Business Strategy and the Environment

WILEY

Business Strategy and the Environment

RESEARCH ARTICLE OPEN ACCESS

From Diversity to Confusion? The Challenge of Biodiversity Footprint Quantification

Raphaela Roeder | Sebastian Utz

Faculty of Business and Economics and Centre for Climate Resilience, University of Augsburg, Augsburg, Germany

Correspondence: Sebastian Utz (sebastian.utz@uni-a.de)

Received: 22 December 2024 | **Revised:** 2 February 2025 | **Accepted:** 11 February 2025

Funding: This research was supported by the University of Augsburg x Green Research Network BRaVE.

Keywords: biodiversity | biodiversity footprint | disagreement

ABSTRACT

This study documents a significant disagreement between the biodiversity footprints of three major providers. This disagreement mainly stems from fundamental disagreement on the underlying methods and data (measurement), while providers agree to a large part on which firm operations contribute to a loss in biodiversity and how they are aggregated (scope and weight). The disagreement is especially high for large firms with a high biodiversity footprint and firms from the industries of Energy, Consumer Staples, and Basic Materials. A transparent and detailed ESG disclosure can decrease the disagreement. The results highlight the importance of being careful when integrating biodiversity footprint into financial decision-making, regulations, and academic research. The results also underline the need for further standardized and transparent biodiversity disclosure on firm level.

1 | Introduction

Humanity is facing an unprecedented loss in biodiversity.[1] Recently, this loss has gained awareness among investors, decision-makers, and firms, driven by increasing regulation around the disclosure and measurement of a firm's impact and dependencies on nature. In December 2022, the Global Biodiversity Framework (GBF) was signed by 196 countries, calling on firms to disclose their impact on biodiversity, and in September 2023, the Taskforce for Nature-related Financial Disclosure (TNFD) published their final set of recommendations for firms and financial institutions to "identify, assess, manage and (…) disclose nature-related issues" (TNFD 2023b, p.7). Already in 2021, the French government obligated financial institutions in Article 29 of the Energy and Climate Law to disclose their exposure to biodiversity-related risk as well as their impact on biodiversity, referring to so-called biodiversity footprints (Art. 29, LEC).

In response to these regulatory developments, firms and investors are increasingly measuring and disclosing their impact and dependencies on nature. Biodiversity footprints—quantitative metrics describing the negative impact of a firm's operations on biodiversity—have emerged as influential tools used by firms, financial institutions, researchers, and more (TNFD 2023a). A variety of data providers now offer firm-level biodiversity footprints. However, measuring a firm's impact on nature is a complex and challenging process as the impact on biodiversity is multilayered and stems for example from resource use, waste and water management, and greenhouse gas emissions. Since the regulatory frameworks require reliable data sources to be effective, understanding the methods and the agreement of biodiversity footprints by different providers is key.

Various studies assess the agreement of other sustainability ratings and find substantial disagreement between different providers for ESG scores (Berg, Kölbel, and Rigobon 2022; Chatterji et al. 2016; Christensen, Serafeim, and Sikochi 2022; Dorfleitner, Halbritter, and Nguyen 2015; Widyawati 2020), SDG ratings (Bauckloh et al. 2024), physical climate risk scores (Hain, Kölbel, and Leippold 2022), and ITR ratings (Kathan, Utz, and Chmel 2023). The low correlation of sustainability ratings raises questions about their usefulness. In general, sustainability ratings have predictive power for future ESG news, but that relationship weakens for firms with a high disagreement between raters (Serafeim and Yoon 2023). Moreover, stronger ESG score disagreement is associated with higher stock return volatility, larger absolute price movements (Christensen, Serafeim, and Sikochi 2022), and higher stock returns, suggesting a risk premium for those firms (Avramov et al. 2022; Gibson, Krueger, and Schmidt 2021). Similarly, a low level of agreement between SDG ratings affects the risk-return characteristics of the rated firms (Bauckloh et al. 2024).

Methods to assess biodiversity impact have been developed and discussed in the Life Cycle Assessment (LCA) literature for some time (e.g., Winter et al. 2017; Wilting et al. 2017). Recently, they are also gaining increasing relevance among scholars and decision-makers in the business and finance communities, where biodiversity footprints are often used as a measurement for firm-level biodiversity impact. It has been shown that investors are including biodiversity footprints in their investment decisions, as a biodiversity footprint premium began emerging after COP15 (Garel et al. 2024). Coqueret et al. (2025) additionally find that the same biodiversity footprint impacts both the expected and realized stock returns. Even when only focusing on the firm-level exposure of land use, one of the main drivers of biodiversity loss, a link to stock returns can be found (Xiong 2024). While this research focuses on biodiversity impact, another stream of literature has investigated biodiversity risk, that is, both the physical risk arising from a loss in biodiversity and the transitional risk associated with new regulations and rules to stop the decline in biodiversity. Giglio et al. (2024) developed an approach to measure the firm-level exposure to biodiversity risk from firms' 10-K reports. This risk already affects equity prices (Giglio et al. 2024) and hinders firm performance (Bach, Hoang, and Le 2024). Moreover, firms that better manage biodiversity risk and the closely connected water and pollution risks profit from better long-term refinancing conditions (Hoepner et al. 2023) and suffer less stock price crashes (Bassen et al. 2024). There is also a positive relationship between firm biodiversity disclosure and return on assets (Elsayed 2023). Further literature in the biodiversity finance field focuses on the biodiversity finance gap and financing mechanisms that can contribute to conserve biodiversity, for instance, blended finance structures (Flammer, Giroux, and Heal 2025; Karolyi and Tobin-de la Puente 2023).

The above mentioned studies emphasize the increasing importance of biodiversity in firm and investment decisions, as well as the use of biodiversity footprints by decision-makers and scholars. They thereby underline the need for a better understanding of the metrics, as well as the severity of potential consequences from its disagreement. This paper aims to contribute to this literature by analyzing the footprints of three major providers (i.e., ISS ESG, Iceberg Data Lab, and Impact Institute). After briefly describing the process of calculating a biodiversity footprint in general, we test the level of agreement between the biodiversity footprints of the three providers on a global set of 941 firms using different measures for pair-wise and multiple provider comparison. We find substantial disagreement for all providers. Subsequently, we investigate the reasons for the disagreement by following Berg, Kölbel, and Rigobon (2022) and distinguishing scope, measurement, and weight disagreement between providers. We find that while providers generally focus on similar factors when calculating the footprint, there are strong differences in the measurement of those factors. Aggregating those factors into impact drivers that are responsible for the loss in biodiversity reveals that the firms' contribution to land use & pollution as well as climate change is a large factor on its overall contribution to biodiversity loss. Consequently, the providers' disagreement stems in a large part from the discrepancies on these factors. Using cross-sectional regressions, we find that the disagreement is particularly strong for large firms and firms from the industries of Energy, Basic Materials, and Consumer Staples. In contrast, firms from the industries of Telecommunications and Financials exhibit a lower disagreement. Moreover, detailed and transparent ESG disclosure on firm level as well as a high share of institutional investors tend to decrease the disagreement by the providers.

Our findings have important implications for businesses, regulators, investors, and other users of biodiversity footprints. The disagreement between the biodiversity footprints can harm the very purpose of them, making it difficult to evaluate the impact of a firm on biodiversity. If the users are not aware of the different methodologies or do not consider them appropriately when choosing and using a biodiversity footprint, the footprints do not contribute sufficiently to decreasing the information asymmetry between businesses and stakeholders about their impact on biodiversity. This has far-reaching consequences: Efforts to reallocate capital into biodiversity-friendly firms are being mitigated, firms' uncertainty about the material factors of biodiversity performance increases, and their incentive to improve their biodiversity performance decreases. In addition, it reduces the reliability of the results of academic studies based on such metrics.

The remainder of the paper is structured as follows. Section 2 describes the theoretical framework that this study is based on. In Section 3, we first describe how biodiversity impacts are measured and how a biodiversity footprint is calculated in general. Subsequently, we describe our sample. Section 4 starts by showing the significant disagreement between the providers, then decomposing the disagreement in scope, measurement, and weight, and identifying the contribution of each to the overall disagreement. Section 5 analyzes determinants of the disagreement, and Section 6 documents the robustness of our main results. We conclude in Section 7.

