Challenges and solutions for ecologists adopting AI

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Abstract

1. **Motivation:** Artificial Intelligence (AI) can rapidly process large ecological datasets, uncover patterns, and inform conservation decisions. However, its adoption by ecologists is often hindered by steep learning curves, overwhelming model options with varying transparency, and uneven access to data, code, and technical skills. We led a workshop, *EcoViz+AI: Visualization and AI for Ecology,* that brought together 35 experts to synthesize this review and related resources that collectively aim to guide ecologists as they navigate, implement, interpret, and contribute to the fast-evolving AI landscape.
2. **Methods:** Workshop facilitators led discussions and collaborative coding sessions around five use cases of AI in ecology for processing image, ecophysiological, and acoustic data. Using workshop discussions and experiences as a foundation, this review article synthesizes the opportunities and risks for AI in ecology as well as practical challenges and solutions for adopting AI.
3. **Outcomes:** Ethical and scientifically sound use of AI requires human review, interpretable methods, and greater technical literacy to minimize risks. However, practical challenges more often prevent adoption than ethical concerns. Four

solutions include: (1) **educational resources** to help researchers assess the *opportunity cost* associated with AI compared to traditional methods, (2) **communities of practice** to combat the *overwhelming landscape* of AI with knowledge, technical skills, collaboration, and inclusivity, (3) **effective visualizations** to address the *transparency deficit* of AI for understanding and communicating results including model outputs, performance, and functionality, and (4) **computational resources** to ease the *implementation burden* of AI through shared data, modifiable code, and accessible computing. Our workshop compiled resources, including science communication videos for five AI use cases and repositories for ecology-related AI models and communities of practice.

4. **Synthesis:** Cultural shifts towards formal incentivization of open-access educational materials, inclusive mentorship, science communication, and open science will empower ecologists to leverage AI responsibly. Aligning AI initiatives with broader movements towards interdisciplinary open science and computational literacy will promote inclusivity and the ecological relevance of novel tools, advancing basic research and impactful translational ecology.

Key words: *artificial intelligence, AI, ecology, education, cyberinfrastructure, visualization, science communication, communities of practice*

Background

Applications of AI in ecology and evolution are now increasing the speed, scale, and resolution of computational analysis (Christin et al., 2019). AI can predict species responses based on environmental conditions (Chollet Ramampiandra et al., 2023), facilitate the integration of models and theory for complex systems-level understanding (Han et al., 2023), and generate novel hypotheses (Stevens et al., 2023) to pave the way for conservation (Chapman et al., 2021). While AI is not necessary in every, or even most, situations, it is nonetheless a powerful, adaptable tool available to ecologists for answering pressing research questions. However, the significant practical challenges to AI-adoption, such as a lack of domain-specific tutorials and communities of practice, and the considerable ethical concerns associated with AI (well described in the literature [Chapman et al., 2024; Cooper et al., 2024; Scoville et al., 2021; Tabassi, 2023]) have generated skepticism and trepidation among ecologists and likely slowed AI adoption. To address this issue, we gathered 35 experts in ecology and artificial intelligence for a week-long facilitated workshop (*EcoViz+AI: Visualization and AI for Ecology*; ecoviz-ai.github.io [Kendall-Bar, 2024a]; see supplement for workshop details and outputs). We defined AI broadly to include the spectrum of machine learning and deep learning models available to ecologists, although strict definitions of AI may preclude machine learning and even deep learning (Fig. 1; Sheikh et al., 2023; Wang, 2019). For this review, we discussed and distilled the following:

1. A summary of the current opportunities and risks for using AI in ecological research.
2. A review of the key challenges to AI adoption for ecologists.
3. Specific examples and ethical considerations for key solutions to these challenges: educational resources, communities of practice, effective visualizations, and computational resources.

Overall, we hope this review will help ecologists who are considering adopting AI methods navigate the tools available to them and apply them with responsibility and rigor.

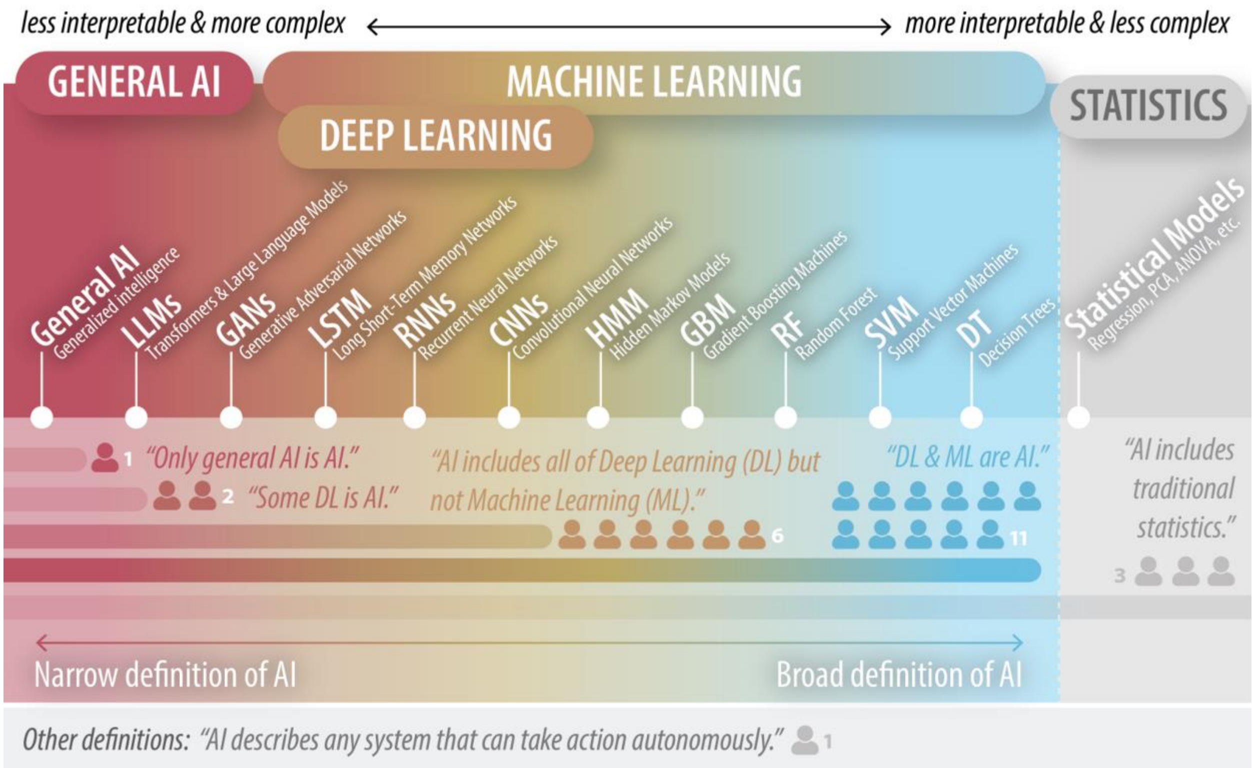

Figure 1. *A diagram describing our workshop participants' definitions of AI, showing a spectrum of models from less interpretable and more complex models on the left (darker red values) to more interpretable and less complex on the right (lighter blue values). Icons next to a definition represent votes from workshop participants. The spectrum is divided into four categories:* ***General AI*** *(or strong AI),* ***Deep Learning*** *(DL including Large Language Models [LLM], Generative Adversarial Networks [GAN], Long Short-Term Memory Networks [LSTM], Recurrent Neural Networks [RNN], and Convolutional Neural Networks [CNN]),* ***Machine Learning*** *(encompassing DL models as well as Hidden Markov Models [HMM], Gradient Boosting Machines [GBM], Random Forest [RF], Support Vector Machines [SVM], and Decision Trees [DT]), and* ***Statistics*** *(including e.g. linear, logistic, and multivariate regressions, Principal Component Analysis [PCA], and Analysis of Variance [ANOVA]).*

(1) Opportunities and risks of AI applications in ecology

AI, defined broadly as a spectrum of machine learning to deep learning models (Fig. 1), can be applied to ecological research through: **(1) data processing**, such as labelling, annotating, clustering, or filtering raw data, **(2) inference**, where processed data can be used to answer ecological or evolutionary questions via testable hypotheses, and **(3) decision-making**, where the answers to these questions can serve as the basis for policy or management recommendations. For example, sleep studies of wild animals could apply AI to help assign labeled sleep states based on electrophysiological datastreams (AI for data processing), as demonstrated by Allocca et al. (2019) and Vallat & Jajcay (2020). Whether or not AI was used to assist sleep scoring, the resulting labelled data could be fed to an AI-based habitat suitability model to identify the locations within an animal's range that are best suited for sleep (AI for inference; e.g., Saarenmaa et al., 1988). Finally, a conservation-focused AI model could incorporate this knowledge with other aspects of animal behavior to recommend the prioritization of sleep habitats for conservation (AI for decision-making) (Silvestro et al., 2022).

We discuss the opportunities and risks of AI applications across these three stages: data processing, inference, and decision-making. Early in the field of Ecology, inference primarily relied on strong experimental design and statistical methods, while data processing and decision-making were led by human experts. While ecologists sought to use statistical models to describe biological systems and observational processes (King, 2014), relatively small datasets allowed manual labeling and annotation (Besson et al., 2022). Traditionally, conservation and management decisions have also relied on the consensus of domain experts (Kirlin et al., 2013). However, the increasing size and complexity of datasets have augmented the burden of manual processing, making it harder for experts to manually process data or to consider all sources of information relevant to conservation (Besson et al., 2022). These complex, multidimensional datasets also present unique opportunities for AI even in the traditionally statistics-dominated space of inference. For each of these three tasks, we discuss emerging uses of AI, particularly pertaining to machine learning and deep learning, as alternatives for more traditionally implemented statistical or manual methods.

AI for data processing

Opportunities. With relatively fast and inexpensive models, AI approaches allow ecologists to rapidly process large datasets with algorithms to detect or classify habitat types, species, or behaviors (Schirpke et al., 2023). AI accelerates tasks like labelling, annotation, and anomaly detection, enabling more data to be processed (i.e., increases scalability), but can lower prediction accuracy compared to manual methods (Mosqueira-Rey et al., 2022). When compared to statistical or signal processing techniques for processing data, AI can improve accuracy in addition to speed, introducing the possibility of edge computing, where models can be deployed to perform reliable real-time detection in the field or while sensors are deployed on animals (Wasimuddin et al., 2020; Yu et al., 2024).

The use of computer vision convolutional neural networks (CNNs) has improved scientists' capacity to process large amounts of video, acoustic, and movement data (Christin et al., 2019; Lauer et al., 2022; Yu et al., 2022) with promise for improving conservation and biodiversity monitoring (Galaz García et al., 2023). For example, new developments in near-real-time automated processing of ship-based thermal imagery can alert captains to potential ship strikes in time to avoid endangered whales (Baille & Zitterbart, 2022). AI tools including WildBook, HappyWhale, FathomVerse, Seek and iNaturalist, and Merlin engage the public in the detection and classification of individual plants and animals, enabling citizen science and local community engagement (Berger-Wolf et al., 2017; Cheeseman et al., 2023; Katija et al., 2022; Manderfield, 2022; Sullivan et al., 2014). The cyberinfrastructure supporting new AI techniques also accelerates and enables traditional signal processing of large datasets. For example, the National Data Platform was built for open and equitable data access and computing for AI, but its benefits extend to researchers using other methods as well (Parashar & Altintas, 2023).

