

# AI in Climate Modeling and Prediction

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By: Jayant Bhaskaruni





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01


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# Traditional Climate Models Limits






# Traditional Climate Models

- Built on physical equations describing atmosphere, ocean, land, and ice interactions
  - Traditional models (GCMs) solve physical equations → slow & compute-heavy.
    - Ex. 1 simulation on a few decades of climate data = weeks to simulate on a supercomputer.
    - Typical model consumes ~ 10 megawatt hours of energy to simulate a century of climate
  - Problem: low spatial resolution, limited number of runs.
  - Such models struggle to simulate small-scale processes (ex. how raindrops form)
    - Often have an important role in large-scale weather and climate outcomes
  - AI (machine learning):
    - Computer programs learn by spotting patterns in data sets
    - Advantage: learns directly from existing data → predicts patterns much faster
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# Traditional vs AI Models





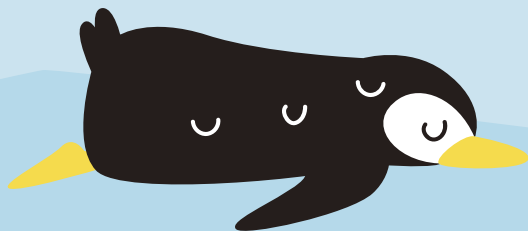
Feature	Traditional Climate Models	AI-Driven Climate Models
Core Approach	Based on physical and mathematical equations (deterministic)	Learns statistical and spatial-temporal patterns directly from data.
Computation Time	Weeks to months per simulation on supercomputers.	Seconds to hours on GPUs or cloud systems.
Data Use	Uses data mainly for initialization and validation.	Uses large historical datasets for training and prediction.
Resolution	Limited by computational cost	Can achieve higher effective resolution via downscaling.
Interpretability	Physically transparent, every process is equation-based.	Difficult to explain predictions physically.
Energy Use	High: massive HPC resources and power consumption.	Lower: efficient inference once trained.
Strengths	Physically grounded, trusted for long-term projections.	Fast, high-resolution, can uncover hidden correlations.
Limitations	Computationally expensive, limited ensemble runs.	Risk of bias, less interpretable, depends on data quality.



03

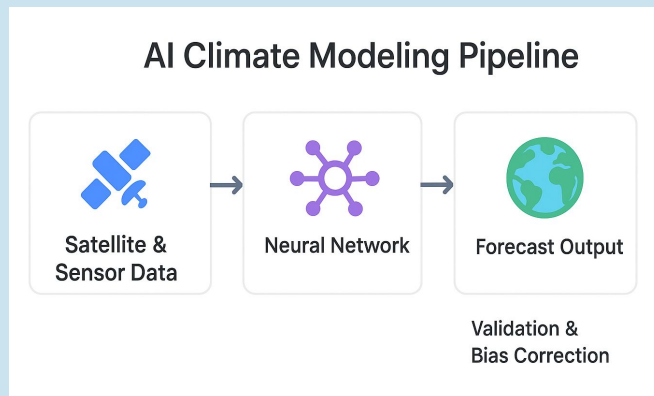
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# How AI Is Used in Practice



# How AI Is Used in Practice

- 3 main AI integration methods:
  - Emulation: AI replaces part of a physical model, like cloud microphysics, to speed up computation.
  - Correction: AI adjusts outputs from physics-based models to reduce bias.
  - Hybrid modeling: combines both—AI fills in data gaps while physics ensures realism.





04


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# AI Strategy #1: Emulators





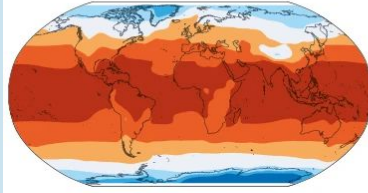
# Emulators ( Copy cats )

