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PERSPECTIVES AND PARADIGMS

The double-edged sword of artificial intelligence in invasion biology

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Abstract Artificial intelligence (AI) is rapidly reshaping the ecological sciences, and invasion biology is no exception. From automated detection of invasive species to large-scale predictive modeling of invasion risk, AI has the potential to substantially change how we detect, forecast, and manage invasive species. Yet these same tools carry significant risks: technical limitations such as misidentification, hallucinations, and lack of vetting; ethical concerns about bias, equity, and reproducibility; and dual-use potential, in which tools designed to protect ecosystems might be exploited to promote activities that facilitate invasions. Here, I argue that invasion biology is uniquely situated at the crossroads of conservation, policy, and trade, making it both an early adopter and a high-risk domain for AI application. Drawing on recent advances in AI-assisted detection, big-data risk modeling, and hypothesis synthesis, I highlight the opportunities, risks, and dual-use dilemmas of AI in invasion science. I conclude with recommendations for responsible integration of AI, including transparent reporting, human-in-the-loop validation, and explicit consideration of dual-use potential when developing and publishing AI tools. Invasion biology, perhaps more than any other ecological subdiscipline, is well-positioned to contribute to shaping a responsible future for AI in environmental science.

Keywords Machine · Learning · Modeling · CNN · Taxonomy · DNA · Barcoding

Introduction

Artificial Intelligence (AI) is a rapidly developing technology that has become integrated into many scientific disciplines, and will very much change the landscape of whole fields for years to come (Xu et al. 2021; Amanov and Pradeep 2023). In July 2025, the Office of the President of the United States issued an "AI Action Plan" that seeks to "achieve global dominance in artificial intelligence" (The White House, 2025). To accomplish this, the action plan calls for urgency in innovation and infrastructure. More importantly, it directs all scientific funding agencies, including the U.S. National Science Foundation, to prioritize AI skill development as a core educational objective, to integrate AI into the training of future scientists, and to invest in "AI-Enabled Science" by incentivizing researchers to develop and release high-quality datasets for AI training. Similar initiatives have been launched in the United Kingdom (Roberts et al. 2023), the European Union (Nikolinakos 2023), Canada (Attard-Frost et al. 2024), South Korea (Park et al. 2024), and the United Arab Emirates (Shamout and Ali et al. 2021). The implications of this shift

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are profound: AI is no longer a peripheral tool but a central force shaping the direction of global scientific research.

To set the stage, it is useful to briefly clarify what "Artificial Intelligence" encompasses. In practice, AI refers to a family of computational approaches that learn patterns from data and make predictions or classifications. The most widely used branch in ecology is *machine learning* (ML)**,** which includes algorithms that can classify species images, detect invaders from environmental DNA (eDNA), or forecast spread based on habitat variables (Pichler and Harting 2023; Yang et al. 2024). Within ML, *deep learning*, especially convolutional neural networks (CNNs), is particularly powerful for analyzing images and sound, making it well suited for species detection. Another branch is *natural language processing* (NLP)*,* which allows models to analyze text or reports, potentially useful for scanning invasion records or citizen-science notes. More recently, *generative AI* (Gen AI) has entered the scene, producing new text, images, or synthetic data, offering opportunities (e.g., creating training datasets) but also risks such as fabricating plausible but false records. Biologists do not need to be computer scientists to engage with these tools, but understanding these basic distinctions is essential for appreciating both their potential and their limitations.

