Situating AI in Environmental Science: Perspectives Across Sectors and Career Stages

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Abstract

The use of Artificial Intelligence (AI) is rapidly proliferating across career sectors, including those in the environmental sciences. The field's reliance on technical analysis, complex and multidimensional datasets, and broad interdisciplinary job responsibilities makes it well-suited to benefit from advancements in AI. However, careers within environmental science are highly diverse and the opportunities and limitations of AI use across these sectors are uneven. We present a first-hand interdisciplinary perspective on these unique opportunities and limitations across roles, career types, and career stages in the environmental sciences. We find that the use of AI has strong potential to augment training, accelerate research workflows, and support resource management by automating routine or labor-intensive computational tasks. At the same time, these tools pose substantive challenges for faculty preparing new graduates for a rapidly evolving technical workforce and for scientists working to maintain standards across the research process as output increases. Differential access, incentives, and norms of use across career types and stages may also disrupt mentorship structures and introduce new barriers to some forms of interdisciplinary collaboration even as others become more tractable. Additionally, for a discipline focused on the environment, the water consumption, energy use, and other societal impacts of the data centers that enable frontier large language models present a sizable, if still rather quantitatively unconstrained, moral concern. In total, the expanding adoption of AI approaches has the potential to produce significant progress in our understanding and management of natural systems. However, careful consideration is required to evaluate the implications of its rapid, uneven, and continually evolving integration across the environmental science profession. Proactively identifying and addressing these limitations will be essential to mitigating unintended consequences and maximizing positive impact.

1. Introduction

Recent years have seen rapid advances in computational approaches designed to emulate aspects of human learning, reasoning, and decision-making; these developments are broadly grouped under the term Artificial Intelligence (AI) (Garcia Quevedo & Kuri, 2026). Despite the recent attention given to generative AI models like OpenAI's ChatGPT, Google's Gemini, and Anthropic's Claude, this term (AI) has referred to a broad range of computational approaches over time. These approaches began with symbolic AI, which originated in the mid-20th century, and have grown to now include *inter alia*

simple statistical classifiers (e.g., logistic regression), machine and deep learning, the current generation of generative AI including large language models (LLMs), and potential future models capable of human-level general cognitive performance (artificial general intelligence) (Bubeck et al., 2023; Jordan & Mitchell, 2015; Kendall-Bar et al., 2025; Triguero et al., 2024). While AI's roots date back more than half a century, generative AI in particular has seen rapid uptake over the last few years in both professional and personal contexts. In the professional world, generative AI tools have rapidly proliferated, supporting functions such as summarizing meeting notes, drafting reports, and substantially lowering barriers to advanced statistical analysis (Garcia Quevedo & Kuri, 2026). Like in many other fields, the presence and capabilities of AI have also increased across the environmental science professions, where complex datasets, multi-criteria decision-making problems, and the need to communicate results to a broad suite of stakeholders make AI (broadly speaking) well-positioned to provide substantial value (Reichstein et al., 2019; Rolnick et al., 2019). However, adoption of and concern surrounding these new tools are uneven across the broad and diverse range of career paths in environmental science (Figure 1). For example, roles in this field range from teaching and training to environmental research and modeling, applied resource management, operations, and advisory decision support (Figure 2). Further, the responsibilities of workers within each of these career types vary by career stage, each of which spans from students and early-career professionals to senior researchers and institutional leaders. Despite a rapidly growing literature on AI applications in the environmental sciences (Alotaibi & Nassif, 2024; Konya & Nematzadeh, 2024; Oliver et al., 2024; Reynolds et al., 2025a), comparatively little work has examined how adoption differs across the field and the unique barriers, risks, and opportunities associated with AI across these contexts.

While AI tools hold the potential to substantially accelerate progress in environmental science, responsible and equitable adoption requires a clear understanding of the current and emerging landscape of uses across our field. This includes recognizing that despite the recent focus on advances in generative AI, AI as a research tool encompasses a broad set of approaches that vary in their use and potential for misuse. Achieving this understanding requires fostering interdisciplinary dialogue among practitioners and across our field's inherently interconnected, yet often isolated, component parts. Ethical adoption also requires users to understand the environmental costs of using AI—to land, water,

air, and energy (Chen et al., 2025; de Vries-Gao, 2026; Jegham et al., 2025), and the corresponding social impacts (Avery & Carpenter, 2025), particularly for communities who are already overburdened with environmental and social injustices (Regilme, 2024). Despite widespread desire to understand these impacts, accurate ongoing quantification of the environmental costs, in particular, has proven challenging, since many of the companies that have created and host large generative AI models (the most computationally expensive of the subgenres of AI) do not publicly release information about their aggregate energy and water use (Jegham et al., 2025).

Here, as a group of environmental science professionals spanning career types (academia, non-profit, government, and private sectors) and career stages (from students to well-established professionals), we aim to foster discussion of these opportunities and challenges by presenting a first-hand interdisciplinary perspective. We first began discussing these issues together at an Environmental Data Science Summit on the Future of AI in Conservation and Management, hosted by the National Center for Ecological Analysis and Synthesis (NCEAS) in Santa Barbara, CA, in 2025. We have organized our perspectives into three broad areas: learning, research, and practice (Figure 2). Across these areas, we identify opportunities as well as sector-specific barriers that shape how AI is being adopted. In doing so, we aim to catalyze transparent and inclusive dialogue on the integration of AI in the environmental sciences, with the goal of maximizing its benefits while minimizing the negative or unintended consequences of this rapidly changing technology.

