

**“Grounding” AI:
Envisioning Inclusive Computing for Soil Carbon Applications**

0: Towards Constructive Carbon Computing

The climate crisis looms, and computing will have to earn its keep. While estimates vary regarding the share of global carbon emissions attributable to computation and data storage (between 1.4% and 23% by 2030),¹ demand for computing power is expected to continue rising, and its environmental impact will increase accordingly.² Simultaneously, computing technologies offer opportunities for climate mitigation through energy and resource efficiency gains. In artificial intelligence (AI), this tension has been framed as requiring a “gambit,” that is, a calculated agenda that makes initial sacrifices in order to cultivate a worthy advantage.³

Many AI applications in the realm of climate mitigation support the justification of continued research despite their energy demands; these include the optimization of energy infrastructure, urban systems, and industrial processes, as well as more aggressive technologies like direct air capture of carbon dioxide and solar geoengineering. These techniques have great potential for managing the climate impacts of human modernity. However, more enticing opportunities lie at the interface between high-tech and low-tech approaches, where advanced technology meets the Earth itself.

Soil carbon management is among the most ancient technologies at our disposal for climate mitigation, and it is one of the highest-impact spheres for AI implementation. Investment in soil health underpins healthy ecosystems, resilient agriculture, and improved water quality, among many co-benefits that attend its massive and largely untapped potential for atmospheric carbon sequestration.⁴ These environmental services underpin the deep traditional meanings and continued relevance of soil to humans from a historical and cultural standpoint.⁵ Thus, soil carbon presents an advantageous pivot point for computing in the age of climate change: perhaps an initiative to “ground” AI in soil carbon will reveal the path to a more environmentally and socially conscious era in computing.

This essay will explore the exciting opportunities for AI-based land management, focusing on state-of-the-art and future applications in soil carbon modeling. It will summarize recent advances in this field and offer a summons for further research in service of an imaginative long-term vision for soil carbon AI. Concurrently with these arguments, it will interrogate the social and ecological risks of deploying such technology, using these critiques to inform a research agenda that prioritizes social equity and ecological responsibility. This essay takes soil carbon modeling as a bellwether case study, striking out towards an environmental ethic for computing that anticipates a decarbonized future.

¹ Cowsls et al. “The AI gambit: leveraging artificial intelligence to combat climate change—opportunities, challenges, and recommendations.” *AI & Society* 38 (2023): 283-307, doi: 10.1007/s00146-021-01294-x

² Pesce, Mark. “Cloud Computing’s Coming Energy Crisis” *IEEE Spectrum*. 21 July 2021, <https://spectrum.ieee.org/cloud-computings-coming-energy-crisis>

³ Cowsls et al. “The AI gambit.”

⁴ Bossio et al. “The role of soil carbon in natural climate solutions.” *Nature Sustainability* 3 (2020): 391-398, doi: 10.1038/s41893-020-0491-z

⁵ Singular, Meghan. “Soils, Culture, and People.” *Soil Science Society of America*. December 2015, <https://www.soils.org/files/sssaiys/december-soils-overview.pdf>

1: Sensing the Soil

Globally, the top one meter of soil holds approximately three times the amount of carbon found in the atmosphere.⁶ This quantity falls in the neighborhood of 2,500 billion tons: more than the total sum of carbon in the atmosphere and all plant life combined.⁷ Despite these staggering comparisons, however, research has shown that over the last 10,000 years the world's cultivated soils have lost between 50 and 70% of their original carbon stock, mainly through oxidation when soil exposed to the air is converted to atmospheric CO₂.⁸ Restoring soil carbon offers a massive opportunity for mitigating the climate crisis: scholars estimate that interventions related to protecting and rebuilding soil carbon stocks represent 25% of the potential of natural climate solutions for atmospheric CO₂ reduction.⁹

The suite of land management techniques that fortify soil carbon storage are known as regenerative agriculture or “carbon farming” practices. These approaches include planting deeper-rooting cultivars, adding nutrient-rich organic matter to the soil, implementing agroforestry (integrating trees and shrubs with cropland or pasture), and limiting tillage (reducing the frequency of soil's exposure to the air) can help re-sequester soil organic carbon stock. They also deliver key benefits beyond carbon sequestration, such as boosting agricultural productivity and increasing resilience to floods and drought.¹⁰ Due to the many advantages of these interventions, traditional agriculture and land management paradigms have included the protection of soil carbon for centuries. In our current age of industrial agriculture, scientific knowledge and awareness of carbon-focused soil chemistry are rapidly expanding, and so are financial and regulatory methods of incentivizing best practices for farmers and land stewards. However, a crucial bottleneck intervenes in the measurement and verification of soil carbon stocks: here is where AI makes an impact.