Risks. Even commonplace AI methods for processing ecological data can have significant downstream consequences. For instance, consistent errors in an AI model that processes video to track locomotion and analyze the sublethal effects of pesticides on insect behavior could lead to a behavioral anomaly being overlooked (Parkinson et al., 2022). Inadequately sensitive AI models to automate species detection for camera traps (images) or automated recording units (audio) could also overlook the presence of an endangered species (Beery et al., 2019; Tuia et al., 2022). This low recall – the ability of a model to identify all relevant instances – could lead to the exclusion of that area from conservation efforts. Conversely, a "cry wolf" effect may also undermine these models and erode public trust. Consistent false alerts from automated whale detection systems could result in those systems being ignored (Baille & Zitterbart, 2022). This highlights the importance of optimizing precision – the proportion of correctly identified positive cases out of all positive detections – to reduce false alarms. Furthermore, if automated detections are the basis for further inference, the impacts of a false result are amplified. For example, a boosted decision tree that aims to identify a rare behavior could boast high accuracy despite low sensitivity, a common issue with rare event detection (Shyalika et al., 2024). Models to detect a rare event such as sleep in wild animals should therefore optimize for sensitivity to prevent the oversight of a critical resting habitat (Kendall-Bar et al., 2023).

Promising solutions. Algorithmic bias can be addressed through alternative evaluation metrics or adaptive sampling techniques that correct for class imbalances where certain types of data are overrepresented (Beery et al., 2021). "Human-in-the-loop" methods include human input in the model training process, incorporating user feedback to refine and supervise classifications (Mosqueira-Rey et al., 2022; Wu et al., 2022). These methods can improve the accuracy, precision, and transparency of automated tools and foster trust in the model predictions. For example, TagLab, an AI-driven tool for coral imagery segmentation, uses semi-automatic methods to maintain high accuracy and ease the burden of manual annotation (Pavoni et al., 2021). Similar manual review is enabled in sleep scoring software (Allocca et al., 2019) and camera trap annotation (Miao et al., 2021). The inclusion of human review helps mitigate the consequences of model error and allows for an opportunity to consider the practical, scientific, and ethical implications of the model output.

AI for inference

Opportunities. AI methods can provide an alternative to traditional statistics for establishing relationships between environmental variables and biological systems. These relationships can be studied at many ecological scales, from individuals (physiology and behavior) and populations (abundance and density) to communities (species interactions) and ecosystems (species and their environment). For instance, species distribution models (SDMs) have been extensively used in Ecology to quantify occupancy, density, and distribution changes, limits, and expanses (Elith & Leathwick, 2009; Grace, 2024). Traditionally, these methodologies are grounded on statistical inference through approaches using Bayesian statistics (i.e., Markov chain simulations) or maximum likelihood estimation (Martínez-Minaya et al., 2018). Recently, however, there has been momentum for applying deep learning methodologies to SDMs (Beery et al., 2021). These novel approaches offer an alternative to traditional statistical inference and the possibility to relax statistical assumptions, such as independent and identically distributed sampling efforts and linear independence of covariates. The numerical efficiency gained doing so is attractive when fitting complex multi-species models (Beery et al., 2021), opening the door for scaling food webs and ecosystem studies at the scale of species distributions.

Risks. AI for inference in ecosystem monitoring is rapidly becoming a reality (Galaz García et al., 2023; Sethi et al., 2020), raising important concerns about how systematic errors in AI alter the derived ecological insights. As causal inference methods develop alongside AI, the ability to make predictions may outpace the ability to explain the mechanisms behind the predictions (Grace, 2024). SDMs require true observations of species and robust environmental sampling, each of which has various sources of error and uncertainty that must be clearly identified, explained, and controlled for (Beale & Lennon, 2012; Beery et al., 2021). Black-box deep learning models further exacerbate the challenges associated with aggregating multimodal ecological data such as spatial and temporal auto-correlation, differences in sampling protocols, and other caveats related to environmental feature generation and ground-truthed datasets (Beery et al., 2021). Challenges with regard to how to fit models and interpret their results are not unique to AI, but its use can exacerbate issues already present with more traditional statistical methods. Even with traditional statistics, ecologists sometimes select improper methods for estimating parameters of mixed effects models (Bolker et al., 2009). For example, the most commonly used package for fitting mixed effects models in R, lme4 (Bates et al., 2015), does not provide functionality for predicting intervals because of disagreements over how to estimate standard errors. These challenges for interpretation may be compounded when using AI methods.

Promising solutions. Improvements in AI interpretability are providing insight into the internal mechanisms of models. For example, explainable AI methods can rank feature importance to provide global explanations for overall model predictions and local explanations for individual model predictions (Alicioglu & Sun, 2022; Molnar, 2024; Ryo et al., 2021; Zhang et al., 2025; see Fig. 3 and Effective Visualizations section). Initiatives to encode domain knowledge explicitly into algorithms (knowledge-guided and model-based AI) aim to improve trust in AI models and address these inherent risks and complexities (Bishop, 2013; Doll et al., 2012; Swischuk et al., 2019). Similar recent efforts within ecology leverage the rich biological structure that underlies taxonomy and phylogeny to build upon the generic OpenAI model CLIP to create the biology-specific BioCLIP model (Stevens et al., 2023). In addition to improving the accuracy and context of image-based species identification, knowledge-guided tools can lead to the generation of new evolutionary hypotheses. They can reveal missing links in high-dimensional networks in complex systems, such as suggesting intermediate phenotypes based on phylogeny (Han et al., 2023; Stevens et al., 2023).

AI for decision-making

Opportunities. Given the complexity and scale of ecosystem management, AI is increasingly being used to support decision-making for conservation (Lapeyrolerie et al., 2022; Scoville et al., 2021) and sustainable management of natural resources (Ebrahimi et al., 2021; Lindkvist et al., 2017; Montealegre-Mora et al., 2023). Conservation prioritization has traditionally involved a spectrum of approaches, from non-algorithmic processes like the California MPA Network Blue Ribbon Task Force, which heavily relied on expert knowledge and stakeholder engagement (Kirlin et al., 2013), to algorithmic tools such as MARXAN, a widely used decision-support software for optimizing reserve design (Ball et al., 2009). Newer AI-driven platforms like CAPTAIN leverage AI and specifically reinforcement learning to model and predict biodiversity outcomes under varying conservation strategies (Silvestro et al., 2022). For instance, reinforcement learning, where the model learns by receiving feedback in the form of rewards or punishments for its actions, has been identified as particularly useful in fishery science when fish stocks display complex patterns in recruitment dynamics (Chapman et al., 2023; Kühn et al., 2024; Lapeyrolerie et al., 2022; Montealegre-Mora et al., 2024). Automated methods, repeatable workflows, and transdisciplinary research are being used to review and aggregate large, multimodal datasets into biodiversity syntheses that assess the status of ecosystems at a global scale (Berger-Tal et al., 2024; Galaz García et al., 2023). These global analyses have the potential to inform international policy, supporting initiatives like 30 by 30 and other worldwide conservation efforts (Scoville et al., 2021).

Risks. When applied to conservation decisions, AI carries serious implications, especially if it prioritizes areas and communities based on biased and uneven data (Chapman et al., 2021; Scoville et al., 2021). In forming the design and objectives of these models, researchers optimize for biodiversity or conservation outcomes that often reinforce predominant colonial conservation paradigms that neglect the needs of local communities and generational knowledge from Indigenous Knowledge Systems (Al-Mansoori & Hamdan, 2023; Layden et al., 2024). Algorithmic approaches can reinforce biases from uneven data or preconceived notions of desirable outcomes, increasing the risk of perpetuating colonialist research practices that neglect the parties most affected by management decisions (Han et al., 2023). As mentioned for SDMs, black-box models compound these issues by adding a layer of obscurity. These ethical risks also arise in the application of AI data processing outputs to conservation and management decisions. For example, the identification of illegal environmental activities (e.g. poaching, fishing in no-take marine reserves) could eventually serve as the basis for future predictive policing practices (Mporas et al., 2020; Swartz et al., 2021). Though this could be viewed as an opportunity, AI for policing practice is fraught with ethical challenges (Davis et al., 2022), including but not limited to perpetuating biases and the extreme negative consequences of errors in detection. Similar to AI for conservation prioritization, the use of AI for automated surveillance and decision-making poses significant social and ethical risks beyond Ecology.

Potential solutions. When AI is involved in decision-making, long-term partnerships with local communities become even more important so that local voices can review what goes into and comes out of models to provide feedback and adjust recommended decisions. Clear data-sharing agreements are needed to ensure informed public engagement that supports environmental justice and improves conservation governance of local communities (Layden et al., 2024). To mitigate compounded ethical issues, models can explicitly include data from social science methods like participatory mapping, surveys, and interviews to promote the inclusion of more diverse knowledge, values, and identities (Bennett et al., 2017). Once algorithmic solutions are suggested by AI, distribution equity assessments using similar social science methods, like focus group discussions or local community-based research on potential outcomes, can help select among several near-optimal solutions to prioritize an equitable distribution of cost and benefits (Kockel et al., 2020). Promoting equity in the use of AI for conservation and management will require the active integration of co-design principles, social science, procedural justice, and equity assessments (Benyei et al., 2020; Chapman et al., 2021; Hsu et al., 2022; Oestreich et al., 2024).

(2) Practical challenges: barriers to AI-adoption in ecology

Alongside the ethical and scientific concerns outlined previously, ecologists encounter practical challenges in understanding when and how to implement AI over more traditional manual or statistical methods (Fig. 2C). While many of these challenges are present in learning any technical skill, we highlight how AI can exacerbate existing burdens. We describe key practical challenges an ecologist faces when applying AI to assist with labelling, clustering, or filtering datasets (AI for data processing), transforming data into knowledge (AI for inference), or translating knowledge into action (AI for decision making):

1. ***Opportunity cost:*** *Based on the ecological question at hand, what are the costs and benefits of using an AI model as opposed to traditional methods?* While it takes time and effort to learn any new skill or method, AI models have a steeper learning curve for ecologists. AI relies on complex computational infrastructure and can require specialized knowledge of algorithms to navigate the rapidly evolving landscape of tools and methods. Additionally, most resources use programming languages that are less familiar to ecologists (e.g., Python instead of R). The scale of investment in learning to use AI can vary based on the researcher's career stage, level of experience, access to collaborators, and the availability of open-access educational materials. Current academic incentive structures (publications, funding, and job opportunities) favor the development and use of novel AI models over the creation of accessible educational resources (i.e., tutorials, blogs, free online courses). The people who are best suited to create educational materials may therefore not have the time or resources to do so.
2. ***Overwhelming landscape:*** *Considering your data and question, which AI model, if any, is relevant and could provide value?* A rapidly evolving landscape of AI models can be overwhelming to an ecologist seeking to responsibly analyze their data. They may be tempted to use traditional statistical methods, which may be more familiar and invite less skepticism than AI models, therefore missing opportunities to use AI to advance their research. Using AI requires keeping pace with rapidly advancing technologies, new architectures, and a proliferation of models with varied baseline assumptions and caveats. Researchers must carefully consider the benefits and drawbacks of increasingly complex models in terms of decreased transparency and increased computational load (Pichler & Hartig, 2023). This can be especially overwhelming for researchers who cannot draw on the collective knowledge of a community of experts. For cutting-edge technical tools such as AI, students often learn informally from more junior mentors, such as senior grad students and postdocs, who are not always recognized for their efforts (Higino et al., 2023).

Academic research incentivizes mentorship at the lab or institutional level, rather than to the broader, interdisciplinary research community.

