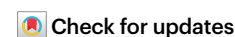


# Collaboration between artificial intelligence and Earth science communities for mutual benefit

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Artificial intelligence is rapidly being integrated into Earth science, but how Earth science may benefit artificial intelligence has been overlooked. We call for mutual balancing between the two disciplines and improving cross-disciplinary collaboration.

The increasing adoption of artificial intelligence (AI) in various fields of Earth science (ES) presents opportunities for progress, but also potentially risks devaluing essential ES methods and expertise, to the potential detriment of the field. To address this issue, here we highlight the unique and irreplaceable characteristics of ES in the era of AI and discuss the mutual benefits of integrating AI with ES, as well as the challenges and opportunities of such integration. Moreover, we propose a framework to improve cross-disciplinary collaboration to address pressing challenges and facilitate future advances in both disciplines.

## Reciprocal benefits of AI and ES

Drawing on extensive discussions of the contributions of AI to ES<sup>1–6</sup>, in Table 1 we summarize AI's transformative role in ES in data management – including collection, curation, and processing – as well as in modelling, prediction, and in enhancing the understanding of processes. ES has amassed knowledge, evidence, datasets, and methodologies over many decades that we argue can also enhance AI development, innovation, benchmarking, and management. Accordingly, in Table 1 we also summarize key areas in which AI would benefit from ES contributions, thereby fostering a more balanced partnership between them. Specifically, ES enhances AI by providing complex, multimodal datasets that foster an extension of AI's capabilities. Integrating ES knowledge, such as physical principles and process-based models, as well as expertise, ensures that AI predictions remain physically realistic. Additionally, ES fosters cross-disciplinary innovation and promotes responsible AI governance by reducing biases and supporting sustainable practices.

## Challenges in improving AI–ES collaboration

The mutual benefits for both disciplines will only be fully realized by cross-disciplinary collaboration, but this would require overcoming technical, domainal, and organizational challenges. Technical

impediments include limited specialized computational resources (such as graphics and tensor processing units) and limited knowledge of the AI community's preferred coding languages in ES. Domain differences, such as distinct methodologies and terminologies, scepticism about the applicability and accuracy of AI in complex scenarios, and debates over the relevance of traditional ES models, still often hamper effective collaboration between AI and ES experts. Organizational barriers include securing consistent funding for cross-disciplinary and international collaboration and for building and maintaining data-sharing and computing infrastructure; designing comprehensive yet student-friendly educational programs in both ES and AI; and tackling the socio-environmental impacts of AI application to ES, which necessitates a continuous dedication to ethical frameworks.

## Opportunities and ways forward for AI–ES collaboration

Emerging theoretical and methodological advances and communication strategies hold promise for overcoming these challenges, particularly if they are integrated through a synergistic approach.

**Earth foundation models.** Recent developments in foundation models (AI systems trained on vast amounts of unlabelled data, enabling capability across various tasks with little fine-tuning, such as GPT<sup>7</sup>) hold promise for solving ES problems. These models can be trained on broad observational and simulation data and adapted to various ES analyses on diverse spatiotemporal scales by minimal training on subject-specific datasets. Moreover, foundation models from various ES domains can be integrated, enabling the development of robust ensemble models that more effectively simulate Earth system dynamics. However, relying solely on foundation models may not be sufficient in the future because these models are generated entirely from data, so the completeness and quality of the training datasets limit their performance.

To better understand Earth's complex dynamics (for example, extreme events), foundation models should be complemented by a probabilistic perspective and ES knowledge and process understanding. Furthermore, it is important to incorporate explainable and interpretable AI techniques and causal inference to improve the reliability of foundation model predictions, which can also be improved by reinforcement learning with stakeholder or expert feedback. This approach can leverage interdisciplinary communication to correct