2. AI for Learning Environmental Science

The introduction of generative AI into academic settings poses a well-documented challenge to traditional frameworks for environmental science trainees, including undergraduate and graduate-level students as well as postdoctoral researchers (Lo, 2023; Milano et al., 2023; UNESCO et al., 2023). Environmental science trainees are expected to enter the workforce with technical skills such as quantitative analysis, statistical programming, and scientific communication, in addition to a solid grounding in ecological and environmental theory. Generative AI models, specifically LLMs, are now capable of solving academic problem sets, generating computer code across myriad programming

languages, and producing written work that is often indistinguishable from human-authored outputs (Georgiou, 2026; Wills et al., 2024). As a result, educators, who are tasked with ensuring trainees are prepared for the workforce, are forced to reconsider how these skills are taught and assessed.

Students are still expected to acquire a strong foundational understanding of environmental science concepts and methods during their training, but they increasingly must also be able to effectively use AI tools if they hope to be competitive in the modern environmental sciences job market. This creates a genuine tension for educators. Students who graduate without meaningful AI proficiency risk being underprepared for a workforce that increasingly expects familiarity with these tools. At the same time, the ease with which AI systems can complete the type of tasks commonly used to assess learning (answering prompts, writing essays, generating code) raises legitimate concerns that students may bypass the process of cognitive formation in favor of automated solutions and subsequently graduate unprepared to execute tasks without reliance on an AI crutch. Indeed, even when used alongside human effort, emerging evidence suggests that reliance on automated systems can reduce understanding, critical reasoning, and long-term skill retention (Shen & Tamkin, 2026). In this rapidly changing landscape, educators must balance helping students learn how to perform core tasks in a range of situations while simultaneously preparing them for a workforce where those tasks may be increasingly supported by AI. This tension results in an urgent challenge for traditional pedagogical approaches, particularly given the uncertainty surrounding the future extent of automation in environmental science careers and the long-term danger of cognitive overdependence on non-deterministic proprietary models.

Despite these challenges, AI tools do also offer substantial opportunities for enhancing training rather than merely undermining it. For example, LLMs can be used to enhance learning through targeted feedback and personalized supplementary instruction (Baidoo-Anu & Ansah, 2023; Liu et al., 2024). These systems can extend engagement beyond the formal curriculum by allowing students to explore concepts at their own pace, in formats tailored to their level of understanding, or in contexts that are familiar to them. For early-career trainees, AI tools can help translate lecture-based material into more applied, subject-specific knowledge relevant to specialized roles in the job market. For instance, a student pursuing a career in fisheries ecology might use AI tools to explore how statistical methods are applied to common datasets, analytical problems, or management questions in fisheries science. By

connecting theoretical instruction to practical applications, this type of learning extension may help trainees develop a more functional understanding of key concepts and strengthen their preparation for applied work in industry. This logic may also extend beyond academic settings. For example, individuals later in their careers may use AI tools to develop personalized learning plans to acquire new skills or update existing knowledge. If deployed well, AI could offer significant opportunities to allow more equitable learning across academic settings, extend core concepts to specialized sub-discipline knowledge, and allow for guided learning opportunities outside of the academic setting, thereby enhancing learning opportunities throughout the full career trajectory. The unifying trait of all of these positive uses of generative AI is that they focus on using AI for augmenting and supporting the process of learning instead of using it as a substitute for the task of learning new content and skills.

One key challenge in realizing the benefits and minimizing the risks of AI use in teaching and learning is the growing gap between the rapid pace of AI adoption among students and faculty and the slower process of academic institutions developing support structures to help guide responsible use. Many faculty members in environmental science were trained before AI technologies such as LLMs became commonplace and are now learning them alongside students. This means that instructors are often operating without the deep technical familiarity, polished pedagogical frameworks, and institutional guidance that would enable meaningful and responsible integration into courses. The relatively slower pace of institutional adoption is in part due to concern about legal security requirements around protected data (e.g., in the United States, student data is protected by the Family Educational Rights and Privacy Act [FERPA] and medical data by the Health Insurance Portability and Accountability Act [HIPAA]). Regardless of the state of institutional support, instructors are increasingly expected to not only understand these tools themselves but to design curricula that teach students to use them critically and responsibly. This mismatch between the pace of tool adoption and institutional frameworks to regulate and support their use may delay the development of effective instructional practices that emphasize critical engagement with these tools, particularly in areas where computational training has historically been uneven. Institutional and university-led policies governing AI use in the classroom remain in flux. As academic institutions continue to develop ethical guidelines, assessment standards, and acceptable-use policies for generative AI, instructors may face uncertainty

regarding how and when AI tools can be incorporated into teaching and evaluation. As a result, students and trainees often encounter inconsistent expectations regarding their use across courses and instructors, creating fragmented guidance and incentivizing students to conceal their use of AI rather than engage with it openly as part of their training. This lack of consistency and institutional guidance not only limits the potential for these tools to enhance learning but may also undermine students' preparedness for a rapidly evolving job market.

3. AI for Environmental Research

The use of AI models in research has progressed gradually over many years, with much of the methodological innovation originating within academia. Although machine learning and deep learning approaches have existed for decades (Borowiec et al., 2022; Pichler & Hartig, 2023), their recent popularization and improved accessibility now allow researchers to apply these tools without the extensive technical expertise previously required (Wills et al., 2024). This means that the adoption of these tools in research contexts has accelerated dramatically in recent years (Alotaibi & Nassif, 2024; Reynolds et al., 2025b). Environmental researchers can now use these tools to detect patterns in complex, multi-scale datasets at spatial and temporal resolutions that were previously difficult or impossible to analyze by hand. For example, the use of convolutional neural networks (CNNs) and computer vision methods applied to imagery and video has unlocked new data streams that were previously difficult to quantify at scale (Jumper et al., 2021; Kazanskiy et al., 2025; Reichstein et al., 2019). These advancements have been further amplified by increases in data availability, including satellite imagery, mobile phone-based community science observations, and widespread continuous environmental sensor data, which are themselves accelerating in their quality and quantity through AI-augmented data collection methods (Abdulmuttalib et al., 2024; Abdul-Rahman et al., 2025; Barnard & Vitousek, 2023). One commonly cited use case is object detection and classification in wildlife ecology, where deep learning models enable large-scale processing of camera trap data (Gadot et al., 2024). Similarly, embedding-based approaches applied to satellite imagery, such as those developed through large-scale foundation models (e.g., AlphaEarth), allow researchers to characterize land cover,

