems degraded by its operations[22]. This metric is calculated by multiplying the firm's total land footprint—sourced from public information, S&P's proprietary datasets, and modelled estimates—by an Ecosystem Significance Index (constructed by S&PS1 using the STAR[23] and Critical Natural Assets[24] indicators) and an Ecosystem Integrity Impact Index (derived from the Ecosystem Integrity Index[25]).

The fourth methodological approach is employed exclusively by NAlpha in its Biodiversity Impact Module. This module produces a composite biodiversity score based on four equally weighted sub-metrics. The first sub-metric, Material Impact, draws on sector-specific materiality assessments. The second, Supplier Impact, evaluates upstream exposure by analyzing known supplier sector activities. These first two modules draw on TNFD and United Nations Environment Programme (UNEP) guidance, with the exact data sources not explicitly identified. The third sub-metric, Proximity Impact, is calculated by mapping the geographics location of a company's physical assets against geospatial biodiversity data provided by the Integrated Biodiversity Assessment Tool (IBAT)[26]. The final sub-metric, Country Impact, incorporates national-level indicators, including the National Biodiversity Index[27, 28], the Environmental Performance Index (EPI)[29], and nature intensity measures derived from the Eora Multi-Regional Input-Output (MRIO) model[30].

**Table 1**: Overview of the methodologies used by the eight biodiversity impact assessment tools included in this study. The table summarizes the analytical approaches and main data sources employed by each tool, including environmentally extended multi-regional input–output (EE-MRIO) databases such as Eora[30], GTAP[31], and EXIOBASE[32]; spatially explicit agricultural land-use models like MapSPAM[33] and FAOSTAT[34]; global ecoregion maps such as the WWF Global Ecoregions Map[35]; biodiversity modeling frameworks including GLOBIO[16]; Life Cycle Impact Assessment methods such as ReCiPe[14] and LC-Impact[15]; and Life Cycle Assessment databases like Ecoinvent[36]. Several tools also rely on Environmental, Social, and Governance (ESG) data platforms, including Impaakt[37], and on the Integrated Biodiversity Assessment Tool (IBAT[26]), which compiles biodiversity data from sources such as the IUCN Red List of Threatened Species[20], the World Database on Protected Areas[38], and the World Database of Key Biodiversity Areas[39]. For each tool, the table specifies: (i) the value chain scope assessed (upstream, direct operations, downstream); (ii) the data sources and models used to quantify environmental pressures; (iii) the specific environmental pressures considered (e.g., global warming, land use, water use); (iv) the method used to link these pressures to biodiversity or ecosystem impacts; and (v) the final biodiversity or ecosystem impact metric reported. Additional methodological detail is provided in Supplementary Note 1.

| **Tool** | **Value-chain scope assessed** | **Pressure calculation** | **Environmental pressures** | **Pressure–impact relationship** | **Biodiversity/ ecosystem impact metric** |
|---|---|---|---|---|---|
| Fair Supply (FSupply) | Upstream | • FairSupply's proprietary Integrated Assessment Engine<br>• IUCN Red List of Threatened Species | 118 key threats mapped to individual species on the IUCN Red-List | Species-specific pressure–impact models linking economic activities to biodiversity impacts | nSTAR |
| Global Impact Database (GID) | Upstream<br>Direct<br>Downstream | • Eora<br>• EXIOBASE<br>• GTAP<br>• MapSPAM<br>• FAOSTAT<br>• WWF Global Ecoregions Map<br>• Impaakt ESG data | • Global warming<br>• Air pollution<br>• Freshwater & marine eutrophication<br>• Ecotoxicity (freshwater, marine, terrestrial)<br>• Land Use<br>• Water use | • ReCiPe<br>• GLOBIO | Biodiversity-hectares lost (Bio-ha) |

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**Table 1**: Overview of the methodologies used by the eight biodiversity impact assessment tools included in this study. (continued)

| **Tool** | **Value-chain scope assessed** | **Pressure calculation** | **Environmental pressures** | **Pressure–impact relationship** | **Biodiversity/ ecosystem impact metric** |
|---|---|---|---|---|---|
| GIST Impact (GIST) | Upstream<br>Direct<br>Downstream | • Company reported data<br>• Proprietary machine learning estimation models<br>• EXIOBASE (land use and value chain only) | • Global warming<br>• Photochemical ozone formation<br>• Terrestrial acidification<br>• Freshwater & marine eutrophication<br>• Land use<br>• Water use<br>• Waste | LC-Impact | Potentially Disappeared Fraction (PDF) |
| Iceberg Data Labs (IDL) | Upstream<br>Direct<br>Downstream | • Company-reported data<br>• Proprietary 'Wunderpus' EE-MRIO (EXIOBASE-derived) | • Global warming<br>• Land use<br>• Air pollution<br>• Water pollution | GLOBIO | Mean Species Abundance (MSA) |
| Carbon4Finance Biodiversity Impact Analytics powered by the Global Biodiversity Score (BIA-GBS) | Upstream<br>Direct<br>Downstream | • EXIOBASE<br>• Carbon4Finance reported and estimated climate data | • Global warming<br>• Land use<br>• Ecotoxicity (freshwater and terrestrial)<br>• Water use<br>• Freshwater eutrophication<br>• Atmospheric nitrogen deposition | GLOBIO | Mean Species Abundance (MSA) |

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**Table 1**: Overview of the methodologies used by the eight biodiversity impact assessment tools included in this study. (continued)

| **Tool** | **Value-chain scope assessed** | **Pressure calculation** | **Environmental pressures** | **Pressure–impact relationship** | **Biodiversity/ ecosystem impact metric** |
|---|---|---|---|---|---|
| MSCI | Direct | • Company-reported data<br>• MSCI proprietary estimation models<br>• EXIOBASE | • Global warming<br>• Land use<br>• Water use | LC-Impact | Potentially Disappeared Fraction (PDF) |
| NatureAlpha (NAlpha) *BioFootprint Module* | Direct | Ecoinvent | • Global warming<br>• Acidification<br>• Photochemical ozone formation<br>• Freshwater & marine eutrophication<br>• Ecotoxicity (freshwater, marine, terrestrial)<br>• Land use<br>• Water use | LC-Impact | Normalised PDF |
| NatureAlpha (NAlpha) *Biodiversity Impact Module* | Upstream<br>Direct<br>Downstream | • TNFD sectoral guidance<br>• UNEP/UNEP FI<br>• IBAT | Four sub-modules:<br>• Material impact<br>• Proximity impact<br>• Supplier impact<br>• Country impacts | Aggregate of all submodules (percentage) | Aggregate Biodiversity Impact (%) |
| S&P Sustainable1 (S&PS1) | Direct | • S&P asset-location database<br>• Country–sector land-footprint model | • Total land footprint<br>• Proprietary Ecosystem Integrity Impact & Ecosystem Significance Indices | Product of the Total land footprint and the Ecosystem Integrity Impact and Significance Indices | Ecosystem Footprint |

## 2.1 Correlation analysis

We evaluated biodiversity impact rankings of S&P 500 firms using two types of metrics. The first, aggregate impact metrics, capture a firm's total biodiversity impact by combining the intensity of its activities with their overall scale. The second, value-adjusted impact metrics, normalize biodiversity impact by a firm's annual revenue, thereby estimating impact per unit of economic output.

When companies were ranked according to each tools' aggregate impact metric, most tools exhibited weak to moderate positive rank correlations. However, some tools showed strong alignment in how they ranked firms, as shown in Fig. 1a. Specifically, FSupply, GID, and the BIA-GBS tool produced closely aligned rankings, with pairwise correlations between 0.77 and 0.78. Similarly, GIST and MSCI yielded highly consistent rankings, with a correlation coefficient of 0.87. Notably, NatureAlpha (NAlpha) generated firm rankings that diverged significantly from other tools.

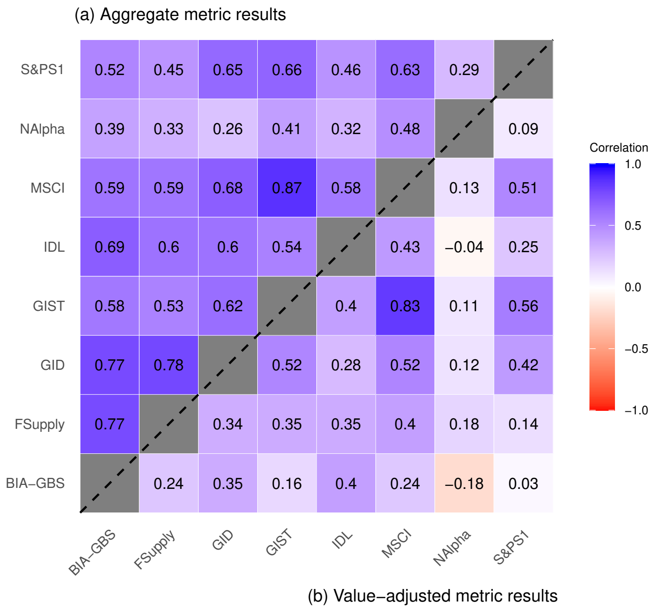


**Fig. 1**: Correlations between the biodiversity impact rankings of eight biodiversity impact assessment tools. Panel a in the upper triangle illustrates Spearman rank correlation coefficients for rankings within the S&P500, derived using aggregate impact metrics. Panel b represents correlations for rankings of companies within the S&P500 using value-adjusted metrics.

When companies in the S&P 500 were ranked using value-adjusted metrics, correlations among most tools declined substantially (Fig. 1b). An exception was the pairing of MSCI and GIST, which continued to yield closely aligned rankings, with a correlation coefficient of 0.83. Further analysis showed that this high correlation was driven primarily by strong agreement on biodiversity impacts attributed to global warming ($R^2 = 0.98$). In contrast, correlations attributed to water and land use impacts were substantially lower ($R^2 = 0.69$ and $R^2 = 0.52$, respectively). This suggests that MSCI and GIST yield similar overall biodiversity impact assessments for S&P 500 companies because both tools collect or model comparable company-level GHG emissions, translate these emissions into biodiversity loss estimates using the same LC-Impact method[15], and assign significant weight to these climate-related impacts.

This overall decline in concordance between tools is likely due to methodological differences across tools becoming more influential when company size is no longer a dominant driver of impact rankings. While aggregate metrics tend to reflect absolute impacts—where larger firms naturally register higher values—value-adjusted metrics normalize for revenue, exposing deeper divergences in each tools assessment.

