

1 The business case for investing in 2 biodiversity data

3 Fevziye Hasan¹, Jakob Nyström², Carina Andersson⁸, André P da Silva⁶, Alice Högström⁹,
4 Emma Granqvist³, Mats Eriksson¹, Robert M Goodsell³, Fabian Roger¹⁰, Fredrik Ronquist³,
5 Tomas Roslin⁷, Olga V Pettersson⁵, Veronika A. Johansson^{3,4}, and Tobias Andermann^{2,5}.

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7 ¹Museum of Evolution, Uppsala University, Norbyvägen 16, 75236, Uppsala, Sweden

8 ²Department of Organismal Biology, Uppsala University, 75236, Uppsala, Sweden

9 ³Department of Bioinformatics and Genetics, Swedish Museum of Natural History, Box
10 50007, SE-104 05, Stockholm, Sweden

11 ⁴Global Biodiversity Information Facility (GBIF) Sweden, Stockholm, Sweden

12 ⁵Science for Life Laboratory, Uppsala University, Uppsala, Sweden

13 ⁶Stockholm Resilience Centre, Stockholm University, Stockholm, Sweden

14 ⁷Swedish University of Agricultural Sciences (SLU), Department of Ecology, Ulls väg
15 18B, 75651, Uppsala, Sweden

16 ⁸Knowit AB, Stockholm, Sweden

17 ⁹Sveaskog, Wallingatan 2, SE-111 60, Stockholm, Sweden

18 ¹⁰DNAir AG, Zurich, Switzerland

19

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21

22 **Fevziye Hasan** ORCID: 0000-0001-9670-9775
23 **Jakob Nyström** ORCID: 0009-0008-0734-0936
24 **Carina Andersson** -
25 **André P da Silva** ORCID: 0000-0002-4722-8497
26 **Alice Högström** -
27 **Emma Granqvist** ORCID: 0000-0002-1513-1674
28 **Mats Eriksson** -
29 **Robert M Goodsell** ORCID: 0000-0002-3349-1876
30 **Fabian Roger** ORCID: 0000-0001-9865-7542
31 **Fredrik Ronquist** ORCID: 0000-0002-3929-251X
32 **Tomas Roslin** ORCID: 0000-0002-2957-4791
33 **Olga V Pettersson** ORCID: 0000-0002-5597-1870
34 **Veronika A. Johansson** ORCID: 0000-0002-3028-9947
35 **Tobias Andermann** ORCID: 0000-0002-0932-1623

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37 **Corresponding author:** Fevziye Hasan; fevziye.hasan@em.uu.se

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39 **Author contributions**

40 FH and TA conceptualised the paper and all authors participated equally in the design. FH, JN,
41 TA developed the framework and all authors contributed critically to writing all drafts and gave
42 final approval for publication. FH drafted the manuscript and all authors contributed to the
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44

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51

52 **Conflict of Interest**

53 The authors have declared that there are no competing interests.

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68 Abstract

- 69 1. The private sector is increasingly aware of its dependence on biodiversity and the financial risks
70 and opportunities involved. This has generated a lot of demand for investing in nature-positive
71 solutions. There is an obvious and non-negotiable basis for such initiatives: biodiversity data.
72 Without this data and the tools built from it, no actor can assess the effects on the ecosystems
73 they rely on. We identify two key barriers to corporate biodiversity action: (1) lack of biodiversity
74 data and (2) challenges with biodiversity data literacy, i.e. the domain knowledge necessary to
75 apply data products for decision making in appropriate contexts. Building on this, we present an
76 end-to-end framework mapping biodiversity data to data products and business use cases, to
77 establish a shared language between business and biodiversity research.
- 78
- 79 2. First, we provide examples of new technologies for generating biodiversity data at unprecedented
80 scales, such as environmental DNA, computer vision and audio monitoring. We discuss the large
81 amount of biodiversity data available in open databases, with a focus on the Global Biodiversity
82 Information Facility (GBIF), including their origins, limitations, and biases. We highlight the one
83 billion untapped primary biodiversity data points in natural history collections, and the
84 opportunity to mobilise them into open databases using technology at relatively low cost.
- 85
- 86 3. Second, we discuss biodiversity data products, focusing on the ability to interpret, communicate,
87 and effectively apply biodiversity models, metrics, and tools in relevant contexts. We address the
88 challenges posed by the complexity of biodiversity, the importance of its definitions, and the use
89 of aggregated metrics for biodiversity and ecosystem services in reporting, including the role of
90 nature tech.

91

92 4. Third, we present the business case for investing in more and open biodiversity data, with
93 examples of actions by companies and the finance sector. We also propose a mechanism to
94 incentivise and reward direct investments in biodiversity data mobilisation. In conclusion, we call
95 on businesses to prioritise financial investment in biodiversity data collection and mobilisation, to
96 create better data products that can accelerate deployment of solutions to the biodiversity crisis.

97 Key words

98 Biodiversity data, Business and biodiversity, data mobilisation, financing biodiversity, Global
99 Biodiversity Information Facility (GBIF), Natural History Collections, Nature Tech, Nature-based
100 Solutions

101 Introduction

102 Biodiversity underpins essential ecosystem services that support our societies and economy (Díaz et al.,
103 2018; Mace et al., 2012). Its rapid decline due to human activities is pushing planetary boundaries
104 (Steffen et al., 2015), already costing the global economy over \$5 trillion annually (Ranger et al., 2023).
105 The World Economic Forum and central banks recognise the risks of biodiversity loss, but the 2024
106 Global Risks Report suggests these risks will only become serious in the next decade (WEF, 2024),
107 downplaying urgency despite biodiversity loss being a current reality.

108
109 Globally, both “hard” mandatory regulations and “soft” voluntary frameworks have been introduced to
110 address concerns about biodiversity loss. The Kunming-Montreal Global Biodiversity Framework
111 (GBF)(COP15, 2022) has emerged as a strong influence on companies, in the same way the Paris
112 Agreement has shaped net-zero commitments in the context of greenhouse gas-emissions (Allen et al.,
113 2025). Target 15 of the GBF requires large companies and financial institutions to monitor, assess, and

114 transparently disclose their biodiversity risks, dependencies, and impacts across operations, supply chains,
115 and portfolios (COP15, 2022). Concurrently, the EU Corporate Sustainability Reporting Directive
116 (CSRD) mandates environmental impact reporting for approximately 50,000 companies by 2025 (Faqih
117 & Kramer, 2024). Market-led initiatives like the Taskforce on Nature-related Financial Disclosures
118 (TNFD) are creating science-based frameworks for managing nature-related risks and opportunities, with
119 substantial engagement from now over 500 organisations representing £17.7 trillion in assets (TNFD,
120 2024).The Science Based Targets Network (SBTN), originally established to guide companies in
121 addressing the climate crisis, is now including nature and biodiversity (SBTN, 2020).

122

123 This emerging intersection of business and biodiversity has stirred both optimism (White et al., 2023) and
124 concern (Smith et al., 2019). Among the sources of optimism is the hope that private sector interest in
125 biodiversity could provide an opportunity to tackle the biodiversity crisis and deliver data-driven
126 solutions to long-studied problems. However, there is also apprehension that corporate sustainability
127 departments may adopt unscientific or oversimplified approaches, inadvertently harming the very
128 ecosystems they aim to protect (Mair et al., 2024). For companies, integrating biodiversity into their
129 reporting presents both challenges and opportunities. In the short term, companies must adapt quickly to
130 comply with mandatory environmental reporting requirements (D’Amato et al., 2024). In the medium
131 term, they face increasing pressure from investors and lenders who are focusing more and more on
132 nature-related risks and sustainability metrics (Ingram et al., 2024). Companies that fail to meet these
133 emerging standards may face reputational damage, higher financing costs, or reduced access to capital –
134 whereas early adopters can gain competitive advantages (Kulionis et al., 2024).

135

136 To meet these new requirements and capitalise on opportunities, businesses are investing in Nature-based
137 Solutions (NbS), which is an umbrella term for working with nature to benefit biodiversity and people
138 (Seddon et al., 2020). New markets for biodiversity credits are also emerging under NbS, raising concerns
139 due to the way carbon credits evolved, and underscoring the pressing need for scientific credibility (Aide,

140 2024; Swinfield et al., 2024). Simultaneously, there is rapid growth of the nature tech sector, referring to
141 any technology that enables, accelerates, and scales businesses' nature-positive transition (Goren, 2024).
142 Technologies that deliver "nature intelligence" analytics and tools to clients include in-situ biodiversity
143 measurement hardware and software-as-a-service (SaaS) platforms, which ingest data from open-access
144 biodiversity databases. The nature tech sector saw investments exceed USD 2 billion in 2022 and a
145 compound annual growth rate of 52% since 2018 (Evison et al., 2022). Unlike the standardised CO2-
146 equivalent metrics for carbon accounting, biodiversity's inherent complexity has resulted in widespread
147 confusion surrounding data, metrics, reporting, and valuation approaches for businesses (Jones &
148 Solomon, 2013).

149

150 To guide decision-making on both local and global scales, there is no substitute for reliable biodiversity
151 data (Gerber & Iacona, 2024; Hawkins, 2024; Hobern et al., 2019; Mason Heberling et al., 2021;
152 Musvuugwa et al., 2021). Without knowing current biodiversity trends and how specific actions impact
153 biodiversity, we cannot make decisions that are truly "evidence-based". Despite current biases, the
154 economic value of open biodiversity data should not be ignored, as open data on platforms like GBIF
155 generate €3 in direct benefits for users and up to €12 in societal returns for every €1 invested, extending
156 to business benefits (Deloitte, 2023). Despite the critical value of information and data-driven solutions,
157 there seems to be a lack of efforts to clearly define the challenges in the biodiversity data pipeline to
158 create suitable data-derived products for integrating business and biodiversity (Panwar et al., 2023).

159

160 The complexity of integrating biodiversity into business contexts is further heightened by its multifaceted
161 nature, which encompasses genetic diversity, species diversity, and ecosystem diversity (CBD, 2011).

162 While species serve as the most commonly used unit of biodiversity, impacts at one level may not reflect
163 changes at another (Exposito-Alonso et al., 2022; Kahilainen et al., 2014). Even seemingly
164 straightforward metrics like species richness do not always indicate better biodiversity outcomes
165 (Hillebrand et al., 2018). Essential Biodiversity Variables (EBVs) are measurements for reporting and

166 monitoring, developed to aid businesses in measuring biodiversity (Pereira et al., 2013), but are often
167 based on top-down methods that rely on indirect or modeled data, which can be biased and incomplete
168 (Granqvist et al., *In prep.*). Interpreting diversity patterns requires context, i.e. biodiversity data literacy.
169 This complexity highlights the need for clear frameworks that can help businesses effectively integrate
170 biodiversity considerations into their operations while maintaining scientific validity.

171
172 Accounting for biodiversity is a process that should be grounded in established scientific methods and
173 fieldwork (Hill et al., 2005). A bottom-up approach prioritising the collection of in-situ biodiversity data
174 at the local scale is needed and necessary to derive other EBVs (Granqvist et al., *In prep.*). Transparent
175 and regular biodiversity data collection, including baseline measurements and ongoing monitoring, are
176 important for scrutinising biodiversity impacts and the direction of progress in stewardship (White et al.,
177 2023). Biodiversity data needs will vary by industry, with larger or more complex operations likely
178 requiring a combination of data sources from field monitoring, satellite data, and open biodiversity data
179 (see Case Study S1).