2 | Theoretical Background

Institutional theory provides the theoretical foundation of why businesses and other stakeholders (such as investors) demand consistent biodiversity footprints. A key element of the institutional theory is the concept of institutional pressures, which, for example, describe a society's ethical expectations on an organization's behavior (Meyer and Rowan 1977; DiMaggio and Powell 1983; Scott and Meyer 1994). The responses of a firm to institutional pressures are mainly driven by the motivation to ensure its legitimacy (Meyer and Rowan 1977). Legitimacy is critical for a firm's survival as it ensures access to important resources such as capital and talent. It also decreases the probability of being targeted with retributions like fines or loss of sales (Deegan 2002a). In that sense, sustainability reports can be seen as means to obtain approval from society, comply with the "community license to operate" and support its continued existence (Deegan 2002b). While reporting on climate-related issues such as carbon emissions is increasingly being standardized, biodiversity-focused disclosure is found to be very limited, inconsistent, and highly variable between firms (Hassan, Roberts, and Atkins 2020; Adler et al. 2017; Adler, Mansi, and Pandey 2018). Alarmingly, firms with a significant negative impact on biodiversity even adopt reporting strategies aimed at neutralizing stakeholder concerns rather than providing transparency (Boiral 2016). This inconsistent reporting environment of biodiversity impact leads to a high level of uncertainty and information asymmetry regarding biodiversity impacts for stakeholders.

Biodiversity footprints, like other third-party sustainability ratings, have the potential to reduce information asymmetry by acting as intermediaries between firms and stakeholders (Bauckloh et al. 2024; Chatterji and Toggel 2010). Still, this potential can only be realized if the available footprint measures provide an accurate and consistent signal of a firm's biodiversity impact. To the best of our knowledge, there is no research around the reliability and consistency of biodiversity footprints yet. Since there are numerous models that can be used for calculating biodiversity impact (e.g., Damiani et al. 2023, with a review of 64 methods), and the usage of different models has been found to lead to different results (Sany-Mengual et al. 2023), the footprints by different providers might also exhibit significant differences. This observation would add to the finding of studies that raise concerns regarding the accuracy and consistency of other sustainability ratings. It has been found that firms implement superficial actions primarily to improve their ratings rather than to achieve substantive environmental improvements (Cornaggia and Cornaggia 2023; Clementino and Perkins 2020; Chelli and Gendron 2013). Moreover, sustainability ratings exhibit significant disagreement among providers (Chatterji et al. 2016; Berg, Kölbel, and Rigobon 2022; Bauckloh et al. 2024; Hain, Kölbel, and Leippold 2022; Kathan, Utz, and Chmel 2023). This lack of clarity can hinder appropriate decision-making by investors and other stakeholders, which has severe asset pricing implications (Avramov et al. 2022; Gibson, Krueger, and Schmidt 2021; Serafeim and Yoon 2023; Christensen, Serafeim, and Sikochi 2022). Discrepancies among biodiversity footprints could lead to similarly adverse consequences, especially considering that financial institutions often apply them too simplistic (TNFD 2023a). Biodiversity disclosure and biodiversity risk are already affecting stock returns (Elsayed 2023; Giglio et al. 2024). Biodiversity footprints of third-party providers have also been found to have implications for asset pricing (Garel et al. 2024; Coqueret et al. 2025).

While the disagreement between ESG scores can be related to different perceptions of what sustainability is, the biodiversity footprint focuses clearly on the firm's impact on the diversity of species. Therefore, on the one hand, biodiversity footprints could provide a clearer signal and agree more strongly than other sustainability ratings, such as ESG scores. On the other hand, differences in ESG scores have been found to be strongly driven by differences in measurement (Berg, Kölbel, and Rigobon 2022). Differences in measurement can also lead to disagreement between biodiversity footprints, in particular taking into account the multitude of possibly underlying methods and models (Damiani et al. 2023; Sany-Mengual et al. 2023). This variability might even be more pronounced, as the impact on biodiversity is multilayered, firm disclosures are unclear (Hassan, Roberts, and Atkins 2020; Adler et al. 2017; Adler, Mansi, and Pandey 2018), and the footprint is explicitly trying to capture the impact through the whole value chain of the firm and the entire life cycle of its products.

Our study empirically tests whether biodiversity footprints are a suitable means for firms (stakeholders) to ensure (assess) legitimacy. For this purpose, we analyze whether the providers create a clear signal of firms' biodiversity impact.

3 | Sample and Data

3.1 | Measuring Biodiversity Impacts

Research institutions (e.g., Oxford Biodiversity Network 2023; University of Cambridge Institute for Sustainability Leadership 2020), firms (e.g., ASN Bank and PRé Sustainability 2022; Kering 2021), governments (e.g., Broer et al. 2021), and data providers have developed methodologies and metrics to measure the impact and dependencies of a firm on nature. Over time, the so-called biodiversity footprint has become the most commonly used method to measure and express a firm's impact on nature.

While there is no clear agreement on a definition for a biodiversity footprint, the Institute for European Environmental Policy (IEEP) mentions that it has to be "measured in terms of biodiversity change as a result of production and consumption of particular goods and services" (IEEP 2021, p. 12), and the Partnership for Biodiversity Accounting Financials (PBAF) emphasizes that the impact must be quantified (PBAF 2022).

The calculation of the biodiversity footprint is based on a LCA approach. LCA is used to quantify a product's or organization's impact on the environment over its full life cycle and in that context the impact on biodiversity has been explored already for over 20 years (Winter et al. 2017), long before biodiversity became a relevant topic in the finance industry. Today, there is a wide variety of methodologies to calculate a biodiversity footprint (Damiani et al. 2023). While the footprints of some providers are developed to analyze the impact of a firm on nature, others focus only on investments, products, and projects, as well as industries and countries. Moreover, the methodologies differ in the data used, the calculations, the outcome metric, and more. In this paper, we employ firm-level footprints generated by third-party data providers.

The first step to calculate the footprint of a firm is to identify environmental inputs and outputs that are linked to the firm's business activities. These aspects include the amount of water used, the emitted greenhouse gas emission, and the amount of land that a firm uses. Factors like the diversity of species and the amount of endangered species in a firm's operating areas also affect the biodiversity footprint. That information is usually based on geospatial data and often stems from further third party providers, for example, the Integrated Biodiversity Assessment Tool (IBAT). If a firm is not providing specific information but their peers do, some providers use a benchmarking approach, others developed sophisticated machine learning methods. In the second step, firm-specific input and output variables are translated into impact drivers which exert pressure on biodiversity by contributing to (1) habitat loss, (2) overexploitation, (3) climate change, (4) pollution, and (5) the introduction of invasive species (IPBES 2019). Lastly, the impact of these pressures is measured and usually expressed in "Mean Species Abundance" (MSA) or "Potentially Disappeared Fraction of Species" (PDF) (PBAF 2022; Broer et al. 2021). Both MSA and PDF are measures of biodiversity intactness. The MSA compares the abundance of an original species in an area to the estimated abundance if the ecosystem would be undisturbed and is expressed as a percentage rate (Hertog, Bor, and de Horde 2022; Schipper et al. 2020). The PDF shows the fraction of species lost in a specific area due to environmental pressures, without taking a decline in species population into account (Hertog, Bor, and de Horde 2022). However, it is also possible to express the footprint in other measures, such as a loss of pristine biodiversity per hectare or in a monetized way.

Besides calculating a biodiversity footprint, the impact and dependencies of a firm on nature can be expressed in other aggregated scores. For instance, the World Benchmark Alliance publishes its assessment of the impact on biodiversity of over 800 firms on a scale from 0 to 100.[2] It is important to note that most biodiversity scores that are not biodiversity footprints focus only on partial aspects of biodiversity or use simplified approaches to capture biodiversity impacts and risks. Examples comprise the rating of the commitment of over 700 financial institutions to deforestation generated by the nonprofit organization Global Canopy,[3] the percentage value stating to what level a firm complies with the "Do No Significant Harm" goal regarding the biodiversity objective of the EU Taxonomy of Bloomberg, and the scoring of the exposure of US firms to biodiversity risks based on a textual analysis of their 10-K statements (Giglio et al. 2024; Bach, Hoang, and Le 2024). Per definition, these scores are not constructed to capture the impact of a firm on biodiversity as a whole, while the marked goal of biodiversity footprints is to include the entire range of biodiversity aspects throughout the whole life cycle of a product or a firm. Therefore, we are limiting the analysis to footprint measures.

