Human-centric skills are essential for the responsible and rigorous application of AI in ecology

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Abstract

Artificial Intelligence (AI) can rapidly process large ecological datasets, uncover patterns, and inform conservation decisions, but responsible adoption depends as much on human-centric skills as on technical methods. Ecologists face steep learning curves, an overwhelming and fast-evolving model landscape, uneven access to data and computing, and a growing transparency deficit. These challenges require human-centric skills like time management, critical thinking, collaboration, communication, creativity, and project management to select, implement, interpret, and responsibly translate AI outputs into ecological insight and action. We led a workshop, EcoViz+AI: Visualization and AI for Ecology, that brought together 35 experts to synthesize practical guidance for navigating these challenges across the AI pipeline. Using workshop discussions and experiences as a foundation, this position paper proposes practical solutions and complementary human-centric skill development to address these challenges: (1) educational resources that support opportunity-cost reasoning (time management) and methodological judgment (critical thinking), (2) communities of practice that build inclusive shared expertise (collaboration and mentorship), (3) effective visualizations that improve interpretability and strengthen transparency of model behavior and uncertainty (creativity and communication), and (4) computational resources that reduce implementation burden through shared data, extensible code, and accessible infrastructure (project management and problem-solving). Our workshop compiled resources, including science communication videos for five AI use cases and repositories for ecology-related AI models and communities of practice. Emphasizing human-centric skills and working in tandem with efforts to promote open science and computational literacy can make AI in ecology more rigorous, equitable, and ecologically relevant, advancing research and conservation.

Impact Statement

AI is increasingly used in ecology to automate data processing, support ecological inference, and inform conservation, yet ecologists may be deterred due to scientific, ethical, or practical concerns. As AI methods become more complex and competent, human-centric skills emerging from shared community values will remain valuable and essential to determine the appropriateness of AI and guide its implementation through mentorship, collaboration, and communication. We therefore propose four interventions that strengthen human-centric skills to promote scientific and ethical rigor while selecting, implementing, interpreting, and communicating AI models: educational resources to reason about opportunity-costs, communities of practice to cultivate expertise and accountability, visualizations to enable interpretation and trust, and computational resources to promote reproducibility and shared stewardship of hardware, data, models, and code.

Contents

1. Introduction

Applications of AI in ecology and evolution are now increasing the speed, scale, and resolution of computational analysis (Christin et al 2019). AI can help predict species responses based on environmental conditions, facilitate the integration of models and theory for complex systems-level understanding, and generate novel hypotheses to pave the way for conservation (Han et al 2023). 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 (Supplemental material: Opportunities and Risks for AI in Ecology). AI is increasingly used for data processing, for example to label sleep states from electrophysiological recordings (Allocca et al 2019) or to detect species and behaviors in large video, acoustic, and movement datasets (Christin et al 2019), substantially reducing the burden of manual annotation tasks. AI can also support ecological inference, for example by integrating labeled behaviors into habitat suitability maps that seek to explain and predict species distributions (Beery, Cole et al 2021). Finally, AI can support decision-making, where inferred ecological patterns can be incorporated into conservation planning and management tools, including reinforcement-learning frameworks that prioritize habitats or evaluate alternative conservation strategies (Lapeyrolerie et al 2022).

Despite these advances, 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 (JM Kendall-Bar 2024b); see Supplementary Material 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 (Sheikh et al 2023; Wang 2019).

Challenges regarding model selection, implementation, interpretation, and communication are not unique to AI, but the use of AI, especially "black-box" deep learning techniques, exacerbates challenges posed by traditional methods and computational analysis more broadly. Difficult-to-implement, rapidly proliferating AI techniques deepen transparency deficits (e.g. opacity in what data AI models use and how they function to make predictions), complicating clear communication of uncertainty and performance metrics. We therefore call for a renewed emphasis on human-centric skills, for which AI tools like chatbots are not suitable substitutes, along with practical solutions related to technical training, communities of practice, and science communication.

