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POLICY DIRECTIONS

Artificial intelligence and decision support in applied ecology

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Abstract

1. Artificial intelligence (AI) is bringing ecological inference closer to decision-making, producing detections, alerts, trends, and prioritisation outputs. Yet, consensus on how to interpret or act on these remains limited.
2. We synthesise AI adoption in applied ecology and identify governance pressures as models become multimodal, transferable, edge-deployable, and increasingly shaped by large language models.
3. We highlight cross-cutting risks where uptake outpaces oversight, including limits in explainability, validation, data sovereignty, environmental costs, cognitive off-loading, and evidence integrity.
4. Using the British Bat Survey as a representative case study, we show how AI can be operationalised through governance principles spanning benchmarking, transparency, auditability, data governance, equity, and sustainability.
5. *Policy implications*: We propose a roadmap for responsible AI in applied ecology linking evaluation to decision context, clarifying responsibility, and ensuring AI strengthens rather than displaces accountable decision-making.

KEYWORDS
applied ecology, artificial intelligence in ecology, biodiversity conservation, conservation decision-making, ecological monitoring, machine learning, policy and governance, responsible AI

1 | INTRODUCTION

Artificial intelligence (AI) is now central to scientific practice, accelerating data processing, pattern detection, and inference across disciplines (Jordan & Mitchell, 2015; Wang et al., 2023). Advances stem from the convergence of machine learning with expanding data streams, enabling applications from climate modelling to medical diagnostics (Lam et al., 2023; Soliman, 2024). Since 2023,

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large language models (LLMs) and other foundation models trained on massive datasets have reshaped how scientific evidence is generated, synthesised, and interrogated (Maslej et al., 2024; Perry et al., 2022).

AI's role in ecology is longstanding: early tools such as Bayesian networks formalised uncertainty and modelled complex, nonlinear systems (Clark & Mangel, 1984; Pascual & Hilborn, 1995). Later, machine learning and deep learning advanced predictive modelling of species distributions, ecological relationships, and environmental change (Brun et al., 2024; Kwok, 2019; Tuia et al., 2022). Recently, AI has gained traction in applied ecology, supporting real-time monitoring, field data acquisition, and semi-automated decision-making (Ahumada et al., 2020; Bierlich et al., 2024; Kellenberger et al., 2021; Vuilliomenet et al., 2026). This marks a second wave of AI in ecology, and the first in applied contexts, where outputs move from retrospective analysis to operational use (Figure 1).

As in other scientific fields, AI's integration into applied ecology has been rapid and largely ungated, driven by technological advances rather than co-produced, question-led research (Kendall-Bar et al., 2025). Policymakers, practitioners, and researchers now face questions not only about what constitutes ‘ethical’ AI (Jobin et al., 2019), but also about how model design, validation, and deployment shape real-world decisions. Broader access to AI tools and user-friendly interfaces has expanded participation beyond specialists (Spillias et al., 2025), creating opportunities for innovation alongside new governance, equity, and accountability challenges as AI approaches operational decision-making.

Applied ecology therefore requires shared principles to ensure AI-enabled inference remains credible, transparent, and decision-appropriate. This paper outlines the main domains of AI use in applied ecology, from data collection and monitoring to analysis and decision support, before examining associated governance challenges and presenting a roadmap for responsible integration into ecological workflows.

2 | ADOPTION OF AI IN DATA-TO-DECISION PIPELINES IN APPLIED ECOLOGY

Applied ecology is converging on a common AI toolchain: transfer and foundation model approaches, expanding benchmarks and shared datasets, platformed workflows that lower coding barriers, and ‘edge’ deployments that support near-real-time inference. Within this common toolchain, a key point of difference among the applied ecology community is the decision products these systems generate (e.g. detections, trends, alerts, prioritisation outputs) and the governance pressures that follow when outputs enter monitoring, enforcement-adjacent settings, or policy reporting.