3.2 | Sample Description

We obtain the most recently available biodiversity footprints in January 2024 from the three providers Iceberg Data Lab (IDL), Impact Institute (II), and ISS ESG (ISS). All three scores are recommended by the Finance for Biodiversity Foundation and the EU Business and Biodiversity Platform (Bailon, Bor, and Redn 2024); the scores by IDL and II are also recommended by the TNFD (TNFD 2023a). Moreover, the biodiversity footprints by IDL have already been used in different research (Coqueret et al. 2025; Garel et al. 2024). IDL discloses the footprint and the underlying impact drivers in MSA.km2, ISS both in PDF.km2 and MSA.km2, and II in MSA.ha and PDF.ha. To ensure comparability, we z-standardize these values for the empirical analysis. A higher number indicates a larger biodiversity footprint, meaning a stronger negative impact of a firm on biodiversity.

Our sample per provider consists of 3388 firms (IDL), 1516 firms (II), and 17,931 firms (ISS). The final data set consists of all firms that have been rated by all three providers and are publicly traded, leaving a set of 941 firms. Henceforth, the providers will be anonymized and labeled only as "Provider 1", "Provider 2", and "Provider 3" to ensure discretion regarding their exact methodologies.

Table 1 shows the average standardized footprint by industry and region per provider. Most of the analyzed firms' headquaters are located in North America (405 firms) and Europe (258 firms), operating in the Financials, Industrials, Consumer Discretionary, and Technology industry. Further, Table 1 indicates a strong disagreement between providers on region- and industry-level. Across regions, Latin America has the highest mean footprint for Providers 2 and 3 but the smallest mean footprint for Provider 1. Similar strong disagreements can be found when comparing the average footprints by industry per provider. There is no agreement on which industry has the most or the least average impact on biodiversity. Still, the Energy and Consumer Staples industries display a high average biodiversity footprint for all providers, with a standardized mean footprint ranging between 0.132 and 1.572, and 0.028 and 0.887, respectively. In contrast to that, the industries Real Estate, Technology, and Telecommunications tend to have a small impact on biodiversity, with a footprint below the mean of zero for all providers.

Table 2 presents the distribution of the standardized footprints per provider. It demonstrates that for all providers, very few firms have an extremely large footprint, with the maximum ranging between 19.369 for Provider 1 and 29.483 for Provider 4.[4] A large share of the remaining firms has very similar-sized footprints well below the mean. The median ranges between −0.248 for Provider 2 and −0.050 for Provider 3.

4 | The Disagreement of Biodiversity Footprints

This section discusses the level of agreement between the biodiversity footprints of different providers.

4.1 | Association Measures

Table 1 indicates strong disagreement between all providers on region- and industry-level. Moreover, anecdotal evidence also suggests disagreement on firm-level. Walmart, for example, has a standardized footprint of 11.58 for Provider 1 but −0.029 for Provider 3. To further understand the agreement on firm-level, we calculate metrics for pair-wise (Pearson and Spearman correlation) and multiple (Krippendorff's alpha) provider comparison. While the Pearson correlation measures the linear and the Spearman correlation the rank-based relationship between two continuous variables, Krippendorff's alpha is commonly used to analyze inter-rater reliability. A value of 1 indicates perfect agreement, a value of 0 the complete absence of agreement, and

TABLE 1 | This table reports the mean and standard deviation of the standardized biodiversity footprint by the different providers, distributed by region (Panel A) and ICB industry classification (Panel B).

		Provider 1		Provider 2		Provider 3	
	N	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Panel A: Regions							
Asia Ex Japan	48	0.271	2.859	−0.069	1.066	−0.038	0.061
Europe	258	0.028	0.827	0.030	1.422	−0.043	0.026
Japan	184	−0.125	0.290	−0.165	0.423	−0.045	0.011
Latin America	6	−0.220	0.093	0.157	0.904	4.872	12.057
North America	405	0.028	0.936	0.071	0.879	−0.015	0.414
Oceania	40	−0.177	0.235	−0.095	0.496	−0.048	0.005
Panel B: Industries							
Basic materials	45	0.271	1.246	−0.052	0.378	−0.041	0.011
Consumer Discretionary	148	0.025	1.148	−0.017	0.902	−0.046	0.008
Consumer Staples	82	0.887	2.415	0.468	1.213	0.028	0.324
Energy	37	0.132	0.447	1.572	3.552	0.986	4.982
Financials	146	−0.073	0.425	−0.173	0.304	−0.050	0.002
Health Care	91	0.011	0.926	−0.047	0.587	−0.044	0.013
Industrials	175	−0.173	0.192	−0.123	0.447	−0.047	0.009
Real Estate	54	−0.271	0.017	−0.347	0.045	−0.050	0.001
Technology	114	−0.240	0.071	−0.204	0.450	−0.048	0.009
Telecommunications	20	−0.271	0.016	−0.081	0.414	−0.049	0.001
Utilities	29	−0.218	0.060	0.105	0.488	−0.049	0.002

TABLE 2 | This table reports the distribution of the standardized footprints per provider by presenting the minimum, maximum, and the 1%, 10%, 50%, 90%, and 99% percentiles.

	Minimum	1% perc.	10% perc.	50% perc.	90% perc.	99% perc.	Maximum
Provider 1	−0.281	−0.281	−0.281	−0.241	0.324	3.606	19.369
Provider 2	−0.379	−0.377	−0.361	−0.248	0.496	3.374	20.923
Provider 3	−0.051	−0.051	−0.051	−0.050	−0.035	0.073	29.483

Note: The mean standardized footprint for all providers is zero, due to the z-standardization.

a negative value indicates systematic disagreement. A value greater than 0.8 can be interpreted as sufficient agreement, while 0.667 is the lowest acceptable limit to conclude any agreement (Krippendorff 2004).

Table 3 shows the correlation matrices of the standardized biodiversity footprint of our sample firms. The Pearson correlation ranges between 0.024 and 0.493 with an average of 0.206, and the Spearman correlation ranges between 0.619 and 0.745 with an average of 0.670. The overall Krippendorff's alpha for all raters is 0.206. We also calculate Krippendorff's alphas for all combinations of two providers and find values in the range of 0.025 and 0.493 (unreported results). No pair of providers displays a Krippendorff's alpha higher than the threshold of 0.667, suggesting no systematic agreement between the different footprints. Overall, the disagreement on firms' biodiversity footprint measured by Krippendorff's alpha is substantially higher than the disagreement on ESG scores, which already has severe consequences (Serafeim and Yoon 2023; Avramov et al. 2022; Christensen, Serafeim, and Sikochi 2022). ESG scores from different providers have a Krippendorff's alpha of 0.55 (Berg, Kölbel, and Rigobon 2022). The average pairwise Pearson correlations between 0.45 (Gibson, Krueger, and Schmidt 2021) and 0.54 (Berg, Kölbel, and Rigobon 2022) are of similar size as the correlations we observe for the biodiversity footprint. Thus, we document indications that the biodiversity footprints of the considered providers differ substantially. In the following sections, we analyze where the disagreement comes from and for which firms it is particularly pronounced.

4.2 | Reasons for Disagreement

In the following section, we explore the reasons for the providers' disagreement. Following Berg, Kölbel, and Rigobon (2022)'s analysis of the disagreement between ESG raters, the causes for inter-rater disagreement can stem from divergence in scope, measurement, and weight. Like ESG scores, biodiversity footprints are based on different indicators. Consequently, also the disagreement in the biodiversity footprints can be decomposed into these factors. In our case, scope refers to the different impact drivers that the providers consider when calculating the footprint, measurement to differences in the calculations on impact driver level, and weight to the weight with which each impact driver contributes to the final score.

Scope. Divergence in scope occurs if the providers are measuring different factors to capture a firm's biodiversity impact. As described above, the biodiversity footprints are calculated by identifying how a firm's activities contribute to different impact drivers. Beneath these impact drivers lie different indicators, for example, specific gas emissions contributing to air pollution or differentiation between freshwater and marine acidification, both contributing to water pollution. The aggregated number of considered indicators varies from 4 to 13 across the three providers. Comparing the number and depth of these indicators only gives insight into the granularity of the data that the providers share with their clients, but it would be false to assume that it can be translated into divergences in scope. Therefore, we summarize the indicators into impact drivers that they contribute to and compare them. Providers 1 and 2 consider the four impact drivers Climate Change, Air Pollution, Water Pollution, and Land Use & Pollution. Provider 3 individually shares indicators for Climate Change, Land Use & Pollution, Water Pollution, and Water Extraction.

