

CLIMATE CHANGE: PREDICTIVE CLIMATE MODELS

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INTRODUCTION

This Technology Explainer examines how climate models help scientists understand Earth's dynamic climate system and predict future climate changes. These models are the primary tool scientists have for evaluating the effects of anthropogenic emissions on our climate.¹ In this capacity, climate models are crucial for providing policymakers with the scientific evidence on which they can prioritize climate action and base their mitigation and adaptation strategies. This Technology Explainer first explores the software components of modeling before turning to an exploration of the most recent advances in the field.

A. WHAT IS A PREDICTIVE CLIMATE MODEL?

Similar to models used by meteorologists to generate weather forecasts, climate models are computational systems that use mathematical equations to represent Earth's complex physical processes and calculate climate patterns.² The most salient difference between climate and weather models, however, is their respective time scales. While weather models produce data on daily or weekly temperatures, precipitation, and other variables, climate models project the averages of these values over longer periods, typically spanning decades to centuries.³

Climate models are *predictive* in their ability to simulate long-term climate changes in forecasting prospective climate patterns. The ability to predict future climate conditions helps climate scientists understand how and to what extent anthropogenic greenhouse gas emissions will interact with and alter atmospheric, oceanic, land-surface, and sea-ice conditions.⁴

I. FOUNDATIONS AND KEY CONCEPTS

Climate models use data on temperature, pressure, and humidity to perform physics-based computations that capture key

¹ KRISTEN ST. JOHN & LAWRENCE KRISSEK, CLIMATE CHANGE: A GEOSCIENCE PERSPECTIVE 387 (Kristen St. John & Lawrence Krissek eds., 1st ed. 2025).

² *Climate Models*, NOAA CLIMATE.GOV (June 26, 2025), <https://www.climate.gov/maps-data/climate-data-primer/predicting-climate/climate-models#:~:text=Climate%20models%20are%20based%20on,the%20equations%20using%20powerful%20supercomputers> [https://perma.cc/K8TK-KV39].

³ *Id.*

⁴ *Climate Modeling*, GEOPHYSICAL FLUID DYNAMICS LAB'Y, <https://www.gfdl.noaa.gov/climate-modeling/> [https://perma.cc/5VJ4-BUDQ] (last visited Nov. 1, 2025).

natural processes, including the conservation of mass, energy, and momentum, as well as thermo-fluid dynamics, and radiative heat transfer.⁵ Each model's collection of physics equations is solved by its "dynamical core."⁶ Dynamical cores are code components that are considered the "heart" of the model due to their critical role in calculating the bulk of the model's computations.⁷ Different models will include slightly different sets of these equations in their dynamical cores, depending on their focus.⁸ For example, an oceanic climate model might contain equations related to salinity in its dynamical core,⁹ while atmospheric models will include equations for gas behavior.¹⁰

The first climate models focused solely on performing the aforementioned physics equations to simulate Earth's four major components: the atmosphere, oceans, land surface, and sea ice. Modern climate models, called Earth system models (ESMs), have since evolved to incorporate calculations of biogeochemical cycles alongside traditional physics-based equations.¹¹ Biogeochemical cycles represent pathways through which elements such as carbon, nitrogen, and phosphorus move through living and non-living components of Earth's systems.¹² These cycles directly affect GHG

⁵ Robert McSweeney & Zeke Hausfather, *Q&A: How Do Climate Models Work?* CARBON BRIEF (Jan. 15, 2018, 8:30 AM), <https://www.carbonbrief.org/qa-how-do-climate-models-work/> [<https://perma.cc/MY6K-5JSH>]; Tim N. Palmer, *The Physics of Numerical Analysis: A Climate Modeling Case Study*, PHIL.

TRANSACTIONS OF THE ROYAL SOC'Y A, MATHEMATICAL, PHYSICAL AND ENG'G SCI., Mar. 6, 2020, at 1, 3.

⁶ Sang-Yoon Jun, Suk-Jin Choi & Baek-Min Kim, *Dynamical Core in Atmospheric Model Does Matter in the Simulation of Arctic Climate*, 45 GEOPHYSICAL RSCH. LETTERS 2805, 2805–06 (2018), <https://doi.org/10.1002/2018GL077478>.

