Nine changes needed to deliver a radical transformation in biodiversity measurement

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Abstract

Biodiversity is declining in many parts of the world. Biological diversity measurement and monitoring are fundamental to the assessment of the causes and consequences of environmental changes, identification of key areas for the protection of biodiversity or ecosystem services, determining the effectiveness of actions, and the creation of decision-support tools critical to maintaining a sustainable planet. Biodiversity measurement is rapidly changing due to advances in citizen science, image recognition, acoustic monitoring, environmental DNA, genomics, remote sensing and artificial intelligence. In this perspective, we outline the exciting opportunities these developments offer but also consider the challenges. Our key recommendations are to (1) Capitalize on the ability of novel technology to integrate data sources (2) agree to standard methods for data collection (3) ensure new technologies are calibrated with existing data; (4) fill data gaps by using emerging technologies and increasing capacity, especially in the tropics; (5) create living safeguarded databases of trusted information to reduce the risk of poisoning by AI hallucinated, or false, information; (6) ensure data generation is valued; (7) ensure respectful incorporation of Indigenous Knowledge; (8) ensure measurements enable the quantification of effectiveness of actions and (9) increase the resilience of global datasets to technical and societal change. Radical new collaborations are needed between computer scientists, engineers, molecular biologists, data scientists, field ecologists, citizen scientists, Indigenous peoples, policy makers, and local communities to create the rigorous, resilient, accessible biodiversity information systems required to underpin policies and practices that ensure the maintenance and restoration of ecological systems.

Keywords: artificial intelligence; remote sensing; image recognition; Indigenous Knowledge; auditory data, eDNA; genomics; biodiversity; biological collections

49 Biodiversity – a major determinant of ecosystem productivity, stability and resilience –
50 delivers a wide range of benefits to society (1-3).
51 Yet, as shown by the summary of key numbers in Figure 1, biodiversity is in rapid and
52 widespread decline in the face of anthropogenic pressures, driving a range of serious
53 problems for society (4).

54 Accurate and reliable biodiversity measurement is fundamental to the conservation,
55 restoration, and stewardship of nature and maintaining benefits from ecosystems. These
56 measurements underpin the delivery of policies and practices that provide necessary
57 change to ensure nature's resilience. Specifically, measurement is foundational to our
58 knowledge of global patterns, including measuring the changes in populations, communities
59 and ecosystems, the nature and magnitude of threats, the effectiveness of potential
60 solutions, and the progress toward conservation targets.

61 Biodiversity measurement is undergoing rapid change, especially through citizen science,
62 image recognition, acoustic monitoring, eDNA, genomics, remote sensing, and artificial
63 intelligence (AI). These changes bring opportunities through increasing the scale and
64 resolution of biodiversity measurement. However, they also bring challenges including
65 ethical concerns surrounding the risks of biodiversity monitoring technology undermining
66 privacy (5), and unequal access to fast moving technology exacerbating
67 existing inequalities and power imbalances (6, 7).

68 There are currently greater demands for biodiversity data than ever before. Businesses
69 increasingly need to measure and manage their impact and dependencies on biodiversity,
70 driven by legislation (for example the EU's Corporate Social Responsibility Directive and
71 Deforestation Regulation) and voluntary compliance with the Taskforce on Nature-related
72 Financial Disclosures, the Science Based Targets Network, or similar initiatives, driven by
73 pressure from consumers (8). There is also an explosion of interest in
74 measuring the effectiveness of conservation policies and practices to inform truly evidence-
75 based decision-making (9) , including recognition of the need to design
76 evaluation into conservation actions (1 0 ,   1 1) . For
77 governments, a major demand is monitoring progress towards their own national
78 legislation, such as England's Environment Act, which includes targets to halt and reverse
79 biodiversity loss, or commitments to international agreements, such as Kunming-Montreal
80 Global Biodiversity Framework (12).