TABLE 3 | This table reports the pair-wise Pearson and Spearman correlation of each provider pair.

	Provider 1	Provider 2	Provider 3
Panel A: Pearson correlation			
Provider 1	—	0.493	0.024
Provider 2	0.493	—	0.100
Provider 3	0.024	0.100	—
Panel B: Spearman correlation			
Provider 1	—	0.619	0.646
Provider 2	0.619	—	0.745
Provider 3	0.646	0.745	—

The providers express the contribution of each indicator to the decline in biodiversity in the same metric that they use for the footprint (PDF or MSA). Aggregated, the values of all indicators add up to the entire footprint. This allows us to measure the contribution of each impact driver to the entire footprint by calculating the average share of the aggregated indicator values that are underlying the respective impact driver to the entire footprint:

$$\text{Contribution}(d_i) = \frac{1}{941} \sum_{f \in \{1,\ldots,941\}} \frac{\sum_{ind \in d_i} ind_{fi}}{F_{fi}} \tag{1}$$

In Equation (1), f denotes one of the 941 investigated firms, d_i the impact driver by Provider i, ind_{fi} the value of the underlying indicator for firm f by Provider i and F_{fi} the complete footprint of firm f by Provider i. Naturally, the contributions of all impact drivers per provider sum up to 1. Table 4 shows the contribution of each impact driver per provider in %. On average, the impact driver Land Use & Pollution contributes 67.17% to the overall footprint and is therefore the most influential impact driver, followed by Climate Change, which contributes on average 17.06%.

Measurement. Divergences in measurement describe how providers use different approaches and data to measure the same factor. This can stem from different ideas about which firm activities contribute in which way to an impact driver, and from different approaches to solving the issue of missing data. As regulations on biodiversity disclosure are globally still in a very early stadium, many firms only provide very limited information about their impact on biodiversity (Adler et al. 2017; Adler, Mansi, and Pandey 2018; Hassan, Roberts, and Atkins 2020). While some providers use a benchmark approach to fill these data gaps, others have developed machine-learning models.

TABLE 4 | This table shows the average contribution of each impact driver to the entire footprint (in %).

Impact driver	Provider 1	Provider 2	Provider 3
Climate Change	22.13	28.18	0.87
Land Use & Pollution	51.53	51.56	98.41
Air Pollution	6.82	19.34	0
Water Pollution	19.52	0.92	0.71
Water Extraction	0	0	0.00

TABLE 5 | This table shows the pair-wise Pearson (Spearman in parentheses) correlations between the providers for each impact driver as well as Krippendorff's alpha measuring the agreement over all raters.

	Climate Change	Land Use & Pollution	Air Pollution	Water Pollution
Pearson (Spearman) correlation between Provider 1 and				
Provider 2	0.546	0.660	0.442	0.158
	(0.667)	(0.507)	(0.651)	(0.344)
Provider 3	0.002	0.311		−0.006
	(0.672)	(0.553)		(0.495)
Pearson (Spearman) correlation between Provider 2 and				
Provider 3	0.083	0.403		0.039
	(0.850)	(0.718)		(0.669)
Krippendorff's alpha	0.211	0.458	0.442	0.064

The divergence in measurement is assessed by calculating the same agreement measures as for the overall footprint for the value of the different impact drivers. A low agreement on impact driver level would point out that the overall disagreement cannot only stem from discrepancies in the provider's perception about what contributes to biodiversity loss (scope) and to which degree (weight) but that they also in fact have different ways of measuring the same aspects. The results in Table 5 show that the highest agreement between the providers is on the Land Use & Pollution of the firms, reaching a Krippendorff's alpha of 0.458. The agreement for the impact drivers Air Pollution and Climate Change is higher than for the overall footprint as well, with a Krippendorff's alpha of 0.442 and 0.211, respectively. On the other hand, there seems to be a lot of uncertainty around Water Pollution. Still, Krippendorff's alpha does not exceed the limit of 0.667 for any of the impact drivers, indicating no systematic agreement also on impact driver level.

Weight. Berg, Kölbel, and Rigobon (2022) also study the weight of the indicators in their study on ESG scores. In our cases, the considered biodiversity footprints of IDL, II, and ISS follow an equally weighted aggregation scheme, that is, the weights are known. As all footprints follow an equal-weighting in general, we expect weight not to be a substantial driver of the observed disagreement. A theoretical argument that weight should not drive the disagreement is based on the unit at which the biodiversity footprints are measured. The footprints are typically expressed in MSA or PDF units, which essentially quantify the number of species or individuals of a species that a firm displaces or eliminates within a particular region. Impact drivers provide more granular data, indicating that a firm's land use results in the extinction of x species/individuals, while water pollution causes the loss of y species/individuals, for instance. Naturally, impact drivers are simply summarized, and while different weighting makes sense for ESG scores, it does not for footprints in MSA and PDF units.

4.3 | Decomposition

The previous section showed that the providers disagree both in scope and measurement. In this section, we follow Berg, Kölbel, and Rigobon (2022) and decompose the footprints to determine how much each factor contributes to the overall disagreement between the footprints.

Let F_{fi} be the not-standardized footprint of a firm f, given by a Provider $i \in \{1;2;3\}$. For each two Providers i, j $(i, j \in \{1;2;3\}, i \neq j)$, it then holds:

$$F_{fi} = D_{fi,com} + D_{fi,ex} \tag{2}$$

where $D_{fi,com}$ is the sum of the impact drivers by provider i that i has in common with provider j for firm f, measured in PDF or MSA depending on the provider, and $D_{fi,ex}$ is the sum of the mutually exclusive impact drivers of provider i and j, by provider i for firm f.

As the original footprints are given in different metrics depending on the provider (PDF or MSA), we have to standardize the footprints to the same unit when we analyze the differences in the footprints of two providers. It follows from the formula of the z-standardization that for the standardized footprint F^z_{fi} of firm f by Provider i, it holds the following:

$$F^z_{fi} = \underbrace{\sum_{d_{fi} \in D_{fi,com}} \frac{d_{fi} - \frac{1}{N_i}\mu_i}{\sigma_i}}_{:=D^z_{fi,com}} + \underbrace{\sum_{d_{fi} \in D_{fi,ex}} \frac{d_{fi} - \frac{1}{N_i}\mu_i}{\sigma_i}}_{:=D^z_{fi,ex}} \tag{3}$$

where d_{fi} is the value of a single impact driver by Provider i for firm f from either the set of common impact drivers $D_{fi,com}$ or the set of exclusive impact drivers $D_{fi,ex}$, μ_i is the cross-sectional mean of all aggregated footprints by Provider i, σ_i the standard deviation of the aggregated footprints by Provider i, and N_i the number of impact drivers (both exclusive and common) that Provider i is including. In our case, N_i is 4 for all providers. For easier readability, we define the first summand of Equation (3) as $D^z_{fi,com}$ and the second summand as $D^z_{fi,ex}$.

Consequently, we can decompose the difference $\Delta^z_{fi,j}$ in the standardized footprints by Providers i and j for firm f in the following way:

$$\begin{aligned}\Delta^z_{fi,j} &= F^z_{fi} - F^z_{fj}\\ &= \underbrace{D^z_{fi,com} - D^z_{fj,com}}_{:=\Delta^z_{fi,j,meas}} + \underbrace{D^z_{fi,ex} - D^z_{fj,ex}}_{:=\Delta^z_{fi,j,scope}}\end{aligned} \tag{4}$$

We define $\Delta^z_{fi,j,meas}$ as the difference between $D^z_{fi,com}$ and $D^z_{fj,com}$, stemming from divergence in the measurement of the common impact drivers, and $\Delta^z_{fi,scope}$ as the difference between $D^z_{fi,ex}$ and $D^z_{fj,ex}$, stemming from differences in the scope of each provider.

