What Artificial Intelligence Cannot Replace in Ecology?

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Abstract

Artificial intelligence is becoming increasingly integrated into ecological research, from literature synthesis and hypothesis generation to statistical modelling and data analysis. As AI systems become more autonomous, discussions about ecology's future are often framed as a competition between human and machine intelligence. Yet this perspective overlooks a more fundamental question: what aspects of ecological reasoning can be delegated to AI, and which aspects remain the responsibility of the researcher? To explore this issue, 11,749 ecology publications indexed in Scopus were analyzed using text mining and Structural Topic Modelling (STM). Publication trends revealed a rapid expansion of AI-related research, particularly following the COVID-19 pandemic and the public release of ChatGPT in late 2022. Topic dynamics indicated growing attention to AI applications, while discussions centered on statistical methodology, inference, and quantitative reasoning became comparatively less prominent within literature. These patterns raise important questions about how technological innovation may reshape scientific reasoning within ecology. Drawing on philosophy of science and discussions of the epistemic limits of AI, this article argues that the central challenge posed by AI is not the replacement of researchers, but the preservation of scientific judgment in increasingly automated workflows. A framework based on three sequential principles for the responsible use of AI in ecology is therefore proposed: (i) Critical Evaluation Capacity, (ii) Intellectual Authorship of Questions and Hypotheses, and (iii) Quantitative Ecology Literacy and Methodological Transparency. Together, these principles clarify which responsibilities can be delegated to intelligent systems and which remain essential to the ecologist's role in producing reliable ecological knowledge.

Introduction

Scientific production has increased rapidly in recent years, partly driven by the use of generative AI (GenAI): tools like ChatGPT reduce writing time and boost research output. Ecology has not been exempted from this shift — if anything, the nature of ecological data has made the adoption of Artificial Intelligence (AI) tools feel less like a choice and more like a necessity, as machine learning, deep learning, and large language models (LLMs) become embedded in how the empirical ecology now operates (Razack et al., 2021; Pichler & Hartig, 2023; Cipriano, 2025; Xie et al., 2025).

These tools have earned that role. AI systems excel at precisely the tasks that have come to define much of contemporary ecological work: processing volumes of remote-sensing and continuous sensor data beyond human capacity — as in ecosystems digital twins such as the European initiative to monitor ocean climate change — detecting patterns across large and high-dimensional datasets, automating image and acoustic classification, and testing hypotheses at a scale and speed no individual researcher could match (Cui et al., 2023; Li et al., 2023; Maniyar et al., 2025; Cowans et al., 2026).

However, this rapid adoption raises concerns about the future role of human researchers, often framing ecology's future as a competition between humans and machines. This framing obscures the true disruption: technology has outpaced epistemological reflection. As autonomous systems integrate into ecological research, critical modelling decisions risk becoming opaque, embedded in outputs the researcher did not fully evaluate (Whytock et al., 2021).

This concern runs deeper than questions of which subfields or tasks remain "safe" from AI and which do not. Regardless of how far autonomous systems advance, there remains a core of the profession — the capacity for ecological thinking itself — that cannot be outsourced, because it is not a task to be automated but the very judgment that gives ecological research its meaning (Spillias et al., 2026).

Leaving this gap unaddressed risks reducing the ecologist to a passive validator of AI outputs. Addressing it requires turning ecology's own analytical lens onto its practice — using metascience to examine how AI is actually being used, and philosophy of science to evaluate what that use means for ecological reasoning itself.

This article argues that anxiety over obsolescence distracts from the more urgent need to reconnect ecological practice with its epistemological foundations. To make this argument, the article's approach turns AI onto itself: the first step uses text mining and machine learning — specifically Structural Topic Modelling (STM) — to map how AI has been discussed and adopted within ecology. The second step then steps back from these tools to examine, through philosophy of science, what this integration means for ecological reasoning. In addition, the third step proposes practical principles for working with autonomous systems, aimed at preserving the core of ecological reasoning that requires human judgment.

Methods

Search Method

Using the PICO/PECO framework proposed by Foo et al. (2021), a search string (Table 1) was developed and applied to the Scopus database to retrieve publications related to artificial intelligence and data analysis in ecological research. Following Cipriano et al. (2025), the search covered the period from the earliest records of machine learning applications in ecology in the early 1970s to May 25, 2026.

Text preprocessing was conducted in R (v.4.5.3) using a natural language processing pipeline that included lemmatization, stopword removal, identification of frequent bigrams, and standardization of compound terms. To reduce noise and sparsity, very short documents and infrequent terms were excluded from the document-feature matrix following established recommendations for topic modelling (Syed & Spruit, 2017; Maier et al., 2020).

Data processing and transformation were performed using the tidyverse ecosystem (Wickham et al., 2019), while additional details regarding text preprocessing, parameter selection, and corpus preparation are provided in the Supplementary Material.

Table 1: Search string used to retrieve Scopus publications on the use of artificial intelligence in ecological research from the 1970s to 2026-05-25.

Search String
("ecology" OR "ecological research") AND ("artificial intelligence" OR "machine learning" OR "statistical methods" OR "quantitative methods" OR "data analysis" OR “large language model" OR "generative AI" OR "ChatGPT" OR "GPT" OR "LLM" OR "chatbot" OR "copilot")

Topic Model

To identify the main themes discussed in the literature, Structural Topic Modelling (STM) – a Machine Learning approach - was applied using the stm package in R (Roberts et al., 2014, 2019), following established text-as-data method(Grimmer et al., 2022). Topics were interpreted using FREX (Frequency and Exclusivity) terms, which identify words that are both common within a topic and distinctive to it. Topic prevalence was then modeled as a function of publication year to evaluate temporal trends.

Although records were available from the early 1970s onward, the topic model corpus was restricted to publications from 2000 onwards (n = 11,749). Earlier years were excluded because the low publication frequency would compromise the estimation of temporal trends.

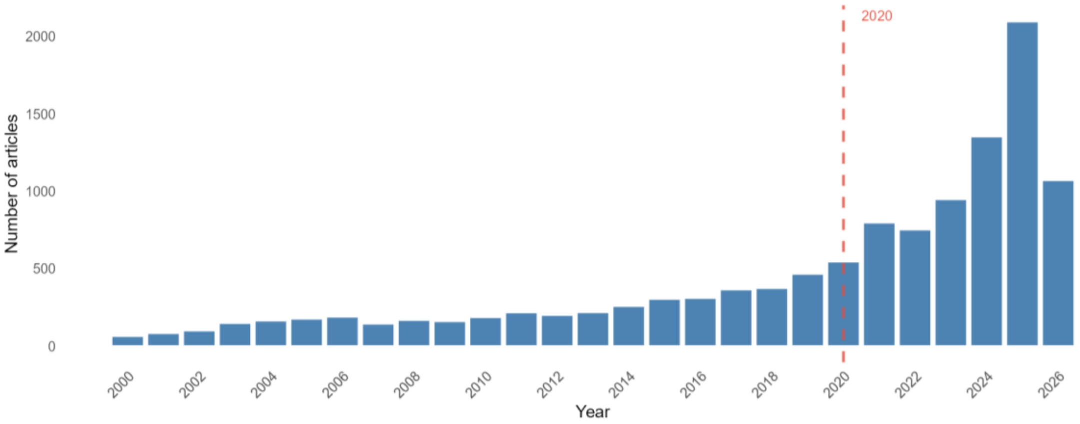
Models ranging from K = 8 to K = 14 topics were evaluated, and the final solution (K = 11) was selected based on model performance, semantic interpretability, and stability across multiple initializations (Weston et al., 2023). Additional details regarding parameter selection, model diagnostics, stability assessment, and topic interpretation are provided in the Supplementary Material.

