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REVIEW ARTICLE

Geography for AI sustainability and sustainability for GeoAI

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ABSTRACT
Recent years have witnessed a boom in the development of multimodal large-scale generative AI models. These computationally intensive AI models, such as GPT-4, and their associated data centers have undergone increasing scrutiny in terms of their energy consumption and carbon emissions. As awareness of the energy costs and carbon footprints of AI models grows, attention has broadened to include other sustainability-related aspects such as their water consumption, transparency, and further environmental and social implications. In this work, we examine existing tools, frameworks, and evaluation metrics, complementing the ongoing discussions regarding AI's environmental sustainability with a geographic perspective. This work, on the one hand, contributes to a geographically aware sustainability evaluation of current AI models. On the other hand, it examines the unique characteristics and challenges of GeoAI models, hoping to engage the GeoAI community in the sustainability discussion. Moving forward, we outline future directions on systematic reporting and geographically aware assessment. We then propose potential solutions, such as the adoption of Retrieval-Augmented Generation (RAG) models. Ultimately, we encourage future GeoAI research to acknowledge and address their environmental and social impact, thereby guiding GeoAI toward a more transparent, responsible, and sustainable future.

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AI sustainability; GeoAI; carbon footprint; transparency; foundation model

1. Introduction

Google searches have a daily volume estimated at 8.5 billion (Flensted, 2024), and a simple search generates approximately 0.5 grams of CO_2 emissions (Berners-Lee, 2020). Since the launch of ChatGPT in November 2022, generative AI has experienced significant growth, as it purportedly enhances user experience by providing more useful results than traditional search engines (Hristidis et al., 2023; Xu et al., 2023). The data centers and training infrastructure required to power the growing AI usage have inevitably increased energy consumption and carbon emissions (Wu et al., 2022). Despite AI having many benefits, the general public has not widely recognized the significant carbon footprint of generative AI. For example, *have you ever wondered how much carbon emissions a single ChatGPT query generates compared to a Google search?*

GPT-4 (OpenAI, 2023), said to have 1.76 trillion parameters (Schreiner, 2023), represents a substantial advance in model complexity and computational requirements. The integration of generative AI technology into the larger search engine market, e.g. GPT-4's collaboration with Microsoft Bing (Blogs, 2023), has further expanded the everyday use of advanced AI. However, the widespread adoption of such large-scale models has raised environmental concerns. There have been increasing calls in the machine learning (ML) community to enhance their energy efficiency (Bender et al., 2021; Schwartz et al., 2020; Strubell et al., 2019). The scale and complexity of AI models continue to grow. Addressing sustainability issues has become more urgent because they are increasingly adopted in more domains, e.g. those developing computationally intensive *Geo*AI models (Cai et al., 2020; Jiao et al., 2018; Pathak et al., 2022). In the context of AI, sustainability refers to the development of AI systems to minimize their environmental impact while promoting greater ecological integrity and social justice (Van Wynsberghe, 2021). In response to these pressing concerns, the ML community has taken steps to measure, report, and ultimately mitigate the environmental impact of model training (Touvron et al., 2023).

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In this work, we integrate the perspectives of *Geography for AI Sustainability* and *Sustainability for GeoAI*. By introducing a geographic lens, we contextualize current efforts within the ML community to improve AI's environmental and social sustainability and highlight geographic considerations that have received limited attention to date. This is followed by a discussion on how these efforts can be applied to GeoAI models. We seek to raise awareness within the GeoAI community, whose models, such as climate models (Rolnick et al., 2022), have potentially greater implications for sustainability than conventional AI models. To offer a comprehensive view, we cover a wide range of topics, including energy and natural resource consumption, carbon emissions, transparency, and associated social consequences of AI deployment. All these factors contribute to our conceptualization of AI sustainability. With this work, we hope to encourage the GeoAI community to prioritize sustainability besides model performance in future research, advocating for resource-conscious decision-making.

The contributions of this paper are twofold:

- *Geography for AI sustainability*: We introduce a geographic perspective on regional disparities and geographically aware assessments of environmental impacts into current AI sustainability discussions.
- *Sustainability for GeoAI*: We examine the applicability of current AI sustainability efforts to the field of GeoAI, highlighting the uniqueness and challenges of GeoAI models in achieving sustainability goals.

The remainder of this paper is structured as follows. Section 2 provides an overview of available software tools, evaluation metrics, benchmarks, and analytical frameworks intended to address AI sustainability. Section 3 outlines the challenges identified from this overview and recent ML literature. Following this, Section 4 introduces a geographic perspective on current AI sustainability discussions. Here, we focus on regional disparities in environmental impacts and the need to incorporate geographic awareness into assessments of AI sustainability. Section 5 discusses the unique characteristics of geospatial data and the challenges of applying current AI sustainability efforts within the field of GeoAI. In Section 6, we propose future directions and potential solutions to improve AI sustainability. Finally, we conclude our findings in Section 7.

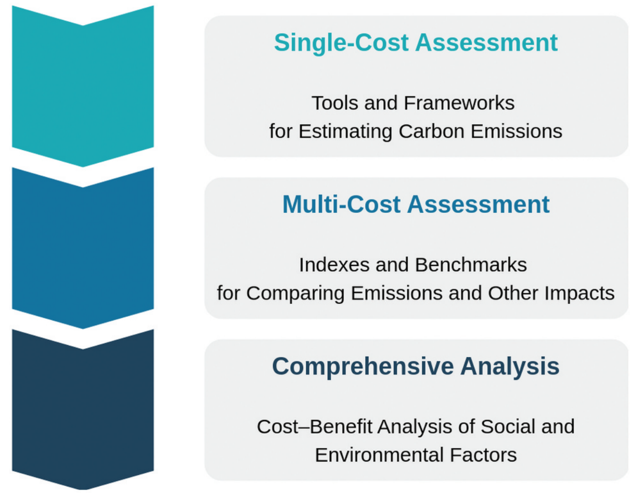

Figure 1. Evolution of model evaluation for AI sustainability assessment.

2. Current sustainability assessment in AI research

Driven by rising public awareness of climate change, scrutiny has grown of the environmental impacts of computing in AI research. Calls for *Green AI* (Schwartz et al., 2020) aim to improve efficiency and reduce carbon footprints of AI research. Early concerns focused on energy consumption and emissions estimation (Gelenbe & Caseau, 2015; Hilty et al., 2009; Malmodin et al., 2013), later broadening to include metrics such as a transparency index (Bommasani et al., 2023, 2024) for model comparison. Furthermore, the ML community has acknowledged social impacts of AI research (Bender et al., 2021) and also discussed to what degree AI benefits outweigh potential costs (Bommasani et al., 2021). We categorize this progression into three stages: (i) single-cost assessment, (ii) multi-cost assessment, and (iii) comprehensive analysis. This evolution of model evaluation for AI sustainability assessment is illustrated in Figure 1 and discussed in more detail in the following three sections.

2.1. Single-cost assessment

In response to calls for more sustainable AI (research), various frameworks and software tools have been developed to estimate, visualize, and transparently report carbon emissions. Starting with a single-cost assessment, which evaluates the single factor of carbon emissions, these tools typically estimate emissions by multiplying energy consumption by carbon intensity. Carbon intensity refers to the amount of CO_2 emitted per unit of energy produced or consumed and is a key factor for accurate estimations. Table 1 summarizes the

Table 1. Summary of available open-source tools and their data sources.

