Aligning evidence and action: The Research-to-Decision (RED) Framework to address modern environmental and ecological challenges

Esther L. Jones[a,*], Ruth King[b], Stuart King[b], Oisín Mac Aodha[c], Robin J. Boyd[d], Susan Jarvis[e], Matthew Silk[f], Jenna Lawson[e], David R. Williams[g], Sallie Bailey[h], Serge Wich[i], Alison Johnston[j], Adam Butler[a], Hannah Worthington[j,k], Kasim Terzić[l], Ben C. Stevenson[j], Eleni Matechou[m], Sarah R. Christofides[n], Eduard Campillo-Funollet[o], Cornelia Oedekoven[j], Danielle V. Harris[j], Tiago A. Marques[j,p], Altea Lorenzo-Arribas[a], Peter A. Henrys[e], Carolina S. Marques[q], Rebecca Wilks[b], Amanda Lenzi[b] and Rachel S. McCrea[o]

[a] *Biomathematics & Statistics Scotland, Edinburgh, UK*
[b] *School of Mathematics and Maxwell Institute for Mathematical Sciences, University of Edinburgh, UK*
[c] *School of Informatics, University of Edinburgh, UK*
[d] *UK Centre for Ecology & Hydrology, Benson Lane, Crowmarsh Gifford, OX10 8BB, UK*
[e] *UK Centre for Ecology & Hydrology, Lancaster, UK*
[f] *Institute of Ecology and Evolution, University of Edinburgh, Edinburgh, UK*
[g] *Sustainability Research Institute, University of Leeds, UK*
[h] *School of Biological and Environmental Sciences, University of Stirling, UK*
[i] *Liverpool John Moores University, UK*
[j] *Centre for Research into Ecological and Environmental Modelling, University of St Andrews, St Andrews, UK*
[k] *School of Mathematics and Statistics, University of St Andrews, UK*
[l] *School of Computer Science, University of St Andrews, UK*
[m] *School of Mathematical Sciences, Queen Mary University of London, London, UK*
[n] *School of Biosciences, Cardiff University, UK*
[o] *School of Mathematical Sciences, Lancaster University, UK*
[p] *Departamento de Biologia Animal, Centro de Estatística e Aplicações, Faculdade de Ciências da Universidade de Lisboa, Portugal*
[q] *Centre of Statistics and its Applications, University of Lisbon, Portugal*

ARTICLE INFO

Keywords:
AI-enabled ecology
AI and domain expertise integration
Biodiversity and climate crises solutions
Ecological data collection
Science-policy interface
Statistics

ABSTRACT

Ecological and biodiversity crises are intensifying amid rapid advances in sensing, computation, and artificial intelligence (AI). AI offers unprecedented capabilities to understand complex ecological systems, provided outputs are interpretable, applied responsibly, and evaluated by domain experts. When addressing key challenges, science-policy frictions arise through different requirements relating to timelines, managing uncertainty, and accountability. We present the Research-to-Decision (RED) framework to better align these differences, using a transdisciplinary approach across the ecological research cycle. The framework is operationalised through embedding responsible AI, identifying where domain expertise should lead, where AI can accelerate research, and where AI-human synergy is essential for producing robust evidence for informed decision-making. Implementation pathways are identified: research & technology, communication & policy alignment, and assets & infrastructure, all underpinned by culture & people. AI synergy relies entirely upon human synergy, and through bridge scientists and institutional change, the RED framework can unlock capacity to tackle complex environmental challenges and support evidence-based policy development for biodiversity conservation.

*Corresponding author

esther.jones@bioss.ac.uk (E.L. Jones)

ORCID(s): 0000-0002-4409-5860 (E.L. Jones); 0000-0002-5174-8727 (R. King); 0000-0002-5787-5073 (O.M. Aodha); 0000-0002-7973-9865 (R.J. Boyd); 0000-0001-5382-5135 (S. Jarvis); 0000-0002-8318-5383 (M. Silk); 0000-0001-5166-5510 (J. Lawson); 0000-0002-0379-1800 (D.R. Williams); 0000-0003-3954-5174 (S. Wich); 0000-0001-8221-013X (A. Johnston); 0000-0002-0860-6475 (A. Butler); 0000-0001-5452-3032 (H. Worthington); 0000-0001-6692-209X (K. Terzić); 0000-0002-0570-3886 (B.C. Stevenson); 0000-0003-3626-844X (E. Matechou); 0000-0002-3806-3416 (S.R. Christofides); 0000-0001-7021-1610 (E.

1. Introduction

Exponential growth in human resource consumption has intensified biodiversity and environmental challenges, demanding urgent action to secure a sustainable future for subsequent generations. International agreements such as the Convention on Biodiversity and UN Sustainable Development Goals emphasise the need for evidence-based strategies (United Nations, 2015). At the same time, technological advances have enabled massive scaling of sensing, computation, and automated reasoning, including Artificial Intelligence (AI), to offer new opportunities to deepen our understanding of complex ecological systems and support goals to increase biodiversity. We broadly define AI as a suite of data-driven computational algorithms designed to perform tasks traditionally requiring human intelligence to interpret or respond to. However, if AI is shorthand for a new suite of techniques to understand patterns in data, then the advent of new methodological approaches is nothing new. One could have perceived the same issues when Bayesian statistics became increasingly popular in the 1990s, which increased the range of methods available for data analyses. As much promise as AI holds, it is an amplifier and using it in a traditional research cycle, where disciplines are siloed, will accelerate ecological errors at scale because the associated algorithms' interpretations and limitations are not well understood (Han et al., 2023; Ren et al., 2023). Rather than approaching AI with scepticism, we can use it to harness diverse knowledge and help overcome the limitations of siloed approaches to ultimately benefit the broader research goal (Reynolds et al., 2025b). Domain experts can provide valuable knowledge that AI alone cannot replicate, making their involvement essential in developing and validating AI solutions (Kendall-Bar et al., 2026). Given the societal importance and diverse stakeholders involved in producing a strong evidence base, trust in AI outputs will only be established when they are developed and interpreted together with human judgment.

However, to address global challenges effectively and urgently, research outputs much be better aligned with policy needs. Here, we address the persistent challenges that separate evidence generation from decision-making, which are differing timelines, approaches to uncertainty, and accountability requirements. These challenges create barriers at the science-policy interface that are not fully addressed by existing approaches developed independently across transdisciplinary research, science-policy engagement, AI-enabled ecology, and responsible AI.

We present the Research-to-Decision (RED) Framework, a transdisciplinary approach that reconciles these challenges through the heterogeneous integration of responsible AI, domain expertise, and stakeholder perspectives across the ecological research cycle. Stepping through the research cycle, we highlight emerging opportunities and barriers that currently exist in the operational framework, but which are overlooked when disciplines operate in isolation. Finally, we set out implementation pathways for embedding the framework in practice, overcoming domain and discipline isolation and ensuring that AI is appropriately and responsibly embedded to maximise knowledge gain and impact in addressing ecological and conservation problems.

2. Research-to-Decision (RED) Framework

Ecological research is increasingly impact-driven, seeking to inform policy and management decisions. However, research and policy operate under different constraints, creating persistent barriers at the science-policy interface that can limit the translation of evidence into decision-making. The different pressures underpinning research and decision-making can be described as:

1. Aligning timelines: Research and policy often operate on different timescales with research developing to accumulate evidence through long-term research programmes. By contrast, policy operates within time-bounded decisions. To bridge this gap and help deliver timely insights to stakeholders, incremental approaches that leverage existing knowledge can be implemented and new research can be undertaken such as systematic reviews, meta-analyses, and expert elicitation (Bainbridge, 2014).
2. Managing uncertainty: Scientific uncertainty is typically framed through repeatability, replication, and long-term frequencies, whilst decision-makers focus on specific outcomes within defined timeframes. Linking uncertainty to adaptive management enables more effective decisions, especially when outcomes are reversible (Young et al., 2014). Where AI is embedded in the research cycle, the use of uncertainty estimates, scenario-based evaluation, and human-in-the-loop approaches are required to support transparent and flexible responses to evolving evidence.