2.1 | Camera trap and proximal imaging

Computer vision automates species detection, counting, and identification from imagery, supporting applications from faunal monitoring to enforcement-adjacent surveillance (Dertien et al., 2023; Norouzzadeh et al., 2018). Recent progress has been driven by deep learning architectures and transfer learning, enabling models trained on large datasets to generalise across taxa and environments with reduced labelling effort (Gadot et al., 2024). As deployments shift towards near-real-time and platformed pipelines (van Lunteren, 2023; Pishdast et al., 2025), outputs extend beyond species lists to actionable products such as intrusion cues (Dertien et al., 2023), morphometrics (Aamir et al., 2025), and distance estimates (Haucke et al., 2022). These developments intensify governance challenges around unequal consequences of different types of errors (e.g. false-positives versus false-negatives), incidental capture of people, and

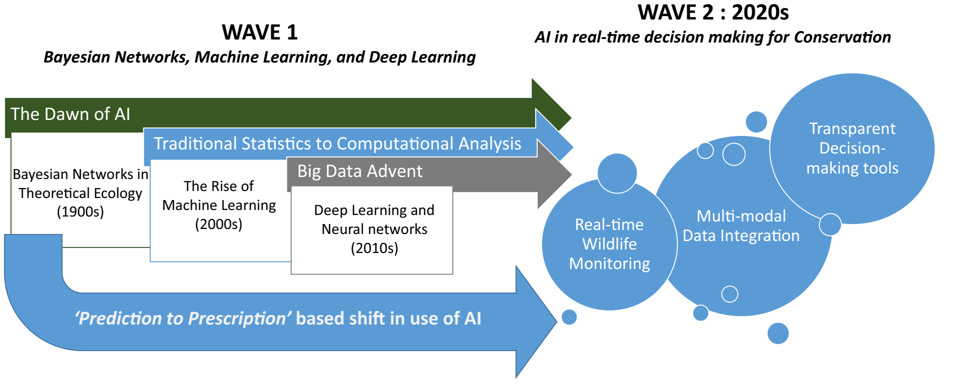

FIGURE 1 Evolution of AI in Ecology and its integration in Applied Ecology and Decision-Making: Wave 1 highlights the evolution of AI from Bayesian networks to deep learning for predictive modelling. Wave 2 represents the shift to real-time, multimodal, and transparent decision-making tools in applied ecology driving conservation efforts in the 2020s.

data sovereignty and benefit-sharing where imagery is processed via centralised platforms.

2.2 | Bioacoustics

AI-enabled bioacoustics extends monitoring to taxa and environmental signals that are difficult to sample visually, from biodiversity surveys to security-relevant detection such as gunshots and vehicles (Pardo et al., 2022; Ross et al., 2023). Standardised pipelines and benchmarks (e.g. BirdNET and emerging cross-taxa benchmarks; van Merriënboer et al., 2026) are improving comparability and reuse. At the methodological frontier, models that can integrate multiple data types and learn generalisable representations (multimodal and embedding-based models) increasingly support detection from little to no labelled training data (few-shot and zero-shot detection), reducing reliance on large, labelled datasets (Allen-Ankins et al., 2025; Colonna et al., 2025; Dumoulin et al., 2025; Miao et al., 2025; Schwinger et al., 2025). However, governance risks remain shaped by uneven taxonomic and geographic coverage, hidden platform defaults, privacy and unequal access to compute and validation capacity, especially where outputs are used operationally rather than retrospectively.

2.3 | Biologgers and behaviour

Biologgers generate fine-scale behavioural data, and AI is increasingly used to infer decision-relevant states such as foraging behaviour, movement corridors, and responses to disturbance, often informing adaptive management in near real time (Browning et al., 2018; Chakravarty et al., 2020; Korpela et al., 2020; Williams et al., 2020). While supervised learning remains common, workflows are shifting toward on-device models and selective data transfer to save battery and bandwidth, alongside methods that work with limited labelled data (Chen et al., 2020; Fayat et al., 2025; Mao et al., 2025; Otsuka et al., 2025; Tatler et al., 2018; Yu et al., 2024). As a result, governance concerns concentrate on auditability (what data are retained versus discarded), validation under autocorrelation and sparse labels, and dual-use and privacy risks, where human intrusion detection becomes possible.