As all ratings are normalized to have a mean of zero, the total difference between two ratings sums to zero as well. However, the firm-specific differences vary from zero. By using the variance as a measure of disagreement, we obtain summary statistics of these differences. Therefore, we take the variance over the sample of firms in Equation (4) and obtain the following:

$$\begin{aligned}Var(\Delta^z_{i,j}) &= Cov(\Delta^z_{i,j}, \Delta^z_{i,j})\\ &= Cov(\Delta^z_{i,j}, \Delta^z_{i,j,meas}) + Cov(\Delta^z_{i,j}, \Delta^z_{i,j,scope})\end{aligned} \tag{5}$$

Now we can calculate the contribution of scope and measurement to the disagreement as

$$\begin{aligned}\text{Contribution Measurement} &= \frac{Cov(\Delta^z_{i,j}, \Delta^z_{i,j,meas})}{Var(\Delta^z_{i,j})}\\ \text{Contribution Scope} &= \frac{Cov(\Delta^z_{i,j}, \Delta^z_{i,j,scope})}{Var(\Delta^z_{i,j})}\end{aligned} \tag{6}$$

Table 6 presents the results of Equation (6) for each pair of providers, and the average for each provider. Overall, the contribution of measurement to the overall disagreement is 96.29% and thus considerably higher than that of scope (3.71%). As Providers 1 and 2 consider the same impact drivers, their disagreement stems only from divergence in measurement. Despite considering a unique set of impact drivers compared to the other providers, the average contribution of scope divergence to the overall disagreement is only 5.56% for Provider 3. This can be explained by the contribution of each impact driver to the entire footprint that is presented in Table 4. The impact driver Water Extraction, which is not considered by Providers 1 and 2, only has a very small impact on the overall footprint by Provider 3, while the impact driver Land Use & Pollution, which is shared with both other providers, contributes by far the most to the entire footprint.

5 | Determinants of the Disagreement

In this section, we analyze how the disagreement between the impact driver and different firm characteristics is driving the overall disagreement. For that purpose, we follow Bauckloh et al. (2024) and calculate the two firm-level disagreement measures *sd* and *max–min*. *sd* is the standard deviation of the three standardized footprints per firm, while *max–min* is the difference between the maximum and the minimum standardized footprint for each firm. The same disagreement measures are calculated at the impact driver level.

TABLE 6 | This table presents the contribution of measurement and scope to the disagreement.

		Measurement	Scope
Panel A: Rater pairs			
Provider 1	Provider 2	100.00%	0.00%
Provider 1	Provider 3	99.45%	0.55%
Provider 2	Provider 3	89.43%	10.57%
Average		96.29%	3.71%
Panel B: Rater averages			
Provider 1		99.73%	0.27%
Provider 2		94.72%	5.28%
Provider 3		94.44%	5.56%

First, we explain the variation in the overall *sd* and *max–min* with the respective disagreement measures at the impact driver level by running the following two regression models, using robust standard errors:

$$\begin{aligned}sd_f = \; & \alpha + \beta_1 \times sd(Land\,Use\,\&\,Pollution)_f\\ & + \beta_2 \times sd(Water\,Pollution)_f\\ & + \beta_3 \times sd(Climate\,Change)_f\\ & + \beta_4 \times sd(Air\,Pollution)_f\\ & + \epsilon_f\end{aligned} \tag{7}$$

$$\begin{aligned}max-min_f = \; & \alpha + \beta_1 \times max-min(Land\,Use\,\&\,Pollution)_f\\ & + \beta_2 \times max-min(Water\,Pollution)_f\\ & + \beta_3 \times max-min(Climate\,Change)_f\\ & + \beta_4 \times max-min(Air\,Pollution)_f\\ & + \epsilon_f,\end{aligned} \tag{8}$$

where $sd(impact\,driver)_f$ and $max–min(impact\,driver)_f$ represent the standard deviation and range of the standardized assessments of the three providers for the respective *impact driver* for each firm f. α is the constant term and $\beta_j (j = 1, \ldots, 4)$ are the coefficients estimated in the regression analysis. As the impact driver Water Extraction is exclusively considered by Provider 3, it is not included in this part of the analysis.

Table 7 shows the results. The high R^2 of 0.876 and 0.874 indicate that the overall disagreement can be explained to a large extent through the disagreement at the impact driver level, which underlines the results found in the decomposition (Section 4.3). The disagreement measures of both impact drivers Climate Change and Water Pollution have coefficients significant at 1%-level. Climate Change (Water Pollution) displays a coefficient of 0.387 (0.352) for the *sd*-regression and 0.382 (0.349) for the *max–min*-regression.

Since the agreement on Climate Change is higher than the one of Water Pollution (see Table 5) and its contribution to the aggregated footprint is high (see Table 4), the Climate Change impact driver has (as expected) a strong impact on the aggregated disagreement. Water Pollution has a lower contribution to the overall footprint, but a very strong disagreement, measured by the Pearson and Spearman correlation as well as Krippendorff's alpha. The coefficients of the disagreement measures for the impact driver Air Pollution are low and insignificant, which can be explained by the fact that only Providers 1 and 2 consider it, and that their agreement on it is relatively high. Finally, as the agreement on the impact driver Land Use & Pollution is comparably high (see Table 5), it is reasonable that this impact driver is only significant at the 10% level for the *max–min*-regression.

Next, we explain the variation in *sd* and *max–min* on impact driver level by regressing them on industry and region dummies, as well as different firm characteristics that are balance sheet or transparency related. The regression models are specified as follows:

$$\begin{aligned} sd(impact\ driver)_f = \ & \alpha + \beta_1 \times log(MV)_f + \beta_2 \times Leverage_f \\ & + \beta_3 \times Current\ Ratio_f \\ & + \beta_4 \times Tangibility_f \\ & + \beta_5 \times Number\ of\ Analysts_f \\ & + \beta_6 \times ESG\ Score_f + \beta_7 \times Disclosure\ Score_f \\ & + \beta_8 \times Inst.\ Owner_f \\ & + \beta_9 \times Industry_f + \beta_{10} \times Region_f + \epsilon_f \end{aligned} \tag{9}$$

TABLE 7 | This table presents the regression results of *sd* and *max–min* on the respective disagreement measures on impact driver level.

	(1) sd	(2) max–min
dis(Land Use & Pollution)	0.431	0.455*
	(1.64)	(1.70)
dis(Water Pollution)	0.352***	0.349***
	(4.63)	(4.37)
dis(Climate Change)	0.387***	0.382***
	(5.87)	(5.73)
dis(Air Pollution)	−0.063	−0.094
	(-0.83)	(-1.04)
Constant	−0.036	−0.072
	(−1.39)	(−1.49)
Observations	941	941
R^2	0.876	0.874

Note: This means that, for instance, "dis(Land Use & Pollution)" represents "sd(Land Use & Pollution)" in Column "sd" and "max–min(Land Use & Pollution)" in Column "max–min". Robust standard errors are used.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

$$\begin{aligned} max-min(impact\ driver)_f = \ & \alpha + \beta_1 \times log(MV)_f + \beta_2 \times Leverage_f \\ & + \beta_3 \times Current\ Ratio_f \\ & + \beta_4 \times Tangibility_f \\ & + \beta_5 \times Number\ of\ Analysts_f \\ & + \beta_6 \times ESG\ Score_f \\ & + \beta_7 \times Disclosure\ Score_f + \beta_8 \times Inst.\ Owner_f \\ & + \beta_9 \times Industry_f + \beta_{10} \times Region_f + \epsilon_f \end{aligned} \tag{10}$$

where $log(MV)_f$ is the logarithm of the market capitalization in USD of firm f, $Leverage_f$ is the ratio of total debt to enterprise value of firm f, $Current\ Ratio_f$ refers to the current assets divided by the current liabilities of firm f, $Tangibility_f$ refers to the ratio of plant, property, and equipment to total assets of firm f, $Number\ of\ Analysts_f$ is the number of analysts observing firm f, $ESG\ Score_f$ is the LSEG (formerly Refinitiv Eikon) ESG Score of firm f, $Disclosure\ Score_f$ is the Bloomberg ESG Disclosure Score of firm f, and $Inst.\ Owner_f$ is the percentage share of stocks owned by institutional owners compared to the outstanding shares of firm f, retrieved from Bloomberg. *Industry* and *Region* are dummy variables indicating the ICB industry classification and the region of the headquarter of the firm f. All data are from end of year 2022 and, unless otherwise stated, retrieved from LSEG. As the firm characteristics are not available for the complete data set, this analysis is performed on a subset of 691 firms.