In this position paper, we argue that in addition to scientific and ethical barriers to AI adoption, ecologists encounter practical challenges to AI adoption that require a newfound emphasis on human-centric skills (a subset of which are often referred to as "soft" skills) that center creativity, collaboration, and critical thinking and are not easily offloaded to LLMs. We describe key challenges to AI adoption for ecologists including AI's: (1) **opportunity cost**, (2) **overwhelming landscape**, (3) **transparency deficit**, and (4) **implementation burden** (i.e. technical challenges involved in applying AI workflows, cyberinfrastructure, and data management systems). Critical bridges to practical solutions to these challenges are human-centric skills such as: (1) **time management** and **critical thinking**, (2) **collaboration** and **mentorship**, (3) **communication** and **creativity**, and (4) **project management** and **problem-solving**. We present four interventions that help foster these human-centric skills, including the development of: (1) **educational resources**, (2) **communities of practice**, (3) **effective visualizations**, and (4) **computational resources**. Overall, we believe an emphasis on human-centric skills will help ecologists considering adopting AI methods to navigate and apply AI methods with responsibility and rigor, while encouraging communities of practice that emphasize critical thinking, collaboration, and transparency.

2. Practical challenges: barriers to AI adoption in ecology

Alongside ethical and scientific concerns, ecologists encounter practical challenges in understanding when and how to implement AI over more traditional manual or statistical methods (Figure 2B). 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:

2.1. 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. Tools may be inappropriate or irrelevant because they do not accept a given data modality

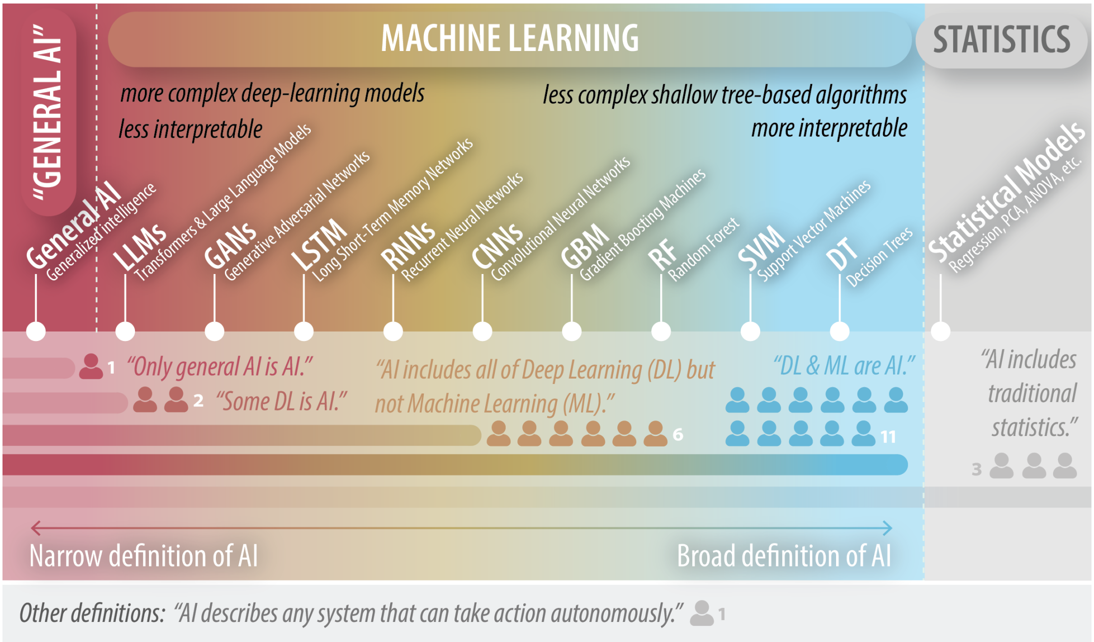

Figure 1. *A diagram describing our workshop participants' definitions of AI, showing a spectrum of AI models from less interpretable and more complex models on the left (darker red values) to more interpretable and less complex on the right (lighter blue values). Icons next to a definition represent votes from workshop participants. The spectrum is divided into three categories:* ***General AI*** *(or strong AI),* ***Machine Learning*** *(spanning from Deep Learning including Large Language Models [LLM], Generative Adversarial Networks [GAN], Long Short-Term Memory Networks [LSTM], Recurrent Neural Networks [RNN], and Convolutional Neural Networks [CNN] to simpler shallow tree-based algorithms such as 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])..*

(and transformation is not an option) or because the receptive field of a model (the temporal or spatial context a model has for a decision) is too wide or narrow to acquire context appropriate for relevant predictions. AI-based tools may be slow or require more processing than is ideal for the projects' scope or experimental design and could suffer from poor generalizability or adaptability to new systems. Additionally, most resources use programming languages that are less familiar to many 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.