180
181 Biodiversity monitoring is valuable but insufficient without broader ecological context. Around four out
182 of five species globally remain undiscovered, even in well-studied regions (Mora et al., 2011; Stork,
183 2018; Miraldo et al., 2024), highlighting critical gaps in our understanding of ecosystems. Alarming,
184 despite the significant returns of investing in biodiversity data infrastructures (Deloitte, 2023), funding
185 remains insufficient. Natural history collections and herbaria—the original biodiversity data
186 infrastructures that house type and voucher specimens essential for confirming species identities, updating
187 species red-list statuses, and advancing technologies such as eDNA—are closing due to short-sighted
188 funding systems. These collections, which contain between 1.2 and 2.1 billion specimens worldwide, are
189 inadequately represented in GBIF, with only around 200 million specimens currently included
190 (Huybrechts et al., 2022). For plants and fungi alone, there are approximately 400 million specimens
191 stored internationally across 3,000 herbaria, which have the potential to aid in advancing understanding of

192 traits and predictive modeling, such as forecasting biodiversity under future climate change (Davis, 2023).
193 The decline of these collections is a catastrophe for biodiversity, driving the silent extinction of both
194 species and taxonomists (Löbl et al., 2023). We cannot expect to advance new technologies that collect
195 large quantities of biodiversity data without supporting the taxonomic foundations from which they are
196 built. Simultaneous investment towards mobilising both specimen- and observation-based primary
197 biodiversity data is needed. Without this comprehensive, scientific approach, efforts to measure and
198 implement biodiversity positive actions may be ineffective.

199

200 The open biodiversity data on GBIF is expansive, however, it is biased geographically and taxonomically
201 (Troudet et al., 2017), with currently around 65% representing birds, which only make up 0.5% of all
202 species currently known to science (GBIF, 2025). Most other groups of species remain poorly
203 represented, leading to our knowledge of biodiversity patterns and responses being mostly restricted to a
204 few data-rich taxonomic groups. Similar biases exist in national databases, including in best-studied
205 regions like Finland (Roslin & Laine, 2022). New technologies offer promising solutions, such as
206 advances in environmental DNA (eDNA) (Deiner et al., 2021), species identification using computer
207 vision (Beery, 2023), and acoustic monitoring (Buxton et al., 2018). These innovations are
208 revolutionising biodiversity data collection (van Klink et al., 2022; Van Klink et al., 2024), reducing the
209 time and expertise needed for species inventories (August et al., 2015).

210

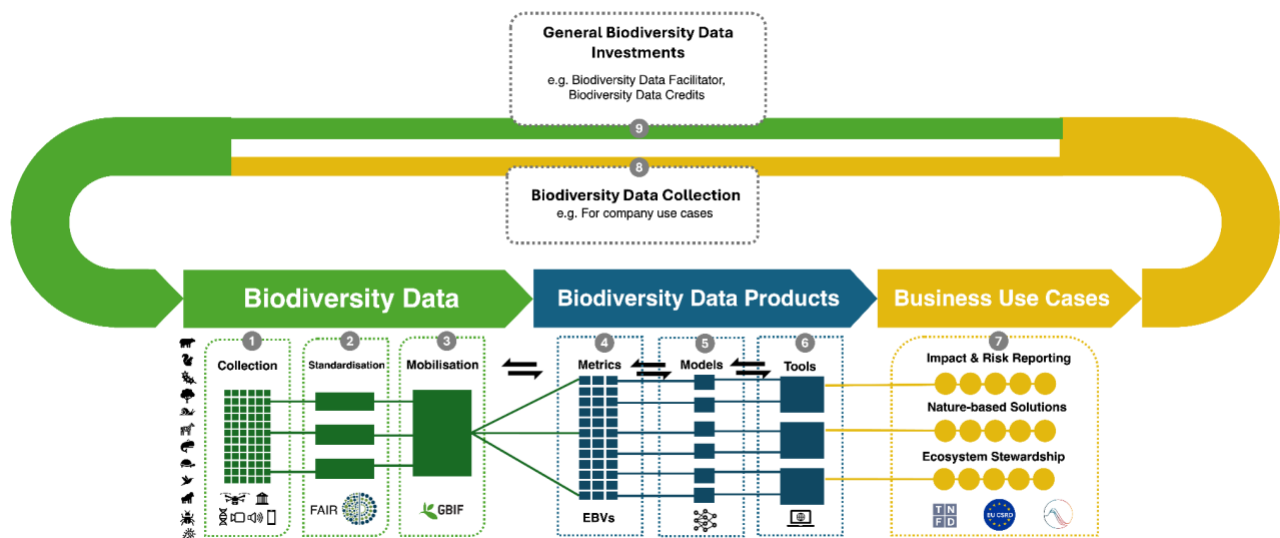
211 Using GBIF data without addressing its biases can lead to misleading conclusions (Boyd et al., 2023).
212 This is particularly concerning for nature tech companies offering SaaS solutions that rely solely on open
213 data for biodiversity analytics. Such practices risk leading to unsupported claims, harming biodiversity,
214 disrupting ecosystems, compromising clients' operations, and eroding trust in biodiversity as a critical
215 business issue. Acknowledging the local and global data biases, some initiatives are now warning
216 companies about the “nature data gap” (Nature Tech Collective, 2024; TNFD, 2024). There is positive
217 growing recognition that biodiversity impact reports must be validated with “ground-truthed” in-situ data

218 collection (WWF, 2024) and enabling “nature intelligence” requires high quality biodiversity data
219 (TNFD, 2024).

220

221 In this perspective, we turn to first principles and present an end-to-end framework (Figure 1) that charts
222 the journey from data to business use cases. First, we explore biodiversity data, focusing on methods for
223 collecting primary biodiversity data using new technologies from the field and natural history collections.
224 Second, we examine biodiversity data products and the methods used to derive them, presenting a non-
225 exhaustive set of quality markers these products should meet. Finally, we explore the business cases for
226 biodiversity data, concentrating on impact and risk reporting, nature-based solutions, and sustainable
227 ecosystem stewardship. We stress the need to prioritise biodiversity data collection and mobilisation,
228 arguing that biodiversity data literacy is crucial for achieving biodiversity-positive outcomes.

229



230

231 **Figure 1.** Framework for integrating business and biodiversity, grounded in data. This pipeline clarifies
232 the steps to get from raw biodiversity data to business use cases. The process begins with biodiversity
233 data (green), divided into three key components: (1) collection of primary biodiversity data from both the
234 field and natural history collections using traditional and new technologies; (2) standardisation of this data

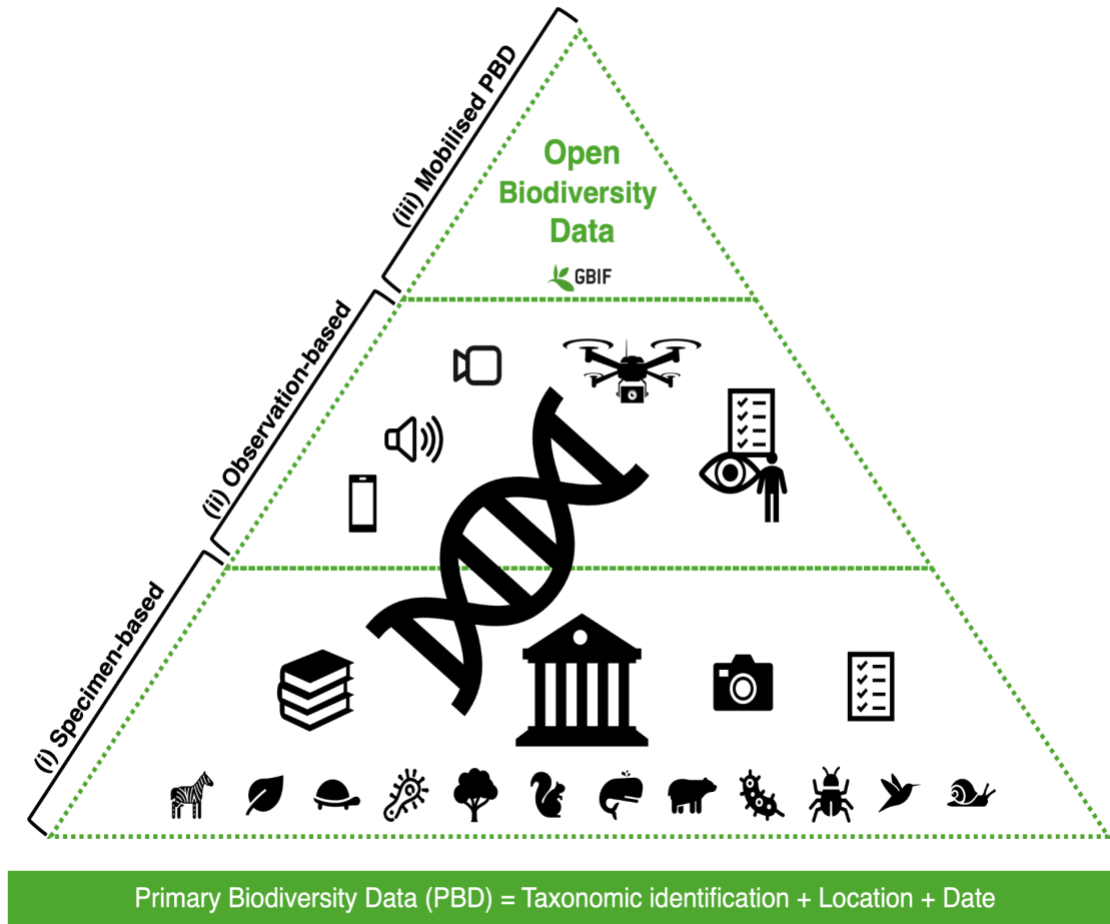
235 in alignment with FAIR data principles and the biodiversity information standards (TDWG); and (3)
236 mobilisation of these data into the Global Biodiversity Information Facility (GBIF), the world’s largest
237 biodiversity data repository. The next step involves biodiversity data products (blue), where biodiversity
238 experts translate raw data into (4) biodiversity metrics (e.g., EBVs); (5) data-driven and predictive
239 models; and (6) data tools for users, which are iteratively updated as new data become available. This
240 biodiversity expertise has traditionally been represented by academic research, consultancies, and public
241 environmental agencies, but is increasingly adopted by the rapidly evolving nature-tech sector. Finally,
242 business (yellow) represents the end-users of the data products (7). Important use cases for biodiversity
243 data products include impact and risk reporting, investments in nature-based solutions (NbS) and
244 monitoring of their outcomes, as well as better management practices through ecosystem stewardship.
245 There are two important feedback loops in the framework. First, businesses are encouraged to invest in
246 data collection and mobilisation of these data to the public domain, to improve their reporting and
247 operational management (8). Second, we propose a mechanism to incentivise direct investment in
248 biodiversity data mobilisation (9). This flow emphasises that biodiversity data is a central priority of the
249 entire pipeline. Without high-quality biodiversity data, none of the subsequent steps are possible.

250 An end-to-end framework from biodiversity data to 251 business use cases

252 1 Biodiversity data

253 The big data revolution has led to a significant increase in biodiversity data (Bayraktarov et al., 2019;
254 Musvuugwa et al., 2021), offering opportunities to fill data gaps related to taxa and geographical
255 distributions (Troudet et al., 2017). Primary biodiversity data, or occurrence data, constitutes the majority
256 of data published through GBIF (GBIF, 2024) and includes three key components: taxonomic level (e.g.,

257 species, genus), location, and date (Spear et al., 2023). Collecting both observation-based and specimen-
258 based primary biodiversity data (Figure 2) is essential to fill the biodiversity data gap, as it is foundational
259 for quantifying abundance, understanding biodiversity patterns, mapping species distributions, assessing
260 red list statuses, and temporal environmental change (GBIF, 2024).



261
262 **Figure 2.** Pyramid diagram illustrating sources of primary biodiversity data showing that specimen-based
263 data is foundational to observation-based data, which is foundational to integrated primary biodiversity
264 data. (i) **Specimen-based data:** Derived from physical specimens in natural history collections, including
265 image files, checklists, and archival materials; (ii) **Observation-based data:** Derived from traditional
266 species inventories and technologies such as DNA methods, camera traps, audio recordings, and citizen
267 science. DNA methods (eDNA and metabarcoding, metagenomics) overlap with both specimen and

268 observation data, as they require physical sample collection to generate verifiable species names; and (iii)
269 **Mobilised primary biodiversity data:** Integrated specimen- and observation-based data on open access
270 biodiversity datasets, such as GBIF.