The results of this regression are presented in Table 8 and provide information on which firms are likely to experience low or high disagreement in their biodiversity footprints. The size of the firm, measured by market capitalization, highly contributes to the disagreement for all impact drivers. Its coefficients, which are significant at the 1%-level, range between 0.172 and 0.211 for the *sd*-regressions and between 0.298 and 0.375 for the *max–min*-regression. Furthermore, the industry plays an important role in influencing the level of agreement. Firms in the reference industry Basic Materials, as well as those in the Consumer Staples and Energy industries, exhibit a high level of disagreement across most impact drivers. The disagreement is particularly strong on the impact driver Land Use & Pollution for firms within the Consumer Staples industry and on the impact drivers Climate Change and Air Pollution for firms from the Energy industry. In contrast, firms in the Telecommunications and Financials industries show lower levels of disagreement for nearly all impact drivers. Firms in Latin America experience a lower disagreement on the impact drivers Land Use & Pollution and Water Pollution, and the dummy for the region Oceania has a negative and significant coefficient for the disagreement measures on Water Pollution. Besides that, the firm's region cannot significantly explain the disagreement. Firm-level transparency seems to contribute to a better agreement between providers for the Climate Change and Air Pollution impact drivers. This is displayed by the negative and significant coefficients of the Disclosure Score, a score between 0.1 and 100 that measures the level of detail of both mandatory and voluntary ESG reporting (Yu, Guo, and Luu 2018). All else being equal, a one-point increase in the Disclosure Score results in a reduction of *sd* (*max–min*) of the influential impact driver Climate Change by 0.008 (0.015) and of Air Pollution even by 0.010 (0.014). This is a

TABLE 8 | This table presents the regression result of the dependent variables *sd* and *max–min* on impact driver level on different firm characteristics.

	Land Use & Pollution		Water Pollution		Climate Change		Air Pollution	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	sd	max–min	sd	max–min	sd	max–min	sd	max–min
Log(MV)	0.172***	0.317***	0.182***	0.328***	0.195***	0.375***	0.211***	0.298***
Current ratio	0.008	0.016	0.009	0.015	0.009	0.017	0.012	0.017
Leverage	0.004**	0.008**	0.005**	0.009**	0.002***	0.005***	0.003***	0.005***
ESG score	0.006**	0.011**	0.008**	0.013**	0.006**	0.010**	0.008***	0.012***
Tangibility	0.138*	0.250*	0.002	-0.013	0.072	0.151	0.073	0.103
Number of analysts	−0.002	−0.003	0.003	0.005	−0.002	−0.005	−0.001	−0.001
Disclosure Score	−0.007	−0.013	−0.005	−0.009	−0.008***	−0.015**	−0.010***	−0.014***
Inst. ownership	−0.002**	−0.004**	−0.003**	−0.006**	−0.002*	−0.005*	−0.002	−0.003
Consumer Discretionary	−0.004	0.002	−0.489**	−0.890**	−0.068	−0.128	−0.192**	−0.271**
Consumer staples	0.485***	0.938***	−0.062	−0.135	−0.110*	−0.211*	−0.062	−0.087
Energy	0.182	0.307	−0.079	−0.172	1.479***	2.830***	0.869**	1.229**
Financials	−0.166**	−0.300**	−0.603***	−1.090***	−0.112	−0.210	−0.279***	−0.395***
Health Care	−0.018	−0.020	−0.319	−0.544	−0.120**	−0.227**	−0.235***	−0.332***
Industrials	−0.102*	−0.181*	−0.546**	−0.990**	0.115**	0.198*	0.058	0.082
Real Estate	−0.198*	−0.370*	−0.566**	−1.016**	−0.069	−0.136	−0.286***	−0.404***
Technology	−0.043	−0.066	−0.502**	−0.903**	−0.037	−0.066	−0.160**	−0.227**
Telecommunications	−0.246***	−0.454***	−0.652***	−1.179***	−0.191***	−0.365**	−0.295***	−0.417***
Utilities	−0.273***	−0.508***	−0.713***	−1.293***	0.084	0.157	−0.022	−0.032
Europe	−0.304	−0.606	−0.128	−0.225	0.053	0.097	−0.179	−0.253
Japan	−0.379	−0.744	−0.155	−0.271	0.068	0.118	−0.226	−0.320
Latin America	−0.666**	−1.287**	−0.387**	−0.692**	0.084	0.176	0.311	0.440
North America	−0.192	−0.391	0.022	0.043	0.009	0.016	−0.266	−0.375
Oceania	−0.328	−0.628	−0.271**	−0.474**	−0.186	−0.367	−0.411	−0.581
Constant	−3.529***	−6.463***	−3.663***	−6.561***	−4.176***	−8.029***	−4.401***	−6.223***
Observations	691	691	691	691	691	691	691	691
R^2	0.171	0.171	0.154	0.155	0.341	0.338	0.195	0.195

Note: The reference category for industries is basic materials and for regions Asia ex Japan. Robust standard errors are used.
*$p < 0.10$.
**$p < 0.05$.
***$p < 0.01$.

substantial amount, considering that the average *sd* (*max–min*) of the aggregated footprint over all firms is 0.29 (0.55). The share of institutional owners, which is associated with a higher level of transparency as well, also displays a negative and significant coefficient for the Land Use & Pollution, Water Pollution, and Climate Change impact driver.

The regression results not only indicate which firm characteristics contribute to a low or high agreement, but they also point out that the variations in disagreements across the impact drivers can be attributed to different firm characteristics. For instance, it is noteworthy that a higher Disclosure Score only limits the disagreement for two of the impact drivers. Moreover, the industry and region to which a firm belongs can decrease the disagreement for some impact drivers and increase the disagreement for other impact drivers. The Conusmer Staples industry, for instance, tends to have a high disagreement on the Land Use & Pollution impact driver but a low disagreement for Climate

Change. Consequently, when considering biodiversity footprints and discussing their agreement, it is essential to break them down into impact drivers.

6 | Robutsness Checks

In this section, we test the robustness of our results by excluding outliers from the sample. Table 2 revealed that for all providers, there are some firms with an extremely high biodiversity footprint. To limit the influence of these outliers and at the same time understand their impact on the disagreement, we construct a second data set that excludes all firms with a footprint above the 99%-percentile for at least one of the providers. The resulting data set consists of 920 firms. Compared to the original sample as presented in Table 1, we observe an exclusion of mostly North American firms from the industries of Consumer Staples and Energy.

We perform the same tests on this sample as we did on the original data set. The outcome only changes slightly, revealing that our results are not driven by the outliers but prevail for all firms. The average Pearson correlation over all providers for this sample is 0.473, the average Spearman correlation is 0.653, and the overall Krippendorff's alpha is 0.248. Thus, the agreement increases slightly for this sample. However, Krippendorff's alpha does still not reach the critical value of 0.667 for any combination of providers, and the Pearson correlation is still very low, even lower than the Pearson correlation between most ESG scores. This shows the existence of a substantial disagreement also in the data set excluding the outliers.

Subsequently, we test the impact of scope and measurement divergence on the disagreement in this data set. Naturally, scope divergence exists for the firms in this data set as well, as their footprint is constructed using the same indicators and impact drivers as described in Section 4. To show the existence of measurement divergence, we calculate the agreement measures on impact driver level for this data set as well. The agreement on impact driver level decreases slightly for all drivers beside Water Pollution. The agreement is now the strongest for Air Pollution (Krippendorff's alpha: 0.319), followed by Land Use & Pollution (0.294), Climate Change (0.203), and lastly Water Pollution (0.141). Still, all agreement measures are critically low, indicating the existence of substantial measurement disagreement.

Next, we identify the contribution of measurement and scope divergence to the overall disagreement by executing the decomposition as explained in Section 4.3. The contribution of measurement divergence to the overall disagreement only changes marginally. The average contribution of measurement now lies at 93.26% and that of scope at 6.74%.

We also perform the same regressions as in Section 5 to understand the determinants of the disagreement. In line with the decrease in agreement on the Land Use & Pollution impact driver, its coefficient increases to 0.539 for the *sd*-regression and 0.552 for the *max–min*-regression, becoming significant on 1%-level. This indicates that the disagreement on Land Use & Pollution is in fact highly responsible for the disagreement for most firms. For the firms with the highest footprints, the impact on the overall disagreement is less strong. The coefficients for the disagreement measures on Water Pollution and Climate Change remain statistically significant on 1%-level, with coefficients of 0.244 (*sd*-regression) and 0.233 (*max–min*-regression) for Water Pollution and 0.123 (*sd*-regression) and 0.131 (*max–min*-regression) for Climate Change. Thus, this robustness test underlines the significance of the Land Use & Pollution impact driver to the disagreement, and confirms the other results found for the original sample.

