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Artificial intelligence and climate change: the potential roles of foundation models

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Abstract

Artificial intelligence (AI) is being developed fast and applied in several areas including education and healthcare with excellent potential for use in fields that require complex analytics, particularly in the case of climate change. Recent developments in AI, such as ChatGPT and OpenAI, machine vision technologies and deep learning, among others, may be deployed in various contexts, including climate change. Of specific interest is the role played by foundation models (FMs), which may help to augment intelligence on climate change and reduce the social risks of adaptation and mitigation initiatives. This article discusses the potential applications of FMs in climate change research and management and illustrates the need for further studies. FMs, built on large unlabelled data sets and enabled by transfer learning, offer versatility in handling complex tasks. Specifically, FMs can aid in climate data analysis, modelling future scenarios, assessing risks, and supporting decision-making processes. Despite their potential, challenges such as data privacy, algorithm bias, and energy consumption require careful consideration. The article emphasizes the importance of interdisciplinary efforts to address these challenges and maximize the positive impact of FMs in mitigation and adaptation. AI, including advanced models like FMs, holds significant promise for addressing climate change challenges.

Keywords Artificial intelligence (AI), Foundation models (FMs), Climate change, Adaptation, Mitigation

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Introduction

Artificial intelligence (AI) is advancing rapidly and seeing use across various fields, including business, communication, and healthcare. AI is a vast term that describes various helpful technologies that mimic human intelligence. Computers and chatbots are programmed to operate similar to humans while learning human behaviour, such as judgment and subsequent decision-making [35, 55]. As a result, AI is beneficial in acquiring new knowledge and data analysis, employing methods analogue to those used by human intelligence, leading to meaningful results [9, 11, 59], also in the context of climate change [8, 30–33, 41].

Machines and robots are commonly used as AI tools, since their deep learning capabilities allow them to consider several variables simultaneously across various sectors [18]. The cross-disciplinary domain of AI encompasses computational science, logic, natural sciences, philosophy, and psychology, among other fields, that allow for applications in speech and pattern recognition, image processing, linguistics, algorithm function, and robotics [19, 44]. In addition, AI is increasingly used for social development and has already assisted in reducing labour costs, increasing labour efficiency, job creation, and human resource management [12, 59]. ChatGPT, an advanced language model developed by the United States-based company OpenAI, has recently attracted much attention. ChatGPT employs deep learning techniques to produce conversational text responses that mimic human language, conceived to comprehend and refine its natural language capabilities based on user input [47].

Overall, AI consists of different models applicable to real-life problems. One such model is the foundation model (FM). An FM is a model trained on broad data that can be adjusted to execute a wide range of simultaneous tasks, considering various variables whose dimensions are illustrated in Fig. 1.

FMs are useful for different functions with minimal changes. They were first popularised by the Stanford Institute for Human-Centered Artificial Intelligence—HAI [26] and are being increasingly used today. FMs, such as generative pre-trained transformer (GPT), bidirectional encoder representations from transformers (BERT), and transformer, have revolutionised natural language processing tasks [6, 56, 58]. They capture the complexities of language and enable applications, such as chatbots, question–answering systems, language translation, sentiment analysis, and more. Given this context, FMs have been successfully used in some key areas, including healthcare, and biomedicine, business, education and more. In the healthcare industry, FMs are a suitable tool for assistance attributable to the model's ability to work with different combinations of medical data, such as health records, medical texts, laboratory results and etc. [37]. The healthcare foundation models (HFMs) have demonstrated a significant potential in addressing complex clinical issues including pancreatic cancer, retinal disease, skin cancer and improving the efficiency and effectiveness of diagnosis or treatment practices [5, 10, 13]. FMs contribute significantly to optimisation of business processes and operations, including automation of repetitive tasks, improvement of customer support and compilation of documentation. According to the forecasts, the application of foundation models can