Within this global push, ecology has emerged as a rapidly expanding frontier for AI adoption (Gerwin et al. 2025; Miao et al. 2025). From prioritizing conservation areas by contextualizing biodiversity metrics (e.g., CAPTAIN—conversation area prioritization through artificial intelligence, see Silvestro et al. 2022) to detecting killer whale sounds in a noisy environment to better understand communication patterns (ORCA-SPOT, see Bergler et al. 2019), AI applications now pervade ecological research, offering unprecedented capacity to process complex, multiscale data. Among ecological subfields, invasion biology stands out as uniquely positioned to benefit from, and be disrupted by, this transformation. Invasive species cause billions of dollars of damage annually, alter ecosystem processes, and represent one of the greatest threats to biodiversity worldwide (Meyerson and Mooney 2007; Clavero et al. 2009; Shabani et al. 2020; Haubrock et al. 2021; Cuthbert et al. 2021; Roy et al. 2023). Tools that accelerate detection, monitoring, and forecasting of invasions are urgently needed, and AI appears ideally suited to this challenge. Indeed, the first systematic review of AI in invasion biology documented 278 papers published between 1999 and 2024, with nearly half (48.16%) appearing between 2022 and 2024; a marked increase in the field's acceleration (Fenollosa and Salguero-Gomez 2025). Plant invasions were the most common focus, representing 45.3% of studies, with many of these emphasizing detection tasks using deep learning models applied to remote sensing imagery. Other applications included forecasting spread, predicting invasion potential, and even synthesizing invasion hypotheses using machine learning. These developments point to substantial changes in how invasions can be studied and managed.

Yet, major technological shifts can also be disruptive. We can group AI applications in invasion biology into two main categories of concern. First are *technical risks*, including misidentification, misattribution, and "hallucinations": errors that can undermine credibility and misdirect management. Second are *dual-use and governance dilemmas*, in which models designed to prevent invasions could be exploited by industries or bad actors to facilitate them, and where open science commitments can collide with biosecurity safeguards. This perspective argues that invasion biology, precisely because of its policy relevance and interface with trade, can be both an early beneficiary and a high-risk frontier for AI adoption.

Opportunities of AI in invasion biology

Artificial intelligence offers transformative opportunities for invasion biology, particularly in addressing the longstanding challenges of early detection, pathway forecasting, and data integration (Table 1). When considering the potential of AI in invasion biology, it is useful to distinguish between established approaches and those that may be considered transformative. Here, I define transformative AI as approaches that either (i) expand the scale or speed of analyses by orders of magnitude, (ii) demonstrate substantially greater accuracy than existing methods, or (iii) enable analyses that were previously impractical or infeasible. Traditional machine learning tools are still widely used and remain valuable, but represent incremental rather than transformative advances. Several initiatives are already charting the use of AI

Table 1 Applications of AI in the study and management of biological invasions

Application area	AI tools/methods	Examples in invasion biology	Advantages	Limitations challenges
Species identification & early detection	Machine learning, computer vision, CNNs, eDNA + AI classifiers	Automated species ID from field photos (e.g. iNaturalist), AI-assisted metabarcoding	Rapid identification; scalable citizen science integration	Accuracy depends on reference databases; bias toward well-photographed taxa
Predicting spread & habitat suitability	Species distribution models (SDMs) with ML algorithms (RF, MaxEnt, deep learning)*	Forecasting invasive plant spread under climate change	Handles complex, nonlinear interactions	Requires large, high-quality datasets; risk of overfitting
Ecological impact assessment	AI-enhanced network analysis, Bayesian models, NLP literature mining	Modeling food web disruptions or competitive interactions	Synthesizes vast ecological data; reveals hidden patterns	Limited interpretability ("black box" issue); ecological nuance often underrepresented
Management & control strategies	Reinforcement learning, optimization algorithms, robotics	AI-guided eradication planning, targeted pesticide/herbicide application	More efficient resource allocation; potential for real-time adaptation	High implementation costs; ethical/environmental concerns
Public engagement & policy	AI-driven citizen science platforms, social media monitoring, NLP sentiment analysis	Tracking public perceptions of invasive species via Twitter/X; AI moderation in citizen science	Expands data sources beyond formal science; engages stakeholders	Data reliability; ethical concerns around privacy and surveillance

*Random Forests and MaxEnt are widely used and valuable, but represent established ML approaches rather than transformative AI. They are included here to illustrate the continuity between traditional modeling approaches and emerging AI applications in ecology and invasion science, such as InsectAI (August et al. 2025). Others are explicitly outline in the 2023 IPBES report (Roy et al. 2023). These highlight opportunities that are now well recognized. Here, we extend these discussions by emphasizing the risks and governance challenges specific to invasion biology, which remain underexplored.