3. ***Transparency deficit:*** *How can we understand the model's performance? How can we understand and trust how the model came to its answer?* AI models, particularly those using deep learning, introduce unique challenges in interpretability and explainability. This makes it difficult to fully understand the reasoning behind their predictions compared to traditional methods, which are often perceived as being more transparent and grounded in well-understood statistical principles. Tools for interpretability in AI are rapidly evolving, but can be challenging to navigate without technical expertise. These tools often lack standardization, leaving researchers with limited guidance on how to evaluate and trust AI predictions effectively. Because ecologists are not typically formally trained in AI methods, they may not be familiar with visualization tools that can support model interpretation or the science communication surrounding the data collection and the model's functionality, caveats, and performance.
4. ***Implementation burden:*** *How do we acquire the resources and data management systems needed to run our models? How hard is it to run the model on new data? How should we share the workflows and models we produce?* Unlike traditional statistical approaches, AI models often require complex preprocessing steps, significant computational power, and fine-tuning of hyperparameters, which can create barriers for researchers with limited technical expertise, indecipherable code repositories, or lack of access to computational resources. Once a researcher has decided to use a particular model, they must alter the model to fit the structure and scale of their dataset. This may mean reconfiguring data pipelines and workflows, engineering features, iteratively evaluating model performance, and eventually scaling up this analysis to larger datasets. This work can be limited by unavailable or unclear data and code, as well as lack of access to computational resources like cloud computing and data management systems (Allen & Mehler, 2019). Once researchers have created useful tools, they also face several obstacles when seeking to share the code, workflows, and models related to reuse concerns, disincentives, and knowledge barriers (Gomes et al., 2022). This perpetuates the cycle and creates challenges for incoming researchers seeking to understand the opportunity cost associated with using AI in ecology.

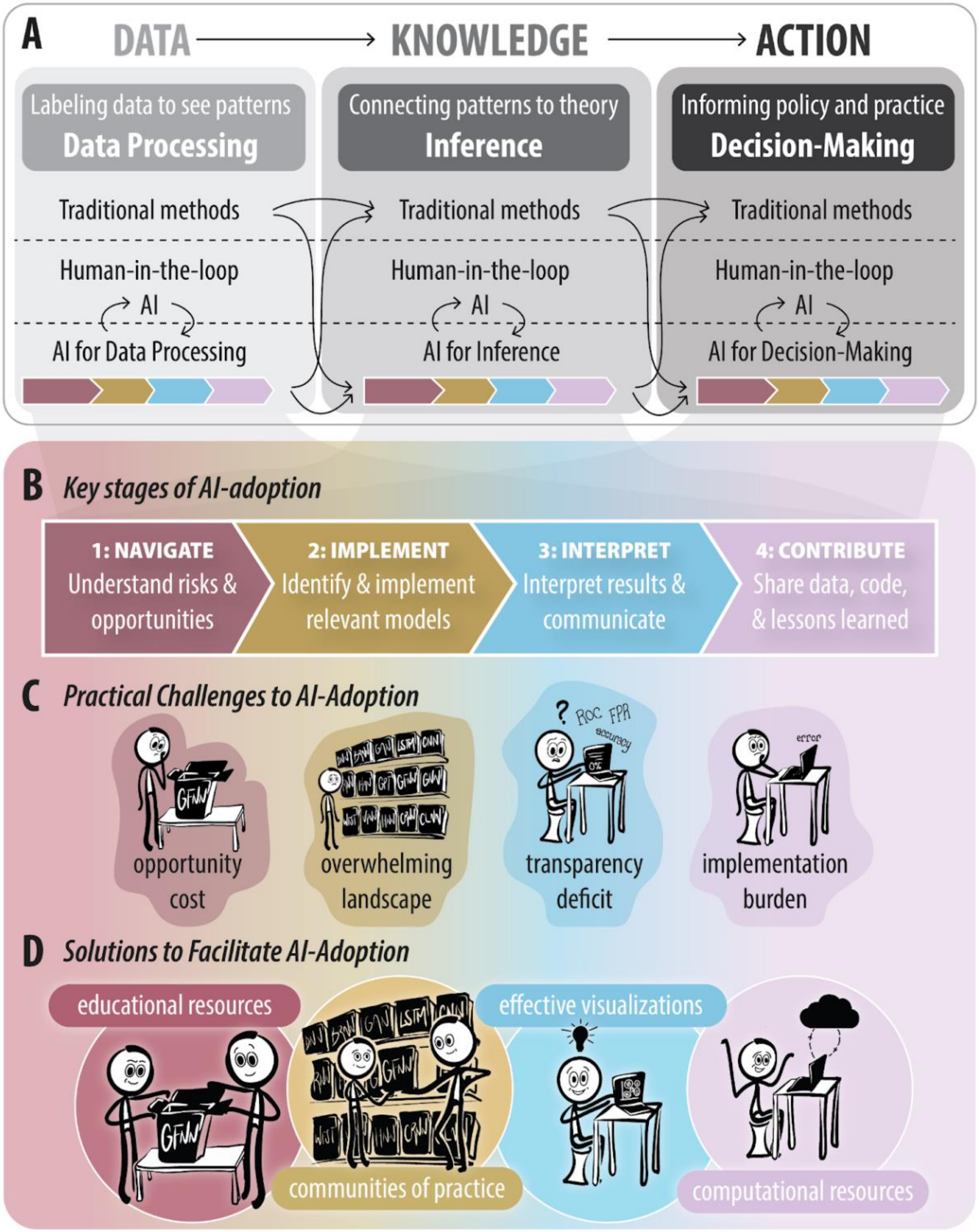

Figure 2. *This synthesis figure outlines a roadmap for AI-adoption in ecology as it is used for data processing, inference, and decision-making.* ***A)*** *Often, human-in-the-loop technologies improve workflows that transform data into knowledge that can inform action by mitigating the scientific and ethical pitfalls of AI.* ***B)*** *The key stages for ecologists adopting AI:* ***(1) Navigate*** *the landscape of risks and opportunities,* ***(2) Implement*** *identified relevant models,*

(3) Interpret and communicate *the results, and* ***(4) Contribute*** *data, code, and lessons learned back to the research community. These stages map* ***(C)*** *key practical challenges onto* ***(D)*** *key solutions: (1) opportunity cost (unclear benefits and costs) of using AI: educational resources, (2) overwhelming landscape of model choices: communities of practice, (3) transparency deficit: effective visualizations, and (4) implementation burden: computational resources.*

(3) Practical solutions: facilitating AI-adoption in ecology

These practical challenges, while considerable, must be overcome if ecologists want to responsibly leverage opportunities offered by AI. We used the wealth of expertise across career stages at our workshop to identify practical solutions that collectively ameliorate key challenges. These solutions align four key challenges—opportunity cost, overwhelming landscape, transparency deficit, and implementation burden—with corresponding interventions: educational resources, communities of practice, effective visualizations, and computational resources. The solutions aim to guide ecologists as they navigate AI-related risks and opportunities, implement relevant models, interpret and communicate their results, and contribute data, code, and lessons learned with their research community.

For each challenge, we identify an overarching solution and provide ecologists new to AI with a starting point for finding resources and initiatives. We pair these examples with broader recommendations for AI practitioners across experience levels to collectively advocate for cultural shifts that will facilitate the responsible adoption of AI in ecology. Ecologists encountering AI for the first time benefit most from accessible educational resources and collaborative communities of practice that demystify AI and provide mentorship. For researchers scaling up their use of AI, visualizations play a critical role in helping researchers understand and communicate data and the outputs, performance, and function of AI models. As researchers advance, they gain valuable expertise that they can share back with their research community by sharing data, code, and lessons learned. For each solution, we invite researchers experienced in AI to lower barriers for future ecologists by advocating for specific cultural shifts and incentives that reward open sharing of data, tools, and expertise.

1. Educational resources

When ecologists begin to use AI, they often benefit from educational resources, especially those that are open-access and available online. Educational resources to learn AI range in accessibility, investment, and impact from informal (i.e., blog posts, YouTube videos, tutorials, review papers) to formalized courses, workshops, and fellowships. Informal resources are an excellent entry point for students, allowing them to learn for free at a flexible pace. While informal resources to learn AI are plentiful, high quality ecology-specific resources are more rare. Some examples include extensive reviews of how deep learning is being used in ecology with practical guides for model selection (Borowiec et al., 2022; Pichler & Hartig, 2023), conceptual tutorials of deep learning for biologists (Aurisano et al., 2017), or specific coding examples of using AI and machine learning in R (Lefcheck, 2015) and Python (Gray, 2024). Ecologists may want to explore tools such as OpenSoundscapes (Lapp et al., 2023), which provide extensive documentation and tutorials to walk ecologists through the process of training a Convolutional Neural Network to identify sounds in audio data (Lapp et al., 2024). When employed cautiously, ChatGPT and other generative AI tools can lower the barrier to entry to Python for ecologists or biologists who may lack formal training, especially for simple tasks such as translating syntax from another more familiar language like MATLAB or R (Lubiana et al., 2023). However, while helpful to get started, ChatGPT alone is inadequate to guide the responsible selection and implementation of a model. Informal, exploratory learning is an important first step for ecologists to understand the opportunity cost associated with implementing AI.

Formal educators, courses, and programs can provide ecologists with a nuanced understanding of the field, as well as tailored guidance for bespoke data processing pipelines. Ecologists may consider formal educational resources such as Massively Open Online Courses (also known as MOOCs) on machine learning (Ng, 2024), but they are not typically aimed at ecologists and may not be accessible in terms of pricing or prior knowledge. If funding is available, in person courses such as the Oxford Research Software Engineering program can introduce rigorous best practices for Python programming to scientists, which can provide the skills needed to implement AI and produce useful scientific software (Course website: (OxRSE, 2024a); Github: (OxRSE, 2024b)). Ecology-specific opportunities with in-person engagement, while harder to come by, can be transformational for ecologists new to AI, by allowing learners to engage directly with instructors and adapt models to their own datasets. In particular, the Computer Vision for Ecology (CV4E) workshop led by Beery et al. (2023; Cole et al., 2023) combines formal instruction with coding support so that students come away with a conceptual understanding of the model to accompany their code and model outputs. Ecologists who are considering significant use of AI in their work may seek out fellowships such as the postdoctoral fellowships by Schmidt Sciences and the Allen Institute (Allen Institute, 2020; Schmidt Sciences, 2022). These opportunities can also give ecologists the time and resources to receive formal training and connect with expert mentors in the field of AI. However, as educational opportunities increase in support, they decrease in accessibility in the form of greater costs and fewer spots available.

Cultural shifts towards greater emphasis on programming education are already underway, as ecology departments increasingly hire dedicated teaching faculty, research software engineers, and data science educators (Harlow et al., 2020). Moving forward, academia should reward the creation of accessible educational resources by recognizing these contributions in tenure and promotion decisions. Increased value and opportunities for interdisciplinary co-instruction by ecology and computer science educators can improve the quality and availability of formal and informal educational resources for ecologists. Finally, education and the resulting increase in understanding will provide ecologists with tools to critically evaluate research using AI. These shifts are essential not only for AI adoption but also for advancing computational literacy more broadly, enabling ecologists to confidently integrate AI, when applicable, alongside other scalable computational methods in their research.