Campillo-Funollet); 0000-0002-5610-7814 (C. Oedekoven); 0000-0003-1447-1420 (D.V. Harris); 0000-0002-2581-1972 (T.A. Marques); 0000-0001-6739-4372 (A. Lorenzo-Arribas); 0000-0003-4758-1482 (P.A. Henrys); 0000-0002-5936-9342 (C.S. Marques); 0009-0001-4110-1102 (R. Wilks); 0000-0001-7618-7164 (A. Lenzi); 0000-0002-3813-5328 (R.S. McCrea)

3. Ensuring accountability: Both research and policy require transparency, although principles are applied differently. Policymaking demands clear, consistent messaging and interpretable metrics. Research evaluates existing metrics and contributes to the design of new metrics as further information becomes available. Within AI-enabled systems, this necessitates explainable, auditable, reproducible, and replicable approaches, ensuring that model outputs can be understood, scrutinised, and appropriately used within policy contexts.

Existing frameworks such as transdisciplinary research, science-policy interfaces, AI-enabled ecology, and responsible AI have largely developed in parallel, and so only partially address the challenges of translating evidence into action. As a result, analytical advances can be technologically beneficial but remain poorly aligned with decision-makers' needs and disconnected from the expertise required for their responsible use.

The Research-to-Decision (RED) Framework brings these complementary approaches together to better address the challenges of aligning timelines, uncertainty, and ensuring accountability across the whole research cycle (Figure 1). Co-creation and problem definition help align research activities with policy and management timescales. Study design, data collection, processing, and modelling provide the mechanisms through which uncertainty is identified, quantified, and interpreted. Communication, stakeholder engagement, and transparent analytical workflows support accountability and responsibility by ensuring that assumptions, limitations, and quality remain visible throughout the decision-making process. The RED Framework is operationalised through embedding AI heterogeneously throughout the research cycle, because some stages benefit most from being led by domain expertise, some are accelerated by AI, and others require strong AI-human synergy. Rather than treating AI as a stand-alone analytical tool, the framework identifies where AI can enhance large-scale monitoring with automated data collection and interactive visualisation, where AI-human synergy is critical to produce interpretable and credible results through correcting for bias and propagating uncertainty, and where domain expertise provides integrity in decision-making, participatory stakeholder engagement, and applying ethics for the thoughtful adoption of AI by quantitative experts in ecology.

We highlight the respective strengths from existing approaches that are integrated into the RED framework across the full research-to-decision pathway: Transdisciplinary research helps overcome the limitations of individual disciplines by engaging researchers from multiple domains and a wide range of stakeholders, facilitating discoveries that extend beyond traditional disciplinary boundaries (Sutherland et al., 2013; Boyd et al., 2023). Stakeholders commit to a shared goal and develop a common language to enable them to work together effectively in each step of the research cycle. A transdisciplinary approach requires sustained engagement through co-constructing aims and processes, allowing choices made at each stage of research to be integrated holistically and assessed in the context of the entire cycle.

Science-policy research highlights that while domain-specific expertise is essential for successful research outcomes, integration requires cross-disciplinary working and so bridges between research disciplines and policy are developed (Cvitanovic et al., 2021).

Integrating ecological theory with advances in AI offers powerful tools to address complex environmental challenges (Cheng and Liu, 2023; Pichler and Hartig, 2023), particularly where synergistic AI-ecology research can advance both fields – ecology through the efficiency of using AI throughout the research cycle and AI through learning from complex ecological systems (Han et al., 2023).

Responsible AI research frameworks have developed principles for the transparent, trustworthy, and socially responsible use of AI, setting out a consistent approach that considers functional, legal, ethical, and philanthropic elements wherever AI is embedded within the research cycle (McGovern et al., 2022; Cheng and Liu, 2023). More recently, application driven machine learning (ADML), motivated by real world needs and stakeholders has demonstrated how transdisciplinary research can deliver impact while also driving major methodological advances such as physics informed neural networks and Fourier Neural Networks (Rolnick et al., 2025).

Moving from a researcher-led evidence-based approach to a participatory approach ensures that delivery partners including stakeholders such as policymakers, Indigenous people, local communities (e.g. visitors, landowners, and managers) co-produce the research process (Wheeler and Root-Bernstein, 2020). In conservation science, research can be dominated by questions that ecologists are well suited to answer rather than those with the greatest potential for real-world impact (Williams et al., 2020). Addressing this, a co-production approach requires early collaboration between researchers and stakeholders to agree on the research questions, data requirements, modelling approaches (including statistical or AI methods), and the level of accuracy needed to provide confidence in the outputs. Integrating multiple knowledge systems such as Indigenous Knowledge to improve species habitat modelling can be used to support better ecological outcomes and decision-making (Gryba et al., 2024; Murray et al., 2025). The RED Framework has

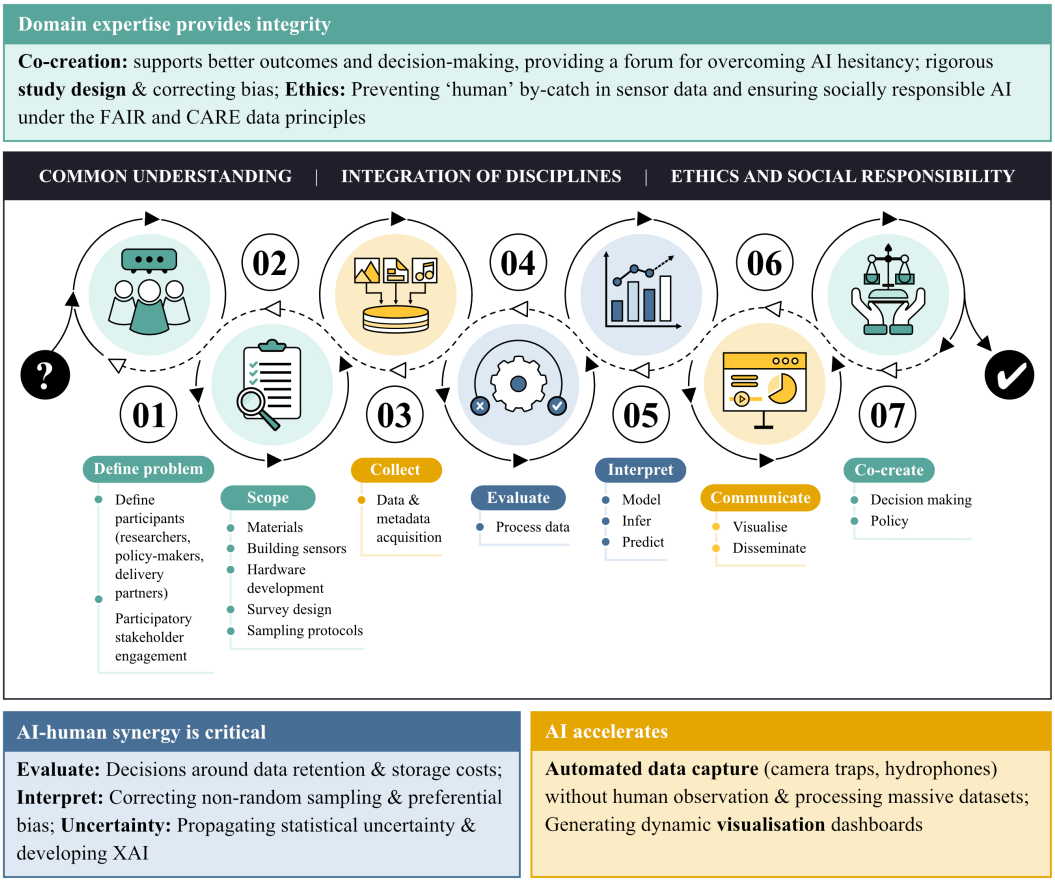

Figure 1: The Research-to-Decision (RED) Framework addresses the persistent science-policy challenges of aligning timelines, managing uncertainty, and ensuring accountability by integrating transdisciplinary research, science-policy interfaces, AI-enabled ecology, and responsible AI. The framework is operationalised through embedding AI heterogeneously across the entire research cycle; coloured circles indicate stages of the research cycle where domain expertise leads (green), AI accelerates (orange), and AI-human synergy is critical (blue). The iterative cycle incorporates reflection (solid black arrows) and feedback (hollow black arrows and dashed line) to support evidence-based decision-making. The cycle ends when a challenge is solved or continues if the challenge needs to be iterated or redefined.

the potential to transform both stakeholder-driven research and fundamental scientific research to accelerate scientific productivity (AI for Science Strategy, 2025; OECD, 2023).