271
272 New technologies offer scalable methods for collecting primary biodiversity data across ecosystems
273 (Stephenson, 2020). For example, environmental DNA (eDNA) in combination with metabarcoding can
274 identify species from samples like water, soil, or air (Deiner et al., 2021)(**Case Study S1**). These methods
275 are well-suited for studying taxa with hidden diversity, such as fungi and insects, which are often
276 challenging to access and/or difficult to identify. Using metabarcoding for biodiversity inventories has
277 been estimated to complete the equivalent of 1,000 years of manual inventory work in just one year
278 (Ronquist et al., 2020). Passive acoustic monitoring with autonomous sound recorders captures species
279 sounds, monitoring birds, insects, amphibians, primates, bats, and even soil biodiversity through unique
280 vibration patterns (Hildebrand et al., 2024; Hoefler et al., 2023; Robinson et al., 2024). AI pattern-
281 recognition techniques analyse sounds to identify species accurately and at scale, reducing human bias
282 and enabling simultaneous data collection across multiple sites (Buxton et al., 2018). Cameras can capture
283 species images over time, targeting specific taxa (Bjerge et al., 2021). A global camera network, akin to
284 meteorological weather stations, could provide real-time biodiversity data (Steenweg et al., 2017). Citizen
285 science projects such as iNaturalist use smartphone cameras and microphones to collect biodiversity data
286 (August et al., 2015). In addition, images and audio files collected on their platform are used as training
287 data to advance deep learning methods, including computer vision for species identification (Beery, 2023;
288 Høye et al., 2021). Thermal, LIDAR, hyperspectral, multispectral, and RGB sensors can be attached to
289 drones and unmanned aerial vehicles (UAVs). Thermal drones track species by detecting heat signatures
290 (Larsen et al., 2023). LIDAR data from stationary devices, drones, or airplanes create 3D vegetation
291 models, while hyperspectral sensors identify tree species by analysing light reflectance patterns. RGB
292 drones, combined with AI, can now identify plants down to species level in some cases (Mäyrä et al.,
293 2021).

294

295 Beyond generating new data from nature, digitisation technology and AI tools are turbo-charging
296 biodiversity data collection from natural history collections and herbaria (Nelson & Ellis, 2019). High
297 throughput specimen digitisation, such as Angled Label Image Capture and Extraction (ALICE), uses a
298 multi-camera setup and an associated software processing pipeline, enabling the standardisation of 800
299 specimens per day (Dupont & Price, 2019), and allowing data upload to GBIF for understudied and
300 functionally important groups, such as ground beetles (Garner et al., 2024). Digitisation of 1 million
301 herbarium specimens is estimated to take just 8 years, and hold great value for quantifying functional
302 traits such as leaf mass per area, water-related traits, carbon fractions, and pigments, comparable to those
303 obtained from fresh tissues (Davis, 2023). Named Entity Recognition (NER) is now used to identify and
304 extract specimen identification, location, and date. Optical Character Recognition (OCR) is employed to
305 convert text from images of specimen labels into machine-readable text, processing approximately 20,000
306 herbarium specimens at an average rate of 20 labels per hour (Takano et al., 2024). It is rare to have the
307 opportunity to travel back in time to fill biodiversity data gaps, but we can do so by collecting data from
308 natural history collections. These specimen-based primary biodiversity data contribute to temporal
309 predictive modeling and link historical specimens to modern technologies, such as DNA-based species
310 identification. Despite advances in digitisation, valuable data remains un-digitised, requiring significant
311 mobilisation efforts (Huybrechts et al., 2022).

312

313 Consistent data standardisation is essential to ensure that biodiversity data collected from heterogeneous
314 sources meet FAIR principles (Findable, Accessible, Interoperable, Reusable) and align with the Open
315 Science Framework (Carroll et al., 2021; Wilkinson et al., 2016). The Biodiversity Information Standards
316 (TDWG) develops and maintains standards for managing and sharing biodiversity data, curating and
317 extending standards like Darwin Core (DwC). DwC ensures biodiversity data sharing by using
318 standardised terms and vocabularies, with a namespace policy enabling universal understanding and
319 making data machine-readable and interoperable. Extensions like the Humboldt Ecological Inventory

320 manage ecological survey data, while the DiSSCo network standardises the aggregation and sharing of
321 specimen-based data from natural history collections. However, big data integration faces limitations
322 regarding metadata standards for cross-scale analysis (Maldonado et al., 2015; Wieczorek et al., 2012;
323 Hardisty et al., 2022). Metadata standards define and manage data context, making their development
324 vital for new technologies. For example, dnaDerivedData with MIxS (Minimum Information about any
325 Sequence) offers guidelines on sample collection location, environmental context, DNA extraction
326 methods, and sequencing techniques (Abarenkov et al., 2023). The Camera Trap Data Package (Camtrap
327 DP) is a data exchange format for image data of larger animals such as mammals and birds (Bubnicki et
328 al., 2023) currently being extended with controlled vocabularies to include broader taxonomic scope,
329 including insects. Additionally, the Ecological Metadata Language (EML standard) provides detailed
330 documentation of dataset characteristics for all types of biodiversity data.

331
332 Despite progress in FAIR data standardisation, challenges persist, including duplication of data points,
333 variable quality, and interoperability issues (Pyle et al., 2021). Taxonomic changes and errors, especially
334 in valid names and classifications, can be addressed with a mix of automation and expert curation
335 (ChecklistBank, 2025; Whitley et al., 2024). These advancements, along with new data collection
336 technologies, make mobilised data accessible on platforms like GBIF, supporting efforts to bridge the
337 biodiversity data gap. Biodiversity data mobilisation involves sharing FAIR data and ensuring it is open
338 access. Despite consensus on the value of open data in biodiversity research, motivating data collectors to
339 digitize and share their data remains challenging. Academic incentives for data sharing include DOI
340 citations and data paper publications, while businesses are increasingly recognising the strategic value of
341 mobilizing biodiversity data. Businesses become data publishers by sharing their data through the GBIF
342 Integrated Publishing Toolkit (IPT) (see Case Study S2). To date, the business sector has contributed a
343 mere 0.3% of the published records to GBIF. Publishing through a national GBIF node's IPT is usually
344 free of charge and enables data citation and impact tracking through assigned DOIs and UUIDs,
345 monitored via GBIF's literature tracking system (Figure 1(8))(Case Study S2).

346 2 Biodiversity data products

347 There is a growing demand to transform raw biodiversity data into metrics and data products that can
348 cater to diverse use cases and needs across different industry sectors (Burgess et al., 2024). This task
349 requires reducing the complexity of biodiversity into manageable metrics, which arguably is an exercise
350 of great oversimplification, yet a necessary one. With this inherent constraint in mind, we reflect on
351 several issues in the current state-of-the-art of biodiversity reporting and the underlying data-products.

352

353 In the context of biodiversity impact reporting, data products that provide regional or global heatmaps of
354 biodiversity metrics are in high demand, as they allow easy area-based calculation of biodiversity value
355 and impact. One example of such a data product is the Biodiversity Intactness Index (BII, Newbold et al.,
356 2015; Phillips et al., 2021), which is proposed as a component indicator in the COP 16 draft of the GBF
357 monitoring framework (CBD, 2024). Another example of a biodiversity model used in business context is
358 GLOBIO (Schipper et al, 2020), also proposed as a GBF indicator (CBD, 2024). However, many of such
359 global heat maps generated (Myers et al., 2000) are only weakly linked to the evaluation of the
360 biodiversity impact of *specific decisions and actions*. For biodiversity data products to be actionable in a
361 corporate setting, they need to relate biodiversity impacts and risks to operational and financial decisions
362 taken by companies, so that impact tradeoff analysis can be performed. Examples include spatial planning
363 for forest and agricultural land management, deciding from which countries and regions to source
364 materials and products, and investments into new factories and logistics facilities. A common
365 denominator for many use cases is the urgent need for regional and local data and models (as opposed to
366 global) to ensure high-quality analysis and drawing the right conclusions.

367

368 While the BII and other similar data-products are being used for company impact assessment and
369 reporting, a concern raised is that the underlying models are largely untested for their predictive
370 performance and their agreement with other indicators of biodiversity impact (Martin et al., 2019,

371 Nyström, 2024). We see a big risk that insufficiently tested data products provide the foundations for
372 company impact reporting and nature investments, with potentially negative consequences. This problem
373 is further exacerbated by the quickly developing nature tech market, driven by the demand for attractive,
374 ready-to-use biodiversity solutions and data. The absence of a thorough quality-checking and peer-review
375 process in this context lends reason for concern and makes it difficult for customers to distinguish
376 between “snake-oil salesmen” with questionable data products and those built on solid foundations.
377 However, as outlined above, even models and data products that have been reviewed by the academic
378 peer-review process, risk being mis-applied for purposes they were not designed for. Part of the reason for
379 this misapplication is a lack of guidance on the use of existing and emerging biodiversity data products
380 and metrics, which we identify in this article as the challenge of **biodiversity data literacy**.

381
382 To provide guidance to help businesses and other stakeholders to identify high-quality data products,
383 which are often based on statistical/machine learning approaches, we have compiled a non-exhaustive set
384 of quality markers that such products should exhibit. These recommendations broadly apply to both data
385 products provided by academic groups and non-profit organisations, as well as nature tech solutions.

386
387 ● **Out of sample testing and ground truthing:** Predictive models should always be tested on data
388 not used for model training, to approximate its performance when used in real-world applications.
389 This tests the model’s ability to generalise patterns beyond its training data. Ideally, when making
390 predictions on smaller scales, new measurement data can be collected and used for testing
391 (ground-truthing). In cases where new measurements are not possible, e.g. when working on very
392 large scales, cross-validation can be used to simulate the application of the model on new data.
393 This involves repeatedly splitting the data into training and test sets (cross-validation folds), and
394 evaluating the performance on each test fold. Importantly, the evaluation should be based on the
395 relevant prediction task to be tackled rather than generic considerations (Abrego & Ovaskainen,
396 2023). It should also account for spatial and environmental dependencies in the data (Roberts et

397 al, 2017). Such a cross-validation approach, if done correctly, will in principle provide similar
398 indications of performance as “real” ground-truthing.

399

400 ● **Local inference:** The location of the training data should be disclosed. This is important as
401 inferences should typically only be made within the given region or set of regions where the
402 model was trained. Inferences outside of the training area can be highly problematic as they might
403 miss different parts of the environmental, anthropogenic, and geographic variable space
404 potentially leading to erroneous predictions.

405

406 ● **Uncertainty quantification:** Any data product based on model predictions should address the
407 issue of uncertainty. Each predicted value needs to have an associated uncertainty measure,
408 expressing how confident the model is in the prediction. This allows users to filter output data
409 based on a required confidence threshold and also addresses the previously mentioned issue with
410 spatial biases in the training data. For instance, regions that are poorly represented in the training
411 data tend to be associated with higher uncertainty. Data products without accessible and
412 transparent uncertainty estimation give a false sense of precision that is detrimental, and
413 sometimes dangerous, for decision-making.

414

415 ● **Transparency and limitations:** All biodiversity data products should have a clear list of
416 limitations to inform users about intended purpose, appropriate and non-recommended use cases,
417 limitations of the underlying data in terms of taxonomic and spatial biases, as well as known
418 cases or areas of poor performance and high uncertainty. The underlying training data should be
419 accessible with an open license. While we acknowledge that nature tech companies need to
420 safeguard code and certain data for competitive reasons, we strongly argue that any data products
421 of academic or non-profit origin should have their data and code repositories publicly available.
422 Without such access, there can be no real peer-review process. Nature tech solutions that rely on

423 underlying scientific models should clearly disclose the sources (academic papers and code) and
424 should ideally include a high-level documentation of the overall quantitative approach used.

425
426 Despite best efforts regarding methodological considerations and quality assessments, data products are
427 only as reliable as the data they are derived from. At present, the biggest bottleneck to better biodiversity
428 models is arguably the lack of contextualised data, particularly in view of the vast taxonomic and spatial
429 biases that exist. Closing the biodiversity data gaps is critical for enhancing the accuracy and reliability of
430 biodiversity metrics. We argue that this can be achieved through significant financial investment in data
431 collection and mobilisation. In the next section, we outline ways to incentivise companies to invest in
432 large-scale biodiversity data generation and mobilisation, to support high-impact use cases.