## 2.2 The ten firms in the S&P500 with the highest biodiversity impact

To clarify the practical implications of the correlation analysis, we examined which companies were identified by each tool as having the highest biodiversity impacts. The results varied considerably. No single firm consistently appeared among the top-ranked companies across all tools. Only four tools identified ExxonMobil (XON) and Archer-Daniels-Midland Co (ADM) among the ten firms with the greatest aggregate biodiversity impact (Fig. 2a). Consistency between tools declined further when using value-adjusted impact metrics, with agreement between tools on any one firm being in the top ten reduced to a maximum of three. Notably, NAlpha produced an entirely unique list of firms.

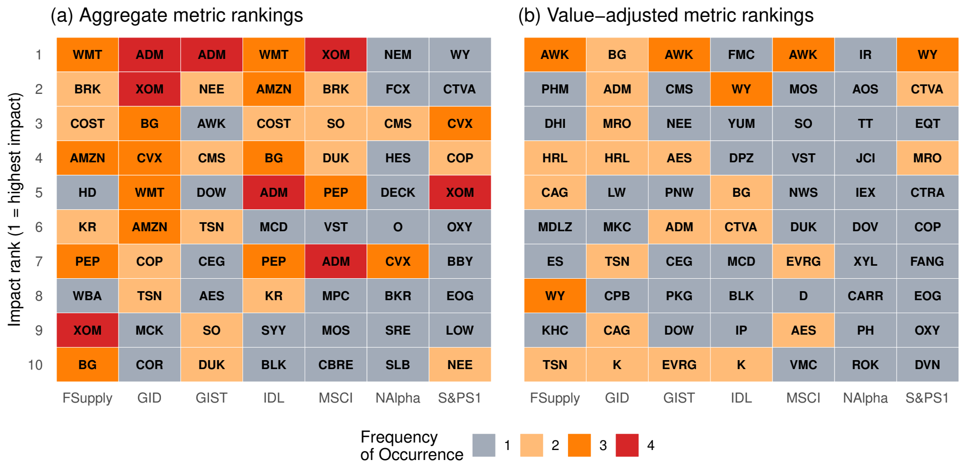


**Fig. 2**: The ten companies, identified by ticker symbols, with the highest biodiversity impacts under two assessment approaches: (a) aggregate impact metrics and (b) value-adjusted impact metrics. In each heatmap, companies are ranked from 1 to 10, where rank 1 indicates the highest estimated impact. Each column corresponds to a different biodiversity impact assessment tool. Colors shading reflects the number of tools that identified a given company among their top ten most impactful firms. These values represent the frequency of selection across tools and do not indicate agreement on precise rank order.

## 2.3 Regression analysis

We used regression analysis to explore how methodological design choices influence biodiversity impact assessments across Global Industry Classification Standard (GICS) sectors. Methodological differences between tools resulted in different rankings of biodiversity impacts for 8 out of the 11 GICS sectors. For example, tools that limit their scope to direct operational impacts consistently assign lower biodiversity scores to firms in the Consumer Staples sector. In contrast, tools that integrate upstream and downstream value-chain effects, tend to assign higher impact estimates to the same firms (Fig. 3). Further, assessment tools that use LC-Impact as the linkage method between environmental pressures and biodiversity impacts tend to assess companies in the Utilities and Real Estate sectors as having comparatively higher biodiversity impacts. This pattern suggests that the choice of impact characterization model—particularly how emissions, land use, and water use are translated into biodiversity loss—has a meaningful influence on sector-level rankings (Fig. 3).

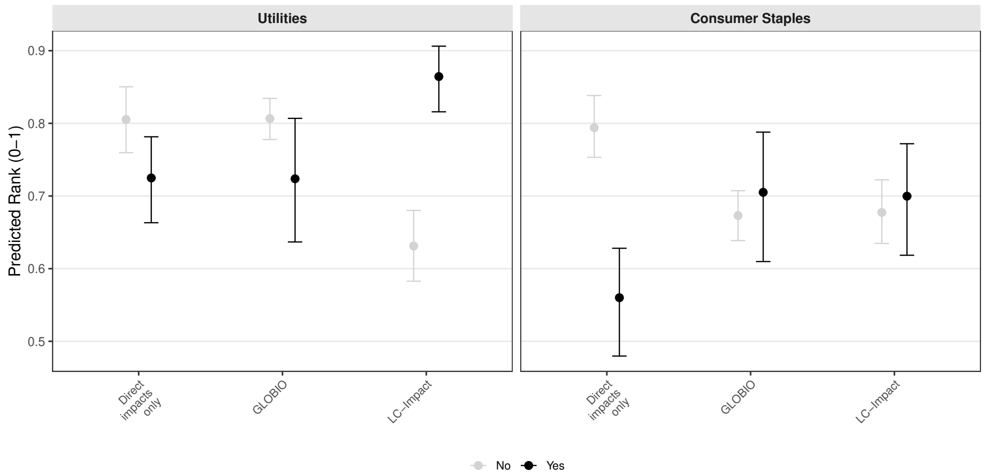


**Fig. 3**: Predicted sector-level biodiversity impact rankings for firms in the Utilities and Consumer Staples sectors, based on a Bayesian beta-regression model. Rankings are scaled from 0 to 1, with 0 indicating the lowest relative biodiversity impact. Posterior mean estimates are shown as points, with vertical bars representing 95 percent credible intervals. The figure presents results across three methodological contrasts: tools that use GLOBIO versus those that do not; tools that incorporate LC-Impact versus those that rely on alternative characterization models; and tools that assess only direct operational impacts versus those that also consider upstream and downstream value-chain effects. The model yielded a Bayesian R-squared of 0.40, with a 95 percent credible interval ranging from 0.39 to 0.42. Full regression outputs are reported in Supplementary Tab. 1 and plots for all GICS sectors provided in Supplementary Fig. 1.

## 2.4 Sector analysis across all tools

By plotting all of the tools impact ranks, trends in the relative biodiversity impacts of different GICS sectors were visible (Fig. 4). On average, companies in the Financials sector were assessed as having the lowest biodiversity impacts, while companies in the Energy sector were rated the most impactful. However, considerable variation was observed within each sector. This variation reflects both genuine differences in impact among firms within the same sector and inconsistencies in how different tools estimate the impact of individual companies. Supplementary Fig. 1 illustrates the distribution of company rankings by sector for each tool. This shows both intra-sector dispersion and discrepancies in assessment of relative impacts of GICS sectors across tools.

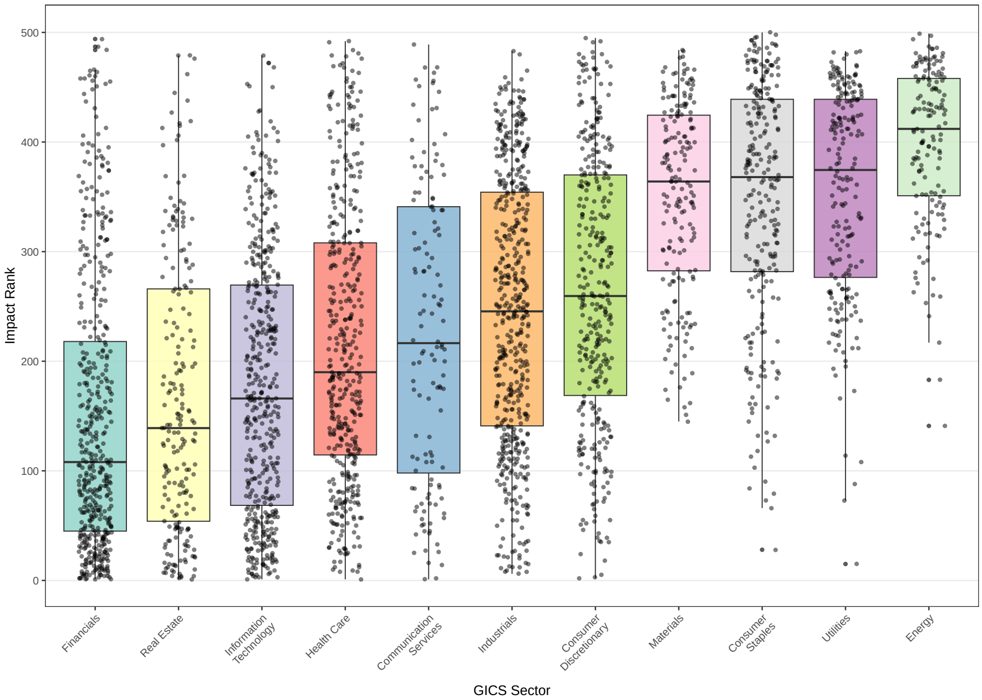


**Fig. 4**: Boxplot of company-level biodiversity impact rankings derived from aggregate impact metrics across all assessment tools, excluding BIA-GBS, for S&P 500 firms. Each dot represents an individual company's rank within its sector. A rank of 1 indicates the lowest impact, and a rank of 500 indicates the highest. Sectors are displayed from left to right in order of increasing median impact rank, with sectors on the left showing lower overall impacts and those on the right showing higher impacts.

# 3 Discussion

When ranking S&P 500 companies from least to most impactful, the tools we analyzed showed low to moderate correlation in their output, with few exceptions (Fig. 1). This variation arises from methodological differences, despite many tools relying on similar EE-MRIO (e.g., EXIOBASE) and biodiversity impact assessment methods (LC-Impact, GLOBIO). Key differences include how each tool sources or models corporate data, assumptions about links between activities and environmental pressures, how they interpret ecological outcomes of those pressures, and inclusion of indirect impacts. Because none of the methodologies are validated against benchmarks or independently tested, it is not possible to determine which tool is more accurate or reliable [40].

In the absence of validated, decision-ready tools there is a risk that financial institutions may disengage from biodiversity concerns altogether. Fear of reputational damage, regulatory scrutiny, or accusations of greenwashing could encourage institutions to avoid disclosure or reduce ambition—a dynamic sometimes described as “greenhushing[41]”. Such disengagement would leave biodiversity impacts unmeasured and unmanaged, increasing systemic environmental and financial risk[42].

A common strategy used by civil society groups and advocacy organizations is to identify high-impact companies or sectors and then engage with them to improve performance[43, 44]. However, our analysis of the top ten most biodiversity-impactful companies in the S&P500 (Fig. 2) shows that the composition of such lists varied widely depending on the tool used. Some tools produced entirely unique sets of top-ranked firms, while others overlapped on just one or two companies. This inconsistency undermines the credibility of tool-based rankings as a basis for prioritizing corporate engagement and could discourage external stakeholders from using them to drive accountability or change.

It is also common in policy and scientific discourse to see certain sectors described as inherently high or low impact. For example, the production of staple foods is often associated with land use change and assumed to carry high biodiversity impact[45]. Our analysis reveals that within-sector variation in company rankings often exceeds the differences observed between sectors (Fig. 4). For example, in the Health Care sector, more than 28 companies had a higher biodiversity impact rank than the median company in the Energy sector—which had the highest median impact of any sector.

