# Neural-Network Meta-Models for Reduced-Complexity Climate Models

The aim of this project is to construct a fast and accurate neural-network meta-model for reduced-complexity climate models. These models map greenhouse-gas emission trajectories into global mean temperature outcomes through simplified representations of gas cycles, radiative forcing, and energy balance dynamics. Reduced-complexity or simple climate models are widely used in integrated assessment, climate-risk analysis, and policy evaluation, where they are repeatedly embedded in economic models, optimization routines, and stochastic simulations.

Despite their relative simplicity compared to full Earth system models, the repeated numerical evaluation of such climate models can become a computational bottleneck in applications involving dynamic optimization under uncertainty, Monte Carlo simulations of climate risks, expectation formation and learning, or large-scale sensitivity and scenario analysis. The objective of the project is therefore to replace repeated numerical solves by a fast and differentiable surrogate, enabling analyses that would otherwise be computationally infeasible.

**Methodology** Let $E_g(\cdot)$ denote the emission trajectory associated with gas or forcing component $g$, and let $T^{AT}(\cdot)$ denote the resulting atmospheric temperature trajectory. The goal is to approximate the operator

$$f : \{E_g(\cdot)\}_{g=1}^{G} \longrightarrow T^{AT}(\cdot),$$

using a neural-network meta-model.

The project follows a three-step methodology inspired by Gobet et al (2025):

1. **Dirichlet encoding of emissions.** Each emission trajectory $E_g(t)$ is approximated using generalized Dirichlet polynomials, providing a low-dimensional representation of long-horizon emission scenarios.
2. **Time rescaling.** A nonlinear change of time maps long or infinite horizons onto a compact domain, improving smoothness and approximation properties.
3. **Neural-network surrogate.** A ReLU neural network is trained to learn the mapping from encoded emission paths and initial climate states to temperature trajectories.

In contrast with Gobet et al. (2025), which focuses on a carbon-cycle-driven climate block, the present project extends the approach to incorporate additional climate-system components beyond $CO_2$, including other greenhouse gases and aerosol forcings. The methodology will be implemented and tested on the FAIR (Finite Amplitude Impulse Response) climate model, a Python-based reduced-complexity climate model that explicitly represents multiple greenhouse gases and aerosol forcings. FAIR allows an extensible number of climate layers and typically includes $G = 9$ forcing components. Students will deliver a neural surrogate of the FAIR climate model, benchmark its accuracy against the original Python solver, and document computational speedups of one to two orders of magnitude.

## References


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