81 This combination of dramatic advances in technology for measuring biodiversity, alongside
82 unprecedented societal demand, creates an extraordinary opportunity to transform
83 evidence-based biodiversity policy and practice. In this perspective, we first introduce the
84 scope of emerging technologies and the flood of new data being generated. We then
85 suggest nine recommendations for ensuring biodiversity measurement can fulfil its potential
86 in helping to address the global biodiversity crisis.
87

A flood of new data from emerging technologies

98   There has been a remarkable explosion in the amount of biodiversity data available (Table
99   1), reflecting the proliferation of new technologies for observation and a culture shift
100 towards data sharing. The scale of the flood of data is illustrated by the Global Biodiversity
101 Information Facility (GBIF), which manages a vast source of species occurrence data and is
102 adding records at a rate exceeding 420 million a year. GBIF is now integrating data from
103 museums and herbaria, eDNA, citizen science like eBird, and data from Environmental
104 Impact Assessments.   These disparate data types are brought together within a central
105 database and then made available via to anyone who wants to use it. Over 10,000 scientific
106 papers have made use of GBIF mediated data, and it is being used widely by governments
107 for various purposes.

108 Robotic and autonomous systems are likely to change many of the technologies described in
109 this section as they deliver sampling, for example through robots or drones (13).

110 Environmental DNA (eDNA), the DNA released into the environment by organisms, can be
111 detected from sampling soil, water or air, enabling the cost-effective identification of
112 species present. It has been widely used in targeted species detection studies with PCR and
113 qPCR assays, and in community (i.e., multi-species) studies using metabarcoding (14).
     Researchers can compare communities through sampling of preserved samples, such
114 as in permafrost, lake sediments, peat, or air samples (15) to examine changes
115 over long periods of time. For example, Kjær et al. (2022) examined a two-million-year-old
116 deposit in Greenland identifying 102 genera from the eDNA, including determining the
117 habitat, identifying many plants missed from macrofossil and pollen recording, and showing
118 the presence of mastodons, reindeer, rodents and geese, all ancestral to their present-day
119 and late Pleistocene relatives (16). eDNA is efficient for monitoring current
     ecosystems,
120 especially from water or soil samples, or for monitoring species at scale (17).
121 The utility of the approach for a given taxonomic group in a geographic area depends on the
122 availability of appropriate reference DNA libraries, and this is rapidly increasing.

123 As well as the ability to identify species based on fragments of eDNA, rapid advances in
124 sequencing technology has enabled the generation of high-quality complete genomes,
125 (including reference genomes), which allow species identification, the understanding of
126 species' genetic diversity and the distribution of variants in space and time (18) as well as
     the species' history. This information can be used to identify genotypes that
127 are more resilient for conservation/assisted migrations and populations that are
128 experiencing stress.

129 Image and acoustic signal recognition, the ability for AI to identify species based on their
130 appearance or the sounds they make, are progressing fast towards large-scale automated
131 data collection, for example, from distributed networks of acoustic sensors or camera traps.
132 Automated identification of auditory recordings is rapidly improving both for species on
133 land and in the oceans (19). For example, in 2021 Kahl et al. reported that
139 BirdNET, using deep artificial neural networks, could identify almost a thousand bird species
140 and replicate seasonal detection patterns obtained by human observers (20). By 2025,
     the

141 number of species BirdNET could identify had trebled (https://birdnet.cornell.edu/). Similar
142 methods applied to frogs from the Philippines show both high recognition accuracy and the
143 capacity to detect species previously undescribed by scientists (21).
144 Improved methods development, the rapid accumulation of recordings that can be used for
145 model training, and the nascent creation of benchmarked data sets for taxa ranging from
146 insects (22) to whales (23), suggests that the use
147 and sophistication of these methods will grow rapidly.

148 Citizen science is another area of rapid growth, including in delivering new technologies.
149 Centralized databases greatly enhance the utility of such data. In 2021, 19 years after its
150 launch, eBird (24) – where people from around the world can submit bird
151 observations – recorded its billionth observation. In 2025, this number surpassed two
152 billion, collected by 1.1 million people. These enormous quantities of data have enabled
153 mapping of species range limits, indices of abundance for almost 3000 species, and trend
154 estimates at spatial resolutions of 27 x 27 km for several hundred species (25).
155 Similarly, by June 2025, iNaturalist had amassed almost 250 million observations of over
156 518,000 species, mostly with photographic documentation, contributed by more than 3.7
157 million people (https://www.inaturalist.org/).