Topic labels were manually assigned based on the semantic coherence of FREX terms. Because FREX terms reflect patterns of word co-occurrence rather than isolated keywords, they provide insight into the broader conceptual themes captured by the model. Accordingly, topic labels were derived from the interpretation of these semantically related term clusters rather than from any individual term considered in isolation.

Results

The search string retrieved 12,411 scientific publications associated with AI, data analysis, and ecological research indexed in the Scopus database, spanning from 1970 to May 25, 2026. Although the search recovered records from the early 1970s, the analytical corpus was restricted to articles published from 2000 onwards (n = 11,749).

From 2000 to 2020, the number of publications involving quantitative tools related to artificial intelligence — such as machine learning, data analysis, and statistical methods — increased steadily. After 2020, this trend accelerated markedly, coinciding with two independent events: the disruptions to research practice associated with the COVID-19 pandemic and the broader commercial availability of generative AI tools, particularly following the release of ChatGPT in late 2022 (Figure 1).



Red dashed line = 2020 (the onset of pandemics and the surge of generative AI)

Figure 1: Temporal distribution of the scientometric corpus (n = 11,856 articles; Scopus, 2000–2026). The dashed red line marks 2020 as a structural inflection point in publication volume. Pre-2000 records (n = 624; average 24 articles/year) were excluded from the analytical corpus due to statistical sparsity.

The STM identified 11 main topics in the research field the topics “Statistical Models and Bayesian Inference” (13.2%) and “AI Education” (12.5%) showing the highest document-level prevalence. In contrast, the topic labeled “Human Behaviour and Reproductive Ecology” suggests that the model was unable to clearly distinguish documents related to human behaviour from those focused on reproductive ecology. This result indicates that similar term usage across distinct contexts may have confounded the model, leading it to infer associations where none existed (Table 2).

Table 2: Structural Topic Model results (K = 11) — Main topics identified in the scientometric corpus (n = 11,749 articles, Scopus, 2000–2026). Topic proportions represent mean document-level prevalence. FREX terms are selected for their frequency–exclusivity balance.

Topic	%	Interpreted Name	FREX Terms
T1	7.0%	Microbial and Metagenomics	microbial_community; microorganism; metagenomics; biofilm; metagenomic; protein; microbial; genome; microbiome; microbe; phylogenetic; phage; bacterial_community; metabolite; sequencing
T2	7.1%	Bio-inspired Optimization and Computing	biogeography_base; optimization; bbo; node; computing; solve; convergence; vehicle; agent; electric; battery; inspire; robot; memory; programming
T3	9.4%	Aquatic Community Ecology	phytoplankton; benthic; species_richness; diatom; habitat; assemblage; zooplankton; freshwater; fishing; trophic; site; ocean; macroinvertebrate; sea; pollen
T4	4.1%	Outbreak of Infection diseases	infection; mosquito; malaria; tick; disease; dengue; permit_unrestricted_use; medium_provide; original_author; pathogen; parasite; mosquitoe; outbreak; infectious_disease; intestinal
T5	10.5%	Water Management	groundwater; runoff; land_use; water_quality; hydrological; water; soil_erosion; river_basin; heavy_metal; land; desertification; river; watershed; restoration

Topic	%	Interpreted Name	FREX Terms
T6	6.3%	Human Behaviour and Reproductive Ecology	female; male; child; household; forage; behaviour; behavioural; adolescent; egg; parent; mortality; woman; age; nest
T7	13.2%	Statistical Models and Bayesian Inference	modelling; bayesian; statistic; statistical; inference; fit; assumption; uncertainty; causal; procedure; random; package; probability; models; assume
T8	11.4%	Green Economy	tourism; industry; big_data; economy; green; economic; internet; decision_support; ecotourism; financial; sustainability; business; market; tourist; service
T9	9.1%	Remote Sensing and Forest Ecosystem Monitoring	lidar; agb; wildfire; fire; forest_fire; multispectral; mangrove; canopy; forest; rf; sentinel; plantation; lai; carbon_stock; rmse
T10	12.5%	AI Education	teacher; ethical; classroom; student; llms; teaching; discourse; engagement; chatgpt; generative_ai; educational; teach; political; language
T11	9.4%	Acoustic and Visual Automated Detection	acoustic; soundscape; computer_vision; deep_learning; underwater; cnn; automated; image; automate; detection; camera_trap; camera; audio; bioacoustic; manual

The STM revealed that the search string retrieved publications spanning both core ecological research and adjacent applied fields that employ ecology-related concepts and terminology. Applied domains such as "Green Economy," "Remote Sensing and Forest Ecosystem Monitoring," "Water Management," and "Bio-inspired Optimization and Computing" accounted for a substantial portion of the corpus.

Whereas core ecological applications were concentrated in topics such as "Aquatic Community Ecology," "Microbial and Metagenomics," "Outbreak of Infectious Diseases," and "Acoustic and Visual Automated Detection." Together, these results indicate that AI and data-analysis tools are being adopted across a broad spectrum of ecological and ecology-inspired research areas.

After 2022, several topics exhibited noticeable shifts in their temporal trajectories, including "Bio-inspired Optimization and Computing," "Outbreak of Infectious Diseases," "Water Management," "Green Economy," "Remote Sensing and Forest Ecosystem Monitoring," "AI Education," and "Acoustic and Visual Automated Detection" (Figure 2).

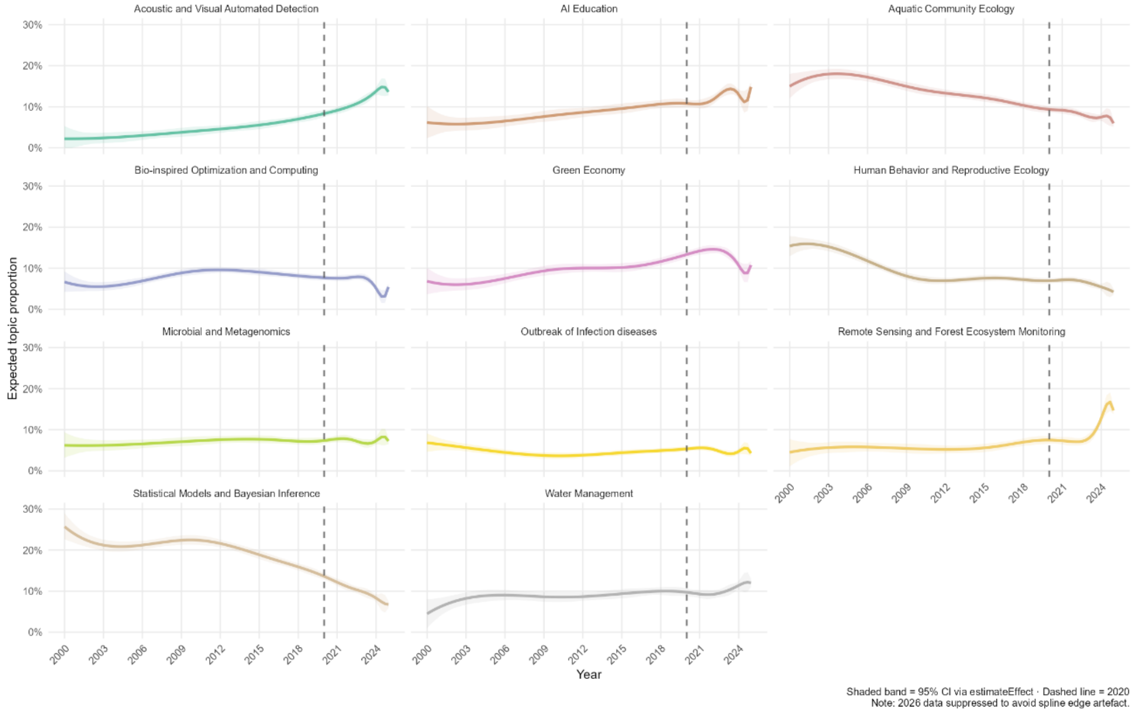


Figure 2: Temporal evolution of the eleven topics identified by the Structural Topic Model (STM; K = 11, n = 11,749 articles; Scopus, 2000–2025). Shaded bands indicate 95% credible intervals. The dashed vertical line marks 2020 as a reference point coinciding with the COVID-19 pandemic and the subsequent surge in generative AI availability. Data from 2026 were suppressed to avoid spline edge.