Next, we regress the disagreement measures on impact driver level on the firm characteristics, as in Section 5. In accordance with the results in Table 8, the logarithm of the market capitalization has a positive and significant coefficient for all impact drivers and the industry is very influential. Firms from the industries of Basic Materials and Energy experience a strong disagreement, while the footprints assigned to firms in the Telecommunications and Financials industry apparently agree stronger. Moreover, the results confirm that a higher degree of ESG transparency can decrease the disagreement. The Disclosure Score has highly significant and negative coefficients for all impact drivers besides Water Pollution. Its coefficient is e.g. −0.004 for both the regression with dependent variables *sd*(Land Use & Pollution) and *sd*(Climate Change), and −0.007 for both regressions with dependent variables *max–min*(Land Use & Pollution) and *max–min*(Climate Change), all significant on 1%-level. The share of institutional investors has negative and significant coefficients for all impact drivers besides Air Pollution. Also, the other coefficients do not vary substantially when compared to the original regression.[5]

We can conclude that the results of all tests with the sample cleaned from outliers confirm the results found throughout the rest of this paper.

7 | Conclusion

In this paper, we document the existence of a significant disagreement between the biodiversity footprints of different providers. This disagreement stems from divergences both in the scope (*What* the providers are trying to measure) and the measurement (*How* the providers are measuring it) of the providers. The decomposition of the disagreement shows that the measurement divergence contributes more strongly to the overall disagreement than the scope divergence. This means that while providers more or less agree on which firm operations contribute to a loss in biodiversity, there is a fundamental disagreement about the underlying methods and data to measure them. In particular, the providers' disagreement on the firms' land use & pollution and its contribution to climate change leads to a strong disagreement of the footprints. Moreover, the size of the footprints differs the most for larger firms and firms from the industries of Energy, Basic Materials, and Consumer Staples. As opposed to that, firms from the industries of Telecommunications and Financials exhibit a lower disagreement. Furthermore, a detailed and transparent ESG disclosure and a higher share of institutional investors can decrease disagreement.

The results of this paper have important implications. The increasing inclusion of biodiversity measures in decision-making by firms, investors, and regulators is crucial in battling the biodiversity crises. An easily applicable and descriptive measure such as a biodiversity footprint can be a handy and user-friendly tool for that purpose. By enabling stakeholders to better understand a firm's biodiversity impact and compare it to their peers, the footprints can help exert pressure on firms to reduce their biodiversity impact. If the methodology behind the footprints is transparent and well-understood, they can even serve as a guidance and indication for businesses about the necessary steps to improve their biodiversity performance. However, there have been some concerns about a too simplistic application of biodiversity footprints (TNFD 2023a). Our results underline the importance of addressing these concerns, as the significant disagreement between biodiversity footprints raises questions about their reliability and usefulness in practice and can lead to misconceptions, if the users of the footprint do not have a clear understanding of the different methods and metrics. Investors' efforts to identify high- or low-impact firms are naturally hindered by strong disagreement. Moreover, firms that want to include their biodiversity impact in their business strategy are currently lacking consistent signals from this measure. This complicates a firm's ability to benchmark its performance against competitors and align its strategies with its sustainability goals. It therefore interferes with true efforts to improve biodiversity performance, but the possibility to choose the measure with the best outcome for disclosure practices can even serve as a greenwashing opportunity for both firms and investors. Furthermore, the usefulness of regulations like the French Article 29 can be limited by the strong disagreement in the biodiversity footprints. If biodiversity footprints are to guide meaningful action by firms, investors, and policymakers, efforts to standardize methodologies and improve transparency are essential.

A critical role is hereby playing the firm-level disclosure. Stricter standards and more resources for firms to measure their biodiversity impact throughout their whole value chain are necessary and will consequently lead to more accurate and homogeneous biodiversity footprints. Firms can take a proactive role in this process by advocating for standardized frameworks and investing in robust data collection systems to measure and manage their biodiversity impact. This can mitigate reputational and regulatory risk and serve as a strategic opportunity to build trust with stakeholders. Moreover, investors should be aware of the methodological differences between different footprints. The use and selection of a footprint must be based on a deep understanding of the underlying methods and an appropriate perception of the insights that a footprint can and cannot offer. Furthermore, diversifying data sources and combining quantitative metrics with qualitative assessments can lead to more informed investment strategies. For researchers and academics, our findings underscore the need for critical evaluation of biodiversity-related data. Scholars should consider including footprints by more than one provider and further biodiversity-related metrics in their research. Finally, it must be noted that the science of footprinting is rapidly advancing and new models that address the shortcomings of older ones are constantly being developed. Users and providers of biodiversity footprints should continuously monitor advancements in research and update their models to reflect the latest theoretical and empirical insights.

Future research could focus on possibilities for developing and adopting a standardized, potentially industry- and geography-specific methodology for calculating biodiversity footprints. There are various aspects that can be examined in this context, including the scope of the footprints (i.e., direct operation vs. value chain) and the inclusion of both near-term and longer-term effects in the calculations. The results of our study indicate that it is particularly important to address discrepancies in the measurement of the firms' contribution to water pollution and climate change and resolve the issue of missing data. Exploring ways on how to incorporate qualitative data can also serve the comprehensiveness and reliability of the biodiversity footprints. Moreover, it needs to be understood better how firms and investors are currently incorporating the footprint and other biodiversity metrics into their decision-making and which barriers and enablers might exist in adopting biodiversity footprints. In this context, the effectiveness of regulatory frameworks like the French Article 29 and its impact on the usage and improvement of biodiversity footprints can be evaluated.

Acknowledgments

Open Access funding enabled and organized by Projekt DEAL.

Conflicts of Interest

The authors declare no conflicts of interest.

Endnotes

[1] Since 1970, the average size of monitored wildlife populations has decreased by 73% (WWF 2024).

[2] See https://www.worldbenchmarkingalliance.org/research/nature-benchmark-data-set-2024/.

[3] See https://globalcanopy.org/what-we-do/corporate-performance/deforestation-action-tracker/.

[4] Since these descriptive statistics indicate that the data set contains very high biodiversity footprints, we conducted robustness tests with a data set that excludes the biodiversity footprints above the the 99% quantile. The results of these additional tests (see Section 6) are similar to the results presented in the following section.

[5] The respective tables are available on request.

References

ASN Bank, and PRé Sustainability. 2022. "ASN Bank Biodiversity Footprint. Biodiversity Footprint for Financial Institutions Impact Assessment 2016 - 2020."

Adler, R., M. Mansi, and R. Pandey. 2018. "Biodiversity and Threatened Species Reporting by the Top Fortune Global Companies." *Accounting, Auditing & Accountability Journal* 31, no. 3: 787–825.

Adler, R., M. Mansi, R. Pandey, and C. Stringer. 2017. "United Nations Decade on Biodiversity: A Study of the Reporting Practices of the Australian Mining Industry." *Accounting, Auditing & Accountability Journal* 30, no. 8: 1711–1745.

Avramov, D., S. Cheng, A. Lioui, and A. Tarelli. 2022. "Sustainable Investing With ESG Rating Uncertainty." *Journal of Financial Economics* 145, no. 2: 642–664.

Bach, T. N., K. Hoang, and T. Le. 2024. "Biodiversity Risk and Firm Performance: Evidence From US Firms." *Business Strategy and the Environment* forthcoming.

Bailon, M., A.-M. Bor, and J. G. Redn. 2024. "Biodiversity Measurement Approaches. A Practitioner's Guide for Financial Institutions." Finance for Biodiversity Foundation.

Bassen, A., D. Buchholz, K. Lopatta, and A. R. Rudolf. 2024. "Biodiversity Management and Stock Price Crash Risk." *Business Strategy and the Environment* 33, no. 5: 4788–4805.

Bauckloh, T., S. Utz, J. Dobrick, A. Höck, and M. Wagner. 2024. "In Partnership for the Goals? The Level of Agreement Between SDG Ratings." *Journal of Economic Behavior & Organization* 217: 664–678.

Berg, F., J. F. Kölbel, and R. Rigobon. 2022. "Aggregate Confusion: The Divergence of ESG Ratings." *Review of Finance* 26, no. 6: 1315–1344.