- **Goal:** mimic full physics-based models at a fraction of the cost.
  - **QuickClim** (CSIRO, 2023):
    - Trained 15 ML models to emulate 15 physical models of atmospheric temperature.
    - Forecasts new emission scenarios **1 million× faster** than traditional models.
    - Enables rapid exploration of “what-if” scenarios for policymakers.
  - **ACE** (Allen Institute, 2023):
    - Learns atmospheric dynamics at 6-hour intervals.
    - 90% more accurate on key variables than reduced-resolution physical models.
    - Runs **100× faster, 100× less energy-intensive**.
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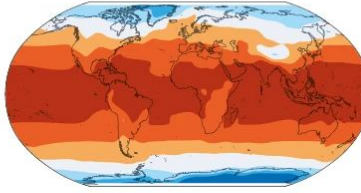
## AI CLIMATE MODEL WORKS AT SPEED

In projections of global surface air temperature up to the year 2100, output from the QuickClim climate emulator (right), a machine-learning system, closely matches that of the physics-based climate model it is trained on (left). However, QuickClim generates the output about one million times faster.

**Physics-based model**

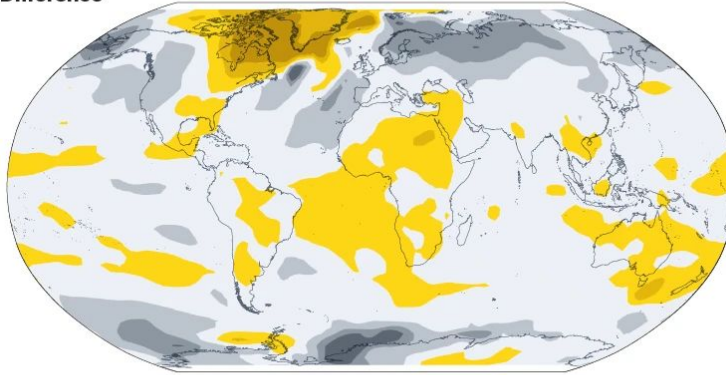


**AI-based emulator**



Surface air temperature (°C)

**Difference**



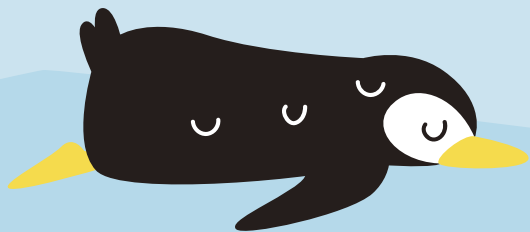
Surface air temperature (°C)