Discussion

Heavy Use, Little Reflection

Publication trends and the temporal patterns associated with the dominant topics suggest a field that is increasingly adopting AI-related approaches while placing comparatively less emphasis on discussions in other quantitative methods. Together, these trends provide a broad diagnostic of how AI is being used within ecology and offer a starting point for understanding how these technologies may be influencing the production of ecological knowledge.

The increase in scientific publications observed from the 2000s to 2026 reflects a recurrent tendency across academic fields, driven by the growing diversification of publications by countries and researchers, the expansion of open access, the rise of mega-journals, the broadening of databases, academic incentives, and publish-or-perish pressures. In ecology, this growth is further associated with global environmental crises and increased policy attention (Bornmann & Mutz, 2015; Savage & Olejniczak, 2022; Thelwall & Sud, 2022; Shen et al., 2023; Jakab et al., 2024).

The scientific publications in data analysis and AI increased markedly after 2020, coinciding with the COVID-19 pandemic. An exception is observed in 2022, when total publications declined relative to 2021 — a dynamic consistent with the broader post-pandemic increasing-contraction in publications rates documented across scientific fields (Rousseau et al., 2023).

The subsequent acceleration in publications between 2023 and 2026 aligns temporally with the release of ChatGPT in late 2022, a pattern that has also been observed in other scientific fields and may partially explain the rapid growth observed in the later years of this corpus. As access to commercial GenAI systems expanded, the speed of data analysis, literature synthesis, and scientific writing also increased, potentially contributing to higher rates of scientific production (Alshalla et al., 2025; Kobak et al., 2025).

However, growth in publication volume alone reveals little about how AI is being discussed within ecology. Over the past 25 years (2000–2025), temporal trends in data analysis and AI-related terminology differed among topics, with the 11 identified topics illustrating how different subfields of ecology have evolved during this period.

In “Aquatic Community Ecology” and “Statistical Models and Bayesian Inference,” topic prevalence declined over time, whereas “Remote Sensing and Forest Ecosystem Monitoring” and “Acoustic and Visual Automated Detection” showed increasing trends during the same period. “AI Education,” in turn, exhibited a marked increase, with a further acceleration after 2020. In contrast, “Microbial and Metagenomics” remained relatively stable over time.

The growth and decline patterns observed in publications on data analysis and AI systems reflect the prominence of these tools within applied ecology, particularly in fields focused on big data applications and image classification as “Remote Sensing and Forest Ecosystem Monitoring” and “Acoustic and Visual Automated Detection”.

Among these trends, the decline of "Statistical Models and Bayesian Inference" deserves particular attention. This topic represents the largest mean document-level prevalence in the corpus (13,2%), yet it has shown a consistent decline over the last 10 years. Notably, the FREX terms defining this topic are not restricted to statistical techniques themselves. They encompass concepts such as inference, uncertainty, causal reasoning, probability, and model assumptions, suggesting that the topic captures a broader dimension of inferential and methodological reasoning within ecological research.

Its decline reflects not merely a reduction in the frequency of specific methodological terms, but a decrease in the prevalence of a broader scientific discourse composed of semantically related concepts that commonly co-occur in ecological publications. In other words, the observed pattern suggests that discussions centered on statistical methodology, inference, model assumptions, uncertainty, and analytical procedures are becoming proportionally less prominent within literature.

This shift could indicate a reduction in the visibility of reliability and transparency as explicit concerns in ecological discourse, even though machine learning, deep learning, and LLM-based approaches themselves rely heavily on probabilistic reasoning and diverse statistical frameworks (Chien, 2019; Volodina & Challenor, 2021; Levi et al., 2022; Telenti et al., 2024; Zhao et al., 2026).

At the same time, increasing reliance on complex methods creates the conditions for an ethical problem to emerge when researchers stop writing about reliability and uncertainty (Anderson et al., 2021; Kimmel et al., 2023). Should discussions of inferential assumptions and uncertainty continue to recede as AI-assisted workflows expand, the field risks moving toward a methodological monoculture (Yanai et al., 2021; Simmonds et al., 2024).

Ecology's engagement with AI has so far been largely instrumental — tools that accelerate bibliographic work, programming, data analysis, and writing. However, the next generation of agentic and autonomous systems represents a qualitative shift: they are beginning to automate not just the workflow, but all the scientific workflow from hypothesis formulation to report finds (Haghighi et al., 2023; Ghafarollahi & Buehler, 2025).

Despite "AI Education" emerging as the second most prevalent topic in the corpus, the epistemological discussion of how, when, and under which conditions these tools should be appropriately applied still appears largely absent from mainstream ecological scientific discourse.

Taken together, the patterns identified suggest a discipline increasingly engaged with AI applications, while discussions of inference, uncertainty, and methodological assumptions occupy a less visible position within the scientific discourse. In this context, examining the limits of AI becomes essential not only to safeguard the integrity of ecological knowledge production, but also to clarify which analytical tasks can be responsibly delegated to intelligent systems and which continue to require human scientific judgment.

The Epistemic Limits of AI Systems in Ecology

The Foundation of Epistemic Limits in AI

AI represents a powerful tool for ecological research, yet even the most advanced models and quantitative approaches are subject to limits. For instance, if Bayesian inference is used to estimate the fecundity rate of an endangered species but the prior distribution is poorly specified or weakly informative, the resulting posterior may fail to answer the question with sufficient fidelity (Lele, 2020).

Or, in the same example, if an influenza outbreak suddenly kills the male birds in the study population, the Bayesian model may have explained previous data reasonably well and still fail to capture the real ecological situation. This reflects a defining characteristic of ecology: many ecological and evolutionary processes are non-ergodic — continuously generating novelties that no algorithm or model trained on past data can fully anticipate (Longo et al., 2012; de Vladar et al., 2017; Dumandan et al., 2023).

These limitations are rooted in a fundamental quantitative constraint: AI systems learn by extracting statistical patterns from past data, and their inferences can never fully escape this dependency. Crucially, the constraints that follow are not merely engineering challenges that future models can overcome through increased scale. Rather, some represent provable theoretical limits grounded in computability and learning theory (Eponon et al., 2026, Mohsin et al., 2026).

Logical and Architectural Limits

More fundamentally, certain classes of problems, particularly those requiring sequential and non-parallelizable reasoning, remain beyond what current parallel-centric architectures can efficiently solve. This limitation stems not from insufficient computational capacity, but from the fact that the computational structure of such problems exceeds what these architectures are designed to accommodate (Liu et al., 2026).

If the solution to a problem lies beyond the hypothesis space represented by a computational architecture, or if the underlying patterns are highly asymmetric, machine learning models, deep learning systems, and LLM may struggle to converge on accurate predictions of future outcomes.

A well-known example is the stock market, where patterns are often nonstationary, asymmetric, and subject to dynamics that fall outside previously learned regularities. Under such conditions, models may fit historical data successfully while still failing to reliably predict future behaviour (Mokhtari et al., 2021; Sonkavde et al., 2023; Vuong et al., 2024).