2. Communities of practice

Educational opportunities provide a launching point, but ecologists who are new to AI may struggle to set their work within a broader, collaborative context. In Ecology and other fields, communities of practice have been a valuable tool for scaling and tailoring education and mentorship opportunities. Communities of practice are social structures composed of individuals who share a common domain of interest and collectively enhance their expertise through sustained interactions and knowledge exchange (Wenger, 2011). We argue that ecologists new to AI, especially "advanced beginners," may benefit from joining a community of practice where they can interact with domain experts (Stevens et al., 2018). Communities of practice for AI in Ecology allow members to share technical knowledge, provide interdisciplinary expertise, and create inclusive environments across expertise levels.

Communities of practice can provide important support for scientists in fields that, like Ecology, require intensive technical skill-building (Stevens et al., 2018). For example, organizations like PyOpenSci (pyOpenSci, 2024) and rOpenSci (rOpenSci, 2024) create supportive environments where scientists can learn how to practice programming and open science. Communities of practice are also key in interdisciplinary fields to understand gaps and areas of synergy between fields. In the AI domain, interdisciplinary communities like Climate Change AI (Climate Change AI, 2024), the NSF-funded COnvergence REsearch (CORE) Institute at San Diego Supercomputer Center (NSF CICORE, 2024), and the NSF- and NSERC-funded AI and Biodiversity Change Center (ABC Global Climate Center, 2024) bridge disciplines between computer science, climate science, and ecology. Such links have improved methods to monitor, analyze, and assess changes in global biodiversity (MacWilliams et al., 2024). Organizations like the Turing Institute and professional societies like NeurIPS also provide structures for interdisciplinary collaboration to establish guiding principles for the ethical use of AI (NeurIPS, 2024; Turing Institute, 2024). While not specific to AI, the National Center for Ecological Analysis & Synthesis (NCEAS) seeks to intentionally foster the Environmental Data Science community through events like their inaugural Summit in 2023 (NCEAS, 2023). Ecologists who would like to use AI can benefit from engaging in communities relevant to their interests and goals that have strong community agreements (Bates et al., 2024), dedicated facilitators (Cravens et al., 2022), and inclusive, engaging events (Woodley & Pratt, 2020). Choosing to join but also contribute to intentional, inclusive spaces can help counteract pervasive challenges associated with impostor syndrome and STEM (Bates et al., 2024).

While vital for ecologists navigating an evolving AI landscape, in-person opportunities with ample funding for travel and accommodation are inherently exclusive and involve difficult ethical decisions regarding who gets invited. This is especially important to consider in cases where participatory decision-making informs conservation through communities of practice focused on translational ecology (Lawson et al., 2017). It is also important to consider the pros and cons of social learning, as has been well-studied in the field of behavioral ecology, where there is the potential for stagnation and inertia without active inclusion of diverse perspectives (Barrett et al., 2019; Johnstone et al., 2002; Laland & Williams, 1998). To prevent this stagnation, AI in Ecology can serve as an opportunity to invite expertise and best practices across disciplines, cross-pollinating across groups, including within a single university. At multiple scales, we hope that communities of practice can be increasingly used to foster science identity and agency as new programmers learn to leverage AI.

3. Effective visualizations

As computational analyses scale and AI models become more complex, ecologists gaining familiarity with AI can benefit from effective data visualization to understand patterns in the data, interpret model functionality, communicate model outputs, and foster transparency with stakeholders. The use of AI, especially black-box deep learning methods, can exacerbate the lack of transparency associated with scientific research; this calls for a renewed emphasis on effective visualizations for diverse audiences. While visualization is important to master at all career stages, leveraging its impact for applied AI has the potential to better engage scientists, decision-makers, and the public (Kendall-Bar et al., 2024).

The design and intent of these visualizations depend heavily on an ecologist's target audience. We present two primary purposes for the visualization of AI in Ecology: exploration and explanation (Fig. 3). Exploratory visualizations for AI include those dedicated to exploring the data and the model to a narrow audience of experts, intimately familiar with the data and questions. These visualizations are used to uncover patterns in the data, identify key features, understand model performance, and diagnose model functionality (Fig. 3A). For example, an ecologist seeking to visualize data prior to fitting an AI-based species distribution model may first examine satellite imagery or maps with color-coded sensor measurements (Fig. 3A1a) to obtain processed features for model inputs (Fig. 3A1c). Visualizations of ground-truthed presence/absence data from manual censuses can help visually assess model accuracy (Fig. 3A1b). After fitting and visualizing the model (Fig. 3A1d), AI predictions of habitat suitability can be assessed against this ground truth, e.g. through a receiver operating characteristic (ROC) curve (Fig. 3A2a). Such a curve helps identify a habitat suitability threshold for the model (above which it is considered habitable) that optimizes for tradeoffs in model performance, between a sensitive model (measured via true positive rate) and one with low false positive rate (or high specificity). Model performance for a given suitability threshold can be visualized with a confusion matrix (Fig. 3A2b). Colors for these performance metrics (true/false positives/negatives) can then be arranged across space (Fig. 3A2b: Spatial accuracy) or time, in the case of time series data. Overall model functionality as well as individual model predictions can then be explained through bar plots that rank the relative contributions of each feature (Fig. 3A3a-b; see supplemental text for more details on Explainable AI methods).

Explanatory visualizations offer a curated presentation of data, key results, model outputs, and implications paired with contextual information to effectively guide a broader audience less familiar with the dataset and question (see example in Fig. 3B). Explanatory visualizations build upon standalone versions of plots, line charts, or heatmaps useful for data exploration, often by adding annotations, infographics, scientific illustrations, voiceover narration, or data-driven animations. The perceived complexity of AI models may alienate or foster distrust with local community partners or decision-makers, making it more important to visually explain the scientific basis of the model's use and its proposed decisions. Interactive web-based data browsers can increase trust and transparency regarding the use of AI in ecology by allowing direct engagement with the public (HappyWhale: Cheeseman et al., 2017; FlukeBook: Blount et al., 2022) or decision makers through decision support tools designed for dynamic management (Welch et al., 2020). While interaction can be valuable for those closely involved, short videos can incorporate visualizations and narration provide a wide-reaching, standalone overview of a topic (Kendall-Bar, 2023, 2021; see supplement for example videos for AI case studies from the workshop).

Shaping a narrative through visualizations involves ethical decisions about what data to highlight, simplify, or omit (Walsh, 2015). Researchers can accurately depict results and uncertainty with responsible visualizations that foster trust in science and broaden who has access to information about AI in ecology, supporting the critical role of science communication (Longdon, 2023). While not exclusive to AI, visualizations can present valuable opportunities for AI-related science communication and stakeholder engagement with the wide array of inherently visual datasets in ecology such as computer vision for camera traps and aerial imagery or physics-based AI models for weather, flood, or fire simulation (Kendall-Bar et al., 2024). To promote technical literacy of AI among ecologists and collaborators, institutions and funding agencies must more formally incentivize science communication (Swain, 2023). Recognizing visual storytelling as a valued contribution—on par with traditional metrics like publications—can incentivize researchers to invest time and effort in creating widely accessible, high-quality visualizations that responsibly and effectively communicate their use of AI.

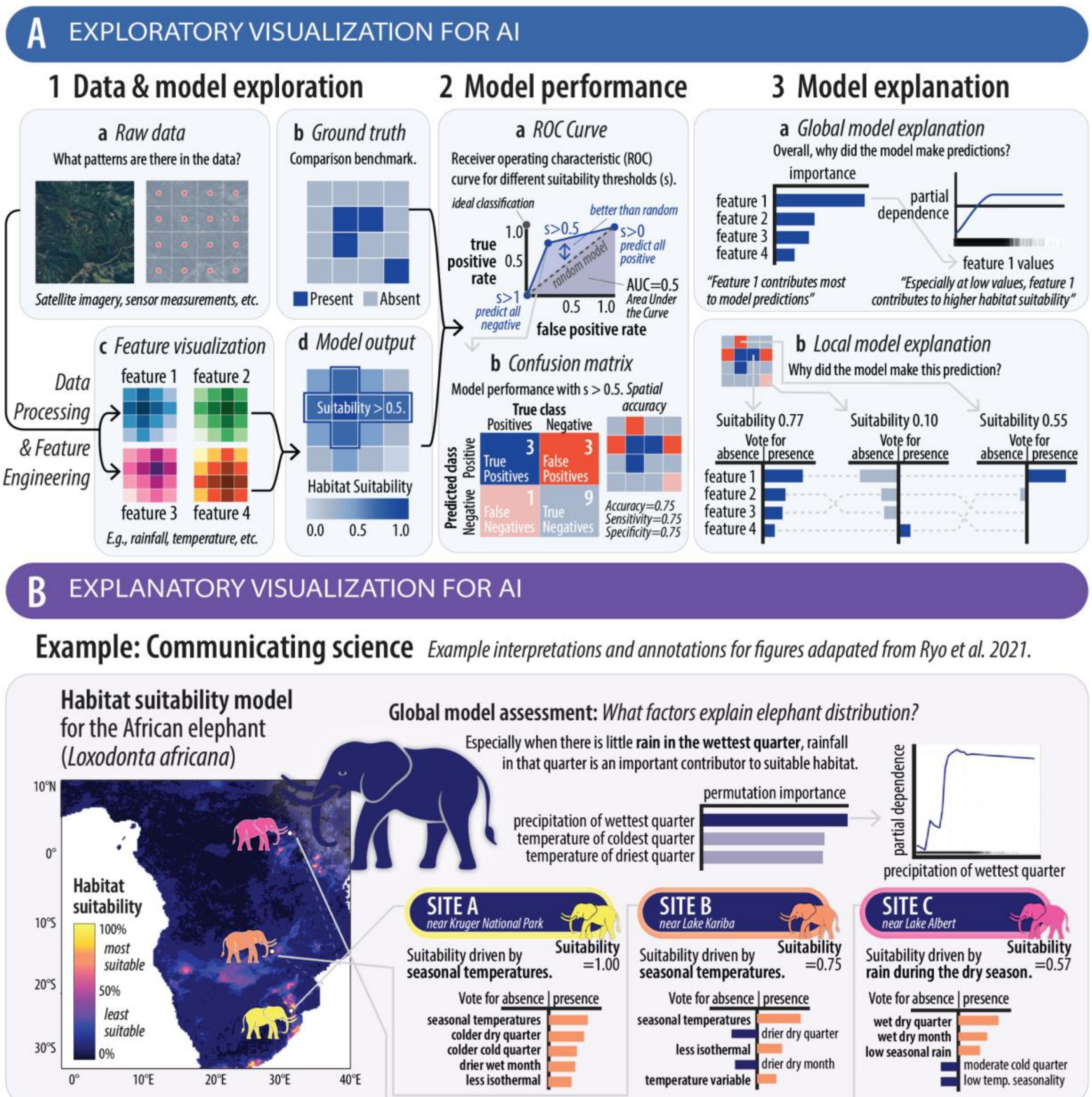

***Figure 3. (A) Exploratory visualizations** to understand AI models include: (**1) Data and model exploration:** (a) Raw data visualization, including satellite imagery and geospatial representations of species' presence/absence, (b) Feature visualizations (e.g., rainfall, temperature) used as model inputs, (c) Model output geospatial predictions of habitat suitability; **(2) Model performance:** (a) Receiver Operating Characteristic (ROC) curve illustrating the tradeoff between true positive rate and false positive rates at different habitat suitability thresholds (s), (b) Confusion matrix for a suitability threshold of 0.5, showcasing true/false positives and negatives, with accuracy ((TP+TN)/(P+N)), sensitivity (i.e., true positive rate; TP/(TP+FN)), and specificity (TN/(FP+TN)); **(3) Model explanation:** (a) Global explanations highlighting feature importance and partial dependence plots to interpret the contributions of key variables, (b) Local explanations illustrating feature-level contributions for individual predictions (possible using explainable AI methods like LIME or SHAP with bar*

plots to rank feature importance for specific predictions). ***(B) Explanatory visualization*** *composite infographic with plots and data adapted from Ryo et al. 2021 to provide example graphics, annotations, and interpretations that can guide the viewer to better understand AI model outputs. For additional details and references for LIME and SHAP, see the Supplemental Text.*

4. Computational resources

As researchers narrow in on the methods essential to their question, their key limitation may shift to their access and expertise with computation. Here, we define computational resources broadly to encompass the hardware and software to train and run AI models, including openly available labelled datasets, transferrable AI models (i.e. usable code repositories), data management systems, and cloud computing resources. Ecologists' use of computational methods, not just AI, is hindered by the lack of formal training on sharing data, curating code repositories, managing datasets, and accessing supercomputers (Stockwell et al., 2000). Open science and its growing support by funding agencies aim to democratize AI and accelerate computational science (Parashar & Altintas, 2023; Würthwein, 2024). Ecologists can act as partners in these efforts to better connect domain-specific needs and existing initiatives with new tools and best practices from AI and computer science.