Year	Name	Type	Carbon Intensity Data Source	Temporal Coverage	Spatial Coverage
2019	ML Emissions Calculator	Dashboard	U.S. EPA (2022)	2016	USA
			Electricity Maps (n.d.)	2021	Global
			Moro and Lonza (2018)	2017	EU-28
			Carbon Footprint (2018)	2017	Global
2019	CodeCarbon	Software	U.S. EPA (2022)	2016	USA
			U.S. EIA (2019)	2016	Global
2020	carbontracker	Software	Energi Data Service	real-time	DNK
			Carbon Intensity API	real-time	GBR
			EEA (2020)	2017	EU-28
2020	experiment-impact-tracker	Software	Electricity Maps (n.d.)	2019	Global
			California ISO	real-time	CA, USA
2021	EnergyVis	Dashboard	NREL (2020)	2020	USA
2021	Green Algorithms	Dashboard	IEA (2019)	2019	Global
2022	Eco2AI	Software	Ember (2022)	2021	Global
			Carbon Footprint (2022)	2021	Global
			DCCEEW (2021)	2021	AUS
			UNFCCC (2021)	2021	CAN
			U.S. EPA (2022)	2020	USA

available free, open-source tools and frameworks for emissions estimation, together with their detailed carbon intensity data sources.

Among the earliest of these tools was the *Machine Learning Emissions Calculator* (Lacoste et al., 2019), which provides an interface to estimate the amount of carbon emissions produced by training machine learning models. By inputting information on *Hardware Type*, *Hours Used*, *Provider*, and *Region of Compute*, users can obtain an estimate of carbon emitted as well as the amount of carbon already offset by the provider. Carbon emissions are calculated by integrating multiple data sources, including the US-centric Emissions & Generation Resource Integrated Database (eGRID) from the Environmental Protection Agency (EPA) (U.S. EPA, 2022), Electricity Maps (n.d.), and various electricity carbon intensity reports.

Around the same time, *CodeCarbon* (Lottick et al., 2019) was introduced as a lightweight software package to be embedded in code. It estimates the amount of CO_2 produced by the cloud or personal computing resources utilized for code execution. Emissions and exemplary equivalents are then displayed through a dashboard visualization. Energy mix and emissions data were provided by eGRID from the U.S. EPA (2022) and the Energy Information Administration (EIA) (U.S. EIA, 2019).

Similar to *CodeCarbon*, *Carbontracker* (Anthony et al., 2020) is a software package for tracking and predicting the energy consumption and carbon emissions of training deep learning models, offering real-time carbon intensity data where available. Currently, real-time data are limited to Denmark and Great Britain through APIs. For other regions, the tool uses an average carbon intensity value for the EU-28 countries provided by the European Environmental Agency (EEA, 2020)

Building on the capabilities of tools like *Carbontracker* and *CodeCarbon*, *experiment-impact-tracker* offers a lightweight framework (Henderson et al., 2020) for tracking real-time energy consumption and carbon emissions of ML research. The tracker requires a simple code addition to gather details of CPU- and GPU-package power draw, memory usage, etc. It includes a script to create standardized online appendices for reporting these metrics. Carbon emissions are estimated using open-source portions of Electricity Maps (n.d.), choosing the carbon intensity of the smallest bounding region for a given location. Currently, real-time carbon emissions data are available only for California in the US.

While some tools focus on code-based integration, others offer a more visual and interactive approach. For instance, *EnergyVis* (Shaikh et al., 2021) is a web-based platform that allows users to track, compare, and visualize energy use and carbon footprints of training machine learning models. The platform helps users explore alternative deployment locations and also hardware options to potentially reduce their carbon footprints. Carbon emissions are calculated using US state-dependent carbon intensity constants from the National Renewable Energy Laboratory (NREL, 2020). This allows EnergyVis to estimate the carbon output of experiments conducted in different locations across the US, thereby helping users evaluate location-based alternatives.

Another dashboard-based tool, similar to *Machine Learning Emissions Calculator* but extending its capabilities by offering more detailed inputs, is *Green Algorithms* (Lannelongue et al., 2021). It provides a methodological framework and online platform that allows users to evaluate the carbon footprint of their computational tasks. *Green Algorithms* supports a wide range of hardware configurations and can estimate the carbon savings or costs of redeploying computations on different architectures. Carbon emissions are computed using an average worldwide carbon intensity value from the International Energy Agency (IEA) emissions report (IEA, 2019).

More recently, *Eco2AI* (Budennyy et al., 2022) has emerged as a Python library designed for CO_2 emissions tracking. It monitors the energy consumption of hardware devices during model training and estimates the equivalent carbon emissions with regional emission coefficients. These coefficients, also known as carbon intensities, are derived from global energy reports such as Ember (2022) and multiple regional datasets, including those from Australia, Canada, Russia, and the US.

On top of the tools summarized in Table 1, Dodge et al. (2022) proposed a framework for estimating the software carbon intensity (SCI) of cloud-based instances by incorporating location-based and time-specific marginal emissions. Ideally, the SCI is calculated by considering both operational emissions and embodied emissions, representing the carbon emitted during model operation and the life cycle of hardware devices (manufacture, usage, and disposal), respectively. However, given the limited information on specialized hardware such as GPUs, the preliminary implementation only addresses operational emissions. Documenting the carbon footprint across all stages of hardware usage remains a key challenge. Still, this framework provides a method to estimate SCI as a proxy for cloud instance carbon emissions.

2.2. Multi-cost assessment

While a lot of attention has been (rightfully) directed toward estimating carbon emissions, a comprehensive assessment goes beyond merely reporting emissions numbers. A multi-cost assessment considers additional factors such as energy efficiency, resource consumption, and broader societal impacts. Indexes and benchmarks are designed to provide a structured framework for assessing these sustainability aspects, offering the chance to compare the performance of different models.

The Foundation Model Transparency Index (FMTI) (Bommasani et al., 2023, 2024) offers a broad range of system-level metrics comprised of 100 fine-grained indicators to evaluate the transparency of foundation models (FMs)—large-scale machine learning models pre-trained on diverse datasets that generalize across tasks (Bommasani et al., 2021)—across stages, from upstream resource consumption and model construction to the future usage downstream. Fourteen major foundation model developers are scored based on their practices for their flagship foundation models. This includes GPT-4 (OpenAI, 2023) for OpenAI, Gemini 1.0 Ultra (Gemini Team, Google, 2023) for Google, and Llama 2 (Touvron et al., 2023) for Meta. Through quantifying transparency and scoring across developers, FMTI aims to encourage these companies at the forefront of large FMs to improve their transparency scores over time.

Besides such indexes, benchmarks also play a key role in sustainable AI practices by providing standardized frameworks to evaluate energy efficiency and environmental impact (X. Zhou et al., 2020). To date, there are no *widely* adopted benchmarks to evaluate such performance. Establishing a set of standardized metrics to evaluate AI models based on environmental factors (e.g. energy consumption, carbon footprint) would make it possible to compare different models. Ongoing efforts like MLCommons provide a benchmark for algorithm efficiency (Dahl et al., 2023), along with a comprehensive benchmark suite (https://mlcommons.org/benchmarks/), including training, inference, and storage benchmarks, to evaluate the performance of machine learning models across different hardware setups (e.g. CPUs, GPUs, and accelerators). The goal of MLCommons benchmarks is to enable informed optimization of machine learning models for deployment, allowing direct comparisons across different models and hardware configurations. With the potential for more information on AI model energy efficiency, these benchmarks can advance the field of AI in an environmentally competitive manner by measuring energy usage and carbon emissions (Wu et al., 2022).