2.2. 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 a maintained awareness of emerging technology and AI model types to continue assessing the relevance of new tools. Researchers must carefully consider the benefits and drawbacks of increasingly complex models in terms of decreased transparency and increased computational load (Pichler and Hartig 2023). This can be especially overwhelming for researchers who cannot draw on the collective knowledge of a community of experts. Mentorship, particularly informal, peer-to-peer mentoring within and across labs, plays a critical role in transferring practical knowledge about model assumptions, failure modes, and appropriate use cases that are rarely captured in documentation or tutorials. However, this labor is often invisible and undervalued, despite being essential for building collective competence and reducing barriers to responsible AI adoption.

2.3. 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.

2.4. 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, code repositories (organized in ways that may be unfamiliar to ecologists), or lack of access to computational resources. However, not all AI approaches are computationally intensive: small model architectures, shallow learning methods commonly used for ecological inference, and transfer learning strategies that adapt larger pretrained models can often be run on consumer-grade hardware and may require no more computational power than Bayesian estimation methods routinely used in ecology.

Once a researcher has decided to use a particular model, they may need to 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 and Mehler 2019). Once researchers have created useful tools, sharing them is often constrained by barriers: concerns about credit and reuse; the substantial "invisible labor" of preparing clean, well-documented code and datasets (e.g., metadata, datasheets, and model cards); and ethical constraints around releasing sensitive data (such as precise locations of endangered species or culturally sensitive information) (Gomes et al 2022). Even when researchers want to share, long-term maintenance (including dependency management, compute requirements, benchmarking, and user support) can be difficult to sustain under current academic incentives (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.