2.4 | Online data

Information available on the web is often used to support conservation outreach and citizen science but also intensify risks in enforcement-adjacent contexts, particularly in monitoring online wildlife trade (Katzner et al., 2022). AI systems increasingly integrate text, images, and metadata to improve context recognition and detection of illicit activity. These systems remain sensitive to changes in platform policies and data access, uneven performance across languages, and adversarial behaviour such as users altering wording or images to evade detection (Momeny et al., 2025; Sharma et al., 2025; Xu et al., 2019), raising governance challenges around legal ambiguity, temporal fragility of listings, escalation risks from false-positives, and accountability as monitoring becomes institutionalised.

2.5 | Remote sensing

AI-enabled Earth observation has expanded access to near-real-time mapping of land-use change, and increasingly supports applied indicators such as biomass, habitat condition, and structural complexity (Fuentes et al., 2024, 2025; McGregor et al., 2024; Santos et al., 2012). Recent advances include the emergence of large pretrained foundation models (e.g. TESSERA; Feng et al., 2026) and transferability benchmarks that promise reuse across sensors, regions, and time (Marsocci et al., 2024; Stamoulis & Marculescu, 2025). However, as workflows become more automated and conversational, the governance bottleneck shifts from detection capability to ecological interpretability, linking predictions to plausible spectral, spatial, and temporal drivers, alongside the sustainability costs of large-scale modelling and the need for credible local validation.

2.6 | Large language models and decision support

LLMs may accelerate conservation by synthesising evidence and supporting information retrieval when carefully designed (Berger-Tal et al., 2024; Castro et al., 2024; Chang et al., 2025; Jaffer et al., 2025), with early trials suggesting comparable performance to experts in information retrieval tasks under controlled evaluation settings (Iyer et al., 2025). However, off-the-shelf use remains unreliable and raises reproducibility and uneven performance concerns across languages, regions, and gender, among broader data and model biases (Ho et al., 2025; Iyer et al., 2025; Ollion et al., 2024). Research is moving toward bespoke quantitative LLMs for ecological extraction and large-scale stress-testing, alongside agentic (systems that can plan and act autonomously) and geospatial systems that automate analysis pipelines (Dorm et al., 2025; Gallois et al., 2025; Walsh et al., 2019; Zhang, Gao, et al., 2025; Zhang, Li, et al., 2025). Closely related decision-support applications include AI-enabled triage for extinction-risk assessment using traits, occurrences, and environmental data, motivated by persistent assessment gaps (Bachman et al., 2024; IUCN, 2025; Zizka et al., 2022). Key challenges include contamination of the evidence base via AI-generated content (Reynolds, Christie, et al., 2025), benchmark leakage (Anwar et al., 2024), and the risk of persuasive but misleading syntheses that obscure uncertainty and diffuse accountability.

3 | TOWARD RESPONSIBLE USE OF AI IN APPLIED ECOLOGY

Building on the cross-cutting challenges identified in the applications above, we present an operational roadmap for responsible use, alongside a system-level view of shared responsibility across actors, illustrated through a case study (Section 3.1).

3.1 | Case study: The British Bat Survey and responsible AI

The British Bat Survey is a long-term, citizen science-led passive acoustic monitoring survey designed to generate population indices for UK bat species and inform conservation policy (https://surveys.bats.org.uk/survey/87) (Figure 2). Its approach illustrates how the roadmap for Responsible AI in Applied Ecology (Figure 3) can be put into practice.

The survey exemplifies **(1) energy-efficient, purpose-driven data use** by defining clear ecological questions from the outset, applying power analysis to limit oversampling, and minimising costs through consumable recycling, data cleaning, and selective audio storage. It ensures **(2) accuracy, benchmarking, and human validation** by employing BatDetect2, an algorithm tested and published (Aodha et al., 2018, 2022), while subjecting outputs to expert verification, particularly for rare or difficult-to-identify species, to improve reliability and model refinement. **(3) Open reporting and oversight** are built in through annual peer-reviewed reports, and data sharing via national and international biodiversity data platforms.