The divergence in company and sector-level impact assessments has important implications for the financial sector. The TNFD’s discussion paper on biodiversity footprinting[10] highlights how institutions have applied tools such as GIST, BIA-GBS, and IDL to measure biodiversity impacts. Our findings show that investors relying on different tools could arrive at fundamentally different conclusions about which firms or sectors pose the greatest biodiversity impact. In practice, not all divergent estimates can be accurate. Misestimation of firm-level impacts could lead to flawed investment strategies, misaligned financial products, and ultimately, financial instruments that contribute to biodiversity loss or fail to meet investor expectations. This creates reputational, regulatory, and fiduciary risks for financial institutions.

Given the material uncertainty surrounding the current nature impact assessment tools, there is a clear need for standardized evaluation and validation protocols. In climate science, model intercomparison projects have become foundational to improving the reliability of emissions modeling and underlie widely used carbon accounting frameworks[46]. A similar effort is urgently needed for biodiversity assessment tools. While achieving comparability will be more difficult due to the spatial heterogeneity of ecosystems and the challenge of attributing ecological outcomes to specific firms[47], progress is essential. Advancing standardization, improving transparency, and conducting robust validation studies will strengthen the credibility of biodiversity data and support more informed decision-making in financial markets. Without these steps, investors will struggle to price nature-related risk effectively, and the broader goal of aligning finance with biodiversity outcomes will remain out of reach.

## 3.1 Opportunities for improvement

Our analysis identifies four key potential improvements of biodiversity impact tools:

First, improving transparency and reproducibility is crucial. Publicly accessible documentation of assumptions, data sources, and workflows enables peer review and scientific refinement, which can improve impact estimates over time[48].

Second, comprehensive spatial information on where and how firms operate is needed. Current approaches that integrate firm asset locations often fail to capture what activities occur at each site, the resulting environmental pressures, or which species and ecosystems are affected. As a result, impact estimates may be incomplete or misleading. Improving accuracy will require combining site-level operational data with ecological evidence about the nature and severity of impacts. This will depend on enhanced corporate disclosures of site-specific activities, and improved analytical workflows that integrate biodiversity data sources such as the IUCN Red List of Threatened Species.

A third challenge relates to the widespread use of EE-MRIO models, such as EXIOBASE[32]. These models use expenditure data as an input to estimate environmental pressures, commonly referred to as mid-points, that are assumed to drive biodiversity impacts. While frequently marketed by some tool providers as providing "company-specific" results, these models aggregate economic activity across broad sectors and cannot meaningfully differentiate between firms with similar expenditure or geographic profiles. For example, EXIOBASE does not distinguish between a construction firm that uses certified sustainable materials in low-impact areas and one that uses unsustainable inputs in ecologically sensitive locations. Paradoxically, firms using sustainable materials may appear more impactful due to higher input costs[49], thereby distorting impact assessments. While better company activity data would help, it is rarely disclosed due to commercial sensitivity[50]. Regulatory incentives or mandates, such as those tied to financial risk disclosure laws, are needed to encourage data sharing relevant to biodiversity.

A fourth limitation concerns the LCIA methods used to translate environmental pressures, such as global warming, water use, land use, and eutrophication, into biodiversity outcomes, such as reduced species diversity or abundance. These models use simplified cause–effect pathways, lack spatial resolution, and are biased toward certain taxa[51]. Metrics like MSA may be useful for characterizing global biodiversity trends(e.g., Millennium Assessment[52], IPBES[53]), but offer limited firm-level insight as they do not capture the probability of species, habitat, or ecosystem loss at the specific locations where a firm operates.

An alternative to these generalized indices is a bottom-up modeling approach that combines spatial data on species distributions and ecosystem boundaries with geospatial data on environmental pressures[54]. By intersecting these datasets, it becomes possible to estimate species-level and ecosystem-level impacts at specific sites. This spatially explicit approach can be aggregated as needed while retaining local detail. Although more technically demanding, it offers a clearer pathway for firms and investors to assess their location-specific impacts and dependencies on nature.

### 3.2 Study limitations

A central limitation of this study is the restricted access to proprietary methods and workflows used by the biodiversity impact assessment tools. Limited information was available on how tools source and process company-specific data, including the methods used to scrape publicly available disclosures and to model missing or undisclosed information.

This constraint is reflected in the modest explanatory power of our regression model ($R^2 = 0.40$). A substantial share of the observed variation in tool outputs likely stems from unobserved methodological differences that we could not capture in the model. These may include the use of proprietary machine learning algorithms to estimate environmental pressures such as water use, internal modifications to EE-MRIOs, or other bespoke modeling approaches that are not documented. These findings underscore the urgent need for greater methodological transparency, standardized documentation, and clear articulation of assumptions to enable peer review, replication, and validation.

## 4 Next Steps

In the short term, caution is warranted when interpreting company-level biodiversity impact estimates produced by existing assessment tools. Given the limitations documented in this study, investors should initially focus on understanding and measuring direct environmental pressures associated with corporate activity, including carbon emissions, water use, and land conversion. At the same time, investors, researchers and tool developers must work collaboratively to address key gaps. These include the mapping of direct operational impacts at the site level, improved documentation and traceability of supply chains to account for indirect impacts, enhanced spatial modeling of how environmental pressures translate into biodiversity loss, and open access to data, assumptions, and workflows that underpin impact estimates.

Given the complexity and variation in biodiversity metrics, investors must understand how these tools operate and what they capture in order to make informed investment decisions[55]. Advancing credible, peer-reviewed modeling approaches is essential to producing reliable firm-level biodiversity impact assessments. These models will form the foundation for aligning investment decisions with global goals for nature and sustainability. While substantial progress is still needed, improving transparency, data quality, and methodological rigor will be critical steps toward enabling nature-positive outcomes in the financial system. There is a long road ahead.

# 5 Method

## 5.1 Tool selection

To identify candidate tools for evaluating biodiversity-related risks and impacts in financial contexts, we reviewed three authoritative sources: the TNFD Tools Catalogue[11], SBTN Toolbox[56], and Finance for Biodiversity Guide[57]. From these sources, we compiled an initial list of tools specifically designed or marketed for use by investment managers. A shortlist of fourteen widely used tools was developed based on relevance and visibility. Each of the shortlisted tools was then screened to assess whether it could meet the information needs of investment managers by providing biodiversity impact data across a large universe of listed companies. Eleven tools satisfied this criterion as of May 2024. We contacted the providers of these tools by email, offering a high-level overview of our research objectives and invited them to participate in a structured interview.

Eight tool providers responded and agreed to participate. During meetings, we outlined the scope of the project and requested both methodological documentation and company-level biodiversity impact data for firms in the S&P 500 index. All participating providers agreed to share this information under three conditions. First, the raw data on S&P 500 companies would not be shared with Franklin Templeton (FT). Second, that any raw data provided would be destroyed upon the completion of the project. Third, that our final report would serve as a review of current practices, without issuing endorsements of specific tools.

Subject to these conditions, all participating providers shared full methodological documentation and S&P 500 datasets, with the exception of Biodiversity Impact Analytics powered by the Global Biodiversity Score (BIA-GBS). BIA-GBS supplied its methodology but only agreed to provide data on a subset of the largest 100 firms in the S&P 500 by market capitalization. The participating tools and data contributions are summarized in Supplementary Tab. 2.

All interviews with tool providers were conducted under University of Melbourne Human Ethics approval, protocol number 30490.

## 5.2 Tool methodology summary

After reviewing the methodological documentation provided by each tool developer, we applied a structured set of questions, outlined in Supplementary Note 2, to evaluate and summarize the core functionality and assumptions of each tool. These responses were synthesized into concise summary paragraphs and a comparative table. To ensure accuracy and representational fairness, each tool provider was given the opportunity to review and suggest revisions to our summary of their methodology.

## 5.3 Metric selection

Most tools reviewed in this study report multiple biodiversity impact metrics. To ensure comparability, we consulted directly with each provider to identify the most appropriate metrics for inclusion in our analysis. Tool developers were asked to nominate the metric they considered most suitable for each of two categories: aggregate impact and value-adjusted impact. Aggregate impact metrics capture the total biodiversity impact of a firm by reflecting both the intensity of its activities and the overall scale of its operations. Value-adjusted impact metrics capture biodiversity impact relative to financial output, typically expressed as impact per dollar of annual sales or revenue.

All tools provided an aggregate impact suitable for analysis, exception for FSupply. Its biodiversity estimates are reported using the nSTAR metric, which reflects supply chain-level extinction risk but is not scaled by company size. To derive a comparable aggregate value for FSupply, we multiplied each firm's nSTAR estimate by its annual net sales. Four tools—GIST, BIA-GBS, S&P, and FSupply—did not provide value-adjusted metrics. For these tools, we derived a value-adjusted metric by dividing the aggregate impact value by each firm's reported net sales. A summary of selected metrics and transformations applied is provided in Supplementary Tab. 3 and Supplementary Tab. 4.

Once metrics were selected and adjusted, we merged all data points with company-level identifiers including Global Industry Classification Standard (GICS) sector and subindustry classifications, stock ticker symbols, and ISIN codes that identify individual firms to create the final dataset. GICS sector classifications and financial data were sourced from Compustat[58]. We used the "Sales/Turnover (Net) (SALE)" variable as the standard sales input. To verify compatibility with NAlpha's value-adjusted metric, we compared this variable with "Revenue - Total (revt)" and found the two measures to be equivalent, suggesting no material impact on results due to differences in sales definitions.

## 5.4 Tool ranking correlation analysis

Each tool was used to generate a biodiversity impact ranking for every firm in its dataset, with lower ranks indicating lower estimated impact. The total number of firms ranked varied by tool, depending on data availability, ranging from 99 for BIA-GBS to 500 for tools such as GID and FSupply. Rankings were constructed separately for both aggregate and value-adjusted metrics.

To evaluate consistency across tools, we calculated pairwise Spearman rank correlation coefficients. Higher coefficients indicate stronger alignment in company rankings between tools, while lower coefficients suggest methodological differences. Correlations were computed separately for aggregate and value-adjusted rankings using the corrplot package in R[59].

To complement the correlation analysis, we developed a heatmap visualization displaying the ten firms ranked as the most impactful by each tool. Each column in the heatmap represents one tool, and each row corresponds to a firm ranked within the top ten. Firms are identified by their stock ticker symbols. A color gradient was applied to indicate the frequency with which each firm appeared in the top ten across tools, without reflecting its exact rank order.