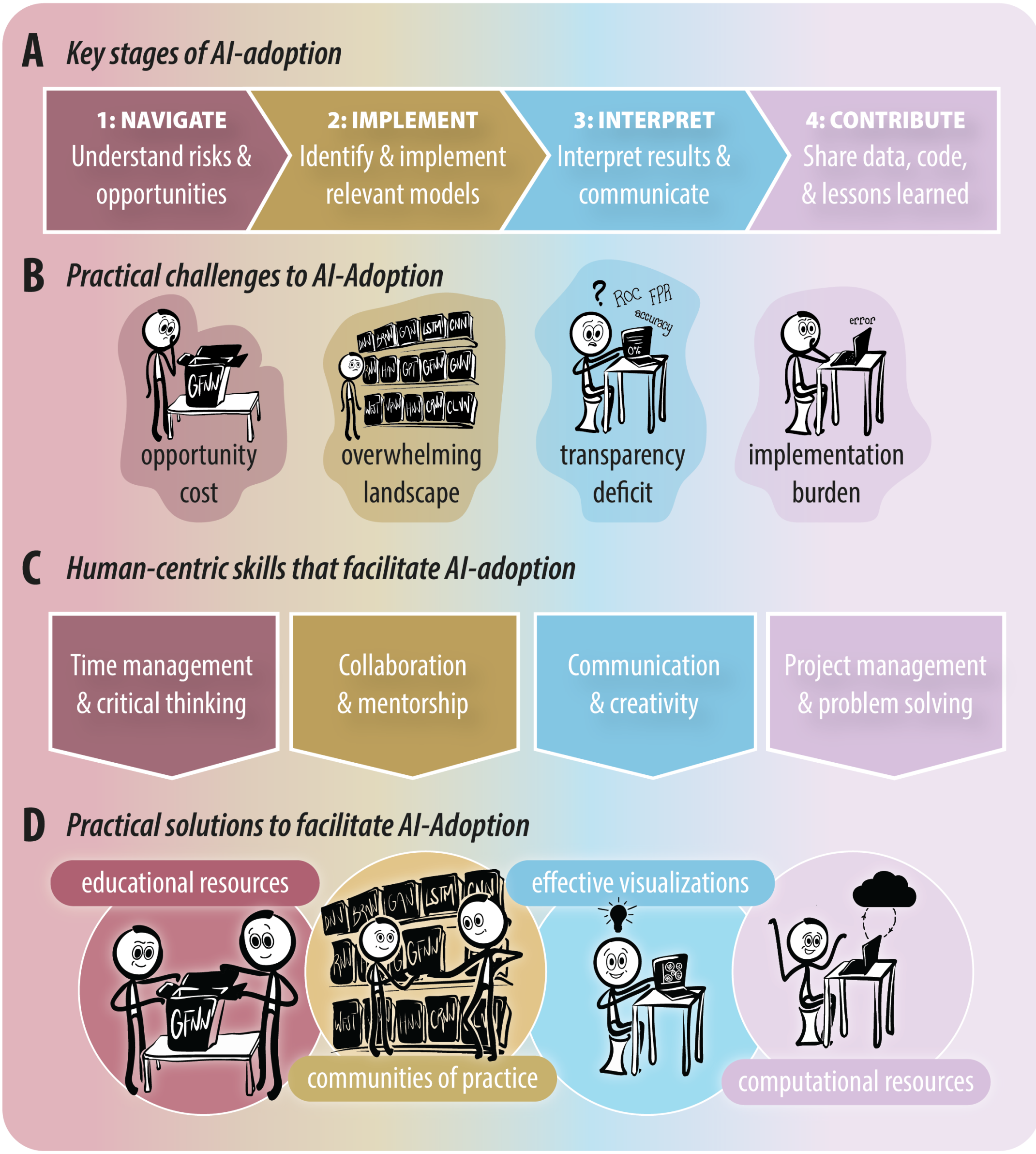

Figure 2. *This synthesis figure outlines a roadmap for AI-adoption in ecology. B) The key stages for ecologists adopting AI: (1) Navigate the landscape of risks and opportunities, (2) Implement identified relevant models, (3) Interpret and communicate the results, and (4) Contribute data, code, and lessons learned back to the research community. These stages map (B) key practical challenges onto (D) key solutions using (C) human-centric skills: (1) opportunity cost (unclear benefits and costs) of using AI: educational resources to teach time management & critical thinking, (2) overwhelming landscape of model choices: communities of practice to foster collaboration and mentorship, (3) transparency deficit: effective visualizations to promote communication and creativity, and (4) implementation burden: computational resources to support project management and problem solving..*

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 challenges. We align the four key challenges—opportunity cost, overwhelming landscape, transparency deficit, and implementation burden—with corresponding interventions focused on human-centric skills: 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.

3.1. Time management and critical thinking to learn to select and implement appropriate AI techniques

When ecologists begin to use AI, they often struggle to assess the opportunity cost of implementing an AI model, especially when alternative methods are more commonly and traditionally applied. In order to leverage the benefits of novel AI techniques, ecologists need to think critically about the relevance of the AI method and assess the time required to implement an AI-based method. In practice, opportunity cost is lowest when AI methods are expected to be reused across multiple projects or applied repeatedly within a single project at targeted spatiotemporal scales, whereas short-term or one-off applications are often better addressed with more familiar, established methods. Here, they benefit from educational resources, especially those that are open-access and available online; however, **time management** and **critical thinking** are essential for choosing what and how to learn, as well as when to apply it.

Critical thinking regarding the appropriateness of AI for ecological questions might include asking yourself: (1) Does the tool accept your data modality? (2) Is the receptive field (i.e. temporal or spatial context of the model) compatible with the signal you seek to describe or predict? (3) Does the tool process data at a speed or spatiotemporal resolution that is acceptable for your experimental sampling design? (4) Is its computational requirement a good fit for the hardware it will run on? (5) Is this tool adaptable enough to generalize to other species, questions, or environmental conditions? (6) Is this method open-source and is it still maintained?

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, but lack the interpersonal benefit of tutoring from peers with shared experience of the time required to learn, modify, and implement models. Ecology-specific opportunities with in-person engagement, while harder to come by and a larger time investment up-front, 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. (Beery, Parham 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.

