DestinE Climate Emulator: Fast, Stable, Scenario-Aware

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1. Motivation & Scope

The **DestinE Climate Digital Twin** produces high-resolution (~5 km), multi-decadal simulations—but at a **high computational cost**. To address this, we develop a machine learning **climate emulator** that replicates key climate properties **with a fraction of the resources**. Key goals:

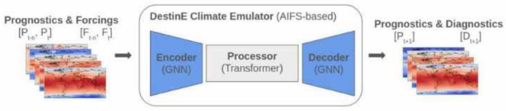
- **Deterministic emulation** with seamless integration of components (atm–lnd–ocn)
- **Replicate physical properties** at 25 km resolution
- **Fast and stable** simulations over 30+ years
- **Scenario-aware emulation** across future forcings scenarios

2. DestinE Climate Emulator Design

The **DestinE Climate Emulator** follows an **encoder–processor–decoder** architecture adapted from *AIFS* (Lang et al., 2024):

➔ Graph Neural Network (GNN) encoder
➔ Transformer-based processor
➔ GNN decoder

This design enables spatial generalization, long-range interactions, and efficient learning across components.



Architecture of the DestinE Climate Emulator. The model follows a GNN encoder → Transformer processor → GNN decoder design, adapted from AIFS. It ingests sequences of prognostic fields and external forcings, evolving them autoregressively to produce high-resolution climate outputs over time.

Inputs:

- **Prognostic fields** from atmosphere, land, and ocean
- **External forcings**: greenhouse gases, aerosols, ozone, solar radiation

Outputs:

- **Prognostic variables** (e.g., temperature, wind, sea surface temperatures)
- **Derived diagnostics** on the native HEALPix or Octahedral Gaussian grid

3. Core Innovations

We introduce several architectural and training advances to improve physical realism, efficiency, and generalization:

- **Residual scaling** emphasizes tendency-based errors (Δt), aligning optimization with temporal evolution rather than absolute fields.
- **Area-weighted loss with spectral components** combines grid-aware MSE with spectral loss terms to enforce energy distribution across spatial scales.
- **Scenario-aware embeddings**. External forcings (GHGs, aerosols, ozone) are introduced via direct input or embedding layers, allowing the model to condition its predictions on evolving boundary conditions. Forcing-aware layers help improve generalization across unseen climate scenarios.

4. Evaluation Strategy

An extended version of **AQUA (DestinE's evaluation tool for Climate Digital Twins)** is used to bridge the gap between physics-based and machine learning simulations. It combines statistical, physical, and process-based diagnostics:

- **Statistical Metrics** to assess predictive skill and spatial fidelity:
  - Root Mean Squared Error (RMSE), Anomaly Correlation Coefficient (ACC), Structural Similarity Index (SSIM)
- **Modes of Variability** to evaluate climate signals and natural variability:
  - Seasonal cycles, seasonal and interannual variability, and low-frequency modes
- **Physical Consistency** to avoid spurious signals:
  - Physical fidelity via spherical harmonics spectra and covariance structures
- **Model Benchmark** to identify strengths and weaknesses:
  - Benchmarked against climate emulators such as *HClimRep* (in development), *ACE* (Watt-Meyer et al., 2023), or *DLESyM* (Cresswell-Clay et al., 2024).

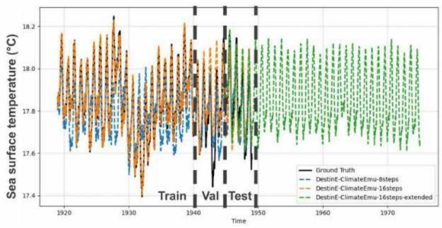
5. Experimental Setup

Dataset. Initial tests use coarse-resolution data from the CESM2 piControl simulation (r1i1p1f1, CMIP6), spanning 98 years at daily frequency and ~6° resolution. Inputs include atmospheric and surface fields (e.g., geopotential, temperature, winds, radiation, SST) and external forcings (e.g., latitude, orography, insolation). Most variables are normalized using residual scaling to emphasize temporal tendencies.

Training follows a fixed rollout strategy with multiple steps. We use an area-weighted MSE loss (AIFS-style), without manual variable scaling. Spectral loss terms were tested but excluded due to limited benefit at this resolution.

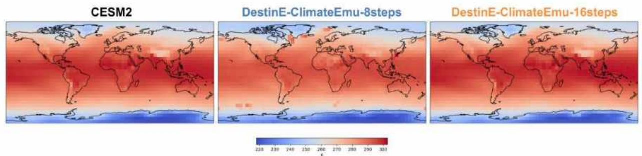
6. Climate Stability & Spatial Fidelity

The emulator exhibits **long-term stability and realistic seasonal variability**. Capturing **low-frequency variability in SSTs remains a challenge** at this coarse resolution.



Global mean time series of sea surface temperature (SST).

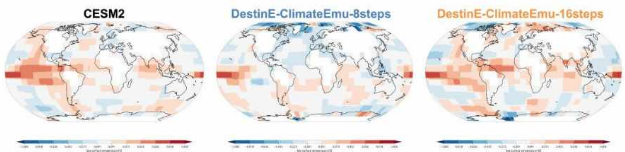
Emulated fields, e.g., surface temperature, show **good spatial climatology, preserving large-scale gradients and realistic global distributions** compared to CESM2.



Time-mean surface temperature (K) over the validation and test sets (8 years).

7. Natural Variability

The emulator demonstrates **emerging skill in capturing the El Niño–Southern Oscillation (ENSO) teleconnections**, including centers of action in the tropical Pacific, North and South Pacific, and the Indian Ocean. These results indicate the model's ability to emulate large-scale coupled variability.



Correlation of sea surface temperature anomalies with the Niño3.4 index.

8. Next Steps & Outlook

Building on initial coarse-resolution experiments, next steps include:

- **Upscaling to finer resolutions** (~1°), including leveraging **Climate Digital Twin simulations** (e.g., IFS-NEMO)
- Capturing **low-frequency variability** via extended inputs and training strategies
- Including **external climate forcings**, exploring 1pctCO2 idealized and historical experiments
- **Benchmarking** against *HClimRep* and other state-of-the-art models
- Preparing for **scenario-aware emulation** under diverse climate pathways

References. Cresswell-Clay, Nathaniel, et al. "A deep learning earth system model for stable and efficient simulation of the current climate." arXiv preprint arXiv:2409.16247 (2024); Lang, Simon, et al. "AIFS--ECMWF's data-driven forecasting system." arXiv preprint arXiv:2406.01465 (2024); Watt-Meyer, Oliver, et al. "ACE: A fast, skillful learned global atmospheric model for climate prediction." arXiv preprint arXiv:2310.02074 (2023).

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