⁷ Laura Snider, *The Rise of MPAS NSF NCAR's Next-Generation Atmospheric Model Garners Significant Community Interest*, U.S. NAT'L SCI. FOUND.: UNIV. CORP. FOR ATMOSPHERIC RSCH. (June 12, 2024), <https://news.ucar.edu/132961/rise-mpas> [<https://perma.cc/HPV8-RF8W>].

⁸ Jun et al., *supra* note 6.

⁹ Stephanie Olson, Malte F. Jansen, Dorain S. Abbot, Itay Halevy & Colin Goldblatt, *The Effect of Salinity on Climate and Its Implications for Earth's Habitability*, GEOPHYSICAL RSCH. LETTERS, May 28, 2022, at 1, 2.

¹⁰ Joanna D. Haigh, *Climate Modelling*, SERIOUS SCI. (May 18, 2018), <https://serious-science.org/climate-modelling-2-9001> [<https://perma.cc/PSY4-USTM>].

¹¹ NOAA CLIMATE.GOV, *supra* note 2.

¹² *Biogeochemical Cycles*, UNIV. CTR. FOR SCI. EDUC.: EARTH AS A SYS., <https://scied.ucar.edu/learning-zone/earth-system/biogeochemical-cycles> [<https://perma.cc/S69-79BR>] (last visited Nov. 16, 2025).

concentrations and serve as critical drivers of natural feedback loops.¹³ The carbon cycle, for example, tracks the exchange and storage of carbon among organisms, the atmosphere, and soil,¹⁴ providing climate scientists with insights into how human activities disrupt the natural carbon balance and contribute to increased atmospheric carbon dioxide.¹⁵ By understanding how carbon and other elements are naturally stored and released, ESMs can better simulate climate dynamics and provide more accurate predictions.

II. COMPUTATIONAL TECHNOLOGY

A. MODEL ARCHITECTURE

Several overarching climate modeling frameworks have been designed to allow varying granularity in model calculations and to place greater emphasis on specific components of Earth's climate. The first of which, and the one which modern climate models are built on, is the General Circulation Model (GCM).¹⁶ GCMs primarily simulate the global circulation of the atmosphere and oceans.¹⁷ The most complex GCMs combine oceanic and atmospheric models to create Atmospheric-Ocean General Circulation Models (AOGCMs).¹⁸ ESMs introduce greater complexity by building on AOGCMs, supplementing the basic GCM physics-based dynamical core with equations for various

¹³ Zeke Hausfather & Richard Betts, *Analysis: How ‘Carbon-Cycle Feedbacks’ Could Make Global Warming Worse*, CARBONBRIEF (Apr. 14, 2020), <https://www.carbonbrief.org/analysis-how-carbon-cycle-feedbacks-could-make-global-warming-worse/> [https://perma.cc/9ATE-222A].

¹⁴ William R. Wieder, Steven D. Allison, Eric A. Davidson, Katerina Georgiou, Oleksandra Hararuk, Yujie He, Francesca Hopkins, Yiqi Luo, Matthew J. Smith, Benjamin Sulman, Katherine Todd-Brown, Ying-Ping Wang, Jianyang Xia & Xiaofeng Xu, Explicitly Representing Soil Microbial Processes in Earth System Models, 29 Glob. Biogeochemical Cycles 1782, 1782 (2015), <https://doi.org/10.1002/2015GB005188>.

¹⁵ For example, human combustion of fossil fuels increases atmospheric carbon dioxide, driving rising temperatures. Increased temperatures accelerate the rate of permafrost melting, which releases stored carbon into the atmosphere, further intensifying warming and continuing the cycle.

¹⁶ Leo Hickman, *Timeline: The History of Climate Modelling*, CARBONBRIEF (Jan. 16, 2018, 8:00 AM), <https://www.carbonbrief.org/timeline-history-climate-modelling/> [https://perma.cc/CSG9-XN8Z].

¹⁷ GEOPHYSICAL FLUID DYNAMICS LAB’Y, *supra* note 4.