158 Digitization of natural history collections, in museums and herbaria, have the potential to
159 make accessible far more of the over 3 billion specimens worldwide linking historical
160 collections with current observations (26). These records have a direct link
161 to a physical voucher in a museum or herbarium and are collected by professional
162 taxonomists/systematists; digitisation of specimen images will also provide well-annotated
163 data sources for AI-based species recognition.

164 There has also been considerable development of remote sensing technologies in recent
165 years. Remote sensing now allows detailed mapping of ecosystems, for example Global

166 Forest Watch ((27) and coastal systems (28)). Technology is continually
167 improving, for example, with hyperspectral satellites and P-band radar there is an expanding
168 frequency range and greater resolution and frequency of surveys and open access datasets,
169 such as the European Space Agency's Sentinel 2 that provides 10m resolution data every 5
170 days. Alongside this enormous increase in data a promising avenue for improving the use of
171 remotely sensed data comes from the development of geospatial foundation models,
172 especially those that integrate data from multiple sources including optical, radar, LiDAR,
173 and other sources, such as those within Google Earth Engine platform
174 (https://earthengine.google.com).   These systems have massive potential to monitor
175 landcover and land-use changes, dynamics in tree species composition, map pressures,
176 model species distribution and examine the consequences of conservation measures. These
177 AI-enabled remote sensing could dramatically change biodiversity measurement. Earth
178 observation data already helps policy frameworks be measurable. For example, 41% of the
179 Global Biodiversity Framework headline indicators are spatially explicit and reliant on earth
180 observation   (https://unbiodiversitylab.org/en/monitoring-framework-of-the-kunming-
181 montreal-global-biodiversity-framework-data-collection/).

182 The development of low-cost wearable sensors means animal movement can be
183 documented at scale, improving the quantification of dispersal, migration (29),
184 behavior, physiology, health and interactions of individuals. These high-resolution, widely
185 distributed data have the potential to greatly improve ecological predictions, for example
186 the capacity of species distribution models to predict responses to climate change.

189

190 **Recommendations for changing biodiversity measurement to help tackle the biodiversity**
191 **crisis**

192 We make nine recommendations for making the most of the rapidly changing landscape for
193 biodiversity measurement to ensure it can contribute to tackling the biodiversity crisis.

194

195   1) **Capitalize on the ability of novel technology to integrate data sources**

196 Biodiversity information typically comprises data from a single different source, including
197 auditory, environmental DNA, genomics, Indigenous Knowledge, museum specimens,
198 remote sensing and visual). A major current development is combining of different sources
199 of information to create holistic models that capture both broad-scale patterns from
200 satellite imagery and fine-scale, ecologically relevant information from ground-based
201 measurements to produce a more comprehensive and accurate picture of global
202 biodiversity (30-32). These
203 complementary data sources offer scalable methods for biodiversity monitoring, providing
204 granular insights that single methods alone cannot capture.

205 Advancements in artificial intelligence, particularly generative AI that is hallucination-free,
206 represent an opportunity to derive insights across these often disconnected data sources.
207 Generative AI enhances our capacity to collect, process, and synthesise biodiversity data at
208 scale by combining and analysing existing datasets efficiently. These tools can reveal
209 undiscovered patterns that would be difficult to achieve through manual synthesis alone.
210 For instance, AI applications have been used to model species distributions more accurately,
211 improve habitat classification, identify invasion pathways of alien species, and predict zones
212 of human-wildlife conflict (6). They can also support the analysis of
213 trade routes in illegal wildlife markets by uncovering hidden patterns in complex data.

214 The bottleneck for depending on insights from generative AI is a robust validation pipeline
215 based on accurate ground truth, especially in spatial regions with historical data gaps. A
216 serious primary challenge therefore lies in funding and implementing integrated monitoring
217 efforts over sufficiently large regions or developing cost-effective methodologies that can be
218 reliably extrapolated over larger geographic areas. Overcoming these logistical and financial
219 hurdles is paramount to developing comprehensive and scalable solutions for global
220 biodiversity and ecosystem condition assessment.