Due to the large size of datasets and associated computing requirements, the use of AI is limited without cloud computing. Ecologists who want to use AI should familiarize themselves with broadly accessible cloud computing services such as Nautilus, the National Research Platform, designed to democratize AI internationally (NRP, 2024; Parashar & Altintas, 2023; Würthwein, 2024). Nautilus and other government-funded initiatives like ACCESS (NSF, 2024) leverage academic institutions to offer low-cost and scalable computational resources. Industry tools, such as Amazon Web Services or Google, can be more expensive but may offer more technical support. As ecologists leverage supercomputing to scale analyses, the non-negligible environmental impacts of AI (Strubell et al., 2020) can be partially alleviated by adjusting the extent, timing, and location of resource use (Dodge et al., 2022).

After adapting AI models to specific use cases, or even developing new models, ecologists often aim to share models and their training data with others, whether to meet publication requirements or to contribute to their communities of practice. Ecology-specific databases may not be designed to enforce existing best practices for AI datasets, such as benchmarking or datasheets for datasets (paper: Gebru et al., 2021; Overleaf template: Garbin, 2021). However, ecologists can learn and adopt AI-specific documentation methods, including dataset datasheets as well as AI model cards (paper: Mitchell et al., 2019; Markdown template: Garbin, 2020 & 2024). BioTrove is a large, well-documented benchmark dataset based on iNaturalist's Open Dataset (iNaturalist, 2024) images, scientific and common names, and taxonomic hierarchies with code and example cards for the data and model (paper: Yang et al., 2024b; website: Yang et al., 2024a). Standardized AI-specific documentation describes caveats associated with models and datasets, specifies appropriate downstream use, and facilitates open sharing via platforms like Hugging Face (Jain, 2022). For instance, the Cookiecutter Data Science framework also provides guidance for sharing AI models in Python; and these structures are flexible to accommodate complex data processing pipelines and model workflows (Rybicki, 2019). Ecologists who want to use AI can learn more about these best practices for Python as well as the recommendations for sharing ecological analyses done in R via research compendia, e.g. (Marwick et al., 2018). There is a growing need for educational materials and explicit recommendations for systematic AI model sharing for ecological audiences that may have less technical expertise or familiarity with Python- or AI-specific best practices.

For ecologists or computer scientists ready to start sharing their AI tools with others, we have curated a list of practical recommendations for how to best facilitate the adoption of these tools by ecologists with little technical training (Fig. S1). We have also illustrated what type of tool may best serve tool-adopters at different levels of technical proficiency and familiarity with ecological datasets and questions (Fig. S2.). Future work in AI in ecology can incorporate model cards and dataset datasheets into browsable model zoos, similar to the one for microscopy computer vision models with the BioImage Model Zoo (Ouyang et al., 2022). We have curated a starter-pack Model Zoo for AI models in Ecology on our website (ecoviz-ai.github.io [Kendall-Bar et al. 2024a] and in supplemental information) which can receive new contributions via Github (Kendall-Bar et al. 2024b).

As more ecologists begin to use AI, the careful and generous sharing of models and datasets will help reduce the need to train models or re-label datasets. As data sharing and data availability statements become more prevalent (Jiao et al., 2024), journals will need to formally incentivize the review of data and code. For instance, the Journal of Open Source Software (JOSS, 2024) and Methods in Ecology and Evolution have dedicated editors for reviewing software, code, and data; we are also aware that other journals have prioritized maintaining data editors as key staff members (Muench, 2023). Practitioners of AI in ecology should be mindful of the ethical considerations associated with sharing code and data. Open-sourcing datasets or models used in large language models like ChatGPT present serious ethical concerns outside the scope of this manuscript (Cooper et al., 2024; Liesenfeld et al., 2023). We recommend that any ecologist new to AI familiarize themselves with the ethical guidelines set forth by NeurIPS and others as they begin to implement and share AI models (NeurIPS, 2024). Within the scope of environmental science, data management plans co-designed with Indigenous and local knowledge-holders have innovated upon open data frameworks like FAIR and CARE to provide local context labels that indicate provenance, protocols, or permission tied to disseminated materials that could contain culturally sensitive or sacred information (Anderson & Christen, 2013; Carroll et al., 2021). Overall, a cultural shift towards incentivizing conscientiously open, modular, and expandable tools moves away from redundant, proprietary, or opaque analyses and contributes to more transparent, robust, and defensible science (Brunsdon & Comber, 2021; Czapanskiy & Beltran, 2022).

(5) Conclusion

The use of AI in ecology is quickly gaining momentum, offering unprecedented opportunities to speed and scale ecological research (Christin et al., 2019). There are several important challenges to leveraging AI for ecology, ranging from a lack of trust in AI approaches to the risk of overeager, undiscerning, and potentially dangerous implementation of existing models. Despite these risks, there are many cases where AI presents significant opportunities and low risk for automating tedious manual tasks or leveraging large datasets (Besson et al., 2022; Galaz García et al., 2023; Han et al., 2023). Here we reviewed the key challenges and solutions facing ecologists seeking to leverage AI in their research. When the benefits of AI outweigh the risks, we argue that ecologists are likely to be dissuaded from using AI due to practical challenges such as: (1) the opportunity costs while understanding the risks and opportunities of AI, (2) an overwhelming landscape while selecting and implementing a model, (3) a transparency deficit when interpreting model performance and function, and (4) the implementation burden when attempting to modify models, scale their use, and share tools with others. Addressing and/or alleviating these challenges likely requires a multifaceted approach combining: (1) educational resources to create openly available informal and formal learning resources, (2) communities of practice to create interdisciplinary and inclusive environments for technical social learning, (3) effective visualizations to interpret and communicate the functionality and performance of models, and (4) computational resources for adapting models, scaling deployments to large datasets, and sharing data, code, and lessons learned with the research community.

Our initiative, EcoViz+AI, has created a website that collates several AI-related resources for ecological researchers (ecoviz-ai.github.io [Kendall-Bar et al., 2024a] and in supplemental information). There, we have curated a list of communities of practice to connect ecological researchers to initiatives in the field of ecology and AI. To reduce the time spent looking for models, we have also curated a list of AI tools into a model zoo. We describe five case studies for AI in Ecology with science communication videos (see supplement for more information). We invite others to contribute additional models or communities of practice via Github (Kendall-Bar et al., 2024b).

Looking to the future, a cultural shift is needed to emphasize and reward efforts to produce open and reproducible science that promotes the responsible reuse of data, code, and models (Czapanskiy & Beltran, 2022; Gundersen et al., 2018). This cultural shift is already underway, as ecologists replace perceived barriers to sharing data and code with the recognition that these efforts will ultimately save us time, help us establish explicit data sharing agreements, avoid proprietary formats, and help us contribute to communities of practice (Gomes et al., 2022). While the benefits of open science are not exclusive to AI, efforts to empower the responsible use of AI are strengthened when deployed synergistically with broad, interdisciplinary initiatives to increase computational and scientific literacy, such as the AAAS Vision and Change Action Plan for undergraduate education (Woodin et al., 2009). AI presents an opportunity to harness new momentum, cyberinfrastructure, and computational techniques to incentivize responsible and generous sharing of resources to educate, train, and empower the next generation of ecologists.

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Supplemental Information

Glossary

Artificial Intelligence (AI): In this paper and in the context of Ecology, AI refers to a broad range of computational techniques, including machine learning and deep learning, used to process data, make inferences, and support decision-making. AI encompasses systems that can perform tasks that typically require human intelligence, such as recognizing patterns, making predictions, and generating new hypotheses. See also Figure 1 for a spectrum of models that fit within and outside of our workshop participants' definition of AI.

AI model: A model in AI refers to a mathematical representation or algorithm designed to learn patterns from data and make predictions or decisions based on that learning. In ecology, AI models can range from simple statistical models to complex deep learning architectures, each tailored to specific research questions and data types.

AI risk: AI risk refers to the potential negative consequences or uncertainties associated with the application of AI in ecological research. These AI risks can stem from model errors, biases, ethical concerns, and the amplification of inaccuracies through downstream applications. Managing these AI risks is crucial to ensure reliable and ethical AI implementations.

AI interpretability: AI interpretability is the ability to understand and explain how an AI model makes its predictions. This involves illustrating the internal workings and prediction-making processes of the model, often through visualizations, diagnostics, and transparent methodologies. High interpretability is essential for building trust and ensuring that AI models are used appropriately in ecological studies while increasing reproducibility.

AI tool: A tool in the context of AI and ecology is any software application, platform, or framework that facilitates the implementation, interpretation, or dissemination of AI models. AI tools can include libraries for data processing, visualization software, interactive platforms for model deployment, and frameworks for collaborative research and reproducibility.

Black-box deep learning models: AI models, often based on deep neural networks, whose internal decision-making processes are opaque or not easily interpretable.

Human-in-the-loop: A methodology in AI that integrates human input at various stages of the model development or application process. In ecology, human-in-the-loop approaches can involve tasks like labelling or annotating data, validating model outputs, or guiding decision-making, ensuring that AI outputs are aligned with expert knowledge and practical needs.

EcoViz+AI Workshop Description

Our week-long EcoViz+AI: Visualization and AI for Ecology workshop (ecoviz-ai.github.io) focused on five examples of AI's use cases in Ecology in active areas of research by workshop attendees. Each example involved data processing, highlighting that this is an area where ecologists are particularly interested in leveraging AI, due to the high potential to speed up tedious manual labor and leverage large datasets with relatively little consequence for model errors, especially when human review is involved. The five use cases were: (1) adapting the BioCLIP (Stevens et al., 2023) model for annotating citizen science photos on Flickr, (2) refining OpenSoundscape (Lapp et al., 2023) to classify Southern California blue whale vocalizations, (3) applying TagLab (Pavoni et al., 2021) image segmentation software to annotate coral reef imagery, (4) adapting Scikit-learn (Pedregosa et al., 2011) and LightGBM (Microsoft, 2024) classifiers to label sleep states in wild animals, and (5) applying TensorFlow (TensorFlow Developers, 2024) to classify Great Lakes fish using sound. We have collated these examples, along with science communication videos explaining each, into a repository specific to our case studies ("Case Studies" tab on ecoviz-ai.github.io) alongside a more comprehensive model zoo for other ecological models ("Model Zoo" tab on website). We invite others to contribute additional models or communities of practice via Github (github.com/ecoviz-ai/ecoviz-ai.github.io).