2.3. Comprehensive analysis

AI models should ideally contribute to the greater social good to help balance their environmental impact. For instance, they can help with healthcare diagnosis, promote precision farming in agriculture, and improve predictions to mitigate the effects of climate change (Bommasani et al., 2021; Tomaev et al., 2020). A comprehensive analysis examines both the costs and benefits of these models, thereby determining whether their overall social and environmental impacts justify their implementation.

In order to assess the trade-off between the social benefits and the associated social and environmental costs of deploying a foundation model, Bommasani et al. (2021) proposed an equation to measure a model's overall impact. This equation takes into account several variables, all expressed in monetary values, including social and environmental benefits, the social cost (future harm to society) of carbon released through energy use, the energy cost of the model, and the social cost of other second-order environmental effects. By examining all these factors, stakeholders can choose a more efficient model or reconsider deployment. This would help ensure the sustainability of FMs prior to their adoption and wide deployment. While quantifying these variables poses challenges, and their empirical estimation may vary significantly, such cost–benefit analysis offers an initial framework for considering environmental and societal trade-offs in training and deploying an FM.

3. Challenges identified in literature

In this section, we summarize the challenges identified from Section 2 and recent ML literature. We focus on transparency, illustrating how different data sources and spatio-temporal model configurations can lead to different carbon emission estimates. Additionally, we synthesize factors mentioned in the ML literature and include them in the overall environmental impact of computing systems through the lens of life cycle assessment (LCA), extending beyond the current emphasis on operational emissions.

3.1. Transparency and reliability

Transparency is the cornerstone of sustainable AI development and is closely related to trust, particularly in terms of information trust (Bishr & Janowicz, 2010). However, many of the tools for estimating carbon emissions mentioned in Section 2.1 lack full transparency regarding which carbon intensity values are adopted from which data sources. Different sources report different types of carbon intensity values, for instance, energy produced versus energy consumed in a region. The resulting values may not match if energy is exported or imported. Such inconsistencies may lead to interoperability issues, as there is no standard for carbon intensity reporting in emissions estimations, making it difficult to compare results across different tools.

As shown in Table 2, the carbon intensity values reported for energy *production* and *consumption* in Austria can differ by as much as 174% within the same year. Even within the category of energy production carbon intensity values, significant variations exist depending on the data source. Furthermore, when data sources provide information at multiple spatial scales (sub-national, national, or regional average), it remains unclear where the carbon intensity value is derived, leaving users unaware of the underlying information used for emissions estimation.

Moreover, the data used for these calculations can sometimes be inconsistent (or incomplete), raising concerns about the accuracy and reliability of the results. According to Henderson et al. (2020), due to spatial heterogeneity, extrapolating estimates with partial information can have significant differences compared to tracking all data. Users may find it difficult to trust and report these estimates if there is no full transparency and regular updates on factors like carbon intensity.

In addition to improving transparency regarding the choice of reported carbon intensity values, there is also a need to increase the transparency of the spatio-temporal configuration of an AI model to better estimate its carbon footprint. Dodge et al. (2022) demonstrated that choosing data centers in different geographic regions and times of day to fine-tune a BERT model results in varying carbon emissions. They found that geographically, carbon intensity can vary between 200 and 755 gCO_2/kWh across the most and least efficient regions. From a temporal perspective, training the model at midnight could yield up to 8% greater carbon emissions compared to training at 6:00 am. This variation in emissions can be attributed to the energy composition within the region, where daytime training could involve a higher proportion of renewable energy to fossil fuel–based sources (de Chalendar & Benson, 2019). Furthermore, P. Li et al. (2023) discussed spatio-temporal diversity in AI models' runtime water efficiency, highlighting that when and where a large AI model is trained can affect its water footprint. This is due to variations in weather conditions and the energy fuel mixes of the grid, which are adapted to meet changing demands over time.

Overall, it is crucial that these estimation tools clearly disclose data sources, provide detailed information on model spatio-temporal configurations, and offer regular

Table 2. Carbon intensity of energy in selected countries by data source.

			Carbon Intensity (gCO_2/kWh)		
Data Source	Carbon Intensity Type	Year	Austria	Belgium	Croatia
EEA (2020)	Production	2017	104	176	188
Carbon Footprint (2018)	Production	2017	148	139	303
Our World in Data (2024)	Production	2017	163	160	256
Electricity Maps (n.d.)	Consumption	2017	285	228	303

updates on factors like carbon intensity. Only in this manner can these tools ensure reliable reporting. By embracing open science and reproducibility, researchers can validate findings and further collaborate, which are critical for building trust and ensuring the effectiveness of these tools in promoting sustainability measures.

3.2. Life cycle assessment

The current tools and frameworks listed in Table 1 focus solely on energy consumption and carbon emissions during the operational phase of devices, especially, the model training phase. However, we need a broader LCA that takes into account more than just *operational emissions from training* to fully understand the environmental impact of computing systems. Additional key components include:

(1) *Embodied Resource Consumption*, representing the natural resources consumed during hardware manufacturing, such as water, aluminum, cobalt, copper, glass, gold, tin, lithium, zinc, and plastic (Gupta et al., 2022);
(2) *Operational Resource Consumption*, including resources like water used for cooling systems in data centers;
(3) *Emissions from Inference*, which involve carbon emissions of pre-trained AI models when they are used to perform tasks;
(4) *Embodied Emissions*, referring to the carbon emissions generated throughout the life cycle of a device, including manufacturing, transporting, and eventual recycling (Wu et al., 2022).

These factors can be examined through the lens of an LCA framework, as illustrated by the five stages in Figure 2, while recognizing that additional factors may also contribute to environmental impact as AI systems continue to evolve.

In the raw material extraction and manufacturing stages of an LCA, estimating *embodied resource consumption* relies heavily on data provided by manufacturers or industry reports. However, there is currently a significant lack of information in this area, confounding efforts to catalog and quantify these resources in practical implementations. Due to the complexity and variability of manufacturing processes, obtaining complete data to fully interpret them remains challenging. Hence, we should encourage efforts such as using life cycle inventory databases or developing standardized reporting frameworks to improve estimations in this area (Ligozat et al., 2022).

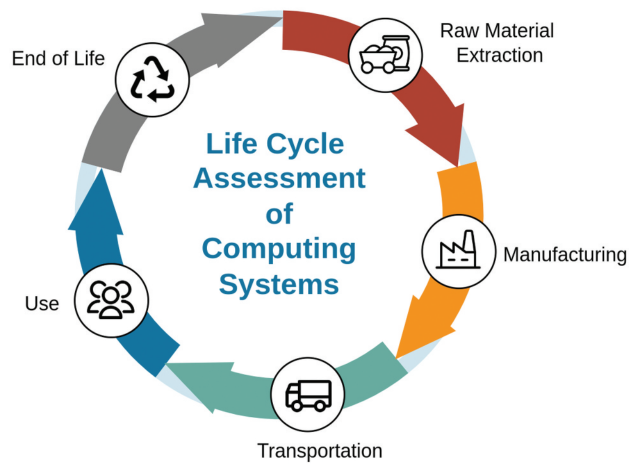

Figure 2. Five stages in an LCA framework of computing systems.

Beyond the consumption of raw material, *operational resource consumption* during the use stage of an LCA includes resources used during device operation, notably on-site water consumption for data center cooling systems. P. Li et al. (2023) proposed a fine-grained methodology for estimating the water footprint of AI models and urged developers to address a model's water footprint along with its carbon footprint to enable more sustainable AI, given the finite nature of water resources. Additionally, they highlight trade-offs between water and energy. To give a concrete example, abundant solar energy can contribute to higher temperatures and increased cooling needs, particularly for data centers in hot and arid regions (Karimi et al., 2022; P. Li et al., 2023).