433 3 Business use cases and incentives for investing in biodiversity data

434 Improved impact and risk reporting

435 Businesses are facing mounting pressure to assess and disclose their biodiversity impacts and risks, from
436 mandatory compliance under frameworks like the CSRD to voluntary reporting initiatives such as TNFD,
437 which are becoming standard expectations for investors and lenders. With regulations like these,
438 businesses must prepare to assess their biodiversity impacts and risks, requiring long-term investment
439 towards biodiversity data. To meet compliance requirements for CSRD, companies set measurable,
440 science-based biodiversity targets to track and improve their impact (ESRS E4, 2023). Some assessments
441 will be needed at different scales, such as biodiversity impact assessments at the product level (life cycle
442 analysis), requiring meaningful, decision-useful data that can withstand scrutiny from regulators,
443 investors, and stakeholders. As we have outlined here, the biodiversity data gap and biases in GBIF
444 reduce the ability for meaningful inference and puts operations and compliance at risk. This was further
445 highlighted in TNFD's 2023 scoping study, highlighting that the available "nature data" is outdated,

446 inconsistent, and lacks the resolution required to inform confident decision-making (TNFD, 2023). With
447 biodiversity data accessibility, quality, comparability, verifiability and assurability being key concerns of
448 market participants, the TNFD proposes testing the efficacy of a “Nature Data Public Facility” to provide
449 accessible, decision-useful nature data for corporate decision-making (TNFD, 2024), which, if approved,
450 will continue to ingest biodiversity data from GBIF.

451
452 Companies that proactively collect ground-truthed biodiversity data and publish it through GBIF can
453 enhance their transparency and gain a competitive edge, as it serves as a compliance indicator for GBF
454 Target 19 under the CBD (Figueira et al., 2023). Using GBIF metrics as KPIs (key performance
455 indicators) in sustainability reports demonstrates a clear commitment to biodiversity disclosure, signaling
456 accountability to investors and other stakeholders. For instance, TotalEnergies became a GBIF data
457 publisher in 2019, sharing over 51,000 biodiversity records across three continents (see Case Study S2 –
458 Figure S2). Publishing through GBIF increases reliability, corporate visibility and compliance reporting,
459 as companies can use their published data to track progress against biodiversity targets and meet
460 regulatory expectations.

461
462 Both the CSRD and TNFD frameworks highlight the need for accessible, high-quality biodiversity data.
463 Since TNFD’s proposed infrastructure will likely rely on platforms like GBIF, businesses and other
464 investors publishing data on GBIF are not only meeting immediate compliance requirements but also
465 build a temporal record of biodiversity action, preparing for future voluntary reporting needs. In the
466 framework presented here (Figure 1), we outline the steps that can be taken to improve biodiversity data
467 coverage on GBIF, highlighting data collection and mobilisation as priority areas where businesses can
468 take impactful action.

469 Nature-based solutions and sustainable ecosystem stewardship

470 NbS includes a broad suite of interventions with nature-positive outcomes for businesses to demonstrate
471 sustainable ecosystem stewardship both within company supply chains and through making biodiversity
472 positive investments towards projects. The NbS interventions for sectors that directly depend on
473 ecosystems within their supply chains increasingly use new technologies for continuous data collection
474 and real-time analysis. This monitors biodiversity impacts and dependencies within the supply chain to
475 aid in informed decision-making for sustainable practices. For example, regenerative farming practices
476 must measure their biodiversity over time to claim biodiversity positive impacts on soil biodiversity,
477 nutrient cycling, carbon sequestration, and water retention through practices like crop rotation and no-till
478 farming (Case Study 1). For companies extracting natural resources, baseline biodiversity surveys prior to
479 business operations are needed to quantify the change in biodiversity and assess the true environmental
480 impact (Case study 2). More examples include ensuring marine biodiversity data are collected to identify
481 needs for selective fishing; agroforestry to improve habitat heterogeneity in agricultural land to increase
482 biodiversity and monitoring functionally important biodiversity, such as pollinators, introducing
483 interventions to enhance ecosystem services through planting native flowers, reducing pesticide use to
484 boost pollination and crop yields. Baseline biodiversity data and continuous monitoring within the supply
485 chain enable long-term stewardship of natural capital by assessing the impacts of various management
486 practices and forecasting possible risks associated with biodiversity loss, such as reduced carbon
487 sequestration (Case Study 1).

488

489 For NbS investments in biodiversity-positive projects beyond business supply chains, including market-
490 based instruments like biodiversity credits, offsets, subsidies, tradable permits, and payments for
491 ecosystem services, which are continually evolving, biodiversity data is essential for monitoring,
492 reporting, and verifying project impacts and contributions to natural capital. A data-driven “Internet of
493 Things” for ecosystems could enable comprehensive monitoring and verification across taxa and

494 environmental variables, ensuring the credibility and effectiveness of biodiversity-positive projects.
495 Initiatives like mangrove restoration, biodiversity-friendly infrastructure (e.g., wildlife corridors),
496 rewilding through native species reintroduction, and seagrass meadow restoration must prioritise
497 monitoring biodiversity and ecosystem variables to ensure logical conclusions of its value. Requiring
498 these projects to mobilise their biodiversity monitoring data to GBIF ensures accountability and
499 reliability. For companies already engaged in NbS projects, including biodiversity credits, mobilising data
500 to GBIF provides an opportunity to create publicly available biodiversity datasets, enhance transparency
501 in their environmental efforts, and contribute to global biodiversity knowledge.

502

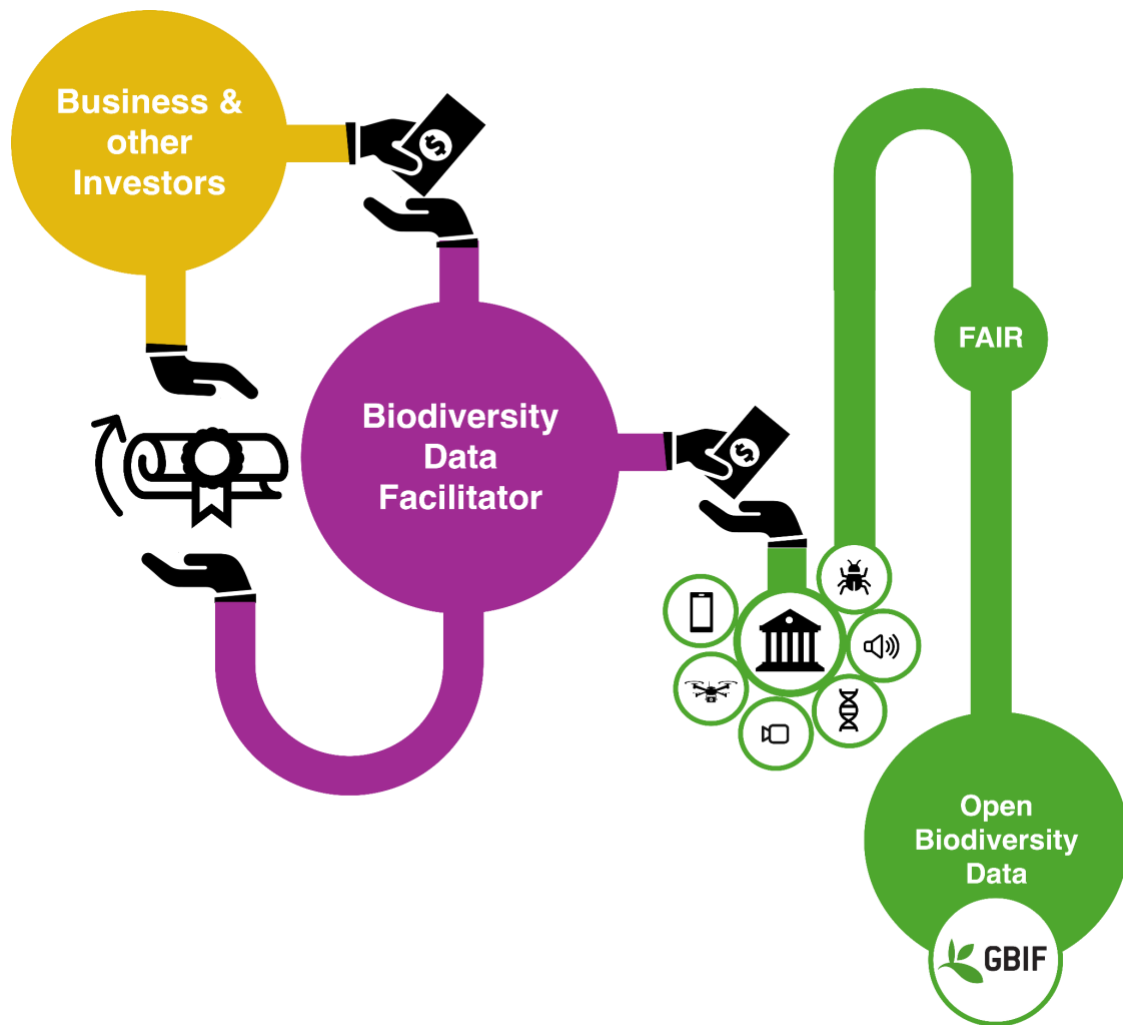
503 With incentives for investing in NbS through supply chains and credit systems, and the recognition of the
504 need to address the “nature data gap”, businesses and investors have a significant opportunity to require
505 evidence of biodiversity data collection and mobilisation to open platforms like GBIF, showcasing
506 responsibility in their portfolios while advancing meaningful ecosystem stewardship.

507 Biodiversity data certification

508 Building on the business use cases and incentives for investing in biodiversity data, we propose
509 biodiversity data certification as a structured approach to quantify, validate, and showcase contributions
510 to biodiversity data collection and mobilisation for quantifiable long-term impact (Figure 3). Many
511 action-oriented initiatives, such as Business For Nature and Finance for Biodiversity, have emerged to
512 raise awareness and secure private sector commitments towards financing biodiversity. In the end-to-end
513 framework presented here (Figure 1), we propose two key feedback loops to support sustainable financing
514 for primary biodiversity data collection and mobilisation from data providers. The first involves
515 businesses collecting and mobilising their own data (Figure 1(8)); the second involves a biodiversity data
516 facilitator, such as a not-for-profit organisation, helping to channel investment from businesses and other
517 stakeholders to address data gaps and biases in global open biodiversity databases (Figure 1(9)).

518

519 This proposed approach of an independent biodiversity data facilitator aligns financial investment with
520 the goals of the GBF, offering a novel way to fund and manage biodiversity data for long-term impact.
521 Businesses and other investors receive biodiversity data certifications, while data providers receive
522 financing for contributing data to the public domain. The economic, societal, and business returns on
523 investment in biodiversity data are manifold. However, there are currently no innovative financial
524 incentives to collect and mobilise primary biodiversity data at scale. Sustainable financing is needed to
525 support the collection, standardisation, and mobilisation of biodiversity data from both specimen-based
526 and observation-based sources (Figure 2). Economic investment and return on investment can be tracked
527 by the number of biodiversity data points shared with platforms like GBIF. The facilitator could apply
528 domain knowledge to enable to target funding for data collection to fill the most important gaps in global
529 biodiversity databases, for example by focusing on understudied taxa, such as fungi or insects, which
530 could have a significant impact on addressing the global biodiversity data gap by creating sustainable
531 financial flows for data providers. Mobilising data onto GBIF ensures credibility, and that biodiversity
532 information is available as a public good—accessible and regularly updated—serving as a valuable
533 resource for businesses, policymakers, and conservation efforts (Figure 3).



534

535 **Figure 3.** Innovative financing model for biodiversity data via a not-for-profit biodiversity data
 536 facilitator. Businesses and other investors (yellow) make financial investments towards data mobilisation
 537 through the biodiversity data facilitator (purple), which channels this investment into funds for partners
 538 that collect biodiversity data, advance data standards and mobilise biodiversity data onto GBIF. In return,
 539 businesses receive certification recognising their positive biodiversity actions.