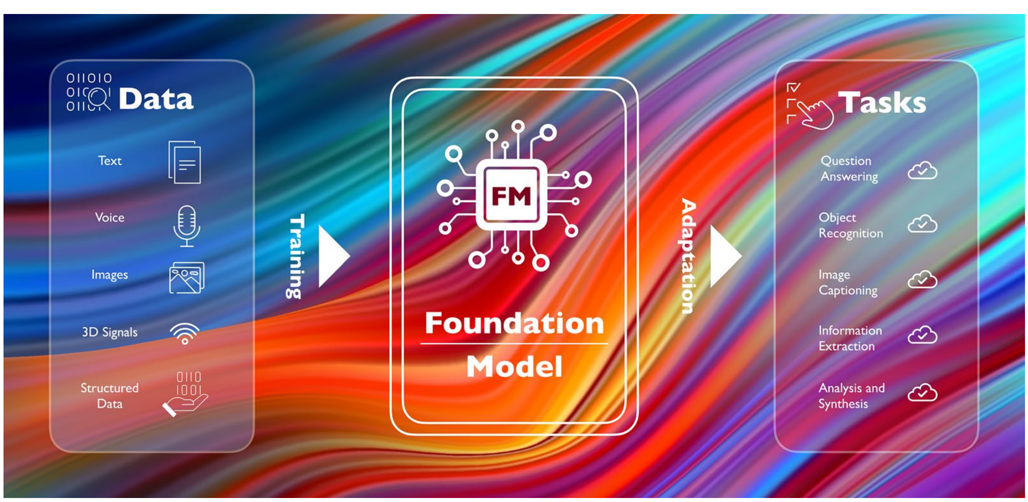

Fig. 1 Overview of some of the dimensions and basic architecture of foundation models within an artificial intelligence context. Source: the authors

contribute to the creation of more than USD 80 trillion in enterprise value by 2030 [1]. Moreover, FMs may also be advantageous to the education sector as they may assist with adaptive and personalised learning experiences that reach multiple groups of people. These include people with disabilities and students with learning difficulties. This can be achieved using data from various forms of learning, including videos, textbooks and tutorials [2, 52]. In addition, different types of FMs have potential applications in complex ecological relationships and test hypotheses [20, 39], natural sciences and sustainability [23], and ecological research through monitoring the Earth's health by satellite imagery [29].

Utilising foundation models in a climate change context

FMs are primarily enabled by transfer learning and scale. Transfer learning involves taking knowledge from one task and applying it to another. A model is trained through several methods to perform surrogate tasks and is then adapted to other studies using fine-tuning processes. Transfer learning makes FMs possible, but the scale gives the model power. The scale has three main properties: improved computer hardware, transformer model architecture, and availability of increased training data sets [2]. Essentially, FMs work through five main steps presented in Fig. 2 from data creation, carried out by humans, to data curation, training of the curated data sets, adaptation of the models to be applied to various tasks, and, finally, deployment through the application to social situations for the benefit of humans [2].

The above-described features make FMs suitable for climate change mitigation and adaptation initiatives, since they can be flexibly deployed to foster a greater understanding of key causal relationships in climate systems' performance. FMs help decide which approaches are more likely to succeed regarding climate change adaptation efforts, consistent with the broad AI framework, which has significant applications (Table 1) in addressing research and teaching on matters related to climate change mitigation [27], climate change

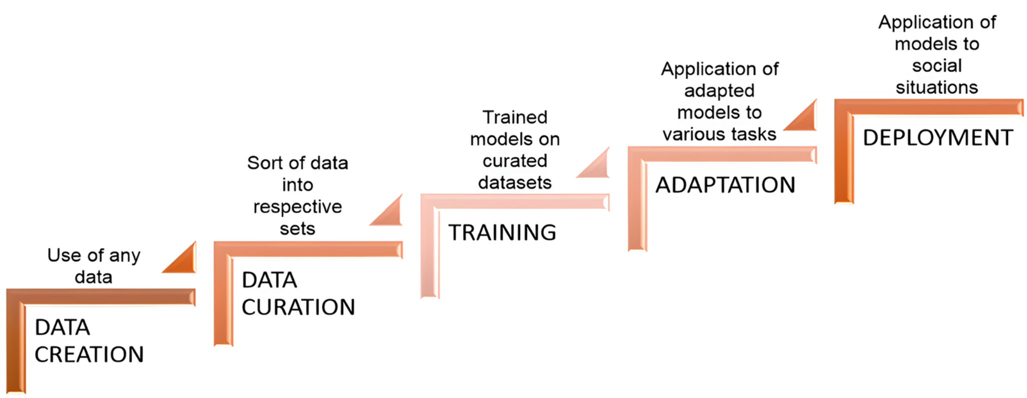

Fig. 2 Main stages of foundations models. Source: the authors, based on the work of Bommasani et al. [2]