221

222   2) **Agree standard methods for data collection**

223 Inconsistency in methods for measuring biodiversity hinders all major uses of data:
224 comparisons of global diversity, assessment of change, determining effectiveness of actions,
225 and reporting on performance. For example, in a meta-analysis of phenological change,
226 (33) found that methodological variation explained almost half as much
227 variance as biological variables. More generally - for country, business, NGO and community
228 use cases - there is a need for a holistic approach that provides a framework for multi-
229 stakeholder global monitoring standards. Potentially coordinated by an international body,
230 such a framework would develop, endorse and promote a tiered and modular monitoring
231 workflow—from data acquisition and management through to analysis, indicator
232 calculation, and reporting (34). The framework would include existing
233 standards for fundamental interoperability (e.g., the Darwin Core (35))
234 and more advanced, specific standards for various biomes, taxa, and technologies (e.g.,
235 eDNA, remote sensing, and the use of AI). Crucially, there is a need for clear guidance,
236 capacity-building programs, and incentives (including linking to funding and regulatory
237 requirements) to ensure widespread adoption. A monitoring standards framework
238 (following FAIR and CARE principles, (36)) would ensure that data workflows
239 are verifiable, discoverable, auditable, reusable and ethically managed, particularly
240 concerning Indigenous peoples and local communities' knowledge.

241 This can build on the standards and lessons from a range of existing communities who have
242 standardised processes, such as The US National Ecological Observatory Network (37), the US
     Forest Service Inventory Analysis (FIA), the grassroots global Nutrient Network
243 (38), Forest GEO (39), and TreeDivNet (40). In forest ecology, standardised methodologies have
     been developed for establishing
244 forest plots and monitoring the trees they contain (e.g. (41)), which has
245 generated a global network of sites yielding long-term data enabling global analyses, greatly
246 strengthened by consistent data.

247 There may be lessons from the biodiversity genomics community, including The Earth
248 BioGenome Project (42), who established an International Science Committee
249 that created a set of standards, whose adoption contributed to the rapid growth of
250 annotated, reference-quality genomes (14). Critical lessons from these
251 precedents are the importance of early integration, collaborative global governance,
252 scalable protocols adopted across institutions, and a robust data-sharing ethos encouraging
253 data reuse and synthesis.

254 The goal of these efforts is to minimize the use of inconsistent methods where viable
255 alternatives exist, while recognizing that standardization is not always appropriate —
256 particularly in long-term monitoring where consistency is important. Methodological
257 differences can also be justified by local conditions or evolving technologies. To address this,
258 standards should offer guidance for comparing new and existing methods in an open and
259 transparent way (discussed in greater detail in the following section). Their adoption
260 depends on strong incentives, capacity building, and inclusive data governance. Ultimately,
261 transforming data comparability, reliability, and utility is essential for evidence-based
262 decisions and tracking progress toward the Global Biodiversity Framework's 2030 targets.
263 The need for increasing standardisation across the monitoring workflow and suggested
264 options for implementing this is explored in much greater detail in a parallel paper
265 (34).

268

269   3) **Ensure new technologies are calibrated with existing data**

270 Despite the many exciting opportunities afforded by the new approaches outlined above,
271 integrating data from multiple sources faces a range of challenges to ensure comparability.

272 A major challenge with any change in observation methodology is that recorded differences
273 in biodiversity could be due either to a genuine change or a methodological difference. This
274 is especially the case for sensor and AI-generated biodiversity measures, highlighting
275 dramatic changes in the observation process from traditional field surveys to autonomous
276 and remote methods. While this presents a challenge for spatial comparisons (e.g. is a site
277 especially rich or subject to a new method?), it poses a greater issue when evaluating

278   changes over time. There is a need to ensure data are interoperable enough for spatial and
279   temporal comparisons.

280   If the new and old schemes are not properly cross-calibrated, the change could confound
281   long-term trends. Analytical frameworks to overcome this challenge of multiple data
282   sources have developed rapidly (43), but their success relies on a clear and
283   detailed documentation of observation metadata for each monitoring scheme, and ideally,
284   the operation of both schemes at overlapping locations for some time to allow direct
285   comparisons. For example, the parallel operation for a six-year period of both the Common
286   Birds Census and the Breeding Bird Survey in the United Kingdom allowed the old and new
287   datasets to be combined whilst enabling coverage to increase more than 15-fold (44, 45).