Financial market data and ecological data share several important characteristics, as both emerge from large adaptive systems composed of interacting agents. These systems often exhibit nonstationarity, feedback loops, complex oscillatory dynamics, and regime shifts. Such similarities have enabled the application of common analytical concepts across ecology and finance, including community matrices, neutrality tests, tipping points, and measures of complexity (Emary & Fort, 2021; Scholl et al., 2021; Van Oort et al., 2022).

Biological phenomena that arise through genuinely novel ecological configurations may therefore fall outside the boundaries of what AI can reliably anticipate. In such cases, scaling up computational power may improve performance on familiar problems without addressing the deeper challenge: that biological novelty could lie beyond what any system trained on past observations can fully represent (Alvarado, 2023; Maleki et al., 2023; Goetz et al., 2024).

The Prediction Limit

The limitation extends beyond artificial intelligence itself and reflects a deeper question about scientific prediction. Even if future systems were connected to global sensor networks — as in initiatives to build a digital twin of the ocean — capable of monitoring ecological processes in real time and continuously updating their models, they would still confront the limitations exposed by Laplace's Demon: the assumption that sufficiently complete knowledge of the present can fully determine the future (Andaur Navarro et al., 2021; Kapoor & Narayanan, 2023).

Laplace’s Demon was a thought experiment proposed by Pierre-Simon Laplace in 1814. It imagined that, if some entity could know all past and present states of the universe, it would also be able to predict the future. Evolutionary systems challenge this ideal because their dynamics are shaped by chaos, stochasticity, and hysteresis, which generate path-dependent and often divergent trajectories through time (Ferriere & Fox, 1995; Doebeli & Ispolatov, 2014; Gompert et al., 2022). As a result, evolutionary outcomes may remain only partially predictable, even when their underlying mechanisms are understood.

As emphasized by Dobzhansky, biological systems are inseparable from their evolutionary histories (Dobzhansky, 1964). Because evolution continuously generates novel combinations of traits, interactions, and ecological conditions, unprecedented biological responses remain a persistent challenge for any inferential framework. This unpredictability operates even below the ecological level: chaos can emerge in single-species systems, driven by nonlinear processes at the intracellular scale (Werner et al., 2022; Werner & Arndt, 2025).

The Ecological Model Selection Limit

The eco-evolutionary constraint represents a longstanding debate in ecological modelling. Following Levins' model selection paradigm, choosing among ecological models requires navigating trade-offs among realism, generality, and precision (Levins, 1966). Although AI systems may assist in optimizing models according to predefined criteria, they cannot independently determine which trade-offs are scientifically preferable.

This is not a claim about the biological nature of ecological questions or the capabilities of AI systems. Rather, it concerns the human nature of the epistemic commitments that precede model optimization. The determination of which trade-offs are acceptable depends on theoretical objectives, research questions, and scientific values that lie beyond the scope of purely statistical or causal procedures (Johnson & Omland, 2004; Fourcade et al., 2018) — that is, beyond what AI can resolve on its own.

When model selection is carried out without explicit consideration of the cognitive and methodological limits of ecological inquiry, AI risks producing outputs that are statistically sophisticated yet epistemically opaque, potentially creating an impression of understanding that exceeds what can be justified by the available evidence (Messeri & Crockett, 2024).

Theoretical ecology offers an instructive counterexample to this risk — models in this tradition are built with explicit assumptions and transparent limitations, treating any formalization as one possible version of a system, not an objective truth about it (Morozov, 2013; Krebs et al., 2025).

The Human - Data Interface Limit

AI systems are constrained by the quality of the data on which they operate, often exhibiting sensitivity to small changes in input and occasionally failing to capture basic contextual interpretations. Even AI models specifically designed for data extraction and manipulation may, in some cases, perform with lower accuracy than careful manual extraction (Aldoseri et al., 2023; Akinnagbe, 2024; Daraqel et al., 2025).

These limitations suggest that the role of AI in scientific research is best understood as complementary rather than substitutive. Effective collaboration therefore involves using AI for tasks which excels, such as large-scale data processing and pattern detection, while relying on human researchers for strategic decisions, contextual interpretation, and ethical judgment (Feuston & Brubaker, 2021; Steyvers & Kumar, 2024; Wei et al., 2025).

However, recognizing the limits of AI is only the first step. These limits create an epistemological obligation for researchers to critically examine how AI participates in the production of scientific knowledge, what can be responsibly delegated to intelligent systems, and where human judgment must remain central.

The presence of these limitations does not negate the value of AI for pattern detection. Instead, it serves as a reminder that automated analyses require continuous human supervision and interpretation. The STM analysis provides a practical example: while the model effectively identified large-scale patterns in the literature, it merged human reproductive behaviour and reproductive ecology into a single topic. Had this result been accepted uncritically, it could have distorted the interpretation of the field's thematic structure and the inferences derived from it.

Philosophy of science offers a framework for addressing these questions by providing conceptual tools to evaluate the links between evidence, inference, explanation, and understanding, thereby helping establish the boundaries used in ecological research (Heger et al., 2025).

Using Philosophy of Science to Guide AI in Ecology

The Multi-Agent System and the Role of the Ecologist

Extracting data and interpreting empirical information is something that tools such as Robin, an autonomous AI researcher, can already do with ease. Robin is the first multi-agent system capable of performing bibliographic review, generating hypotheses, creating graphs, suggesting experiments and performing data analysis (Ghareeb et al., 2026).

It has already been used successfully to improve a therapeutic strategy, yet it still operates within what Thomas Kuhn described as normal science — the operational arm of scientific practice, primarily concerned with problem-solving within an established framework, where theories and methods are already in place and used to address problems the scientific community assumes to be solvable (Kuhn, 1996).

Through this lens, the contributions of AI systems to ecology are most accurately understood as extensions of normal science: they expand the reach and precision of established knowledge, refine existing models, and accelerate the accumulation of results within accepted theoretical frameworks (Schindler, 2024).

This becomes particularly evident in ecology through the problem of theory dependence — where the implementation of a theory guides each step of the methodological framework and shapes the interpretation of outcomes (Layman & Rypel, 2023). A system that operates within normal science inherits these theoretical commitments without being able to scrutinize them: it can optimize what the discipline already does but not question whether what the discipline does remains sufficient.

An illustrative example is the theory commonly known as "Why Is the World Green?". Before the 1960s, ecological thinking about population regulation was divided between two competing frameworks: one emphasizing density-dependent biotic factors such as competition — associated with Nicholson and others — and another stressing the role of climate and resource availability in limiting populations — associated with Andrewartha and Birch (Andrewartha & Birch, 1954; Nicholson, 1954).

Both frameworks shared a crucial blind spot — neither assigned a central regulatory role to predators. Had an autonomous system analyzed the ecological literature between 1920 and 1959, it would likely have mapped this debate accurately and perhaps helped adjudicate between the two camps, but it would have had no reason to look beyond them.

It took human ecologists, Hairston, Smith, and Slobodkin (HSS) to reframe the question entirely. Starting from a deceptively simple observation that both camps had taken for granted — the world is, in fact, green — they proposed a paradigm shift: herbivores are kept in check not by food scarcity or weather, but by top-down predator control (Hairston et al., 1960).

The argument contained no data, no figures, no methods in the conventional sense; it was an act of conceptual reframing. HSS was immediately challenged — Murdoch (1966) and Ehrlich & Birch (1967) raised counterarguments about plant chemical defenses and logical gaps in the hypothesis — and the debate eventually expanded into the richer framework of trophic cascades and complex multi-level interactions. But the genesis of the shift required something prior to data analysis: the capacity to recognize that a mundane, ubiquitous fact had never been properly explained (Paine, 1980; Terborgh & Estes, 2010).