To cultivate an inclusive community of practice, we hired a science facilitator as well as a workshop organizer to guide a collective discussion on community agreements, continuously seek feedback to iterate with attendees, and structure the workshop agenda with a mix of seminars, collaborative work sessions, and intentional social engagement. We also hired a technical facilitator to create interactive coding sessions and shared computational resources for code, data, and computing (Github, FigShare, Nautilus).

During the workshop, we observed first-hand the benefits of education, communities of practice, visualization, and computational resources for adopting AI for ecology. Collaboration and peer-to-peer learning significantly reduced the time required to select, implement, and evaluate ecologically-relevant models. Visualization, whether by hand-drawn diagrams or interactive dashboards, critically facilitated peer learning by allowing team members to communicate key features of datasets, model functions, and performance. Even at a well-resourced institution and among participants who were mostly familiar with Python, considerable effort had to be allocated to ensure each person could access the computational resources for collaboration. A team of technical synthesis facilitators created repository templates and helped participants leverage new cyberinfrastructure initiatives through Nautilus and the National Data Platform. This enabled participants to create accessible computational ecosystems complete with data downloaded from Figshare, code from Github, and specific Python libraries via containerized Docker images. Beyond the technical aspects of the workshop, participants remarked that the value of this type of community of practice is not only in learning tools, but also in learning to critically assess the use of AI in our field.

Explainable AI: Extended description for Figure 3

Ecologists interested in implementing AI must also become familiar with using exploratory visualizations to explain model behavior (Fig 3A3), either locally (i.e., a specific prediction by the model) or globally (i.e., the behavior of the model as a whole). Visualizations are often the most straightforward way to interpret the outputs of "Explainable AI" methods, which allow humans to understand how AI systems make decisions (Alicioglu & Sun, 2022). While global explanations such as permutation importance and partial dependence help explain what features are important to model behavior overall (Fig. 3A3a), local explanations can be particularly helpful for understanding spatially-explicit species distribution models. Bar plots often represent the output of feature-ranking tools such as LIME (Local Interpretable Model-Agnostic Explanations) to detail, for a single location the extent to which each feature contributes to a vote for absence or presence in such a suitability model (Fig. 3A3b). In Figure 3B, we adapt a figure from a study that used LIME to provide local explanations for an SDM for African elephants (Ryo et al., 2021). In this case, LIME demonstrated that the feature that was most important globally (precipitation of the wettest quarter) was different from those that drove predictions at individual sites (Ryo et al., 2021). Bar plots can also represent outputs from SHAP (SHapley Additive exPlanations) a tool that uses concepts borrowed from game theory to assign marginal contributions (i.e., Shapley values) for each feature for a specific model prediction (Molnar, 2024). SHAP has been used to identify important environmental variables for predicting fishing grounds of albacore in the Atlantic Ocean (Zhang et al., 2025). For time series data, time series forests can efficiently generate temporal importance curves that can be used to show the most important feature at a given time (Fig. 5 adapted from (Deng et al., 2013)). For images, a variety of methods in addition to SHAP and LIME including Grad-CAM (Gradient-weighted Class Activation Mapping) can be used to identify sources for misclassification by CNN deep learning models, such as a new leaf improperly identified as an animal in camera trap imagery (Selvaraju et al., 2017; Velasco-Montero et al., 2023).

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Considerations for tool developers to facilitate adoption of AI in Ecology

Here we present several practical recommendations for ecologists or engineers seeking to design AI tools for Ecology, from the perspective of enhancing accessibility and usability of these tools. We recognize that tools developed by ecologists and engineers are often shaped by funding and time constraints, which drive tradeoffs that affect how effectively they can tailor tools to different audiences or end goals (Fig. S2). Some aspects of this guide are more technical than others; our hope is that ecologists can find value in the different sections in accordance with their goals, experience, and values (e.g., sharing adapted models, building custom models, or standalone software, assessing the use of a tool for decision-making). These recommendations apply regardless of whether ecologists and their collaborators are developing new models and tools or refining existing ones. We summarize our key recommendations in Figure S1.

1. **Project planning - *Usability:*** When planning a new tool, researchers should consider their audience's goals and competencies to provide appropriate technical and theoretical documentation for both users and developers (Fig. S2). The extensiveness of documentation will depend on the tool type that the researchers decide to create.
    a. **Theory documentation:** Beyond software usability, does the tool provide ecological and AI context to understand the tools' scientific implications?
    b. **User documentation:** Are the instructions adequate for reproducibility by an ecologist with minimal software development expertise?
    c. **Developer documentation:** Are the instructions adequate for modifiability or extensibility by software developers?

    To assess usability, we should consider a tool's key audience and its users' presumed competencies, as the depth and standardization will vary greatly based on the tool type (Fig. S2). To document the ecological and AI theory behind the tool, a vignette with a short video can be used to succinctly describe the model's relevance and function. Theory documentation can also point users to open-access educational materials and lectures on the model in question. Visualizations should be included throughout the documentation to help illustrate the function of the model including model performance metrics as well as diagnostic visualizations. Tools developed for ecologists who are often not formally trained in software engineering should contain adequate instructions to deploy the model and run the tool based on the documentation provided (Rule et al., 2019). Step-by-step instructions should be provided to run the model with a small dataset as well as to modify the existing code base to accommodate differences in dataset format or model objective. For developers, documentation should outline desirable feature contributions and the preferred methods for implementing them.

2. **Model selection - *Ecological value:*** The ecological value of a tool can be assessed by its relative **timeliness** in addressing the needs of its community, its **relevance** to ecological questions, and its ability to **minimize consequences** associated with its errors or misapplication.
    a. **Timeliness:** Does this tool address the community's current and anticipated, future needs?
    b. **Relevance:** Is the tool relevant to answer the proposed ecological question?
    c. **Risk mitigation:** How does the tool manage risks associated with its errors or misapplication?

    Ecological value of an AI tool could be evidenced by the number of recent perspectives, reviews, or synthesis papers calling for features of the tool or the tool itself. After the tool has been released, its relevance and timeliness can be reflected through paper citations, the number of downloads, or attendance for related workshops, courses, and seminars. The extensive use of tools like eBird, Merlin, and HappyWhale indicates the value of these tools to ecologists and community members alike (Cheeseman et al., 2017;

Sullivan et al., 2014). It is important to note that these metrics may not fully capture the value of AI applications that attract fewer users, whether that be due to smaller scientific communities, a lack of funding or perceived value, or the difficulty or risks associated with AI implementation. Therefore, it is important to critically assess our biases when considering the value of method development for less charismatic species, lesser-known ecosystems, and understudied areas of the world. In terms of risk mitigation, the consequences of a model error must either be low impact or able to be mitigated by human review at each stage (model selection, implementation, and dissemination). If the tool influences local conservation policy, the tool should implement plans for equitable handling of sensitive information, ensuring diverse datasets and perspectives, reviewing model outputs, and communicating the research back to the local community, using their feedback as a tool for risk mitigation.

3. **Model implementation - *Modifiability:*** A tool's modifiability refers to its compartmentalization into modular components that can be built upon (extensibility) and repurposed (depends on licensing).
    a. **Modularity:** How modular is the tool?
    b. **Extensibility:** How easily can one build on the tool?
    c. **Licensing:** How can the tool be used?

    To enhance AI tool modifiability, developers should consider how and whether certain audiences should be able to access, modify, and add to their tools. Licenses like GPL (GNU Public license) or MIT allow complete modification and reuse, promoting the development of open-source software (German & González-Barahona, 2009; Saltzer, 2020). Open-sourcing datasets or models for large language models like ChatGPT presents serious ethical concerns, which are beyond the scope of this manuscript (Liesenfeld et al., 2023). Within the scope of environmental science, data management plans co-designed with Indigenous and local knowledge holders should promote data sovereignty through frameworks like FAIR and CARE to provide local context (Carroll et al., 2021). For example, local context labels include Traditional Knowledge labels to indicate provenance, protocols, or permission tied to disseminated materials that could contain culturally sensitive or sacred information (Anderson & Christen, 2013). Tools should be organized modularly with self-sufficient modules or functions to facilitate the reuse and modification of individual components. Extensibility can be facilitated with test frameworks for adding new features (e.g. pytest and continuous integration) and documentation for how to integrate changes and additions to software.

4. **Model interpretation - *Transparency:***
    a. **Visualization**: Does the tool provide effective visualizations that help interpret the AI model's function? Are those the same that can be used to communicate with different audiences with different baseline expertise?

b. **Diagnostics:** Does the tool provide useful and informative model diagnostics?
c. **Complexity:** How complex is the tool? Does this impact its explainability?

Visualizations and statistics are critical to build trust in an AI model by understanding its function and performance. This includes visualizing data alongside model outputs, including raw and processed datastreams as well as manual labels, model performance metrics, and model diagnostics. Interactive visualizations that allow the user to adjust model hyperparameters can help explain the impact of these choices on model performance. Additionally, iterative visual interfaces can facilitate human-in-the-loop workflows where experts review data, images, or sound associated with model predictions. Model diagnostic visualizations should go beyond the performance of the model to allow the viewer to review the function of the model, using tools like attention scores and Shapley values. Visualizations should include a mix of modalities accessible to domain experts, AI model developers, and non-experts. Especially when using more complex AI models and in decision-making contexts, these visualizations and model diagnostics will increase explainability and trust (Ryo et al., 2021).

5. **Model dissemination - *Reproducibility:***
   a. **Installation:** Can the tool be installed easily?
   b. **Reproducibility:** Can the tool be used to replicate a computational experiment?
   c. **Product sustainability:** Will the tool be maintained reliably in the future?

Methods for ensuring a tool's availability and functionality over long periods may vary depending on the tool type and project funding structure. Besides research compendia, all other tool types require significant ongoing investment to ensure they are accessible and functioning as technology changes. While practical challenges sometimes arise, a research compendium theoretically allows flawless reproducibility at any time in the future by pointing to previous software versions and explicitly specifying the configuration of computational environments. Many tools rely on the user to have a base knowledge of Python, which is less commonly taught to ecologists than R. Python package managers can help facilitate reproducibility by managing dependencies, but can present steeper learning curves for ecologists who are more familiar with R than Python. At a minimum, each Python tool should include a list of dependencies and could further facilitate reproducibility by including YAML configuration files for virtual containerization via Docker. Step-by-step tutorials could be helpful additions to help newcomers install or run Python and Docker. Other technical best practices for reproducibility include minimizing the number of dependencies, absolute file paths, the length of individual scripts, and the overall complexity of the analytical pipeline. While most software and web applications are supported by teams of full-time developers, many packages and libraries for ecology are maintained by small teams of volunteers. To create sustainable support for these community-led efforts, a cultural shift is needed to honor and fund long-term work that curates and maintains analytical tools to better train and equip the next generation of ecological researchers.

