Thirty years after "The Naturalists Are Dying Off": Regrounding Conservation Biology in a predictive era

Jingrui Sun[1,2,3*]

[1.] *Yunnan Key Laboratory of International Rivers and Transboundary Eco-Security, Institute of International Rivers and Eco-Security, Yunnan University, Kunming 650091, China*

[2.] *State Key Laboratory for Vegetation Structure, Function and Construction (VegLab), Kunming, China*

[3.] *Ministry of Education Key Laboratory for Transboundary Eco-Security of Southwest China, Yunnan University, Kunming, 650091, China*

** Correspondence; jingrui.sun@ynu.edu.cn*

Abstract

Thirty years after Reed Noss warned that naturalists were dying off, conservation biology has entered an era of unprecedented analytical capacity, driven by global biodiversity databases, remote sensing, and artificial intelligence. This transformation has coincided with declining visibility and support for field-based natural history and taxonomy. The resulting losses extend beyond primary biodiversity observations. Declining taxonomic expertise can compromise species identification and data reliability, while reduced firsthand engagement with nature may constrain observation-driven discoveries and the generation of novel ecological hypotheses. The erosion of organismal and place-based knowledge may also weaken our ability to interpret ecological changes and evaluate predictive models, particularly as climate change, biological invasions, and novel ecosystems alter historical ecological relationships. Addressing these challenges requires sustained investment in field observations, specimen collections, and taxonomic expertise, alongside stronger integration of natural-history knowledge into quantitative and AI-enabled research. Universities, funding agencies, and journals should recognize and support the empirical foundations of conservation science through interdisciplinary training, transparent data provenance, and greater recognition of long-term ecological research.

Keywords: field-based knowledge; taxonomy; biodiversity monitoring; ecological judgment; predictive ecology

Main text

In 1996, Reed Noss warned that conservation biology was drifting toward a form of "armchair ecology" in which students were increasingly trained to model populations, analyze remotely sensed data, and manipulate theoretical representations of nature, yet were no longer learning to identify organisms, read landscapes, or build the kind of ecological intuition that comes only from sustained contact with the living world. Noss's central fear was that conservation biologists might become highly competent analysts with little firsthand knowledge of the organisms and systems they claimed to study (Noss 1996). Thus, his concerns became a warning about a growing imbalance, namely that once analytical sophistication becomes detached from taxonomy, field observation, organismal knowledge, and natural history, conservation biology ultimately risks becoming technically impressive but biologically impoverished.

Thirty years later, the question is no longer whether that warning was justified. In many respects, conservation biology is broader and more analytically powerful than it was in the 1990s. Researchers now work with global biodiversity databases, satellite archives, trait repositories, genomic tools, automated sensors, citizen-science platforms, and increasingly sophisticated forms of artificial intelligence (Anderson et al. 2021, Tuia et al. 2026). The scale, speed, and integrative power of both biological and ecological research have been transformative (Forbes et al. 2025). Moreover, conservation biology has been broadened to include systematic conservation planning, environmental economics, and conservation social science, linking biodiversity science more directly to governance, human behavior, and policy implementation (Kareiva and Marvier 2012, Anderson et al. 2021, Niemiec et al. 2021). In this sense, the field has become more capable of engaging real-world conservation problems across ecological, social, and economic dimensions (Giakoumi et al.

2025).

At the same time, however, the imbalance identified by Noss persists, although the scientific context in which it now operates has changed substantially. Contemporary ecology and conservation science are increasingly data-intensive, predictive, and AI-enabled, while climate change, biological invasions, and novel ecosystems are simultaneously weakening the stability of historical ecological relationships. The erosion of natural-history expertise may weaken several fundamental capacities of conservation science, including accurate species identification, the discovery of previously unrecognized ecological processes, and the development of biologically informed hypotheses. These losses become particularly consequential under non-stationary conditions, where understanding species' life histories, ecological interactions, and local environmental contexts can help explain changing relationships, identify the mechanisms underlying unexpected observations, and inform the evaluation and revision of predictive models. I argue that the continued decline of natural-history knowledge risks weakening the empirical and conceptual foundations of conservation biology, particularly its capacity to understand and predict ecological responses to rapid environmental change.

Publication Patterns and Shifting Priorities in Conservation Biology

A central tension in contemporary conservation science is the growing mismatch between the expanding power of biodiversity data and the field-based foundations on which those data ultimately depend. Forbes et al. (2025), using more than 150 million specimen-based records, showed substantial long-term declines in the collection of new specimen data. They showed that biological data are becoming increasingly valuable, but the collection, curation, and taxonomic expertise required to maintain such data are becoming more

difficult to sustain (Forbes et al. 2025). This key paradox of contemporary conservation science may reflect multiple interacting drivers, including limited funding, rising labour costs, shifting workforce priorities, and reduced training in collection techniques, curation, and taxonomy (Rohwer et al. 2022, Nachman et al. 2023). Related shifts are visible in publication profiles and research incentives. For instance, fieldwork-centered studies now occupy a smaller share of conservation literature than they once did, while modelling, synthesis, and data-analysis studies have expanded rapidly (McCallen et al. 2019, Soga and Gaston 2025). From 1980 to 2014, the proportion of conservation papers reporting fieldwork decreased by about 20%, while modelling and data-analysis studies rose by roughly 600% and 800%, respectively (Ríos-Saldaña et al. 2018).

These tendencies do not necessarily demonstrate that there are fewer field ecologists active today than in 1996 (although that may also be occurring); rather, they indicate that fieldwork-centered research now occupies a smaller proportion of the literature and is less visible in higher-ranked journals. However, as conservation biology has broadened, a smaller proportion of published work is expected to take the form of classic field-based studies, even when such work remains essential. Concerns about academic incentives favoring synthesis, modelling, and secondary analysis over slower forms of field-based knowledge production are not new and have been discussed across ecology and taxonomy for decades. The problem is therefore not that field-based work now shares space with other important forms of conservation inquiry, but that diversification becomes risky when academic reward systems more consistently favor secondary analysis, rapid synthesis, and computational novelty over the slower production and maintenance of primary ecological knowledge (White 2025). Under these conditions, field-derived knowledge remains essential but may become less visible, less cited, and less attractive to early-career

researchers (Ditchkoff and Belsare 2025). Academic cultures that reward synthesis, modelling, and secondary analysis more strongly than primary knowledge production can therefore shape what young researchers choose to learn and what institutions choose to support (Hicks et al. 2015, McKiernan et al. 2019, Choi et al. 2025;Figure 1).