To **(4) navigate legal and ethical risks**, the survey complies with the UK General Data Protection Regulations and Data Protection Act 2018, secures volunteer and landowner permissions, uses sound frequency filters to reduce capture of human speech, and assesses risks to wildlife and people. **(5) Safeguarding rights and co-benefits** is achieved by combining consent, clear governance over what is shared, and proportionate data stewardship, while FAIR data principles (Findable, Accessible, Interoperable, Reusable) support responsible reuse of resulting species records for science and conservation. Governance is distributed across volunteers, the Bat Conservation Trust (BCT), and downstream biodiversity infrastructures, with volunteers collecting data and metadata, and BCT processing, verifying, and disseminating outputs. The survey contributes to **(6) evidence-informed AI-assisted decisions** by informing UK bat species population trend monitoring, biodiversity indicators, and conservation status

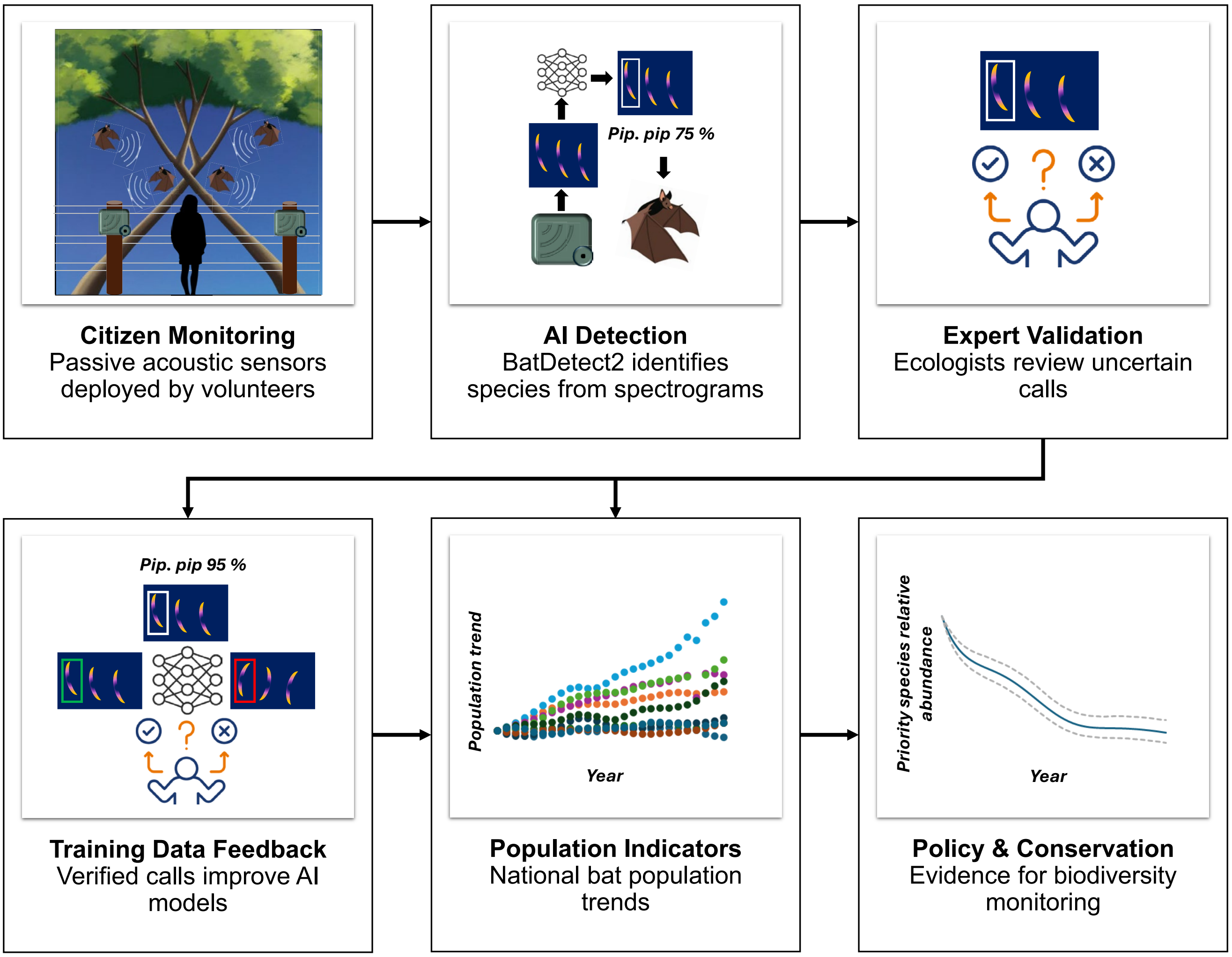

FIGURE 2 The British Bat Survey's AI-enabled monitoring system, from citizen-led acoustic data collection and automated species detection to expert validation, model improvement, and the generation of population indicators that inform conservation policy.

BRITISH ECOLOGICAL SOCIETY Journal of Applied Ecology

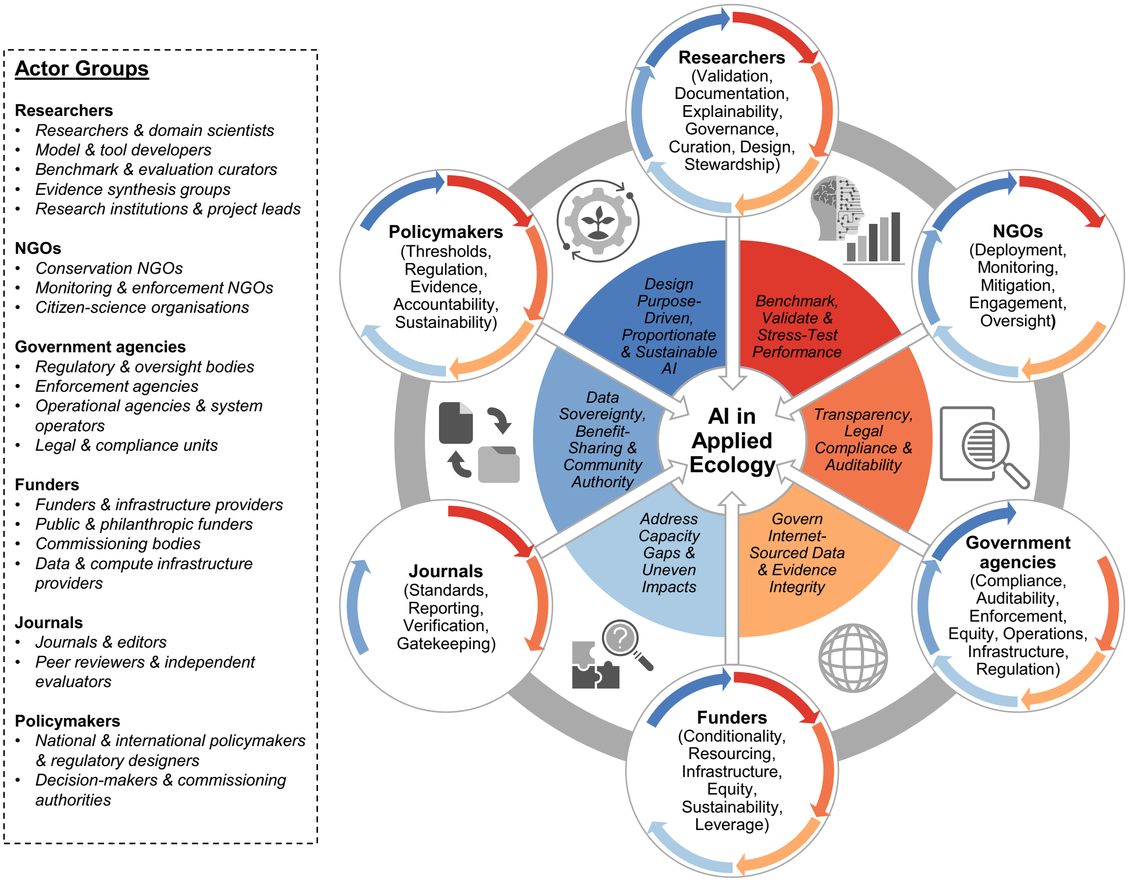

FIGURE 3 System-level overview depicting shared responsibility across actors for governing AI in applied ecology, aligned with the principles in Table 1. In this light, the roadmap presented here is not a call for wider AI adoption, but a guide for shaping its evolution so that technological advances strengthen evidence quality, equity, and ecological integrity rather than undermine them.

assessments used in national and international reporting. Finally, AI is designed to **(7) complement, not replace, field expertise**, working alongside traditional monitoring methods and expert interpretation to provide a robust and comprehensive evidence base.

