https://doi.org/10.1038/s41558-026-02624-x

Artificial intelligence to support cross-disciplinary climate change research

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Integrating knowledge across climate risks, societal responses and their interactions is a critical yet persistently challenging goal. We argue that advanced artificial intelligence frameworks, specifically foundation models, offer a new opportunity to unify these domains and support climate decision-making.

As human-caused climate change progresses and societies increasingly experience its harmful effects, research is providing insights into the physical, ecological, societal and economic consequences of climate change, and helping to identify potential responses[1]. Currently, such analysis often depends on complex multi-stage processes, where experts across physical climate modelling, climate impact assessment, and techno- and socio-economic analysis each contribute their part to a bigger picture. An example is the community-wide initiative producing global scenarios such as the IPCC's Representative Concentration Pathways and Shared Socioeconomic Pathways framework[2]. While this has enabled major advances, existing tools remain fragmented and resource-intensive, limiting timely and coherent policy support[2].

These long-standing limitations call for a renewed effort to pursue more agile and unified approaches enabled by recent advances in artificial intelligence (AI). First, fragmentation across climate physical modelling, impact assessment, and techno- and socio-economic analysis makes representing linked dynamics slow and disjointed. Second, while tools such as integrated assessment models (IAMs) and Earth system models (ESMs) are increasingly flexible within their own domains, inconsistent assumptions, diverging baselines and incompatible frameworks often complicate and delay cross-disciplines synthesis. Third, most workflows are not designed for rapid adaptation or interoperability across regions, sectors or decision types, which reduces responsiveness to new questions. Earlier initiatives such as the Platform for Regional Integrated Modeling and Analysis (PRIMA)[3] sought to bridge these divides, but were limited by rigid architectures and constrained computational capabilities. However, emerging AI tools allow us to revisit this integration challenge with new methods.

We argue that foundation models – that is, self-supervised systems trained on heterogeneous datasets and designed to generalize across a wide range of downstream applications – offer a promising path forward. By embedding a common logic and shared representation into a unified system architecture, such models would be capable of navigating diverse, policy-relevant tasks at accelerated speed. For example, advanced AI models like Aurora already demonstrate the ability to predict weather, air quality, ocean waves and cyclone tracks within a single unified system[4]. Unlike existing integrated tools, a foundation model embeds cross-domain knowledge into a shared, reusable architecture to enable faster iteration and more coherent decision support (see conceptual overview in Fig. 1). In this Comment, we outline the rationale for such a model, current modelling challenges, a technical framework for integration, and conclude with key opportunities and barriers to implementation.

Revisiting integration challenges in the age of AI

The challenge in building an integrated AI model for climate change analysis lies in how cross-domain structures could be translated into well-posed computational tasks. AI models typically require clearly defined inputs and outputs with consistent supervision, yet many climate-relevant applications involve exploratory or counterfactual reasoning that defies such rigid formulation, as they often lack the singular, verifiable outcomes required for model supervision. For instance, decision-makers often consider layered interventions that span fiscal policy, land-use regulation, adaptation efforts and innovation support. However, these are frequently distilled into stylized levers such as carbon pricing or technology support, limiting the ability to assess the potential efficacy of real-world policies. Notably, the literature rarely offers systematic evaluations of how specific instruments translate into intended outcomes[5], which in turn limits the historical data available to train predictive models of policy impact[6]. Translating these dynamic strategies into machine learning-friendly structures therefore raises core design questions: what is the model trying to predict? What constitutes 'ground truth' in a counterfactual world[7]? Should tasks simulate plausible transitions or push the boundaries and suggest innovative solutions? Should they quantify probabilistic outcomes, where likelihoods can be estimated, and compare strategies under deep uncertainty, where they cannot? These questions are amplified by sparse observations and the imperative for interpretability in high-consequence, societally embedded decisions.

AI is increasingly being leveraged across all three climate research domains, although often in isolation. In physical climate modelling, some efforts use machine learning to improve the resolution and speed of Earth system modelling[8], while others focus on enhancing the parametric representation of specific physical processes[9]. In the socio-economic domain, one recent proof-of-concept study[10] demonstrated how generative AI can replicate and expand mitigation scenarios from IAM data, while multi-agent reinforcement learning has been proposed to synthesize climate policy under uncertainty[11]. However, these applications are not typically designed to embed cross-discipline feedback. Physical emulators rarely account for human actions, while socio-economic models often use simplified climate inputs. A key next step, therefore, is to extend this paradigm