## 5.5 Regression analysis on impact rankings

To investigate the drivers of convergence and divergence in biodiversity impact rankings across tools, we estimated a beta regression model, with company-level impact rankings as the dependent variable. The original ranks, which ranged from 1 to 500, were rescaled to a 0 to 1 interval to satisfy the distributional assumptions of the beta regression. On this normalized scale, a value of 0 indicates the lowest relative biodiversity impact, and a value of 1 indicates the highest.

The regression was implemented in R using the brms package, which interfaces with Stan, a probabilistic programming language for Bayesian inference[60]. Each model was estimated using four chains, with 3,000 iterations per chain. Standard convergence diagnostics confirmed the reliability of posterior estimates. The full specification of variables is presented in Table 2.

The final model that was fitted is given below, where $\beta_i$ are the regression coefficients and the independent variables are defined in Table 2:

$$
\begin{aligned}
y_i &\sim \operatorname{Beta}\big(\mu_i \phi,\, (1-\mu_i)\phi\big), \qquad 0 < y_i < 1, \\
\operatorname{logit}(\mu_i) &= \beta_0 + \beta_1\, \text{GICS\_Sector}_i + \beta_2\, \text{STAR}_i + \beta_3\, \text{GLOBIO}_i \\
&\quad + \beta_4\, \text{LC\_Impact}_i + \beta_5\, \text{DirectImpactsOnly}_i \\
&\quad + \beta_6\, (\text{GICS\_Sector}_i \times \text{STAR}_i) + \beta_7\, (\text{GICS\_Sector}_i \times \text{GLOBIO}_i) \\
&\quad + \beta_8\, (\text{GICS\_Sector}_i \times \text{LC\_Impact}_i) \\
&\quad + \beta_9\, (\text{GICS\_Sector}_i \times \text{DirectImpactsOnly}_i).
\end{aligned}
$$

**Table 2**: Definition of independent variables in the regression model.

| Variable Name | Description |
|---|---|
| GICS Sector$_i$ | The GICS sector classification of companies. |
| STAR$_i$ | Classifies tools into a binary on whether they use STAR or not. Includes FS and S&P. |
| GLOBIO$_i$ | Classifies tools into a binary based on whether they use GLOBIO or not. Includes IDL, GID, and BIA-GBS. BIA-GBS was excluded from the model due to providing a smaller and skewed sample. |
| LC Impact$_i$ | Classifies tools into a binary based on whether they use LC-Impact or not. Includes NAlpha, GIST, and MSCI. |
| Direct Impacts Only$_i$ | Classifies tools into a binary based on whether they only include direct impacts in their assessment flow or they include other value chain features. Includes MSCI, S&P, and NAlpha Biodiversity Footprint module. |

## 5.6 Boxplot of company rankings across GICS sectors

To compare biodiversity impact rankings across sectors, we constructed a box-and-whisker plot showing the distribution of aggregate impact ranks by GICS sector. Firms included in the BIA-GBS subset were excluded to ensure consistency in sample coverage. The x-axis of the plot displays sectors ordered from left to right by increasing median rank, with lower medians indicating lower average biodiversity impact. To illustrate the dispersion of firm-level rankings within each sector, we overlaid individual company data points as lightly jittered markers. The visualization highlights both between-sector differences in median impact and within-sector heterogeneity in how tools assess biodiversity impact at the firm level.

# Supplementary Material

## Supplementary Note 1 – Tool method summaries

We found substantial differences in the quality and detail between the tool's methodological descriptions. This has resulted in the summaries having varying levels of detail. None of the documentation offered enough information to fully understand or replicate each tool's outputs. This section is largely unreferenced as many of the tools methods are not available online.

### Fair Supply (FSupply)

FSupply is an Australia-based for-profit company that provides tools for evaluating environmental, social, and governance (ESG) risks and impacts in supply chains. Their cloud-based platform, built around their proprietary 'Integrated Assessment Engine,' includes modules designed to address specific issues such as modern slavery, greenhouse gas emissions, and biodiversity loss.

Originally focused on modern slavery risk, the platform has expanded its scope to provide broader supply chain impact assessments. Members of the FSupply team have also contributed to peer-reviewed research on related topics, including work by Amanda Irwin[1],[2]. Here we focus on data from FSupply's Biodiversity Module.

#### ***Company pressure data***

At the company level FSupply employs a combination of AI and manual checking to assign each company to the economic sector(s) that it operates in and then link that sector to corresponding sectoral MRIO flows. Here the tool relies heavily on established input-output methods (i.e. Leontief Inverse) to link company or investment expenditures to an intermediate demand matrix, allowing for an analysis of company-associated implied exposures at the sectoral and regional level via an appended satellite matrix. This is a well-established methodology underpinning much of the published 'embodied' trade literature. The underlying EE-MRIO model used by FSupply was developed in-house. This EE-MRIO was built using National Accounts data prepared by statistical agencies in each country. FSupply's assessment approach focuses entirely on the impacts embedded in supply-chains.

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[1] Irwin, A., Geschke, A., Brooks, T.M. et al. Quantifying and categorising national extinction-risk footprints. *Sci Rep* **12**, 5861 (2022). https://doi.org/10.1038/s41598-022-09827-0

[2] Irwin, A. and Geschke, A. A consumption-based analysis of extinction risk in Australia. *Conservation Letters* **16**(3), e12942 (2023). https://doi.org/10.1111/conl.12942

***Biodiversity impact assessment***

To calculate impacts on biodiversity, FSupply uses the non-normalised Species Threat Abatement and Restoration (nSTAR) metric. nSTAR provides a quantification of extinction risk for each species. It is based on the species' extinction risk category and the scope and severity of threats currently acting on it or expected to act on it in the future. Extinction risk categories are assigned values ranging from 0 to 4, with higher values indicating greater risk, as determined by the IUCN Red List categories. Threat impact scores are calculated based on the scope of the population affected and the severity of decline caused by each threat, with higher scores representing more significant impacts. The nSTAR metric is currently unique to Fair Supply and serves as a standardised measure of biodiversity impact, allowing integration of species extinction risk into global supply chain assessments.

The nSTAR value is linked to sectors and countries by allocating each species' nSTAR value to the countries where its distribution is recorded, based on the proportion of its Area of Habitat within each country. These country-specific values are then distributed across relevant industry sectors by mapping threats recorded in the IUCN Red List[3] to economic activities, considering the scale of each sector's contribution to the threat. This integration enables the nSTAR metric to connect biodiversity impacts to global supply chains.

To determine the impact of an individual company on biodiversity through the nSTAR metric, the nSTAR value for each company is scaled based on the amount invested in that company. For the purposes of the report presented here, a uniform investment amount of USD$1,000,000 has been assumed for all companies. With clients, FSupply use the actual investment amount from a client's portfolio. The methodology currently relies on industry-average Enterprise Value to Revenue ratios to calculate the final nSTAR value for each company when assessing investments. The nSTAR score is designed to capture sector-level economic interactions, rather than being directly tied to the specific supply chains of individual companies or proxy measures such as revenue or book value.

## Global Impact Database (GID)

GID[4], developed by the Netherlands-based Impact Institute, provides quantitative and monetised impact data to help businesses and financial institutions understand, manage, and reporting on the societal impacts of their value chains, operations, and

[3] https://www.iucnredlist.org
[4] https://www.impactinstitute.com/global-impact-data/

investment portfolios. It delivers insights into environmental, social, and economic impacts across companies, countries, and sectors worldwide.

This analysis focuses specifically on GID's Biodiversity Asset data. To quantify biodiversity impacts, GID utilises a top-down sector analysis approach, which assesses how companies contribute to biodiversity loss through their operations and value chains.

### *Company pressure data*

Company-level midpoint data is either collected or modelled, depending on the availability of data. For midpoint impacts, priority is given to company-reported data (such as reported GHG emissions and volume of water usage), which is sourced from the external provider Impaakt[5]. When reported data is unavailable, modelling techniques are applied to estimate impacts. For direct impacts without company-reported data and for value chain (indirect) impacts, GID uses a combined approach. It maps companies to multiple country-sectors by leveraging their proprietary country-sector level data and the geographic breakdown of companies' operating revenues. When revenue data and geographic revenue splits are not available, GID relies exclusively on country-sector level data, mapping the company to a single country-sector that best reflects its operations. Upon request, GID can provide details on the specific measurement or estimation methods used for data points associated with each company.

### *Biodiversity impact assessment*

*Land-use*

To model impacts from land use, three types of activity are considered: crops, forestry and pastures. For crops, the analysis draws data from MapSpam's Spatial Production Allocation Model[6], WWF's Global Ecoregions Map[7], and FAOSTAT[8]. For pastures and forestry, data from Eora[9] and EXIOBASE[10] are utilised. The impacts of land use on biodiversity are quantified using the pressure-impact relationships embedded in GLOBIO, expressed in terms of MSA.ha.

*Impacts originating from emissions and extraction*

When reported data is unavailable, impacts on biodiversity arising from climate change, air pollution, water pollution, and water usage are modelled using data from

[5] https://www.impaakt.com/investor
[6] https://mapspam.info
[7] https://www.worldwildlife.org/publications/terrestrial-ecoregions-of-the-world
[8] https://www.fao.org/faostat/en/#home
[9] Lenzen, M., Moran, D.D., Kanemoto, K., & Geschke, A. (2013). Building Eora: A Multi-region Input–Output Database at High Country and Sector Resolution. *Economic Systems Research*, 25(1), 20–49. https://doi.org/10.1080/09535314.2013.769938
[10] https://www.exiobase.eu

EXIOBASE, Eora, and GTAP[11]. To translate this data into biodiversity impacts, GID utilises the ReCiPe[12] LCIA method. The ReCiPe species.yr metrics is transformed into the PDF.M$^2$.yr metric by multiplying it by the number of species assumed to exist in ReCiPe.

*Combining the impacts resulting from emissions, extraction, and land use*

The impacts from emissions, extraction, and land use are combined into a unified metric called 'biodiversity hectares lost (Bio-ha)' metric. This is achieved by assuming equivalency between the metrics: one MSA.ha is considered equal to one Bio-ha, and 10,000 PDF.m$^2$.yr are also considered equal to one Bio-ha. However, depending on a client's specific requirements, GID can provide final data points in any of the three metrics: MSA.ha, PDF.m$^2$.yr, or Bio-ha. Bio-ha is the default, and the metric used for this analysis.

## GIST Impact (GIST)

GIST is a for-profit data and analytics firm specialising in assessing corporate impacts on society and the environment. Founded in 2008 with origins in the non-profit sector, it has evolved into a leading provider of impact data and intelligence. The firm employs over 100 specialists, including scientists, engineers, and economists, and offers services such as monetised impact valuation, biodiversity risk assessment, and support for compliance with sustainability reporting frameworks. This report focuses on their biodiversity impact metrics.