From this perspective, the role of the ecologist extends beyond accepting the outputs of complex models. It is precisely through the careful examination of anomalies — the observations that resist explanation, the residuals that statistical models dismiss as error, and the uncertainties that quantitative frameworks tend to absorb — that normal science reaches its limits.

In Kuhn's framework, it is the accumulation of these unresolved anomalies that creates the conditions for paradigm shifts: moments when the existing theoretical structure can no longer accommodate what the discipline is observing. The ecologist who treats unexplained variation as a signal rather than only noise is doing the kind of science that AI, operating within the boundaries of normal science, is structurally unable to do.

Paul Feyerabend would go even further in this discussion, arguing that scientific progress has never been achieved by following a single methodological rule (Feyerabend, 2010). When a single methodology begins to dominate the production of scientific results, the diversity of explanatory approaches that sustain scientific progress is at risk.

Methodological Pluralism

The STM results suggest that AI does not occupy a single epistemic role across ecology. Topics such as Metagenomics and Water Management showed relatively stable levels of AI-related activity throughout the study period, suggesting that intelligent systems may be functioning primarily as tools of normal science in the Kuhnian sense, increasing analytical efficiency while operating within established research programs.

In contrast, topics such as Remote Sensing, Forests, and Green Economy exhibited a pronounced expansion of AI-related terms after 2022. Although such patterns do not by themselves demonstrate the emergence of a new scientific paradigm, they may indicate domains undergoing accelerated methodological change, where AI is enabling new forms of observation, data integration, and hypothesis generation.

Taking together, these contrasting trajectories suggest that AI can simultaneously reinforce existing scientific practices and facilitate the exploration of new research directions. Rather than occupying a single role across ecology, intelligent systems appear to be incorporated differently across subfields, reflecting distinct research traditions, analytical needs, and modes of inquiry.

Feyerabend's critique of methodological monism offers one way of interpreting this heterogeneity. If AI contributes to ecological research through multiple and sometimes contrasting pathways, then no single methodological approach — however powerful or computationally sophisticated — should be granted epistemic authority over the others. The history of science repeatedly shows that progress emerges from the coexistence of alternative perspectives and methods, rather than from the consolidation of a single dominant framework.

In this sense, AI represents a double-edged methodological tool. When granted epistemic privilege over alternative quantitative approaches, it risks contributing to methodological homogenization. Yet, when used alongside complementary methods and perspectives, it can instead strengthen the methodological pluralism that underpins scientific progress.

Falsificationism and the Critical Evaluation of AI

But pluralism alone is not sufficient. Popper's falsificationism offers a complementary demand: that AI-generated models and hypotheses must be subjected to the most rigorous possible empirical testing, with explicit criteria for what would count as evidence against them (Popper, 2002).

Together, although these two ideas were initially opposed, they define the conceptual space within which AI can be used responsibly in ecology: broad enough to resist methodological closure, yet rigorous enough to prevent the proliferation of untestable outputs.

Drawing on Popper's falsificationism and Kuhn's concept of normal science, AI can be understood not as an oracle of conclusions, but as a mechanism for conjecture generation. Its scientific value lies not in replacing ecological judgment, but in helping researchers explore explanations that ecologists may later integrate into broader theoretical developments.

Viewed through this lens, the decline of the STM topic related to statistical methodology is significant because these discussions are central to the critical appraisal of scientific claims and help make the logical structure of ecological arguments open to examination and potential refutation.

Rather than accepting model outputs as final answers, ecologists should use AI to test scenarios, explore hidden patterns, and confront hypotheses — while reserving for themselves the irreplaceable role of refutation and biological validation. In this sense, AI becomes most scientifically valuable not when it replaces ecological judgment, but when it sharpens the questions that judgment must answer.

AI clearly produces results, and normal science remains a valid form of inquiry. The real challenge is ensuring ecologists understand the meaning and limitations of these tools. Here, philosophy of science emerges not as an abstract exercise, but as a practical guide for ethical ecological research in the age of AI.

The philosophical and ethical discussions in this paper are meant to be introductory. Using Kuhn, Popper, and Feyerabend offers an accessible starting point for ecologists lacking formal philosophical training, rather than an exhaustive critique. Modern philosophy of science provides much deeper insights into scientific reasoning and complex systems, just as the ethics of AI stretch far beyond what is covered here. Ultimately, these boundaries highlight a pressing issue: if a researcher's judgment remains irreplaceable, what does the responsible use of AI actually look like in practice?

Responsibility in the Black Box

The epistemic limits of AI systems, together with the philosophical implications of their use and the risks associated with uncritical confidence in their outputs, necessitate a reconsideration of the ethical posture underlying contemporary research practices. This need becomes particularly important at a time when AI systems are increasingly capable of performing tasks that were once the exclusive responsibility of researchers (Alvarado, 2023).

Relying on a 'black box' to generate conclusions — without the capacity to discern ecological reality from algorithmic artifacts — is an unethical outsourcing of scientific judgment (Hatherley, 2025). The emergence of the “AI Education” topic also provides an interesting illustration of this tension. Although the topic includes discussions of ethics and responsible AI use, its dominant vocabulary is largely oriented toward training, instruction, and the practical adoption of AI tools.

This emphasis may suggest a stronger focus on learning how to use AI systems than on critically evaluating their assumptions, limitations, and appropriate reporting practices. If such reflection remains secondary to tool adoption, the reliability and transparency of AI-assisted quantitative analyses may become more difficult to assess.

This problem is not entirely new to ecology. While AI democratizes access to highly complex statistical tools, it does not impart an understanding of their mathematical foundations. Consequently, researchers gain substantial analytical power without the proportional knowledge required to apply it responsibly. This dynamic may suggest that the ecological community is investing considerable effort in learning how to use these technologies, while devoting comparatively less attention to the epistemological questions surrounding when, why, and under what conditions their outputs should be trusted (Lingo, 2023; Schwarz, 2025).

Ecology has faced related methodological challenges before — practices such as HARKing, pseudoreplication, and p-hacking have long been recognized as sources of systematic distortion in literature. The critical difference today is that intelligent systems can reproduce these same methodological failures at a scale and speed that manual workflows never could, and without producing the kind of visible inconsistencies that would ordinarily prompt critical scrutiny (Hurlbert, 1984; Fraser et al., 2018; Chen et al., 2024; Suchak et al., 2025).

Addressing this requires more than methodological caution. The philosophy of science — and specifically the epistemological and ethical dimensions of scientific inquiry — provides the foundations to a framework for defining what responsible use of AI in ecology looks like in practice. Epistemology clarifies what kinds of claims a given method can legitimately support and where its inferential boundaries lie (Alvarado, 2023).

Ethics establishes the researcher's accountability for those boundaries — including the obligation to understand, at least in broad terms, the assumptions and limitations of the tools being used. Together, they shift the ecologist's relationship to AI from passive reception of outputs to active and informed interpretation. This is not an argument against the use of intelligent systems in ecology; it is an argument for the conditions under which their use remains scientifically defensible.

Decision Framework for Ecologists Working with AI

This framework does not aim to demonize AI. These tools save time and handle repetitive tasks, freeing researchers to focus on scientific reasoning. The proposed framework is rooted in the scientific method, data-analysis workflows, and research ethics to guide ecologists using commercial generative AI (such as ChatGPT, Claude, Perplexity, and Gemini) and autonomous AI systems.

The framework consists of three broad principles applied sequentially. Researchers must meet each condition before moving to the next. While it does not dictate specific tools or analyses, it defines how to use AI without compromising the integrity of ecological research.