01

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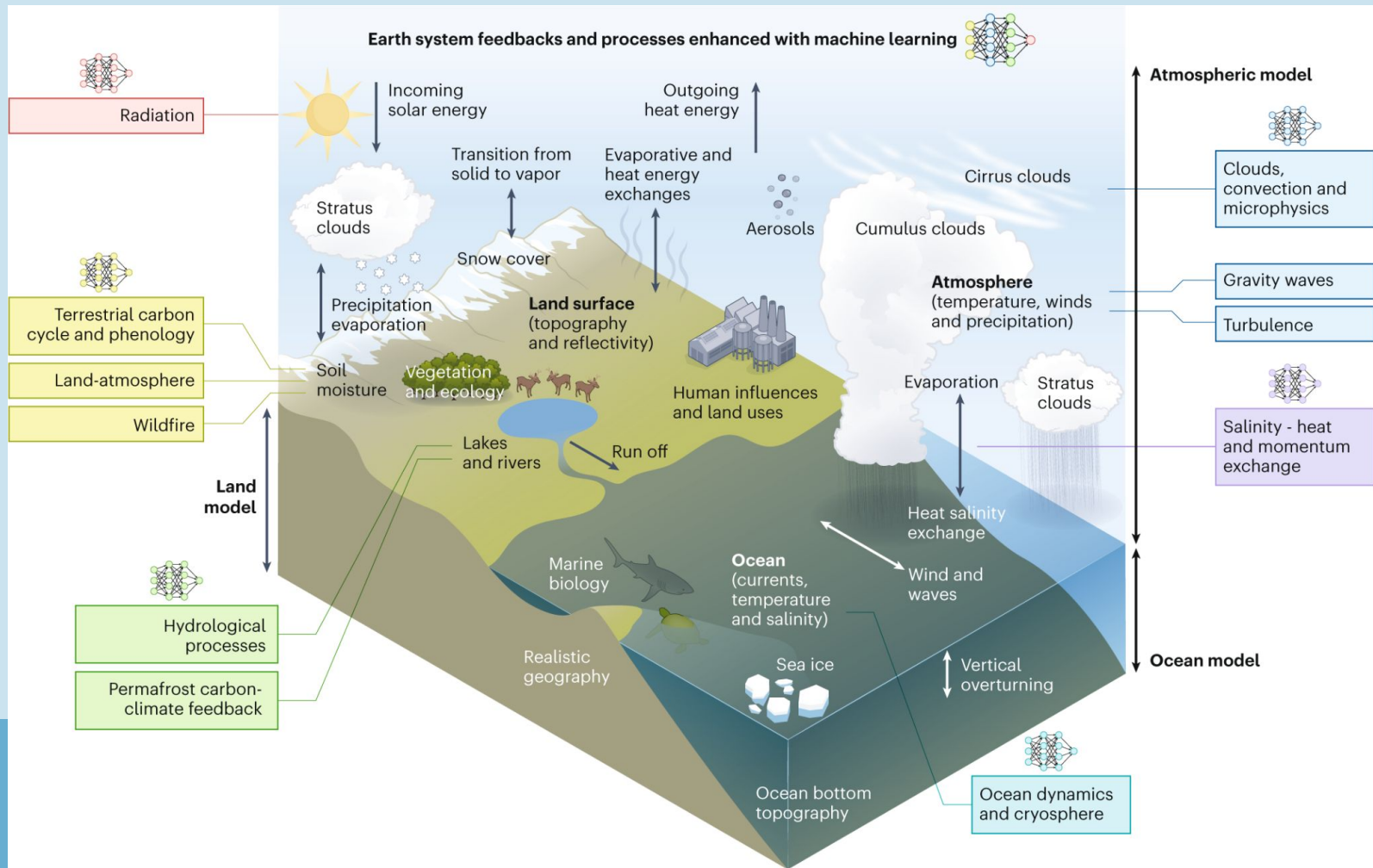
# Impacts on Science and Society






# Impact / Relevance to Society

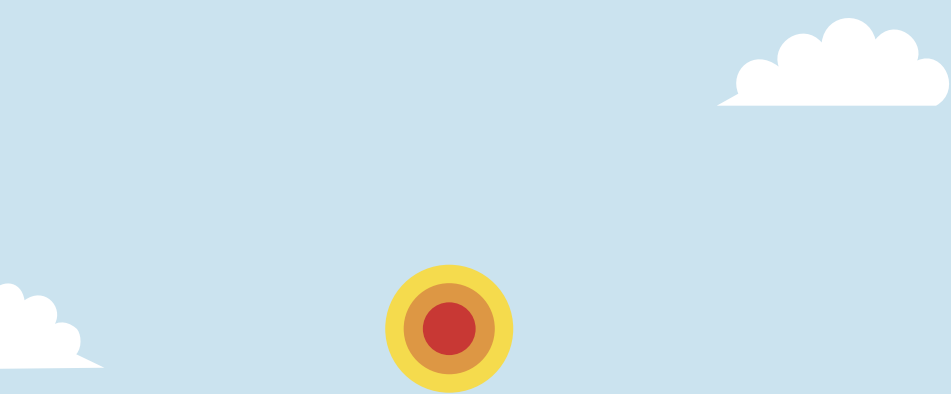
- Speed: allows thousands of model runs for probabilistic forecasting.
  - Efficiency: drastically lowers computational energy demand.
  - Precision: downscales global data to local predictions.
  - Policy impact: helps explore more scenarios
  - Equity: faster, cheaper modeling makes access possible for smaller nations
  - Disaster preparedness: early warnings for floods, wildfires, and hurricanes.
  - Agriculture: optimized planting schedules based on localized forecasts.
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# **Sources**

1. <https://www.nature.com/articles/d41586-024-00780-8>
  2. <https://today.ucsd.edu/story/accelerating-climate-modeling-with-generative-ai>
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