Boiral, O. 2016. "Accounting for the Unaccountable: Biodiversity Reporting and Impression Management." *Journal of Business Ethics* 135, no. 4: 751–768.

Broer, W., D. Kan, R. Patel, C. van Leenders, and K. Melis. 2021. "Biodiversity Footprint for Financial Institutions." The Netherlands Enterprise Agency.

Chatterji, A. K., R. Durand, D. I. Levine, and S. Touboul. 2016. "Do Ratings of Firms Converge? Implications for Managers, Investors and Strategy Researchers." *Strategic Management Journal* 37, no. 8: 1597–1614.

Chatterji, A. K., and M. W. Toggel. 2010. "How Firms Respond to Being Rated." *Strategic Management Journal* 31, no. 9: 917–945.

Chelli, M., and Y. Gendron. 2013. "Sustainability Ratings and the Disciplinary Power of the Ideology of Numbers." *Journal of Business Ethics* 112: 187–203.

Christensen, D. M., G. Serafeim, and A. Sikochi. 2022. "Why Is Corporate Virtue in the Eye of the Beholder? The Case of ESG Ratings." *Accounting Review* 97, no. 1: 147–175.

Clementino, E., and R. Perkins. 2020. "How Do Companies Repond to Environmental, Social and Governance (ESG) Ratings? Evidence From Italy." *Journal of Business Ethics* 171: 379–397.

Coqueret, G., T. Giroux, and O. D. Zerbib. 2025. "The Biodiversity Premium." *Ecological Economics* 228: 108435.

Cornaggia, J., and K. Cornaggia. 2023. "ESG Rating Management." SSRN Journal.

Damiani, M., T. Sinkko, C. Caldeira, D. Tosches, M. Robuchon, and S. Sala. 2023. "Critical Review of Methods and Models for Biodiversity Impact Assessment and Their Applicability in the LCA Context." *Environmental Impact Assessment Review* 101: 107134.

Deegan, C. 2002. *Australian Financial Accounting.* McGraw Hill Book Company.

Deegan, C. 2002. "The Legitimising Effect of Social and Environmental Disclosures. A Theoretical Foundation." *Accounting, Auditing & Accountability Journal* 15, no. 3: 282–311.

DiMaggio, P. J., and W. W. Powell. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields." *American Sociological Review* 48, no. 2: 147–160.

Dorfleitner, G., G. Halbritter, and M. Nguyen. 2015. "Measuring the Level and Risk of Corporate Responsibility: An Empirical Comparison of Different ESG Rating Approaches." *Journal of Asset Management* 16: 450–466.

Elsayed, R. A. A. 2023. "Exploring the Financial Consequences of Biodiversity Disclosure: How Does Biodiversity Disclosure Affect Firms' Financial Performance?." *Future Business Journal* 9, no. 22.

Flammer, C., T. Giroux, and G. M. Heal. 2025. "Biodiversity Finance." *Journal of Financial Economics* 164: 103987.

Garel, A., A. Romec, Z. Sautner, and A. F. Wagner. 2024. "Do Investors Care About Biodiversity?." *Review of Finance* 28, no. 4: 1151–1186.

Gibson, R., P. Krueger, and P. S. Schmidt. 2021. "ESG Rating Disagreement and Stock Returns." *Financial Analysts Journal* 77: 105–127.

Giglio, S., T. Kuchler, J. Stroebel, and X. Zeng. 2024. "Biodiversity Risk." NBER Working Paper.

Hain, L. I., J. F. Kölbel, and M. Leippold. 2022. "Let's Get Physical: Comparing Metrics of Physical Climate Risk." *Finance Research Letters* 46: 102406.

Hassan, A. M., L. Roberts, and J. Atkins. 2020. "Exploring Factors Relating to Extinction Disclosures: What Motivates Companies to Report on Biodiversity and Species Protection?." *Business Strategy and the Environment* 29, no. 3: 1419–1436.

Hertog, I., A.-M. Bor, and A. de Horde. 2022. "Guide on Biodiversity Measurement Appraoches." Finance for Biodiversity Pledge.

Hoepner, A. G. F., J. Klausmann, M. Leippold, and J. Rillaerts. 2023. "Beyond Climate: The impact of Biodiversity, Water, and Pollution on the CDS Term Structure." Swiss Finance Institute Research Paper 23–10.

IEEP. 2021. "Biodiversity Footprints in Policy- and Decision-Making: Briefing on the State of Play, Needs and Opportunities and Future Directions." Institute for European Environmental Policy.

IPBES. 2019. "Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services." Brondzio, E. S., Settele, J., Daz, S., Ngo, H. T. (eds).

Karolyi, G. A., and J. Tobin-de la Puente. 2023. "Biodiversity Finance: A Call for Research Into Financing Nature." *Financial Management* 52, no. 2: 229–405.

Kathan, M. C., S. Utz, and L. Chmel. 2023. "Are Implied Temperature Rise Metrics as Inconsistent as ESG Ratings?: Examining Firm-Level Disagreement Among Data Providers." SSRN Working Paper No.4494958.

Kering. 2021. "Environmental Profit and Loss (E P&L). 2021 Group Results." Kering.

Krippendorff, K. 2004. *Content Analysis: An Introduction to Its Methodology.* Sage Publications, Inc.

Meyer, J. W., and B. Rowan. 1977. "Institutionalized Organizations: Formal Structure as Mythand Ceremony." *American Jourrnal of Sociology* 83, no. 2: 340–363.

Oxford Biodiversity Network. 2023. "Benchmark for Nature." Accessed: 11/21/2024.

PBAF. 2022. "Taking Biodiversity Into Account, PBAF Standard v2022 - Biodiversity Impact Assessment - Footprinting."

Sany-Mengual, E., F. Biganzoli, A. Valente, S. Pfister, and S. Sala. 2023. "What Are the Main Environmental Impacts and Products Contributing to the Biodiversity Footprint of EU Consumption? A Comparison of Life Cycle Impact Assessment Methods and Models." *International Journal of Life Cycle Assessment* 28: 1194–1210.

Schipper, A. M., J. P. Hilbers, J. R. Meijer, et al. 2020. "Projecting Terrestrial Biodiversity Intactness With GLOBIO 4." *Global Change Biology* 26, no. 2: 760–771.

Scott, W. R., and J. W. Meyer. 1994. *Institutional Environments and Organizations: Structural Complexity and Individualism.* SAGE.

Serafeim, G., and A. Yoon. 2023. "Stock Price Reactions to ESG News: The Role of ESG Ratings and Disagreement." *Review of Accounting Studies* 28, no. 3: 1500–1530.

TNFD. 2023. "Discussion Paper on Biodiversity Footprinting Approaches for Financial Institutions." Taskforce on Nature-related Financial Disclosures.

TNFD. 2023. "Recommendations of the Taskforce on Nature-Related Financial Disclosures." Taskforce on Nature-related Financial Disclosures.

University of Cambridge Institute for Sustainability Leadership. 2020. "Measuring Business Impacts on Nature: A Framework to Support Better Stewardship of Biodiversity in Global Supply Chains." Cambridge, UK: University of Cambridge Institute for Sustainability Leadership.

WWF. 2024. "Living Planet Report 2024- A System in Peril." WWF.

Widyawati, L. 2020. "A Systematic Literature Review of Socially Responsible Investment and Environmental Social Governance Metrics." *Business Strategy and the Environment* 29, no. 2: 619–637.

Wilting, H. C., A. M. Schipper, M. Bakkenes, J. R. Meijer, and M. A. Huijbregts. 2017. "Quantifying Biodiversity Losses Due to Human Consumption: A Global-Scale Footprint Analysis." *Environmental Science & Technology* 51, no. 6: 3298–3306.

Winter, L., A. Lehmann, N. Finogenova, and M. Finkbeiner. 2017. "Including Biodiversity in Life Cycle Assessment: State of the Art, Gaps and Research Needs." *Environmental Impact Assessment Review* 67: 88–100.

Xiong, W. W. 2024. "The World Market Price of Biodiversity Risk." SSRN Working Paper, https://dx.doi.org/10.2139/ssrn.5043322.

Yu, E. P., C. Q. Guo, and B. V. Luu. 2018. "Environmental, Social and Governance Transparency and Firm value." *Business Strategy and the Environment* 27, no. 7: 987–1004.