In order to furnish a material intervention in the climate crisis, soil carbon stocks must be monitored and managed at very large scales, but traditional methods of quantifying soil carbon are not up to this task. The oldest and most accurate methods of soil carbon measurement rely on laboratory processing of soil samples; these include wet oxidation, which uses a detailed titration procedure, and dry combustion, which involves analyzing samples that have been thermally decomposed in a furnace.¹¹ Both techniques are time consuming and expensive, so scientific and industry communities are investing in alternative ways to model soil carbon at large scales. Some in-situ options have been developed to improve efficiency over laboratory methods, but the forefront soil carbon sensing applies machine learning techniques to multispectral remote sensing data, which captures the electromagnetic radiation or “spectral signature” of the soil and can be correlated to soil carbon stocks.

The key advantage of AI in the sphere of monitoring soil carbon is its ability to scale beyond the ground-truth data available. After training on paired examples that show a multispectral image of a given area and the corresponding ground-truth soil carbon measurements for that area, machine learning models can learn a multidimensional probability function that relates the satellite data to its on-the-ground counterpart. Of course, the specific soil carbon metabolism of a given site is dependent on its agro-

⁶ Acharya et al. “Data driven approach on in-situ soil carbon measurement.” *Carbon Management* 13 (2022): 401-419, doi: [10.1080/17583004.2022.2106310](https://doi.org/10.1080/17583004.2022.2106310)

⁷ Schwartz, Judith D. “Soil as Carbon Storehouse: New Weapon in Climate Fight?” *Yale Environment* 360. 4 March, 2014, https://e360.yale.edu/features/soil_as_carbon_storehouse_new_weapon_in_climate_fight

⁸ “Fact Sheet: Soil Carbon Sequestration.” *American University*. 24 June, 2020, <https://www.american.edu/sis/centers/carbon-removal/fact-sheet-soil-carbon-sequestration.cfm#:~:text=But%20over%20the%20last%2010%2C000,of%20their%20original%20organic%20carbon>

⁹ Bossio et al. “The role of soil carbon in natural climate solutions.”

¹⁰ Schwartz, Judith D. “Soil as Carbon Storehouse.”

¹¹ Acharya et al. “Data driven approach on in-situ soil carbon measurement.”

climatic zone, the type and intensity of land use, and the specific land management techniques in place;¹² this means that some localization of training data is necessary, and so is the inclusion of land management information in the formation of AI models. While these key details necessitate the geographic calibration of soil carbon prediction models, that calibration can be achieved with a small fraction of the time and investment necessary to sense each new land parcel using direct measurement methods. Within the global project of rebuilding soil carbon stocks, this exponential difference in monitoring efficiency is an indispensable asset.

2: Pitfalls and Footholds

AI-based soil carbon sensing has the potential to usher in a new era of land management that prioritizes intelligent, carbon-focused predictive modeling as its organizing principle. This overall objective is attended by various social and ecological side effects, some of which are advantageous co-benefits while others represent serious risks. A critical look at this technology reveals potential shortfalls that can inform a more robust and equitable research agenda for the future.

Ecologically, rebuilding stocks of soil carbon is an effective way to improve soil health in general: it increases the concentration of nutrients available to plants, supports microbial activity, expands water storage, and adds structure by aggregating soil particles, which supports resilience to erosion and physical degradation.¹³ These benefits to soil health can form the basis of improved agricultural efficiency and sustainability, supporting the emergence of more environmentally resilient (and less extractive) food systems. Risks to ecology emerge when carbon sequestration is pursued as a unilateral goal, without attention to local geography, native plants, or traditional land management practices. The global trend of large-scale government-sponsored tree planting projects offers a cautionary tale in this regard: when millions of fast-growing nonnative trees are planted in massive tracts of monoculture, only a small minority of the seedlings tend to survive.¹⁴ The resulting proliferation of “phantom forests” around the world as greenwashing PR stunts fail illustrates the importance of long-term thinking and attention to local dynamics in carbon sequestration projects. In order to avoid similar outcomes as a result of soil carbon AI, models must include as much site-specific data as possible, and their outputs should include transparency about the geographic imprecision of generalized predictions.

Socially, the risks of applying AI to soil carbon management revolve around issues of equity in its deployment. Like many frontier technologies, AI-driven regenerative agriculture is most accessible to organizations with the time, management, foresight, and financial resources to invest in it. This means that the insights it produces are disproportionately available to industrial farmers and agriculture companies in wealthy regions in the present day, and the risk exists that future soil carbon datasets will develop biases that favor early adopters in ways that intensify this initial inequity. Especially as carbon sequestration is financialized in carbon offset markets, there is a substantial risk of formalizing existing inequalities in the future of climate economics. Similarly to the risks that accompany oversimplified ecological approaches, contemporary frameworks for incentivizing soil carbon sequestration may operate efficiently towards their single objective of reducing atmospheric CO₂, but they fail to intervene in the larger equity issues that face modern agriculture. Regulation and governance of these systems are called upon to address these challenges.