Extensive reviews often provide lists of AI methods available to address ecological questions with practical guides for model selection (Borowiec et al 2022; Pichler and 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). Some of these tools such as OpenSoundscapes (Lapp, Rhinehart, Freeland-Haynes, Khilnani, Syunkova and Kitzes 2023) provide extensive documentation and tutorials to walk ecologists through the process of training a Convolutional Neural Network to generalize models to new audio data (Lapp, Rhinehart, Freeland-Haynes, Khilnani, Syunkova, Viotti et al 2024). For many AI methods, employment of large language models (e.g. ChatGPT, Claude) accompanied by critical thinking can reduce the time required for implementation by lowering the barrier to entry to Python for ecologists, 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. Human guidance is essential to foster critical thinking to determine which AI method is most appropriate, given its scientific relevance, ethical caveats, and time required to tailor one's data.

Formalized educators, courses, and programs can provide ecologists with a nuanced understanding of the field, as well as tailored guidance for bespoke data processing pipelines. Formal educational resources such as Massively Open Online Courses (also known as MOOCs) on machine learning (Ng 2024) provide important technical details, but 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 those offered by 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 (online tutorials are also available online via course website: (OxRSE 2024b) 'I&' Github: OxRSE 2024a). Ecologists who are considering significant use of AI in their work may seek fellowships such as those offered 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 financial 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). People in these positions are perfectly poised to champion human centric skills like critical thinking and time management in the context of AI. 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 critical thinking skills for time management as they learn to use AI and evaluate research using AI. For example, in studies focused on within-individual or within-population pattern discovery, such as identifying rare behaviors, annotating sleep states from electrophysiological signals, or detecting fine-scale anomalies in time-series data from a single deployment, the goal may be to maximize sensitivity and faithfully capture structure in a specific dataset rather than to generalize across individuals or systems. In these cases, a deliberately overfit or highly tuned model that incorporates idiosyncrasies of individual datasets can be scientifically appropriate, whereas penalizing such models for limited generalization would reflect a misunderstanding of the ecological question rather than a methodological flaw. Such critical evaluation is important not only for AI adoption but also for advancing computational literacy and algorithmic approaches more broadly, enabling ecologists to confidently integrate AI, when applicable, alongside other scalable computational methods in their research.

3.2. Collaboration and mentorship to foster communities of practice, co-design best practices, and share expertise

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 that emphasize collaboration and mentorship and are composed of individuals who share a common domain of interest and collectively enhance their expertise through sustained interactions and knowledge exchange (Wenger 2011). 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 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 (CICORE 2024), and the NSF- and NSERC-funded AI and Biodiversity Change Center (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 (Institute 2024; NeurIPS 2024). While not specific to AI, the National Center for Ecological Analysis 'I&' Synthesis (NCEAS) seeks to intentionally foster the Environmental Data Science community through events like their inaugural Summit in 2023 and Environmental Data Science Innovation 'I&' Impact Lab (ESIIL) (NCEAS 2023). Ecologists who would like to use AI can benefit from strengthening collaborative skills by engaging in communities that have strong community agreements (Bates et al 2024), dedicated facilitators (Cravens et al 2022), and inclusive, engaging events (Woodley and Pratt 2020). Choosing to join and contribute to intentional, inclusive spaces can help counteract pervasive challenges associated with the 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; Giraldeau et al 2002; Laland and Williams 1998). To prevent this stagnation, an emphasis on collaboration and mentorship within 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.

3.3. Communication and creativity to make effective visualizations that increase transparency and trust

As computational analyses scale and AI models become more complex, ecologists gaining familiarity with AI can benefit from effective data visualization to 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 communication and creativity to produce effective visualizations for diverse audiences. Leveraging the impact of visualizations for applied AI has the potential to better engage scientists, decision makers, and the public (JM Kendall-Bar et al 2024).