3. Co-create & problem definition: Policy and decision-making

Understanding the broader societal context and anticipating future shifts in research framing are essential from the outset to align outcomes with underlying motivations. Research outputs and dissemination underpin evidence, which are evaluated to inform policy development (Kemp, 2018). While blue skies research may not be driven by current policy, it can shape future decision-making through horizon scanning.

Effective relationships are crucial for policy-relevant research: policymakers can co-develop research aims whilst delivery partners and researchers are involved in shaping policy from the outset, and so establishing and maintaining trust is essential (Cvitanovic et al., 2021). Stakeholders must trust researchers to clearly communicate assumptions and caveats, while researchers must trust that these will be considered in decision-making and policy development. When applied effectively, this framework preserves academic freedom and stakeholder agency, strengthening timely connections between research and decision-making, and helping maximise the value of publicly funded research.

AI can only be effective in real-world contexts when the people who will use it help define the problem and the criteria for success (Rolnick et al., 2025). Working with policymakers from the outset is necessary for AI to be useful and responsible. Without this, models may be data-driven but irrelevant or misleading for decision-making. We extend this argument and apply it to ecological and environmental challenges, where policy needs define the constraints of the problem.

Underpinning the process requires multilateral communication rather than unilateral dissemination that occurs towards the end of a research project and so is not solely the responsibility of scientists. For example, the European Commission's Joint Research Centre recognises the value of science-policy interface and has diverse expertise in effective dissemination throughout various stages of the project cycle (Topp et al., 2018).

Terms relating to the interpretation of uncertainty such as significance, confidence, risk, and precaution are often defined and interpreted differently across research and policy contexts. Therefore, it is critical to establish a common language to avoid ambiguity and miscommunication that arise when domain-specific language is used within the research community and terminology in policy and decision-making fields (Young et al., 2014).

4. Scope: Study design and sampling protocols

Ecological inference relies on robust study design, and statistical methods depend on representative sampling. Similarly, AI algorithms require high-quality training data to minimise bias and generate reliable predictions. However, obtaining sufficiently large, good quality samples for accurate inference and prediction are often constrained by available resources. Controlling for external variables and documenting procedural changes, particularly in long-term studies, ensures consistency and reliability across samples (Schweiger et al., 2016).

Achieving gold standard sampling protocols and study design in natural ecosystems is challenging due to constraints on time, cost, accessibility, and rare species or population dispersion (Albert et al., 2010). Sampling errors - non-detection, erroneous counts, selection bias, and observer bias - which are common in studies that involve opportunistic sampling, can lead to biased data, estimates, inference, and predictions and ultimately ineffective decision-making (Elphick, 2008). For example, Conn et al. (2017) showed a 40% bias in density estimates for a population due to non-random sampling approaches. Adaptive study designs, which modify sampling protocols over time, offer cost-effective solutions and improved performance but remain underutilised in ecological applications (Henrys et al., 2024).

When the principles of sampling protocols cannot be met, acknowledging and accounting for resulting biases and unavoidable stochasticity during analysis is critical (Conn et al., 2017). This facilitates understanding of how sampling protocols influence analyses, which parameter estimates and algorithms are suitable for the chosen sampling protocols, and where changes may be required to reduce potential bias. Retaining domain expertise through embedding statisticians and AI data analysts in study design and analysis discussions with delivery partners and field ecologists helps to identify data collection limitations and other viability constraints early so that they do not propagate forwards through the remainder of the research cycle (Tiwari and Farag, 2025).

5. Collect: Data acquisition

Historically, ecological data were primarily collected through visual observations by trained ecologists, requiring considerable time and strong taxonomic expertise. Over the past 30 years, data collection has increased substantially in response to growing conservation needs (Tuia et al., 2022). This expansion has been driven in part by the emergence of organised citizen science and community science initiatives, extending the spatial and temporal coverage of observations. Simultaneously, advances in technology, with improved accessibility and reduced costs, have enabled large-scale monitoring at higher spatial and temporal resolutions (Dębicki et al., 2021), without the need for direct human observation (Hartig et al., 2024). These data can be extracted from a wide range of sources, including imagery (e.g. aerial and satellite data), audio recordings, radar, or DNA sequences (Besson et al., 2022).

Citizen science has an established body of research to understand and account for different types of reporting bias and observation error arising from opportunistic recording (Johnston et al., 2020). In contrast, novel acquisition approaches, particularly those obtained without explicit human guidance such as autonomous vehicles, new community data or AI-derived outputs introduce new sources of bias and uncertainty (Buckland et al., 2023). These arise from technical processes, such as PCR amplification errors in eDNA analyses or data artefacts from cloud masking in remote sensing. Furthermore, as datasets are increasingly reused beyond their original purpose, there is a growing need to reconsider study design and ensure they are collected and stored appropriately for future use (Silva et al., 2023).

Addressing these challenges requires interdisciplinary collaboration to both identify the underlying causes of bias and develop robust correction methods (Hartig et al., 2024). However, concerns have also been raised about both targeted data collection and human bycatch (accidental capture of human data via technologies including camera traps, drones, acoustic devices, and eDNA) (Sandbrook et al., 2021; Whitmore et al., 2023). Participatory and technology-driven approaches offer substantial gains in scale, coverage, and efficiency; however, their successful use depends on the development of methods capable of recognising and accounting for the biases and uncertainties introduced by increasingly heterogeneous data sources.

6. Evaluate: Data processing

AI-enabled methods can extract ecologically meaningful metrics, such as species presence or abundance, from large and complex datasets (Besson et al., 2022). Increasingly, autonomous vehicles, biologging devices, and other automated data collection technologies integrate data acquisition with real-time analysis through approaches such as edge computing. These advances require decisions about data processing and retention, often made at the point of collection. This creates trade-offs where biologically important information may be lost if automated processing fails to account for temporal changes in ecological signals. For example, detectors trained on historical data may degrade in performance over time when a signal has changed characteristics, as demonstrated by blue whale (*Balaenoptera musculus*) song frequencies declining over 60 years (Rice et al., 2022). Data processing and storage decisions are also shaped by financial constraints and the environmental costs of computation, including carbon footprint, water consumption, and land use (Krumm and Hoffman, 2020; Mytton, 2021).

The consequences of errors in fully automated systems can be substantial, particularly when outputs inform conservation policy. For example, the automated processing of camera trap data may result in false negative or misclassifications leading to erroneous conclusions about species absence, population trends, or behavioural change (Collar, 1998). Without human oversight, periodic auditing, and transparent reporting of uncertainty, AI-driven data processing systems are vulnerable to bias and the propagation of errors, potentially leading to incorrect conclusions and impacting wildlife management in practice.

Ecological data management is context-dependent, and designing efficient, reproducible, and ethical data processing pipelines requires transdisciplinary collaboration tailored to the research context. For relatively simple datasets, such as observational behavioural data, a small team including an ethologist and statistician may suffice. In contrast, processing multi-stream optical thermal infrared video and acoustic data from drones requires domain expertise from computer scientists, mathematicians and engineers with image processing and audio classification skills. Including ethicists into these teams is becoming increasingly important to ensure socially responsible AI practices, identifying biases in training data and supporting principled modelling decisions (McGovern et al., 2022).