Table 1 | Reciprocal benefits of AI and ES

	Benefits	Examples
AI for ES	Collecting, curating, and processing data	(1) AI transforms raw observations into curated, high-resolution land use and land cover information. (2) AI systems surpass traditional methods in filling gaps and reconstructing observational climate data <sup>11</sup> . (3) Generative AI tools like ChatGPT and Gemini streamline database creation and narrative construction from extensive texts, enhancing the communication of risk in early warning systems.
	Modelling and prediction	(1) AI systems outperform traditional models in terms of efficiency or accuracy in simulating complex processes like cloud formation and specific tasks like medium-range weather forecasting <sup>1</sup> . (2) AI optimizes parameters for process-based models more efficiently and objectively than manual tuning. (3) Generative AI enhances climate data through bias correction and downscaling in impact assessments <sup>12</sup> . (4) AI provides a more accurate and reliable alternative to empirical methods in fields with elusive physical equations, such as vegetation biogeochemical processes <sup>13</sup> .
	Enhancing process understanding	(1) AI enables studies in ES at finer scales and broader scopes, leading to unprecedented insights and discoveries. For example, AI-driven computer vision techniques enhance global tree detection from satellite imagery, promoting more accurate tree counts, distributions, and carbon stock estimates. (2) AI accelerates ES research by using large language models to summarize scientific reports and inspire new ideas, as well as symbolic regression and causal inference to generate hypotheses from data <sup>14</sup> .
ES for AI	Enhancing AI performance by data	(1) The ES community has amassed diverse data, offering AI opportunities to learn about Earth system states and processes and to enhance model benchmarking and uncertainty quantification <sup>15</sup> . (2) ES datasets feature complex modalities, unlike standard formats like red–green–blue images or pure texts, pushing advancements in AI's multimodal processing. (3) While AI models are running out of new training data and certain benchmark datasets are now deemed too simple for them, ES still possesses vast volumes of untapped and challenging data. (4) The lack of annotations in ES data prompts the development of self-supervised or semi-supervised AI methods.
	Refining AI by domain knowledge and expertise	(1) AI systems struggle to grasp Earth system dynamics from sparse observational data alone, but process-based models can bridge these gaps by providing continuous state predictions over time. (2) Integrating ES physical equations into AI helps ensure that AI predictions follow physical laws and fundamental principles to learn complex geographic phenomena. (3) Hybrid models that combine process-based models with AI enhance the ability to generalize various problems, especially those exacerbated by human-induced climate change <sup>1</sup> . (4) ES data scientists play a vital role in AI development, leveraging their deep knowledge of spatiotemporal data to assist in data collection and communication.
	Promoting the integration of AI and other fields	(1) ES connects with other natural sciences and social sciences, indicating that AI solutions developed for ES could be adapted to these fields. For example, AI analysis of geochemical databases to predict mineral deposit distribution could be useful in materials science for discovering new materials. Similarly, AI interpreting seismic data for Earth's structure can analyse neutron starquakes, providing insights into their composition and structure. (2) The cross-application of AI could also spark inspiration and discovery for some applications in unrelated fields. For example, AI for weather and climate modelling could be applied and useful to tackle challenges with similar complex data in financial markets or epidemiology.
	Governing AI	(1) Spatial thinking and environmental measurements in ES boost data representativeness and mitigate bias in AI development, enhancing fairness and equity. (2) ES methodologies facilitate identifying and reducing carbon and water footprints throughout the AI system lifecycle, advancing greener and more sustainable AI practices <sup>9</sup> .

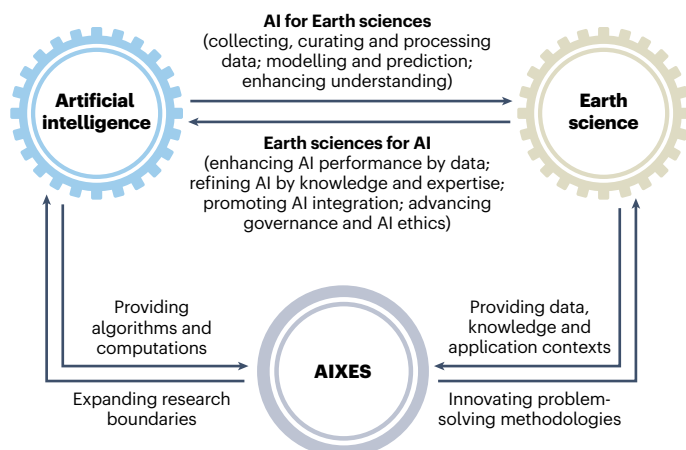
model inaccuracies and prevent unrealistic predictions; such communication would also support open-science efforts by promoting transparent sharing of data, code, and model weights.