While LLMs can provide useful starting points for iterating on visual styling, figure layout, or code for data visualizations, they are not yet proficient at creating editable, complex diagrams that creatively apply design principles in the same way as humans, especially those with digital art training. Using LLMs to write code for data visualization can accelerate and effectively render data-heavy vector and raster graphics for maps, interactive plots, and network diagrams such as phylogenetic trees (e.g.. Newick files) or entity-relationship diagrams (e.g. Mermaid javascript). Generative AI methods (e.g., DALL-E, StableDiffusion, Midjourney) can rapidly render raster illustrations in a variety of styles including with transparent backgrounds that can provide accurate illustrations suitable for composing scientific figures. However, these methods are generally unable to create reliable diagrams and draw on immense datasets of original artwork (e.g. LAION) which has led to many copyright infringement lawsuits (Murray 2023). Scientific illustrators, on the other hand, are professionally trained to render accurate depictions of ecological processes that strategically accentuate certain details while obscuring others. Along with the ethical pitfalls of relying on AI methods for producing artwork, we lose the opportunity to support and be supported by artists who apply their communication and creative skills to illuminate and emphasize these important scientific details.

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 (Figure 3). Exploratory visualizations for AI include those dedicated to exploring the data and the model to a communicate creatively 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 (Figure 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 (Figure 3A1a) to obtain processed features for model inputs (Figure 3A1c). Visualizations of ground-truth presence/absence data from manual censuses can help visually assess model accuracy (Figure 3A1b). After fitting and visualizing the model (Figure 3A1d), AI predictions of habitat suitability can be assessed against this ground truth, e.g. through a receiver operating characteristic (ROC) curve (Figure 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 (Figure 3A2b). Colors for these performance metrics (true/false positives/negatives) can then be arranged across space (Figure 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 (Figure 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 communicate creatively to a broader audience less familiar with the dataset and question (see example in Figure 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 (J Kendall-Bar et al 2021; JM Kendall-Bar et al 2024).

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 (JM 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.

3.4. Project management and problem-solving to promote cultural shifts towards open data, models, and code

As ecologists narrow in on the methods most appropriate to their questions, limitations often shift from conceptual design to the practical realities and tradeoffs inherent to decisions regarding computation, data management, and long-term maintenance of software and hardware. We define computational resources broadly to encompass the hardware and software to train and deploy AI models, as well as labeled datasets, transferable codebases, data management systems, and cloud computing resources. While these resources are technical in nature, their effective use hinges on human-centric skills throughout implementation, including problem-solving and project management to weigh tradeoffs while managing complex AI workflows across people, platforms, and timescales.

Ecologists' use of computational methods, including AI, is frequently constrained by the lack of formal training in collaborative coding, software organization, data stewardship, and access to supercomputers (Stockwell et al 2000). These gaps are widened by the systematic devalorization of the invisible labor required to responsibly curate and maintain data, software, and hardware. Open science and its growing support by funding agencies aim to democratize access to data, AI, and scalable computing more broadly (Parashar and Altintas 2023; Würthwein 2024), but realizing these goals requires project-management skills to allow ecologists to connect domain-specific needs with emerging methods and best practices from computer science.

Due to the large size of datasets and associated computing requirements, the use of AI is limited without cloud computing. Ecologists adopting AI can benefit from publicly-funded and widely-accessible cloud computing services such as Nautilus, the National Research Platform, and ACCESS (NSF 2024) designed to lower financial barriers to computing (NRP 2024; Parashar and Altintas 2023; Würthwein 2024). Industry services, such as Amazon Web Services or Google Cloud, can be more expensive but may offer more technical support. Navigating these options requires strategic planning and ethical decision-making during project management that can include decisions on how to address the non-negligible environmental impacts of AI (Strubell et al 2020), potentially by adjusting the extent, timing, and location of resource use (Dodge et al 2022).