¹⁸ *Id.*

biological and chemical processes.¹⁹ Because modern climate models build on earlier frameworks, understanding how the base model functions provides valuable context for understanding state-of-the-art models used today.

i. General Circulation Model

General circulation models (GCMs) are computer systems that simulate atmospheric and oceanic processes to predict how the climate may respond to human activity.²⁰ Scientists input historical climate data for specific variables such as temperature, pressure, precipitation, and humidity,²¹ which the model processes through its dynamical core of equations. The model then produces variable outputs for a defined time span, ranging from days to centuries.²²

To run GCMs, the input data must first be discretized into data points. GCMs do so by defining variables spatially on a three-dimensional grid of Earth's surface and atmosphere, where each grid cell represents a singular computational unit.²³ The atmosphere is divided into discrete layers (e.g., 20-40 layers) to approximate interactions across varying altitudes, which are overlaid with a two-dimensional horizontal grid, spanning around 100-200 kilometers.²⁴ Differences between climate models often derive from variation in the size and number of cells in the models' three-dimensional grid. The smaller and more numerous the cells of a model's grid are, the higher its "spatial resolution."²⁵ While GCMs typically have spatial resolutions of hundreds of kilometers,²⁶ scientists can use

¹⁹ *GFDL Earth System Models*, GEOPHYSICAL FLUID DYNAMICS LAB'Y, <https://www.gfdl.noaa.gov/earth-system-models/> [https://perma.cc/BX92-KU8D] (last visited Nov. 16, 2025).

²⁰ NOAA CLIMATE.GOV, *supra* note 2.

²¹ GEOPHYSICAL FLUID DYNAMICS LAB'Y, *supra* note 4; McSweeney & Hausfather, *supra* note 5.

²² *Id.*

²³ *Grid*, SWEDISH METEOROLOGICAL HYDROLOGICAL INST., <https://climateinformation.org/about/> [https://perma.cc/KZ3S-B6QV].

²⁴ DAVID C. BADER, CURT COVEY, WILLIAM J. GUTOWSKI, ISAAC M. HELD, KENNETH E. KUNKEL, RONALD L. MILLER, ROBIN T. TOKMAKIAN & MINGHUA H. ZHANG, CLIMATE MODELS: AN ASSESSMENT OF STRENGTHS AND LIMITATIONS 14 (Judy Wyrick & Anne Adamson, eds., 2008).

²⁵ GEOPHYSICAL FLUID DYNAMICS LAB'Y, *supra* note 4.

²⁶ SUZANNA CLARK, HEIDI ROOP, NATHAN MEYER, STEFAN LIESS, JAMIE MOSEL, BRENDA HOPPE & AMANDA FARRIS, CLIMATE MODELING: AN INTRODUCTORY PRIMER FOR PRACTITIONERS 9 (1st ed. 2023).

contemporary downscaling techniques to produce higher-resolution outputs.²⁷

Using the discretized data, GCMs apply the dynamical core equations to each cell to produce output values indicating how specified variables have changed over time. Because the atmosphere and oceans are highly dynamic, calculations on individual grid cells alone cannot fully capture their evolving interactions.²⁸ To account for the natural exchange of matter, heat, and energy from one particle to another, the results from each cell are passed to its neighbors, which are then factored into their calculations.²⁹ This process is broken into discrete time periods, known as “time steps,” that represent the model’s “temporal resolution.”³⁰ As with spatial resolution, the smaller and more frequent the time steps, the higher the temporal resolution. A singular time step is typically defined as one run of the dynamical core equations through each cell.³¹ The model uses the information calculated in the first time step as input to the second.³² Running *each* equation for *each* cell at *each* time step is computationally demanding, and this burden increases with higher resolution.³³ For example, a model attempting a century-long simulation with 1-hour time steps would require 876,000 time steps.³⁴ For a model with thousands to millions of grid cells, in which dozens of equations are run, it can require solving billions to trillions of equations.³⁵

While the majority of the model’s equations are expressed in the dynamical core, for processes that are either too complex, too small-scale, or not sufficiently understood to be accurately simulated at each grid cell, simplified approximations that represent their average effects are used by the model instead.³⁶ These physical “parameterizations” often account for physical parameters that would require a significant amount of the computer’s processing time, memory, and power if solved out in their

²⁷ Catherine M. Cooney, *Downscaling Climate Models: Sharpening the Focus on Local-Level Changes*, 120 ENV’T HEALTH PERSP. 22, 24 (2012), <https://doi.org/10.1289/ehp.120-a22>.

²⁸ NOAA CLIMATE.GOV, *supra* note 2.

²⁹ *Id.*

³⁰ *Id.*

³¹ S. CLARK ET AL., CLIMATE MODELING: AN INTRODUCTORY PRIMER FOR PRACTITIONERS 5 (1st ed. 2023); SUZANNA CLARK ET AL., *supra* note 26.