### *Company pressure data*

GIST use a combination of direct disclosures, and six different estimation methodologies depending on data availability:

1. **Disclosed Data**: Data sourced directly from a company's disclosures, typically in sustainability reports or corporate websites including company-reported data such as GHG emissions and water use.
2. **Revenue-Based Year-on-Year Trend Estimation**: Estimates derived using arithmetic operations of disclosed KPIs or revenue-based intensity averages for undisclosed years.

[11] https://www.gtap.agecon.purdue.edu

[12] Huijbregts, M.A.J., Steinmann, Z.J.N., Elshout, P.M.F., Stam, G., Verones, F., Vieira, M., Zijp, M., Hollander, A., & van Zelm, R. (2017). ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. *The International Journal of Life Cycle Assessment*, 22, 138–147. https://doi.org/10.1007/s11367-016-1246-y (Open Access)

3. **Data Gap Filling/Secondary Estimation**: Secondary estimates based on primary KPIs using emission factors or coefficients from scientific literature and lifecycle databases.
4. **Machine Learning Estimates**: Data derived via machine learning algorithms trained on financial and operational metrics, such as business segmentation and geographical presence.
5. **Machine Learning Secondary Estimations**: Secondary estimates using ML-imputed primary KPIs with coefficients/emission factors from LCA databases.
6. **EXIOBASE Estimates**: Estimates based on the EXIOBASE dataset, a global input-output database detailing environmental and economic interactions.

As of November 2024, GIST specifies the measurement or estimation method used for each datapoint within their data portal to provide a greater level of transparency and traceability in their datasets[13].

***Biodiversity impact assessment***

To evaluate impacts on biodiversity, GIST employs the LC-Impact LCIA method[14]. The spatial precision of the analysis varies depending on data availability. The highest level of precision is achieved when data is directly provided by companies. For such cases, PDF calculations are performed at the finest level of granularity available from LC-IMPACT for the specific pressure. For example, water consumption characterisation factors at a 0.05-degree latitude/longitude resolution are applied when company-reported data includes this level of detail.

When impact pressures can be reliably estimated at the country level, the analysis uses LC-Impact's country-level characterisation factors. In cases where data is insufficient to allocate pressures at the country level, regional allocations are made at the most granular level possible, with regional characterisation factors calculated through area-weighted averages of country-specific factors. GIST specifies the spatial precision of the endpoint characterisation factor from LC-Impact used in its calculation for each PDF value.

[13] "Traceable Sustainability Data" - https://gistimpact.com/impact-intelligence/#nature-biodiversity
[14] https://www.lc-impact.eu

## Iceberg Data Lab (IDL)

IDL is a European for-profit company that develops metrics and tools to quantify environmental impacts. This analysis will focus on IDL's Corporate Biodiversity Footprint (CBF), which measures a company's biodiversity impact in both absolute and relative terms.

### *Company pressure data*

IDL utilises its proprietary Wunderpus model to assess the environmental impacts organisations have on nature. Wunderpus is based on the EXIOBASE EE-MRIO, and was refined using International Energy Agency (IEA)[15], Food and Agriculture Organisation (FAO)[16], International Monetary Fund (IMF)[17], and World Bank[18] data as well as in-house enhancement from IDL's own research.

The Wunderpus model maps the flows and purchases of goods and services to the statistical classification of economic activities in the European Community, known as the Nomenclature of Economic Activities (NACE)[19]. This creates an 'activity mix', capturing the different types of activity a business is engaged in. This activity mix is then translated into a series of four environmental pressures: land use, climate change, air pollution, and water pollution. Values are modelled from revenue data by default (top-down analysis) and then company-specific data is used to refine the analysis (bottom-up analysis) which can be company-specific revenue, product volumes output and consumed, product certifications, or environmental pressure data.

### *Biodiversity impact assessment*

To calculate how company-specific mid-point pressures impact biodiversity, IDL uses the GLOBIO[20] model. Utilising the pressure-impact relationships contained within GLOBIO, the effects of climate change, land use, water pollution, and air pollution have on biodiversity are quantified in the MSA.km$^2$ metric. Pressures are calculated along the entire value chain, aggregated into scope 1, 2 and 3 (upstream and downstream).

*Data quality level*

[15] https://www.iea.org
[16] https://www.fao.org/home/en
[17] https://www.imf.org/en/Home
[18] https://www.worldbank.org/ext/en/home
[19] https://ec.europa.eu/eurostat/statistics-explained/index.php/Business_economy_by_sector_-_NACE_Rev._2
[20] https://www.globio.info

The data flow for building the footprint analysis follows these steps: revenues, quantities of goods and services, quantified environmental pressures, and finally, translation into biodiversity impact expressed in $km^2$.MSA. IDL assigns a Data Quality Level (DQL) to each data point, reflecting the quality of the primary raw data underlying the final biodiversity impact. The most robust level of data is environmental data reported by companies, and so in this instance the impact will be assigned the highest DQL. The second DQL level involves impacts that IDL models using reported volume outputs from the company. The third level is when only sales data is reported, and volumes of commodities are modelled. Finally, when sales data is not available, IDL models the impact of companies based on their sector. Any one company may use a mixture of these methods.

## Biodiversity Impact Analytics powered by the Global Biodiversity Score (BIA-GBS)

CDC Biodiversité is a private company dedicated to designing and implementing practical actions for restoring, preserving, and sustainably managing biodiversity. Carbon4Finance (C4F) is a private company founded in 2007 with a focus on providing financial institutions with information for climate decision making, but since its collaboration with CDC Biodiversité, has extended its offerings to also include biodiversity analytics. The focus of this review is on BIA-GBS, which is a collaboration between French CDC Biodiversité and C4F which begun in 2021. BIA-GBS measures the impacts of companies, financial portfolios and sovereign entities on biodiversity, as well as their dependencies on ecosystem services. By offering insights into these impacts and dependencies, the tool helps financial institutions understand their exposure to biodiversity-related risks.

### *Company pressure data*

C4F provides the mapping between instrument identifiers (ISIN) and the issuer. After having identified the issuer, Carbon4 Finance maps it with its underlying company, and the corresponding revenues by sector of activity and geographic location. Production and corresponding purchases are obtained by providing this input into the EXIOBASE model. When available, purchases by industry and country or region are directly used instead. EXIOBASE also converts the sector and country specific revenue data into inventories, where the whole upstream value chain of companies is considered.

The GHG scope 1, 2 and 3 emissions are extracted from the Carbon Impact Analytics (CIA) database of C4F and cover both upstream and downstream value chain for scope 3. Inventories, production and purchases are translated to commodities, refined products, water consumption and emissions using the EXIOBASE environmental extensions. The midpoint pressures (terrestrial and aquatic) are derived from the inventories using in-house tools and it is completed by LCAs. When available, data is expressed in units and perimeters compatible with GLOBIO cause-effect relationships. The impact on biodiversity is assessed using the GLOBIO model pressure-impact relationships.

***Biodiversity impact assessment***

Four biodiversity pressures are considered, which are land use, direct exploitation, climate change and pollution. The pressures as well as the impacts are categorised as terrestrial and freshwater/aquatic (based on the realm) and static and dynamic (based on the accounting category). The impacts are assessed using the GLOBIO model. The absolute biodiversity impacts are expressed in Mean Species Abundance (MSA).km2[2]. To account for the difference in surface area occupied between terrestrial (130 million $km^2$) and aquatic freshwater ecosystems (11 million $km^2$), the MSA.$km^2$ is normalised to obtain the MSAppb metric. There are also impact intensities in terms of value (impact per euro invested) and activity (intensity of the issuer independent of the financial institution), in addition to the aggregate absolute metric.

*Land use*

In the terrestrial category, land use is further subdivided into land use, fragmentation and encroachment. In the aquatic category, it is wetland conversion. Each of these categories derives its own MSA value based on the GLOBIO model.

*Direct exploitation*

Direct exploitation refers to the pressures due to resource extraction (crops, wood logs, mining etc.) in the terrestrial category, while it refers to the hydrological disturbance due to direct water use in the aquatic category.

*Climate change*

Climate change has no subdivision in the terrestrial category. In the aquatic category, hydrological disturbance due to climate change is considered.

*Pollution*

In the terrestrial realm, atmospheric nitrogen deposition and terrestrial ecotoxicity are considered under pollution. In the aquatic realm, land use in catchment of rivers and wetlands, freshwater eutrophication and freshwater ecotoxicity are considered.

## MSCI ESG Manager (MSCI)

MSCI is a US-based for-profit company specialising in data and tools to support investment decision-making. Among its offerings is the MSCI ESG Manager, an online platform designed to help asset managers and asset owners integrate environmental, social, and governance (ESG) into their decision processes.

MSCI's Nature and Biodiversity Solutions draw on research and expertise in nature-related themes from its ESG & Climate Research division and related tools. This report focuses on MSCI's biodiversity footprint metrics.

### *Company pressure data*

MSCI's PDF based biodiversity footprint takes into account biodiversity impacts from companies' GHG emissions, water consumption, and land use. The footprint metrics currently only incorporate the direct operations of companies. To calculate how companies' pressures on nature could result in biodiversity loss, MSCI uses both reported and estimated data as input. For GHG emissions, MSCI uses a combination of reported company data and estimation. All input data are modeled when it comes to companies' land use and water consumption.

*GHG emissions*

For GHG emissions, reported data is prioritised. Where MSCI's GHG emissions data criteria is not met, an inhouse Carbon Emissions Estimation Methodology is utilised to calculate a company's GHG emissions.

*Land use*

MSCI models the land footprint of companies through four land-use estimation models: (i) Base model, (ii) Office-based industries, (iii) Utilities, and (iv) Commodities-based industries. For each type of land use, a Land Use Intensity (LUI) factor per (sub-) industry is calculated and applied.

1. Base Model: Land Use Intensity (LUI) factors for each GICS sub-industry are determined by dividing the total site area of companies with known land footprints within that sub-industry by their revenues. The median LUI value for the sub-industry serves as its LUI factor. A company's land footprint is modeled by multiplying its revenue by the sub-industry LUI factor.

2. Office-based Industries: For office-based sectors (e.g., financials), the model uses workforce size instead of revenue. The LUI factor represents the median land area per employee within the industry. A company's workforce size is multiplied by this LUI factor to estimate its land use.

3. Utilities: LUI factors are based on a US study of land use for various energy generation types (e.g., solar, wind, hydro). A company's reported installed energy production capacity (in MW) is multiplied by the LUI specific to each energy type to estimate land use.