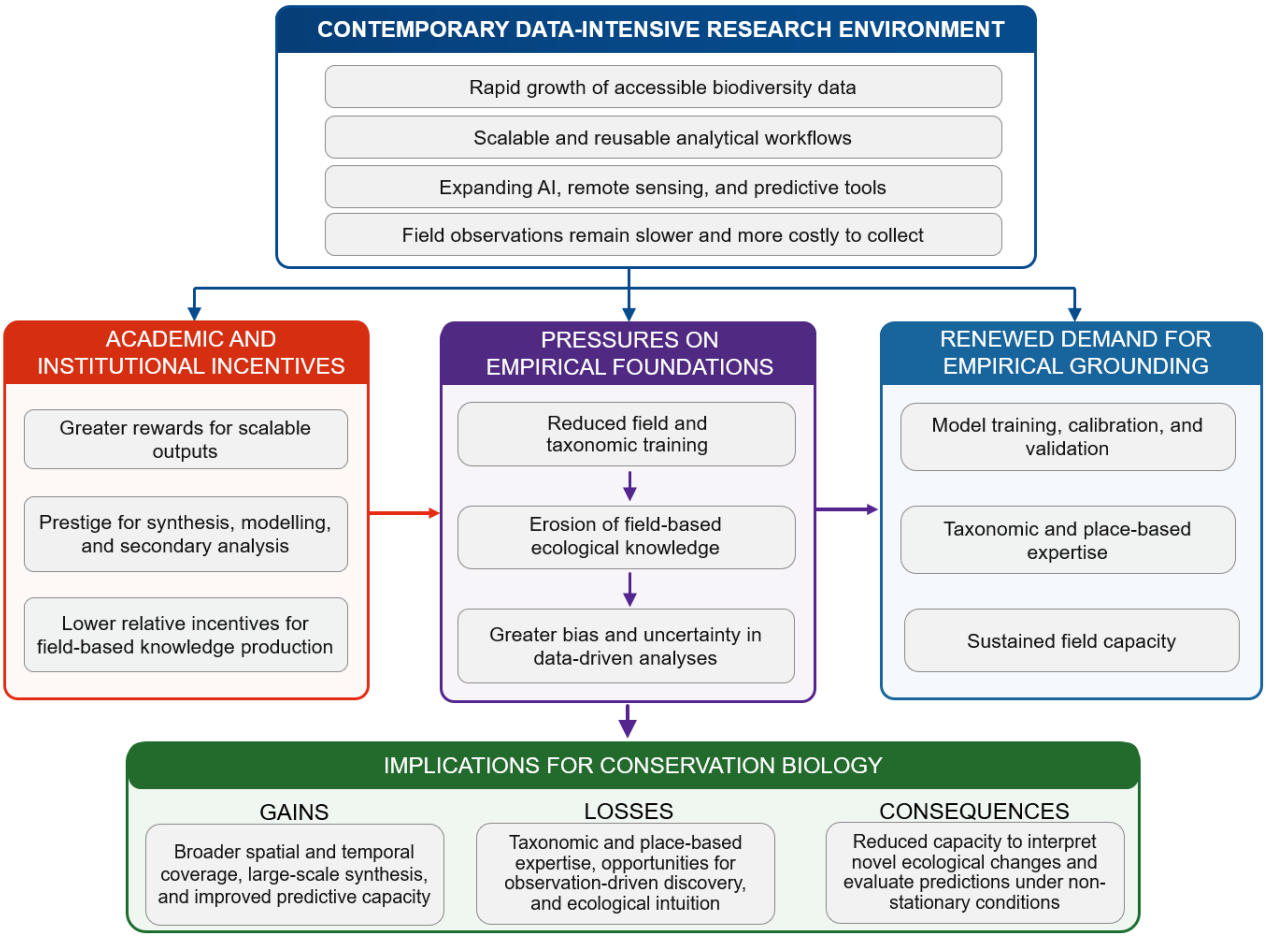


Figure 1. Pathways linking data-intensive research to the empirical foundations and scientific capacity of conservation biology. The expansion of biodiversity databases, remote sensing, and artificial intelligence enables ecological analyses across broader spatial and temporal scales, strengthening biodiversity synthesis and predictive capacity. However, associated academic and institutional incentives may contribute to the erosion of field-based observations, taxonomic and place-based expertise, and opportunities for observation-driven scientific discovery. These losses may increase uncertainty in biodiversity data, constrain the generation of new ecological

hypotheses, and weaken the biological interpretation of predictive models. Meanwhile, growing demands for reliable reference data, model training and validation, and ecological interpretation create opportunities to sustain and strengthen natural-history expertise. Together, these pathways illustrate the gains and potential losses associated with data-intensive conservation biology and their implications for understanding ecological change and evaluating predictions under non-stationary conditions.

Importantly, this relationship is not uniformly antagonistic. In some cases, the growing sophistication of remote sensing, Earth observation, and automated monitoring is creating new demand for the very field-based knowledge these approaches appear to displace. Programs such as GEO-TREES illustrate this emerging interdependence: advances in Earth observation have increased investment in permanent forest plots, standardized ground measurements, botanical expertise, and integrated field and analytical training because remotely sensed estimates cannot be reliably interpreted without high-quality field reference data (Chave et al. 2019, Labrière et al. 2023, GEO-TREES 2025, Sutherland et al. 2026). Rather than simply replacing natural history, new technologies may therefore create opportunities to re-embed it within contemporary ecological infrastructure.

Observation Before Analysis: The Empirical Foundations of Data-Intensive Ecology

The era of big-data has intensified contemporary trends in the conservation biology publishing space (McCleery et al. 2023). Big-data approaches and related analytical frameworks allow inferences at scales earlier conservation biologists could barely imagine (McCallen et al. 2019), but they do not remove the need for field knowledge, because the data themselves are products of observation, classification, collection, curation, and interpretation (Hortal et al. 2015). Species-distribution models, threat assessments, trait databases, and global syntheses inherit the taxonomic uncertainty, sampling bias, uneven

spatial coverage, and historical gaps of the records on which they depend (Boakes et al. 2010, Moudrý et al. 2024). This is precisely where Noss now appears prophetic. In the 1990s, he worried about students who could model population viability but not identify warblers, tracks, or plants. Today the equivalent problem has expanded across the discipline. A student may build a species distribution model without ever having handled the organisms whose range is being predicted. Another may use biodiversity repositories without understanding the taxonomic uncertainty, historical sampling bias, or regional knowledge gaps embedded in the records (Maldonado et al. 2015, Sun 2025). None of these approaches is inherently flawed, but problems arise when they are practiced without enough grounding in the biological reality from which the data were derived. Data-intensive conservation biology depends on observational foundations that are often overlooked by researchers working mainly with secondary data and downstream analyses. In addition, the increasing public availability of biodiversity records also raises conservation concerns, as precise occurrence data may facilitate the illegal collection or poaching of rare and commercially valuable species (Lindenmayer and Scheele 2017).