One of the most immediate and impactful applications lies in detection and monitoring. Traditional field surveys for invasive species are resource-intensive, geographically constrained, and often too slow to intercept invasions at an early stage. In contrast, AI-assisted systems can process large volumes of image and sensor data in real time. Convolutional neural networks (CNNs) can "learn" the visual signature of an invasive species and have been used to classify invasive plants such as *Phragmites australis* in aerial imagery with higher accuracy than manual classification, and to detect invasive reptiles using drone footage with relatively high precision (i.e., the proportion of AI-flagged detections that were correct; Aota et al. 2021; Anderson et al. 2023). Similar approaches have also been adapted for invasive insects and aquatic organisms, and smartphone applications now enable the public to contribute real-time observations that can be automatically validated by AI classifiers.

Beyond visual detection, models originally developed for speech recognition are being repurposed for acoustic monitoring of invasive frogs, birds and insects (Wood et al. 2024; Bota et al. 2024), while ML methods are improving signal-to-noise in eDNA surveys. Linking these streams into multimodal surveillance networks suggests a path toward continuous, real-time monitoring. In parallel, AI could also serve as a quality control mechanism for the enormous influx of citizen science data, filtering erroneous reports and thereby increasing both efficiency and confidence in community-based monitoring programs.

Beyond detection, AI has the capacity to transform how invasion pathways are forecasted and managed. Machine learning excels at integrating diverse datasets, making it particularly well suited for modeling invasion risk across complex ecological and social systems. For example, Weir et al. (2024) modeled invasion risk for five aquatic species across 30,000 lakes using environmental and recreational-use data. While this illustrates big-data integration, the algorithm itself (XGBoost) is a mature method; the transformative potential lies in coupling such models with real-time trade or transport data. For example, trade network data, including shipping, air traffic, and even e-commerce records, could be analyzed in near real time to identify emerging pathways of introduction. Deep learning frameworks, coupled with dynamic climate models, may be able to anticipate not only present invasion risks but also future "climate-proof" hotspots where species are likely to thrive under changing conditions. Moreover, AI could be employed to move beyond single-species predictions toward modeling multi-species interaction, capturing the complex ways in which one invader may facilitate or inhibit another's establishment. In addition to ecological datasets, predictive models could incorporate non-ecological streams such as customs declarations, agricultural import records, shipping manifests, air-traffic data, and even e-commerce transactions. By assigning risk scores to commodities and transport pathways, such models could enable early interception of high-risk shipments before they cross borders. Taken together, these developments suggest that AI has the potential, under certain conditions, to move beyond incremental advances and significantly broaden the scale and scope of what is possible. The integration of AI into detection and forecasting holds the potential to dramatically reduce response times, increase the precision of management intervention, and open new avenues of surveillance and risk assessment. Yet these benefits will only be realized if the field continues to explore and adapt AI innovations that, while developed in other domains such as speech recognition, trade analytics, or climate forecasting, have not yet been systematically applied to biological invasions.

Machine learning and NLP can also accelerate literature synthesis, not only by dramatically reducing the time needed for reviews but also by uncovering hidden patterns across heterogenous studies. For example, Ryo et al. (2020) reanalyzed studies of the enemy release hypothesis, revealing regional variation in outcomes that had not been evident in prior reviews. Looking ahead, LLMs are already being tested in ecology for automated text synthesis (Gougherty and Clipp 2024; Moorthy et al. 2025) and could underpin "living reviews" that continuously update as new research emerges: a capability especially valuable for fast-moving invasions.

One of the most important opportunities lies in how AI can democratize access to invasion science. Traditional tools such as statistical modeling, GIS, and molecular assays are resource-intensive and concentrated in well-funded institutions. By embedding advanced analytics in user-friendly interfaces, AI platforms can enable non-specialists to train models or generate species distribution predictions without coding expertise. Such "deskilling" (Sidorkin 2024) could empower local managers, NGOs, and community scientists in regions with high invasion pressure but limited technical capacity. Cloud-based systems may further provide real-time decision support—flagging detections, issuing warnings, and suggesting interventions. At a global scale, shared training datasets could help reduce geographic inequities that have long shaped invasion science (Pysek et al. 2008; Measey et al. 2019). Finally, education is essential: incorporating AI into invasion biology curricula will prepare the next generation to use these tools responsibly. More than just new models, AI offers the possibility of a more inclusive and collaborative scientific community.