4. Commodities-based Industries: This model relies on data from input-output databases (EXIOBASE), linking 52 SIC codes to five GICS sub-industries: Agricultural Products & Services, Packaged Foods & Meats, Forest Products, Industrial Conglomerates, and Tobacco. LUI factors are defined per SIC code and region. A company's revenue breakdown by SIC code and region is multiplied by the respective LUIs to estimate its land use for each sector and country.

In cases where multiple models could apply to a company, a 'waterfall' approach is used, prioritising estimates from the industry-specific models (office-based, utilities, or commodities) before defaulting to the base model. Asset-specific data is used when available to refine estimates, with aggregated values reflecting the overall company land footprint.

*Water consumption*

Due to the lack of consistent corporate disclosures on water withdrawal and consumption, water withdrawal and consumption is modeled at both the company and asset levels. To do this, water withdrawal and consumption intensity factors for a given GICS sub-industry are calculated based on reported data on water withdrawal, consumption and revenue values of companies classified in the respective GICS sub-industry. These intensity factors, combined with reported revenue data, are then used to calculate the overall water consumption and withdrawal for any company.

To calculate the water withdrawal and consumption of individual assets, MSCI proportionally distributes a company's overall water consumption and withdrawal across all assets in the GeoSpatial database based on their size, as measured by the land footprint, and the activity taking place at the asset.

### ***Biodiversity impact assessment***

To assess the impacts on biodiversity, MSCI employs the LC-Impact LCIA method. Notably, out of the ten pressure-impact relationships included in LC-Impact, MSCI currently calculates the biodiversity footprint of a company for three pressure categories: GHG emissions, water stress, and land use. The output of this assessment is the PDF metric. MSCI scales the PDF values by the factor $10^8$. The scaled value may be interpreted as an upper limit to the potentially disappeared number of species. A PDF of e.g. 1,000 indicates a company's potential contribution to the extinction of

1,000 species in relation to an estimated number of 100 million species on Earth over the course of the next 100 years.

## NatureAlpha (NAlpha)

NAlpha[21] is a UK-based for-profit company specialising in datasets that evaluate nature and biodiversity-related impacts, dependencies, controversies, and management practices at the asset, company, and portfolio levels. Offering a suite of modules with a total of 135 different metrics, NAlpha provides insights into nature and biodiversity risks, impacts, and dependencies, including metrics like Nature Value at Risk and governance assessments.

NAlpha's full suite of different modules and metrics is designed to be used together. This analysis concentrates on NAlpha's Biodiversity Impact Module and BioFootprint Module. The Biodiversity Impact Module quantifies a company's possible overall impacts on biodiversity, whereas the BioFootprint Module provides a normalised intensity metrics per dollar of revenue between companies.

### *Biodiversity Impact module*

The Biodiversity Impact module enables investors to identify a company's propensity to material impacts on biodiversity. It is calculated by averaging the values of four submodules:

*Material impact (MI)*

Material Impact measures a company's biodiversity impact based on a materiality assessment of its direct operational activities, aligned with TNFD, United Nations Environment Programme (UNEP), and United Nations Environment Programme Finance Initiative (UNEP FI) guidance. It is expressed as a weighted percentage of revenue across subindustries materiality.

*Proximity impact (PI)*

Proximity Impact assesses a company's global locations relative to nature and biodiversity-sensitive areas using IBAT data. Locations are weighted by proximity (1km, 5km, 10km) to Key Biodiversity Areas and World Protected Areas. The final score is expressed as the percentage of a company's operating locations that fall within these specified buffer zones.

*Supplier impact (SI)*

Supplier Impact evaluates the biodiversity impact of a company's main known suppliers based on a TNFD and UNEP-aligned materiality assessment of their relevant

[21] https://www.naturealpha.ai/

sectors and sub-industries. The final score is calculated as the average of these values, divided by the number of materiality categories, to determine the overall impact percentage.

*Country impact (CI)*

Country Impact assesses a company's operational impact exposure in each country, based on factors like species intactness, nature intensity, and environmental management enforcement. It calculates the risk of impact per country and ranks it from low to very high. The total company locations in each country are weighted averaged to determine the impact exposure. The final score is expressed out of 100 and normalised between 0 and 1.

*Overall biodiversity impact (Aggregate BI)*

Overall Biodiversity Impact is calculated as an equally weighted composite score of all four impact factors using the formula:

$$Aggregate\ BI\ =\ \frac{PI\ +\ CI\ +\ SI\ +\ MI}{TBI}$$

The result, expressed as a percentage, enables percentile rankings for peer comparisons, indicating an entity's biodiversity impact within its cohort.

### ***BioFootprint module***

The BioFootprint module is different to the Biodiversity Impact module. The BioFootprint module uses LCA methods to evaluate the biodiversity footprint of a company per dollar of revenue.

### ***Company pressure data***

To assess the biodiversity footprint of products and services created and used by a company, NAlpha combines the NatureAlpha database, which contains the percentage of revenue each company earns from specific products and services, with the Ecoinvent[22] life cycle inventory database. This integration links products and services to key environmental impact categories (Climate Change, Photochemical Ozone Formation, Acidification, Land Stress, Toxicity, Eutrophication, and Water Stress), while incorporating geographic considerations.

### ***Biodiversity impact assessment***

To quantify a company's biodiversity footprint in PDF over time, NAlpha employs the ReCiPe and LC-Impact impact methodologies.

[22] https://ecoinvent.org

ReCiPe is utilised to convert environmental impacts from 'midpoint impacts' to 'endpoint impacts' that reflect biodiversity loss. ReCiPe midpoint impact data is integrated within Ecoinvent. Ecoinvent provides differing levels of geospatial detail which can be integrated with LC-Impact database.

To evaluate impacts on biodiversity loss, NAlpha utilises LC-Impact which provides spatially explicit pressure-impact relationships, quantifying biodiversity impacts in PDF.$m^2$.yr. However, given the highest spatial resolution Ecoinvent provides is at the state/provincial level, the ability of NAlpha to fully employ the spatial specificity of some of the more detailed pressure-impact relationships in LC-impact is constrained.

Once PDF values are calculated, NAlpha ranks products and services based on their biodiversity impact. Companies are then mapped to geographic distribution of their revenue across products and services and the associated intensity of biodiversity impact, providing a biodiversity footprint score that reflects the proportional impact of their products and services. This score, presented on a 0-1 scale, allows for cross-company of biodiversity impacts comparisons.

## S&P Global Sustainable1 (S&P)

S&P Global[23], a U.S.-based for-profit corporation, specialises in financial information and analytics. S&P provides data-driven tools to help companies and financial institutions assess and manage nature-related risks tied to location-specific business activities. Its Nature & Biodiversity Risk dataset, developed in partnership with the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC), is based on the principles of the TNFD and evaluates dependencies on and impacts to nature. This methodology, supported by a proprietary database of over 1.6 million assets and covering more than 20,000 companies globally, enables businesses to assess risks to terrestrial ecosystems, dependency on ecosystem services, and proximity to protected areas.

Here we will focus on S&P's proprietary Ecosystem Footprint metric, which aims to measure how organisations direct operations (not considering supply chain) impact ecosystem structure, composition, and function.

### *Company pressure data*

To assess the land use of companies, S&P defines a two-tier approach. The Tier 1 method is used when detailed asset-level data is unavailable, estimating land use

[23] https://www.spglobal.com/ratings/en/

footprints and ecosystem impacts based on country and sector averages. Companies' activities are categorised across countries and sectors using S&P's proprietary Trucost Environmental and GeoSeg datasets, and combined with the Trucost Environmental model to estimate and allocate land use in hectares in each country of operation. Geo-explicit allocation at the country level utilise GDP-weighted metrics derived from spatial GDP data at a 5-arc minute resolution[24] and global land use data from 2019[25]. This approach also incorporates additional geospatial layers to capture activities extending beyond typical land classifications, such as mining, oil and gas extraction, and infrastructure development in order to allocate business activities to the areas where they are most likely to take place in each country.

The Tier 2 approach utilises asset-level data sources to provide precise measurements of company-specific land footprints. This data is scraped from a variety of sources, differentiated by macro industry. The majority of these data originates from existing proprietary S&P products, with the inclusion of some other government regulatory datasets. Each asset is assigned a unique owner identifier, facilitating linkage to additional datasets within the S&P Global Capital IQ database. This identifier also connects the asset to its ultimate parent entity, enabling the aggregation of metrics at both the owner and parent levels.

***Biodiversity impact assessment***

To calculate impacts on nature and biodiversity, S&P has developed an 'Ecosystem Footprint' metric that accounts for both the magnitude of impact and the significance of the areas impacted. This metric is a condition-adjusted footprint in hectares relative to a pristine ecosystem, and it weights each location impacted by its relative significance to account for ecosystem specificities and criticalness. The result is a footprint expressed in hectares equivalent of the most pristine and significant areas globally.

Ecosystem Footprint Calculation (EFC):

$$\begin{aligned} EFC = &\text{ Land Use (ha)} \times \text{Ecosystem Integrity Impact Index} \\ &\times \text{ Ecosystem Significance Index} \end{aligned}$$

Land use is the Tier 1 and Tier 2 data as described in the Company Input Data section above, Ecosystem integrity impact index the difference between a pristine state

[24] Kummu, M., Taka, M., & Guillaume, J. H. A. (2018). Gridded global datasets for Gross Domestic Product and Human Development Index over 1990–2015. *Scientific Data*, 5, 180004. https://doi.org/10.1038/sdata.2018.4

[25] Winkler, K., Fuchs, R., Rounsevell, M. D. A., & Herold, M. (2021). Global land use changes are four times greater than previously estimated. *Nature Communications*, 12(1), Article 2501. https://doi.org/10.1038/s41467-021-22702-2

and the ‘remaining condition’, combining data on ecosystem structure, composition and function, and the Ecosystem Significance Index that combines the $\mathrm{STAR_T}$ metric to quantify the relative significance of locations for biodiversity conservation and Critical Natural Assets data to convey ecosystem services provision value for humans of biodiversity at a site-level.

The EFC has two applications; Tier 1 for when asset-level information is not available, the Ecosystem Integrity Index and Ecosystem Significance Index is the average value of the of the indices over the relevant area of each country in which a sector likely operates, and Tier 2 when asset-level information is available and the indices for any asset are calculated as the average value of the index layer over the area occupied by a given asset.