When considering data re-use, ethical issues around data sharing and privacy concerns need to be considered so that contextually appropriate data are shared in a socially responsible manner (Carroll et al., 2021; Sandbrook et al., 2021). Historically, data processing decisions were made on a project-specific basis, for example, researchers collecting high-frequency acoustic data may store selected sound snippets, apply duty cycling, or retain summary statistics generated onboard sensors (e.g., Todd et al. 2023). Data confidentiality or sensitivity when studying rare or vulnerable species for conservation are examples where full datasets cannot typically be made publicly available, although best practice guidance seeks to partially address these issues (Tulloch et al., 2018). The adoption of data management frameworks such as the FAIR principles (Findable, Accessible, Interoperable, and Reusable; Wilkinson et al. 2016) has supported the growth of global open science initiatives. Established repositories, such as GenBank (Benson et al., 2013) and GBIF (Telenius, 2011), exemplify efforts internationally to maximise data usability and facilitate future research. Complementary frameworks such as the CARE principles (Collective benefit, Authority to control, Responsibility, Ethics) were developed for Indigenous Data Governance, recognising that responsible data stewardship and use should align with cultural values and community interests (Carroll et al., 2021). Contemporary ecological research increasingly relies on synthetic approaches, such as meta- and mega-analyses, which integrate datasets across studies to address complex, questions (Eisenhauer, 2021). As a result, preserving data in formats that enable reuse and scrutiny is critical, particularly as advances in generative AI increase the risk of producing plausible, but fabricated, data (Taloni et al., 2023).

7. Interpret: Modelling

The next step is drawing inferences about quantities of interest by fitting or training a process-based or empirical model, (e.g., based on machine learning or statistical reasoning). The target of inference is typically model parameters or predictions, although in some cases the model structure or functional form are also of interest (e.g. van der Vaart et al. 2015). Capturing ecological processes within models is particularly important when extrapolating predictions to novel conditions and interpreting parameters causally (Grace and Irvine, 2020). Successful examples of embedding domain expertise into AI-driven ecological modelling include INQUIRE, which integrates ecologist-informed queries, labelling strategies, and evaluation metrics for text-to-image retrieval benchmarks (Vendrow et al., 2024), and BioCLIP, which incorporates the tree of life to inform model design in relation to the abundance and diversity of images (Stevens et al., 2024).

While goodness-of-fit and predictive performance are commonly used metrics (Sequeira et al., 2018), a close fit does not necessarily indicate a well-specified model when data are not representative of the underlying population (Meng, 2022). Domain experts, whose knowledge extends beyond the sample, are better placed to assess whether model outputs are ecologically plausible. For example, taxon experts have evaluated species distribution models based on their ability to capture environmental preferences and predict suitable habitats (Beck et al., 2014).

Standardised training and evaluation datasets help computational researchers engage in model development, improve benchmarking and comparison of models (Cole et al., 2023). Transparent benchmarks, such as ImageNet (Russakovsky et al., 2015), have driven advances in AI methods. However, caution is required to ensure that performance improvements on newly developed benchmarks align with measures of success defined by domain experts. For example, ADML benchmarks, grounded in real-world applications and specific evaluation criteria, improve interpretation by ensuring that model performance is assessed using ecologically meaningful measures rather than generic metrics such as accuracy (Rolnick et al., 2025).

Statistical methods have benefitted from AI-driven advances in computational tools, such as large-scale gradient-based learning on GPUs (Paszke et al., 2019). These developments enable complex deep learning approaches that can jointly analyse multiple species and their interactions (Davis et al., 2023). Reinforcement learning, where data-driven rules are used to develop hypotheses, has synergies with modelling based on ecological theory of complex systems. Although these approaches are promising for prediction and understanding emergent properties, incorporating social dimensions requires transdisciplinary collaboration, as this information is typically offline, and may be harder to access at national and global scales (Han et al., 2023).

Uncertainty in deterministic or process-based models, such as those used in environmental monitoring, can be communicated to policymakers through decision support approaches that integrate model outputs (Uusitalo et al., 2015). However, propagating uncertainty through current AI models is challenging, as they often struggle to provide well-calibrated uncertainty estimates (Wang, 2024). Statistical models are often interpretable by design, whereas many AI models with millions of parameters are not. Improving transparency and interpretability of AI models is therefore critical if they are to be used by decision-makers. Making predictions and potential biases from models understandable to stakeholders is essential, requiring uncertainty propagation and development of explainable AI (XAI) approaches (Arrieta et al., 2020).

8. Communicate: Communication of outputs

Effective communication requires integrating visualisation, uncertainty, and stakeholder engagement, forming a critical pathway from research to decision-makers. Tailored outputs, such as interactive dashboards, support co-creation, shared understanding, and policy evaluation (Raineri and Molinari, 2021). They are also increasingly used by governments to present metrics and assess policy and intervention outcomes, e,g., the DEFRA Outcome Indicator Framework, visualising a comprehensive set of indicators describing environmental change and the Scottish Government Environment Strategy Monitoring Framework (Grainger et al., 2016). However, balancing visual appeal with accuracy is crucial, and accessibility and inclusiveness must account for diverse user needs including disabilities (Krause et al., 2024). Visualisation alone often struggles to represent uncertainty, especially in spatial data, highlighting the need for complementary approaches. Storytelling, through infographics, or data comics, can be helpful in establishing a narrative when communicating to a general audience.

AI offers opportunities to enhance communication through real-time updating, translation across audiences, and customisation of outputs, supporting more responsive engagement. For example, generative AI has been integrated into decision-support systems visualised using platforms such as PowerBI to evaluate research initiatives with the

Sustainable Development Goals (da Silva Barros et al., 2024). However, AI has visualisation challenges, and clearly conveying caveats, limitations, protocols, and data ‘frictions’, including how uncertainty is managed, helps build trust and accountability, particularly when outputs are synthesised from multiple sources (Panagiotidou et al., 2022).

9. Discussion

The RED Framework integrates science-policy interfaces, disciplinary expertise, stakeholder perspectives, and responsible AI within a single operational approach to align the requirements of research and policy for evidence-based decision-making. It highlights that the successful integration of AI into ecological research depends on how it is embedded and used within the research process rather than on the technology itself. AI is most effective as an amplifier of well-designed, domain-informed research, and does not replace the need for human decision-making. Its effectiveness depends on being embedded within transdisciplinary research where socially responsible AI can accelerate parts of the research cycle and its assumptions, limitations and outputs can be interrogated by domain experts and align with stakeholder needs.

Domain expertise is fundamental to co-creation and problem definition. They foster shared understanding of scientific questions, instill trust and open dialogue among stakeholders, and help navigate differing priorities so can provide a forum to address hesitation in embedding AI. Study design requires domain expertise to ensure valid, unbiased and decision-relevant outcomes. Rapid advances in novel data collection technologies generate vast datasets, allowing monitoring to be scaled, but methods are required to account for complex data and biases. AI can be used for efficient data processing where AI-human synergy supports decisions for data retention and reuse. We emphasise that AI methods do not replace statistical inference but rather extend the analytical toolbox because ecological insights depend on integrating these approaches, particularly for quantifying and communicating uncertainty. Although AI methods can identify patterns at scale, their outputs remain sensitive to training data, model assumptions, and extrapolation beyond observed conditions, requiring domain expertise to assess ecological plausibility.

Here, we identify four key implementation pathways that will allow take-up of the opportunities the RED Framework creates and address the current barriers that we have highlighted: research and technology, communication and policy alignment, culture and people, and assets and infrastructure (Figure 2).

10. Establishing implementation pathways

10.1. Research and technology

As models grow more complex to accommodate diverse data-generating processes and derived quantities, robust evaluation methods are essential to address issues like parameter identifiability, overfitting, and model robustness. To support informed decision-making, insights from systematic reviews, meta-analyses, and expert elicitation should be leveraged to strengthen the evidence base.

XAI provides a mechanism for connecting model outputs to ecological interpretation. XAI aims to make machine learning models transparent, interpretable, and accountable by providing explanations for their predictions or behaviours (Arrieta et al., 2020). However, the utility of XAI depends on whether these explanations are meaningful within an ecological context and comparable to the interpretation of established statistical approaches. New approaches and technologies for monitoring increase the likelihood of biased data relevant to the population and so simple approaches, such as risk-of-bias software ROBITT (Boyd et al., 2022), are needed to identify when bias may significantly affect analysis and alert researchers to potential pitfalls.