540 Summary and call-to-action

541 The private sector faces an urgent challenge: understanding and managing biodiversity risks that directly
 542 impact business operations. While companies increasingly recognize their dependence on nature, two

543 critical barriers persist - insufficient biodiversity data and limited data literacy. Recognising that positive
544 biodiversity actions take time to show effects, biodiversity data collection and mobilisation should be
545 prioritised. New technologies mean that we have the opportunity to prioritise the mobilisation of both
546 specimen- and observation-based primary biodiversity data. New technologies like environmental DNA
547 and computer vision are providing unprecedented opportunities for data collection at scale, while vast
548 untapped resources exist in natural history collections that have great potential in advancing predictive
549 models. GBIF provides extensive open data, but businesses need better tools to interpret and apply this
550 information effectively. Creating meaningful biodiversity data products requires bridging the gap between
551 scientific expertise and corporate users through reliable metrics and models grounded in biodiversity data.
552 We call on businesses and stakeholders to urgently invest in biodiversity data collection and mobilisation
553 towards open data infrastructures like GBIF. Such investment is crucial for developing effective
554 biodiversity models, metrics, and data products that enable informed decision-making and support
555 biodiversity conservation efforts. With proper investment in data collection and analysis, companies can
556 better assess their environmental impact, manage risks, and have a positive impact on biodiversity.

557 References

- 558 barenkov, K., Andersson, A. F., Bissett, A., Finstad, A. G., Fossøy, F., Grosjean, M., Hope, M., Jeppesen, T.
559 S., Kõljalg, U., Lundin, D., Nilsson, R. H., Prager, M., Provoost, P., Dmitry, Saara, S., Cecilie, S., Tobias,
560 S., & Frøslev, G. (2023). *Publishing DNA-derived data through biodiversity data platforms*.
561 <https://doi.org/10.35035/doc-vf1a-nr22>
- 562 Aude, T. M. (2024). The Biodiversity Credit Market needs rigorous baseline, monitoring, and validation
563 practices. *Npj Biodiversity* 2024 3:1, 3(1), 1–4. <https://doi.org/10.1038/s44185-024-00062-6>
- 564 Allen, M. R., Friedlingstein, P., Girardin, C. A. J., Jenkins, S., Malhi, Y., Mitchell-Larson, E., Peters, G. P., &
565 Rajamani, L. (2025). *Annual Review of Environment and Resources Net Zero: Science, Origins, and*
566 *Implications*. 58. <https://doi.org/10.1146/annurev-environ-112320>

567 August, T., Harvey, M., Lightfoot, P., Kilbey, D., Papadopoulos, T., & Jepson, P. (2015). Emerging
568 technologies for biological recording. *Biological Journal of the Linnean Society*, 115(3), 731–749.
569 <https://doi.org/10.1111/BIJ.12534>

570 Bayraktarov, E., Ehmke, G., O'Connor, J., Burns, E. L., Nguyen, H. A., McRae, L., Possingham, H. P., &
571 Lindenmayer, D. B. (2019). Do big unstructured biodiversity data mean more knowledge? *Frontiers in*
572 *Ecology and Evolution*, 7(JAN), 426167. <https://doi.org/10.3389/FEVO.2018.00239/BIBTEX>

573 Beery, S. M. (2023). *Where the Wild Things Are: Computer Vision for Global-Scale Biodiversity Monitoring*.

574 Burgess, N. D., Ali, N., Bedford, J., Bhola, N., Brooks, S., Cierna, A., Correa, R., Harris, M., Hargey, A.,
575 Hughes, J., McDermott-Long, O., Miles, L., Ravilious, C., Rodrigues, A. R., Soesbergen, A. van,
576 Sihvonen, H., Seager, A., Swindell, L., Vukelic, M., ... Butchart, S. H. M. (2024). Global Metrics for
577 Terrestrial Biodiversity. *Annual Review of Environment and Resources*, 49(Volume 49, 2024), 673–709.
578 <https://doi.org/10.1146/ANNUREV-ENVIRON-121522-045106>

579 Jørgen, K., Nielsen, J. B., Sepstrup, M. V., Helsing-Nielsen, F., & Høye, T. T. (2021). *An Automated Light*
580 *Trap to Monitor Moths (Lepidoptera) Using Computer Vision-Based Tracking and Deep Learning*.
581 <https://doi.org/10.3390/s21020343>

582 Boyd, R. J., Powney, G. D., & Pescott, O. L. (2023). We need to talk about nonprobability samples. *Trends in*
583 *Ecology & Evolution*, 38(6), 521–531. <https://doi.org/10.1016/J.TREE.2023.01.001>

584 Buxton, R. T., McKenna, M. F., Clapp, M., Meyer, E., Stabenau, E., Angeloni, L. M., Crooks, K., &
585 Wittemyer, G. (2018). Efficacy of extracting indices from large-scale acoustic recordings to monitor
586 biodiversity. *Conservation Biology*, 32(5), 1174–1184. <https://doi.org/10.1111/COBI.13119>

587 Bubnicki, J. W., Norton, B., Baskauf, S. J., Bruce, T., Cagnacci, F., Casaer, J., Churski, M., Cromsigt, J. P. G.,
588 M., Farra, S. D., Fiderer, C., Forrester, T. D., Hendry, H., Heurich, M., Hofmeester, T. R., Jansen, P. A.,
589 Kays, R., Kuijper, D. P. J., Liefjing, Y., Linnell, J. D. C., ... Desmet, P. (2024). Camtrap DP: an open
590 standard for the FAIR exchange and archiving of camera trap data. *Remote Sensing in Ecology and*
591 *Conservation*, 10(3), 283–295. <https://doi.org/10.1002/RSE2.374>

592 Carroll, S. R., Herczog, E., Hudson, M., Russell, K., & Stall, S. (2021). Operationalizing the CARE and FAIR
593 Principles for Indigenous data futures. In *Scientific Data* (Vol. 8, Issue 1). Nature Research.
594 <https://doi.org/10.1038/s41597-021-00892-0>

595 CBD. (2011). *Convention on Biological Diversity : text and annexes / Secretariat of the Convention on*
596 *Biological Diversity*.

597 CBD. (2024). *Monitoring framework for the Kunming-Montreal Global Biodiversity Framework: Sixteenth*
598 *meeting Cali, Colombia, 21 October–1 November 2024 Agenda item 10 Mechanisms for planning,*
599 *monitoring, reporting and review.* [https://www.cbd.int/doc/c/5044/ea79/105d29801a3efae8df742c93/cop-](https://www.cbd.int/doc/c/5044/ea79/105d29801a3efae8df742c93/cop-600-16-1-26-en.pdf)
600 [16-1-26-en.pdf](https://www.cbd.int/doc/c/5044/ea79/105d29801a3efae8df742c93/cop-16-1-26-en.pdf)

601 ChecklistBank. (2025). <https://www.checklistbank.org/>

602 COP15. (2022). *The Convention on Biological Diversity Kunming-Montreal Global Biodiversity Framework*
603 *15/4.*
604 [https://www.cbd.int/conferences/post20202CBD/WG8J/11/7,CBD/SBSTTA/23/9,CBD/SBSTTA/24/12a](https://www.cbd.int/conferences/post20202CBD/WG8J/11/7,CBD/SBSTTA/23/9,CBD/SBSTTA/24/12a-605-ndCBD/SBI/3/21,respectively.)
605 [ndCBD/SBI/3/21,respectively.](https://www.cbd.int/conferences/post20202CBD/WG8J/11/7,CBD/SBSTTA/23/9,CBD/SBSTTA/24/12a-ndCBD/SBI/3/21,respectively.)

606 Davis, C. C. (2023). The herbarium of the future. *Trends in Ecology & Evolution*, 38(5), 412–423.
607 <https://doi.org/10.1016/J.TREE.2022.11.015>

608 d’Amato, D., La Notte, A., Damiani, M., & Sala, S. (2024). Biodiversity and ecosystem services in business
609 sustainability: Toward systematic, value chain-wide monitoring that aligns with public accounting.
610 *Journal of Industrial Ecology*, 28(5), 1030–1044. <https://doi.org/10.1111/JIEC.13521>

611 Dasgupta, P. (2021). *The Economics of Biodiversity: The Dasgupta Review*.

612 Deloitte. (2023). *Economic valuation and assessment of the impact of the GBIF network*.
613 [https://www.deloitte.com/au/en/services/economics/perspectives/total-economic-value-open-access-](https://www.deloitte.com/au/en/services/economics/perspectives/total-economic-value-open-access-614-database-living-world.html)
614 [database-living-world.html](https://www.deloitte.com/au/en/services/economics/perspectives/total-economic-value-open-access-database-living-world.html)

615 Deiner, K., Yamanaka, H., & Bernatchez, L. (2021). The future of biodiversity monitoring and conservation
616 utilizing environmental DNA. *Environmental DNA*, 3(1), 3–7. <https://doi.org/10.1002/EDN3.178>

61 Díaz, S., Pascual, U., Stenseke, M., Martín-López, B., Watson, R. T., Molnár, Z., Hill, R., Chan, K. M. A.,
618 Baste, I. A., Brauman, K. A., Polasky, S., Church, A., Lonsdale, M., Larigauderie, A., Leadley, P. W.,
619 Van Oudenhoven, A. P. E., Van Der Plaat, F., Schröter, M., Lavorel, S., ... Shirayama, Y. (2018).
620 Assessing nature's contributions to people: Recognizing culture, and diverse sources of knowledge, can
621 improve assessments. In *Science* (Vol. 359, Issue 6373, pp. 270–272). American Association for the
622 Advancement of Science. <https://doi.org/10.1126/science.aap8826>

623 Engel, M. S., Ceriaco, L. M. P., Daniel, G. M., Dellapé, P. M., Löbl, I., Marinov, M., Reis, R. E., Young, M.
624 T., Dubois, A., Agarwal, I., Lehmann, P. A., Alvarado, M., Alvarez, N., Andreone, F., Araujo-Vieira, K.,
625 Ascher, J. S., Baêta, D., Baldo, D., Bandeira, S. A., ... Zacharie, C. K. (2021). The taxonomic
626 impediment: a shortage of taxonomists, not the lack of technical approaches. *Zoological Journal of the*
627 *Linnean Society*, 193(2), 381–387. <https://doi.org/10.1093/ZOOLINNEAN/ZLAB072>

628 SRS E4. (2023). *Annex 1 - ESRS-E4: European Sustainability Reporting Standards Environmental standard*
629 *No.4 - Biodiversity and Ecosystems, Delegated Act*. [https://eur-lex.europa.eu/legal-](https://eur-lex.europa.eu/legal-content/en/ALL/?uri=CELEX:32023R2772#anx_I)
630 [content/en/ALL/?uri=CELEX:32023R2772#anx_I](https://eur-lex.europa.eu/legal-content/en/ALL/?uri=CELEX:32023R2772#anx_I)

631 Evison, W., Gill, E., Moussa, T., & O'Brien, D. (2022). *A surge in nature tech investing | PwC*.
632 <https://www.pwc.com/gx/en/services/sustainability/publications/surge-in-nature-tech-investing.html>

633 Exposito-Alonso, M., Booker, T. R., Czech, L., Gillespie, L., Hateley, S., Kyriazis, C. C., Lang, P. L. M.,
634 Leventhal, L., Nogues-Bravo, D., Pagowski, V., Ruffley, M., Spence, J. P., Toro Arana, S. E., Wei, C.,
635 L., & Zess, E. (2022). Genetic diversity loss in the Anthropocene. *Science (New York, N.Y.)*, 377(6613),
636 1431–1435. <https://doi.org/10.1126/SCIENCE.ABN5642>