³² *Id.*

³³ *Id.*

³⁴ *Id.* at 8.

³⁵ *Id.*

³⁶ GEOPHYSICAL FLUID DYNAMICS LAB’Y, *supra* note 4.

entirety.³⁷ Just as 3.14 is commonly used as a practical approximation for π , which allows for easier calculations, simplifying parameters through approximation can make equations more manageable and less time-consuming for models to compute.

ii. Earth Systems Model and Coupled Models

ESMs are coupled models that combine multiple stand-alone models into a single framework.³⁸ Stand-alone models are designed to accurately simulate only one of Earth's four major components, either atmosphere, oceans, land surface, or sea ice, in isolation.³⁹ Coupled models aim to unite stand-alone models into a single system to inform internal calculations more effectively and improve accuracy.⁴⁰ Like specialized organs that function individually but combine to form the human body, coupled models leverage the specialized capabilities of individual models and combine them to create a model better equipped to simulate complex and dynamic interactions. To achieve this, a software component known as a "coupler" helps to manage information transfers among models.⁴¹ The coupler receives variable data from one model and, through interpolation into another grid, converts its units into a readable input for another model's use.⁴²

B. CALIBRATION AND VALIDATION TECHNIQUES

A standard part of operating a climate model includes validating its predictions and calibrating it accordingly. Climate scientists can test a model's predictive power by feeding it past climate data, of which the outcomes are known.⁴³ The model's predictions are then compared with real-world data. Any discrepancy between the model's predictions and the historical data

³⁷ Omar M. M. Nofal, Omar Al-Jaghbeer, Zaid Bakri & Tareq Hussein, *A Simple Parameterization to Enhance the Computational Time in the Three Layer Dry Deposition Model for Smooth Surfaces*, ATMOSPHERE, July 27, 2022, at 1, 1–2, <https://doi.org/10.3390/atmos13081190>.

³⁸ Sophie Valcke, *The OASIS3 Coupler: A European Climate Modelling Community Software*, 6 GEOSCIENCE MODEL DEV. 373, 373–74 (2013), <https://doi.org/10.5194/gmd-6-373-2013>, 2013.

³⁹ *Id.*

⁴⁰ *Id.*

⁴¹ Sophie Valcke, V. Balaji, A. Craig, C. DeLuca, R. Dunlap, R. W. Ford, R. Jacob, J. Larson, R. O'Kuinghttons, G. D. Riley & M. Vertenstein., *Coupling Technologies for Earth System Modelling*, 5 GEOSCIENCE MODEL DEV. 1589, 1589 (2012), <https://doi.org/10.5194/gmd-5-1589-2012>.

⁴² *Id.*

⁴³ McSweeney & Hausfather, *supra* note 5.

is addressed in a calibration period.⁴⁴ Calibration can take many forms, all of which involve adjusting the model’s parameters to better fit the historical data.⁴⁵ Through either statistical analysis or expertise,⁴⁶ scientists can identify uncertain parameters (often the same parameters included in parameterizations) that, if adjusted, provide a better match to historical data. The internal parameters are adjusted in the model’s code until the model’s output aligns with the actual data.

C. SUPERCOMPUTING

Given the processing power required to analyze vast datasets and perform numerous complex computations necessary to model climate change, supercomputing is an essential component of climate modeling.⁴⁷ As their name suggests, supercomputers are high-performance computers designed to handle complex calculations efficiently.⁴⁸ Supercomputers work by dividing data-intensive problems among their smaller parts called “nodes.”⁴⁹ Each node acts as a smaller computer with its own memory and processors,⁵⁰ allowing it to perform separate data analysis. What enables the supercomputer to be so powerful is its ability for “parallel processing,” or connecting and facilitating communication among all its nodes on its high-speed network.⁵¹ This enables the simultaneous resolution of smaller components across multiple tasks, resulting in a significantly reduced processing time for the larger project.

⁴⁴ *Id.*

⁴⁵ Juliane Mai, *Ten Strategies Towards Successful Calibration of Environmental Models*, 620 J. HYDROLOGY (SPECIAL ISSUE) 1 (2023), <https://doi.org/10.1016/j.jhydrol.2023.129414>.