In addition to resource consumption and operational emissions from training in the use stage of an LCA, *emissions from inference*—the phase where a trained model is used to make predictions (Crankshaw et al., 2017)—constitute a significant proportion of overall emissions in the AI model life cycle, not to mention model distillation, fine-tuning, deployment, and re-training (Eilam et al., 2023; Wu et al., 2024). As highlighted by Lacoste et al. (2019), existing carbon emissions estimation tools mainly focus on the model training phase, often overlooking the energy-intensive nature of model inference, especially when conducted continuously, frequently, and at scale. This remains true for the tools listed in Table 1. Chien et al. (2023) further emphasized that emissions from inference can account for the majority of operational carbon emissions associated with generative AI models. Their study showed that for ChatGPT-like services, inference emissions in one year could produce 25 times the carbon emissions of training GPT-3.

Embodied emissions occur across multiple stages of an LCA. They accumulate from processes including the construction of hardware manufacturing facilities, raw material procurement, and the fabrication, assembly, packaging, transportation, and recycling of devices (Shi et al., 2023). When estimating the embodied emissions associated with the use of the BLOOM Model (Scao et al., 2022), Luccioni et al. (2023) based their estimates on a six-year replacement rate and 85% average usage of their GPUs, concluding that the servers and GPUs collectively contributed 11.2 tonnes of CO_{2eq} embodied emissions, which accounted for 22.2% of the model's total carbon footprint.

Most attention has focused on emissions from energy use during the model training phase. However, the broader aspects revealed in an LCA—such as embodied resource consumption, operational resource consumption, emissions from inference, and embodied emissions – can be more significant (Gupta et al., 2022). These aspects pose additional environmental challenges and deserve more attention.

4. A geographic perspective in AI sustainability

According to the IEA (2023a), data centers accounted for 1% of global energy-related GHG emissions in 2022, and this percentage is expected to increase with the rapid growth of AI. This section points out the need to address regional disparities in the environmental impacts of data centers. More specifically, we discuss why incorporating a geographical perspective is critical for a more comprehensive understanding of AI's environmental and social impacts on local communities.

4.1. Regional disparities in data center environmental impact

The distribution and carbon intensity of data centers vary geographically, as shown in Figure 3, suggesting regional disparities in their environmental impacts. Lacoste et al. (2019) provided the initial data on the carbon intensity of major cloud computing providers, including Google Cloud Platform, Amazon Web Services, and Microsoft Azure. We have since updated this data to reflect the most recent values, as detailed in Appendix.

While some regions benefit economically from these facilities, others bear environmental burdens because of their high carbon intensity. These disparities are often caused by differences in energy sources, infrastructure, and local regulations (Dodge et al., 2022). Despite commitments from major cloud computing providers like Google to achieve carbon-free energy goals by 2030, currently, they still rely on carbon-emitting energy sources (Google, 2023). Furthermore, even in regions with low-carbon energy production, the energy consumed locally may come from a different, more carbon-intensive source. This happens when the region exports locally produced "clean" energy and imports "dirtier" energy to meet local demand (Shi et al., 2023).

Water consumption has emerged as another major concern regarding data center operations (P. Li et al.,

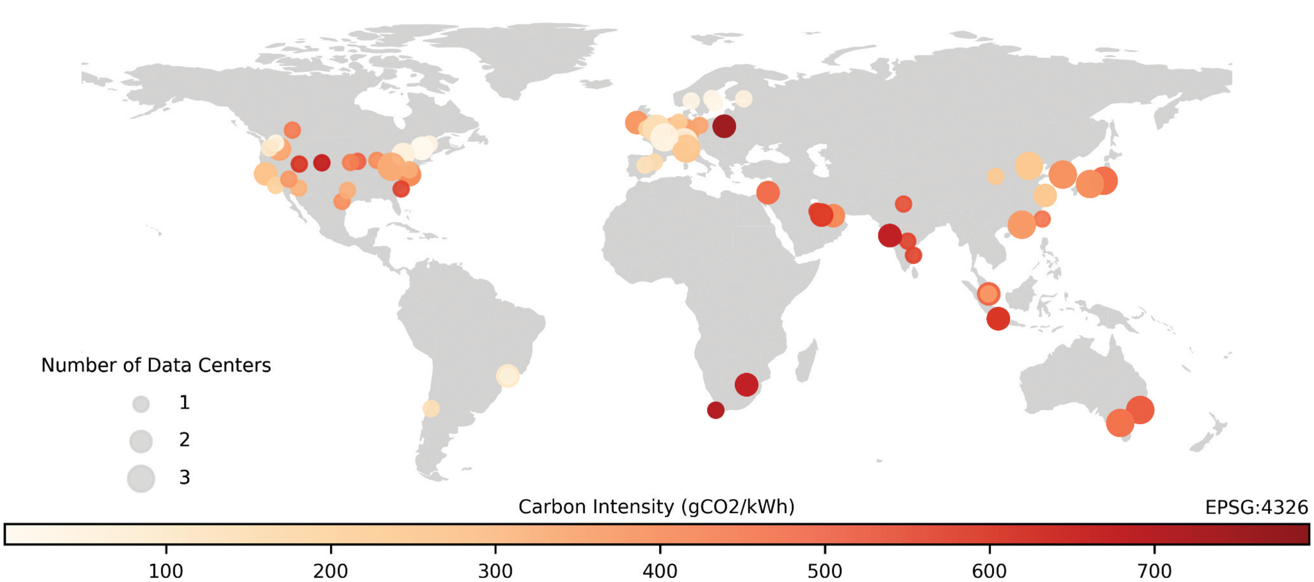

Figure 3. Distribution and carbon intensity of data centers from major cloud computing providers: Google Cloud Platform, Amazon Web Services, and Microsoft Azure. Circle size indicates the count of data centers, and color represents carbon intensity. More details on location and carbon intensity can be found in Appendix.

2023; Osaka, 2023). For example, Google's water use in The Dalles, Oregon, has nearly tripled in the past five years, and its data centers now consume more than a quarter of all the water used in the city (Rogoway, 2023). Water usage effectiveness (WUE) is a common metric used to evaluate its impact, which computes the amount of water used (in liters) annually for humidification and cooling of a data center relative to the total annual kilowatt hours powering its IT equipment. A lower WUE indicates better water efficiency. Given the publicly available WUE values for Microsoft data centers across the contiguous U.S., we observe in Figure 4 that these numbers can vary by as much as *10 times* by region. Facilities in arid regions, such as Arizona, have higher WUEs, underscoring their disproportionate impact on local water resources and raising potential environmental justice concerns for nearby communities.

These disparities highlight that when assessing the broader sustainability impacts of data centers, we need to take local environmental contexts into account. A geographically aware assessment, as described in the following section, can assist decision-makers in understanding how data centers affect a local population, including energy and water resources, and can also contribute to informed decisions on future data center siting to mitigate potential harms.