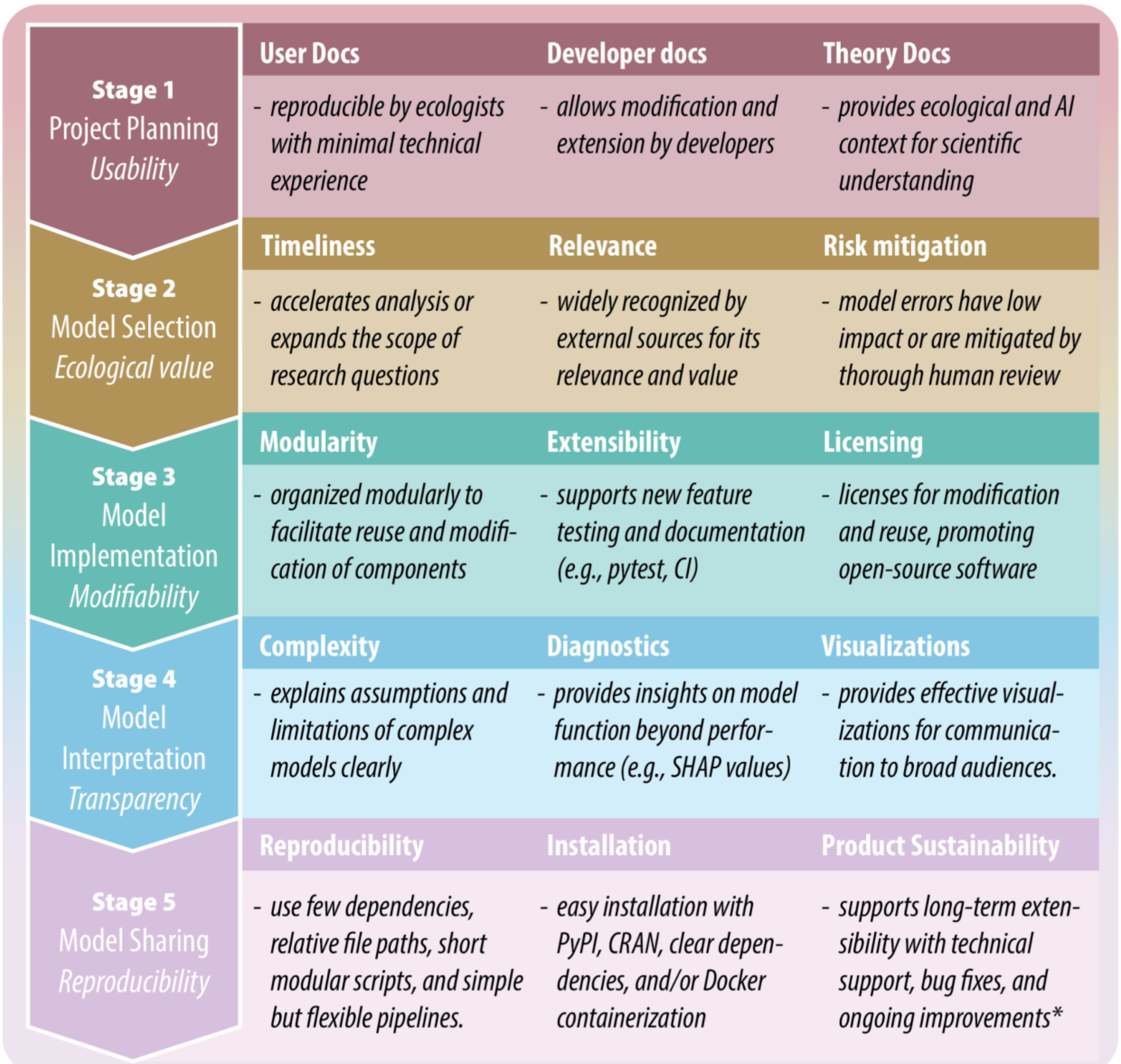

Figure S1. *Recommendations and best practices for ecologists creating AI tools that are: (1) usable (have documentation for users, developers, and theory), (2) ecologically valuable (timely, relevant, and risk-mitigating), (3) modifiable (modular, extensible, and openly licensed), (4) transparent (manage complexity through model diagnostics and visualization), and (5) reproducible (reproducibility through coding best practices, easy installation, and long-term software sustainability). *The quality and continuity of technical support and tool improvement will depend directly on funding and an accompanying culture that rewards the long-term maintenance of community-led tools.*

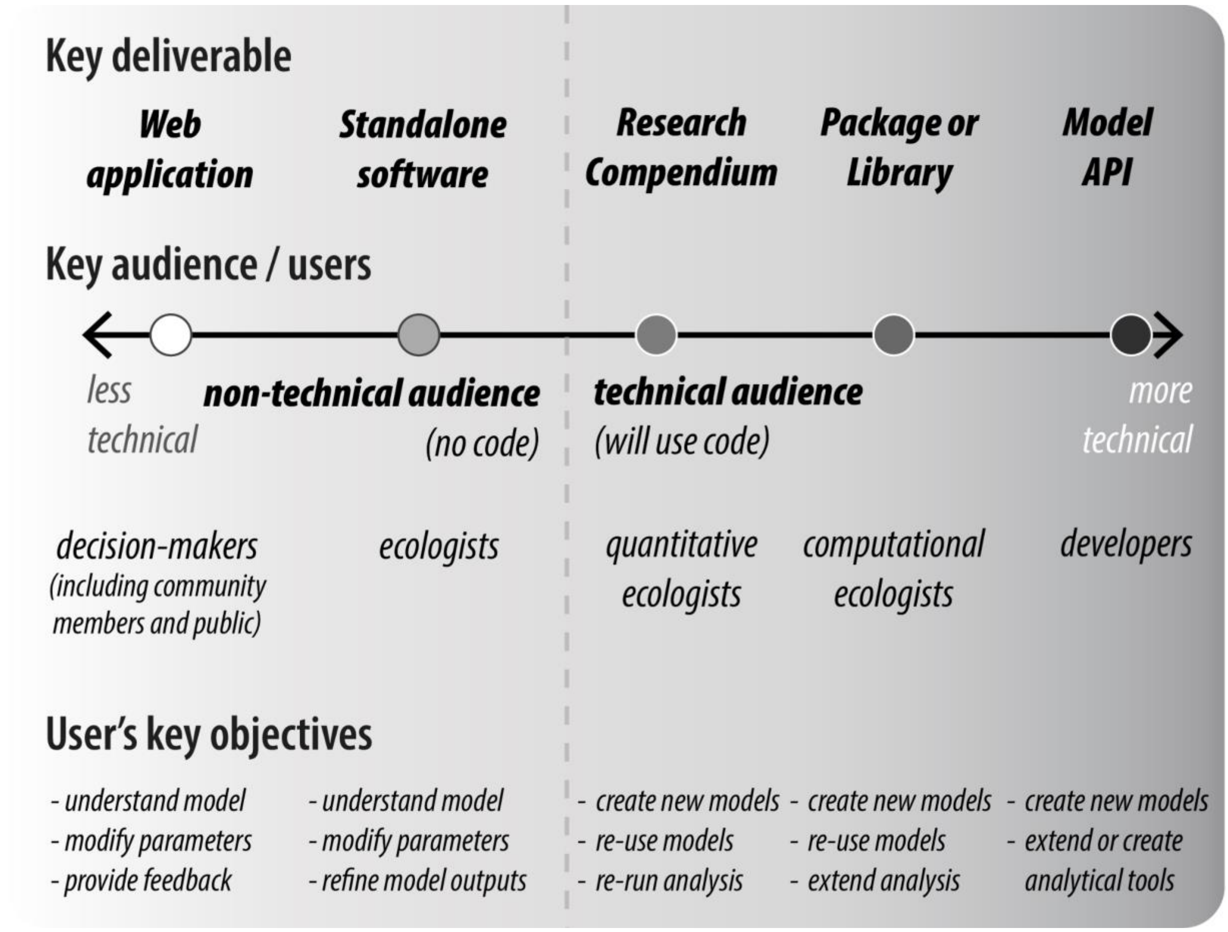

Figure S2. *Schematic diagram of the spectrum of AI tool types and their corresponding audiences. Less technical users, such as decision-makers or community members, may prefer interactive tools like web applications or standalone software that require minimal coding. Moderately technical users, such as ecologists with some coding background, may engage with research compendiums that combine data, code, and documentation into reproducible repositories. Highly technical users, including computational ecologists and developers, may favor customizable packages, libraries, or APIs for data sharing and model deployment. This framework emphasizes user-centered design to align tool development with audience competencies, goals, and shared values like equity, reproducibility, and open science.*

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Ecology+AI Model Zoo Starter Pack

1. **Model Name:** yasa
   Description: YASA (Yet Another Spindle Algorithm) is a command-line sleep analysis toolbox in Python with automatic sleep staging and signal processing functions.
   Broad task: Timeseries segmentation
   Specific task: Sleep Scoring
   Language(s): Python
   Tool URL (Github or Link): https://github.com/raphaelvallat/yasa
   Ecology specific: No
   Related publication (with DOI): https://doi.org/10.7554/eLife.70092
   Model type: Gradient Boosted Decision Tree
   Contact email: raphaelvallat9@gmail.com
   Contact name: Raphael Vallat
   Key package dependencies: antropy, ipywidgets, joblib, lightgbm, lspopt, matplotlib, mne, numba, pandas, pyRiemann, scikit-learn, scipy, seaborn, sleepecg, tensorpac
   Last Update (time since): Last updated within the month
   License: BSD-3-Clause
   Task specific: Yes
   Tool Type: Package or Library

2. **Model Name:** somnotate
   Description: Probabilistic sleep scoring software to combine linear discriminant analysis (LDA) and hidden Markov models (HMM).
   Broad task: Timeseries segmentation
   Specific task: Sleep Scoring
   Language(s): Python
   Tool URL (Github or Link): https://github.com/paulbrodersen/somnotate/tree/master
   Ecology specific: No
   Related publication (with DOI): https://doi.org/10.1371/journal.pcbi.1011793
   Model type: Hidden Markov Model
   Contact email: paulbrodersen+github@gmail.com
   Contact name: Paul Brodersen
   Key package dependencies: matplotlib, numpy, pomegranate, scikit-learn
   HuggingFace URL:
   Last Update (time since): Last updated within 6 months
   License: GNU General Public License
   Reproducibility methods:
   Task specific: Yes
   Tool Type: Package or Library

3. **Model Name:** silbido profundo
   Description: An open source package for the use of deep learning to detect odontocete whistles.
   Broad task: Acoustics processing
   Specific task: Tonal Call Detection
   Language(s): C, C++, Java, MATLAB
   Tool URL (Github or Link): https://github.com/MarineBioAcousticsRC/silbido
   Ecology specific: Yes
   Related publication (with DOI): https://doi.org/10.1121/10.0016631
   Model type: Convolutional Neural Network, Graph Search Algorithms

Contact email: marie.roch@sdsu.edu
Contact name: Marie Roch
Last Update (time since): Last updated within 6 months
Reproducibility methods: makefile
Task specific: Yes
Tool Type: Package or Library

6. **Model Name:** BioLingual
Description: Text prompt to search through audio by species, call type, or verbal description. Also receives audio input.
Broad task: Acoustics processing
Specific task: Call Identification
Language(s): Python
Tool URL (Github or Link): https://github.com/david-rx/BioLingual
Ecology specific: Yes
Related publication (with DOI): https://doi.org/10.48550/arXiv.2308.04978
Model type: Transformer
Contact name: David Robinson
Key package dependencies: pytorch, torchvision, transformers, etc.
HuggingFace URL: https://huggingface.co/davidrrobinson/BioLingual
Last Update (time since): Last updated within a year
License: Apache-2.0
Reproducibility methods:
Task specific: Yes
Tool Type: Model API

7. **Model Name:** noisereduce
Description: noisereduce is a domain-general noise reduction tool for bioacoustics and other time domain signals.
Broad task: Acoustics processing
Specific task: Signal Processing
Language(s): Python
Tool URL (Github or Link): https://github.com/timsainb/noisereduce
Ecology specific: No
Related publication (with DOI): https://doi.org/10.1371/journal.pcbi.1008228
Model type: Neural Network, Preprocessing, Spectral Gating
Contact email: timsainb@gmail.com
Contact name: Tim Sainburg
Key package dependencies: numpy, pytorch, scipy
Last Update (time since): Last updated within 6 months
License: MIT
Task specific: Yes
Tool Type: Package or Library