Artificial intelligence is further reshaping how natural-history knowledge is generated, verified, and used. For example, AI-assisted identification tools embedded in citizen-science platforms can substantially lower barriers to species recognition and expand participation in biodiversity recording. Computer-vision systems used by iNaturalist (https://www.inaturalist.org/taxa) can provide rapid taxonomic suggestions from uploaded photographs, while Merlin (https://merlin.allaboutbirds.org/) uses machine-learning and AI approaches to assist bird identification from images and acoustic recordings. These tools can accelerate the accumulation of biodiversity observations, broaden the geographic and taxonomic reach of monitoring, and help non-specialists contribute records that may later

support ecological research (Høye et al. 2021). However, these systems depend on large quantities of accurately identified, curated, and context-rich observations for training, benchmarking, and validation. Citizen-science observations often exhibit geographic and taxonomic biases, reflecting differences in observer participation, accessibility, and interest in particular taxa (Di Cecco et al. 2021). Such biases can affect the representativeness of biodiversity records and the reliability of datasets used for training and evaluating automated identification systems. Their expansion therefore increases dependence on reliable reference collections, expert verification, careful assessment of sampling biases, and well-documented data provenance.

The same technological shift also introduces new risks. Generative AI can produce wildlife images and videos that are increasingly difficult to distinguish from genuine observations, creating the possibility that synthetic records enter citizen-science platforms or are subsequently incorporated into biodiversity databases. Guerrero-Casado et al. (2026), for example, highlighted the conservation risks posed by AI-generated wildlife media, including the potential for false or misleading records to distort perceptions of species occurrence and status. Similarly, Lees et al. (2026) argued that citizen-science platforms need explicit safeguards against generative-AI content because synthetic observations could contaminate datasets that are increasingly reused for ecological analysis, monitoring, and model development. AI therefore creates a paradox for contemporary natural history: it can greatly expand the scale and accessibility of biodiversity observation, while simultaneously increasing the importance of expert verification, provenance, trusted reference data, and mechanisms for distinguishing authentic observations from synthetic ones.

Ríos-Saldaña et al. (2018) argued that synthetic analyses and large-data approaches,

though vital for setting broad conservation priorities, are “severely handicapped” when not supported by sound observational data. Likewise, Forbes et al. (2025) note that data streams including citizen science, environmental DNA, and remote sensing bring their own biases and errors, and still rely on specimen-based knowledge and taxonomic expertise for calibration, verification, and interpretation. For example, eDNA metabarcoding illustrates this dependence, as incomplete reference libraries, mislabelled sequences, and unresolved taxonomic classifications can compromise species identification, highlighting the continuing importance of specimen-based taxonomy and expert-curated reference databases (Keck et al. 2023). In this sense, big-data approaches do not replace natural history but deepen their dependence on the observational and taxonomic foundations from which biodiversity data are generated (Figure 1).

While climate change, invasive species, and habitat fragmentation create conditions in which yesterday’s correlations may fail tomorrow, long-term and field-based research become more valuable (Lindenmayer et al. 2022). Yet, long-term field studies accumulate not only data but also contextual knowledge that allows researchers to notice anomalies, refine questions, validate models, detect regime shifts, and interpret observations in light of life history, local history, and environmental change (Rouby 2026). Natural-history experience also contributes to scientific discovery by inspiring research questions and hypotheses, informing study design, and providing the empirical foundations for subsequent investigations (Sridhar et al. 2026). Declining opportunities for such firsthand experiences may therefore constrain observation-driven scientific discovery and the development of new ecological ideas. Such contextual knowledge is not fully captured in standardized databases (Reinke et al. 2019, Ditchkoff and Belsare 2025), but the monitored ecological processes often unfold on biological timescales that far exceed normal grant cycles and, in

some cases, career spans. Compounding these vulnerabilities is a more fundamental structural problem: long-term ecological monitoring remains difficult to sustain within funding systems dominated by short grant cycles, even as the scientific and societal value of longitudinal data continues to increase (Lindenmayer et al. 2022).

Many taxonomists, curators, and field naturalists whose careers were built on sustained engagement with specimens, regional floras and faunas, and the resolution of taxonomic uncertainty are now retiring, with some of their accumulated tacit knowledge at risk of being lost. (Ahrends et al. 2011, Pearson et al. 2011). For example, a nationwide assessment in Hungary found that active biodiversity experts were unavailable for identifying nearly half of the approximately 36,000 recorded animal species, while more than a quarter of the fauna had only one or two active experts capable of identification (Páll-Gergely et al. 2024). As this cohort diminishes, the very expertise required to calibrate, validate, and correct the outputs of species-distribution models, trait repositories, and citizen-science platforms is becoming scarcer. The loss of experienced taxonomists, curators, and field naturalists therefore compounds the structural fragility of long-term monitoring by weakening the continuity of organismal and place-based knowledge needed to interpret ecological change.

The challenge is therefore not only to preserve long-term monitoring, but to make its value more visible within forecasting and decision-making systems (Lindenmayer 2018). The Living Planet Index, for example, synthesizes thousands of population time series into a globally influential biodiversity indicator, illustrating how long-term observations can acquire substantial scientific and policy value when integrated at scale (Loh et al. 2005, McRae et al. 2025). Such products also raise an important question of reciprocity: whether part of the visibility, funding, and institutional value generated by global syntheses can be returned to

the field networks and researchers responsible for maintaining the underlying observations. Such feedbacks could, in principle, provide a more durable basis for sustaining natural-history knowledge than relying on short-term project funding alone.

Ecological Judgment in a Non-Stationary World

The loss of field-based and taxonomic expertise would be concerning even in a stable world. It becomes more consequential under conditions of rapid, non-linear environmental change. Climate change, invasive species, and novel ecosystems are eroding the stationarity assumptions that underpin many data-driven models. For example, climate-driven changes in species' phenology, physiological responses, and biotic interactions can alter the relationships between species occurrence and environmental predictors (Alexander et al. 2015). Similarly, biological invasions may introduce novel species interactions that change the ecological processes underlying historically observed distribution patterns (Kester et al. 2026). Correlations and species–environment relationships derived from historical data are increasingly likely to break down, sometimes abruptly (Brown et al. 2025). In such contexts, the ability to detect anomalies, recognize when a system is behaving outside its historical range, and interpret new observations in light of species' natural history and local context becomes not merely desirable but essential for effective conservation action (Wagner et al. 2023).

Big-data approaches and automated tools are powerful for detecting statistical departures from historical patterns, but interpreting whether those departures represent biologically meaningful changes often requires additional ecological context (Yates et al. 2018, Bueno de Mesquita et al. 2021). A model trained on historical conditions may identify deteriorating fit or changing associations, while natural-history knowledge can help explain the biological

mechanisms underlying these changes and assess whether the relationships are likely to persist. Detailed understanding of species' life histories, ecological interactions, and local environmental conditions can inform hypotheses about the drivers of non-stationarity, guide the selection of biologically meaningful predictors, and support the refinement of models under changing environmental conditions. This form of ecological judgment develops through accumulated experience and may be slow to rebuild once lost (Tewksbury et al. 2014a, Filbee-Dexter et al. 2017). As the cohort of researchers with deep, long-term familiarity with particular systems continues to retire, some of this capacity risks being lost precisely when it is becoming increasingly important.