Finally, the social positioning of AI more broadly plays a role in global equity concerns associated with AI for soil carbon. In 2023, the World Economic Forum identified an “AI divide” between

¹² “Sustainable soil/land management for Climate-Smart Agriculture.” *Food and Agriculture Organization of the United Nations*. 2023, <https://www.fao.org/climate-smart-agriculture-sourcebook/production-resources/module-b7-soil/chapter-b7-3/ar/>

¹³ “Soils and carbon for reduced emissions.” *Agriculture Victoria*. 7 November 2022: <https://agriculture.vic.gov.au/climate-and-weather/understanding-carbon-and-emissions/soils-and-carbon-for-reduced-emissions#:~:text=Soil%20carbon%20provides%20a%20source,and%20protects%20soil%20from%20erosion.>

¹⁴ Pearce, Fred. “Phantom Forests: Why Ambitious Tree Planting Projects Are Failing.” *Yale Environment* 360. 6 October 2022: <https://e360.yale.edu/features/phantom-forests-tree-planting-climate-change>

the Global North and the Global South that emerges from structural differences in the capacity to implement AI solutions at a national scale.¹⁵ The component elements of readiness to deploy AI include computing infrastructure, local training data, technical expertise, and informed policy guidelines; these resources tend to be overall less available in the Global South while the United States and China dominate the field globally. Meanwhile, a 2021 Stanford University study determined unambiguously that “The people building AI systems are not representative of the people those systems are meant to serve,” citing the plurality of AI PhDs who are white, and the 83.9% of them who are men.¹⁶ In the case of soil carbon sensing, these issues are especially relevant: effective carbon management systems can only be produced with the direct involvement of the land stewards who implement them, and with attention to the insights of traditional land management approaches.¹⁷

3: Solving for Carbon Equity

Many of the structural equity issues that face soil carbon AI involve themes surrounding inclusive development and socially responsible deployment of this technology. These risks can be reformulated in terms of specific goals, such as integrating diverse perspectives with the construction and testing of soil carbon models, or supporting access to soil carbon AI in communities where machine learning expertise is unavailable. To address these intentions, inspiration can be drawn from the unlikely source of large language models.

The recent explosion in popularity of generative models like Open AI’s Dall-E and ChatGPT indicate a major step forward in the democratization of AI: now that image and text generation can be conducted through straightforward requests in natural language, these models are not only accessible but wildly popular in the general public.¹⁸ The key innovation represented by these models is not their ability to create convincing outputs. On the contrary, both of OpenAI’s models generate predictions that are only plausible on the surface level, but whose structural or factual errors become glaring at a close look.¹⁹ Instead, the crucial breakthrough of these platforms is that any person can communicate with them, and they answer in real time. Currently, these models operate on limited datatypes, focusing on media that are easy to imitate and exciting for users to consume. However, these products could be seen as the start to a new era in AI, in which a vastly increased pool of users communicate in natural language with models that represent much more than just text and images.

The goal of the research agenda proposed here is to link soil carbon models to language models, creating multimedia AI systems (henceforth referred to as “carbon-language models”) that communicate naturally with users to relay accurate soil carbon insights. Crucial to this objective is training language models for factual accuracy, which today’s chat-based text generation models like ChatGPT, Google’s Bard, or Bing’s BingAI do not ensure.²⁰ This limitation runs deep: reinforcement learning approaches that

¹⁵ “The ‘AI divide’ between the Global North and the Global South.” *World Economic Forum*. 16 January 2023, <https://www.weforum.org/agenda/2023/01/davos23-ai-divide-global-north-global-south/>

¹⁶ *Artificial Intelligence Index Report*. “Chapter 6: Diversity in AI,” 3-17. https://aiindex.stanford.edu/wp-content/uploads/2021/03/2021-AI-Index-Report-_Chapter-6.pdf

¹⁷ Handelsman et al. “COP26: Indigenous Voices in Global Soil (And Climate) Policy.” 3 November 2021, <https://yalebooks.yale.edu/2021/11/03/cop26-indigenous-voices-in-global-soil-and-climate-policy/>

¹⁸ Foy, Peter. “ChatGPT crosses 1 million users in its first week.” blog: <https://www.miq.ai/chatgpt-crosses-1m-users-internet-this-week-in-ai/>

¹⁹ McCracken, Harry. “If ChatGPT doesn’t get a better grasp of facts, nothing else matters.” 11 January, 2023, <https://www.fastcompany.com/90833017/openai-chatgpt-accuracy-gpt-4>