vegetation dynamics, and anthropogenic change across regions without task-specific retraining (Ayush et al., 2022; Brown et al., 2025). The application of deep learning for analyzing complex bioacoustics data has enabled new opportunities for species detection and ecological research from acoustic data (Merriënboer et al., 2026; Winiarski et al., 2026). Collectively, the increased popularity of AI models in both data collection and analysis has substantially increased the inference available from ecological datasets as well as the scope of analysis that can be addressed in research settings (Reynolds et al., 2025). A factor uniting many of these current analytical approaches is that they rely on non-generative AI classification tools built on machine learning and deep learning approaches.

Beyond the use of AI as an analytical tool, recent advances in generative AI are reshaping the broader research workflow in the environmental sciences. Over several decades, the field has increasingly relied on quantitative analyses implemented in programming languages such as R, MATLAB, and Python. As a result, researchers often encounter limitations arising from differences among research team members in terms of proficiency with these tools and the technical expertise required to implement new analytical approaches. Researchers trained before these tools became commonplace or early-career scientists who have not yet become proficient with them have often historically been limited in their ability to effectively collaborate on complex quantitative research projects. In addition to differences in skill level, differences in preferred analytical tools (e.g., Microsoft Excel vs Python vs R) create barriers to collaboration across teams and institutions (Hampton et al., 2017; Lai et al., 2019). For example, many of the most advanced packages for machine learning were developed in Python, while many ecologists are primarily trained in R; this mismatch has likely impeded the adoption of machine learning among ecologists and environmental scientists. This challenge is compounded in sectors where there is limited incentive to remain at the cutting edge of rapid technological change, producing barriers to collaboration across institutions, sectors, or research groups.

The adoption of LLMs has begun to alleviate this bottleneck. AI-based tools can increasingly generate, translate, and debug code, allowing researchers to describe their data and analytical goals in plain language and receive the code necessary to implement analyses regardless of their technical expertise (Merow et al., 2023). In turn, these tools can reduce technical barriers across individuals and institutions and enable the use of a wider range of analytical methods independent of programming (or

spoken) language. At the same time, AI tools are accelerating how researchers discover, engage with, and synthesize scientific literature. Although early generations of LLMs performed poorly at these tasks, recent years have seen rapid growth in AI-assisted literature platforms (e.g., Perplexity, Elicit, Scite) and substantial improvements in the ability of leading models to identify and recommend relevant scientific publications. Recent advances in agent-based systems, such as Anthropic's Claude Code and Claude Cowork, further extend these capabilities by allowing AI systems to follow complex, multi-step instructions and execute longer tasks with limited human oversight (Merow et al., 2023; Xiong et al., 2024). These systems can modify and execute code, generate research presentations in software such as Microsoft PowerPoint, and synthesize results alongside properly formatted academic citations. They have also demonstrated the ability to propose sub-hypotheses and explore patterns across large datasets with minimal instruction (Fernández-Iglesias et al., 2024). Taken together, the rapid development of AI-based research tools is shifting key constraints in the research process. Whereas technical expertise with programming previously represented the primary bottleneck for complex quantitative analyses, limitations are now shifting toward hypothesis generation, data interpretation, data collection, and data management. As a result, AI has the potential to substantially accelerate the pace at which datasets are analyzed and expand the range of analytical approaches available to scientists across areas and career stages.

Despite the potential to rapidly develop analysis code, remove technical barriers, and accelerate literature review, the use of AI in research carries serious limitations. LLMs do not "know" information in any traditional sense; they generate responses by predicting probable word sequences, making them capable of generating plausible-sounding but factually incorrect or unsupported outputs, a phenomenon known as "hallucination" (Ji et al., 2023). Such errors can include misinterpretation or fabrication of data, the fabrication of non-existent citations (Bhattacharyya et al., 2023), or the recommendation of inappropriate statistical models. As the use of generative AI for development of analytical code increases, the risk of undetected error is heightened. This is particularly acute if the models are used to implement analyses beyond a researcher's own expertise. Further, many AI synthesis systems rely on open-access sources when suggesting reference articles, which may result in bias due to incomplete model access to the scientific literature. Increased research output may also further strain

the peer review process, which has faced well-documented challenges for decades (Checco et al., 2021). As AI-generated content becomes more common in academic manuscripts, there is a need for new and consistent standards to ensure that research quality and integrity are maintained (Bagenal, 2024). In the absence of such standards, there is a risk that AI-enabled research could accelerate publication volume but dilute the quality and rigor of outputs, leading to a decline in the reliability of peer-reviewed publications as a means of communicating scientific findings.

These risks and opportunities play out differently across career stages and types. Many early-career professionals, who have recently transitioned away from academic environments that encourage experimentation, are often enthusiastic adopters that have embraced agentic workflows as a method to accelerate output. However, this enthusiasm can outpace the development of the domain expertise needed to critically evaluate AI-generated results, increasing the risk of undetected errors in their work (Blau et al., 2024; Helmy et al., 2025). AI adoption by later career researchers may lag behind due to more significant administrative responsibilities and a decreased incentive to continue to learn new skills. Mid-career researchers may find themselves caught in the middle: navigating the need to stay current with rapid technology change while balancing increased administrative burden or required institutional workflows. Researchers in some sectors, such as government agencies or private industry, may be explicitly restricted from using publicly accessible AI models due to concerns surrounding proprietary or sensitive data. While some institutions provide pre-approved internal models or platforms, these restrictions can limit access to the newest capabilities, which are evolving on the scale of months (Maslej et al., 2025). The rapid pace of development may continue to produce discrepancy in the use of and proficiency with these tools across career types and career stages. As these technologies become increasingly ubiquitous, this may exacerbate competitive imbalances, limit scientific potential, disrupt mentorship across career stages, and weaken collaboration across institutional and disciplinary boundaries.