Historical examples illustrate the value of such place-based ecological judgment. Long-term field observations of amphibian populations in Central America were crucial for recognizing unusual and rapid population collapses, linking these declines to chytridiomycosis, and informing subsequent emergency conservation responses (Lips 1998, 1999, Lips et al. 2006, Gagliardo et al. 2008). A similar lesson emerged from Guam, where persistent field observations helped reveal the spread and ecological consequences of the introduced brown tree snake (*Boiga irregularis*), whose expansion closely tracked the collapse of native forest bird populations (Savidge 1987, Rodda and Savidge 2007). In both cases, the critical contribution was not simply the accumulation of observations, but the ability of researchers familiar with the system to recognize changes that departed sharply from previous ecological expectations.

These examples also point to a broader shift in ecology from describing observed change toward anticipating future ecological dynamics. Prediction in complex and rapidly changing systems depends on sufficiently long and biologically grounded observational records to

distinguish persistent signals from short-term variability, identify the processes underlying change, and evaluate when historical relationships cease to hold. In this sense, natural-history observations are not simply descriptive records of the past; they constitute part of the empirical foundation for ecological prediction. These predictions increasingly inform not only conservation decisions but also economic and operational choices in sectors such as forestry, land management, agriculture, and environmental risk assessment.

The growing demand for ecological prediction is accompanied by a widening gap between analytical capacity and the biological expertise needed to interpret it. The volume and sophistication of ecological data continue to increase, yet the organismal, taxonomic, and place-based expertise needed to interpret departures from historical expectations may be becoming less secure. Models and statistical diagnostics therefore still benefit from organismal and place-based ecological knowledge to interpret why relationships change, assess whether apparent departures are ecologically meaningful, and determine when historically derived relationships may no longer apply (Yates et al. 2018, Bueno de Mesquita et al. 2021) Long-term studies additionally provide the baseline against which ecological surprises can be distinguished from ordinary variation (Lindenmayer et al. 2010, Filbee-Dexter et al. 2017). The erosion of this interpretive capacity may therefore constrain our ability to understand the biological mechanisms driving ecological change, evaluate the transferability of predictive models, and develop conservation responses to increasingly non-stationary environmental conditions (Knapp et al. 2012, Tewksbury et al. 2014b).

This challenge is compounded by global inequities in capacity (Collen et al. 2008, Amano and Sutherland 2013, Schmeller et al. 2017). Many of the specimen records, occurrence data, and ecological observations used in global biodiversity databases concern

biodiversity-rich regions of the Global South, although these regions remain disproportionately underrepresented in digitally accessible biodiversity information and research capacity (Collen et al. 2008, Meyer et al. 2015). Yet taxonomic expertise, collections infrastructure, and sustained field capacity in many of these regions remain limited and are often themselves under pressure. As Northern institutions increasingly depend on these data streams for large-scale analyses and policy-relevant syntheses, the erosion of organismal expertise in both the Global North and South creates a shared vulnerability: the analytical power of conservation biology rests on observational foundations whose long-term maintenance is insecure on a global scale.

Restoring Balance in Conservation Biology

Has conservation biology improved or deteriorated over the past thirty years? The fairest answer is that conservation science has become more powerful, but not necessarily more grounded. It is better in scale, speed, integration, accessibility, and technical sophistication and, in that sense, has had more opportunities than ever before to combine technological power with biological realism (Tuia et al. 2026). The challenge is therefore not simply to persuade institutions to support natural history as an activity competing with data-intensive science, but to embed natural-history knowledge within the scientific infrastructures that institutions already have strong incentives to support (McCleery et al. 2023). Earth observation, AI, biodiversity forecasting, and other forms of predictive ecology increasingly depend on long-term observations, taxonomic verification, and high-quality reference data. Reconnecting these activities can therefore provide a more durable basis for sustaining natural-history capacity than treating field observation and technological innovation as competing priorities (Figure 2).

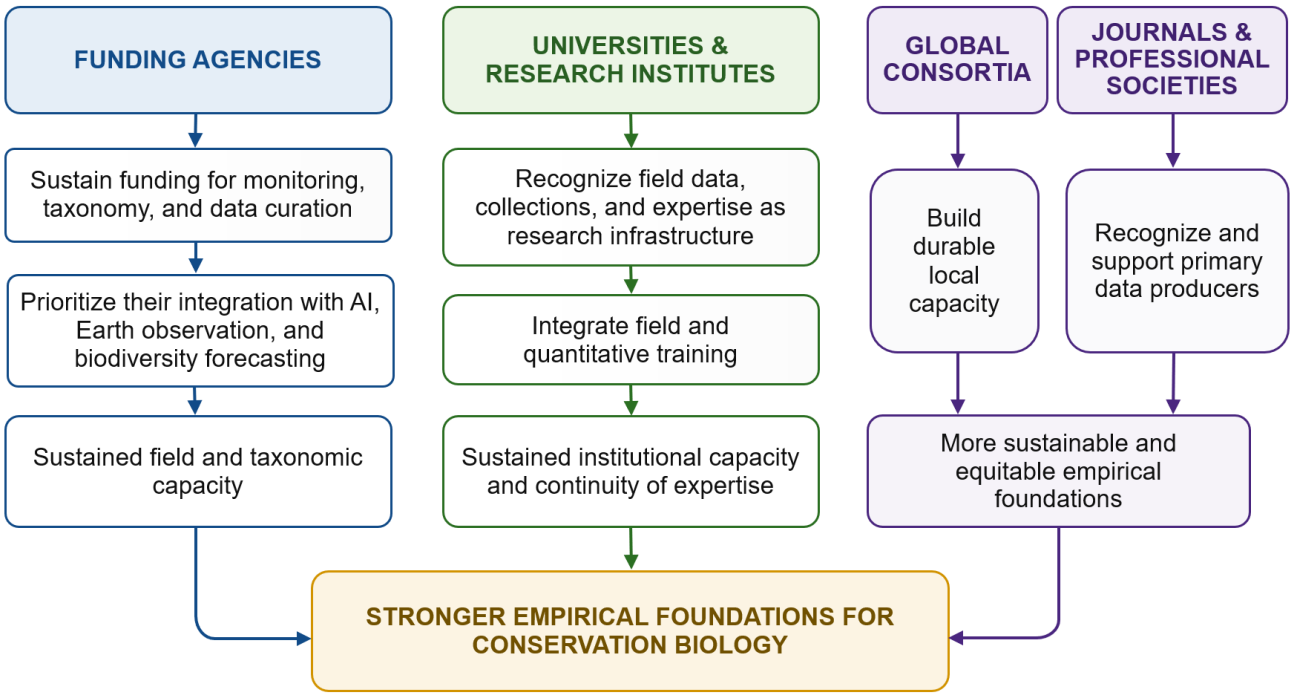


Figure 2. Institutional mechanisms for strengthening the empirical foundations of conservation biology.