²⁰ Roose, Kevin. “A Conversation With Bing’s Chatbot Left Me Deeply Unsettled.” *The New York Times*. 16 February 2023. <https://www.nytimes.com/2023/02/16/technology/bing-chatbot-microsoft-chatgpt.html>

train on real human interactions rely on these conversations as ground truth.²¹ In order to develop models that capture both soil carbon data and the linguistic fluency to explain it, a new training approach is necessary. Such an alternate method might start by taking cues from text-to-image models like Dall-E or Midjourney, using a label-based approach to associate data analysis results with accurate descriptions in scientific papers, textbooks, or video transcripts from reputable sources. Models trained this way could eventually explain to a user the significance of soil carbon measurements, or articulate their own analysis of future land management scenarios. They would fall under the emerging category of “self-explaining” AI, which describes models that can explain their decisions and qualify their confidence in them.²²

Ideally, carbon-language models will extend past simply communicating their findings and eventually support productive exchange of multimedia environmental information. Researchers have called for AI in agriculture to be trained not only on science but also citizen science, indigenous knowledge systems, crowdsourced volunteer data, and conventional farming knowledge.²³ Today’s soil carbon models operate on numerical data like soil chemistry measurements, tillage dates, and crop codes as well as multispectral image data. However, their functionality and positive social impact would be vastly extended by the ability to update their representations based on text, video, and audio prompts. Such “multimedia” inputs might include official crop reports and policy documents as well as anecdotes and management histories written in plain text, news media and weather reports, smartphone videos of field conditions, or audio files of farmers or other land managers verbally describing their observations. Imagining a carbon-language AI that can process and respond to such a wide variety of materials may sound like a far-off and idealized possibility, but with the advent of foundation models and other techniques that have begun to separate AI from its historic dependence on manually labeled data,²⁴ it may become possible on an accelerated schedule.

By endowing sophisticated soil carbon models with the natural language interaction capabilities that have popularized generative AI, computing can support an equitable and sustainable future for land management at every scale. One can imagine farmers asking a virtual assistant to explain various planting scenarios and their effects on the soil carbon stock of their land, or indigenous community leaders implementing AI-generated instructions in order to enroll in a carbon offset program that monetizes their traditional stewardship practices. Furthermore, policymakers could use such tools to understand the implications of their proposals, using AI to help bridge the ongoing and problematic gap between climate science and politics. Extended globally, carbon-language models equipped to communicate their own representations could even begin to close the AI implementation gap that exists between the Global North and Global South, purely by alleviating some of the dependence of these methods on local technical expertise.

4: From the Ground, Up

Soil carbon management represents one of the most approachable climate change mitigation techniques, and AI is already accelerating its progress by helping to scale soil carbon measurements efficiently. However, the present applications of AI to soil carbon projects are dwarfed by the scale of the positive impact these technologies could have in the future. As more soil data becomes available in more locations across the planet, the utility of existing approaches will expand linearly. But with innovations like the integration of self-explanation and natural-language text generation into “carbon-language

²¹ Evans, Owain. “Truthful AI: Developing and governing AI that does not lie.” *Computers and Society*: submitted 13 October 2021. [arXiv:2110.06674v1](https://arxiv.org/abs/2110.06674v1)

²² Elton, Daniel C. “Self-explaining AI as an Alternative to Interpretable AI.” Conference paper. 6 July 2020, https://link.springer.com/chapter/10.1007/978-3-030-52152-3_10

²³ Lin et al. “Train artificial intelligence to be fair to farming.” *Nature Correspondence*. 20 December 2017, <https://www.nature.com/articles/d41586-017-08881-3>

²⁴ Murphy, Mike. “What are foundation models?” *IBM: blog*. 9 May 2022, <https://research.ibm.com/blog/what-are-foundation-models>

models,” the adoption of these approaches could explode as they transcend the current limitations of expertise and investment.

While improvements to the accessibility of soil carbon management techniques can help widen the adoption of carbon-focused land management, they also offer key advantages in the realm of climate equity. There are deep social inequalities facing the deployment of AI tools in general, and soil carbon applications have their own specific challenges. Such equity issues should shape the research agenda for soil carbon AI going forward, according to the belief that better technologies are those that work for everyone.

This essay foregrounds soil carbon modeling as a globally relevant and especially promising segment of climate AI, but its orientation towards an inclusive and multivalent research agenda is relevant to computing at the broadest scale. As computing technologies across the field become more powerful and impactful with every passing year, it becomes increasingly important to ground our research the fundamental human priorities that frame our relationships to the planet and to each other. Taking soil carbon AI as the seedling form of this larger research mandate, we can cultivate a future of computing that is green, ethical, and dazzlingly bright.

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