637 Faqih, A., & Kramer, R. (2024). The Corporate Sustainability Reporting Directive (CSRD): An Effective
638 Approach to Implementation. *DIPONEGORO JOURNAL OF ACCOUNTING*, 13(4), 1–9. [http://ejournal-](http://ejournal-s1.undip.ac.id/index.php/accounting)
639 [s1.undip.ac.id/index.php/accounting](http://ejournal-s1.undip.ac.id/index.php/accounting)

640 Figueira, R., Beja, P., Villaverde, C., Vega, M., Cezón, K., Messina, T., Archambeau, A.-S., Rukaya, Dag, J.,
641 & Dairo Escobar, E., (2023). *Guidance for private companies to become data publishers through GBIF*.
642 <https://doi.org/10.35035/doc-b8hq-me03>

643 inBio. (2023). *FinBio annual report 2023*. [https://finbio.org/wp-content/uploads/2024/04/FinBio-annual-](https://finbio.org/wp-content/uploads/2024/04/FinBio-annual-report-2023.pdf)
644 [report-2023.pdf](https://finbio.org/wp-content/uploads/2024/04/FinBio-annual-report-2023.pdf)

645 Garner, B. H., Creedy, T. J., Allan, E. L., Crowther, R., Devenish, E., Kokkini, P., Livermore, L., Lohonya, K.,
646 Lowndes, N., Wing, P., & Vogler, A. P. (2024). *The taxonomic composition and chronology of a museum*
647 *collection of Coleoptera revealed through large-scale digitisation*. *Frontiers in Ecology and Evolution*,
648 *12*. <https://doi.org/10.3389/fevo.2024.1305931>

649 GBIF. (2024). <https://www.gbif.org/>

650 GBIF. (2024). *GBIF Science Review No.11*.
651 <https://www.gbif.org/document/5N9YVBkTP3y7kqhFQviowM/gbif-science-review-no-11>

652 Berber, L. R., & Iacona, G. D. (2024). Aligning data with decisions to address the biodiversity crisis. *PLOS*
653 *Biology*, *22*(6), e3002683. <https://doi.org/10.1371/JOURNAL.PBIO.3002683>

654 Goren, G. (2024). *Developing the Nature Tech Taxonomy Framework*.
655 [https://www.naturetechcollective.org/stories/nature-tech-taxonomy-](https://www.naturetechcollective.org/stories/nature-tech-taxonomy-framework#Download%20Whitepaper)
656 [framework#Download%20Whitepaper](https://www.naturetechcollective.org/stories/nature-tech-taxonomy-framework#Download%20Whitepaper)

657 Gonzalez, A., Chase, J. M., & O'Connor, M. I. (2023). *A framework for the detection and attribution of*
658 *biodiversity change*. *Philosophical Transactions of the Royal Society B*, *378*(1881).
659 <https://doi.org/10.1098/RSTB.2022.0182>

660 Granqvist, E., Goodsell, R. M., & Ronquist, F. (In prep). The transformative potential of eDNA-based
661 biodiversity. *Current Opinion in Environmental Sustainability*.

662 Hawkins, F. (2024). How will better data (and better use of data) enable us to save the planet? *PLOS Biology*,
663 *22*(6), e3002689. <https://doi.org/10.1371/JOURNAL.PBIO.3002689>

664 Hildebrand, J., Wiggins, S., Baumann-Pickering, S., Frasier, K., & Roch, M. A. (2024). The past, present and
665 future of underwater passive acoustic monitoring. *The Journal of the Acoustical Society of America*,
666 *155*(3_Supplement), A96–A96. <https://doi.org/10.1121/10.0026934>

667 Hillebrand, H., Blasius, B., Borer, E. T., Chase, J. M., Downing, J. A., Eriksson, B. K., Filstrup, C. T., Harpole,
668 W. S., Hodapp, D., Larsen, S., Lewandowska, A. M., Seabloom, E. W., Van de Waal, D. B., & Ryabov,

669 A. B. (2018). Biodiversity change is uncoupled from species richness trends: Consequences for
670 conservation and monitoring. *Journal of Applied Ecology*, 55(1), 169–184. [https://doi.org/10.1111/1365-](https://doi.org/10.1111/1365-2664.12959)
671 [2664.12959](https://doi.org/10.1111/1365-2664.12959)

672 Hill D, Fasham M, Tucker G, Shewry M & Shaw P. (2005). Handbook of Biodiversity
673 Methods: Survey, Evaluation and Monitoring. Cambridge: Cambridge University Press.
674 <https://doi.org/10.1017/CBO9780511542084>

675 Jobern, D., Baptiste, B., Copas, K., Guralnick, R., Hahn, A., van Huis, E., Kim, E. S., McGeoch, M., Naicker,
676 I., Navarro, L., Noesgaard, D., Price, M., Rodrigues, A., Schigel, D., Sheffield, C. A., & Wieczorek, J.
677 (2019). Connecting data and expertise: A new alliance for biodiversity knowledge. *Biodiversity Data*
678 *Journal*, 7. <https://doi.org/10.3897/BDJ.7.e33679>

679 Hofer, S., McKnight, D. T., Allen-Ankins, S., Nordberg, E. J., & Schwarzkopf, L. (2023). Passive acoustic
680 monitoring in terrestrial vertebrates: a review. In *Bioacoustics* (Vol. 32, Issue 5, pp. 506–531). Taylor and
681 Francis Ltd. <https://doi.org/10.1080/09524622.2023.2209052>

682 Øye, T. T., Ärje, J., Bjerge, K., Hansen, O. L. P., Iosifidis, A., Leese, F., Mann, H. M. R., Meissner, K.,
683 Melvad, C., & Raitoharju, J. (2021). Deep learning and computer vision will transform entomology.
684 *Proceedings of the National Academy of Sciences of the United States of America*, 118(2), e2002545117.
685 <https://doi.org/10.1073/PNAS.2002545117/-/DCSUPPLEMENTAL>

686 Hughes, A. C., Orr, M. C., Ma, K., Costello, M. J., Waller, J., Provoost, P., Yang, Q., Zhu, C., & Qiao, H.
687 (2021). Sampling biases shape our view of the natural world. *Ecography*, 44(9), 1259–1269.
688 <https://doi.org/10.1111/ECOG.05926>

689 Huybrechts, P., Trekels, M., & Groom, Q. (2022). How Much of Biodiversity is Represented in Collections: A
690 big data workflow of aggregated occurrence data. *Biodiversity Information Science and Standards* 6:
691 *E94279*, 6, e94279-. <https://doi.org/10.3897/BISS.6.94279>

692 Ingram, J. C., McKenzie, E. J., Bagstad, K. J., Finisdore, J., van den Berg, R., Fenichel, E., Vardon, M.,
693 Posner, S., Santamaria, M., Mandle, L., Barker, R., & Spurgeon, J. (2024). Leveraging natural capital

694 accounting to support businesses with nature-related risk assessments and disclosures. *Philosophical*
695 *Transactions of the Royal Society B*, 379(1903). <https://doi.org/10.1098/RSTB.2022.0328>

696 Jones, M. J., & Solomon, J. F. (2013). Problematising accounting for biodiversity. *Auditing & Accountability*
697 *Journal*, 26(5), 668–687. <https://doi.org/10.1108/AAAJ-03-2013-1255>

698 Kahilainen, A., Puurtinen, M., & Kotiaho, J. S. (2014). Conservation implications of species–genetic diversity
699 correlations. *Global Ecology and Conservation*, 2, 315–323.
700 <https://doi.org/10.1016/J.GECCO.2014.10.013>

701 Kulionis, V., Pfister, S., & Fernandez, J. (2024). Biodiversity impact assessment for finance. *Journal of*
702 *Industrial Ecology*, 28(5), 1321–1335. <https://doi.org/10.1111/JIEC.13515>

703 Barsen, H. L., Møller-Lassesen, K., Enevoldsen, E. M. E., Madsen, S. B., Obsen, M. T., Povlsen, P., Bruhn, D.,
704 Pertoldi, C., & Pagh, S. (2023). Drone with Mounted Thermal Infrared Cameras for Monitoring
705 Terrestrial Mammals. *Drones*, 7(11). <https://doi.org/10.3390/drones7110680>

706 öbl, I., Klausnitzer, B., Hartmann, M., & Krell, F.-T. (2023). *The Silent Extinction of Species and*
707 *Taxonomists-An Appeal to Science Policymakers and Legislators*. <https://doi.org/10.3390/d15101053>

708 iu, D. (2024). We must train specialists in botany and zoology — or risk more devastating extinctions.
709 *Nature*, 633(8031), 741. <https://doi.org/10.1038/D41586-024-03072-3>

710 Mace, G. M., Norris, K., & Fitter, A. H. (2012). Biodiversity and ecosystem services: A multilayered
711 relationship. *Trends in Ecology and Evolution*, 27(1), 19–26.
712 [https://doi.org/10.1016/J.TREE.2011.08.006/ASSET/0F6FA3A0-5727-4F75-8747-](https://doi.org/10.1016/J.TREE.2011.08.006/ASSET/0F6FA3A0-5727-4F75-8747-D6780EB3193C/MAIN.ASSETS/FX2.GIF)
713 [D6780EB3193C/MAIN.ASSETS/FX2.GIF](https://doi.org/10.1016/J.TREE.2011.08.006/ASSET/0F6FA3A0-5727-4F75-8747-D6780EB3193C/MAIN.ASSETS/FX2.GIF)

714 Mair, L., Elnahass, M., Xiang, E., Hawkins, F., Siikamaki, J., Hillis, L., Barrie, S., & McGowan, P. J. K.
715 (2024). Corporate disclosures need a biodiversity outcome focus and regulatory backing to deliver global
716 conservation goals. *Conservation Letters*, 17(4), e13024. <https://doi.org/10.1111/CONL.13024>

717 Maldonado, C., Molina, C. I., Zizka, A., Persson, C., Taylor, C. M., Albán, J., Chilquillo, E., Rønsted, N., &
718 Antonelli, A. (2015). Estimating species diversity and distribution in the era of Big Data: To what extent

719 can we trust public databases? *Global Ecology and Biogeography*, 24(8), 973–984.
720 <https://doi.org/10.1111/GEB.12326/SUPPINFO>

721 Mason Heberling, J., Miller, J. T., Noesgaard, D., Weingart C , S. B., Schigel, D., & Soltis, D. E. (2021). *Data*
722 *integration enables global biodiversity synthesis*. <https://doi.org/10.1073/pnas.2018093118/->
723 */DCSupplemental*

724 Musvuugwa, T., Gladmond Dlomu, M., Adebawale, A., Mahmoud, M., & Antonio Gutiérrez, P. (2021). Big
725 Data in Biodiversity Science: A Framework for Engagement. *Technologies 2021, Vol. 9, Page 60, 9(3)*,
726 60. <https://doi.org/10.3390/TECHNOLOGIES9030060>

727 Mäyrä, J., Keski-Saari, S., Kivinen, S., Tanhuanpää, T., Hurskainen, P., Kullberg, P., Poikolainen, L., Viinikka,
728 A., Tuominen, S., Kumpula, T., & Vihervaara, P. (2021). Tree species classification from airborne
729 hyperspectral and LiDAR data using 3D convolutional neural networks. *Remote Sensing of Environment*,
730 256. <https://doi.org/10.1016/j.rse.2021.112322>

731 Martin, P. A., Green, R. E., & Balmford, A. (2019). The biodiversity intactness index may underestimate
732 losses. *Nature Ecology & Evolution 2019 3:6*, 3(6), 862–863. <https://doi.org/10.1038/s41559-019-0895-1>

733 Miraldo, A., Sundh, J., Iwazskiewicz-Eggebrecht, E., Buczek, M., Goodsell, R., Johansson, H., Fisher, B.,
734 Raharinjanahary, D., Rajoelison, E., Ranaivo, C., Randrianandrasana, C., Rafanomezantsoa, J.-J.,
735 Manoharan, L., Granqvist, E., Dijk, L. van, Alberg, L., Åhlén, D., Aspebo, M., Åström, S., ... Ronquist,
736 F. (2024). Data of the Insect Biome Atlas: a metabarcoding survey of the terrestrial arthropods of Sweden
737 and Madagascar. *BioRxiv*, 2024.10.24.619818. <https://doi.org/10.1101/2024.10.24.619818>