Table 1 Recent literature on applications of artificial intelligence and foundation models in a global environmental change context

Study	Scope	References
ClimaX: An FM for weather and climate	Develop deep learning models for weather forecasting and climate projections	Nguyen et al. [40]
Deploying artificial intelligence for climate change adaptation	Investigates the associations between AI and research on climate change, as well as strategies for climate adaptation	Leal Filho et al. [30]
Developing FMs for Geospatial Artificial Intelligence (vision paper)	Develop multimodal FMs for geospatial artificial intelligence (GeoAI)	Gengchen et al. [16]
Sustainable AI: environmental implications, challenges and opportunities	To examine the environmental consequences of the superlinear trends in AI expansion comprehensively, encompassing data, algorithms, and hardware systems, and to assess the carbon emissions associated with AI computing	Wu et al. [54]
Analysis of environmental factors using AI and machine learning (ML) techniques	To apply a deep neural network model (a type of FM) for time series forecasting of environmental variables, e.g., snow cover, temperature, and NDVI for hydrological models and prediction of the spread of forest	Haq et al. [22]
Toward FMs for Earth Monitoring	Use of FMs to monitor global changes on a worldwide level	Lacoste et al. [29]

adaptation [30], environmental implications [54], geospatial artificial intelligence [16] and ecological variables, e.g., vegetation index (NDVI) to predict the spread of forest [22]. The nature of FMs makes them more accurate than conventional means to perform tasks, such as modelling carbon dioxide (CO_2) emissions (e.g., [28]). For instance, the relationship between CO_2 emissions and global temperature increase is observed to be complex, and the prediction power of conventional correlation and regression modelling techniques are observed as not as useful and reliable when compared to the adaptive neuro-fuzzy inference systems (ANFIS) and artificial neural networks (ANNs) models to analyse such correlations in the context of climate change [28]. Moreover, FMs have a variety of features, which may assist in using them as part of efforts to better understand and cope with climate change:

i. FMs are highly capable of language processing. They can quickly adapt and create new ways to comprehend linguistic problems (e.g., [45]).
ii. FMs may assist in visually comprehending certain phenomena, such as the connections between global warming and sea level rise [53], using various data to convey a more straightforward message.
iii. FMs may be used for object and image recognition and identification of specific actions (e.g., effects of heat waves on human health) [43, 54].
iv. FMs may enhance user engagement by replicating human intelligence and actions. This is particularly useful in social development [52] and when it comes to raising awareness among the population about the impacts of climate change and the need for individual action.

A promising area is the potential use of FMs for monitoring the impacts of climate change across geographical regions [48]. The wide range of data available today means they can substantially assist in processing climate data on a wide range of downstream tasks as well as provide an overview of trends in continents or specific regions in different parts of the world. In addition, FMs will assist to assess the environmental impacts and carbon footprint of AI computing [54].

Table 1 presents a brief review of recent studies on the applications of AI and FMs in monitoring global changes, geospatial artificial intelligence, weather forecasting and climate projections, the environmental impacts of hardware for FMs on the carbon footprint, and for time series forecasting of ecological variables.

Integration of foundation models into existing regulatory or governance structures

FMs can be integrated into existing regulatory and governance structures by aligning their development and deployment with established AI ethics frameworks, industry standards, and legal requirements. Governments and regulatory bodies can mandate transparency in training data sources, bias audits, and impact assessments to ensure accountability. Sector-specific regulations, such as in healthcare, finance, or law, can define permissible use cases while prohibiting high-risk applications like unchecked automated decision-making. Collaboration between policymakers, researchers, and industry leaders can help set benchmarks for model safety, fairness, and environmental sustainability. In addition, certification mechanisms, similar to data protection compliance (e.g., General Data Protection Regulation (GDPR) used in Europe [15]), could verify that FMs meet ethical and operational standards before deployment. By embedding these models within a structured governance ecosystem, stakeholders can mitigate risks while fostering responsible innovation.

Ethical issues associated with foundation models

FMs raise significant ethical concerns, including bias amplification, as they often replicate and amplify harmful stereotypes present in training data. Their misuse for deepfakes, misinformation, or automated harassment poses societal risks. In addition, their opaque decision-making processes challenge accountability, making it difficult to address unfair or harmful outputs. Privacy is another concern, as these models may inadvertently expose sensitive data from their training sets. Without proper safeguards, they can deepen digital inequities by favoring organizations with vast computational resources.