**Unified experimental platforms.** Conducting experiments to model the physical world requires considerable technical effort; for example, heterogeneity in the characteristics of different Earth system models leads to compatibility issues that must be overcome. To address this problem, some organizations have established initiatives and infrastructure to manage, share, and utilize resources such as data, models, and computing software. Such programs could evolve into unified experimental platforms, which would generate adaptive guidance plans to facilitate scientific experiments, including formulating questions, processing data, modelling and prediction, and gaining insights. Platform unification requires implementing the recommendation and question-answering functions using advanced AI systems and ES knowledge bases<sup>5</sup>.

Unified experimental platforms would be valuable in mitigating the environmental and socioeconomic impacts of AI–ES collaboration. By integrating human insights with automated analysis, these platforms could improve early warning systems and strengthen

decision-making processes, ultimately leading to more effective risk management and loss mitigation. Environmental sustainability can be compromised by inefficient experimental practices, including in coding and model design, especially when handling complex tasks and large datasets<sup>8,9</sup>. By analysing the energy consumption of various models and computational methods deployed, these platforms could estimate the carbon footprint for the entire lifecycle of experiments, enabling the development of accurate, customized, and environmentally friendly solutions to specific challenges.

**Communication and education.** Effective communication is crucial, not only between the academic AI and ES communities, but also with sectors such as business and government. Enhanced communication within academia can clarify differing perspectives and minimize the domainial challenges in cross-disciplinary collaboration. As the development of AI technologies increasingly shifts towards commercial entities, it is essential to enhance partnerships with them to avoid a future for AI dominated solely by business interests. Policymakers must also actively engage with AI and ES researchers and the private sector, and vice versa, to ensure that advances in these fields are pursued responsibly and equitably.



**Fig. 1 | Collaboration between AI and ES towards AIXES.** AIXES integrates AI with ES, where 'X' symbolizes cross-disciplinary collaboration and the extension and exploration of both scientific frontiers. At the core of AIXES is the recognition of a balanced partnership between AI and ES, ensuring mutual benefits. AI contributes advanced technologies to form AIXES, while ES brings valuable observations, theories, mechanisms, and Earth system challenges. The establishment of AIXES has the potential to broaden the research boundaries of AI and introduce innovative problem-solving methodologies into ES.

Cross-disciplinary education is also crucial to equip the next generation of Earth scientists and AI engineers with a comprehensive understanding and skills from both fields. Therefore, it is essential to develop educational programmes that integrate the curricula and practical experiences from AI and ES, and that encourage diverse thinking, data literacy, ethical awareness, and informatics skills in programming, modelling, and analysis at the nexus of AI and ES. Unified experimental platforms can provide comprehensive educational resources that facilitate a deeper understanding of Earth systems<sup>10</sup>. By leveraging these platforms to create a digital representation of the Earth, non-scientists can explore complex Earth systems and AI technology in an immersive virtual reality environment that makes the learning process intuitive and accessible and encourages a broader engagement with scientific concepts.

## Cross-disciplinary collaboration by AIXES

To promote collaboration between AI and ES, we call for developing a new field and an epistemic community, here called 'AIXES' (Fig. 1). This nexus embraces a balanced and mutually beneficial relationship between AI and ES, aiming for cross-disciplinary collaboration and the extension and exploration of both scientific frontiers. AIXES would use extensive ES data and knowledge, often coded in models, and advanced AI technologies to tackle various challenges about location-specific and global phenomena and processes. AIXES would also enhance ES by providing new and innovative methodologies for problem-solving and policy analysis, as well as expand AI's research boundaries to explore more unknowns, thus improving the underlying theory and techniques. The technical, domainal, and organizational barriers to establishing AIXES should be surmountable by developing Earth foundation models and unified experimental platforms alongside enhancements in communication and education.

Maintaining a balanced and mutually beneficial perspective on AI and ES is crucial for fostering their ongoing development and

innovation. To build the cross-disciplinary field and community of AIXES, we advocate for coordinated efforts among scientists, technologists, policymakers, and educators.

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## Competing interests

The authors declare no competing interests.