Ecologists are increasingly incentivized to share training data, AI models, and workflows to meet publication requirements and contribute to communities of practice. While many eagerly seek to contribute, ecologists often seek to maintain credit for re-use of the data collected during arduous and expensive field expeditions. Metadata and study-specific documentation must accompany datasets across pipelines to avoid downstream misinterpretation. Ecology-specific datasets often lack mechanisms to enforce AI-specific standards like benchmarking, dataset documentation, or explicit statements of appropriate use in AI models. Adopting AI-specific practices such as datasheets for datasets (paper: Gebru et al 2021; Overleaf template: Garbin 2021) and AI model cards (paper: Mitchell et al 2019; Markdown template: Garbin 2024) can alleviate these challenges, but requires planning and organization that combines technical knowledge with anticipating downstream use, understanding ethical constraints, and maintaining clarity about assumptions and limitations of the data and AI method. Frameworks such as the Cookiecutter Data Science framework (Rybicki 2019) and research compendia in R (Marwick et al 2018)

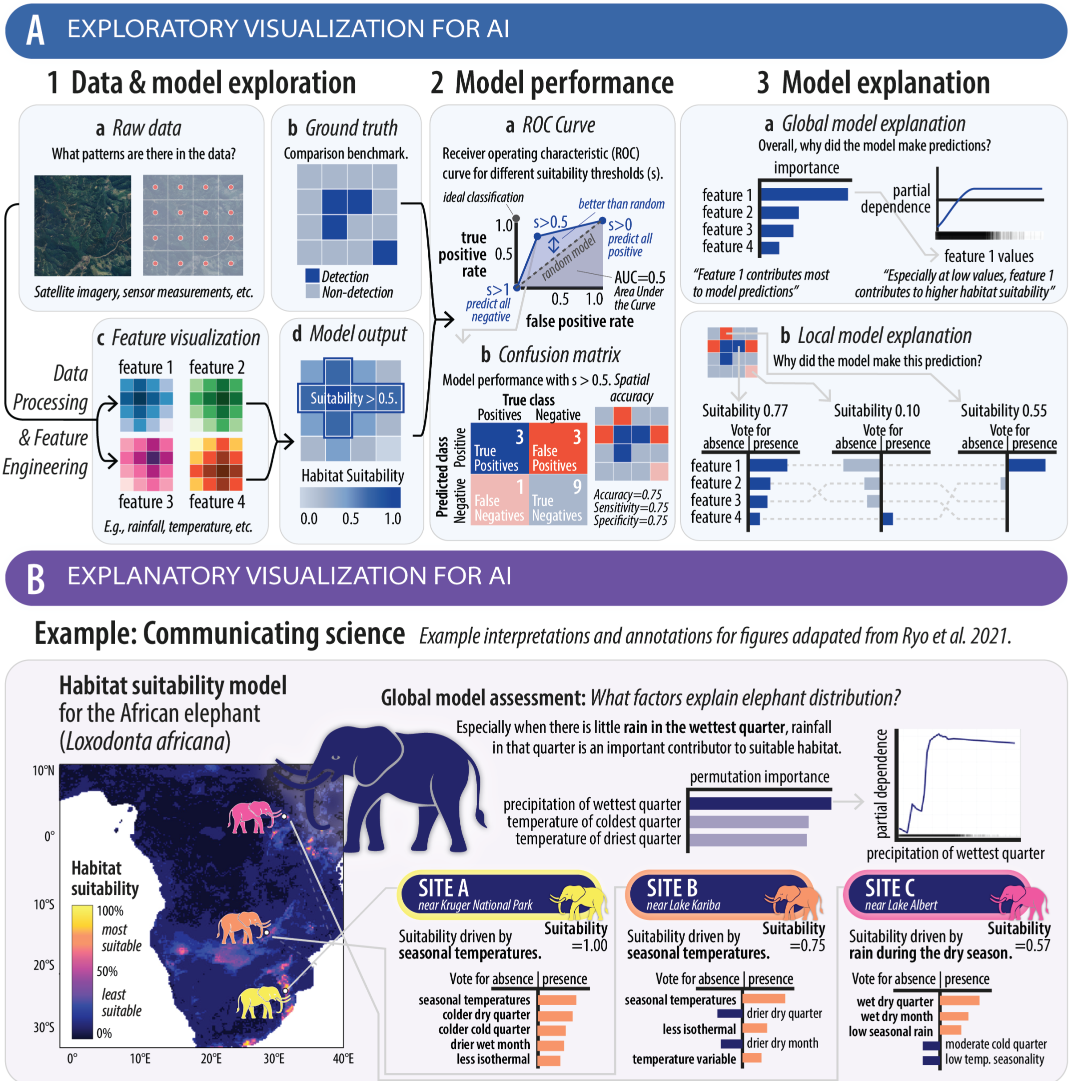

Figure 3. *(A) Exploratory visualizations to understand AI models include: (1) Data and model exploration: (a) Raw data visualization, including satellite imagery and geospatial representations of species' presence/absence, (b) Feature visualizations (e.g., rainfall, temperature) used as model inputs, (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..*

offer structure for these practices, but their uptake requires project-management that values training and stewardship.