4. AI for Environmental and Conservation Practice

In contrast to many academic research positions, roles in environmental science such as local resource managers, conservation practitioners, and environmental consultants are tasked with engaging with community stakeholders, planning conservation actions, and guiding resource management outcomes. In these roles, referred to here collectively as "environmental science practitioners", AI can be a useful tool to synthesize data in real time to support decision-making or to communicate data in a format that is more accessible to diverse stakeholders (Nie & Liu, 2025). In addition, a large portion of conservation and resource management work involves reporting, permitting, grant discovery, proposal writing, and other forms of documentation: tasks that often consume a substantial share of time. AI tools, which are effective at these tasks, can be used to automatically produce and update documentation, reducing administrative burdens. As a result, these tools may allow staff time to be reallocated towards on-the-ground management actions, community engagement, and analytical work.

In practice, strict organizational policies surrounding AI use, often driven by data privacy and security concerns, can create a cautious environment for widespread adoption of AI in conservation or resource management. Entities that engage in this type of work are broad, including government agencies, nonprofits, or private sector companies (e.g., environmental consulting). However, adoption across these agencies is often shaped by established AI policies, typically set by a centralized IT, security, or legal team, with a strong focus on security boundaries, data handling rules, and compliance with emerging local and federal legislation. The choice of AI features approved in institutional software systems may either encourage or explicitly limit their use to a single model. The incentives driving AI adoption also vary by sector. For example, in private sector or industry settings, organizations are often motivated by efficiency to maintain a competitive advantage in delivering insights to clients and generating revenue. On the other hand, government and non-profit organizations may be more likely to prioritize risk mitigation, public accountability, and compliance. As a result, private sector organizations may be more likely to experiment and deploy AI tools rapidly, while adoption in government and non-profit settings tends to proceed more cautiously. This tension

is also present across career stages, where early-career professionals are subject to limitations in AI use despite their proximity to day-to-day workflows where AI can provide significant efficiency gains in reporting, synthesis, or documentation. In contrast, senior professionals guiding AI use policies may view these technologies primarily through a risk tolerance lens and engage less frequently with them on a daily basis. Mid-career professionals often act as intermediaries between the two, responsible for navigating top-down AI guidance into daily workflows, and supervising staff on AI use without formal training on AI integration. Across environmental science practitioners, users face heightened responsibility to ensure that AI-supported outputs are accurate, transparent, reproducible, and aligned with client-specific regulatory and environmental contexts. Decisions based on errors or overreliance on opaque models can introduce legal, ethical, reputational, and financial risks that are significantly higher than many of those encountered in academia, producing a heightened tension between pressure to innovate and optimize operations with immediate and tangible risks of AI over-reliance as the technology matures.

Beyond organizational policy and incentive structures, hesitation around AI is further compounded by responsibilities related to data stewardship, privacy, community trust, and place-based governance. This is particularly relevant when working with environmental datasets that include sensitive species locations, proprietary data, or culturally sensitive information associated with Indigenous or tribal governments and communities. The use of AI tools that are trained on user data may directly conflict with principles of Indigenous data sovereignty and governance (Carroll et al., 2019, 2020; Regnault, 2026). Without clear safeguards, AI-enabled workflows risk exposing sensitive information and in doing so, undermining trust between environmental data scientists, their institutions, and the communities with whom they work. In such contexts, uncertainty around data ownership, consent, and downstream applications can constrain the adoption of AI tools, especially when governance structures and data-sharing expectations are not explicitly addressed. Frameworks such as FAIR (Findable, Accessible, Interoperable, Reusable), which emerged from the broader data science community, and CARE (Collective Benefit, Authority to Control, Responsibility, and Ethics), which was developed to center Indigenous data sovereignty, provide complementary guidance for navigating these challenges (Carroll et al., 2020, 2021). In particular, CARE principles emphasizing

authority to control and ethical responsibility are directly impacted by AI systems that aggregate or are trained across user-contributed data. While data sovereignty concerns center on how information is collected and used, a related challenge emerges downstream: the risk that AI-generated outputs could overshadow human judgement in important and consequential decisions about conservation and resource management. A core limitation of AI systems is their inability to incorporate contextual understanding and place-based ecological insight. Although a useful tool for synthesis, decisions which impact resource or land use should be undertaken with careful consideration of social and environmental equity, justice, value systems and inherent tradeoffs associated with these decisions. Outsourcing these judgments to AI, or relying on analyses that neglect these considerations, risks ineffective or socially harmful outcomes.

Despite these limitations, AI offers significant opportunities to strengthen conservation outcomes and operational efficiency for resource practitioners if used responsibly in appropriate contexts. AI tools are well positioned to aid in roles involving document-heavy workflows that require synthesizing reports, environmental impact documentation, and policy text. AI-driven analytics can support conservation decision-making by synthesizing monitoring datasets and improving the speed with which scientific analysis informs management action. This is increasingly important in resource-constrained settings, where more efficient translation from data to action can help practitioners target high-leverage interventions and enhance ecosystem stewardship. If used well, AI can allow practitioners to spend more of their time building and contributing to community relationships. These benefits can be extended through the creation of accessible documentation, multilingual summaries, and tutorial content, improving outreach to diverse stakeholders. Together, these capabilities have the potential to strengthen conservation and resource management outcomes by enhancing community involvement and input. However, failure to consider data sensitivity and the role of human centered values in environmental decision making risks undermining community trust and institutional credibility among scientists, managers, and stakeholders.