8. **Model Name:** OpenSoundscape
Description: Python package for analyzing bioacoustic data.
Broad task: Acoustic classification
Specific task: Call Identification, Signal Processing
Language(s): Python
Tool URL (Github or Link): https://github.com/kitzeslab/opensoundscape
Ecology specific: Yes

Related publication (with DOI): https://besjournals.onlinelibrary.wiley.com/doi/10.1111/2041-210X.14196
Model type: Convolutional Neural Network
Contact email: sam.lapp@pitt.edu
Contact name: Sam Lapp
Key package dependencies: docopt, ipykernel, librosa, pandas, pytorch, torchvision
Last Update (time since): Last updated within the month
License: MIT
Task specific: Yes
Tool Type: Package or Library

9. **Model Name:** xPLNet
Description: AI classification of leaf pictures into different environmental stresses/diseases. Explainable model.
Broad task: Image classification
Specific task: Plant stress phenotyping
Language(s): Python
Tool URL (Github or Link): https://github.com/SCSLabISU/xPLNet
Ecology specific: Yes
Related publication (with DOI): https://www.pnas.org/doi/10.1073/pnas.1716999115
Model type: Convolutional Neural Network
Contact email: soumiks@iastate.edu; arti@iastate.edu
Contact name: Soumik Sarkar; Arti Singh
Key package dependencies: keras, numpy, theano
Last Update (time since): Last updated more than a year ago
License: BSD-3-Clause
Task specific: Yes
Tool Type: Research Compendium

10. **Model Name:** HappyWhale
Description: AI-assisted individual ID of humpback whale flukes and multi-species dorsal fin ID.
Broad task: Image classification
Specific task: Marine mammal photo identification
Language(s): Java, Python, Typescript
Tool URL (Github or Link): https://happywhale.com/home
Ecology specific: Yes
Related publication (with DOI): https://rdcu.be/cCOtw
Model type: Computer vision
Contact email: ted@happywhale.com
Contact name: Ted Cheeseman
Last Update (time since): Last updated within the month
Task specific: Yes
Tool Type: Web GUI

11. **Model Name:** BioCLIP
Description: BioCLIP is a computer vision model, fine-tuned for species identification.
Broad task: Image classification
Specific task: Species Identification
Language(s): Python
Tool URL (Github or Link): https://github.com/Imageomics/bioclip

Ecology specific: Yes
Related publication (with DOI): https://arxiv.org/abs/2311.18803
Model type: Convolutional Neural Network, Transformer
Contact email: stevens.994@buckeyemail.osu.edu
Contact name: Samuel Stevens
Key package dependencies: open_clip
HuggingFace URL: https://huggingface.co/imageomics/bioclip
Last Update (time since): Last updated within the month
License: Custom License
Task specific: Yes
Tool Type: Package or Library

12. **Model Name:** SatBird
Description: SatBird is a dataset and benchmark model for the task of predicting bird species encounter rates jointly at a specific location using remote sensing data.
Broad task: Species distribution model
Specific task: Habitat suitability
Language(s): Python
Tool URL (Github or Link): https://github.com/RolnickLab/SatBird/
Ecology specific: Yes
Related publication (with DOI): https://doi.org/10.48550/arXiv.2311.00936
Model type: Convolutional Neural Network, ResNet, SATLAS, SatMAE
Contact email: tengmeli@mila.quebec
Contact name: Melisande Teng
Key package dependencies: pytorch, torchaudio, torchvision, etc.
Last Update (time since): Last updated within 6 months
License: GPL-3.0
Reproducibility methods: makefile
Task specific: Yes
Tool Type: Benchmarked Dataset

13. **Model Name:** Voxaboxen
Description: Voxaboxen is a deep learning framework designed to find the start and stop times of (possibly overlapping) sound events in a recording.
Broad task: Acoustic classification
Specific task: Call Identification
Language(s): Python
Tool URL (Github or Link): https://github.com/earthspecies/voxaboxen
Ecology specific: Yes
Related publication (with DOI): https://doi.org/10.5281/zenodo.8381019
Model type: AVES, Transformer
Contact email: benjamin@earthspecies.org
Contact name: Benjamin Hoffman
Key package dependencies: PyYAML, einops, intervaltree, librosa, matplotlib, mir_eval, numpy, pandas, plumbum, pytorch, scipy, seaborn, soundfile, torchaudio, tqdm
Last Update (time since): Last updated within 6 months
License: AGPL-3.0
Task specific: Yes
Tool Type: Package or Library

14. **Model Name:** Ecological Niche Modelling With R
    Description: A workflow to simplify the process of estimating spatial probability distributions (species presence/absence) given a set of environmental parameters.
    Broad task: Species distribution model
    Specific task: Ecological Niche Modeling
    Language(s): R
    Tool URL (Github or Link): https://github.com/cybprojects65/EcologicalNicheModellingWithR
    Ecology specific: Yes
    Related publication (with DOI): https://doi.org/10.1007/s41060-024-00517-w
    Model type: MaxEnt, Neural Network
    Contact email: gianpaolo.coro@isti.cnr.it
    Contact name: Gianpaolo Coro
    Last Update (time since): Last updated within 6 months
    Task specific: Yes
    Tool Type: Research Compendium

15. **Model Name:** Merlin Sound ID Bird App
    Description: An app for identifying birds to species level worldwide.
    Broad task: Acoustic classification
    Specific task: Species Identification
    Language(s): Python
    Tool URL (Github or Link): https://merlin.allaboutbirds.org/
    Ecology specific: Yes
    Related publication (with DOI): https://doi.org/10.1371/journal.pcbi.1001220
    Model type: Convolutional Neural Network, MobileNet
    Last Update (time since): Last updated within 6 months
    Task specific: Yes
    Tool Type: Mobile App

16. **Model Name:** FrogID App
    Description: An app for identifying frogs to species level worldwide.
    Broad task: Acoustic classification
    Specific task: Species Identification
    Language(s): Python
    Tool URL (Github or Link): https://www.frogid.net.au/
    Ecology specific: Yes
    Related publication (with DOI): https://doi.org/10.1093/biosci/biad012
    Model type: Convolutional Neural Network
    Contact email: jodi.rowley@unsw.edu.au
    Contact name: Jodi Rowley
    Task specific: Yes
    Tool Type: Mobile App

Ecology+AI Communities of Practice Starter Pack

1. **Community Name:** ABC AI and Biodiversity Change
   Description: A global center to develop and implement a variety of AI-based methods and tools for integration and analysis of biodiversity data from remote sensing imagery from satellites and low-flying aircrafts, ground-based visual and audio sensors, DNA sequences, and citizen science efforts, enabling the global monitoring, analysis, and assessment of biodiversity changes.
   Website: https://abcclimate.org
   LinkedIn: https://www.linkedin.com/company/abc-global-center/
   Organizations: MIT, McGill University, Ohio State University, University of British Columbia, University of Guelph, University of Pittsburgh
   Funding Organizations: NSF, NSF NSERC, NSF OISE
   Tags: AI, biodiversity, climate

2. **Community Name:** EcoViz+AI
   Description: An international community of practice to discuss and democratize AI and visualization for use cases in ecology.
   Website: https://ecoviz-ai.github.io
   Organizations: Cornell University, Ohio State University, Oxford University, San Diego Supercomputer Center, Scripps Institution of Oceanography, UC San Diego, UC Santa Cruz, University of Michigan, University of Moncton, University of Toronto
   Funding Organizations: Schmidt Sciences
   Tags: AI, biodiversity, climate change, conservation, cyberinfrastructure, ecology, education, visualization

3. **Community Name:** OceanVisionAI
   Description: An initiative for annotating video and imagery data from deep sea expeditions with citizen science - associated initiatives: https://fathomnet.org/ (database), https://www.fathomverse.game/ (game).
   Website: https://www.oceanvisionai.org/
   LinkedIn: https://www.linkedin.com/company/ocean-vision-ai/
   Organizations: MBARI
   Funding Organizations: Dalio Foundation, NOAA, NSF, Nat Geo, Packard Foundation
   Tags: AI, citizen science, deep sea, visualization

4. **Community Name:** eLife Community
   Description: eLife works with researchers across the globe to promote a research culture that values openness, integrity, equity, diversity, and inclusion.
   Website: https://elifesciences.org/community/
   LinkedIn: https://www.linkedin.com/company/elife-sciences-publications-ltd
   Funding Organizations: HHMI, Knut and Alice Wallenberg Foundation, Max Planck Institute, Wellcome
   Tags: ecology

5. **Community Name:** DSE Data Science & Environment
   Description: The Eric and Wendy Schmidt Center for Data Science & Environment (DSE) combines the power of computing and environmental science with open science principles and a commitment to inclusivity—all towards the purpose of building tangible, replicable, and accessible solutions to problems compromising the health of our environment.
   Website: https://dse.berkeley.edu/
   LinkedIn: https://www.linkedin.com/company/schmidtdse/

Organizations: Schmidt Sciences, UC Berkeley
Funding Organizations: Schmidt Sciences, UC Berkeley
Tags: AI, biodiversity, climate, ecology

6. **Community Name:** Imageomics Institute
   Description: The Imageomics Institute GitHub organization hosts the development and distribution of a collection of open-source ML tools used to study the biological information encoded in images and videos integrated with structured biological knowledge.
   Website: https://github.com/Imageomics/
   LinkedIn: https://www.linkedin.com/company/imageomics-institute
   Organizations: Ohio State University
   Funding Organizations: NSF
   Tags: AI, ecology

7. **Community Name:** EcoViz
   Description: A collaborative initiative to co-design climate data visualizations that leverage computational advances to display model outputs, communicate science, and inform policy and practice.
   Website: ecoviz.org
   LinkedIn: https://www.linkedin.com/company/ecoviz-collaborative-initiative-for-climate-visualization/
   Organizations: Center for Coastal Climate Resilience, San Diego Supercomputer Center, Scripps Institution of Oceanography, UC San Diego, UC Santa Cruz
   Funding Organizations: AXA Research Fund, Army Corps of Engineers, CalOES, Department of Homeland Security, Intervalien, NSF, SDG&E, Schmidt Sciences, State of California, The Nature Conservancy, The World Bank
   Tags: AI, climate, climate change, cyberinfrastructure, visualization

8. **Community Name:** AI4Life
   Description: Research services and infrastructure to support life scientists in the adoption of machine learning solutions that improve the utility and interpretability of image data – the key to future biological and biomedical research.
   Website: https://ai4life.eurobioimaging.eu/
   LinkedIn: https://www.linkedin.com/company/ai4life-eu-project
   Organizations: BioImage, European Marine Biological Resource Centre, KTH, Universidad Carlos III de Madrid
   Funding Organizations: European Union
   Tags: AI, cyberinfrastructure, ecology

9. **Community Name:** ClimateChangeAI
   Description: Climate Change AI is a global non-profit that catalyzes impactful work at the intersection of climate change and machine learning.
   Website: https://www.climatechange.ai/
   LinkedIn: https://www.linkedin.com/company/climatechangeai/
   Organizations: Google DeepMind, Centre for AI & Climate, Carbon Re, Schmidt Futures, Cornell Tech, etc.
   Funding Organizations: Google DeepMind, Centre for AI & Climate, Carbon Re, Schmidt Futures, Cornell Tech, etc.
   Tags: AI, climate, climate change