To support these efforts, we have curated a list of practical recommendations and examples to facilitate project-management decisions for ecologists (Fig. S1-S2), including guidance on tailoring digital tools that use AI to the technical expertise and tasks of the tool's target audience (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) and Bioacoustics Model Zoo by the Kitzes lab (*kitzeslab/bioacoustics-model-zoo* 2026). We have curated a starter-pack Model Zoo for AI models in ecology on our website (ecoviz-ai.github.io/modelzoo [JM Kendall-Bar 2024a] which invites new contributions via Github [JM Kendall-Bar 2024b]).

Journals and funding agencies play a critical role in incentivizing the review of data and code, as seen with journals that hire editors for data and code (e.g. Journal of Open Source Software; JOSS 2024). At the same time, responsible sharing requires attention to ethical constraints, including risks associated with releasing sensitive datasets or models used in large language systems (Cooper et al 2024; Liesenfeld et al 2023). Guidelines on best practices by the British Ecological Society (*Better Science Guides* 2025) and ethics by NeurIPS (NeurIPS 2024) can help guide ecologists as they start to implement and share AI models. 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 and Christen 2013; Carroll et al 2021). Strategic problem-solving and project-management human-centric skills will help manage the cultural shift from redundant, proprietary, or opaque analyses and contribute to more transparent, robust, and defensible science that incentivizes open, modular, and expandable AI methods (Brunsdon and Comber 2021; Czapanskiy and Beltran 2022).

4. Conclusion

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. Compared to traditional statistical methods, AI often entails a higher transparency deficit and implementation burden, increasing the risk that training data could encode biases or lead to misleading results. 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). In these cases, we must emphasize human-centric skills, not readily outsourced to AI, that will help guide AI applications in ecology that maintain trust and transparency due to their ethical and scientific rigor.

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 AI methods with others. Addressing and/or alleviating these challenges requires a multifaceted approach emphasizing human-centric skills including: (1) time management and critical thinking to learn to select and implement appropriate AI techniques (2) collaboration and mentorship to foster communities of practice, co-design best practices, and share expertise, (3) communication and creativity to make effective visualizations that increase transparency and trust (4) project management and problem-solving to promote cultural shifts and open data, models, and code.

Our initiative, EcoViz+AI, has created a website that collates several AI-related resources for ecological researchers (ecoviz-ai.github.io; JM Kendall-Bar 2024a). 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 methods 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 (github.com/ecoviz-ai/ecoviz-ai.github.io; JM Kendall-Bar 2024b).

Looking to the future, a cultural shift is needed to emphasize and reward human-centric skills that will become increasingly valuable as university graduates seek employment in a rapidly-evolving landscape, shaped by improving AI models. This continued emphasis on irreplaceable human-centric skills will allow AI to serve as a vital partner as we seek to promote open science through communities of practice that focus on data standardization efforts, benchmarking requirements, and code-sharing best practices (Czapanskiy and Beltran 2022; Gundersen et al 2018). This cultural shift is already underway, as ecologists increasingly convene communities of practice dedicated to open data and reproducible workflows, recognizing that collective investment in collaboration and collective stewardship ultimately accelerates impactful science (Gomes et al 2022). While open science, technical training, and the value of human-centric skills predate AI, the speed, opacity, and implementation of modern AI systems heighten the need to prioritize critical thinking, communication, and community building. Aligning responsible AI adoption with interdisciplinary educational initiatives, such as the AAAS Vision and Change Action Plan for undergraduate education (Woodin et al 2009), creates opportunities to increase the value of education as we generously share data, code, and training material that empowers the next generation of ecologists to responsibly and rigorously harness the opportunities presented by AI.

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