Principle 1 — Critical Evaluation Capacity

Before delegating any task to an AI system, ecologists should first assess whether they possess sufficient domain knowledge to critically evaluate the output. The issue is not whether AI can assist the analysis, but whether the researcher can distinguish an algorithmic artifact from a genuine biological pattern — and, ultimately, whether the results reflect what actually happens in the natural system.

A practical rule follows from this principle: researchers should only delegate tasks whose outputs they can independently scrutinize. When AI-generated results become difficult to verify or reconcile with existing biological knowledge, this should be treated as a signal to pause, revisit the literature, or consult domain experts.

Crucially, when results are statistically coherent but biologically implausible, ecologists should treat the discrepancy as a signal rather than an error to be ignored. Such anomalies may reveal the limits of existing models, echoing Kuhn's description of unresolved observations that precede scientific change (Kuhn, 1996). Rather than forcing data into an inadequate framework, researchers should examine these anomalies critically — they may point toward new ecological explanations that no AI system can generate on its own.

Principle 2 — Intellectual Authorship of Questions and Hypotheses

Ecologists should formulate their core research questions and hypotheses independently of AI systems, even when working in highly automated workflows. Although AI may assist in generating ideas and exploring alternative explanations, biological questions should remain grounded in the researcher's own scientific reasoning rather than in machine-generated inference.

AI should therefore be treated as a tool for hypothesis exploration, not a substitute for critical thinking. Researchers must continually ask under what conditions an AI-generated explanation could be wrong; otherwise, they risk accepting outputs without adequate scrutiny.

Following a falsification-oriented approach, the objective is not only to seek evidence that supports a hypothesis, but also to identify observations, assumptions, or conditions that could challenge it (Popper, 2002). As a practical safeguard, AI-generated interpretations should be compared across different systems whenever possible: convergences may increase confidence, while divergences can reveal hidden assumptions, platform-specific biases, or overlooked alternatives.

Principle 3 — Quantitative Ecology Literacy and Methodological Transparency

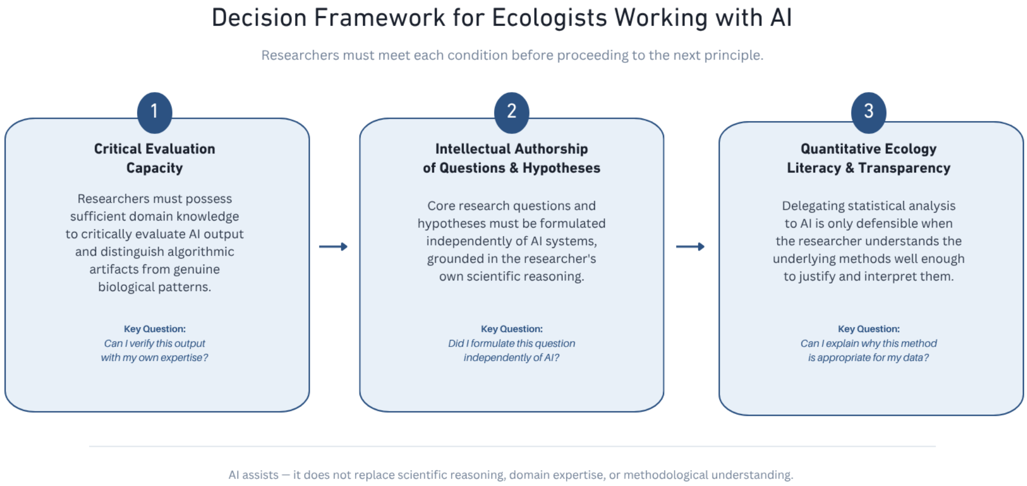
Delegating statistical analysis to AI is only defensible when the researcher understands the underlying methods well enough to justify and interpret them. If an AI suggests a model the ecologist cannot explain in biological terms, proceeding without that understanding undermines the scientific validity of the work.

Major errors in ecological statistics, including pseudoreplication, ignored data dependence, and model misspecification, often arise because researchers apply methods they do not fully understand. AI does not resolve this problem; it may instead amplify it by making sophisticated analyses easier to deploy without a corresponding understanding of their assumptions and limitations.

Developing a broad quantitative foundation in ecology is therefore one of the most effective ways to avoid becoming overly dependent on AI-mediated analyses. A wide range of mathematical and statistical tools is available for investigating ecological problems, and different approaches may provide distinct insights into the same dataset.

In this respect, a moderate interpretation of Feyerabend's perspective remains valuable: researchers should avoid restricting themselves to a single quantitative method and instead explore multiple analytical approaches when evaluating ecological questions.

Consequently, ecologists must be able to explain why a model is appropriate for their data, verify its assumptions, and interpret effect sizes and confidence intervals in ecological rather than purely statistical terms (Popovic et al., 2024). When AI suggests an unfamiliar method, researchers should first understand its rationale, assumptions, and limitations before incorporating it into their analyses.



Decision Framework for Ecologists Working with AI

Researchers must meet each condition before proceeding to the next principle.

1

Critical Evaluation Capacity

Researchers must possess sufficient domain knowledge to critically evaluate AI output and distinguish algorithmic artifacts from genuine biological patterns.

Key Question:
Can I verify this output with my own expertise?

2

Intellectual Authorship of Questions & Hypotheses

Core research questions and hypotheses must be formulated independently of AI systems, grounded in the researcher's own scientific reasoning.

Key Question:
Did I formulate this question independently of AI?

3

Quantitative Ecology Literacy & Transparency

Delegating statistical analysis to AI is only defensible when the researcher understands the underlying methods well enough to justify and interpret them.

Key Question:
Can I explain why this method is appropriate for my data?

AI assists — it does not replace scientific reasoning, domain expertise, or methodological understanding.

Figure 3: Decision framework for ecologists working with artificial intelligence tools. The three principles must be met sequentially before AI assistance is incorporated into any stage of the research workflow. Principle 1 (Critical Evaluation Capacity) requires sufficient domain knowledge to distinguish algorithmic artefacts from genuine biological patterns. Principle 2 (Intellectual Authorship of Questions & Hypotheses) establishes that core research questions and hypotheses must originate independently of AI systems. Principle 3 (Quantitative Ecology Literacy & Transparency) holds that delegating statistical analysis to AI is only defensible when the researcher can justify and interpret the underlying methods. Each principle is anchored by a diagnostic question the researcher must be able to answer affirmatively before proceeding.

Final Remarks

Researchers and AI systems are both fallible. Human judgment is shaped by theoretical commitments and cognitive limitations, while AI systems inherit biases from their training data and remain constrained by the architectures through which they operate. Neither provides a privileged path to truth.

Scientific progress has always depended on the continuous revision of ideas, methods, and assumptions. As AI becomes increasingly integrated into ecological research, the challenge is not to resist these technologies, but to avoid reducing scientific inquiry to a single mode of discovery. Progress depends not only on analytical efficiency, but also on maintaining a diversity of perspectives, methods, and forms of reasoning.

The patterns identified in this study suggest a discipline increasingly engaged with AI applications while discussions centered on inference, uncertainty, and methodological assumptions occupy a less visible position within the scientific discourse. Whether this reflects a broader shift in ecological reasoning remains an open question. Nevertheless, the trend highlights the importance of maintaining epistemological reflection alongside technological innovation.

The Philosophy of Science may offer important conceptual tools for addressing these challenges, not by rejecting AI, but by clarifying the conditions under which its use remains scientifically meaningful. Such reflection becomes increasingly important as intelligent systems assume a larger role in scientific workflows.

What, then, can AI not replace in ecology? Fundamentally, it cannot replace the ecologist's role in cultivating scientific judgment, critical reflection, and ecological understanding, nor the responsibility to test ideas critically, develop new methodological approaches, and recognize when existing paradigms are no longer sufficient to explain the natural world.