## Supplementary Note 2 – Structured questions

### Collection of Company Data

1. What data is collected to represent nature-related information about the company? Where is the data used to represent nature-related company activity sourced from?
2. How is the data collected (e.g., scraping methods)?
3. Is there direct engagement with companies to collect the data?
4. How frequently is the data updated?
5. How extensive is the coverage?
6. Is data collected on the full scope of a company’s value chain (e.g., upstream, direct, and downstream)?
7. Is data associated with companies company-specific or derived from input-output tables? If completely derived, what input-output table (or other) source is used and what is the derivation method? If partially derived, what proportion of the data is specific to individual companies versus sectoral data?
8. Is the company data spatially resolved? To what level of detail (e.g., national, state, municipality, site)?
9. How is the accuracy of the data verified?

### Processing of Company Data

1. Once collected, how is company activity data processed for impact assessment?

### Environmental Impact Data

1. What public or proprietary datasets are used to model impacts?
2. What is the granularity of the dataset (e.g., 100 or 1000 economic services/products, sectoral coverage only)?
3. Is the impact data spatially resolved? To what level of detail (e.g., national, state, municipality, site)?
4. How is the accuracy of the data verified?

### Impact Assessment Method

1. How are environmental impacts calculated/standardised? What are the midpoints and endpoints used, assuming this is a relevant distinction?
2. What specific aspects of biodiversity, nature, or nature capital are being measured by the tool (e.g., species extinctions, ecosystem intactness, composite indices, or just threatened species)?
3. Does the method measure realised or expected declines?
4. Does it assess impact relative to a historical baseline? If so, what is the reference point?
5. Is the impact method spatially resolved? To what level of detail (e.g., national, state, municipality, site)?
6. Does the assessment method disaggregate the impacts within the value chain (e.g., upstream, direct, downstream)?
7. Does the assessment method take into account the relative impact of companies/assets based on their revenue, equity, or market capitalization?
8. Does the data provide information on biodiversity sensitive areas that aligns with PAI 7 within the SFDR regulation in the EU?
9. Outside of impacts, what other data is reported on (e.g., dependencies, risks, opportunities, etc)?
10. Does the method account for any restorative impacts on nature?
11. What assumptions or approximations are made in the impact assessment method, and how are they justified and documented?
12. Has the company (rating/tool provider agency) made any efforts to validate the chosen impact assessment method?

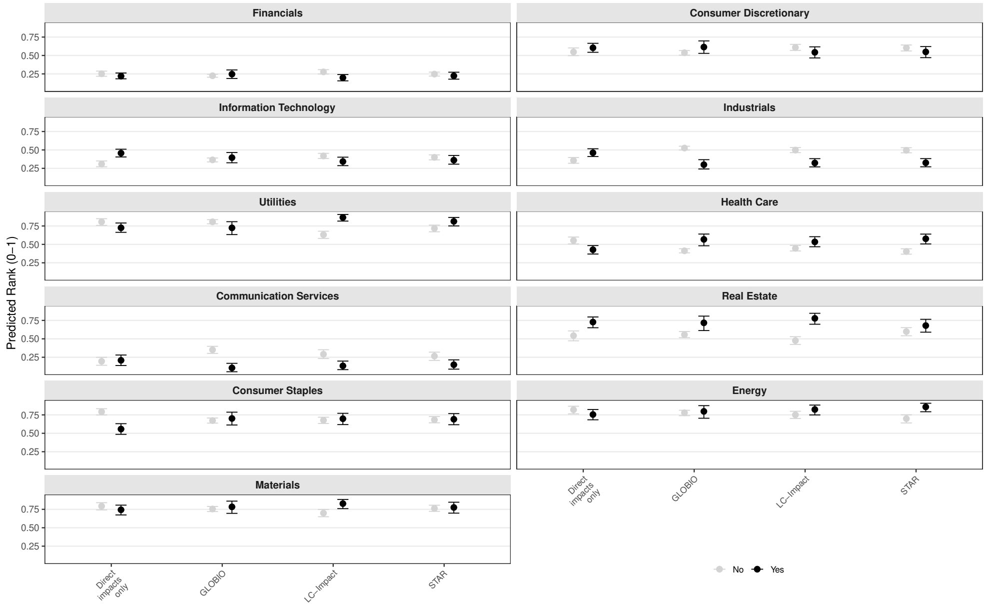
### Transparency and Documentation

1. Is the tool's methodology transparent and publicly available?

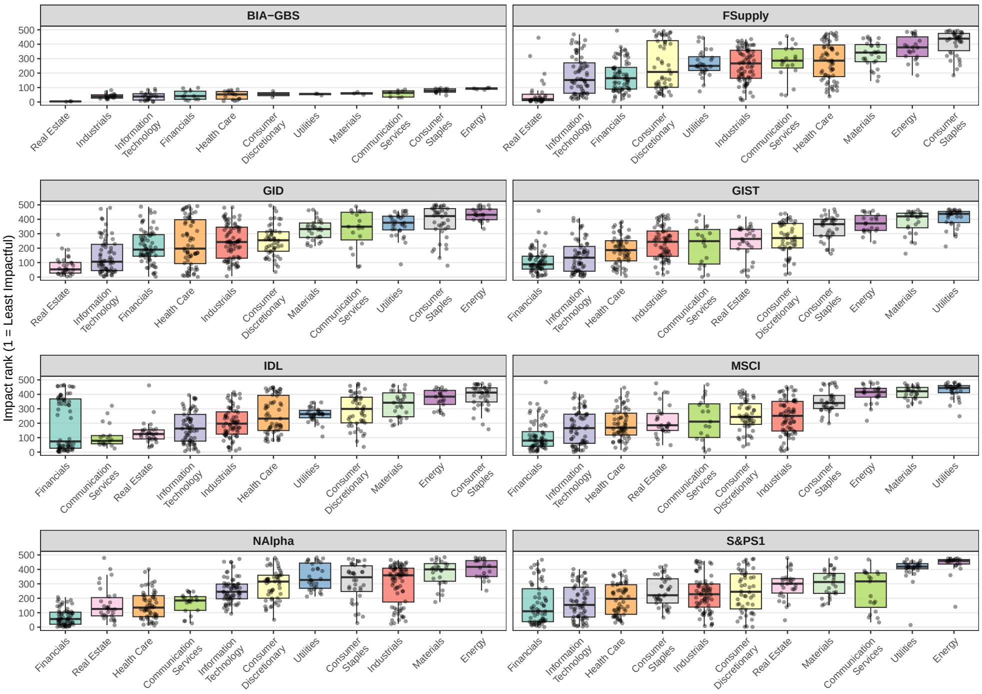
2. Is each step of the tool's methodology well-documented?
3. What proportion of the tool relies on open-source data compared to proprietary data?
4. If they have made variations to publicly available tools/datasets, is it clear what changes they have made? Is there justification/evidence that is documented?

### Company and Sectoral Coverage

1. How many companies are included in the existing tool's database? What capacity exists for the tool provider to extend coverage to assets of interest? What different type of asset classes are included?
2. Does the tool cover all sectors? Are there any sectors where the collection of company-specific data and modelling are exposed to more limitations? What sectoral classification scheme do they use (e.g., ISIC 4, SIC, HSIC, etc)?
3. What different exchanges are covered?




**Supplementary Fig. 1:** Predicted sector-level biodiversity impact rankings for firms all GICs sectors, based on a Bayesian beta-regression model. Rankings are scaled from 0 to 1, with 0 indicating the lowest relative biodiversity impact. Posterior mean estimates are shown as points, with vertical bars representing 95 percent credible intervals. The figure presents results across three methodological contrasts: tools that use GLOBIO versus those that do not; tools that incorporate LC-Impact versus those that rely on alternative characterization models; tools that incorporate STAR versus those that do not; and tools that assess only direct operational impacts versus those that also consider upstream and downstream value-chain effects. The model yielded a Bayesian R-squared of 0.40, with a 95 percent credible interval ranging from 0.39 to 0.42. Full regression outputs are reported in Supplementary Table 4.




**Supplementary Fig. 2:** Boxplot of company-level biodiversity impact rankings derived from aggregate impact metrics across all assessment tools for S&P 500 firms faceted by tool. Each dot represents an individual company's rank within its sector. A rank of 1 indicates the lowest impact, and a rank of 500 indicates the highest. Sectors are displayed from left to right in order of increasing median impact rank, with sectors on the left showing lower overall impacts and those on the right showing higher impacts.