3.2 | Accuracy, benchmarking, and validation

AI systems, like other modelling frameworks, carry biases and uncertainties, yet many ecological uses, especially acoustic and image-based monitoring, lack standardised error detection, reporting, and management (Cowans et al., 2024). This gap is critical when outputs guide urgent or high-stakes decisions. To build trust, developers should test models on diverse benchmarks (Rauch et al., 2025), re-evaluate them in new contexts, and report metrics beyond accuracy. In applied ecology, measures such as precision and recall better capture trade-offs between false-positives and false-negatives (Sofaer et al., 2019). For management or policy use, performance thresholds should be set in advance and, ideally, co-designed with end-users to match decision-specific risk tolerances.

A key challenge is ensuring independent and valid evaluations. While data leakage is well understood in traditional machine learning (Kapoor & Narayanan, 2023), large foundation models and LLMs complicate assessment due to opaque training pipelines and limited data provenance (Anwar et al., 2024; Bommasani et al., 2022). Without disclosure, benchmark scores may reflect memorisation rather than generalisation. Stronger practices include testing on post-training data and favouring models with documented datasets (e.g. AllenAI Olmo3; Ettinger et al., 2025), with journals, funders, and commissioners enforcing such standards. Shared evaluation frameworks are also needed to link performance to decision-relevant evidence (Hutchinson et al., 2022). Validation should be embedded in hybrid human–AI workflows, where experts retain interpretive responsibility (Kitzes et al., 2026; Mosqueira-Rey et al., 2023) and should assess not only accuracy but also gains in efficiency, sensitivity, timeliness, and clarity of uncertainty.

3.3 | Transparency, legal compliance, and auditability

Transparent reporting of model training, performance metrics, validation, and human oversight enables scrutiny by policymakers, users, and the public, while clarifying how the rights of people and

TABLE 1 To translate the roadmap principles outlined in Section 3 into operational guidance, this table summarises for each principle the key checks, suggested actions, and examples from the British Bat Survey.

Principle	Key checks	Actions	Example (British bat survey)
Benchmark, Validate & Stress-Test Performance	1. Independent benchmarking 2. Transferability across contexts 3. Metrics beyond accuracy 4. Independence from training data 5. Human-in-the-loop validation	1. Benchmark on diverse public datasets 2. Re-evaluate before transfer 3. Report precision/recall & error trade-offs 4. Test on held out or newly collected data 5. Embed expert review	BatDetect2 is peer-reviewed and benchmarked; thresholds prioritise sensitivity with expert filtering; annual surveys provide independent validation data
Transparency, Legal Compliance, and Auditability	1. Documentation of data, performance, and oversight 2. Legal/ethical constraints 3. Evidentiary standards 4. Auditability 5. Interpretability	1. Publish accessible model documentation 2. Conduct jurisdiction-specific legal scoping 3. Separate detection from decision thresholds 4. Document model configuration and versioning 5. Use interpretable reporting	Annual reports document methods and updates; GDPR-compliant consent; detections inform indicators but not enforcement; workflows are transparent and reproducible
Govern Internet-Sourced Data and Evidence Integrity	1. Curated vs. open-web evidence 2. Temporal fragility and adversarial risk	1. Use curated, versioned evidence repositories 2. Apply timestamping, archiving, and human review where relevant	Controlled survey data and expert-validated records; no reliance on mutable online sources
Address Capacity Gaps and Uneven Impacts	1. Community standards 2. Data security 3. Uneven performance across taxa or regions	1. Develop shared deployment standards 2. Secure field data 3. Report stratified performance and uncertainty	Standardised citizen science protocols; species-specific uncertainty acknowledged
Data Sovereignty, Benefit-Sharing & Community Authority	1. Contributor recognition 2. Consent and authority	1. Apply FAIR alongside CARE principles 2. Use provenance metadata and appropriate licensing	Species records openly shared under FAIR principles, supporting conservation and research
Design Purpose-Driven, Proportionate & Sustainable AI	1. Question-led design 2. Proportional complexity 3. Resource and energy costs	1. Define objectives upstream 2. Justify sampling effort 3. Prefer efficient models and workflows	Survey targets population trends; selective audio retention and equipment reuse minimise costs