⁴⁶ James M. Murphy, David M. H. Sexton, David N. Barnett, Gareth S. Jones, Mark J. Webb, Matthew Collins & David A. Stainforth *Quantification of Modelling Uncertainties in a Large Ensemble of Climate Change Simulations*, 430 NATURE 768, 769 (2004), <https://doi.org/10.1038/nature02771>; McSweeney & Hausfather, *supra* note 5.

⁴⁷ McSweeney & Hausfather, *supra* note 5.

⁴⁸ *What is Supercomputing?*, INT’L BUS. MACH., <https://www.ibm.com/think/topics/supercomputing> [https://perma.cc/9HPQ-WFDJ] (last visited Nov. 2, 2025).

⁴⁹ *Id.*

⁵⁰ *Id.*

⁵¹ *Id.*

III. INNOVATIONS AND DEVELOPMENTS

Recent years have seen significant innovation in climate modeling, primarily driven by the increased use of artificial intelligence (AI) and machine learning (ML).⁵² AI-driven modeling enables faster and more efficient computation, higher-resolution projections, and more accurate predictions of extreme weather events.⁵³ While traditional models have struggled to provide resolution at the level necessary to capture regional and local climate variations, AI models improve modular spatial resolution, creating predictive data more relevant to local decision-makers.⁵⁴

A. ARTIFICIAL INTELLIGENCE DRIVE MODELING

A surge in AI integration has transformed the field, significantly addressing or resolving limitations of previous models.⁵⁵ While AI-based models have limitations, ongoing advancements in AI technology enable them to continually adapt, offering greater efficiency at significantly lower computational costs.⁵⁶ This reduction in computational cost stems from the AI's ability to shortcut complex computations by leveraging its statistical learning capabilities,⁵⁷ significantly reducing time required to simulate without compromising accuracy and, in some cases, even improving it.⁵⁸

⁵² For the purposes of this Explainer, artificial intelligence and machine learning are treated as synonymous terms although they are distinct and nuanced concepts. Machine learning is a specific method of learning from data which is practiced by machines capable of artificial intelligence.

⁵³ Carissa Wong, *How AI Is Improving Climate Forecasts*, 628 NATURE 710, 711–12 (2024) (describing the ACE AI model), <https://doi.org/10.1038/d41586-024-00780-8>.

⁵⁴ *Climate Model Downscaling*, EPRI: CLIMATE DATA USER GUIDE, <https://apps.epri.com/climate-data-user-guide/en/climate-model-downscaling.html> [https://perma.cc/L38U-FJ8M] (last visited Nov. 2, 2025).

⁵⁵ Kingsley Ukoba, *Predictive Modeling of Climate Change Impacts Using Artificial Intelligence: A Review for Equitable Governance and Sustainable Outcome*, 32 ENV'T SCI. & POLLUTION RSCH. 10705, 10706 (2025), <https://doi.org/doi: 10.1007/s11356-025-36356-w>.

⁵⁶ Wong, *supra* note 53.

⁵⁷ *Id.* at 711.

⁵⁸ Neeta Nandgude, T.P. Singh, Sachin Nandgude & Mukesh Tiwari, *Drought Prediction: A Comprehensive Review of Different Drought Prediction Models and Adopted Technologies*, SUSTAINABILITY (SPECIAL ISSUE) 1 (2023) (finding that machine learning models outperformed traditional models in improved drought prediction accuracy), <https://doi.org/10.3390/su151511684>.

Rather than performing the time-intensive calculations done by traditional models, AI-driven models use their ability to recognize patterns to learn the statistical relationships between variables, equations, and output data. To establish this knowledge base, AI models are first trained using data from traditional models.⁵⁹ Training an AI model involves running calculations on input data and continuously adjusting the model's parameters until it produces the desired output.⁶⁰ After a model is trained, it can enter a post-training phase during which it is fine-tuned on a specific subset of data to accomplish a target task (e.g., medium-range weather forecasting at a particular resolution).⁶¹

There are three primary approaches to incorporating ML into climate models: emulator models, foundation models, and hybrid models.⁶² An emulator model is an AI model trained solely to replicate the input-output behavior of another model.⁶³ Because the AI model is trained only on data from a single model, it is limited in its predictive abilities by that model. However, for the limited purpose of increasing efficiency and reducing uncertainty associated with a specific traditional model, emulators are particularly useful.⁶⁴ A foundation model also capitalizes on AI's ability to recognize patterns but does so on a much larger dataset.⁶⁵ Compared with emulator models, foundational models are trained on multiple models and millions of hours of geophysical data to build a more robust model capable of more independent climate modeling.⁶⁶

The third approach to AI modeling is a hybrid model that combines the strengths of traditional models with ML's

⁵⁹ Wong, *supra* note 53 (describing the training of AI models using traditional model's projections).