4.2. Energy use in a social context

Referring back to the question posed at the beginning of the paper and taking the energy consumption of ChatGPT as an illustration, Kolbert (2024) reports that ChatGPT receives approximately two hundred million daily requests and is estimated to consume more than half a million kilowatt-hours per day. Assuming a global average carbon intensity of 436 gCO_2/kWh (Ember, 2023), this translates to approximately 1.09 gCO_2 emissions for a single query, more than twice that of a Google search (Berners-Lee, 2020). It is important to note that this estimate only accounts for emissions from inference. de Vries (2023) estimates energy consumption for ChatGPT to be nearly 10 times that of a Google search at 2.9 Wh per query, compared to Google's 0.3 Wh. Models like BLOOM have even higher demands, consuming about 4 Wh per request. According to such scenarios, running an AI-powered Google search could reach up to 9 Wh per query, potentially requiring around 29 TWh annually. For comparison, this would rank

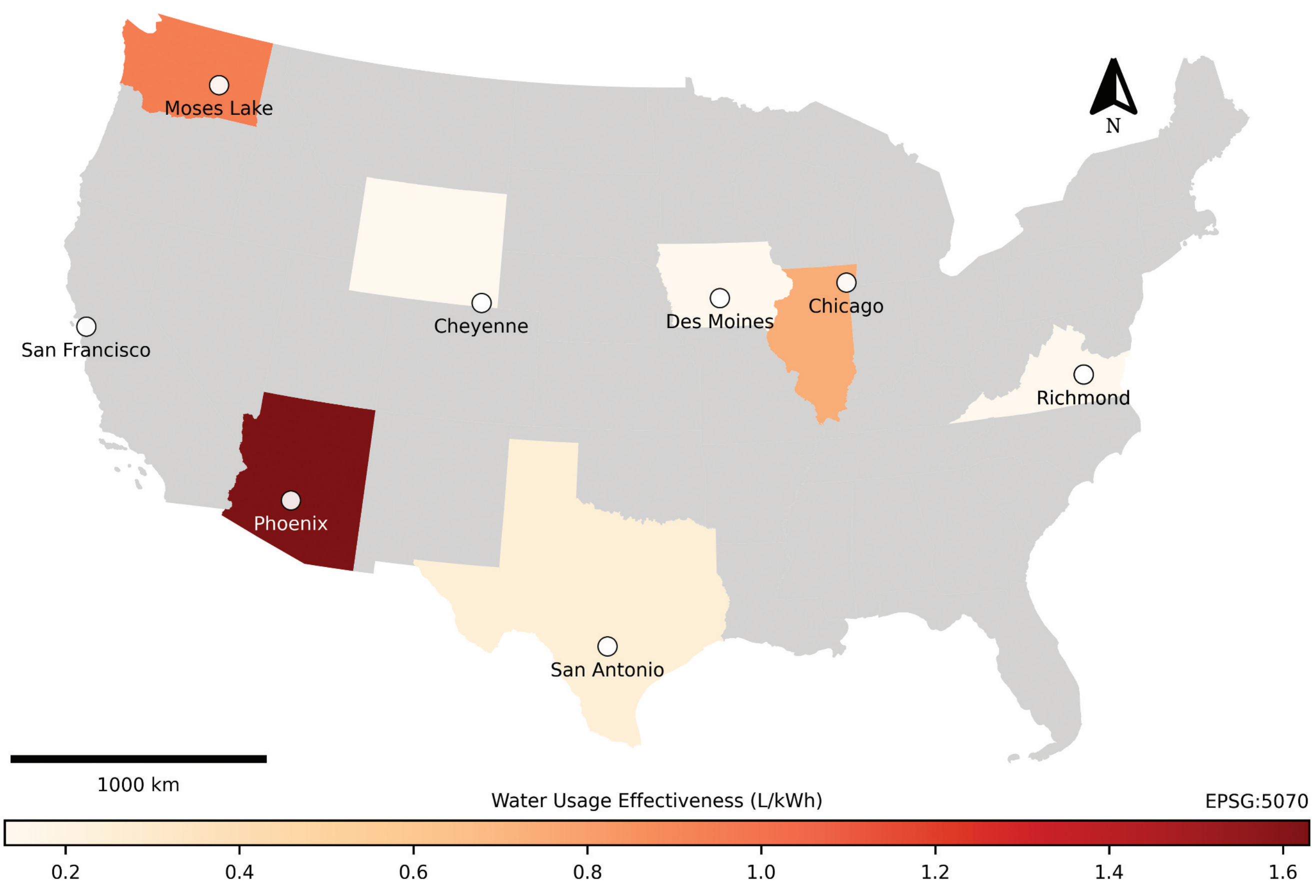

Figure 4. Water usage effectiveness for Microsoft data centers in the contiguous United States, reflecting the only publicly available data. Lower values indicate higher effectiveness. Data sourced from Microsoft (2024) for the fiscal year 2023 (07.2022–06.2023).

between Ecuador's and Nigeria's annual electricity use, according to the IEA (2023b).

Interpreting these consumption statistics of computing systems requires contextual awareness, because they may reflect vastly different realities across countries. The daily energy usage of ChatGPT, for example, could equate to the annual energy consumption of three people in Qatar or approximately 2,300 people in Somalia. Figure 5a) illustrates this comparison by mapping the global daily energy usage of ChatGPT versus the yearly energy usage of individuals by country. Figure 5b) presents these numbers relative to population size. For example, when ChatGPT's daily energy usage equals the annual consumption of eight people in Greenland and Belgium, it represents 0.01% of Greenland's population but less than 0.0001% of Belgium's population. This implies that countries with smaller populations are more affected by the same level of energy use. Given the skewed distribution of per capita energy usage worldwide, a one-size-fits-all interpretation of these statistics fails to capture the social impact across regions. Economic disparities also play a key role in this context. Wealthier nations typically have better resources and greater access to sustainable technologies, whereas poorer regions often struggle to meet basic energy needs (Yao et al., 2020).