10.2. Communication and policy alignment

The EU AI Act 2024 sets out regulation on AI, providing opportunities for scientists and policymakers to work together to address risks and challenges associated with AI, and develop socially responsible working, transparency, and reproducibility. Operationalising these principles within the RED Framework, such as developing standardised documentation of model assumptions, uncertainty reporting, and explainability requirements, are critical for building trust in AI-enabled systems. The research community must consider ways to quantify uncertainty, distinguish between aleatoric and epistemic sources, and convey this information in a clear, audience-appropriate manner.

10.3. Culture and people

Embedding AI throughout the research cycle requires human skills to be addressed as well as improved technological advances (Royal Statistical Society, 2026). Key barriers arising from AI include the pace of technological

Figure 2: Implementation pathways to support the Research-to-Decision (RED) Framework in ecological research. Four complementary pathways help overcome barriers that currently exist. Together, key advances in research and technology, communication and policy alignment, culture and people, and assets and infrastructure will align evidence generation with decision-making.

development, unequal access to data and storage, ethical considerations, and interpretation and communication issues (Kendall-Bar et al., 2026). Integrated research is commonplace in large-scale areas such as environment and climate science (Tress et al., 2005; Vienni-Baptista et al., 2023), yet transdisciplinary approaches that bridge policy, research, and stakeholders, are rarely fully undertaken in practice within research settings (Pohl, 2008). This implementation gap highlights the need for institutional structures, career pathways, and training programmes that support transdisciplinary research.

Bridge scientists are vital for overcoming discipline-specific language and misconceptions of different techniques and theories, as they have strong metacognitive skills that facilitate collaboration across domains and disciplines (Vienni-Baptista et al., 2023). Research cultures must reward cross-disciplinary careers, provide clear pathways, and offer training that builds capacity beyond disciplinary silos (Cobbold et al., 2024). Application-led teaching that introduces scientists to real-world data and full project lifecycles lay the foundation for transdisciplinary environments (Rolnick et al., 2025). Effective transdisciplinary research requires dedicated time, space, and funding to build relationships, support inclusive dialogue, and ensure continuity despite staff turnover. Long-term impact relies on retaining knowledge across both scientific and stakeholder communities (Vienni-Baptista et al., 2023).

The expansion of AI-enabled ecological data collection raises ethical and social concerns (e.g., (Jackman et al., 2023) that data collection could drift into surveillance, with potentially serious impacts for privacy, safety, and data security (Sandbrook et al., 2021). These impacts could exacerbate existing power imbalances, a particular concern given the oppression and exclusion that has accompanied some biodiversity conservation practices both historically and today (Chaudhury and Colla, 2021). As AI becomes more effective, socially responsible practices are essential (McCrea et al., 2024). These seek to solve technical and societal challenges while embedding values within wider principles of fairness and justice, transparency, reliability and safety, privacy and security, and beneficence, recognising that tensions between these values will vary by context and technology (Cheng and Liu, 2023).

Data-centric FAIR principles promote data sharing and interoperability (Carroll et al., 2022) but do not address historical inequities or power imbalances. CARE principles address these limitations through incorporating cultural values into data use, and combining FAIR and CARE, such as the Nga Tikanga Paihere framework, can support more equitable, socially responsible AI by addressing both technical and ethical dimensions of data reuse (Han et al., 2023).

10.4. Assets and infrastructure

The large volume of data that are now being generated creates challenges for data storage and retention, leading to practical logistical issues and increasing demand for cloud storage and data sharing across (multi-national) teams. Further, identifying when raw data holds long-term value for future use is critical and depends on research questions and scale. Minimising information loss during transformation to derived metrics requires better tools and guidance, and results should be reproducible.

Adopting green coding practices and developing energy-efficient methods can help reduce water and energy consumption of data storage and high-performance computing (Guthrie, 2024). Collaborative environments such as accessible cloud-based environments should be developed for sharing and executing analyses. Substantial scientific insight has been gained from the contributions of volunteer scientists, and this type of engagement enables the training of automated techniques using AI methodology.

11. Conclusion

Addressing modern environmental and ecological challenges requires more than innovative technical advances. The RED Framework addresses the different demands of research and policy by aligning evidence generation and decision-making within a single operational approach. The framework achieves this by embedding responsible AI heterogeneously across the ecological research cycle and integrating domain expertise and stakeholder engagement throughout. Co-creating with policymakers at the inception stage helps to align research timelines with decision-making needs, so that evidence is available when it is required rather than after key decisions have been made. Supporting rigorous science for evidence-informed decision-making requires AI tools to be developed and implemented equitably within the ecological community, alongside socially responsible practices that minimise bias, prevent incorrect inference, and incorporate diverse perspectives (Reynolds et al., 2025a). This includes the ability to propagate uncertainty through the research cycle so that decision-makers can understand the strengths and limitations of the evidence they are using. Making data, models, and assumptions transparent further strengthens accountability, ensuring that outputs can be scrutinised and trusted in policy contexts.

Therefore, a cultural shift is required by the scientific community to embed this ethos. Funding bodies have a role in enabling knowledge retention and career satisfaction for researchers, whilst governments should engage with researchers to ensure policy integration is embedded within research planning (OECD, 2023). However, there is an equally important obligation for researchers to engage with aspects that fall outside of traditional metrics of research success. There is also a recognised need for sustained investment in constructing viable career paths and support at an institutional level (Cobbold et al., 2024; Rolnick et al., 2025). By providing a practical route from research to decision-making, the RED Framework offers a pathway for strengthening evidence-based conservation and environmental management in an increasingly data-rich world. Environmental and ecological challenges will accelerate, becoming substantially more difficult to solve, and it is essential that we embrace transdisciplinary approaches, integrating AI responsibly into domain expertise, to tackle these challenges and facilitate the best possible conservation outcomes.

12. Funding

We thank the International Centre for Mathematical Sciences for funding a workshop “Building interdisciplinary solutions to modern ecological challenges” (organised by Ruth King, David L. Borchers, Stuart King and Rachel McCrea) held in June 2023 where the ideas for this paper were conceived. R.S.M was supported by a Leverhulme Research Fellowship (RF-2022-197). T.A.M. was partially supported by CEAUL (funded by FCT - Fundação para a Ciência e a Tecnologia, Portugal DOI: 10.54499/UIDB/00006/2020). C.S.M. thanks support by CEAUL and FCT under the doctoral scholarship FCT/CEAUL (UI/BD/154258/2022). E.L.J., A.B. and A.L-A were supported by funding from the Rural and Environment Science and Analytical Services Division of the Scottish Government (RESAS).

13. CRediT authorship contribution statement

Conceptualisation: E.L.J., R.K., S.K., O.M.A., R.B., S.J., M.S., J.L., D.R.W., S.B., S.W., A.J., A.B., H.W., K.T., B.C.S., E.M., S.R.C., E.C.F., C.O., D.V.H., T.A.M., P.A.H., C.S.M., R.W., A.L., R.S.M. Funding acquisition: E.L.J., R.K., S.K., A.B., T.A.M., A.L.A., C.S.M., R.S.M. Methodology and writing: E.L.J., R.K., S.K., O.M.A., R.B., S.J., M.S., J.L., D.R.W., S.B., S.W., A.J., A.B., H.W., K.T., B.C.S., E.M., S.R.C., E.C.F., C.O., D.V.H., T.A.M., A.L.A., P.A.H., C.S.M., R.W., A.L., R.S.M. Visualisation: E.L.J., H.W., R.S.M. All authors contributed critically to the drafts and gave final approval for publication.

14. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

15. Acknowledgments

Thank you to Dr Phil Bouchet for producing the graphics for this paper.

References

Albert, C.H., Yoccoz, N.G., Edwards, T.C., Graham, C.H., Zimmermann, N.E., Thuiller, W., 2010. Sampling in ecology and evolution - bridging the gap between theory and practice. Ecography 33. doi:10.1111/j.1600-0587.2010.06421.x.

Arrieta, A.B., Díaz-Rodríguez, N., Ser, J.D., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., Herrera, F., 2020. Explainable artificial intelligence (xai): Concepts, taxonomies, opportunities and challenges toward responsible ai. Information Fusion 58. doi:10.1016/j.inffus.2019.12.012.