5. Conclusions

Across the environmental sciences, AI represents both a disruption to established norms and a potential catalyst for accelerating progress. By lowering technical barriers, enabling large-scale data synthesis, supporting tailored training pathways, and reducing administrative burdens, AI has the potential to expand the scope, speed, and impact of environmental work. Realizing this potential could meaningfully strengthen conservation, resource management, and climate adaptation efforts.

The rapid and uneven nature of AI integration across the field, however, presents several current and emerging challenges. Despite their increasing sophistication, current AI systems remain inherently prone to errors. As their use increases across sectors and domains, there will remain a need to verify and closely monitor outputs. As the potential to automate large portions of scientific and regulatory workflows expands, so too does the risk that accelerated output will not be matched by comparable rigor, placing additional strain on systems that underpin the reliability of and trust in the environmental sciences. Traditional pedagogical approaches are challenged to rethink the necessary skills for a quickly transforming workforce as well as the best way to teach core disciplinary conceptual skills alongside AI literacy. On-the-ground practitioners are presented with new opportunities to help inform decision making, but are also faced with a need to systemically consider bias and the need for human involvement. Uneven adoption across roles and career stages may also limit the full potential of these tools. Disparities between early adopters and those working within legacy or institutionally-restricted workflows produce competitive disadvantages and erode collaborative and mentorship opportunities. Variation in AI literacy limits the ability to fully harness the power of these tools, and the absence of consistent and clear guidance on their role in environmental sciences produces haphazard outputs with inconsistent oversight.

Realizing the potential of AI while minimizing its possible negative impacts in environmental science will require open and sustained dialogue across the field. As environmental scientists adapt to a rapidly changing technological landscape, clear and honest discussion of where AI can meaningfully advance the goals of the field, as well as the emerging pitfalls and unintended consequences, is an important first step in guiding the discipline through what is likely to be a substantial transformation. There is an urgent need to identify shared standards across the field, including rigorous standards for metadata and documentation of AI outputs, transparency on AI use, and guardrails for the use of these

tools to sensitive or inherently human-driven applications. Paired with cross-sector training to reduce disparities in AI literacy, these efforts could help ensure that AI becomes a shared asset for collaborative research rather than a source of technical inequity.

In total, the emergence of AI provides meaningful opportunities to improve the efficacy of roles across the field, but careful consideration and consistent dialogue on how to maximize these benefits across the full spectrum of career roles in this field is necessary. The advancements in AI are accelerating rapidly, and are predicted to increase in pace in the coming years. By some accounts, the pace of innovation in AI means models are likely to begin consistently outperforming humans in many commonplace tasks in the field such as coding and academic writing (Grace et al., 2018). This possibility is forcing a large-scale reevaluation of processes across many fields, and the environmental sciences are no exception. While AI may reduce the demand for certain computational skills, new ones will be required, and the role of human expertise and decision-making will remain an important dimension in the work accomplished in the environmental sciences. As we as a field continue to rethink research priorities, necessary skillsets, and job descriptions, we urge a continuation of the initial dialogue presented here—many voices are needed if we are to collectively guide the environmental sciences equitably and effectively through this period of technological change.

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Figures:

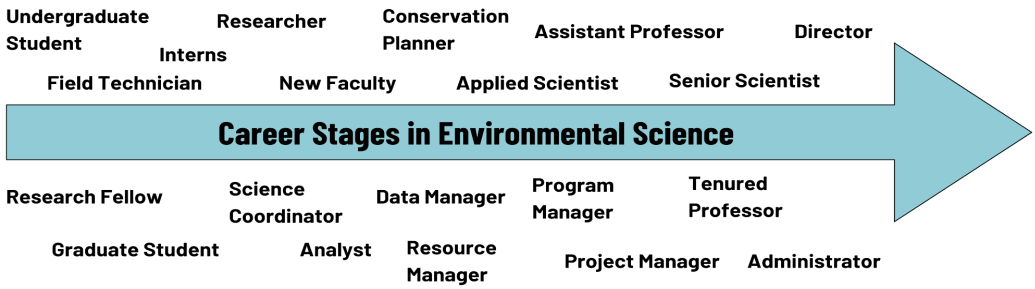

Figure 1: Representation of career stages in environmental science and conservation practice. The roles shown are not exhaustive but reflect common academic, applied, and organizational positions relevant to AI adoption across career stages.

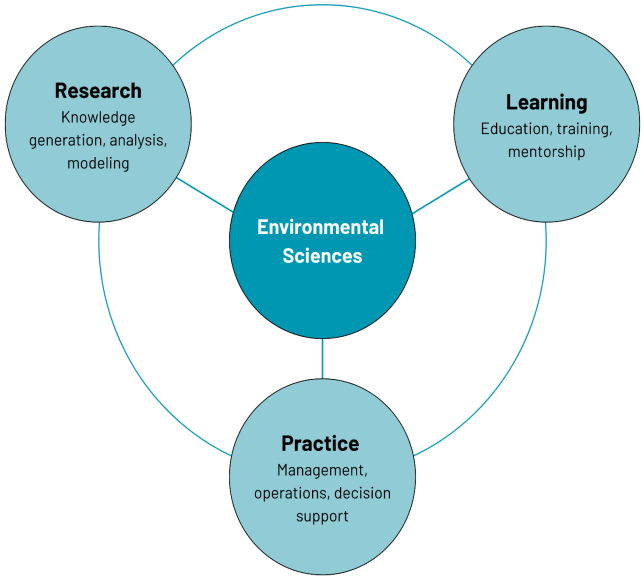

Figure 2: Three broad but interconnected role types in environmental sciences. AI integration has the potential for both positive impact and potential harm to all three, but the success of the environmental sciences field as a whole depends on the ability to realize these benefits and mitigate these harms across all sectors.