⁶⁰ Ukoba, *supra* note 55 at 10710.

⁶¹ Kaifeng Bi, Lingxi Xie, Hengheng Zhang, Xin Chen, Xiaotao Gu & Qi Tian, *Accurate Medium-Range Global Weather Forecasting with 3D Neural Networks*, 619 NATURE 533, 533 (2023), <https://doi.org/10.1038/s41586-023-06185-3>.

⁶² Carissa Wong, *supra* note 53.

⁶³ *Id.*

⁶⁴ *Id.*

⁶⁵ *Id.*

⁶⁶ Cristian Bodnar, Wessel P. Bruinsma, Ana Lucic, Megan Stanley, Anna Allen, Johannes Brandstetter, Patrick Garvan, Maik Riechert, Jonathan A. Weyn, Haiyu Dong, Jayesh K. Gupta, Kit Thambiratnam, Alexander T. Archibald, Chun-Chieh Wu, Elizabeth Heider, Max Welling, Richard E. Turner & Paris Perdikaris, *A Foundation Model for the Earth System*, 641 NATURE 1180, 1180 (2025), <https://doi.org/10.1038/s41586-025-09005-y>.

computational efficiency and pattern recognition.⁶⁷ Predictions from the traditional model can serve as input to the ML-based model for its statistical analyses. Some hybrid models operate entirely on their own, independent of the traditional model they were trained on.⁶⁸ Other “coupled” hybrid structures allow the AI model to run in parallel with the traditional model.⁶⁹ Sometimes this is done by replacing or supplementing specific components of the physical model with an AI model.⁷⁰ Most often, parameterizations are replaced by ML models that better capture these complex relationships.⁷¹ Rather than calculating the majority of the sophisticated mathematical equations that represent these parameterizations, the ML model conducts statistical analysis of the data to predict the most likely output from the patterns it observes.

B. REGIONAL PROJECTIONS

Producing higher-resolution models that allow for more detailed regional or local climate analysis requires creating a model capable of running its dynamical core equations on a much larger set of small grid cells, sometimes as small as couple kilometers.⁷² While traditional models have achieved resolution close to that of AI models,⁷³ the computational energy required to achieve such

⁶⁷ Wong, *supra* note 53, at 712.

⁶⁸ Louise J. Slater, Louise Arnal, Marie-Amélie Boucher, Annie Y.-Y. Chang, Simon Moulds, Conor Murphy, Grey Nearing, Guy Shalev, Chaopeng Shen, Linda Speight, Gabriele Villarini, Robert L. Wilby, Andrew Wood & Massimiliano Zappa, *Hybrid Forecasting: Blending Climate Predictions with AI Models*, 27 HYDROLOGY & EARTH SYS. SCI. 1865, 1865–68 (2023), <https://doi.org/10.5194/hess-27-1865-2023>.

⁶⁹ *Id.*

⁷⁰ *Id.*

⁷¹ Paul A. O’Gorman & John G. Dwyer, *Using Machine Learning to Parameterize Moist Convection: Potential for Modeling of Climate, Climate Change, and Extreme Events*, 10 J. ADVANCES IN MODELING EARTH SYS. 2548, 2548 (2018), <https://doi.org/10.1029/2018MS001351>.

⁷² Ja-Yeon Moon, Jan Streffing, Sun-Seon Lee, Tido Semmler, Miguel Andrés-Martínez, Jiao Chen, Eun-Byeoul Cho, Jung-Eun Chu, Christian L. E. Franzke, Jan P. Gärtner, Rohit Ghosh, Jan Hegewald, Songyee Hong, Dae-Won Kim, Nikolay Koldunov, June-Yi Lee, Zihao Lin, Chao Liu, Svetlana N. Loza, Wonsun Park, Woncheol Roh, Dmitry V. Sein, Sahil Sharma, Dmitry Sidorenko, Jun-Hyeok Son, Malte F. Stuecker, Qiang Wang, Gyuseok Yi, Martina Zappolini, Thomas Jung & Axel Timmermann, *Earth’s Future Climate and its Variability Simulated at 9 km Global Resolution*, 16 EARTH SYS. DYNAMICS 1103, 1103–04 (2025) (simulating climate change on the scale of nine kilometers of atmosphere and four to twenty-five kilometers in the ocean), <https://doi.org/10.5194/esd-16-1103-2025>.