Artificial Intelligence Statement

Artificial intelligence tools were used during the development of this manuscript. Large language models, including ChatGPT, Claude, Gemini, and Microsoft Copilot, were used to assist with code generation and troubleshooting during data analysis, as well as to improve the clarity, coherence, grammar, and readability of the text. All scientific questions, study design, methodological decisions, data analyses, interpretation of results, and conclusions were developed and evaluated solely by the author. The author reviewed, verified, and takes full responsibility for all content presented in the manuscript.

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Supplemental Information

What Artificial Intelligence Cannot Replace in Ecology?

Table of Contents:

Text Preprocessing Details

Text preprocessing was conducted in R (v.4.5.3) using a natural language processing pipeline comprising the following steps:

(1) Lemmatisation using the udpipe package with the English-EWT model, reducing inflected word forms to their base lemma.

(2) Stopword removal based on a standard English stopword list, supplemented by domain-specific terms identified during exploratory analysis (e.g., copyright-related strings such as 'elsevier', 'springer', 'right', 'reserve').

(3) Identification and standardisation of frequent bigrams using the quanteda package. Compound terms with high collocation strength (lambda ≥ 4.0, z-score ≥ 80) were concatenated with underscores (e.g., machine_learn, remote_sensing) to preserve multi-word concepts as single tokens during modelling.

(4) Construction of a document-feature matrix (DFM) after removing documents with fewer than 10 tokens and features appearing in fewer than 10 documents, following established recommendations for topic modelling.

Table S1 lists the 30 most frequent bigrams detected in the corpus and retained for standardisation.

Table S1. Thirty most frequent bigrams detected in the corpus (ranked by z-score). Only bigrams with lambda ≥ 4.0 and z-score ≥ 80 were retained and standardised as compound tokens.

Bigram	Count
machine learn	4,524
data analysis	2,550
artificial intelligence	2,542
author s	1,935
© elsevier	1,555
right reserve	1,402
remote sense	691
statistical method	846
neural network	1,194
deep learning	929
climate change	1,347
random forest	1,224
case study	961
land use	1,119
machine learning	859
large scale	748
time series	630
water quality	687
ecosystem service	524

Bigram	**Count**
decision make	522
learn algorithm	685
microbial community	580
high resolution	535
intelligence ai	572
sustainable development	734
land cover	642
remote sensing	1,232
result show	1,235
result indicate	486
long term	927

Corpus Preparation and Parameter Selection

The analytical corpus was restricted to publications from 2000 onwards (n = 11,749) to ensure sufficient document frequency for reliable topic modelling. The 624 records retrieved from 1970–1999 (average 24 articles/year) were excluded due to statistical sparsity that would compromise the estimation of temporal trends.

The search string was applied to the Scopus database on 25 May 2026 and retrieved 12,411 records. After deduplication and restriction to the 2000–2026 period, the analytical corpus comprised 11,749 abstracts.

Data processing and transformation were performed using the tidyverse ecosystem (Wickham et al. 2019). The STM was fitted using the stm package in R (Roberts et al. 2014, 2019). Topic prevalence was modelled as a smooth function of publication year using a spline covariate (s(year)) via the estimateEffect function. Data from 2026 were suppressed in temporal trajectory plots to avoid spline edge artefacts arising from the partial year of data.

Search String

```
("ecology" OR "ecological research") AND ("artificial intelligence" OR
"machine learning" OR "statistical methods" OR "quantitative methods" OR
"data analysis" OR "large language model" OR "generative AI" OR "ChatGPT"
OR "GPT" OR "LLM" OR "chatbot" OR "copilot")
```

Model Diagnostics: K Selection

Models were fitted for K = 8 to K = 14 topics. The final solution (K = 11) was selected based on four diagnostic criteria evaluated jointly: held-out likelihood (higher is better), residuals (lower is better), semantic coherence (higher is better), and lower bound (higher is better). Figure S1 shows diagnostic values across all candidate solutions.

K = 11 was selected as the solution that best balanced model fit (held-out likelihood and lower bound), residual dispersion, and semantic interpretability across topics. Solutions with K ≥ 13 showed improved fit metrics but produced semantically redundant topics upon manual inspection.

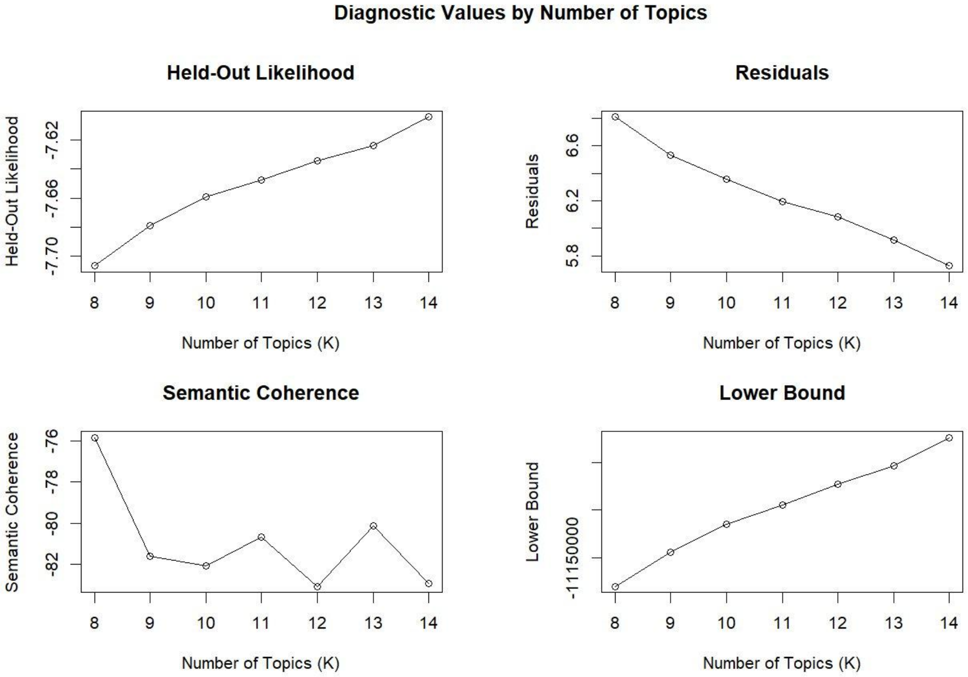

Figure S1. Diagnostic values by number of topics (K = 8–14). Panels show held-out likelihood, residuals, semantic coherence, and lower bound. The selected solution (K = 11) balances model fit and interpretability.

