Training Module: Using AI To Reduce Uncertainty In Climate Modelling

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Module Overview

The course contains six training modules with an aim to provide students with an understanding of how earth system models (ESMs) are used to simulate Earth's climate, sources of uncertainty in the climate system, and how we can make use of machine learning (ML), and artificial intelligence (AI) to reduce those uncertainties. Each module will allow students to develop an understanding of the theory, and then apply this knowledge in laboratory exercises, using data from ESMs.

Module 1: A Brief Introduction to Earth System Models

Learning Outcomes:

1. Understand the complexities of earth's mean climate and variability
2. Identify the main components of a climate model and how Earth's climate is represented in them
3. Appreciate the range of Earth System Model configurations and their application
4. Understand why the members of an ensemble of Earth System Models differ

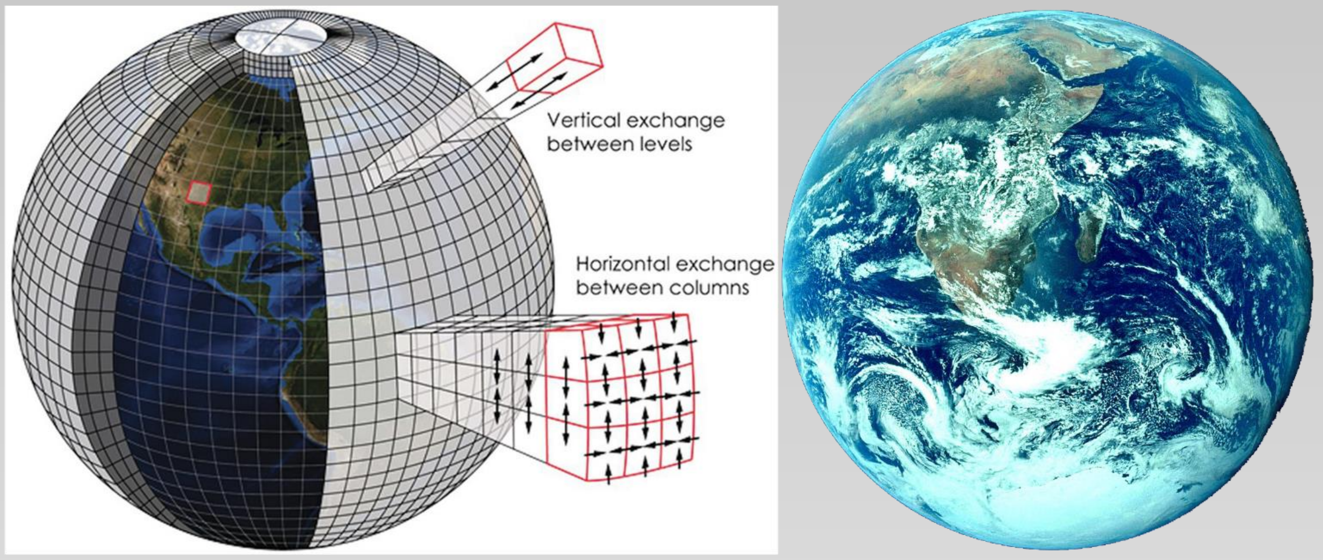


Figure 1. A comparison of a climate model and a satellite image of Earth (adapted from Kotamarthi et al., 2021).

Lab Exercise: Reflection exercise on conceptual and numerical models you rely on in your daily life. Consider the assumptions behind these models, and why they are useful to you.

Module 2: How Well Do ESMs Represent The Present Day Climate?

Learning Outcomes:

1. Develop an understanding of the metrics of climate model performance
2. Quantify model performance of temperature and precipitation over the recent past
3. Understand how and why spatial and temporal scale affects model performance