Why AI could be a high-risk domain

While these opportunities illustrate the transformative potential of AI in reshaping the biological sciences, from accelerating discovery to expanding accessibility, the same features that make AI promising also warrant critical reflection. Questions of bias, reproducibility, ethical responsibility and the preservation of biological expertise remind us that integration must be thoughtful, not automatic. Just as previous revolutions in biology, from molecular cloning to genetic engineering to high-throughput sequencing, brought breakthroughs and unforeseen complications, so too will AI require us to navigate a delicate balance between innovation and responsibility.

Artificial intelligence models in invasion biology inherit the limitations of the data they are trained on i.e. the proverbial "garbage in/garbage out". Current invasion datasets and monitoring programs are themselves uneven, with a strong bias toward plant invasions and a handful of high-profile animal species, while fungi, microbes, and invertebrates (especially aquatic invertebrates) remain comparatively underrepresented (Warren II et al. 2017). Occurrence records—individual records of species presence, typically contributed through biodiversity databases, are also heavily skewed toward well-studied regions (primarily Europe and North America) and charismatic taxa, leaving vast geographic areas and many taxonomic groups under-sampled. These records form a subset of broader invasion datasets, which may also include experimental, genetic, and trait data. Training models on such uneven information risks producing predictions that appear precise but are systematically biased, potentially misidentifying invasion hotspots or underestimating risk in biodiversity-rich regions in the Global South. Patchy or incomplete genetic sampling introduces another layer of uncertainty. If models rely on genomic markers to infer invasion potential, missing lineages or poor-quality reference genomes, can distort outputs. It is important to note that such challenges are not unique to AI; all modeling approaches are susceptible to bias, uneven data, and misuse. However, AI amplifies these risks because of its scalability, speed, and the extent to which advanced methods can be packaged into accessible, deskilled platforms. This amplification matters because outputs are not just faster, they are also often perceived as more authoritative than traditional models (Romeo and Conti 2025), making it more likely that biased results enter decision-making unchecked.

An important and sometimes underappreciated risk in invasion biology is the potential of AI for dual use**.** Indeed, the dual-use dilemma of AI in the life sciences has been flagged as a major biosecurity concern, and was explicitly included in the 2023 United States Research Service report on AI in biology (Congressional Research Service 2023). A telling example comes from pharmaceutical research, where AI is routinely leveraged to accelerate drug development by designing novel molecules more efficiently than traditional screening approaches. These models typically operate by penalizing predicted toxicity while rewarding predicted therapeutic activity. Yet, in a widely cited "thought experiment", one pharmaceutical company inverted this logic, retraining its model to reward toxicity instead of avoiding it (Urbina et al. 2022a, b). Within six hours, the system generated more than 40,000 candidate molecules, including several resembling known chemical warfare agents such as nerve toxins (Urbina et al. 2022a, b). This example illustrates how quickly a system built for beneficial purposes can be redirected toward harmful ends. The same logic applies in invasion biology: AI systems designed to forecast, detect, and prevent invasions could be inverted to facilitate them. Knowledge of "what thrives where" is not just useful for conservationists and regulators; it is also economically valuable to aquaculture industries, ornamental plant breeders, pet traders, and even actors engaged in intentional biocontrol introductions. A climate suitability model highlighting regions vulnerable to zebra mussel establishment is not only a management tool, it is also, in effect, a recipe for successful introduction. Although the misuse of predictive tools to select potentially invasive species is not new, AI amplifies this risk in critical ways. Deskilled AI platforms can integrate vast and diverse datasets at unprecedented speed, lower the expertise barrier for non-specialists, and even generate synthetic or misleading records that complicate detection. The danger is therefore not simply prediction engines per se, but the ease, scale and concealment with which non-specialists can now access and misuse them. Unlike earlier climate-matching tools, which required technical expertise, AI's deskilling makes forecasting accessible to actors who may have little understanding of ecological consequences. The lowering of the expertise barrier is the genuinely novel risk. A recent study by Soice et al. (2023) demonstrated this point vividly: undergraduate students with no background in biology were able, using large language model (LLM) chatbots, to "design" a pandemic scenario within an hour. The AI-bot provided them with lists of candidate pathogens, explanations of how these could be synthesized from DNA, the names of companies unlikely to screen synthetic orders, and even detailed laboratory protocols with troubleshooting guidance. If non-experts can be guided so readily toward bioterrorism, it is not difficult to imagine similar misuse of AI-driven invasion tools. Bad actors would not need deep expertise to repurpose models meant for conservation into blueprints for ecological disruption.