Technical limitations associated with foundation models

Despite their capabilities, FMs suffer from key technical limitations. They frequently generate incorrect output due to a lack of true understanding. They are also associated with increasing environmental costs due to high energy demand. Fine-tuning for specific tasks remains resource-intensive, and their black-box nature complicates debugging and bias mitigation. In addition, they struggle with real-time learning, relying solely on static training data, which can become outdated.

The influence of governance frameworks on foundation models

Governance frameworks play a crucial role in mitigating the risks of FMs. Regulations like the European Union

(EU) Artificial Intelligence Act aim to enforce transparency, accountability, and bias mitigation [14]. However, inconsistent global standards create compliance challenges. Industry self-regulation, such as ethical AI guidelines, can help but may lack enforcement. Effective governance must balance innovation with safeguards against misuse, ensuring equitable access and environmental sustainability. Without coordinated efforts, unchecked development could exacerbate societal harms.

Future trends

FMs will evolve and increasingly become a tool to handle additional information and data processing challenges associated with climate change, its environmental implications and ecological processes. It is important to evaluate an organisation's environmental sustainability and the impacts of its ongoing operations on climate change to yield the expected benefits [4, 38]. As accelerated transformation towards environmental sustainability is anticipated under escalating climate risks worldwide, deploying an AI FM becomes necessary to better understand how ecological systems work and how these influence—or are influenced—by global climate change [24]. In this context, potential contributions of FMs to climate change mitigation and adaptation are:

- *Data analysis* FMs can ingest and analyse vast volumes of climate data, including temperature records, atmospheric measurements, satellite imagery, and more (e.g., [7]),
- *Climate modelling* In the context of FMs, it refers to the use of large-scale, data-driven AI systems to simulate and predict Earth's climate systems (e.g., [40, 60]). Unlike traditional physics-based climate models, FMs—rained on vast amounts of observational, satellite, and simulation data—can identify complex patterns, improve resolution, and accelerate predictions. These models are particularly useful across the climate value chain: from fundamental tasks, such as high-resolution weather forecasting and long-term climate projections, to intermediate applications, such as assessing regional risks (e.g., floods or droughts), and ultimately supporting decision-making for policymakers, urban planners, and disaster response teams. By integrating real-time data and generating actionable insights, FMs can bridge the gap between scientific research and practical climate adaptation strategies,
- *Risk assessment* FMs can assess climate-related risks and vulnerabilities across different sectors, regions and societies (e.g., [48]), and
- *Decision support* FMs provide decision-makers with evidence-based insights to guide policy formulation, planning, and strategic governance for enterprises (e.g., [57]).

Over the recent years, there have been growing initiatives among key technology-based enterprises to develop their FMs for climate change mitigation and adaptation in collaboration with various institutions. Accordingly, Table 2 highlights recent AI application initiatives through FM developments among four leading technology-based enterprises and their partnering institutions as an initial form of public–private partnership, which is expected to become growingly imperative for success, specifically in the context of climate change.

This study presents a comprehensive examination of the role of FMs in climate change research and management, highlighting both their potential contributions and the challenges that need to be addressed. It should be noted that the examples provided mostly apply to atmosphere-related applications. There are various other uses of FMs. In addition, it is not the intention of this paper to suggest that FMs are in competition with physically-based climate models. Rather, this is a further, emerging area.

Figure 3 aims to summarise the main aspects of FMs being addressed in this article, in the context of climate change.

Conclusions

This article aims to provide a contribution to the climate change field, considering that the use of AI as a whole, and FMs in particular, can assist in data-driven decision-making for climate policy formulation. In addition to providing climate change intelligence to entities in both public and private sectors, FMs may facilitate public engagement and awareness about climate change by generating interactive visualisations and simplified explanations to make complex climate concepts validated by experts and authorities more accessible to the general public. The ongoing FMs development processed through public–private partnership could provide welcome support towards visualising the complexity of climate change and its environmental impacts, allowing researchers to study the dynamism of the interactions between humans, living systems and the world's climate. Specifically, AI algorithms can analyse data from sensors and monitoring networks to assess water and air quality in real time. This information can assist in the early detection of pollution incidents and prompt response measures. Moreover, AI-powered systems can optimise agricultural practices by analysing soil data, weather patterns, and crop health. This can lead to more efficient resource use, reduced pesticide and fertilizer usage, and improved land management practices. Finally, it is emphasised that AI can be