Works Cited :

Abdulmuttalib, H., Al Doori, M., Barsi, Á., Blaschke, T., Gao, Y., Kugler, Z., Lang, S., Szabo, G., & Tiede, D. (2024). Remote Sensing Data Quality in the Era of AI. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *X-3–2024*, 1–11. ISPRS TC III Mid-term Symposium “Beyond the canopy: technologies and applications of remote sensing” - 4–8 November 2024, Belém, Brazil. https://doi.org/10.5194/isprs-annals-X-3-2024-1-2024

Abdul-Rahman, G., Zwitter, A., & Haleem, N. (2025). A systematic literature review on the role of artificial intelligence in citizen science. *Discover Artificial Intelligence*, *5*(1), 165. https://doi.org/10.1007/s44163-025-00437-z

Alotaibi, E., & Nassif, N. (2024). Artificial intelligence in environmental monitoring: In-depth analysis. *Discover Artificial Intelligence*, *4*(1), 84. https://doi.org/10.1007/s44163-024-00198-1

Avery, G., & Carpenter, A. (2025). Supply Chain Energy and Greenhouse Gas Analysis Using the Materials Flows Through Industry (MFI) Tool: Examination of Alternative Technology Scenarios for the U.S. Chemical Sector. *Journal of Advanced Manufacturing and Processing*, *7*(3), e70012. https://doi.org/10.1002/amp2.70012

Ayush, K., Uzkent, B., Meng, C., Tanmay, K., Burke, M., Lobell, D., & Ermon, S. (2022). *Geography-Aware Self-Supervised Learning* (arXiv:2011.09980). arXiv. https://doi.org/10.48550/arXiv.2011.09980

Bagenal, J. (2024). Generative artificial intelligence and scientific publishing: Urgent questions, difficult answers. *Lancet*, *403*(10432), 1118–1120. https://doi.org/10.1016/S0140-6736(24)00416-1

Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting Teaching and Learning. *Journal of AI*, *7(1)*.

Barnard, P. L., & Vitousek, S. (2023). Earth science looks to outer space. *Nature Geoscience*, *16*(2), 108–109. https://doi.org/10.1038/s41561-023-01123-4

Bhattacharyya, M., Miller, V. M., Bhattacharyya, D., & Miller, L. E. (2023). High Rates of Fabricated and Inaccurate References in ChatGPT-Generated Medical Content. *Cureus*, *15*(5), e39238. https://doi.org/10.7759/cureus.39238

Blau, W., Cerf, V. G., Enriquez, J., Francisco, J. S., Gasser, U., Gray, M. L., Greaves, M., Grosz, B. J., Jamieson, K. H., Haug, G. H., Hennessy, J. L., Horvitz, E., Kaiser, D. I., London, A. J., Lovell-Badge, R., McNutt, M. K., Minow, M., Mitchell, T. M., Ness, S., … Witherell, M. (2024). Protecting scientific integrity in an age of generative AI. *Proceedings of the National Academy of Sciences*, *121*(22), e2407886121. https://doi.org/10.1073/pnas.2407886121

Borowiec, M. L., Dikow, R. B., Frandsen, P. B., McKeeken, A., Valentini, G., & White, A. E. (2022). Deep learning as a tool for ecology and evolution. *Methods in Ecology and Evolution*, *13*(8), 1640–1660. https://doi.org/10.1111/2041-210X.13901

Brown, C. F., Kazmierski, M. R., Pasquarella, V. J., Rucklidge, W. J., Samsikova, M., Zhang, C., Shelhamer, E., Lahera, E., Wiles, O., Ilyushchenko, S., Gorelick, N., Zhang, L. L., Alj, S., Schechter, E., Askay, S., Guinan, O., Moore, R., Boukouvalas, A., & Kohli, P. (2025). *AlphaEarth Foundations: An embedding field model for accurate and efficient global mapping from sparse label data* (arXiv:2507.22291). arXiv. https://doi.org/10.48550/arXiv.2507.22291

Bubeck, S., Chandrasekaran, V., Eldan, R., Gehrke, J., Horvitz, E., Kamar, E., Lee, P., Lee, Y. T., Li, Y., Lundberg, S., Nori, H., Palangi, H., Ribeiro, M. T., & Zhang, Y. (2023). *Sparks of Artificial General Intelligence: Early experiments with GPT-4* (arXiv:2303.12712). arXiv. https://doi.org/10.48550/arXiv.2303.12712

Carroll, S. R., Garba, I., Figueroa-Rodríguez, O. L., Holbrook, J., Lovett, R., Materechera, S., Parsons, M., Raseroka, K., Rodriguez-Lonebear, D., Rowe, R., Sara, R., Walker, J. D., Anderson, J., & Hudson, M. (2020). The CARE Principles for Indigenous Data Governance. *Data Science Journal*, *19*(1). https://doi.org/10.5334/dsj-2020-043

Carroll, S. R., Herczog, E., Hudson, M., Russell, K., & Stall, S. (2021). Operationalizing the CARE and FAIR Principles for Indigenous data futures. *Scientific Data*, *8*(1), 108. https://doi.org/10.1038/s41597-021-00892-0

Carroll, S. R., Rodriguez-Lonebear, D., & Martinez, A. (2019). Indigenous Data Governance: Strategies from United States Native Nations. *Data Science Journal*, *18*(1). https://doi.org/10.5334/dsj-2019-031

Checco, A., Bracciale, L., Loreti, P., Pinfield, S., & Bianchi, G. (2021). AI-assisted peer review. *Humanities and Social Sciences Communications*, *8*(1), 25. https://doi.org/10.1057/s41599-020-00703-8

Chen, X., Wang, X., Colacelli, A., Lee, M., & Xie, L. (2025). *Electricity Demand and Grid Impacts of AI Data Centers: Challenges and Prospects* (arXiv:2509.07218). arXiv. https://doi.org/10.48550/arXiv.2509.07218

de Vries-Gao, A. (2026). The carbon and water footprints of data centers and what this could mean for artificial intelligence. *Patterns*, *7*(1), 101430. https://doi.org/10.1016/j.patter.2025.101430