animals are upheld. Such transparency is vital for trust, especially where AI intersects with conservation tensions or risks unintended harm (Reynolds, Beery, et al., 2025). Legal and ethical considerations should be integrated from the outset. In enforcement-adjacent contexts, compliance is complicated by platform rules, jurisdictional differences, and contested definitions of illegality (Di Minin et al., 2021; Morcatty et al., 2021; Xu et al., 2019). This calls for documented evidentiary standards and decision thresholds before operational use. Regulatory frameworks such as the EU Artificial Intelligence Act (European Union, 2024) already mandate safety, rights protection, and transparency.

For high-stakes ecological decisions, best practice should move towards audit-ready or 'white-box' governance (Casper et al., 2024; Rudin, 2019). This requires standardised documentation of model architecture, training configuration, versioning, and data composition. Interpretability extends transparency by allowing experts to assess the basis of predictions, not just performance metrics (Hassija et al., 2024). For large pretrained foundation models, scale and multimodality can decouple outputs from meaningful spectral, spatial, or temporal drivers (Schiller et al., 2025). Explainability should therefore link learned representations to domain knowledge and physically relevant processes (e.g. relating predictions of vegetation condition to known spectral indices), with uncertainty explicitly characterised (Gevaert, 2022; Hall et al., 2022; Reichstein et al., 2019). In edge AI systems, auditability depends on minimum logging, data retention rules, and documentation of discarded information. Even without full public disclosure, meaningful audit access is essential for accountability.

3.4 | Internet-sourced data and emerging risks

Debate continues over whether web-sourced information can be certified free of AI-generated contamination (Sadasivan et al., 2025). Detection tools remain unreliable at scale; OpenAI withdrew its own in 2023 due to low accuracy (Kirchner et al., 2023). As ecological research increasingly uses online datasets and automation, AI risks amplifying existing data flaws. Weak underlying information

Journal of Applied Ecology

can spread more widely and rapidly through AI-assisted synthesis. Addressing this requires frameworks to manage contamination of scientific evidence infrastructure. Expanding 'living' evidence databases, curated, continually updated resources that track retractions, flag suspect content, and limit reliance on uncontrolled web data, offers one practical step (Reynolds, Christie, et al., 2025; Sutherland et al., 2019). While not eliminating contamination, such governed resources reduce its prevalence and help prevent the normalisation of low-quality, AI-mediated synthesis in place of rigorous evidence assessment.

When web-sourced data are used for ecological monitoring or enforcement, safeguards such as automated filtering and human review should be seen as risk mitigation, not complete solutions. Models trained on web-scraped data require ongoing reassessment and transparent reporting of assumptions, limitations, and uncertainty (Géron, 2019). Evidentiary standards, time-stamped archives of flagged content, and routine adversarial testing can help keep AI-assisted findings traceable, contestable, and defensible, even when source material changes (Athalye et al., 2018).

3.5 | Data sovereignty, benefit-sharing, and community authority

In applied ecology, AI governance depends not only on transparency and legal compliance but also on data sovereignty: who controls data, authorises its use, and benefits from AI-enabled decisions. A key ethical issue is the asymmetry in data ownership and benefit-sharing: Indigenous peoples and local communities, especially in the Global South, often supply biodiversity data for AI training yet retain little control or benefit (Carroll et al., 2020; Reynolds, Beery, et al., 2025). Addressing this requires operational governance mechanisms, such as applying CARE principles alongside FAIR practices, embedding community authority and consent throughout the data lifecycle, and using provenance metadata, licensing, or Traditional Knowledge Labels to ensure ethical reuse (Carroll et al., 2021). These principles also apply to individual rights and privacy, demanding clear protocols for collection, storage, access, and deletion, particularly where personal data may be captured (Simlai & Sandbrook, 2021).