First, funding agencies could make the dependence of data-intensive studies on field observations, taxonomic identifications, and primary data more explicit (Figure 2). Research proposals could include a concise provenance statement describing the observations, expert identifications, monitoring programs, or local knowledge that generated the records, along with known sampling biases, geographic gaps, and taxonomic uncertainties. Such requirements would make transparent the extent to which data-intensive analyses depend on observational infrastructure and taxonomic expertise that require continued maintenance and renewal. Funding mechanisms could preferentially support programs in which long-term monitoring, taxonomic expertise, and data curation are embedded directly within Earth-observation, biodiversity-forecasting, and AI-enabled initiatives, so that investment in analytical and predictive capacity simultaneously sustains the empirical systems required to calibrate, validate, and update them. This framing may also provide a stronger institutional

and economic rationale for support: rather than treating natural-history capacity as a separate activity competing for limited resources, it positions field observations, taxonomic expertise, and long-term datasets as enabling infrastructure for research areas that already attract substantial scientific, policy, and financial investment.

Second, universities and research institutes could recognize field data, natural-history collections, and associated expertise as research infrastructure rather than treating them primarily as supporting activities. They should also avoid treating field and quantitative skills as alternative professional identities (Figure 2). Students specializing in modelling, remote sensing, or synthesis still need structured, assessed exposure to taxonomy, specimen work, and field sampling; conversely, students trained primarily through fieldwork need sufficient quantitative literacy to link local observations to broader inference. Institutional evaluation systems could better recognize contributions to long-term datasets, taxonomic verification, monitoring networks, and other empirical infrastructures when these outputs underpin broader analytical, predictive, or policy-relevant research. For universities and research institutes, this linkage can also make long-term datasets, collections, and field expertise more visible as institutional assets that support externally funded research, interdisciplinary collaboration, and broader research capacity. Recognizing these contributions as part of the infrastructure that enables competitive research programs may provide a more realistic basis for institutional support than treating natural-history work primarily as a separate academic tradition.

Third, global consortia can play an important role in building durable research capacity, particularly in biodiversity-rich regions where scientific investment and long-term monitoring remain limited. The Tropical Ecology, Assessment and Monitoring (TEAM) Network

provides one example of this model, combining standardized field monitoring, camera-trap technology, advanced data management, and partnerships across tropical countries to generate long-term biodiversity data relevant to conservation decision-making (Rovero and Ahumada 2017). Similarly, ForestGEO and more recent initiatives such as GEO-TREES demonstrate how global networks can combine taxonomically intensive long-term field observations with analytical training and emerging remote-sensing technologies (Davies et al. 2021, Labrière et al. 2023). Such initiatives illustrate how technological investment can strengthen, rather than replace, the empirical foundations of field ecology. A continuing challenge is to ensure that these benefits are sustained, equitably distributed, and translated into durable local research capacity.

Fourth, professional societies and journals can also increase the visibility of long-term and infrastructure-building work (Figure 2), such as the “Long-term Studies in Animal Ecology” article type already offered by the *Journal of Animal Ecology* (https://besjournals.onlinelibrary.wiley.com/hub/journal/13652656/features/Synthesis-papers), as well as formats for biodiversity data resources. Such recognition is most valuable when it connects these contributions to the analytical, forecasting, and decision-making systems that depend on them, while making their scientific value more visible within existing reward structures. These mechanisms will necessarily vary among national research systems, some of which have developed more durable support for long-term ecological monitoring and collections than others; identifying transferable features of these models may provide useful lessons for broader reform.

Final remark

Thirty years after Noss’s warning, the central question is no longer simply whether

naturalists are disappearing, but how natural-history knowledge is being repositioned within an increasingly predictive and AI-enabled science. Modern ecology can detect and model patterns at unprecedented scales, yet these capacities remain dependent on long-term observations, taxonomic expertise, and place-based knowledge for training, validation, and interpretation. So, contemporary naturalists should integrate firsthand knowledge of organisms and ecosystems with quantitative and technological expertise, drawing on these complementary skills to interpret ecological changes, generate biologically informed hypotheses, and evaluate the reliability of ecological predictions. The task for 2026 is therefore not to retreat from analytical sophistication, but to build scientific systems in which technological advances reinforce rather than erode the empirical foundations on which prediction depends.

References

Ahrends A, Rahbek C, Bulling MT, Burgess ND, Platts PJ, Lovett JC, Kindemba VW, Owen N, Sallu AN, Marshall AR, Mhoro BE, Fanning E, Marchant R. 2011. Conservation and the botanist effect. Biological Conservation 144: 131–140.

Alexander JM, Diez JM, Levine JM. 2015. Novel competitors shape species' responses to climate change. Nature 525: 515–518.

Amano T, Sutherland WJ. 2013. Four barriers to the global understanding of biodiversity conservation: wealth, language, geographical location and security. Proceedings of the Royal Society B: Biological Sciences 280: 20122649.

Anderson SC, Elsen PR, Hughes BB, Tonietto RK, Bletz MC, Gill DA, Holgerson MA, Kuebbing SE, McDonough MacKenzie C, Meek MH, Veríssimo D. 2021. Trends in ecology and conservation over eight decades. Frontiers in Ecology and the Environment 19: 274–282.

Boakes EH, McGowan PJK, Fuller RA, Chang-qing D, Clark NE, O'Connor K, Mace GM. 2010. Distorted Views of Biodiversity: Spatial and Temporal Bias in Species Occurrence Data. PLoS Biology 8: e1000385.

Brown CJ, Buelow CA, Stuart-Smith RD, Barrett NS, Edgar GJ, Oh ES. 2025. Assessing predictive accuracy of species abundance models in dynamic systems. Methods in Ecology and Evolution 16: 2036–2047.

Bueno de Mesquita CP, White CT, Farrer EC, Hallett LM, Suding KN. 2021. Taking climate change into account: Non-stationarity in climate drivers of ecological response. Journal of Ecology 109: 1491–1500.