Fernández-Iglesias, J., Buitrago, F., & Sahelices, B. (2024). Detecting the edges of galaxies with deep learning. *Astronomy & Astrophysics*, *683*, A145. https://doi.org/10.1051/0004-6361/202347216

Gadot, T., Istrate, Ștefan, Kim, H., Morris, D., Beery, S., Birch, T., & Ahumada, J. (2024). To crop or not to crop: Comparing whole-image and cropped classification on a large dataset of camera trap images. *IET Computer Vision*, *18*(8), 1193–1208. https://doi.org/10.1049/cvi2.12318

Garcia Quevedo, D., & Kuri, J. (2026). Overview of Artificial Intelligence, Machine Learning, Natural Language Processing, and Large Language Models. In D. Garcia Quevedo & J. Kuri (Eds.), *AI for Qualitative Research: A Hands-On Guide for Management Scholars* (pp. 7–21). Springer Nature Switzerland. https://doi.org/10.1007/978-3-032-08872-7_2

Georgiou, G. P. (2026). What Distinguishes AI-Generated from Human Writing? A Rapid Review of the Literature. *Big Data and Cognitive Computing*, *10*(2). https://doi.org/10.3390/bdcc10020055

Grace, K., Salvatier, J., Dafoe, A., Zhang, B., & Evans, O. (2018). Viewpoint: When Will AI Exceed Human Performance? Evidence from AI Experts. *Journal of Artificial Intelligence Research*, *62*, 729–754. https://doi.org/10.1613/jair.1.11222

Hampton, S. E., Jones, M. B., Wasser, L. A., Schildhauer, M. P., Supp, S. R., Brun, J., Hernandez, R. R., Boettiger, C., Collins, S. L., Gross, L. J., Fernández, D. S., Budden, A., White, E. P., Teal, T. K., Labou, S. G., & Aukema, J. E. (2017). Skills and Knowledge for Data-Intensive Environmental Research. *BioScience*, *67*(6), 546–557. https://doi.org/10.1093/biosci/bix025

Helmy, M., Jin, L., Alhossary, A., Mansour, T., Pellagrina, D., & Selvarajoo, K. (2025). Ten simple rules for optimal and careful use of generative AI in science. *PLOS Computational Biology*, *21*(10), e1013588. https://doi.org/10.1371/journal.pcbi.1013588

Jegham, N., Abdelatti, M., Koh, C. Y., Elmoubarki, L., & Hendawi, A. (2025). *How Hungry is AI? Benchmarking Energy, Water, and Carbon Footprint of LLM Inference* (arXiv:2505.09598). arXiv. https://doi.org/10.48550/arXiv.2505.09598

Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., Ishii, E., Bang, Y. J., Madotto, A., & Fung, P. (2023). Survey of Hallucination in Natural Language Generation. *ACM Computing Surveys*, *55*(12), 1–38. https://doi.org/10.1145/3571730

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255–260. https://doi.org/10.1126/science.aaa8415

Jumper, J., Evans, R., Pritzel, A., Green, T., Figurnov, M., Ronneberger, O., Tunyasuvunakool, K., Bates, R., Žídek, A., Potapenko, A., Bridgland, A., Meyer, C., Kohl, S. A. A., Ballard, A. J., Cowie, A., Romera-Paredes, B., Nikolov, S., Jain, R., Adler, J., … Hassabis, D. (2021). Highly accurate protein structure prediction with AlphaFold. *Nature*, *596*(7873), 583–589. https://doi.org/10.1038/s41586-021-03819-2

Kazanskiy, N., Khabibullin, R., Nikonorov, A., & Khonina, S. (2025). A Comprehensive Review of Remote Sensing and Artificial Intelligence Integration: Advances, Applications, and Challenges. *Sensors*, *25*(19), 5965. https://doi.org/10.3390/s25195965

Kendall-Bar, J., Payne, A., Czapanskiy, M., Fox, N., Leivesley, J., Alksne, M., French, B., Malivert, A., O'Leary, G., Biswas, A., Nealey, I., Parkinson, R., Lowrie, C., Perez, I., Miller, E., Costello, I., Sainburg, T., Rissolo, D., Severance, L., … Lecomte, N. (2025). *Challenges and solutions for ecologists adopting AI*. Computer Sciences. https://doi.org/10.32942/X2FK8J

Konya, A., & Nematzadeh, P. (2024). Recent applications of AI to environmental disciplines: A review. *Science of The Total Environment*, *906*, 167705. https://doi.org/10.1016/j.scitotenv.2023.167705

Lai, J., Lortie, C. J., Muenchen, R. A., Yang, J., & Ma, K. (2019). Evaluating the popularity of R in ecology. *Ecosphere*, *10*(1), e02567. https://doi.org/10.1002/ecs2.2567

Liu, R., Zenke, C., Liu, C., Holmes, A., Thornton, P., & Malan, D. J. (2024). Teaching CS50 with AI: Leveraging Generative Artificial Intelligence in Computer Science Education. *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1, SIGCSE 2024*, 750–756. https://doi.org/10.1145/3626252.3630938

Lo, C. K. (2023). What Is the Impact of ChatGPT on Education? A Rapid Review of the Literature. *Education Sciences*, *13*(4), 410. https://doi.org/10.3390/educsci13040410

Maslej, N., Fattorini, L., Perrault, R., Gil, Y., Parli, V., Kariuki, N., Capstick, E., Reuel, A., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Niebles, J. C., Shoham, Y., Wald, R., Walsh, T., Hamrah, A., Santarlasci, L., … Oak, S. (2025). *Artificial Intelligence Index Report 2025* (arXiv:2504.07139). arXiv. https://doi.org/10.48550/arXiv.2504.07139