It should be emphasized here that these risks are not merely theoretical. The history of biological invasions is replete with examples of deliberate introductions that later proved disastrous (e.g. cane toads in Australia, Asian carp in North America). In each case, species were moved for economic or biocontrol purposes with little anticipation of long-term consequences. AI could accelerate these dynamics by lowering the barriers to predicting establishment success. Even publicly accessible tools trained on open biodiversity databases could inadvertently function as "invasiveness ranking engines", guiding actors, from commercial industries to hobbyists, in selecting species likely to thrive in new markets. The dual-use dilemma also interacts with the open science movement (Smith and Sandbrink 2022). While transparency and reproducibility are core values in ecology, making AI models and training datasets freely available may create unintended security vulnerabilities. The very openness that facilitates collaboration among scientists could simultaneously provide the raw material for exploitation by actors whose interests are at odds with conservation goals. Unlike traditional ecological tools, AI's predictive power scales rapidly, meaning that once a model is released, its misuse may be challenging to track or regulate.

Beyond technical limitations and malicious use lies the broader terrain of ethics and governance. AI is often framed as a neutral or objective tool, but in reality, it reflects the biases embedded in its training data and the choice of its developers. In invasion biology, this can reinforce existing inequities. For example, models built predominantly from data-rich regions in the Global North may underperform in the Global South, where biodiversity is greatest (Raven et al. 2020) and where the social and ecological costs of invasion are often most severe (Loos 2021). This risks creating a feedback loop in which the regions most in need of robust forecasts receive the least accurate ones. This inequity is not new in ecology, but the risk is magnified if AI ouputs are adopted into policy under the assumption of objectivity, entrenching existing data gaps rather than correcting them.

AI predictions also carry the potential to influence policy decisions in problematic ways. A forecast identifying a species as a high invasion risk could be used to justify aggressive interventions such as widespread pesticide use, culling, or habitat modification—sometimes without sufficient community input, consideration of alternative approaches, or ground-truthing of AI outputs. Conversely, forecasts that understate risk might lead to complacency, delaying management action until eradication is no longer possible. There are also concerns about accountability. If a government agency acts on the recommendation of an AI model and the outcome is harmful, whether ecologically, economically, or socially, who bears responsibility? The ecologists who trained the model, the policymakers who applied it, or the AI developers who created the underlying architecture? While similar risks exist with traditional model-based approaches, AI may amplify them because of its scalability, opacity, and tendency to be perceived as more authoritative. This can lead to overconfidence and adoption into policy frameworks without the critical oversight required. Without these clear frameworks for accountability, decision-making could become high-stakes and difficult to trace. These concerns take on an added urgency in light of the White House's AI Action Plan, which explicitly directs all federal agencies to accelerate the adoption of AI tools in their operations. While the plan emphasizes innovation and efficiency, it offers little guidance on how agencies should navigate issues of interpretability, accountability, or dual-risk use. In the context of invasion biology, this means AI-derived forecasts could rapidly become embedded in regulatory and management decisions without adequate safeguards, amplifying both the benefits and the dangers of the technology.