288   Similar cross-comparisons will be particularly crucial when sequencing, or sensor-based
289   approaches, provide a different biodiversity measure than existing schemes, for example,
290   when monitoring switches from counting individual animals to counting vocalisations or
291   other acoustic indices (46), or from traditional observational field surveys to
292   eDNA (47). Archiving samples used for eDNA analyses and the raw data
293   from such monitoring schemes can help facilitate reanalysis and understand the
294   consequences of evolving hardware and software pipelines (48).

296

297   4)   **Fill data gaps by using emerging technologies and increasing capacity,**
298   **especially in the tropics**

299   The geographic and taxonomic distribution of biodiversity data show profound and complex
300   biases (e.g., (49, 50)) that hamper the production of ready-to-
301   use information on spatial patterns and temporal trends. The paucity of data from the
302   tropics, soils, mesopelagic zones and deep ocean - all rich in unique biodiversity and all
303   facing threats from human actions - places such systems at a disadvantage when decisions
304   are made that affect them (51).

305   The wealth of data for a few charismatic taxa (most obviously birds, which dominate the
306   largest global biodiversity database, GBIF (52)) facilitates conservation
307   decisions tailored to those groups, but these choices may not be optimal for other groups
308   with different distributions (e.g. Insects (53)). Invertebrates are particularly
309   underrepresented in biodiversity conservation thinking. So are undescribed species ("dark
310   biodiversity"), many of which are likely to be endemic insects. Soil biota and microorganisms
311   are even less well understood.

312   Beyond taxonomic groups, geographic gaps are evident, especially in the tropics where, as
313   well as a shortage of trained people and equipment, there is also usually little eDNA

reference material or auditory training material. The need for increased capacity in the tropics is a clear priority. As a result of these gaps and biases, conservation goals, targets and policies are set based on information from species that are much more widely distributed and much more ecologically generalist than most of Earth's species.

5) **Create living databases of trusted information to reduce the risk of poisoning by AI hallucinated, or false, information**

There is long history of fraudulent specimens, including the creation of new species (Piltdown man (54)), importing birds and claiming found in Britain (The Hasting's rarities; (55)), stealing bird specimens from collections and relabelling (Colonel Meinertzhagen (56)). Similarly, there is an increasing problem of fictitious research papers, including those created by paper mills.

AI algorithms are known to generate plausible but fictitious details, known as AI hallucination. A second issue with AI is its role in facilitating the creation of ever larger numbers of convincing, but fabricated, data. These could be through AI-generated images for image-based databases of field observations (or auditory equivalents) or through the creation of fabricated papers with invented data. The novel challenge is that with AI this fabrication can be achieved easily and at scale. The motives include career gain, being disruptive or pushing an agenda (for example, by making an 'at risk' species threatened by a project seem more common or purporting to show biodiversity gains, or no harms, in previous projects). This represents an existential crisis for AI data analysis and evidence Synthesis (57).

Current processes seem poorly equipped to deal with this problem. Gold standard systematic reviews are resource-intensive, yet many already unwittingly cite retracted publications (58), with 89% remaining uncorrected a year after being notified of retractions (59), this problem will be exacerbated by an increasing volume of AI-fabricated material.

Rather than depending on the individuals analysing information to judge validity a suggested better approach for the literature is an institutionally federated network of living-evidence (i.e. continuously updated) databases to ensure the scientific integrity of the results. Dynamic, specialized hallucination-free AI systems could continuously gather, screen and index literature relevant to defined themes and its measured outcomes, automatically tagging compromised studies for scholarly review. This could provide a robust,

347 transparent and dynamic source of scientific knowledge, enabling high-quality systematic
348 reviews. Rapid reviews could be undertaken and updated in real time through processes
349 such as dynamic meta-analysis (60). This approach could safeguard
350 evidence synthesis against the rising tide of potentially poisoned literature (57).
351 For biodiversity data a similar process of active vetting of databases is likely to be
352 required.

353

354   6) **Ensure data generation is valued**

355 The process of collecting biodiversity data is often difficult and time-consuming and must
356 not be undervalued. While some new technologies may reduce reliance on field-based data
357 collection, there remains a crucial role for locally-based expertise. Even satellite mounted
358 sensors recording changes in habitat extent or condition require fine-scale ground-truthing
359 drawing on local field effort. Systems to support citizen scientists require investment as
360 coordination is crucial.