Table 2 Summary of the ongoing industry initiatives of FMs development supporting climate change management

Key Technology-based Enterprises	FM Initiatives	Partnering Institutions	Corporate Websites and Communications Sources
Google	Work with over 500 cities and local governments to reduce carbon emissions annually by 2030 with the deployment of Environmental Insights Explorer (EIE), which uses advanced ML techniques to provide "actionable data and insights". In addition, develop Project Green Light, an AI tool that advises city planners to optimise traffic light timing to reduce stop-and-go traffic	United States of America (USA) Local Governments for Sustainability (ICLEI)	Brandt [3], Google [17]
IBM	Develop a geospatial FM to help enterprises mitigate and adapt to climate change by converting National Aeronautics and Space Administration (NASA)'s satellite observations into customised maps of natural disasters and other environmental changes. The model is part of IBM's watsonx.ai geospatial system offered through its Environmental Intelligence Suite. It aims to estimate climate-related risks pertinent to infrastructures, monitor forests for carbon-offset programs, and develop predictive models	NASA	Raghavan and Shim [48]
Microsoft	Develop a generalisable deep learning FM called ClimaX for weather and climate modelling to enhance climate change adaptation decisions. Such a generalisable FM is trained to handle heterogeneous data sets of different variables and provide spatiotemporal coverage	University of California (UCLA)	SYNCED [51]; Microsoft [36]
NVIDIA	Launch the Earth-2 initiative to build a digital twin of the Earth to address climate change issues by improving predictions of extreme weather and climate change projections and supporting effective mitigation and adaptation strategies based on scientifically principled ML methods. Combine accelerated computing with physics-informed ML at scale run on the supercomputing systems. Provide realistic atmospheric chaos dynamics to update strategy for future climate emulation	Destination Earth (DestinE), an initiative of the European Union to create a digital twin or an interactive computer simulation of the Planet Earth	NVIDIA [42], Posey [46]

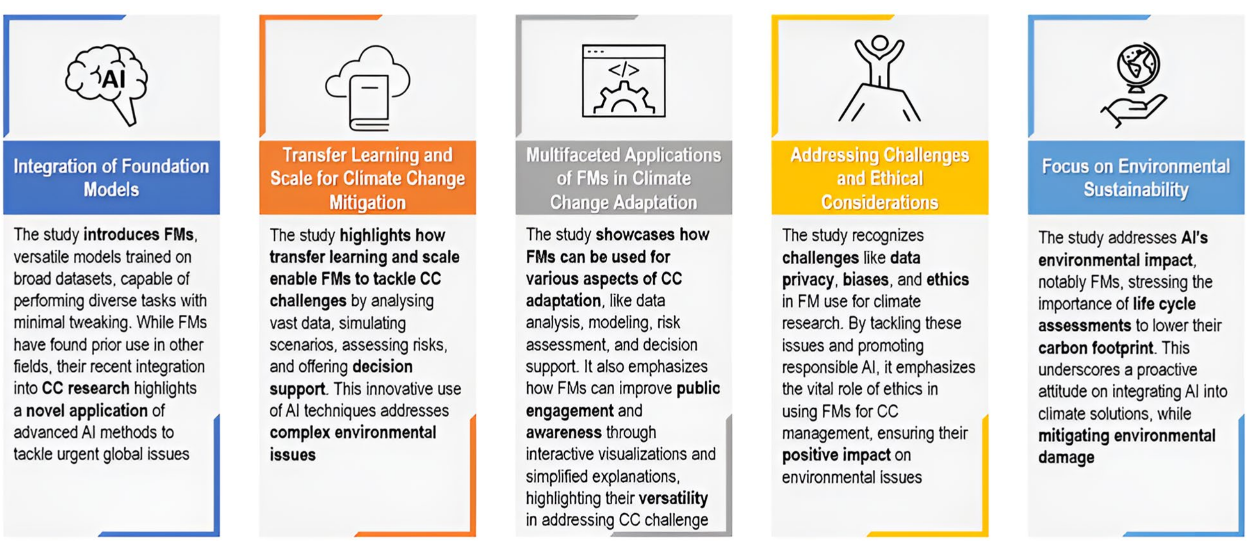

Fig. 3 Content of the application of foundation models in addressing climate change (CC), as explored in this study. Source: authors

deployed to analyse historical and real-time data to predict natural disasters, such as wildfires, hurricanes, and floods through climate modelling, as highlighted by Schneider et al. [49]. These predictions could enable quicker response times and more effective evacuation and relief efforts, assisting in combating the consequences of climate change.