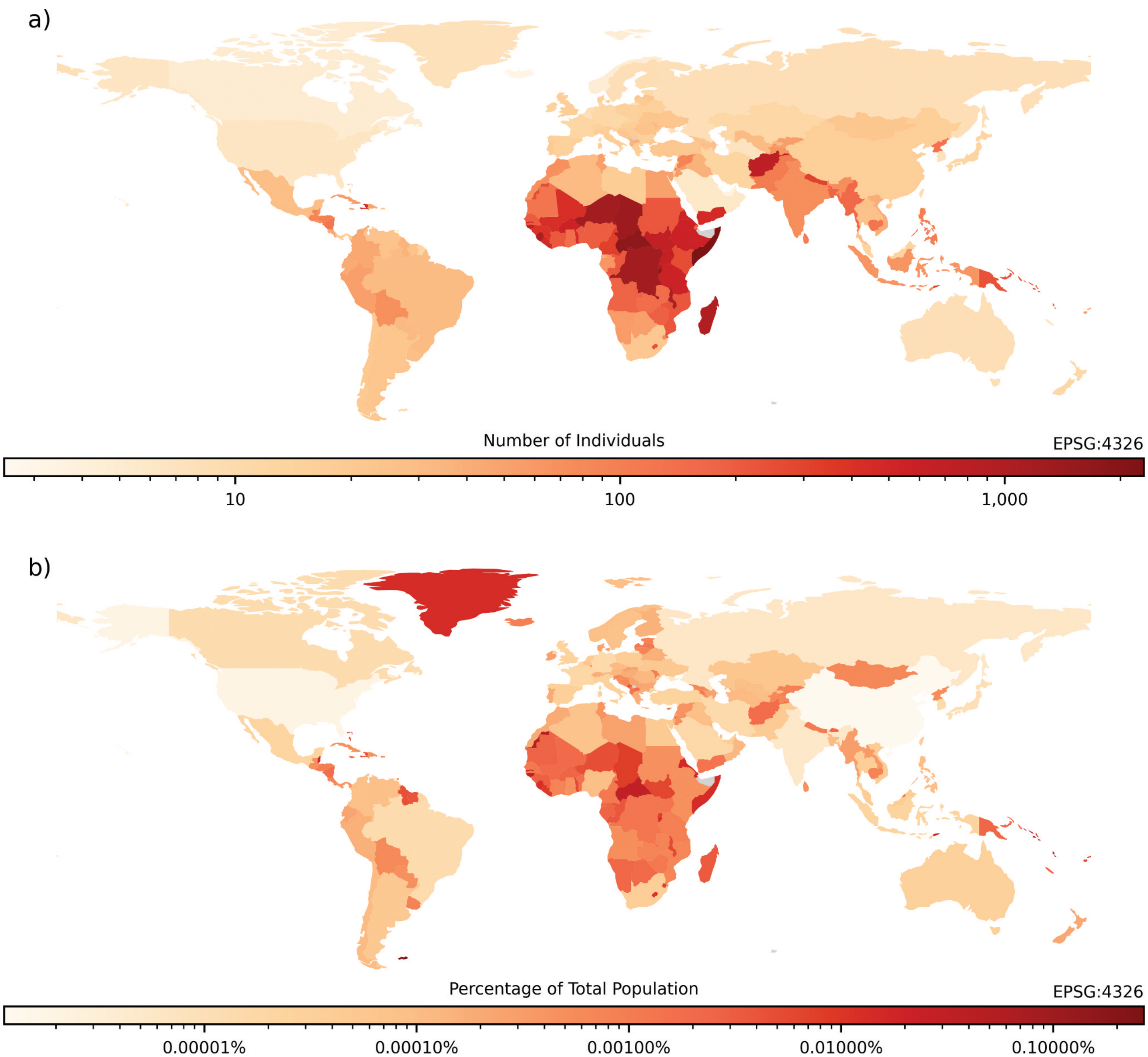

Figure 5. Comparison of ChatGPT's global daily energy consumption with per capita energy usage by country in 2021: a) absolute values and b) relative values, expressed as a percentage of the total population. A logarithmic color scale is used. Data sources: primary energy consumption per capita (Ritchie, Rosado, et al., 2023) and population (Ritchie, Rodés-Guirao, et al., 2023).

The sustainability reports that are now available for AI models only provide an overall number on energy consumption and carbon emissions. However, we need geographically aware assessments of the data centers involved to gain a deeper understanding. This should at least include examining metrics such as per capita energy and water consumption of the local population, and also accounting for different environmental conditions and socio-economic contexts. To date, there are no country-specific statistics on ChatGPT usage available. However, W.-R. Chen et al. (2024) showed that the model performs unevenly when it comes to tasks like language recognition, with particularly poor performance on African languages. Therefore, countries with poorer performance and fewer requests may disproportionately face higher per capita CO_2 emissions. These findings highlight the need to take energy use into account in a broader societal context where access to AI tools and their advantages are not evenly distributed.

5. Sustainability challenges for GeoAI models

Unlike large language models (LLMs), which operate on standardized textual datasets, GeoAI models leverage geospatial data that inherently vary in type. This includes text, remote sensing imagery, trajectory and network data, and more. Furthermore, distinct environmental features in different regions introduce complexities, because patterns observed in one location may not readily apply to another. This section examines the uniqueness of GeoAI models, highlighting their sustainability challenges given their spatial heterogeneity and multimodality.

5.1. Constant need for retraining

In the context of GeoAI sustainability, one unique characteristic is the dynamic nature of geospatial data, which is subject to temporal variations due to evolving physical environments, urban settings, cultural changes, migration patterns, and so on (Li et al., 2024). For example, an urban land cover classification model requires frequent retraining because construction projects or new infrastructure is being developed regularly. Spatial heterogeneity—representing the variability of observations and effect sizes across space – often poses challenges to the generalization of GeoAI models to new regions (H. Li et al., 2023). This challenge has led to the development of localized modeling methods (e.g. Geographically Weighted Regression) and corresponding machine learning methods (e.g. Geographically Weighted Random Forest). Since more advanced deep learning methods are unlikely to fully address this challenge, GeoAI models may often require an entirely new cycle of training, tuning, and deployment on a more frequent basis to remain relevant (Janowicz, 2023). In this way, GeoAI models are also expected to consume more energy than traditional AI models. This serves as a reminder to the GeoAI community to incorporate sustainability considerations into the development and maintenance of GeoAI models to ensure their effectiveness despite the dynamic nature of geospatial data.

5.2. Costs vs. benefits of spatially scoped GeoAI models

Compared to LLMs, GeoAI models tend to be more confined to a specific spatial scope. For instance, Castrejon et al. (2023) developed a machine learning–based wildfire prediction model that focuses on California. When evaluating their cost–benefit tradeoffs, we need to consider the regions that benefit from the model and those that bear the environmental costs. To give a concrete example, a global model predicting the spread of COVID-19 May not raise ethical concerns regarding its training and deployment regions because it benefits the entire global population. For a model forecasting traffic conditions in Los Angeles, however, the environmental costs for training and deploying the model should not be borne by distant countries across the globe.

The cost–benefit analysis of GeoAI models should consider factors such as adaptability to different spatial extents, spatial performance accuracy, distribution of costs (e.g. computational resources used for training and inference), and distribution of benefits (e.g. improved services, reduced risks). To complement the cost–benefit analysis framework proposed by Bommasani et al. (2021) (see section 2.3 for details), we propose a Spatial Benefit–Cost Ratio (SBCR) tailored to spatially scoped GeoAI models. This ratio, expressed in Equation 1, compares the beneficiary populations (P_{bi}) to those impacted (P_{cj}). It incorporates an interaction factor (I_{ij}) from the gravity model (Fotheringham & O'Kelly, 1989), as expressed in Equation 2, to reflect the spatial interaction between regions i and j. Here, I_{ij} is normalized between 0 and 1. A value of 1 indicates self-interaction and values closer to 0 indicate low interaction. To avoid the division-by-zero issue when the training and benefit locations are the same, we set I_{ij} to 1 in such cases.

$$SBCR = \frac{P_{bi}}{\sum_j \frac{P_{cj}}{I_{ij}}} \quad (1)$$

$$I_{ij} = \frac{P_i \cdot P_j}{D_{ij}^2} \tag{2}$$

As no GeoAI models have yet produced a sustainability report, let alone disclosed the specific data center locations used for their training, we provide some hypothetical examples here to demonstrate the SBCR. Consider a traffic prediction model designed for Los Angeles that serves its 3.82 million residents, while being trained in Las Vegas, with a population of 0.66 million, and Columbus, Ohio, with a population of 0.91 million. Following the SBCR formula, we calculate the interaction factor I_{ij} between LA and each training location, considering distances of approximately 360 km to Las Vegas and 3,600 km to Columbus. In this case, the SBCR would be close to 0 due to the distant training locations. For comparison, a model both trained and benefiting locally in LA would yield an SBCR of 1. If a model, such as one predicting COVID-19 cases, benefits the entire global population while being trained in LA, the SBCR would significantly exceed 1. This ratio serves as a relative metric, allowing for comparisons across different scenarios for the same model and facilitating informed decision-making regarding data center selection and model deployment strategies. Ultimately, this geographically aware ratio, together with other factors in the cost–benefit analysis, should be thoroughly evaluated before adopting and deploying such models.