361 While there are increasing calls for all biodiversity data to be public (61),
362 making all data publicly accessible could lead to a producer-scrounger model, as without
363 appropriate incentives it pays to use data rather than generate it. Despite widespread
364 acceptance of the importance of open science (62), data underpinning scientific
365 publications, many journal articles, including in ecology, still fail to make data available
366 (63), however change is underway. The lessons learned from the
367 experience of efforts to increase data sharing in ecology have been: (i) there needs to be
368 governance for wholesale change, in this case through the journals and societies involved;
369 (ii) credit for reuse of data should be given, through co-authorship and citable sources, such
370 as digital object identifiers (DOI), alleviating concerns over data ownership and credit; (iii)
371 the production of data can be regarded as a creditable output in itself, e.g. through
372 recognition by grant bodies and in research assessment exercises; (iv) there needs to be
373 sufficient resourcing, in this case through direct funding or contributions of learned societies
374 to archiving costs (e.g., the British Ecological Society covers archiving costs of papers
375 published in its 7 journals).

376 Many of the classic early descriptions of tropical biodiversity attributed to European
377 explorers, such as von Humboldt, Darwin, and Wallace, relied heavily on local and
378 Indigenous assistants to find, collect, and classify the specimens (64).
379 Emogor et al. describe a process for giving extended credit when it is inappropriate or
380 against the journal's policy to include contributors as authors (65).

381

382   7) **Ensure respectful incorporation of Indigenous Knowledge**

383 Indigenous Knowledge (IK) is a collective term representing the many place-based
384 knowledges, innovations and practices accumulated across generations through interaction
385 with the environment (66, 67). While each Indigenous
386 community has a unique culture, so definitions and terminology may vary, these knowledge
387 systems are inseparable from their culture's spiritual and social fabric and incorporate moral
388 values, such as kinship with nature, humility, and reciprocity (68-70).

389 Indigenous communities have felt pressure by colonizers to assimilate, which has led to the
390 loss of medical, ecological and cultural information (71). Given the history of
391 forced assimilation, it is important that indigenous knowledge is collated and shared by
392 Indigenous peoples themselves and on their own terms (72). The Pisuna program
393 in the Arctic is an example of a successful community-based monitoring program
394 documenting their knowledge in a culturally appropriate manner (73).
395 The development of AI risks widening the gap between Indigenous peoples and scientists,
396 although there are good examples of AI being used with Indigenous Knowledge to inform
397 decision making (74).

398 The value of indigenous and local knowledge is increasingly recognized in science policy
399 arenas such as Intergovernmental Panel on Biodiversity and Ecosystem Services and the
400 Convention of Biological Diversity (75). For example, the Global Biodiversity
401 Framework's "monitoring framework" provides pathways for indigenous knowledge to be
402 incorporated synergistically. Indigenous voices are also increasingly being heard in these
403 international agreements - for example through the International Indigenous Forum on
404 Biodiversity (IIFB) under the CBD (https://iifb-indigenous.org/about-us/). Such initiatives are
405 crucial both for moral reasons, and practical reasons given the role of Indigenous peoples as
406 stewards of biodiversity (76).

408

409   8) **Ensure measurements enable the quantification of effectiveness of actions**

410 Monitoring biodiversity outcomes without a focus on designs which allow insights into the
411 impact of actions to address the biodiversity crisis has been referred to as 'counting the
412 books while the library burns' (77). Such an approach can only describe
413 declines, rather than help address the biodiversity crisis directly. There is therefore an
414 explosion of interest in measuring the effectiveness of conservation policies and practices
415 (11) to inform truly evidence-based policy making (9).
416 New technologies can help provide the biodiversity data at sufficiently high spatial
417 and temporal resolution needed to estimate the counterfactual: what would have happened
418 without the action (78). However, large amounts of data do not
419 overcome the need for study designs that allow causation to be separated from correlation.