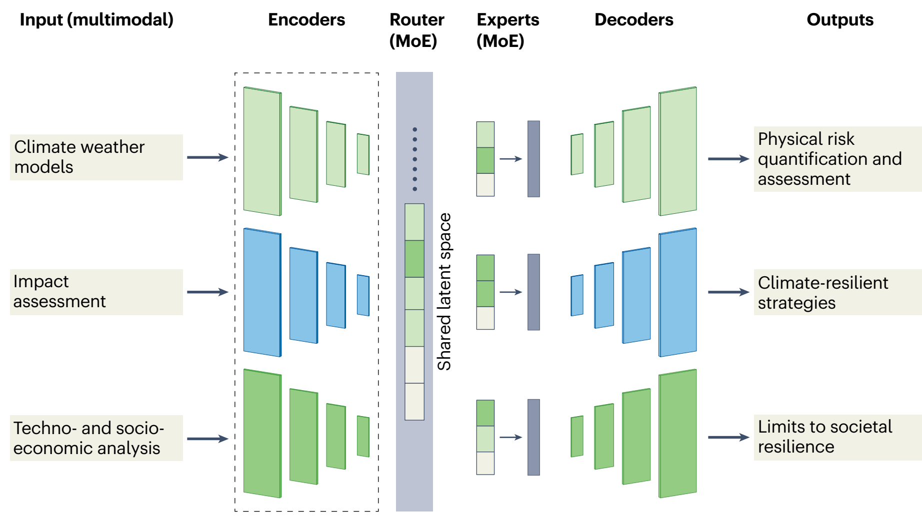

Fig. 1 | A general-purpose AI framework for climate research. When grounded in domain-specific knowledge, this framework creates pathways towards structured reasoning and dynamic adaptation. Inputs from diverse sources are processed through specialized AI modules tailored to each data type[14,15]. A unified architecture enables integration across domains, and the resulting outputs support applications such as climate projections, adaptation strategies and mitigation pathways. MoE, mixture of experts.

by integrating these approaches and embedding new processes into unified modelling architectures.

A general-purpose AI framework for climate research

We propose an integrated AI framework designed to seamlessly unify diverse climate and socio-economic data streams (Fig. 1). Inputs from diverse sources, such as Earth observations, climate–energy–economy modelling simulations and regional policy indicators (for example, carbon pricing levels, renewable targets or institutional constraints) are processed through specialized AI modules tailored to each data type or task. A unified underlying architecture enables cross-domain integration by aligning this heterogeneous information, allowing the model to directly connect physical observations with economic indicators. To illustrate the approach, consider evaluating how extreme heat influences electricity demand and clean energy deployment at high spatial and temporal resolutions. Such an assessment requires projections of physical extremes, building energy use, demographic vulnerability and investment behaviour to be combined. Advanced AI algorithms can integrate these inputs and generate coordinated outputs across multiple tasks, such as demand forecasting, infrastructure planning and adaptation strategy evaluation. The crucial advantage is its reusability: the underlying insights learned in this case, such as temperature extremes and grid vulnerability, can be repurposed to address related questions, such as how heatwaves interact with drought to affect water–energy trade-offs, or how rising cooling demand may reshape emissions and inequality in urban populations.

Another important feature is that expert modules need not be purely neural. Some can embed physics-informed components[12], such as simplified climate equations, to preserve physical consistency alongside statistical learning. In technical terms, it reflects advances in latent-space reasoning and conditional decoding, which allow models to generalize across interdependent systems while preserving task specificity. By combining reusable AI modules with physics-informed components, the proposed framework offers a path towards a highly adaptive AI model for climate research.

While grounded in policy-relevant analysis, the model proposed here also opens new avenues for exploring high-impact events and complex transitions, such as identifying the precursors and characteristics of tipping elements in climate and socio-ecological systems, saturation effects in carbon sinks, and disruptive shifts in energy and technology.

Challenges and future directions

Despite the promise of these advanced models, realizing this vision will require several challenges to be addressed. Integrating disparate elements that include physics-informed neural networks, geospatial embeddings and socio-economic data into a coherent system is a core hurdle. These sources differ in scale, structure and uncertainty, creating incompatibilities that current AI architectures, which often lack modularity and higher-level reasoning, are ill-equipped to resolve. Training such models across modalities is also technically demanding, and success in other scientific domains has often depended on massive, sometimes synthetic, datasets[13].

Uncertainty propagation is another major challenge. A climate foundation model would need to account for structural and parametric uncertainty from Earth system, climate impact and socio-economic models, as well as from measurement errors from observations, while making these uncertainties transparent and tractable for decision support. Addressing such issues is likely to require new methodological advances, including causal deep learning for explainability, geospatial embeddings for spatio-temporal dynamics and methods to integrate unstructured information[14]. If these obstacles are overcome, a foundational model offers the opportunity to explore model and parametric uncertainties much better than current methods, by reducing computational times and integration costs. Crucially, the proposed model is not intended to replace tools like IAMs or ESMs. Instead, it seeks to extend them through AI-based integration, enabling faster iteration, clearer propagation of consistent assumptions and tailoring of their insights for specific policy-relevant questions.

Beyond technical barriers, socio-political challenges will be equally important. Building such a system will require open and transparent governance, clear mechanisms of accountability, and inclusive participation across disciplines and regions. Questions of access, equity and control may prove as consequential as the technical hurdles. Framed this way, developing a climate foundation model should be seen not as an imminent breakthrough but as a grand challenge for the coming decade. A shared research agenda across various communities, including strategically staged use cases, prototypes and community-building efforts, can help guide future work. This will require sustained collaboration and long-term science diplomacy to build trust and integration across disciplines and countries in support of climate response, adaptation and mitigation.

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Published online: 28 April 2026

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Acknowledgements

Y.O. was supported by the National Natural Science Foundation of China (no. 72474002), the National Key R&D Program of China (no. 2024YFF1307000) and the Fundamental Research Funds for the Central Universities. C.R.-P. and M.T. received funding from the European Union European Research Council (ERC) grant project no. 101044703 (EUNICE). H.M. was supported by the National Research Foundation of Korea (grant no. RS-2025-02312954). A.A.K was supported by the Horizon Europe R&I Programme projects IAM COMPACT (grant no. 101056306) and DIAMOND (grant no. 101081179).

Competing interests

The authors declare no competing interests.