Di Cecco GJ, Barve V, Belitz MW, Stucky BJ, Guralnick RP, Hurlbert AH. 2021. Observing the Observers: How Participants Contribute Data to iNaturalist and Implications for

Biodiversity Science. BioScience 71: 1179–1188.
Chave J, Davies SJ, Phillips OL, Lewis SL, Sist P, Schepaschenko D, Armston J, Baker TR, Coomes D, Disney M, Duncanson L, Hérault B, Labrière N, Meyer V, Réjou-Méchain M, Scipal K, Saatchi S. 2019. Ground Data are Essential for Biomass Remote Sensing Missions. Surveys in Geophysics 40: 863–880.
Choi JJ, Gaskins LC, Morton JP, Bingham JA, Blawas AM, Hayes C, Hoyt C, Halpin PN, Silliman B. 2025. Role of low impact - factor journals in conservation implementation. Conservation Biology 39.
Collen B, Ram M, Zamin T, McRae L. 2008. The Tropical Biodiversity Data Gap: Addressing Disparity in Global Monitoring. Tropical Conservation Science 1: 75–88.
Davies SJ, Abiem I, Abu Salim K, Aguilar S, Allen D, Alonso A, Anderson-Teixeira K, Andrade A, Arellano G, Ashton PS, Baker PJ, Baker ME, Baltzer JL, Basset Y, Bissiengou P, Bohlman S, Bourg NA, Brockelman WY, Bunyavejchewin S, Burslem DFRP, Cao M, Cárdenas D, Chang L-W, Chang-Yang C-H, Chao K-J, Chao W-C, Chapman H, Chen Y-Y, Chisholm RA, Chu C, Chuyong G, Clay K, Comita LS, Condit R, Cordell S, Dattaraja HS, de Oliveira AA, den Ouden J, Detto M, Dick C, Du X, Duque Á, Ediriweera S, Ellis EC, Obiang NLE, Esufali S, Ewango CEN, Fernando ES, Filip J, Fischer GA, Foster R, Giambelluca T, Giardina C, Gilbert GS, Gonzalez-Akre E, Gunatilleke IAUN, Gunatilleke CVS, Hao Z, Hau BCH, He F, Ni H, Howe RW, Hubbell SP, Huth A, Inman-Narahari F, Itoh A, Janík D, Jansen PA, Jiang M, Johnson DJ, Jones FA, Kanzaki M, Kenfack D, Kiratiprayoon S, Král K, Krizel L, Lao S, Larson AJ, Li Y, Li X, Litton CM, Liu Y, Liu S, Lum SKY, Luskin MS, Lutz JA, Luu HT, Ma K, Makana J-R, Malhi Y, Martin A, McCarthy C, McMahon SM, McShea WJ, Memiaghe H, Mi X, Mitre D, Mohamad M, Monks L, Muller-Landau HC, Musili PM, Myers JA, Nathalang A, Ngo KM, Norden N, Novotny V, O'Brien MJ, Orwig D, Ostertag R, Papathanassiou K, Parker GG, Pérez R, Perfecto I, Phillips RP, Pongpattananurak N, Pretzsch H, Ren H, Reynolds G, Rodriguez LJ, Russo SE, Sack L, Sang W, Shue J, Singh A, Song G-ZM, Sukumar R, Sun I-F, Suresh HS, Swenson NG, Tan S, Thomas SC, Thomas D, Thompson J, Turner BL, Uowolo A, Uriarte M, Valencia R, Vandermeer J, Vicentini A, Visser M, Vrska T, Wang X, Wang X, Weiblen GD, Whitfeld TJS, Wolf A, Wright SJ, Xu H, Yao TL, Yap SL, Ye W, Yu M, Zhang M, Zhu D, Zhu L, Zimmerman JK, Zuleta D. 2021. ForestGEO: Understanding forest diversity and dynamics through a global observatory network. Biological Conservation 253: 108907.
Ditchkoff SS, Belsare A V. 2025. Much ado about modeling: Why fieldwork should remain the soul of wildlife ecology and management. Wildlife Society Bulletin 49.
Filbee-Dexter K, Pittman J, Haig HA, Alexander SM, Symons CC, Burke MJ. 2017. Ecological surprise: concept, synthesis, and social dimensions. Ecosphere 8.
Forbes O, Young AG, Thrall PH. 2025. Global sampling decline erodes science potential of natural history collections. Nature Communications 16: 9255.
Gagliardo R, CRUMP P, GRIFFITH E, MENDELSON J, ROSS H, ZIPPEL K. 2008. The principles of rapid response for amphibian conservation, using the programmes in Panama as an example. International Zoo Yearbook 42: 125–135.
GEO-TREES. 2025. GEO-TREES: high-accuracy ground data for satellite-derived biomass mapping.
Giakoumi S, Richardson AJ, Doxa A, Moro S, Andrello M, Hanson JO, Hermoso V, Mazor T, McGowan J, Kujala H, Law E, Álvarez-Romero JG, Magris RA, Gissi E, Arafeh-Dalmau N, Metaxas A, Virtanen EA, Ban NC, Runya RM, Dunn DC, Fraschetti S, Galparsoro I, Smith RJ, Bastardie F, Stelzenmüller V, Possingham HP, Katsanevakis S. 2025. Advances in systematic conservation planning to meet global biodiversity goals. Trends in Ecology & Evolution 40: 395–410.

Guerrero-Casado J, Murillo-Jiménez T, Carpio AJ, Tortosa FS, Serrano-Rodríguez R. 2026. Threats to conservation from artificial-intelligence-generated wildlife images and videos. Conservation Biology 40.
Hicks D, Wouters P, Waltman L, de Rijcke S, Rafols I. 2015. Bibliometrics: The Leiden Manifesto for research metrics. Nature 520: 429–431.
Hortal J, de Bello F, Diniz-Filho JAF, Lewinsohn TM, Lobo JM, Ladle RJ. 2015. Seven Shortfalls that Beset Large-Scale Knowledge of Biodiversity. Annual Review of Ecology, Evolution, and Systematics 46: 523–549.
Høye TT, Ärje J, Bjerge K, Hansen OLP, Iosifidis A, Leese F, Mann HMR, Meissner K, Melvad C, Raitoharju J. 2021. Deep learning and computer vision will transform entomology. Proceedings of the National Academy of Sciences 118.
Kareiva P, Marvier M. 2012. What Is Conservation Science? BioScience 62: 962–969.
Keck F, Couton M, Altermatt F. 2023. Navigating the seven challenges of taxonomic reference databases in metabarcoding analyses. Molecular Ecology Resources 23: 742–755.
Kester NJ, Kharouba HM, Smith TW. 2026. Niche Expansion in an Invasive Plant Has Significant Influence on the Modelling of Its Current and Future Geographic Distributions. Journal of Biogeography 53.
Knapp AK, Smith MD, Hobbie SE, Collins SL, Fahey TJ, Hansen GJA, Landis DA, La Pierre KJ, Melillo JM, Seastedt TR, Shaver GR, Webster JR. 2012. Past, Present, and Future Roles of Long-Term Experiments in the LTER Network. BioScience 62: 377–389.
Labrière N, Davies SJ, Disney MI, Duncanson LI, Herold M, Lewis SL, Phillips OL, Quegan S, Saatchi SS, Schepaschenko DG, Scipal K, Sist P, Chave J. 2023. Toward a forest biomass reference measurement system for remote sensing applications. Global Change Biology 29: 827–840.
Lees AC, Iwane T, Seeholzer GF, Seltzer C, Webster MS. 2026. Citizen science platforms must mitigate against the threat of generative AI. Nature Ecology & Evolution 10: 1389–1390.
Lindenmayer D. 2018. Why is long-term ecological research and monitoring so hard to do? (And what can be done about it). Australian Zoologist 39: 576–580.
Lindenmayer D, Scheele B. 2017. Do not publish. Science 356: 800–801.
Lindenmayer DB, Lavery T, Scheele BC. 2022. Why We Need to Invest in Large-Scale, Long-Term Monitoring Programs in Landscape Ecology and Conservation Biology. Current Landscape Ecology Reports 7: 137–146.
Lindenmayer DB, Likens GE, Krebs CJ, Hobbs RJ. 2010. Improved probability of detection of ecological “surprises”. Proceedings of the National Academy of Sciences 107: 21957–21962.
Lips KR. 1998. Decline of a Tropical Montane Amphibian Fauna. Conservation Biology 12: 106–117.
Lips KR. 1999. Mass Mortality and Population Declines of Anurans at an Upland Site in Western Panama. Conservation Biology 13: 117–125.
Lips KR, Brem F, Brenes R, Reeve JD, Alford RA, Voyles J, Carey C, Livo L, Pessier AP, Collins JP. 2006. Emerging infectious disease and the loss of biodiversity in a Neotropical amphibian community. Proceedings of the National Academy of Sciences 103: 3165–3170.
Loh J, Green RE, Ricketts T, Lamoreux J, Jenkins M, Kapos V, Randers J. 2005. The Living Planet Index: using species population time series to track trends in biodiversity. Philosophical Transactions of the Royal Society B: Biological Sciences 360: 289–295.
Maldonado C, Molina CI, Zizka A, Persson C, Taylor CM, Albán J, Chilquillo E, Rønsted N, Antonelli A. 2015. Estimating species diversity and distribution in the era of Big Data: to