5.3. Adoption of (Geo-)foundation models

FMs are increasingly being incorporated into geospatial research with recent advancements in GeoAI. For instance, ChatGPT and GPT models have been applied to tasks including interpreting remote sensing images (Guo et al., 2024), creating maps (Zhang, He, et al., 2024), enriching map content (Juhász et al., 2023), geolocalizing images (Z. Zhou et al., 2024), predicting sustainability indexes (Manvi, Khanna, Burke, 2024; Manvi, Khanna; Mai et al., 2024), vision-and-language navigation (J. Chen et al., 2024), and spatial query and analysis (Zhang, Wei, et al., 2024). They can act as purifiers, converters, generators, and reasoners in these tasks (Wang et al., 2024). Despite the high computational costs, FMs have a major advantage: their extensive pre-training enables them to apply their prior knowledge to new tasks, reducing the need for further training and curbing overall carbon emissions (Bommasani et al., 2021). Similarly, when integrated with domain-specific knowledge, geo-foundation models (Geo-FMs) could improve the efficiency and accuracy of a wide range of downstream tasks, thereby contributing to the long-term sustainability of geospatial research (Mai, 2024; Xie et al., 2023).

However, the adoption of Geo-FMs poses several challenges, particularly because of the multimodal nature of geospatial tasks, as noted by Mai et al. (2024). Within GeoAI, each modality—text, remote sensing or street-view images, knowledge graphs, and trajectory data – possesses important geometric and semantic details that require unique representations for optimal use. An early example of a Geo-FM is Prithvi-100 M for remote sensing, trained on extensive satellite image datasets. Its downstream tasks include burn scars detection, flood mapping, and crop classification (Jakubik et al., 2023). Even though developing a comprehensive Geo-FM remains challenging, leveraging pre-trained models should be encouraged to enable the reuse of learned representations and reduce the carbon footprint of training new models from scratch.

6. Future directions

Global efforts are underway to establish regulations and guidelines for ethical and sustainable AI (Jobin et al., 2019). For instance, the US Congress introduced the Artificial Intelligence Environmental Impacts Act in February 2024 (United States Congress, 2024), and the European Union's Artificial Intelligence Act (European Union, 2024) came into effect in August 2024. UNESCO and other international organizations have also issued guidelines (UNESCO, 2021) to address the environmental impact of AI systems.

Moving forward, these guidelines and regulations should help companies, institutions, researchers, developers, and others to foster sustainable AI. Proactive measures must be taken to prioritize fairness, transparency, and sustainability in the use of AI technologies (Jay et al., 2024). This section outlines future directions, including more systematic reporting, geographically aware assessments, and solutions to lower emissions through greater efficiency, that can be applied in both the GeoAI and general AI fields.

6.1. Towards systematic reporting and geographically aware assessment

Despite the availability of emissions estimation tools and frameworks outlined in Section 2.1, systematic reporting of carbon footprints remains uncommon in research publications. Moreover, as identified in Section 3, current emissions reporting still lacks several key components:

(1) Transparency regarding data sources and spatio-temporal model configurations;
(2) An LCA that includes factors such as water (and other natural resources) consumption, emissions during model inference and deployment, and embodied emissions throughout the entire life cycle of AI models;
(3) An overall geographically aware cost–benefit analysis.

In the future, as more information becomes available regarding data centers' energy and resource consumption, metrics such as per capita electricity and water demand of data centers relative to the local population can be employed. Such geographically aware assessments consider the diverse environmental settings in which AI systems operate, thus offering a comprehensive understanding of their environmental impact.

In addition to addressing systematic reporting gaps and implementing geographically aware assessments, initiatives such as establishing leaderboards for energy-efficient algorithms (Henderson et al., 2020), developing certification systems for Green AI (Dodge et al., 2022), and providing sustainability badges for conference papers (Shi et al., 2023), may also promote sustainable and responsible research practices in the field.

6.2. Towards low-emission and resource-efficient (Geo)AI

Recent advances in Retrieval-Augmented Generation (RAG) (Lewis et al., 2020), which integrates retrieval-based and generative models in natural language processing, offer a promising approach to advancing AI sustainability. RAG employs a pre-trained retriever to efficiently extract relevant information from a designated database, hence enhancing the model's ability to generate correct responses. By combining FMs with up-to-date external knowledge repositories, such as knowledge graphs (Janowicz et al., 2022), RAG-based systems have the potential to reduce the computational resources required for training and inference. Instead of relying solely on large-scale resource-intensive language models, RAG can provide a more efficient retrieval mechanism to access external knowledge and improve the accuracy and relevance of results in the meantime.

Additional efforts in recent AI research include quantization techniques, which convert model parameters from floating point numbers to integers with lower bit widths, while maintaining model accuracy (Nagel et al., 2021). This reduction in processing demand lowers not only energy consumption during training and inference, but also infrastructure costs associated with data center maintenance and operation. One example is the development of 1-bit LLMs (Ma et al., 2024), where each parameter adopts a ternary form with values of $\{-1, 0, 1\}$. This method substantially reduces computational demands while preserving performance. Model pruning, which removes less critical weights or neurons from a neural network, complements quantization by lowering the model size and complexity (Blalock et al., 2020). Recent efforts, such as those by Paganini and Forde (2020), have resulted in faster and more energy-efficient models. These techniques collectively mark the beginning of a new computing paradigm and offer means to substantially mitigate the environmental impact of AI systems.

7. Conclusion

Since the debut of ChatGPT in November 2022, generative AI models have received unprecedented public attention. Increasing discussions regarding their energy consumption and carbon emissions have prompted a more environmentally conscious community to advocate for AI sustainability.

In this paper, we explore the intersection of *Geography for AI Sustainability* and *Sustainability for GeoAI*. We provide an overview of available tools and frameworks for emissions estimation, evaluation metrics, and analytical frameworks. Following this, we identify challenges from this overview and recent ML literature, including transparency and trust in data sources, spatio-temporal model configurations, and an LCA that encompasses resource consumption beyond just energy and carbon considerations. By introducing a geographic perspective into the current AI sustainability discussion, we aim to highlight overlooked aspects in the ML field regarding regional disparities and engage the GeoAI community. We point out the uniqueness of GeoAI models in their pursuit of sustainability objectives, particularly addressing spatial heterogeneity and the multimodal nature of geospatial data, along with the associated challenges. Finally, we discuss future directions for both GeoAI and the broader AI field regarding systematic reporting, geographically aware assessment, and potential solutions to reduce the environmental impact of AI systems, such as the adoption of RAG and the implementation of emerging quantization and pruning techniques.

With this paper, we aim to provide a comprehensive perspective on current sustainability efforts and encourage GeoAI research to become more carbon-conscious in the future. In the context of *Geography for AI Sustainability*, we hope that regional disparities are acknowledged and geographically aware assessments are integrated into the evaluation of environmental impacts in general AI research. Meanwhile, in the context of *Sustainability for GeoAI*, we advocate for the adoption of tools from the general AI field in GeoAI to establish systematic reporting practices concerning model configurations and carbon emissions. Positioned at the intersection of Geography and AI, the GeoAI community should align with the call for Green AI and actively contribute toward the overarching goal of sustainability.

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Data availability statement

The data that support the findings of this study are available on Figshare at https://doi.org/10.6084/m9.figshare.25982476.

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Appendices

Appendix. Carbon intensity of major cloud computing data centers

Among the three major cloud computing providers, only Google publicly discloses the carbon intensity of its data centers (Google, 2025b), as shown in Table A3. According to their documentation (Google, 2025a), Google sources emission factor (carbon intensity) data from Electricity Maps, (n.d.). When data from Electricity Maps is unavailable, Google uses country-specific annual average carbon emission intensity factors released by the IEA (n.d.).