420 Embedding impact evaluation into conservation action at a much larger scale is therefore
421 needed (10, 79).

424   9) **Increase the resilience of global datasets to technical and societal change.**

425 Challenges to maintaining information are not new, as illustrated by the destruction of the
426 grand library of Baghdad in 1258. Recent events, including the fire in the National Museum
427 of Brazil in 2018 destroying most of the 20 million items, the cyberattack attack on the
428 British Library, and the closure of key herbaria (e.g., Duke) and museums that have been
429 home to precious collections, illustrate the potential damage that could be done to
430 biological collections and data. We note with particular concern actions taken by the US
431 government to close US datasets, including more than 2,000 from data.gov (80).
432 Another issue is data storage that uses proprietary software, since all software eventually
433 becomes obsolete. Data should always also be stored in universal formats, such as comma
434 separated data files with associated text metadata.

435 Solutions include ensuring data backups in resilient forms, multiple funding sources such as
436 public-private partnerships to reduce the reliance on single sources, dispersed systems with
437 multiple versions, geopolitically diverse hosting to reduce the impact of political change,
438 and, where appropriate, condemnation by society and global researchers. An important goal
439 is to incorporate biodiversity data into a nationally or internationally mandated system with
440 explicit backup and resilience mechanisms, as is provided for DNA sequence data by the
441 International Nucleotide Sequence Database Collaboration (INSDC; linking GenBank, the
442 European Nucleotide Archive and the DNA Database of Japan).

443 A comprehensive deployment of sensors for biodiversity measurements could easily
444 encompass tens of millions of devices being deployed in remote areas of the planet, which
445 need to be networked together to collate the information. There are similar concerns with
446 the resilience of the Internet itself as the long term mesh for this. The global network is
447 expected to expand to a trillion nodes this decade, but faces a range of challenges from
448 large quantities of fake, generative or poor data, sophisticated AI-driven malware, botnets
449 commandeering huge numbers of machines to launch attacks, and even alteration of the
450 physical world through the manipulation of Internet of Things (IoT) devices. Madhavapeddy
451 et al. (in press) explore how the core Internet architecture might draw from ecological
452 theory to find means of ensuring it remains a resilient, sustainable, and trustworthy
453 network, which is vital given our growing dependency on digital measurements of global
454 biodiversity (81). Ideas for a biologically inspired resilient Internet include ensuring
     greater
455 diversity in the software stacks that comprise Internet nodes, active response to challenges
456 (much like antibodies respond to infections) and providing shielding to hosts unable to

457 deploy countermeasures. All these approaches will help ensure the security and integrity of
458 primary biodiversity measurements over longer periods of time.

459

460 **Final thoughts**

461 Biodiversity scientists are on the cusp of a transformative flood of new data, due to the
462 combination of increasing demands for ecological information, more comprehensive and
463 sophisticated analyses, and astonishing technological developments. Here we identify a set
464 of recommendations which will make the most of these opportunities while addressing the
465 challenges. Delivering on these will require novel collaborations between communities who
466 have not traditionally collaborated closely. Computer scientists, engineers, molecular
467 biologists, data scientists, field ecologists, citizen scientists, Indigenous peoples, policy
468 makers, and local communities need to work together to create rigorous, resilient and
469 accessible biodiversity information systems. The ultimate aim is to deliver real-time,
470 localized but globally-scalable assessments of biodiversity dynamics to inform decision
471 making by diverse stakeholders at the temporal and spatial scales that are needed.

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Figure 1. **Key Numbers in Biodiversity.** A summary of key numbers measuring the current state of biodiversity globally. We report highlights from the global quantification of this inherently multi faceted and heterogenous concept and phenomena. The number of significant digits used tried to reflect the variation in expert opinion and references.

Key Numbers in Biodiversity

Global biodiversity and stocks

Estimated number of animal and plant species (82):
~10 million

Total biomass on Earth (83): 500 GtC (10^9 tonne carbon)
Plants ≈450 GtC (≈90% of global biomass)
Bacteria and archaea ≈30 GtC (≈5%) (84)
Fungi ≈10 GtC (≈3%)
Animals ≈2 GtC (≈0.5%)

Extinctions linked to human activity

Mammal extinctions (Late Quaternary): (85, 86)
≈200 (about half of) large-bodied species lost
The global biomass of wild land mammals today is
≈10-fold lower than prior to these extinctions

Documented extinctions since 1500:
≈1000 animal species (87)