what extent can we trust public databases? Global Ecology and Biogeography 24: 973–984.
McCallen E, Knott J, Nunez-Mir G, Taylor B, Jo I, Fei S. 2019. Trends in ecology: shifts in ecological research themes over the past four decades. Frontiers in Ecology and the Environment 17: 109–116.
McCleery R, Guralnick R, Beatty M, Belitz M, Campbell CJ, Idec J, Jones M, Kang Y, Potash A, Fletcher RJ. 2023. Uniting Experiments and Big Data to advance ecology and conservation. Trends in Ecology & Evolution 38: 970–979.
McKiernan EC, Schimanski LA, Muñoz Nieves C, Matthias L, Niles MT, Alperin JP. 2019. Use of the Journal Impact Factor in academic review, promotion, and tenure evaluations. eLife 8.
McRae L, Cornford R, Marconi V, Puleston H, Ledger SEH, Deinet S, Oppenheimer P, Hoffmann M, Freeman R. 2025. The utility of the Living Planet Index as a policy tool and for measuring nature recovery. Philosophical Transactions of the Royal Society B: Biological Sciences 380.
Meyer C, Kreft H, Guralnick R, Jetz W. 2015. Global priorities for an effective information basis of biodiversity distributions. Nature Communications 6: 8221.
Moudrý V, Bazzichetto M, Remelgado R, Devillers R, Lenoir J, Mateo RG, Lembrechts JJ, Sillero N, Lecours V, Cord AF, Barták V, Balej P, Rocchini D, Torresani M, Arenas-Castro S, Man M, Prajzlerová D, Gdulová K, Prošek J, Marchetto E, Zarzo-Arias A, Gábor L, Leroy F, Martini M, Malavasi M, Cazzolla Gatti R, Wild J, Šímová P. 2024. Optimising occurrence data in species distribution models: sample size, positional uncertainty, and sampling bias matter. Ecography 2024.
Nachman MW, Beckman EJ, Bowie RC, Cicero C, Conroy CJ, Dudley R, Hayes TB, Koo MS, Lacey EA, Martin CH, McGuire JA, Patton JL, Spencer CL, Tarvin RD, Wake MH, Wang IJ, Achmadi A, Álvarez-Castañeda ST, Andersen MJ, Arroyave J, Austin CC, Barker FK, Barrow LN, Barrowclough GF, Bates J, Bauer AM, Bell KC, Bell RC, Bronson AW, Brown RM, Burbrink FT, Burns KJ, Cadena CD, Cannatella DC, Castoe TA, Chakrabarty P, Colella JP, Cook JA, Cracraft JL, Davis DR, Davis Rabosky AR, D'Elía G, Dumbacher JP, Dunnum JL, Edwards S V., Esselstyn JA, Faivovich J, Fjeldså J, Flores-Villela OA, Ford K, Fuchs J, Fujita MK, Good JM, Greenbaum E, Greene HW, Hackett S, Hamidy A, Hanken J, Haryoko T, Hawkins MT, Heaney LR, Hillis DM, Hollingsworth BD, Hornsby AD, Hosner PA, Irham M, Jansa S, Jiménez RA, Joseph L, Kirchman JJ, LaDuc TJ, Leaché AD, Lessa EP, López-Fernández H, Mason NA, McCormack JE, McMahan CD, Moyle RG, Ojeda RA, Olson LE, Kin Onn C, Parenti LR, Parra-Olea G, Patterson BD, Pauly GB, Pavan SE, Peterson AT, Poe S, Rabosky DL, Raxworthy CJ, Reddy S, Rico-Guevara A, Riyanto A, Rocha LA, Ron SR, Rovito SM, Rowe KC, Rowley J, Ruane S, Salazar-Valenzuela D, Shultz AJ, Sidlauskas B, Sikes DS, Simmons NB, Stiassny MLJ, Streicher JW, Stuart BL, Summers AP, Tavera J, Teta P, Thompson CW, Timm RM, Torres-Carvajal O, Voelker G, Voss RS, Winker K, Witt C, Wommack EA, Zink RM. 2023. Specimen collection is essential for modern science. PLOS Biology 21: e3002318.
Niemiec RM, Gruby R, Quartuch M, Cavaliere CT, Teel TL, Crooks K, Salerno J, Solomon JN, Jones KW, Gavin M, Lavoie A, Stronza A, Meth L, Enrici A, Lanter K, Browne C, Proctor J, Manfredo M. 2021. Integrating social science into conservation planning. Biological Conservation 262: 109298.
Noss RF. 1996. The Naturalists Are Dying off. Conservation Biology 10: 1–3.
Páll-Gergely B, Krell F-T, Ábrahám L, Bajomi B, Balog LE, Boda P, Csuzdi C, Dányi L, Fehér Z, Hornok S, Horváth A, Kóbor P, Koczor S, Kontschán J, Kovács P, Kovács T, Lukátsi M, Majoros G, Murányi D, Németh T, Pernecker B, Puskás G, Rózsa L, Soltész Z, Szita É, Szűts T, Tóth B, Tőke A, Vas Z, Zsuga K, Zsupos V, Csabai Z, Móra A. 2024.