Bainbridge, I., 2014. How can ecologists make conservation policy more evidence based? ideas and examples from a devolved perspective. Journal of Applied Ecology 51. doi:10.1111/1365-2664.12294.

Beck, J., Böller, M., Erhardt, A., Schwanghart, W., 2014. Spatial bias in the gbif database and its effect on modeling species' geographic distributions. Ecological Informatics 19. doi:10.1016/j.ecoinf.2013.11.002.

Benson, D.A., Cavanaugh, M., Clark, K., Karsch-Mizrachi, I., Lipman, D.J., Ostell, J., Sayers, E.W., 2013. Genbank. Nucleic Acids Research 41, D36–D42. URL: https://doi.org/10.1093/nar/gks1195, doi:10.1093/nar/gks1195.

Besson, M., Alison, J., Bjerge, K., Gorochowski, T.E., Høye, T.T., Jucker, T., Mann, H.M., Clements, C.F., 2022. Towards the fully automated monitoring of ecological communities. Ecology Letters 25. doi:10.1111/ele.14123.

Boyd, R.J., August, T.A., Cooke, R., Logie, M., Mancini, F., Powney, G.D., Roy, D.B., Turvey, K., Isaac, N.J., 2023. An operational workflow for producing periodic estimates of species occupancy at national scales. Biological Reviews 98, 1492–1508. doi:10.1111/brv.12961.

Boyd, R.J., Powney, G.D., Burns, F., Danet, A., Duchenne, F., Grainger, M.J., Jarvis, S.G., Martin, G., Nilsen, E.B., Porcher, E., Stewart, G.B., Wilson, O.J., Pescott, O.L., 2022. Robitt: A tool for assessing the risk-of-bias in studies of temporal trends in ecology. Methods in Ecology and Evolution 13. doi:10.1111/2041-210X.13857.

Buckland, S.T., Borchers, D.L., Marques, T.A., Fewster, R.M., 2023. Wildlife population assessment: Changing priorities driven by technological advances. Journal of Statistical Theory and Practice 17. doi:10.1007/s42519-023-00319-6.

Carroll, S.R., Garba, I., Plevel, R., Small-Rodriguez, D., Hiratsuka, V.Y., Hudson, M., Garrison, N.A., 2022. Using indigenous standards to implement the care principles: Setting expectations through tribal research codes. Frontiers in Genetics 13. doi:10.3389/fgene.2022.823309.

Carroll, S.R., Herczog, E., Hudson, M., Russell, K., Stall, S., 2021. Operationalizing the care and fair principles for indigenous data futures. doi:10.1038/s41597-021-00892-0.

Chaudhury, A., Colla, S., 2021. Next steps in dismantling discrimination: Lessons from ecology and conservation science. doi:10.1111/conl.12774.

Cheng, L., Liu, H., 2023. Socially responsible AI: Theories and practices. doi:10.1142/13150.

Cobbold, C., Dawes, A., Schwartz, E.J., Tyson, R.C., 2024. Exploring interdisciplinary appointments: a focused perspective on mathematical biology. Notices of the American Mathematical Society 71, 757–760.

Cole, E., Horn, G.V., Lange, C., Shepard, A., Leary, P., Perona, P., Loarie, S., Aodha, O.M., 2023. Spatial implicit neural representations for global-scale species mapping, in: Proceedings of Machine Learning Research.

Collar, N.J., 1998. Extinction by assumption; or, the romeo error on cebu. doi:10.1046/j.1365-3008.1998.d01-51.x.

Conn, P.B., Thorson, J.T., Johnson, D.S., 2017. Confronting preferential sampling when analysing population distributions: diagnosis and model-based triage. Methods in Ecology and Evolution 8. doi:10.1111/2041-210X.12803.

Cvitanovic, C., Shellock, R.J., Mackay, M., van Putten, E.I., Karcher, D.B., Dickey-Collas, M., Ballesteros, M., 2021. Strategies for building and managing 'trust' to enable knowledge exchange at the interface of environmental science and policy. Environmental Science and Policy 123. doi:10.1016/j.envsci.2021.05.020.

Davis, C.L., Bai, Y., Chen, D., Robinson, O., Ruiz-Gutierrez, V., Gomes, C.P., Fink, D., 2023. Deep learning with citizen science data enables estimation of species diversity and composition at continental extents. Ecology 104. doi:10.1002/ecy.4175.

Dębicki, I.T., Mittell, E.A., Kristjánsson, B.K., Leblanc, C.A., Morrissey, M.B., Terzić, K., 2021. Re-identification of individuals from images using spot constellations: A case study in arctic charr (salvelinus alpinus). Royal Society Open Science 8. doi:10.1098/rsos.201768.

Eisenhauer, J.G., 2021. Meta-analysis and mega-analysis: A simple introduction. Teaching Statistics 43. doi:10.1111/test.12242.

Elphick, C.S., 2008. How you count counts: The importance of methods research in applied ecology. doi:10.1111/j.1365-2664.2008.01545.x.

Grace, J.B., Irvine, K.M., 2020. Scientist's guide to developing explanatory statistical models using causal analysis principles. Ecology 101. doi:10.1002/ecy.2962.

Grainger, S., Mao, F., Buytaert, W., 2016. Environmental data visualisation for non-scientific contexts: Literature review and design framework. doi:10.1016/j.envsoft.2016.09.004.

Gryba, R., Vonduyke, A., Huntington, H., Adams, B., Frantz, B., Gatten, J., Harcharek, Q., Sarren, R., Henry, G., Auger-Methé, M., 2024. Indigenous knowledge as a sole data source in habitat selection functions. Proceedings of the National Academy of Sciences 122, e2411946122. doi:https://doi.org/10.1073/pnas.2411946122.

Guthrie, C., 2024. How green is green it? a multidisciplinary bibliometric study and research agenda. Procedia Computer Science 239, 701–709. URL: https://www.sciencedirect.com/science/article/pii/S1877050924014698, doi:https://doi.org/10.1016/j.procs.2024.06.226.

Han, B.A., Varshney, K.R., LaDeau, S., Subramaniam, A., Weathers, K.C., Zwart, J., 2023. A synergistic future for ai and ecology. Proceedings of the National Academy of Sciences of the United States of America 120, 1–7. doi:10.1073/pnas.2220283120.

Hartig, F., Abrego, N., Bush, A., Chase, J.M., Guillera-Arroita, G., Leibold, M.A., Ovaskainen, O., Pellissier, L., Pichler, M., Poggiato, G., Pollock, L., Si-Moussi, S., Thuiller, W., Viana, D.S., Warton, D.I., Zurell, D., Yu, D.W., 2024. Novel community data in ecology-properties and prospects. doi:10.1016/j.tree.2023.09.017.

Henrys, P.A., Mondain-Monval, T.O., Jarvis, S.G., 2024. Adaptive sampling in ecology: Key challenges and future opportunities. doi:10.1111/2041-210X.14393.

Jackman, A., Millner, N., Cunliffe, A.M., Laumonier, Y., Lunstrum, E., Paneque-Gálvez, J., Wich, S.A., 2023. Protecting people and wildlife from the potential harms of drone use in biodiversity conservation: interdisciplinary dialogues. Global Social Challenges Journal 2. doi:10.1332/imlh5791.

Johnston, A., Moran, N., Musgrove, A., Fink, D., Baillie, S.R., 2020. Estimating species distributions from spatially biased citizen science data. Ecological Modelling 422. doi:10.1016/j.ecolmodel.2019.108927.

Kemp, A., 2018. Uk perspective on evidence based policy planning.

Kendall-Bar, J.M., Payne, A.R., Czapanskiy, M.F., Fox, N., Leivesley, J., Alksne, M.N., French, B.J., Malivert, A., O'leary, G., Biswas, A., Nealey, I., Parkinson, R.H., Lowrie, C., Perez, I., Miller, E., Costello, I., Sainburg, T., Rissolo, D., Severance, L., Mukherji, R., Montealegre-Mora, F., Nguyen, K.H., Calvó-Tusell, C., Oestreich, W., Sorenson, M., Gurvich, S., Walker, J., Kellum, A., Berger-Wolf, T., Altintas, I., Sandin, S., Lecomte, N., 2026. Human-centric skills are essential for the responsible and rigorous application of AI in ecology. Technical Report. doi:https://doi.org/10.32942/X2FK8J.