738 Mora, C., Tittensor, D. P., Adl, S., Simpson, A. G. B., & Worm, B. (2011). How Many Species Are There on
739 Earth and in the Ocean? *PLOS Biology*, 9(8), e1001127.
740 <https://doi.org/10.1371/JOURNAL.PBIO.1001127>

741 Musvuugwa, T., Dlomu, M. G., & Adebawale, A. (2021). Big Data in Biodiversity Science: A Framework for
742 Engagement. In *Technologies* (Vol. 9, Issue 3). MDPI. <https://doi.org/10.3390/technologies9030060>

743 Myers, N., Mittermeyer, R. A., Mittermeyer, C. G., Da Fonseca, G. A. B., & Kent, J. (2000). Biodiversity
744 hotspots for conservation priorities. *Nature* 2000 403:6772, 403(6772), 853–858.
745 <https://doi.org/10.1038/35002501>

746 Nature Tech Collective. (2024). *Nature Fintech Sector Map*. https://twitter.com/naturex_ntc

747 Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., Börger, L., Bennett, D. J.,
748 Choimes, A., Collen, B., Day, J., De Palma, A., Díaz, S., Echeverria-Londoño, S., Edgar, M. J., Feldman,
749 A., Garon, M., Harrison, M. L. K., Alhousseini, T., ... Purvis, A. (2015). Global effects of land use on
750 local terrestrial biodiversity. *Nature* 2015 520:7545, 520(7545), 45–50.
751 <https://doi.org/10.1038/nature14324>

752 Nyström, J. (2024). *Large-scale biodiversity intactness estimation using Bayesian hierarchical models*
753 [Uppsala University]. <https://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-538994>

754 Panwar, R., Ober, H., & Pinkse, J. (2023). The uncomfortable relationship between business and biodiversity:
755 Advancing research on business strategies for biodiversity protection. *Business Strategy and the*
756 *Environment*, 32(5), 2554–2566. <https://doi.org/10.1002/BSE.3139>

757 Pereira, H. M., Ferrier, S., Walters, M., Geller, G. N., Jongman, R. H. G., Scholes, R. J., Bruford, M. W.,
758 Brummitt, N., Butchart, S. H. M., Cardoso, A. C., Coops, N. C., Dulloo, E., Faith, D. P., Freyhof, J.,
759 Gregory, R. D., Heip, C., Höft, R., Hurtt, G., Jetz, W., ... Wegmann, M. (2013). Essential biodiversity
760 variables. *Science*, 339(6117), 277–278.

761 Phillips, H., De Palma, A., Gonzalez, R. E., & Contu, S. (2021). The Biodiversity Intactness Index - country,
762 region and global-level summaries for the year 1970 to 2050 under various scenarios. *Natural History*
763 *Museum Data Portal*. <https://doi.org/10.5519/HE1EQMG1>

764 Pyle, R. L., Barik, S. K., Christidis, L., Conix, S., Costello, M. J., van Dijk, P. P., Garnett, S. T., Hobern, D.,
765 Kirk, P. M., Lien, A. M., Orrell, T. M., Remsen, D., Thomson, S. A., Wambiji, N., Zachos, F. E., Zhang,
766 Z. Q., & Thiele, K. R. (2021). Towards a global list of accepted species V. The devil is in the detail.
767 *Organisms Diversity and Evolution*, 21(4), 657–675. [https://doi.org/10.1007/S13127-021-00504-](https://doi.org/10.1007/S13127-021-00504-0)
768 [0/FIGURES/2](https://doi.org/10.1007/S13127-021-00504-0)

768 Ronger, N., Alvarez, J., Freeman, A., Harwood, T., Obersteiner, M., Paulus, E., Sabuco, J., Svartzman, R.,
770 Althouse, J., Gabet, M., Hurst, I., Ladze, I., Millard, S., Sanchez Juanino, P., David Craig, T., McKenzie,
771 E., Goldner, T., Dutt, N., Baker, L., ... de Sousa Almeida, I. (2023). *The Green Scorpion: the Macro-*
772 *Criticality of Nature for Finance Foundations for scenario-based analysis of complex and cascading*
773 *physical nature-related financial risks* Published as Oxford-NGFS Occasional Paper 2 Citation the Task
774 *force on biodiversity loss and nature-related risks (Task force Nature) of the Network of Central Banks*
775 *and Supervisors for Greening the Financial System (NGFS). We express our sincere thanks to.*
776 <https://www.ngfs.net/en/the-green-scorpion-macro-criticality-nature-for-finance>

778 Robinson, J. M., Annells, A., Cavagnaro, T. R., Liddicoat, C., Rogers, H., Taylor, A., & Breed, M. F. (2024).
779 Monitoring soil fauna with ecoacoustics. *Proceedings of the Royal Society B*, 291(2030).
780 <https://doi.org/10.1098/RSPB.2024.1595>

781 Roslin, T., & Laine, A.-L. (2022). The changing fauna and flora of Finland – discovering the bigger picture
782 through long-term data. *Memoranda Societatis pro Fauna et Flora Fennica*, 98(Supplement 2), 40–53.
783 <https://journal.fi/msff/article/view/122353>

784 Ronquist, F., Forshage, M., Häggqvist, S., Karlsson, D., Hovmöller, R., Bergsten, J., Holston, K., Britton, T.,
785 Abenius, J., Andersson, B., Buhl, P. N., Coulianos, C. C., Fjellberg, A., Gertsson, C. A., Hellqvist, S.,
786 Jaschhof, M., Kjærandsen, J., Klopstein, S., Kobro, S., ... Gärdenfors, U. (2020). Completing Linnaeus's
787 inventory of the Swedish insect fauna: Only 5,000 species left? *PLOS ONE*, 15(3), e0228561.
788 <https://doi.org/10.1371/JOURNAL.PONE.0228561>

789 Roslin, T., Somervuo, P., Pentinsaari, M., Hebert, P. D. N., Agda, J., Ahlroth, P., Anttonen, P., Aspi, J.,
790 Blagoev, G., Blanco, S., Chan, D., Clayhills, T., deWaard, J., deWaard, S., Elliot, T., Elo, R., Haapala, S.,
791 Helve, E., Ilmonen, J., ... Mutanen, M. (2022). A molecular-based identification resource for the
792 arthropods of Finland. *Molecular Ecology Resources*, 22(2), 803–822. [https://doi.org/10.1111/1755-](https://doi.org/10.1111/1755-0998.13510)
793 [0998.13510](https://doi.org/10.1111/1755-0998.13510)

794 SBTN. (2020). *SCIENCE-BASED TARGETS for NATURE Initial Guidance for Business.*

794 eddon, N., Chausson, A., Berry, P., Girardin, C. A. J., Smith, A., & Turner, B. (2020). Understanding the
795 value and limits of nature-based solutions to climate change and other global challenges. *Philosophical*
796 *Transactions of the Royal Society B*, 375(1794). <https://doi.org/10.1098/RSTB.2019.0120>

797 eidl, A., Cumming, T., Arlaud, M., Crossett, C., & van den Heuvel, O. (2024). Investing in the wealth of
798 nature through biodiversity and ecosystem service finance solutions. *Ecosystem Services*, 66, 101601.
799 <https://doi.org/10.1016/J.ECOSER.2024.101601>

800 mith, T., Paavola, J., & Holmes, G. (2019). Corporate reporting and conservation realities: Understanding
801 differences in what businesses say and do regarding biodiversity. *Environmental Policy and Governance*,
802 29(1), 3–13. <https://doi.org/10.1002/EET.1839>

803 spear, D., van Wilgen, N. J., Rebelo, A. G., & Botha, J. M. (2023). Collating biodiversity occurrence data for
804 conservation. *Frontiers in Ecology and Evolution*, 11, 1037282.
805 <https://doi.org/10.3389/FEVO.2023.1037282/BIBTEX>

806 teffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S.
807 R., De Vries, W., De Wit, C. A., Folke, C., Gerten, D., Heinke, J., Mace, G. M., Persson, L. M.,
808 Ramanathan, V., Reyers, B., & Sörlin, S. (2015). Planetary boundaries: Guiding human development on a
809 changing planet. *Science*, 347(6223).
810 https://doi.org/10.1126/SCIENCE.1259855/SUPPL_FILE/STEFFEN-SM.PDF

811 teenweg, R., Hebblewhite, M., Kays, R., Ahumada, J., Fisher, J. T., Burton, C., Townsend, S. E., Carbone, C.,
812 Rowcliffe, J. M., Whittington, J., Brodie, J., Royle, J. A., Switalski, A., Clevenger, A. P., Heim, N., &
813 Rich, L. N. (2017). Scaling-up camera traps: monitoring the planet's biodiversity with networks of remote
814 sensors. *Frontiers in Ecology and the Environment*, 15(1), 26–34. <https://doi.org/10.1002/FEE.1448>

815 winfield, T., Shrikanth, S., Bull, J. W., Madhavapeddy, A., & zu Ermgassen, S. O. S. E. (2024). Nature-based
816 credit markets at a crossroads. *Nature Sustainability* 2024 7:10, 7(10), 1217–1220.
817 <https://doi.org/10.1038/s41893-024-01403-w>

818ork, N. E. (2018). How Many Species of Insects and Other Terrestrial Arthropods Are There on Earth?
819 *Annual Review of Entomology*, 63(Volume 63, 2018), 31–45. <https://doi.org/10.1146/ANNUREV-ENTO->
820 020117-043348/CITE/REFWORKS

821Takano, A., Cole, T. C. H., & Konagai, H. (2024). A novel automated label data extraction and data base
822 generation system from herbarium specimen images using OCR and NER. *Scientific Reports*, 14(1).
823 <https://doi.org/10.1038/s41598-023-50179-0>Troudet, J., Grandcolas, P., Blin, A., Vignes-Lebbe, R., &
824 Legendre, F. (2017). Taxonomic bias in biodiversity data and societal preferences OPEN. *Nature*.
825 <https://doi.org/10.1038/s41598-017-09084-6>

826Troudet, J., Vignes-Lebbe, R., Grandcolas, P., & Legendre, F. (2018). The Increasing Disconnection of
827 Primary Biodiversity Data from Specimens: How Does It Happen and How to Handle It? *Systematic*
828 *Biology*, 67(6), 1110–1119. <https://doi.org/10.1093/SYSBIO/SYY044>

829 IPCC (2023) Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the
830 Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team,
831 H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland, pp. 35-115, doi: 10.59327/IPCC/AR6-
832 9789291691647.

833 TNFD. (2024). *A roadmap for upgrading market access to decision-useful nature-related data*.
834 https://tnfd.global/wp-content/uploads/2024/10/Discussion-paper_Roadmap-for-enhancing-market-
835 [access-to-nature-data.pdf?v=1730281144](https://tnfd.global/wp-content/uploads/2024/10/Discussion-paper_Roadmap-for-enhancing-market-access-to-nature-data.pdf?v=1730281144)

836TNFD. (2023). *Findings of a high-level scoping study exploring the case for a global nature-related public*
837 *data facility*. <https://wedocs.unep.org/bitstream/handle/20.500.11822/41335/state>

838TNFD. (2024, December 10). *Over 500 organisations and \$17.7 trillion AUM now committed to TNFD-*
839 *aligned risk management and corporate reporting*. <https://Tnfd.Global/over-500-Organisations-and-17->
840 [7-Trillion-Aum-Now-Committed-to-Tnfd-Aligned-Risk-Management-and-Corporate-](https://Tnfd.Global/over-500-Organisations-and-17-7-Trillion-Aum-Now-Committed-to-Tnfd-Aligned-Risk-Management-and-Corporate-)
841 [Reporting/](https://Tnfd.Global/over-500-Organisations-and-17-7-Trillion-Aum-Now-Committed-to-Tnfd-). <https://tnfd.global/over-500-organisations-and-17-7-trillion-aum-now-committed-to-tnfd->
842 [aligned-risk-management-and-corporate-reporting/](https://tnfd.global/over-500-organisations-and-17-7-trillion-aum-now-committed-to-tnfd-aligned-risk-management-and-corporate-reporting/)

843 roudet, J., Grandcolas, P., Blin, A., Vignes-Lebbe, R., & Legendre, F. (2017). Taxonomic bias in biodiversity
844 data and societal preferences. *Nature*. <https://doi.org/10.1038/s41598-017-09084-6>.