Merow, C., Serra-Diaz, J. M., Enquist, B. J., & Wilson, A. M. (2023). AI chatbots can boost scientific coding. *Nature Ecology & Evolution*, *7*(7), 960–962. https://doi.org/10.1038/s41559-023-02063-3

Merriënboer, B. van, Dumoulin, V., Hamer, J., Harrell, L., Burns, A., & Denton, T. (2026). *Perch 2.0: The Bittern Lesson for Bioacoustics* (arXiv:2508.04665). arXiv. https://doi.org/10.48550/arXiv.2508.04665

Milano, S., McGrane, J. A., & Leonelli, S. (2023). Large language models challenge the future of higher education. *Nature Machine Intelligence*, *5*(4), 333–334. https://doi.org/10.1038/s42256-023-00644-2

Nie, Q., & Liu, T. (2025). Large language models: Tools for new environmental decision-making. *Journal of Environmental Management*, *375*, 124373. https://doi.org/10.1016/j.jenvman.2025.124373

Oliver, R. Y., Chapman, M., Emery, N., Gillespie, L., Gownaris, N., Leiker, S., Nisi, A. C., Ayers, D., Breckheimer, I., Blondin, H., Hoffman, A., Pagniello, C. M. L. S., Raisle, M., & Zimmerman, N. (2024). Opening a conversation on responsible environmental data science in the age of large language models. *Environmental Data Science*, *3*, e14. https://doi.org/10.1017/eds.2024.12

Pichler, M., & Hartig, F. (2023). Machine learning and deep learning—A review for ecologists. *Methods in Ecology and Evolution*, *14*(4), 994–1016. https://doi.org/10.1111/2041-210X.14061

Regilme, S. S. F. (2024). Artificial Intelligence Colonialism: Environmental Damage, Labor Exploitation, and Human Rights Crises in the Global South. *SAIS Review of International Affairs*, *44*(2), 75–92.

Regnault, C. (2026, February 9). Understanding the CARE Principles: Why They Matter for Open Research and Indigenous Data Sovereignty. *Open Access and Digital Scholarship Blog*. https://blogs.imperial.ac.uk/openaccess/2026/02/09/understanding-the-care-principles-why-they-matter-for-open-research-and-indigenous-data-sovereignty/

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, *566*(7743), 195–204. https://doi.org/10.1038/s41586-019-0912-1

Reynolds, S. A., Beery, S., Burgess, N., Burgman, M., Butchart, S. H. M., Cooke, S. J., Coomes, D., Danielsen, F., Di Minin, E., Durán, A. P., Gassert, F., Hinsley, A., Jaffer, S., Jones, J. P. G., Li, B. V., Mac Aodha, O., Madhavapeddy, A., O'Donnell, S. A. L., Oxbury, W. M., … Sutherland, W. J. (2025a). The potential for AI to revolutionize conservation: A horizon scan. *Trends in Ecology & Evolution*, *40*(2), 191–207. https://doi.org/10.1016/j.tree.2024.11.013

Reynolds, S. A., Beery, S., Burgess, N., Burgman, M., Butchart, S. H. M., Cooke, S. J., Coomes, D., Danielsen, F., Di Minin, E., Durán, A. P., Gassert, F., Hinsley, A., Jaffer, S., Jones, J. P. G., Li, B. V., Mac Aodha, O., Madhavapeddy, A., O'Donnell, S. A. L., Oxbury, W. M., … Sutherland, W. J. (2025b). The potential for AI to revolutionize conservation: A horizon scan. *Trends in Ecology & Evolution*, *40*(2), 191–207. https://doi.org/10.1016/j.tree.2024.11.013

Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A. S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A., Maharaj, T., Sherwin, E. D., Mukkavilli, S. K., Kording, K. P., Gomes, C., Ng, A. Y., Hassabis,

D., Platt, J. C., … Bengio, Y. (2019). *Tackling Climate Change with Machine Learning* (arXiv:1906.05433). arXiv. https://doi.org/10.48550/arXiv.1906.05433

Shen, J. H., & Tamkin, A. (2026). *How AI Impacts Skill Formation* (arXiv:2601.20245). arXiv. https://doi.org/10.48550/arXiv.2601.20245

Triguero, I., Molina, D., Poyatos, J., Del Ser, J., & Herrera, F. (2024). General Purpose Artificial Intelligence Systems (GPAIS): Properties, definition, taxonomy, societal implications and responsible governance. *Information Fusion*, *103*, 102135. https://doi.org/10.1016/j.inffus.2023.102135

UNESCO, Miao, F., & Holmes, W. (2023). *UNESCO Guidance for Generative AI in Education and Research*. https://policycommons.net/artifacts/6942367/guidance-for-generative-ai-in-education-and-research/7852269/

Wills, S., Poon, S. T. S., Salili-James, A., & Scott, B. (2024). The use of generative AI for coding in academia. *Methods in Ecology and Evolution*, *15*(12), 2189–2191. https://doi.org/10.1111/2041-210X.14454

Winiarski, J. M., Whitmore, S. A., Wood, C. M., Eiseman, J. P., Netoskie, E. C., Bieber, M. E., Kramer, H. A., Kelly, K. G., McGinn, K., Thompson, C., Sawyer, S. C., Kahl, S., Klinck, H., & Peery, M. Z. (2026). Passive acoustic monitoring can provide insights into occupancy dynamics and impacts of disturbance for at-risk species. *Ecological Applications*, *36*(1), e70177. https://doi.org/10.1002/eap.70177

Xiong, G., Xie, E., Shariatmadari, A. H., Guo, S., Bekiranov, S., & Zhang, A. (2024). *Improving Scientific Hypothesis Generation with Knowledge Grounded Large Language Models* (arXiv:2411.02382). arXiv. https://doi.org/10.48550/arXiv.2411.02382