⁷³ *Id.*

high resolution over longer time periods comes with significant computational costs.⁷⁴ AI-driven models overcome this by *downscaling* traditional models or converting coarse-resolution data into higher resolution. ML models downscale traditional models using their ability to perform pattern recognition to bypass the computationally intensive equations that drive traditional modeling.⁷⁵ The ML model learns the statistical relationship between larger-scale data (from conventional models like GCMs) and smaller-scale data inputs (observed local climate) and uses this relationship to generate smaller-scale projections relevant to local climate planning.⁷⁶

IV. STRENGTHS AND LIMITATIONS

A. STRENGTHS AND USE CASES

ML models and coupled ESMs represent the state-of-the-art technology available to climate scientists today. These advanced modeling approaches enable scientists to project future climate trends with greater accuracy and granularity, allowing for simulations at regional and local scales. Climate models have been particularly instrumental in the development of climate attribution science, a field that aims to attribute historical and current greenhouse gas emissions to specific sources.⁷⁷ Recent innovations have enabled the attribution of emissions and extreme events at the level of individual corporations or, in some cases, individuals.⁷⁸ Additionally, by developing more sophisticated projections, these models play a critical role in guiding policymakers as they develop strategies to mitigate and adapt to climate change.

⁷⁴ *High-Resolution Climate Modeling*, GEOPHYSICAL FLUID DYNAMICS LAB’Y, <https://www.gfdl.noaa.gov/high-resolution-climate-modeling/#:~:text=Although%20it%20is%20essential%20for,robust%20results%20to%20be%20established> [https://perma.cc/3QYK-AJKE] (last visited Nov. 2, 2025).

⁷⁵ *Climate Model Downscaling*, *supra* note 54.

⁷⁶ Douglas Maraun, Fredrik Wetterhall, Andrew M. Ireson, *Precipitation Downscaling Under Climate Change: Recent Developments to Bridge the Gap Between Dynamical Models and the End User*, REV. OF GEOPHYSICS, Sept. 24, 2010, at 1, <https://doi.org/10.1029/2009RG000314>.

⁷⁷ Aisha Saad, *Attribution for Climate Torts*, 64 B.C. L. REV. 867, 870–71 (2023).

⁷⁸ Fraser C. Lott, Andrew Ciavarella, John J. Kennedy, Andrew D. King, Peter A. Stott, Simon F. B. Tett & Dongqian Wang, *Quantifying the Contribution of an Individual to Making Extreme Weather Events More Likely*, ENV’T RSCH. LETTERS, Oct. 12, 2021, at 1, 2 (quantifying an individual’s contribution to intensity of a specific extreme weather event), <https://doi.org/10.1088/1748-9326/abe9e9>.

B. LIMITATIONS

While integrating ML into climate change modeling has helped overcome some technical limitations, challenges remain. Chief among these is the inability of models to fully represent Earth's complex systems, thereby preventing a wholly comprehensive understanding of the climate. Although AI-driven models can address some uncertainties, including parameterizations, approximations, and scenario reduction imposed by the computational limitations of traditional models, uncertainty as a whole cannot be completely expunged from these models. ML itself introduces inherent uncertainties due to its use of statistical analysis rather than directly solving the underlying physics equations. Questions remain whether AI models can accurately account for natural variation and complex feedback loops that often accompany these highly sophisticated, not fully understood, physical processes. Additionally, environmental concerns over AI data centers' water usage and greenhouse gas emissions place another limitation on their usefulness as an environmental tool.⁷⁹

⁷⁹ Renée Cho, *AI's Growing Carbon Footprint*, COLUMBIA CLIMATE SCHOOL: STATE OF THE PLANET (June 9, 2023), <https://news.climate.columbia.edu/2023/06/09/ais-growing-carbon-footprint/#:~:text=with%20current%20information.-,Training,powered%20cars%20for%20a%20year> [https://perma.cc/P3N2-PFMY].