



The role of AI in ecology's computational carbon footprint

Kari E Norman^{1,2*}, Carl Boettiger³, Timothée Poisot⁴, and Gavin M Jones^{1,2}

¹USDA Forest Service Rocky Mountain Research Station, Albuquerque, NM; ²Center for Fire Resilient Ecosystems and Society, University of New Mexico, Albuquerque, NM (*knorman1@unm.edu); ³Department of Environmental Science, Policy, and Management, University of California Berkeley, Berkeley, CA; ⁴Département de Sciences Biologiques, Université de Montréal, Montréal, Quebec, Canada

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Ecologists increasingly recognize that novel computational approaches are critical for effectively addressing the ongoing climate and biodiversity crises. Some of the century's most substantive methodological developments are in artificial intelligence (AI), including generative AI (GenAI) as well as classical AI and machine learning (ML) approaches, which collectively have spurred advances across all fields of science. In ecology, AI has already been leveraged for diverse applications, ranging from large-scale image recognition for monitoring to conservation decision-making in complex systems. Recently, multiple calls for its application to address the biodiversity crisis (e.g., Pollock *et al.* 2025) outline past successes and avenues for its continued adoption.

Academic conversations about the potential power of AI for biodiversity science have happened concurrently with, but largely independent from, an increasing popular awareness of the skyrocketing carbon emissions of GenAI tools. Data centers underpinning corporate GenAI application are one of the fastest growing consumers of electricity, with use on track to double by 2030 and current rates already accounting for 1.5% of global electricity consumption (Chen 2025). The environmental impacts of GenAI also extend beyond electricity consumption. For example, training for only one model—Microsoft's GPT-3 (*sensu* ChatGPT)—necessitated consumption of approximately 5.4 million liters of freshwater in the US alone; moreover, training-related water consumption was regionally biased both domestically and internationally, raising serious social-justice concerns (Li *et al.* 2025). Generally, an increased emphasis on resource-heavy computational approaches may further exacerbate differences in resource accessibility between the Global North and South, leading to “AI colonialism”. Ecologists, who are committed to biodiversity protection, climate justice, and global equity, therefore feel a growing unease that the continued adoption of AI writ large could undermine the goals of their field. Although our primary focus here is on AI's carbon footprint, we acknowledge many other ethical issues involved in AI use, including governance of algorithms, violations of privacy and intellectual property rights, and a lack of social responsibility surrounding AI outputs.

■ What is artificial intelligence?

In the discussion of AI use in ecology, one of the central challenges is the ongoing conflation of GenAI with the entire field of AI. Colloquially, the term “AI” is increasingly perceived as exclusively synonymous with GenAI approaches that create text (e.g., ChatGPT), images (e.g., Stable Diffusion), or video (e.g., SORA). However, GenAI is only a single branch of AI that is arguably both the most energy-consumptive and the least relevant to ecology. The stigma attached to the ethical implications of adopting these large corporate models therefore runs the risk of painting with too broad a brush, deterring exploration of the other AI branches that have demonstrated relevance for ecological application (e.g., deep learning, ML, computer vision, etc.).

Ecologists may be surprised to realize that applications drawing from other branches of AI are already ubiquitous in ecology and were adopted with very little fanfare surrounding their relative carbon costs. For example, ML classifiers like random forest models and support vector machines have been common in the development of species distribution models since the field's inception. While these methods were some of the most data-intensive and cutting-edge approaches in use at the time of their origin, their current absence from the broader conversation on environmental impacts is due in part to their unremarkable computational needs relative to those of recent AI advances. This is an example of how the methods implicated by the term “AI” change over time to maintain the connotation of novelty, leading to AI's classification as a “floating signifier”, one that cannot be easily defined (Suchman 2023). The concept of AI is strategically vague to maintain its societal relevance, further clouding discussions of what qualifies as AI and what environmental impacts its applications have.

Based on data volume and runtime, the energy consumption of non-GenAI applications in ecology is actually on par with that of traditional statistical and simulation approaches. For instance, ecologists now routinely apply multi-species occupancy models across hundreds of species and entire continents, develop mechanistic whole ecosystem models, and perform complex fine-scale simulations like multi-species

agent-based models. Conversely, a deep learning algorithm can be trained locally on the power required by a typical PC. There is therefore no strong evidence currently that AI applications in ecology are inherently more costly than their non-AI counterparts, which go largely unscrutinized.

■ Recommendations for conscientious computation

We advocate for conversations on computational ecology's energy consumption to move beyond AI as “good” or “bad”, to a method-agnostic examination of computation in general, grounded in empirical data. Such an approach facilitates informed decisions and reduces the risk of underutilizing potentially powerful methods due to unfounded stigma surrounding their classification as AI. With very little available data on the relative costs of different approaches, there is an urgent need for even basic benchmarking of the methods and programming languages used in ecology. As energy consumption is a function not only of the method and how it is implemented, but also of the volume of data analyzed and the hardware it is run on, benchmarks may be heavily context dependent. Nevertheless, community uptake of tools like CodeCarbon (Courty *et al.* 2024) for estimating the carbon footprint of individual studies may provide informative first indications of how methods stack up against one another. Concrete numbers on ecology's computational emissions will also be important for establishing what we believe is already a comfortable assumption: that ecology's consumption is minimal relative to that of corporate GenAI.

In the absence of this data, we offer a few accessible but potentially powerful interim recommendations for empowering ecologists to embrace computation with frugality. First, reduce “statistical machismo”, or the tendency to adopt and advocate for more complex approaches for their own sake rather than because they are the best tool for the job (McGill 2017). When selecting a method, consideration of its ability to address the scientific goal should be closely followed by the relative computational cost of that method if reduced environmental impact is truly a goal of the field. This point is closely related to our second recommendation, which is for formal community-based identification of outstanding ecological questions that are otherwise intractable without major computational investment. These would be areas where the potential scientific benefits outweigh the environmental costs and may include, but are not limited to, already identified future avenues for AI. Finally, we echo calls for improved training and coding standards in ecology. Most ecologists develop ad hoc coding skills over the course of their training and therefore have little exposure to standard efficiency improvement practices. As every line of code written has a carbon footprint, ecologists should take advantage of existing initiatives like the green software movement (Caballar 2024) to minimize the impacts of our software development.

Ecologists' overall impact reduction is challenged substantially by hidden costs in other aspects of the scientific process, which are increasingly GenAI integrated. For example, code editors now frequently incorporate code-generating large language models (LLMs) into their platforms, and similar models are being used to fill the code training gaps described above. Advocacy for the use of GenAI to create figures and science communication materials may normalize considerable computational investment in place of effort by artists or graphic designers. AI is also prevalent in the scholarly publication process, where some authors use LLMs to “refine” their writing and prominent publishers are now “AI-enabled”, using AI for peer reviewer identification and keyword generation, as well as in place of editorial assistants. We worry these GenAI applications could quickly and easily outpace any gains made by the steps advocated for here.

Finally, it is critical to note that no amount of individual action will fix what is really a lack of regulation. Just as policy-making is fundamental for broad-scale solutions to the climate and biodiversity crises, so too will it be essential for meaningful reductions in AI environmental impact. Still, we believe aligning our choices as scientists with the values that motivate our work maintains our integrity as individuals and as a field.

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