3.6 | Equitable access and best-practice guidance

Biases in training data and uneven access to AI tools risk concentrating benefits in well-studied taxa and regions with strong research infrastructure and capacity, while leaving others under-represented (Khan et al., 2024; Troudet et al., 2017). Decision-support tools do not impact communities equally and may perpetuate existing inequities or conservation tensions (Reynolds, Beery, et al., 2025; Sandbrook, 2025). Community-driven standards for the use and validation of automated tools are therefore critical, alongside effective data security practices to mitigate risks such as misplaced or stolen field devices (Bubnicki et al., 2024). Equity checks, such as disaggregated performance audits across ecological and social contexts, should also extend to decision-support systems, including stratified performance reporting across relevant groups (e.g. taxa, habitats, regions, or affected communities), and explicit warnings where models are applied outside their validated scope (Caton & Haas, 2024).

3.7 | Purpose-driven and sustainable data use

The value of AI in ecological policy depends on the quality and sustainability of its training data. While AI can ease data processing bottlenecks (Chalmers et al., 2023), its financial and environmental costs are significant: energy-intensive data centres have large carbon and water footprints (Gupta et al., 2020), and excessive data collection creates unsustainable storage and processing demands. This risks a contradiction between large-scale AI adoption and sustainable research. Green-AI governance should include transparency on energy and water use, and responsible adoption should begin upstream, with well-defined ecological questions, power analyses to justify sampling, selective data retention, and proportionate, energy-efficient models and energy-efficient workflows where comparable performance can be achieved (Patterson et al., 2022). Where large-scale computation is necessary, training and deployment choices can meaningfully affect carbon-water trade-offs (Li et al., 2025).

4 | FUTURE-PROOFING AI-ENABLED DECISION SUPPORT IN APPLIED ECOLOGY

As AI systems become more autonomous, agentic, and accessible, applied ecology risks having decision-support tools advance faster than the institutional norms, oversight, and accountability needed to govern them. AI is already moving ecological inference closer to high-stakes decisions, increasing the risk of cognitive offload, where fast, off-the-shelf models replace established evidence synthesis and expert judgement due to convenience and cultural normalisation rather than superiority. Evidence links AI adoption to reduced diversity in scientific exploration, with greater focus on data-rich, well-trodden problems at the expense of exploratory or low-data areas (Hao et al., 2026). The potential for AI to support applied ecology is, in principle, positive, but the core challenge is determining whether it is designed and deployed in ways that preserve transparency, contestability, and responsibility across the system of actors involved (Figure 3). Future-proofing AI in applied ecology depends less on technical capability than on embedding AI within governance frameworks that explicitly link model performance to decision contexts, safeguard the integrity of the evidence base, respect data sovereignty, and retain human judgement at the centre of accountability. Translating these principles into practice requires clear operational guidance, including the definition of checks, actions, and responsibilities across contexts (Table 1).

AUTHOR CONTRIBUTIONS

Elmontaserbellah Ammar, Aashna Sharma, and Rowena Gordon conceived the ideas for the policy directions paper; Elmontaserbellah Ammar and Aashna Sharma led the writing of the manuscript and created the visualisations; Elmontaserbellah Ammar, Aashna Sharma, Tom August, Jake E. Bicknell, Katherine Boughey, Carolyn E. Dunford, Don A. Driscoll, Sicily Fiennes, Javier Lopatin, Melanie Hartley, Joseph Hillier, Philip A. Martin, Rory S. O'Connor, Felipe Parodi, Benno I. Simmons, Matthew J. Struebig, Ruth M. Thompson, Ardiantiono, Tally Yoh, and Chris Sutherland wrote original sections of the manuscript and reviewed the final manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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No data were used in this article.

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