845 van Klink, R., August, T., Bas, Y., Bodesheim, P., Bonn, A., Fossøy, F., Høye, T. T., Jongejans, E., Menz, M.
846 H. M., Miraldo, A., Roslin, T., Roy, H. E., Ruczyński, I., Schigel, D., Schäffler, L., Sheard, J. K.,
847 Svenningsen, C., Tschan, G. F., Wäldchen, J., ... Bowler, D. E. (2022). Emerging technologies
848 revolutionise insect ecology and monitoring. *Trends in Ecology & Evolution*, 37(10), 872–885.
849 <https://doi.org/10.1016/J.TREE.2022.06.001>

850 van Klink, R., Sheard, J. K., Høye, T. T., Roslin, T., Do Nascimento, L. A., & Bauer, S. (2024). Towards a
851 toolkit for global insect biodiversity monitoring. In *Philosophical Transactions of the Royal Society B:*
852 *Biological Sciences* (Vol. 379, Issue 1904). Royal Society Publishing.
853 <https://doi.org/10.1098/rstb.2023.0101>

854 WEF. (2024). *World Economic Forum Global Risks Report*. www.weforum.org

855 White, T. B., Mukherjee, N., Petrovan, S. O., & Sutherland, W. J. (2023). Identifying opportunities to deliver
856 effective and efficient outcomes from business-biodiversity action. *Environmental Science & Policy*, 140,
857 221–231. <https://doi.org/10.1016/J.ENVSCI.2022.12.003>

858 White, T. B., Petrovan, S. O., Bennun, L. A., Butterworth, T., Christie, A. P., Downey, H., Hunter, S. B.,
859 Jobson, B. R., zu Ermgassen, S. O. S. E., & Sutherland, W. J. (2023). Principles for using evidence to
860 improve biodiversity impact mitigation by business. *Business Strategy and the Environment*, 32(7), 4719–
861 4733. <https://doi.org/10.1002/BSE.3389>

862 Wilkinson, M. D., Dumontier, M., Aalbersberg, Ij. J., Appleton, G., Axton, M., Baak, A., Blomberg, N.,
863 Boiten, J. W., da Silva Santos, L. B., Bourne, P. E., Bouwman, J., Brookes, A. J., Clark, T., Crosas, M.,
864 Dillo, I., Dumon, O., Edmunds, S., Evelo, C. T., Finkers, R., ... Mons, B. (2016). The FAIR Guiding
865 Principles for scientific data management and stewardship. *Scientific Data* 2016 3:1, 3(1), 1–9.
866 <https://doi.org/10.1038/sdata.2016.18>

866 Wieczorek, J., Bloom, D., Guralnick, R., Blum, S., Döring, M., Giovanni, R., Robertson, T., & Vieglais, D.
868 (2012). Darwin Core: An Evolving Community-Developed Biodiversity Data Standard. *PLOS ONE*, 7(1),
869 e29715. <https://doi.org/10.1371/JOURNAL.PONE.0029715>

870 Whitley, B. S., Abermann, J., Alsos, I. G., Biersma, E. M., Gårdman, V., Høye, T. T., Jones, L., Khelidj, N.
871 M., Li, Z., Losapio, G., Pape, T., Raundrup, K., Schmitz, P., Silva, T., Wirta, H., Roslin, T., Ahlstrand, N.
872 I., & Vere, N. de. (2024). Harmonising digitised herbarium data to enhance biodiversity knowledge:
873 creating an updated checklist for the flora of Greenland. *BioRxiv*, 2024.12.01.626242.
874 <https://doi.org/10.1101/2024.12.01.626242>

875 WWF. (2024). *WWF Position Voluntary Biodiversity Credits*.
876 <https://wwfint.awsassets.panda.org/downloads/biodiversity-credits-position---october-2024---final.pdf>
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892 Supporting Information

893 Case study S1. Biodiversity Data for Financial Metrics: MISTRA

894 FinBio, Sweden



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896 **Figure S1.** Photo of Malaise traps in pilot fields, taken by E Granqvist May 2024.

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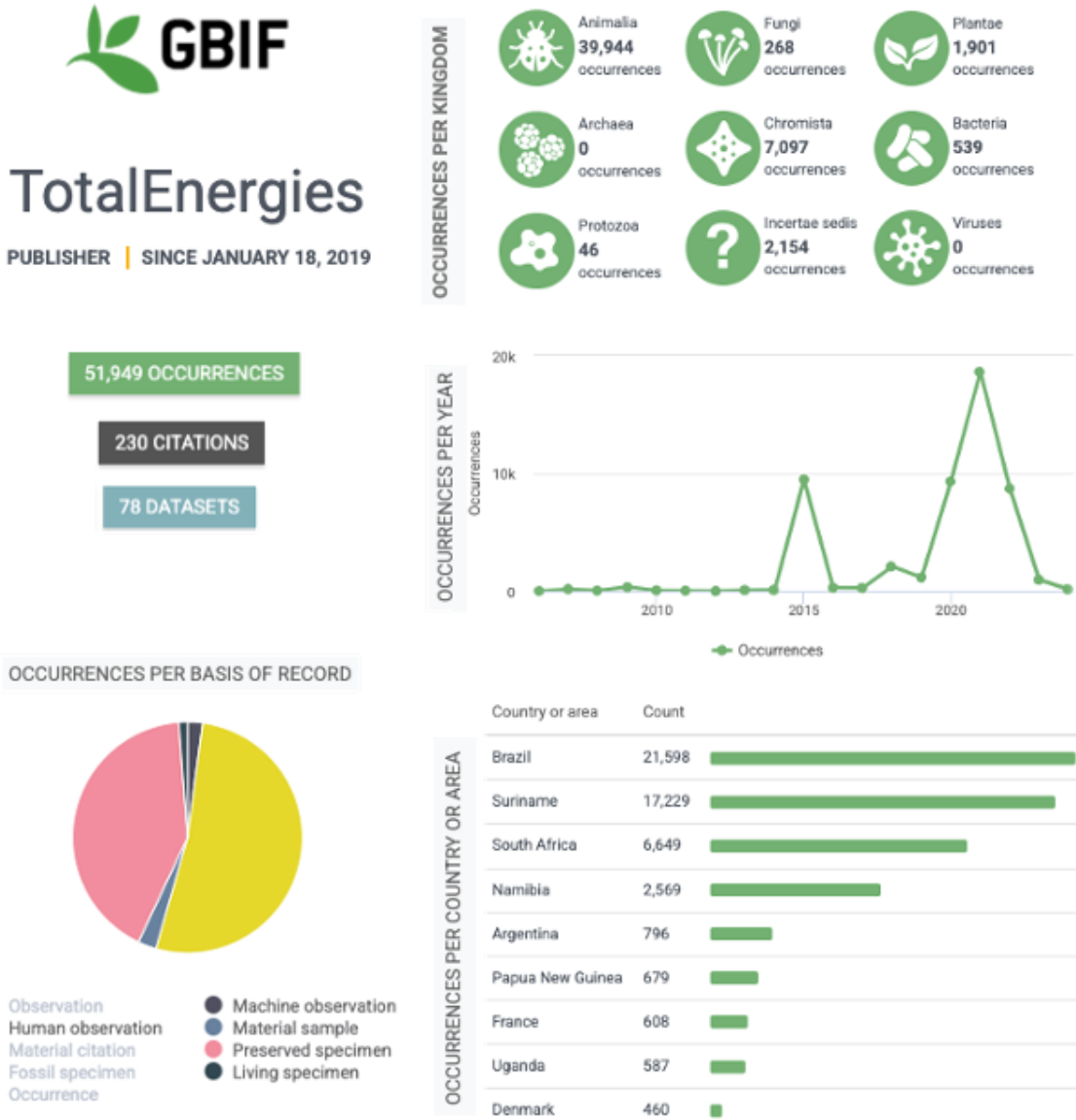
898 The “Biodiversity Data for Financial Metrics” work package connects biodiversity data to financial
899 decision-making in the FinBio research program hosted at the Stockholm Resilience Centre (FinBio,
900 2023). The overall program aims to support financial institutions in contributing to biodiversity and
901 nature-positive outcomes. FinBio operates as a collaborative partnership between academic and financial
902 institutions. The program brings together academic and impact partners to develop practical tools that
903 guide investment decisions, promoting both the greening of finance and the financing of green initiatives
904 that can be adopted throughout the financial sector. The program explores several key areas, and the
905 “Biodiversity Data for Financial Metrics” work package focuses on the application of modern monitoring
906 technologies such as environmental DNA (eDNA) and Earth Observations for assessing biodiversity
907 impact. This includes methods for assessing Essential Biodiversity Variables (EBVs). The methodology
908 encompasses eDNA collection from Malaise traps and soil samples, focusing on laboratory and

909 bioinformatic protocols, accuracy measurements, and abundance estimation, with trend analyses covering
910 a five-year period in Sweden. A pilot project within the work package involves collaboration with Svensk
911 Kolinlagring, a non-profit organization launched in 2019 that connects stakeholders to increase soil health
912 and carbon storage in Swedish agricultural soils. This organization currently works with approximately 40
913 farms. The pilot project with FinBio focuses on measuring biodiversity in agricultural farmland targeting
914 carbon sequestration, which the IPCC has identified as one of the most cost-effective and scalable climate
915 action solutions. The pilot project aims to deliver several key outcomes, including biodiversity data from
916 the agricultural sector using eDNA monitoring methods, analysis of biodiversity changes in carbon
917 sequestration management systems, and the development of a biodiversity index for farmers. This index
918 will serve as both a measurement tool and a component of potential business cases to attract investment in
919 sustainable agricultural practices. Open data and open methods are core principles within the Biodiversity
920 Data for Financial Metrics work package, and the collected pilot data will be shared via GBIF upon
921 completion of the project.

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923 Case study S2. TotalEnergies share biodiversity data on GBIF

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926 **Figure S2.** TotalEnergies data publisher metrics displayed on their GBIF publisher page, showcasing key
 927 performance indicators (KPIs) for company reporting. Metrics include: occurrences per kingdom,
 928 occurrences per year, occurrences per country or area, and occurrences per basis of record. These metrics
 929 provide insights into data distribution and can be used to evaluate the company's contribution to
 930 biodiversity monitoring.

931

932 TotalEnergies, a global energy company operating in 120 countries, became a publisher of the Global
933 Biodiversity Information Facility (GBIF) in 2018 to strengthen its efforts in biodiversity data sharing. The
934 company committed to sharing biodiversity data collected through environmental impact assessments,
935 including field surveys in remote and offshore locations, with both the scientific community and the
936 public. By publishing its data to GBIF, TotalEnergies considers this a valuable contribution to global
937 scientific research and international conservation efforts. The company employs a variety of data
938 collection methods, such as sediment, soil, and water sampling, camera transects, and passive acoustic
939 monitoring and opportunistic observations of marine megafauna and birds. This data encompasses
940 hydrocarbons, metals, microbiology, and benthic fauna, helping to assess habitat sensitivity.
941 TotalEnergies' biodiversity data adheres to GBIF's quality standards, following DarwinCore (DwC)
942 standard and FAIR principles, and has committed to contribute data annually from a minimum of five
943 projects or sites to GBIF, with regular reports on these contributions.

944

945 Companies publish biodiversity data by establishing institutional agreements and complying with GBIF's
946 Data Publisher and Data User Agreements. Registration as a data publisher requires endorsement from a
947 national GBIF node. The process typically involves collaboration with contractors and field technicians to
948 ensure data and metadata quality. Companies must establish internal workflows, select and prepare
949 biodiversity data according to the DwC, define access restrictions, and publish under a Creative
950 Commons license.

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