**Supplementary Table. 1:** Posterior summaries for beta regression model.

| Effect | Component | Parameter | Mean | SD | 2.5% | 97.5% |
|---|---|---|---|---|---|---|
| fixed | cond | (Intercept) | -0.86 | 0.09 | -1.05 | -0.68 |
| fixed | cond | GICS_sectorConsumerDiscretionary | 1.14 | 0.14 | 0.87 | 1.42 |
| fixed | cond | GICS_sectorInformationTechnology | 0.23 | 0.13 | -0.02 | 0.49 |
| fixed | cond | GICS_sectorIndustrials | 1.46 | 0.13 | 1.20 | 1.72 |
| fixed | cond | GICS_sectorUtilities | 1.59 | 0.16 | 1.28 | 1.90 |
| fixed | cond | GICS_sectorHealthCare | 0.24 | 0.14 | -0.03 | 0.51 |
| fixed | cond | GICS_sectorCommunicationServices | 1.06 | 0.20 | 0.67 | 1.44 |
| fixed | cond | GICS_sectorRealEstate | -0.17 | 0.18 | -0.53 | 0.17 |
| fixed | cond | GICS_sectorConsumerStaples | 2.07 | 0.16 | 1.76 | 2.39 |
| fixed | cond | GICS_sectorEnergy | 1.62 | 0.17 | 1.29 | 1.97 |
| fixed | cond | GICS_sectorMaterials | 1.74 | 0.17 | 1.40 | 2.07 |
| fixed | cond | STAR1 | -0.14 | 0.12 | -0.36 | 0.09 |
| fixed | cond | GLOBIO1 | 0.12 | 0.15 | -0.17 | 0.42 |
| fixed | cond | LC_Impact1 | -0.45 | 0.12 | -0.68 | -0.22 |
| fixed | cond | vc_direct_only1 | -0.18 | 0.10 | -0.37 | 0.01 |
| fixed | cond | GICS_sectorConsumerDiscretionary:STAR1 | -0.08 | 0.17 | -0.42 | 0.24 |
| fixed | cond | GICS_sectorInformationTechnology:STAR1 | -0.02 | 0.16 | -0.34 | 0.28 |
| fixed | cond | GICS_sectorIndustrials:STAR1 | -0.57 | 0.16 | -0.87 | -0.27 |
| fixed | cond | GICS_sectorUtilities:STAR1 | 0.67 | 0.21 | 0.26 | 1.06 |
| fixed | cond | GICS_sectorHealthCare:STAR1 | 0.83 | 0.17 | 0.51 | 1.15 |
| fixed | cond | GICS_sectorCommunicationServices:STAR1 | -0.59 | 0.24 | -1.05 | -0.12 |
| fixed | cond | GICS_sectorRealEstate:STAR1 | 0.50 | 0.20 | 0.10 | 0.90 |
| fixed | cond | GICS_sectorConsumerStaples:STAR1 | 0.17 | 0.20 | -0.21 | 0.55 |
| fixed | cond | GICS_sectorEnergy:STAR1 | 1.09 | 0.24 | 0.62 | 1.56 |
| fixed | cond | GICS_sectorMaterials:STAR1 | 0.19 | 0.21 | -0.22 | 0.61 |
| fixed | cond | GICS_sectorConsumerDiscretionary:GLOBIO1 | 0.19 | 0.23 | -0.26 | 0.64 |
| fixed | cond | GICS_sectorInformationTechnology:GLOBIO1 | 0.01 | 0.21 | -0.41 | 0.43 |
| fixed | cond | GICS_sectorIndustrials:GLOBIO1 | -1.07 | 0.21 | -1.49 | -0.66 |
| fixed | cond | GICS_sectorUtilities:GLOBIO1 | -0.59 | 0.25 | -1.07 | -0.10 |
| fixed | cond | GICS_sectorHealthCare:GLOBIO1 | 0.50 | 0.22 | 0.08 | 0.92 |
| fixed | cond | GICS_sectorCommunicationServices:GLOBIO1 | -1.65 | 0.32 | -2.28 | -1.04 |
| fixed | cond | GICS_sectorRealEstate:GLOBIO1 | 0.59 | 0.27 | 0.06 | 1.13 |
| fixed | cond | GICS_sectorConsumerStaples:GLOBIO1 | 0.03 | 0.26 | -0.47 | 0.53 |
| fixed | cond | GICS_sectorEnergy:GLOBIO1 | -0.01 | 0.30 | -0.59 | 0.57 |
| fixed | cond | GICS_sectorMaterials:GLOBIO1 | 0.03 | 0.28 | -0.50 | 0.58 |
| fixed | cond | GICS_sectorConsumerDiscretionary:LC_Impact1 | 0.17 | 0.17 | -0.17 | 0.51 |
| fixed | cond | GICS_sectorInformationTechnology:LC_Impact1 | 0.12 | 0.16 | -0.20 | 0.45 |
| fixed | cond | GICS_sectorIndustrials:LC_Impact1 | -0.29 | 0.16 | -0.62 | 0.03 |
| fixed | cond | GICS_sectorUtilities:LC_Impact1 | 1.76 | 0.21 | 1.35 | 2.19 |
| fixed | cond | GICS_sectorHealthCare:LC_Impact1 | 0.80 | 0.18 | 0.45 | 1.14 |
| fixed | cond | GICS_sectorCommunicationServices:LC_Impact1 | -0.54 | 0.25 | -1.02 | -0.05 |
| fixed | cond | GICS_sectorRealEstate:LC_Impact1 | 1.80 | 0.22 | 1.37 | 2.23 |
| fixed | cond | GICS_sectorConsumerStaples:LC_Impact1 | 0.55 | 0.20 | 0.15 | 0.95 |
| fixed | cond | GICS_sectorEnergy:LC_Impact1 | 0.88 | 0.23 | 0.42 | 1.33 |
| fixed | cond | GICS_sectorMaterials:LC_Impact1 | 1.16 | 0.22 | 0.73 | 1.61 |
| fixed | cond | GICS_sectorConsumerDiscretionary:vc_direct_only1 | 0.41 | 0.14 | 0.13 | 0.69 |
| fixed | cond | GICS_sectorInformationTechnology:vc_direct_only1 | 0.81 | 0.14 | 0.55 | 1.07 |
| fixed | cond | GICS_sectorIndustrials:vc_direct_only1 | 0.61 | 0.13 | 0.35 | 0.87 |
| fixed | cond | GICS_sectorUtilities:vc_direct_only1 | -0.27 | 0.18 | -0.63 | 0.07 |
| fixed | cond | GICS_sectorHealthCare:vc_direct_only1 | -0.33 | 0.14 | -0.59 | -0.05 |
| fixed | cond | GICS_sectorCommunicationServices:vc_direct_only1 | 0.26 | 0.20 | -0.12 | 0.65 |
| fixed | cond | GICS_sectorRealEstate:vc_direct_only1 | 0.99 | 0.17 | 0.66 | 1.34 |
| fixed | cond | GICS_sectorConsumerStaples:vc_direct_only1 | -0.93 | 0.16 | -1.26 | -0.61 |
| fixed | cond | GICS_sectorEnergy:vc_direct_only1 | -0.22 | 0.19 | -0.60 | 0.16 |
| fixed | cond | GICS_sectorMaterials:vc_direct_only1 | -0.10 | 0.18 | -0.46 | 0.25 |

**Supplementary Table. 2:** The fourteen biodiversity impact tools considered, accompanied by the rationale for the inclusion or exclusion of that tool. The final column indicates the date in 2024 when each tool's methods and data were shared.

| **Tool Provider** | **Inclusion/Exclusion** | **Date** |
|---|---|---|
| FairSupply (FS) | Included with full participation. | 8/28 |
| Global Impact Database (GID) | Included with full participation. | 9/17 |
| GIST Impact (GIST) | Included with full participation. | 10/31 |
| Iceberg Data Labs (IDL) | Included with full participation. | 8/1 |
| Biodiversity Impact Analytics powered by the Global Biodiversity Score database (BIA-GBS) | Included with partial participation. | 9/7 |
| MSCI Nature & Biodiversity Solutions (MSCI) | Included with full participation. | 7/8 |
| NatureAlpha (NAlpha) | Included with full participation. | 10/31 |
| S&P Sustainable1 (S&P) | Included with full participation. | 9/19 |
| Biodiversity Impact Assessment Tool (BIAT) | Excluded, did not respond. | – |
| Global Biodiversity Score for Financial Institutions (GBS-FI) | Excluded as the tool is a component of BIA-GBS, but without the Carbon4Finance data. Including both was deemed unnecessary. | – |
| Biodiversity Footprint for Financial Institutions (BFFI) | Excluded, as while designed for financial institutions, BFFI does not provide pre-calculated datasets for listed companies meaning it does not suit most FI's needs. | – |
| NatureMetrics | Excluded as eDNA analysis is not something that can be scaled to high numbers of listed companies at present. | – |
| FOREST-IQ | Excluded because its data scope is very narrowly focused, primarily designed to measure deforestation as a specific, isolated impact. | – |
| TRASE | Excluded due to its limited data focus on high-impact commodities in high-risk areas, and does not provide complete impact data on companies. | – |

**Supplementary Table. 3:** Overview of each tool's selected aggregate (non-value-adjusted) impact metrics. The "Companies included" column indicates the number of matching companies from that tool included for analysis. The "Period of observations" column shows the range of years for which each metric was reported. If multiple years of data were available for a company, the most recent year was used; however, some tools had different "most recent" data for different companies within their provided sample which is why some tools have a range of years.

| **Tool** | **Metric** | **Definition** | **Firms** | **Years** |
|---|---|---|---|---|
| GID | total_non_monetized | - Estimates the total impact of companies in the bio.ha. The bio.ha is an aggregation of PDF and MSA values into a single unit (bio.ha = msa.ha = pdf.ha = 10 000 pdf.$m^2$.yr). | 500 | 2022 |
| GIST | TOTAL_GLOBAL_PDF | Estimates the total impact of companies using the PDF metric. | 469 | 2022 |
| IDL | CBF Value | Estimates the total impacts of companies, measured in MSA.$km^2$. | 474 | 2021–23 |
| MSCI | GLOBAL_SPECIES_EXTINCT_RECENT | Estimates the total impact of companies using the PDF metric. The PDF metric is scaled by $10^8$ for better readability. | 485 | 2022-23 |
| NAlpha | b_module_total | Estimates a company's propensity for short, medium and long-term material impacts on biodiversity. It is the mean value of all of Nature Alpha's Biodiversity Impact submodules, presented as a percentage. | 484 | 2024 |
| S&P | Aggregate Impact: Ecosystem Footprint (HSA) | A significance-weighted and condition-adjusted area footprint of a company's operations. | 479 | 2021 |
| BIA-GBS | corpo-FINormalized Score | Estimates the total impacts of companies, measured in MSA.pbb. | 99 | 2016–21 |
| FSupply | nSTAR*sales | The nSTAR metric estimates the proportional biodiversity impact of a standardised USD$1 000 000 investment per company. The value does not take into account company size. Given this, to make the nSTAR metric comparable to the other tool's metrics, it was multiplied by company sales. | 495 | 2023 |

**Supplementary Table. 4:** Overview of each tool's selected value-adjusted impact metric for the quantitative analysis, and the number of observations aligned with other tools.

| **Tool** | **Metric** | **Definition** | **Firms** | **Years** |
|---|---|---|---|---|
| GID | MSA-loss.ha / USD2022output + PDF.ha / USD2022output | Sum GID's PDF and MSA impacts per dollar of 2022 metrics were aggregated to calculate total firm bio-ha metrics. | 500 | 2022 |
| GIST Impact | TOTAL_GLOBAL PDF/sales | TOTAL_GLOBAL_PDF divided by annual sales. | 469 | 2022 |
| IDL | CBF Indicator Sales Value | CBF Value divided by total sales. | 474 | 2021–23 |
| MSCI | GLOBAL_SPECIES EXTINCT INTENS RECENT | GLOBAL_SPECIES_EXTINCT divided by total sales. | 485 | 2022–23 |
| NAlpha | l_module total | Normalised biodiversity impact score per dollar of revenue. | 485 | 2024 |
| S&P | Ecosystem Footprint/sales | Ecosystem Footprint divided by annual sales. | 476 | 2021 |
| BIA-GBS | corpoFINormalized-Score/sales | corpoFINormalizedScore divided by annual sales. | 99 | 2016–21 |
| FSupply | nSTAR | nSTAR divided by annual sales. | 500 | 2023 |

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- Funding - This research was supported by Franklin Templeton. The funder had no role in the design, analysis, interpretation, or decision to publish the findings, and the research was conducted independently by the authors.
- Conflict of interest/Competing interests (check journal-specific guidelines for which heading to use) - The authors have no competing interests to declare.
- Ethics approval and consent to participate - All interviews with tool providers were conducted under University of Melbourne Human Ethics approval, protocol number 30490
- Data availability - Data from biodiversity impact tools used for analysis is protected under Non-Disclosure Agreements (NDA) and cannot be shared publicly.
- Code availability - GitHub repository


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