However, it is also important to note that while AI holds great promise, it also poses challenges, such as data privacy concerns, robustness in data curation, bias in algorithms, and ethical considerations (e.g., [25]). In addition, the language used in FMs still need to be fully understood, which may limit the reliability of some of the information collected. Responsible and well-informed application of AI in climate change management is crucial to ensure the positive contributions of FMs. Therefore, researchers need more interdisciplinary engagements that meaningfully address these limitations, reduce the scope of discrepancies, and increase the efficiency of current FMs [52].

FMs, such as GPT-4 and BERT, offer transformative potential but come with significant limitations and risks. One major limitation is their reliance on vast data sets, which can embed biases present in the training data, leading to unfair or harmful outputs. In addition, these models often lack true understanding, generating plausible but incorrect or nonsensical responses—a phenomenon known as "hallucination."

Another risk is their potential misuse, such as generating deepfakes, disinformation, or malicious code. The opacity of their decision-making processes ("black-box" nature) also raises accountability concerns, making it difficult to diagnose errors or biases. Furthermore, their high computational demands contribute to environmental costs, raising sustainability issues. The use of AI as a whole and FMs in particular in the design of climate scenarios need to be further investigates and the various uses need to be duly evaluated.

Finally, FMs may centralise power among a few organisations with the resources to develop them, exacerbating inequities in AI access. Addressing these challenges requires robust governance, transparency, and ongoing research into ethical AI development.

In the case of remote sensing, more specific criteria should be developed to assess the efficiency of FMs for climate change downstream tasks, adjusting innumerable remote sensing data sets to a more current ML pipeline and providing codes for fine-tuning and evaluating individual tasks [29]. Doing so may catalyse the development of FMs, which can make innovative generalisations of various climate change-oriented downstream tasks, enabling new data utilisation, such as determining the best times for sowing new crops. Furthermore, since an FM is, in fact, an AI application, there are concerns about the energy used to power FMs. Strubell et al. [50] demonstrated how power consumption and associated emissions might vary using different FMs. In addition, the carbon footprint may be influenced by the share of non-renewables in the energy source portfolio [50]. According to Ligozat et al. [34], there is a perceived need for more research on addressing the environmental problems and, particularly, the excessive emissions of greenhouse gases related to the powering of AI machinery. In addition, there are some concerns that AI needs to consider its net environmental and ethical impacts [41]. Studies demonstrate that AI-driven technologies can amplify social inequality and risks, particularly among vulnerable groups [21]. Therefore, there is a perceived need to undertake life cycle assessments associated with AI services, particularly FMs, to reduce their carbon footprint. The recent article from Wu et al. [54] on FM's sustainability and environmental implications explores these concerns. In synthesis, this work puts an emphasis on descriptive aspects and focused the analysis of how FMs can impact climate change research and management, shedding light on their potential benefits and the obstacles and challenges that must be addressed. For the future, the use of cutting-edge FM and AI methodologies in the context of climate change science, may assist global efforts to better understand and handle the challenges posed by a changing climate.

Abbreviations

AI	Artificial intelligence
ANFIS	Adaptive neuro-fuzzy inference systems
ANNs	Artificial neural networks
BERT	Bidirectional encoder representations from transformers
CO_2	Carbon dioxide
DestinE	Destination earth
EIE	Environmental insights explorer
EU	European Union
FM	Foundation model
GDPR	General data protection regulation
GeoAI	Geospatial artificial intelligence
GPT	Generative pre-trained transformer
GeoAI	Geospatial artificial intelligence
HFMs	Healthcare foundation models
ML	Machine learning
NASA	National aeronautics and space administration
NDVI	Normalised difference vegetation index
UCLA	University of California
USA	United States of America

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Declarations

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Consent for publication
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Competing interests
The authors declare no competing interests.

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