617 Identification crisis: a fauna-wide estimate of biodiversity expertise shows massive
618 decline in a Central European country. Biodiversity and Conservation 33: 3871–3903.
619 Pearson DL, Hamilton AL, Erwin TL. 2011. Recovery Plan for the Endangered Taxonomy
620 Profession. BioScience 61: 58–63.
621 Reinke BA, Miller DAW, Janzen FJ. 2019. What Have Long-Term Field Studies Taught Us
622 About Population Dynamics? Annual Review of Ecology, Evolution, and Systematics 50:
623 261–278.
624 Ríos-Saldaña CA, Delibes-Mateos M, Ferreira CC. 2018. Are fieldwork studies being
625 relegated to second place in conservation science? Global Ecology and Conservation
626 14: e00389.
627 Rodda GH, Savidge JA. 2007. Biology and impacts of Pacific island invasive species. 2.
628 Boiga irregularis, the brown tree snake (Reptilia: colubridae) 1. Pacific Science 61: 307–
629 324.
630 Rohwer VG, Rohwer Y, Dillman CB. 2022. Declining growth of natural history collections fails
631 future generations. PLOS Biology 20: e3001613.
632 Rouby E. 2026. Why 50-year studies are needed in a 3-year-grant world. Nature Reviews
633 Biodiversity 2: 75–75.
634 Rovero F, Ahumada J. 2017. The Tropical Ecology, Assessment and Monitoring (TEAM)
635 Network: An early warning system for tropical rain forests. Science of The Total
636 Environment 574: 914–923.
637 Savidge JA. 1987. Extinction of an Island Forest Avifauna by an Introduced Snake. Ecology
638 68: 660–668.
639 Schmeller DS, Böhm M, Arvanitidis C, Barber-Meyer S, Brummitt N, Chandler M,
640 Chatzinikolaou E, Costello MJ, Ding H, García-Moreno J, Gill M, Haase P, Jones M,
641 Juillard R, Magnusson WE, Martin CS, McGeoch M, Mihoub J-B, Pettorelli N, Proença
642 V, Peng C, Regan E, Schmiedel U, Simaika JP, Weatherdon L, Waterman C, Xu H,
643 Belnap J. 2017. Building capacity in biodiversity monitoring at the global scale.
644 Biodiversity and Conservation 26: 2765–2790.
645 Soga M, Gaston KJ. 2025. Extinction of experience among ecologists. Trends in Ecology &
646 Evolution 40: 212–215.
647 Sridhar H, Chanam J, Hariharan P. 2026. Spark, Scaffold, Substrate: The Multiple Hidden
648 Roles of Natural History in Ecology and Evolutionary Biology. The American Naturalist
649 208: 235–249.
650 Sun J. 2025. Ambiguous Definitions of “Non-Native” and “Translocated” Species Confound
651 Assessments of Freshwater Fish Homogenization. Global Change Biology 31.
652 Sutherland WJ, Burgess ND, Edwards S V., Jones JPG, Soltis PS, Tilman D, Allen JM,
653 Andrianandrasana HT, Armour CJ, August T, Bawa KS, Bailey S, Birch T, Boersch-
654 Supan PH, Cavender-Bares J, Blaxter M, Chaplin-Kramer R, Daru BH, De Palma A,
655 Eisenberg C, Elphick CS, Freckleton RP, Frick WF, Gonzalez A, Goetz SJ, Greenspoon
656 L, Grozinger CM, Hankins DL, Hazell J, Isaac NJB, Lambertini M, Lewin HA, Mac Aodha
657 O, Madhavapeddy A, Milner-Gulland E, Milo R, O’Dwyer J, Purvis A, Salafsky N, Tallis
658 H, Tanshi I, Vijay V, Wikelski M, Williams DR, Woodard SH, Robinson GE. 2026. Nine
659 changes needed to deliver a radical transformation in biodiversity measurement.
660 Proceedings of the National Academy of Sciences 123.
661 Tewksbury JJ, Anderson JGT, Bakker JD, Billo TJ, Dunwiddie PW, Groom MJ, Hampton SE,
662 Herman SG, Levey DJ, Machnicki NJ, del Rio CM, Power ME, Rowell K, Salomon AK,
663 Stacey L, Trombulak SC, Wheeler TA. 2014a. Natural History’s Place in Science and
664 Society. BioScience 64: 300–310.
665 Tewksbury JJ, Anderson JGT, Bakker JD, Billo TJ, Dunwiddie PW, Groom MJ, Hampton SE,
666 Herman SG, Levey DJ, Machnicki NJ, del Rio CM, Power ME, Rowell K, Salomon AK,

Stacey L, Trombulak SC, Wheeler TA. 2014b. Natural History's Place in Science and Society. BioScience 64: 300–310.
Tuia D, Beery S, Costelloe BR, Oliver RY, Lecomte N. 2026. Towards 'digital ecology': Advances in integrating artificial intelligence from data generation to ecological insight. Methods in Ecology and Evolution 17: 222–227.
Wagner T, Schliep EM, North JS, Kundel H, Custer CA, Ruzich JK, Hansen GJA. 2023. Predicting climate change impacts on poikilotherms using physiologically guided species abundance models. Proceedings of the National Academy of Sciences 120.
White ER. 2025. Measuring what matters in the era of big data. Frontiers in Ecology and the Environment 23.
Yates KL, Bouchet PJ, Caley MJ, Mengersen K, Randin CF, Parnell S, Fielding AH, Bamford AJ, Ban S, Barbosa AM, Dormann CF, Elith J, Embling CB, Ervin GN, Fisher R, Gould S, Graf RF, Gregr EJ, Halpin PN, Heikkinen RK, Heinänen S, Jones AR, Krishnakumar PK, Lauria V, Lozano-Montes H, Mannocci L, Mellin C, Mesgaran MB, Moreno-Amat E, Mormede S, Novaczek E, Oppel S, Ortuño Crespo G, Peterson AT, Rapacciuolo G, Roberts JJ, Ross RE, Scales KL, Schoeman D, Snelgrove P, Sundblad G, Thuiller W, Torres LG, Verbruggen H, Wang L, Wenger S, Whittingham MJ, Zharikov Y, Zurell D, Sequeira AMM. 2018. Outstanding Challenges in the Transferability of Ecological Models. Trends in Ecology & Evolution 33: 790–802.

Acknowledgement

J.S. was funded by the National Natural Science Foundation of China (grant no. 42301064). The author thanks Philip Haubrock for helpful discussions on the manuscript content and Yushan Tang for contributions to figure preparation. During the preparation of this manuscript, the author used ChatGPT (OpenAI) to identify and correct grammatical errors in the English text. All content was reviewed and verified by the author.

Author contributions

J.S. contributed to the conceptualization of the paper and preparation of the manuscript.

Competing interests

The author declares no competing interests.