Rate of vertebrate extinctions: ~10 times higher
in last century than pre-human background rates (88)

Animal & plant species threatened with extinction:
~1 million (89)

Species threatened with extinction: ≈30%
of species assessed by IUCN RedList (87)

Threats to marine life

Fishing: ≈30% of fish stocks globally are overfished,
≈60% are at the maximal exploitation limit (90)

Ocean acidification: ≈25% increase since 1750s (91)

Coral reef cover: ≈50% decline since the 1950s (92)

Plastic Pollution in oceans: ≈10 million tonnes/year (93)

Threats to terrestrial life

Habitable land used for agriculture: ≈50 million km^2
Half of all habitable land, includes pasture (94)

Land use: ≈75% of ice-free land altered by humans (95)

Deforestation: ≈10 million km^2 lost (≈20%) since 1900 (96)

Fragmentation: ≈70% of forest area
is within 1 km of a forest edge (road etc.) (97)

Illegal wildlife trade: >100 million
plants and animals trafficked annually (98)

Harmful invasive alien species: ≈4,000 species,
estimated cost ≈400 billion USD/year (99)

Indicators of modern biodiversity loss

Living Planet Index decline: ≈70%
Indicator of change in monitored wildlife populations
since 1970 (100)

Loss of natural habitat due to land use change: ≈20%,
mean across land vertebrate species since 1850 (101)

Biodiversity Intactness Index (global mean): ≈77%
Indicator of plant and animal population intactness.
Critical threshold: ≈90% (102)

Wild mammal global biomass:
Estimated to have declined ≈70% since 1850 (103)
Domesticated to wild land mammal biomass: 30:1 (104)

Wild birds:
≈20-30% of decline in population size in N. America and
the EU over the last few decades (105, 106)

Insects:
Reported population declines ≈10% per decade (107)

749   Table 1. Some types of biodiversity data and their coverage

Type of data	Examples of extent
Atlases	Cover a range of taxa including over 600 bird atlases across 93 countries, with over 380,000 participants. The Xerces Society bumble bee atlas covers 20 US states, and with >110,000 records from >4000 participants.
Auditory	Xeno-canto is approaching 1 million wildlife sound recordings (mostly birds); Macaulay Library (Cornell) has 2.8 million bird recordings, and is growing at an annual rate of over 15%.
Camera traps	A number of camera trap platforms streamline data processing. The Wildlife Insights platform has over 200 million images from almost 3000 projects and includes over 4000 species.
Citizen science	In June 2025 eBird passed 2 billion observations from over 14 million checklists and 1.1 million eBird participants.
Citizen science with standard processes	Many large monitoring schemes (North American Breeding Bird Survey, Pan-European Common Bird Monitoring Scheme, Southern African Bird Atlas Project, European Butterfly Monitoring Scheme, Snapshot USA, Snapshot Europe, etc) have a rigorous process.
Flora	Thousands of flora, covering local, national and broader regions, are published that list species, describe habitat and their status.
DNA marker data	The Barcode of Life database collates marker gene information from over 20 million specimens corresponding to approximately 1.3 million species. The database is growing rapidly with contributions from around the globe.
Genomes	Earth Biogenome Project plans to generate high-quality reference genomes for 10,000 unique species before the end of 2027, and 150,000 by 2031. As of June 2025, data for 3,956 species was publicly available.
Herbaria	Index Herbariorum lists 3,567 herbaria worldwide containing 396 million specimens. Many are digitising specimens, which are often then made available online
Image recognition	iNaturalist has 248 million observations supported by photographs taken by citizen scientists, who may be aided by AI identification, with 155 million being verified by the community.
Indigenous and local knowledge	PISUNA (Piniakkanik Sumiiffinni Nalunaarsuineq) has 1052 items of Inuit knowledge on animal abundance, distributions, condition and behaviour and ice conditions.
Local and national data centres	These occur in at least a hundred countries with data sources that often overlap the others included here.

Museums	Museums globally contain about 3 billion specimens with digitisation, including with AI, underway at many institutions.
Tracking data	MOVEBANK has 8 billion locations of 1,546 taxa from 9,113 studies
Remote sensing	1000+ datasets are provided in the Google Earth Engine Data Catalog.