When collecting data, we adopted the same approach for the data centers of Amazon Web Services (Table A1) and Microsoft Azure (Table A2). All numbers sourced from Electricity Maps (n.d.) are yearly averages for 2023. Notably, the carbon intensity of mainland China is not available on Electricity Maps; therefore, we used the most recent 2022 average from the IEA (2023c).

Table A1. Data centers of Amazon Web Services.

Region	Country	State	Location	Launched	gCO_2eq/kWh
Asia Pacific (Hong Kong)	China		Hong Kong SAR	2019	435
Asia Pacific (Hyderabad)	India		Hyderabad	2022	556
Asia Pacific (Jakarta)	Indonesia		Jakarta	2021	652
Asia Pacific (Melbourne)	Australia		Melbourne	2023	498
Asia Pacific (Mumbai)	India		Mumbai	2016	747
Asia Pacific (Osaka)	Japan		Osaka	2021	370
Asia Pacific (Seoul)	South Korea		Seoul	2016	444
Asia Pacific (Singapore)	Singapore		Singapore	2010	487
Asia Pacific (Sydney)	Australia		Sydney	2012	545
Asia Pacific (Tokyo)	Japan		Tokyo	2011	536
China (Beijing)	China		Beijing	2014	399
China (Ningxia)	China		Ningxia	2017	399
US East (N. Virginia)	USA	Virginia	Northern Virginia	2006	396
US West (N. California)	USA	California	San Francisco	2009	262
US East (Ohio)	USA	Ohio	Columbus	2016	397
US West (Oregon)	USA	Oregon	Eastern	2011	234
GovCloud (US-East)	USA	Ohio	Columbus	2018	396
GovCloud (US-West)	USA	Oregon	Eastern	2011	341
Canada (Central)	Canada		Montreal	2016	31
Canada West (Calgary)	Canada		Calgary	2023	438
South America (São Paulo)	Brazil	São Paulo	São Paulo	2011	90
Europe (Frankfurt)	Germany		Frankfurt	2014	400
Europe (Ireland)	Ireland		Dublin	2007	371
Europe (London)	UK		London	2016	200
Europe (Milan)	Italy		Milan	2020	306
Europe (Paris)	France		Paris	2017	53
Europe (Spain)	Spain		Aragón	2022	160
Europe (Stockholm)	Sweden		Stockholm	2018	23
Europe (Zurich)	Switzerland		Zurich	2022	86
Africa (Cape Town)	South Africa		Cape Town	2020	701
Middle East (Bahrain)	Bahrain		Manama	2019	700
Israel (Tel Aviv)	Israel		Tel Aviv	2023	534
Middle East (UAE)	UAE		Dubai	2022	404

Table A2. Data centers of Microsoft Azure.

Region	Country	State	Location	Launched	gCO_2eq/kWh
North Europe	Ireland		Dublin	2009	371
West Europe	Netherlands		Amsterdam	2010	304
France Central	France		Paris	2018	53
Germany West Central	Germany		Frankfurt	2019	400
Italy North	Italy		Milan	2023	306
Norway East	Norway		Oslo	2019	29
Poland Central	Poland		Warsaw	2023	794
Sweden Central	Sweden		Gävle	2021	23
Switzerland North	Switzerland		Zurich	2019	86
UK South	UK		London	2016	200
UK West	UK		Cardiff	2016	200
South Africa North	South Africa		Johannesburg	2019	701
Qatar Central	Qatar		Doha	2022	471
UAE North	UAE		Dubai	2019	404
East Asia	China		Hong Kong SAR	2010	435
Southeast Asia	Singapore		Singapore	2010	487
Australia Central	Australia		Canberra	2018	545
Australia East	Australia		Sydney	2014	545
Australia Southeast	Australia		Melbourne	2014	498
China East	China		Shanghai	2014	399
China East 2	China		Shanghai	2018	399
China North	China		Beijing	2014	399
China North 2	China		Beijing	2018	399
China North 3	China		Langfang	2022	399
Central India	India		Pune	2015	747
South India	India		Chennai	2015	556
Japan East	Japan		Tokyo	2014	536
Japan West	Japan		Osaka	2014	370
Korea Central	South Korea		Seoul	2017	444
Canada Central	Canada		Toronto	2016	76
Canada East	Canada		Quebec City	2016	31
Central US	USA	Iowa	Des Moines	2014	502
East US	USA	Virginia	Richmond	2012	396
East US 2	USA	Virginia	Richmond	2014	396
North Central US	USA	Illinois	Chicago	2009	396
South Central US	USA	Texas	San Antonio	2008	389
West Central US	USA	Wyoming	Cheyenne	2016	647
West US	USA	California	San Francisco	2012	262
West US 2	USA	Washington	Moses Lake	2007	27
West US 3	USA	Arizona	Phoenix	2021	313
Brazil South	Brazil	S˜ao Paulo	S˜ao Paulo	2014	90

Table A3. Data centers of Google Cloud Platform.

Region	Country	State/Province	Location	Launched	gCO_2eq/kWh
Africa-South 1	South Africa		Johannesburg	2024	646
Asia-East 1	China	Taiwan	Changhua County	2014	451
Asia-East 2	China		Hong Kong SAR	2018	360
Asia-Northeast 1	Japan		Tokyo	2016	459
Asia-Northeast 2	Japan		Osaka	2019	385
Asia-Northeast 3	South Korea		Seoul	2020	378
Asia-South 1	India		Mumbai	2017	648
Asia-South 2	India		Delhi	2021	529
Asia-Southeast 1	Singapore		Jurong West	2017	369
Asia-Southeast 2	Indonesia		Jakarta	2020	580
Australia-Southeast 1	Australia		Sydney	2017	501
Australia-Southeast 2	Australia		Melbourne	2021	456
Europe-Central 2	Poland		Warsaw	2021	723
Europe-North 1	Finland		Hamina	2018	46
Europe-Southwest 1	Spain		Madrid	2022	131
Europe-West 1	Belgium		St. Ghislain	2013	122
Europe-West 2	UK		London	2017	136
Europe-West 3	Germany		Frankfurt	2017	345
Europe-West 4	Netherlands		Eemshaven	2018	236
Europe-West 6	Switzerland		Zurich	2019	59
Europe-West 8	Italy		Milan	2022	249
Europe-West 9	France		Paris	2022	34
Europe-West 10	Germany		Berlin	2023	345
Europe-West 12	Italy		Turin	2023	249
Me-Central 1	Qatar		Doha	2023	575
Me-Central 2	Saudi Arabia		Dammam	2023	569
Me-West 1	Israel		Tel Aviv	2022	463
Northamerica-Northeast 1	Canada		Montreal	2018	2
Northamerica-Northeast 2	Canada		Toronto	2021	47
Southamerica-East 1	Brazil	São Paulo	São Paulo	2017	56
Southamerica-West 1	Chile		Santiago	2021	138
Us-Central 1	USA	Iowa	Council Bluffs	2013	430
Us-East 1	USA	South Caroline	Moncks Corner	2015	560
Us-East 4	USA	Virginia	Ashburn	2017	322
Us-East 5	USA	Ohio	Columbus	2022	322
Us-South 1	USA	Texas	Dallas	2022	321
Us-West 1	USA	Oregon	The Dalles	2013	94
Us-West 2	USA	California	Los Angeles	2018	198
Us-West 3	USA	Utah	Salt Lake City	2020	588
Us-West 4	USA	Nevada	Las Vegas	2020	373