Finally, widespread adoption of AI in the discipline raises fundamental questions about data ethics and surveillance. The integration of AI with citizen science platforms, social media, or even customs data offers powerful tools for early detection of invasions, but it also creates the potential for unintended privacy breaches and governance problems. This is not hypothetical: Meta (Facebook/Instagram), for example, has acknowledged that it repurposed user content including text and images stretching back to 2007—to train its AI systems, without explicit individual consent (The Verge 2024). While invasive species monitoring may not collect the same kind of personal data, the same technical route (public images and metadata feeding into AI models), could inadvertently expose sensitive information about contributors, such as their locations, routines, or other private attributes, without appropriate safeguards or informed consent. A parallel risk comes from generative AI itself: LLMs can fabricate plausible but false records, which, if fed into biodiversity databases or citizen science platforms, could create "ghost invasions" that waste management resources and erode public trust.

Recommendations and path forward

To maximize the transformative benefits of AI while minimizing the risks of error, misuse, and dual-use exploitation, invasion biology must adopt proactive safeguards (Fig. 1). Other disciplines, from medicine to climate science, have already begun to wrestle with the ethical, technical, and governance challenges posed by AI. Drawing on these precedents, invasion

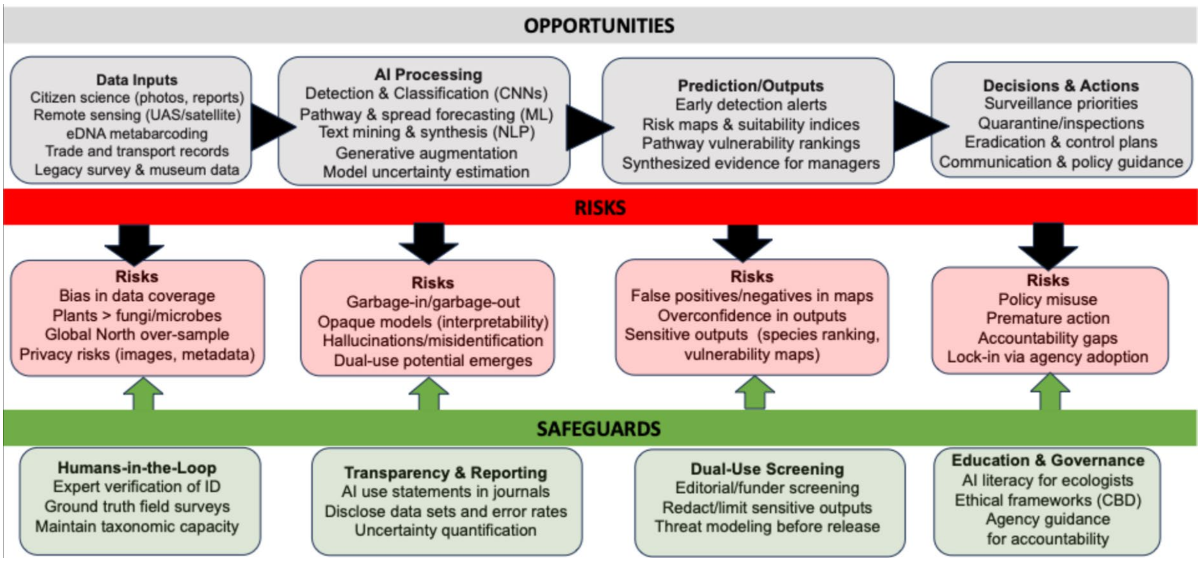

Fig. 1 Conceptual pipeline of artificial intelligence in invasion biology, highlighting both opportunities and risks. Data inputs feed into AI processing. Outputs in turn inform management decisions and policy action. At each stage risks are paired with safeguards

biology can position itself as both a beneficiary of AI and a contributor to responsible adoption.

Despite AI's remarkable accuracy in tasks such as image recognition and risk forecasting, outputs should never be treated as authoritative without expert oversight. Human-in-the-loop systems, in which AI serves as an assistant or even a co-pilot rather than a replacement, can reduce errors and prevent misinterpretation. In medicine, for instance, diagnostic AI tools are routinely paired with physician review to ensure clinical soundness (Adler-Milstein et al. 2022). A parallel approach in invasion biology would mean that species identifications must be confirmed by taxonomic experts or validated through field surveys before guiding management or policy interventions. This safeguards against false positives, misidentifications, or overconfidence in black-box models (Davinack 2023).