Krause, A., Rennie, N., Tarran, B., 2024. Introductory guide to the art and science of data visualisation. Insights, advice, and examples. Technical Report. Royal Statistical Society.

Krumm, N., Hoffman, N., 2020. Practical estimation of cloud storage costs for clinical genomic data. Practical Laboratory Medicine 21. doi:10.1016/j.plabm.2020.e00168.

McCrea, R., Coates, R., Hobman, E.V., Bentley, S., Lacey, J., 2024. Responsible innovation for disruptive science and technology: The role of public trust and social expectations. Technology in Society 79, 102709. URL: https://www.sciencedirect.com/science/article/pii/S0160791X24002574, doi:https://doi.org/10.1016/j.techsoc.2024.102709.

McGovern, A., Ebert-Uphoff, I., Gagne, D.J., Bostrom, A., 2022. Why we need to focus on developing ethical, responsible, and trustworthy artificial intelligence approaches for environmental science. Environmental Data Science 1. doi:10.1017/eds.2022.5.

Meng, X.L., 2022. Comments on "statistical inference with non-probability survey samples" – miniaturizing data defect correlation: A versatile strategy for handling non-probability samples. Survey Methodology 48.

Murray, K.I., Hockings, K.J., Hodgson, D., 2025. The potential for ai to divide conservation: Response to 'the potential for ai to revolutionize conservation: a horizon scan'. doi:10.1016/j.tree.2025.03.003.

Mytton, D., 2021. Data centre water consumption. doi:10.1038/s41545-021-00101-w.

OECD, 2023. Artificial Intelligence in Science: Challenges, opportunities and the future of research. Technical Report. URL: https://www.oecd.org/en/publications/artificial-intelligence-in-science_a8d820bd-en.html, doi:10.1787/a8d820bd-en.

Panagiotidou, G., Poblome, J., Aerts, J., Moere, A.V., 2022. Designing a data visualisation for interdisciplinary scientists. how to transparently convey data frictions? Computer Supported Cooperative Work: CSCW: An International Journal 31. doi:10.1007/s10606-022-09432-9.

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Köpf, A., Yang, E., DeVito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., Bai, J., Chintala, S., 2019. Pytorch: An imperative style, high-performance deep learning library, in: Advances in Neural Information Processing Systems.

Pichler, M., Hartig, F., 2023. Machine learning and deep learning—a review for ecologists. Methods in Ecology and Evolution 14, 994–1016. doi:10.1111/2041-210X.14061.

Pohl, C., 2008. From science to policy through transdisciplinary research. Environmental Science and Policy 11. doi:10.1016/j.envsci.2007.06.001.

Raineri, P., Molinari, F., 2021. Innovation in Data Visualisation for Public Policy Making. doi:10.1007/978-3-030-63693-7_4.

Ren, Y., Deng, X.N., Joshi, K.D., 2023. Unpacking human and ai complementarity: Insights from recent works. Data Base for Advances in Information Systems 54. doi:10.1145/3614178.3614180.

Reynolds, S.A., Beery, S., Burgess, N., Burgman, M., Butchart, S.H., Cooke, S.J., Coomes, D., Danielsen, F., Minin, E.D., Durán, A.P., Hinsley, A., Jaffer, S., Jones, J.P., Li, B.V., Madhavapeddy, A., Peck, L., Pettorelli, N., Rodríguez, J.P., Sutherland, W.J., 2025a. Conservation changed but not divided. Trends in Ecology and Evolution 40, 424–425. doi:10.1016/j.tree.2025.04.002.

Reynolds, S.A., Beery, S., Burgess, N., Burgman, M., Butchart, S.H.M., Cooke, S.J., Coomes, D., Danielsen, F., Minin, E.D., Durán, A.P., Gassert, F., Hinsley, A., Jaffer, S., Jones, J.P.G., Li, B.V., Aodha, O.M., Madhavapeddy, A., O'Donnell, S.A.L., Oxbury, W.M., Peck, L., Pettorelli, N., Rodríguez, J.P., Shuckburgh, E., Strassburg, B., Yamashita, H., Miao, Z., Sutherland, W.J., 2025b. The potential for ai to revolutionize conservation: a horizon scan. Trends in Ecology & Evolution 40, 191–207. URL: https://doi.org/10.1016/j.tree.2024.11.013, doi:10.1016/j.tree.2024.11.013.

Rice, A., Širović, A., Hildebrand, J.A., Wood, M., Carbaugh-Rutland, A., Baumann-Pickering, S., 2022. Update on frequency decline of northeast pacific blue whale (balaenoptera musculus) calls. PLoS ONE 17. doi:10.1371/journal.pone.0266469.

Rolnick, D., Aspuru-Guzik, A., Beery, S., Dilkina, B., Donti, P.L., Ghassemi, M., Kerner, H., Monteleoni, C., Rolf, E., Tambe, M., White, A., 2025. Position: Application-Driven Innovation in Machine Learning. Technical Report. doi:10.48550/arXiv.2403.17381.

Royal Statistical Society, 2026. Ai is statistics URL: https://rss.org.uk/RSS/media/File-library/Policy/2026/AI-is-Statistics-FINAL.pdf.

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A.C., Fei-Fei, L., 2015. Imagenet large scale visual recognition challenge. International Journal of Computer Vision 115. doi:10.1007/s11263-015-0816-y.

Sandbrook, C., Clark, D., Toivonen, T., Simlai, T., O'Donnell, S., Cobbe, J., Adams, W., 2021. Principles for the socially responsible use of conservation monitoring technology and data. Conservation Science and Practice 3, 1–12. doi:10.1111/csp2.374.

Schweiger, A.H., Irl, S.D., Steinbauer, M.J., Dengler, J., Beierkuhnlein, C., 2016. Optimizing sampling approaches along ecological gradients. Methods in Ecology and Evolution 7. doi:10.1111/2041-210X.12495.

Sequeira, A.M., Bouchet, P.J., Yates, K.L., Mengersen, K., Caley, M.J., 2018. Transferring biodiversity models for conservation: Opportunities and challenges. doi:10.1111/2041-210X.12998.

Silva, D., Menezes, R., Serra-Pereira, B., Azevedo, M., Figueiredo, I., 2023. Adapting the sampling design of research surveys to improve the biomass estimation of secondary species-the case study of raja clavata. ICES Journal of Marine Science 80. doi:10.1093/icesjms/fsad089.

da Silva Barros, M.H.L.F., Neto, L.M., Santos, G.L., da Silva Leal, R.C., da Silva, R.C.L., Lynn, T., Dourado, R.A., Endo, P.T., 2024. Leveraging ai and data visualization for enhanced policy-making: Aligning research initiatives with sustainable development goals. Sustainability (Switzerland) 16. doi:10.3390/su162411050.

Stevens, S., Wu, J., Thompson, M.J., Campolongo, E.G., Song, C.H., Carlyn, D.E., Dong, L., Dahdul, W.M., Stewart, C., Berger-Wolf, T., Chao, W.L., Su, Y., 2024. Bioclip: A vision foundation model for the tree of life. ArXiv URL: http://arxiv.org/abs/2311.18803, doi:https://doi.org/10.48550/arXiv.2311.18803.

Sutherland, W.J., Freckleton, R.P., Godfray, H.C.J., Beissinger, S.R., Benton, T., Cameron, D.D., Carmel, Y., Coomes, D.A., Coulson, T., Emmerson, M.C., Hails, R.S., Hays, G.C., Hodgson, D.J., Hutchings, M.J., Johnson, D., Jones, J.P., Keeling, M.J., Kokko, H., Kunin, W.E., Lambin, X., Lewis, O.T., Malhi, Y., Mieszkowska, N., Milner-Gulland, E.J., Norris, K., Phillimore, A.B., Purves, D.W., Reid, J.M., Reuman, D.C., Thompson, K., Travis, J.M., Turnbull, L.A., Wardle, D.A., Wiegand, T., 2013. Identification of 100 fundamental ecological questions. Journal of Ecology 101, 58–67. doi:10.1111/1365-2745.12025.