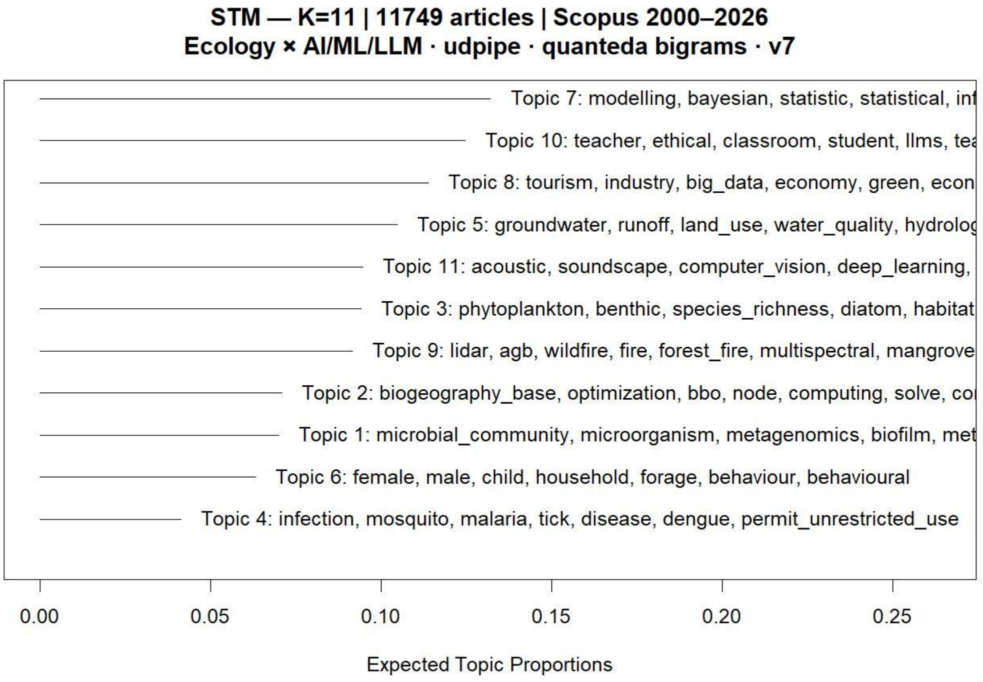

Figure S2. Expected topic proportions for the K = 11 solution. Topics are ranked by mean document-level prevalence. FREX terms shown are the five most distinctive terms per topic.

Stability Assessment

To assess the stability of the K = 11 solution, the model was run three times using different random seeds (2024, 2025, 2026). Table S2 reports mean document-level topic proportions for each run. Variation across seeds was zero percentage points for all 11 topics, indicating full stability of the selected solution.

Table S2. Stability of the K = 11 STM solution across three random seeds. Values represent mean document-level topic proportions (%). Max variation = maximum absolute difference across seeds (percentage points).

Topic	Seed 2024	Seed 2025	Seed 2026	Max variation (pp)
T1	7.0	7.0	7.0	0.0
T2	7.1	7.1	7.1	0.0
T3	9.4	9.4	9.4	0.0
T4	4.1	4.1	4.1	0.0
T5	10.5	10.5	10.5	0.0
T6	6.3	6.3	6.3	0.0
T7	13.2	13.2	13.2	0.0
T8	11.4	11.4	11.4	0.0
T9	9.1	9.1	9.1	0.0
T10	12.5	12.5	12.5	0.0
T11	9.4	9.4	9.4	0.0

Topic Interpretation: Full FREX and High-Probability Terms

Table S3 presents the complete set of FREX (Frequency and Exclusivity) terms and high-probability terms for each of the 11 topics identified by the STM. FREX terms are words that are both frequent within a topic and exclusive to it; high-probability terms are the most frequent words within each topic regardless of exclusivity. Topic labels were manually assigned based on the semantic coherence of FREX term clusters.

Table S3. Complete FREX and high-probability terms for the K = 11 STM solution (n = 11,749 articles; Scopus, 2000–2026). Topic proportions represent mean document-level prevalence.

Topic	Prop.	Interpreted Name	FREX Terms	High-Prob. Terms
T1	7.0%	Microbial and Metagenomics	microbial_community; microorganism; metagenomics; biofilm; metagenomic; protein; microbial; genome; microbiome; microbe; phylogenetic; phage; bacterial_community; metabolite; sequencing	microbial; plant; data; ecology; trait; diversity; soil; microbiome; sequence; environmental; interaction; functional; microbial_community; gene
T2	7.1%	Bio-inspired Optimization and Computing	biogeography_base; optimization; bbo; node; computing; solve; convergence; vehicle; agent; electric; battery; inspire; robot; memory; programming	system; network; algorithm; problem; optimization; model; design; can; energy; control; process; environment; simulation; dynamic; complex
T3	9.4%	Aquatic Community Ecology	phytoplankton; benthic; species_richness; diatom; habitat; assemblage; zooplankton; freshwater; fishing; trophic; site; ocean; macroinvertebrate; sea; pollen	species; community; site; habitat; ecosystem; diversity; environmental; distribution; change; landscape; plant; area; ecological; conservation; biodiversity
T4	4.1%	Outbreak of Infectious Diseases	infection; mosquito; malaria; tick; disease; dengue; pathogen; parasite; mosquitoe; outbreak; infectious_disease; intestinal	population; disease; human; risk; health; host; control; ecology; species; genetic; infection; patient; associate; vector
T5	10.5%	Water Management	groundwater; runoff; land_use; water_quality; hydrological; water; soil_erosion; river_basin; heavy_metal; land; desertification; river; watershed; restoration; zn	water; ecological; area; spatial; factor; soil; change; region; restoration; land; landscape; urban; land_use; china; index
T6	6.3%	Human Behaviour and Reproductive Ecology	female; male; child; household; forage; behaviour; behavioural; adolescent; egg; parent; mortality; woman; age; nest	level; data; effect; individual; factor; group; activity; population; behaviour; behavior; age; time; rate; exposure
T7	13.2%	Statistical Models and Bayesian Inference	modelling; bayesian; statistic; statistical; inference; fit; assumption; uncertainty; causal; procedure; random; package; probability; models; assume	model; data; can; ecological; ecology; statistical; spatial; methods; apply; estimate; set; variable; predict; process; information
T8	11.4%	Green Economy	tourism; industry; big_data; economy; green; economic; internet; decision_support; ecotourism; financial; sustainability; business; market; tourist; service	development; research; ecological; management; technology; data; system; environmental; resource; urban; information; sustainable; economic; environment; evaluation
T9	9.1%	Remote Sensing and Forest Ecosystem Monitoring	lidar; agb; wildfire; fire; forest_fire; multispectral; mangrove; canopy; forest; rf; sentinel; plantation; lai; carbon_stock; rmse	forest; model; data; tree; machine_learn; vegetation; map; biomass; prediction; area; remote_sensing; algorithm; management; fire

Topic	Prop.	Interpreted Name	FREX Terms	High-Prob. Terms
T10	12.5%	AI Education	teacher; ethical; classroom; student; llms; teaching; discourse; engagement; chatgpt; generative_ai; educational; teach; political; language; ai	research; ai; ecology; human; technology; social; student; education; challenge; learn; knowledge; artificial_intelligence; new
T11	9.4%	Acoustic and Visual Automated Detection	acoustic; soundscape; computer_vision; deep_learning; underwater; cnn; automated; image; automate; detection; camera_trap; camera; audio; bioacoustic; manual	data; classification; image; model; species; monitoring; dataset; detection; machine_learn; can; ecological; feature; identification; research; animal

Additional Figure

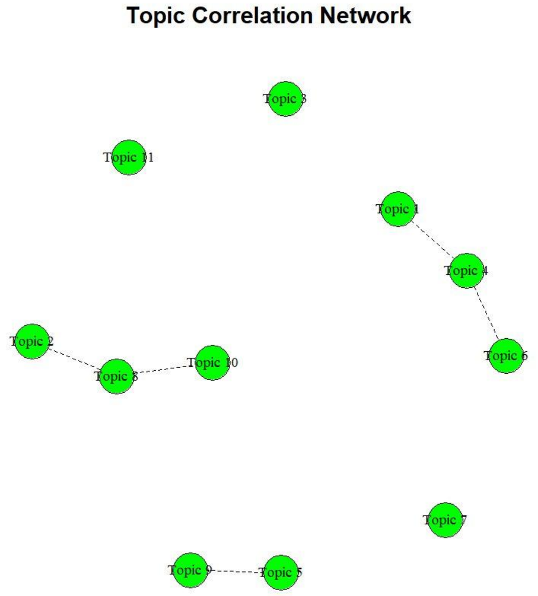

Figure S2. Topic correlation network for the K = 11 STM solution. Edges connect topics with positive pairwise correlation in document-level proportions (threshold > 0.01). The sparse network indicates that most topics occupy largely distinct regions of the document space.