Transparency is also central to building trust in AI-driven science. At a minimum, authors should disclose training datasets, error rates, and sources of uncertainty when publishing AI applications in invasion biology. Journals in medicine and machine learning now increasingly require "AI use statements", modeled after data and code availability declarations, which specify how models were trained, tested, and validated (Alfonso and Crea 2023). Adopting similar standards in invasion biology would promote reproducibility, enable more accurate interpretation of findings, and guard against inadvertent bias.

In terms of the dual use dilemma: the possibility that predictive tools may be exploited for harmful ends, other fields have already begun to experiment with screening mechanisms. In the biomedical sciences, for instance, both journals and policymakers have called for risk–benefit reviews and, in some cases, restrictions on publishing AI-enabled pathogen design methods when the potential for misuse outweighs the value of open dissemination (Moulange et al. 2023; Undheim 2024). Invasion biology should adopt a similar ethos. Reviewers, editors, and funders must evaluate whether outputs such as species ranking models, invasion pathway forecasts, or vulnerability maps could be misused, and when necessary, redact or restrict particularly sensitive outputs. Such practices will require cultural adjustments but are essential to balancing transparency with responsibility.

AI governance in invasion biology should also not exist in isolation but be aligned with broader international frameworks. Agreements such as the Convention on Biological Diversity (CBD) and the Nagoya Protocol on Access and Benefit Sharing already emphasize precaution, equity, and responsible use of biodiversity data (Buck and Hamilton 2011). This aligns with the precautionary principle widely applied within the European Union, which holds that new interventions must demonstrate safety or benefit before adoption, rather than the evidentiary principle more common elsewhere, such as the US, in which interventions are presumed harmless until proven otherwise. Explicitly situating AI within a precautionary framework underscores that the burden of proof should rest on demonstrating responsible and beneficial use, not on waiting for harm to accumulate. These principles can provide a scaffold for AI applications: ensuring that benefits are equally distributed, that indigenous and local communities are not excluded, and that ecological stewardship remains central. In public health, ethical frameworks for AI now explicitly address fairness, bias, and global disparities (WHO Guidance 2021; Dankwa-Mullan 2024). Invasion biology must do no less, particularly given then global inequities in data availability and invasion impacts.

Finally, a durable path forward requires investment in education. Ecologists, managers, and policymakers must be trained not only to use AI tools but also to recognize their limitations, including risks of misidentification, hallucinations, and dual-use misuse. The biomedical community has already begun to embed "AI literacy" into medical training (Wood et al. 2021; Cai et al. 2025), and similar curricular innovations are increasingly important in the ecological sciences. Courses, workshops, and professional development programs should prepare the next generation of scientists to engage critically with AI, combining computational fluency with ecological judgement. Importantly, this aligns with broader policy directions: the AI action plan explicitly calls for strengthening AI education and training at all levels, from schools to universities and through lifelong learning, with the goal of creating a diverse and AI-literate workforce. Invasion biology, therefore, should not only adopt these priorities but adapt them to its own needs, ensuring that capacity-building in AI includes ethical reasoning, ecological context, and an awareness of dual-use risks.

Conclusion

Artificial Intelligence offers invasion biology notable opportunities: to detect invaders earlier, forecast their spread more accurately, and democratize access to cutting-edge science. But these same tools introduce important risks that require careful consideration By adopting proactive safeguards such as human validation, transparent reporting, dual-use screening, alignment with ethical frameworks, and education, invasion biology can set a precedent for how ecology at large integrates AI responsibly. Other disciplines have already learned, sometimes painfully, that enthusiasm without guardrails invites misuse. Invasion biology now has the opportunity to anticipate those pitfalls and chart a path that is innovative yet responsible, ensuring that AI strengthens rather than undermines our ability to protect ecosystems.

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