Taloni, A., Scorcia, V., Giannaccare, G., 2023. Large language model advanced data analysis abuse to create a fake data set in medical research. JAMA Ophthalmology 141. doi:10.1001/jamaophthalmol.2023.5162.

Telenius, A., 2011. Biodiversity information goes public: Gbif at your service. Nordic Journal of Botany 29, 378–381. doi:10.1111/j.1756-1051.2011.01167.x.

Tiwari, A., Farag, H.E., 2025. Responsible ai framework for autonomous vehicles: Addressing bias and fairness risks. IEEE Access 13, 58800–58822. doi:10.1109/ACCESS.2025.3556781.

Todd, N.R.E., Kavanagh, A.S., Rogan, E., Jessopp, M.J., 2023. What the f-pod? comparing the f-pod and c-pod for monitoring of harbor porpoise (phocoena phocoena). Ecology and Evolution 13. doi:10.1002/ece3.10186.

Topp, L., Mair, D., Smillie, L., Cairney, P., 2018. Knowledge management for policy impact: the case of the european commission's joint research centre. Palgrave Communications 4. doi:10.1057/s41599-018-0143-3.

Tress, G., Tress, B., Fry, G., 2005. Clarifying integrative research concepts in landscape ecology. Landscape Ecology 20, 479–493. doi:10.1007/s10980-004-3290-4.

Tuia, D., Kellenberger, B., Beery, S., Costelloe, B.R., Zuffi, S., Risse, B., Mathis, A., Mathis, M.W., van Langevelde, F., Burghardt, T., Kays, R., Klinck, H., Wikelski, M., Couzin, I.D., van Horn, G., Crofoot, M.C., Stewart, C.V., Berger-Wolf, T., 2022. Perspectives in machine learning for wildlife conservation. doi:10.1038/s41467-022-27980-y.

Tulloch, A.I., Auerbach, N., Avery-Gomm, S., Bayraktarov, E., Butt, N., Dickman, C.R., Ehmke, G., Fisher, D.O., Grantham, H., Holden, M.H., Lavery, T.H., Leseberg, N.P., Nicholls, M., O'Connor, J., Roberson, L., Smyth, A.K., Stone, Z., Tulloch, V., Turak, E., Wardle, G.M., Watson, J.E., 2018. A decision tree for assessing the risks and benefits of publishing biodiversity data. Nature Ecology and Evolution 2. doi:10.1038/s41559-018-0608-1.

United Nations, 2015. Sustainable development goals. URL: https://sdgs.un.org/goals.

Uusitalo, L., Lehikoinen, A., Helle, I., Myrberg, K., 2015. An overview of methods to evaluate uncertainty of deterministic models in decision support. Environmental Modelling and Software 63, 24–31. URL: http://dx.doi.org/10.1016/j.envsoft.2014.09.017, doi:10.1016/j.envsoft.2014.09.017.

van der Vaart, E., Beaumont, M.A., Johnston, A.S.A., Sibly, R.M., 2015. Calibration and evaluation of individual-based models using approximate bayesian computation. Ecological Modelling 312, 182–190. URL: http://dx.doi.org/10.1016/j.ecolmodel.2015.05.020, doi:10.1016/j.ecolmodel.2015.05.020.

Vendrow, E., Pantazis, O., Shepard, A., Brostow, G., Jones, K.E., Aodha, O.M., Beery, S., Horn, G.V., 2024. Inquire: A natural world text-to-image retrieval benchmark. arXiv URL: http://arxiv.org/abs/2411.02537, doi:https://doi.org/10.48550/arXiv.2411.02537.

Vienni-Baptista, B., I, F., Lyall, C., 2023. Foundations of Interdisciplinary and Transdisciplinary Research. 1st ed., Bristol University Press. doi:10.47674/9781447368892.

Wang, C., 2024. Calibration in deep learning: A survey of the state-of-the-art. arXiv 2308.01222. doi:https://doi.org/10.48550/arXiv.2308.01222arXiv-issuedDOIviaDataCite.

Wheeler, H.C., Root-Bernstein, M., 2020. Informing decision-making with indigenous and local knowledge and science. Journal of Applied Ecology 57, 1634–1643. doi:10.2307/48586411.

Whitmore, L., McCauley, M., Farrell, J.A., Stammnitz, M.R., Koda, S.A., Mashkour, N., Summers, V., Osborne, T., Whilde, J., Duffy, D.J., 2023. Inadvertent human genomic bycatch and intentional capture raise beneficial applications and ethical concerns with environmental dna. Nature Ecology and Evolution 7. doi:10.1038/s41559-023-02056-2.

Wilkinson, M.D., Dumontier, M., Aalbersberg, I.J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J.W., da Silva Santos, L.B., Bourne, P.E., Bouwman, J., Brookes, A.J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C.T., Finkers, R., Gonzalez-Beltran, A., Gray, A.J., Groth, P., Goble, C., Grethe, J.S., Heringa, J., t Hoen, P.A., Hooft, R., Kuhn, T., Kok, R., Kok, J., Lusher, S.J., Martone, M.E., Mons, A., Packer, A.L., Persson, B., Rocca-Serra, P., Roos, M., van Schaik, R., Sansone, S.A., Schultes, E., Sengstag, T., Slater, T., Strawn, G., Swertz, M.A., Thompson, M., Lei, J.V.D., Mulligen, E.V., Velterop, J., Waagmeester, A., Wittenburg, P., Wolstencroft, K., Zhao, J., Mons, B., 2016. Comment: The fair guiding principles for scientific data management and stewardship. Scientific Data 3, 1–9. doi:10.1038/sdata.2016.18.

Williams, D.R., Balmford, A., Wilcove, D.S., 2020. The past and future role of conservation science in saving biodiversity. Conservation Letters 13, 1–7. doi:10.1111/conl.12720.

Young, J.C., Waylen, K.A., Sarkki, S., Albon, S., Bainbridge, I., Balian, E., Davidson, J., Edwards, D., Fairley, R., Margerison, C., McCracken, D., Owen, R., Quine, C.P., Stewart-Roper, C., Thompson, D., Tinch, R., van den Hove, S., Watt, A., 2014. Improving the science-policy dialogue to meet the challenges of biodiversity conservation: Having conversations rather than talking at one-another. Biodiversity and Conservation 23. doi:10.1007/s10531-013-0607-0.

A. Glossary

Artificial Intelligence (AI) Computer-based methods that perform tasks (e.g. analysing images or audio for events of interest, language understanding, or general reasoning) that previously required human intelligence.

Explainable AI (XAI) Refers to a set of AI methods and techniques that enable human users to comprehend and interpret the output of AI systems.

Statistical inference The process of inferring the population properties of some variable(s) of interest using information in the sample. Inference is sometimes divided into causal (concerned with the effect of explanatory variables on a response), descriptive (the estimation of some parameter describing the variable of interest in the population) and predictive (i.e. estimating the values of the variable of interest where/when data are not available).

Interdisciplinarity Research/work practice that attempts to integrate knowledge and skills from several disciplines.

Machine Learning (ML) refers to a set of AI methods that learn from data to predict outcomes.

Model A mathematical description or algorithm that is designed to represent a system.

Sample The subset of observation units in the population for which data are available.

Sample representativeness In a representative sample, the distribution of the variable of interest mirrors its population distribution in expectation (i.e. on average over an infinite number of possible samples collected in the same way). It is impossible to verify this theoretical assumption in practice, so representativeness is sometimes defined in terms of key covariates, which are measured for all population units, rather than the variable of interest (i.e. the response).

Stakeholders The set of individuals, organisations, and other groups that have a vested interest in the success of a project. This can encompass private individuals, local communities, businesses, government, among other parties.

Statistical population The set of all observation units of interest. Observation units might be, say, sites in a landscape or species in a taxon group.

Transdisciplinary Research/work practice that builds a conceptual framework transcending the narrow scope of disciplinary worldviews and involving in the process of knowledge production those stakeholders affected by or interested in the issue of concern (Bracken et al., 2015; Vienni-Baptista et al., 2023).

Figure 3: Glossary of Terms