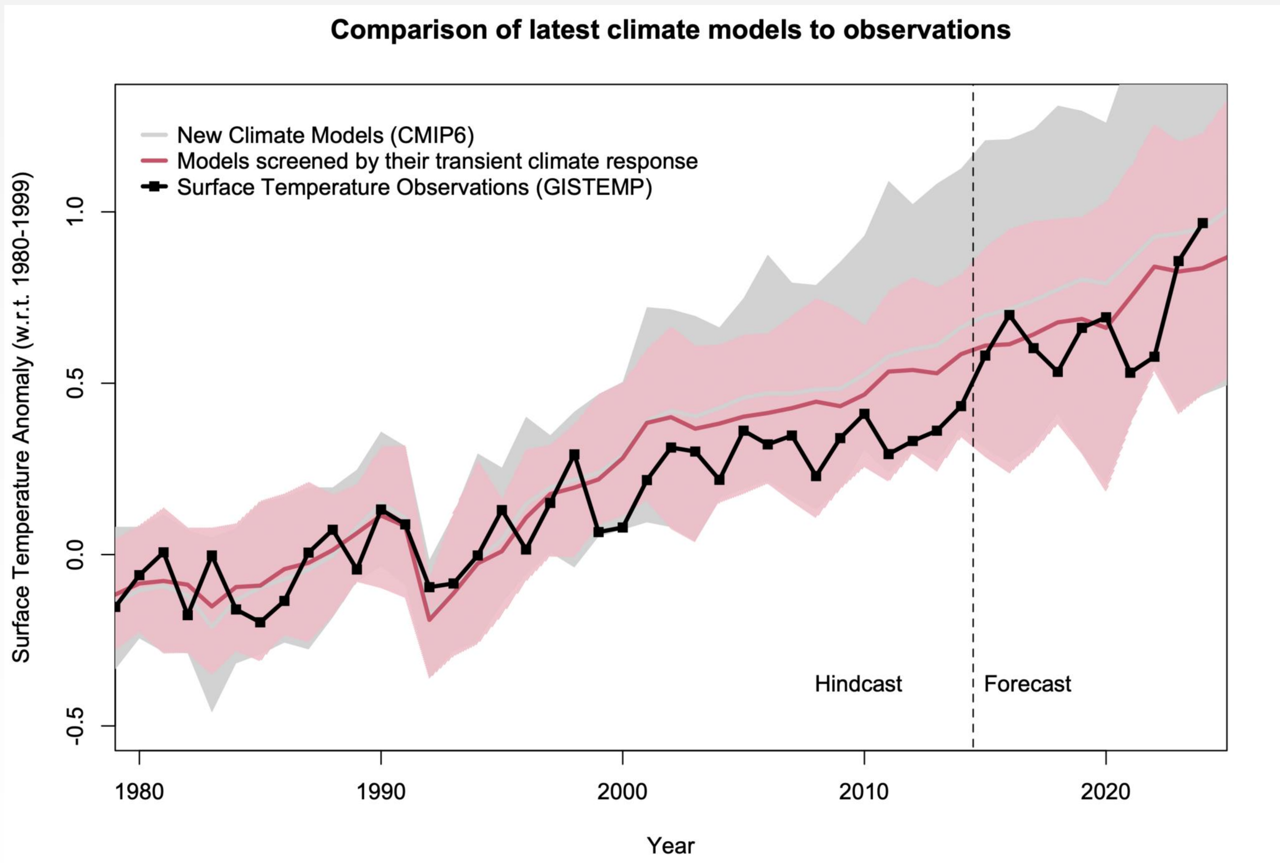


Figure 2. CMIP6 model estimates of global mean surface temperature anomalies relative to the 1980-1999 mean, as compared with GISTEMP (from Schmidt, 2025).

Lab Exercise: Quantify differences in the temperature and precipitation from ESMs and observations and discuss what aspects of the observed climate models capture well, and what aspects remain a challenge.

Module 3: Model Intercomparisons and Future Climate Scenarios

Learning Outcomes:

1. Explain the concepts of climate sensitivity, radiative forcing and climate feedbacks
2. Describe what the Coupled Model Intercomparison Project (CMIP) is and its purpose
3. Understand what future emission scenarios are and how they are developed
4. Explain the differences between predictions, forecasts and projections

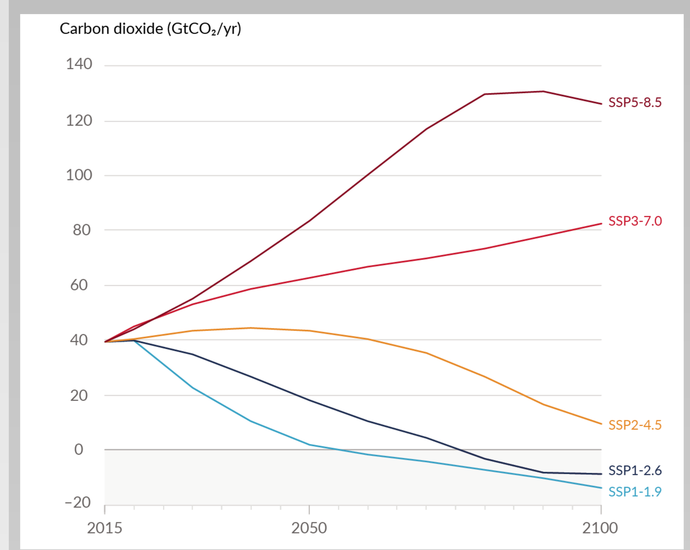


Figure 3. Future emissions of CO2 across five different Shared Socioeconomic Pathways (SSPs) (from IPCC, 2021).

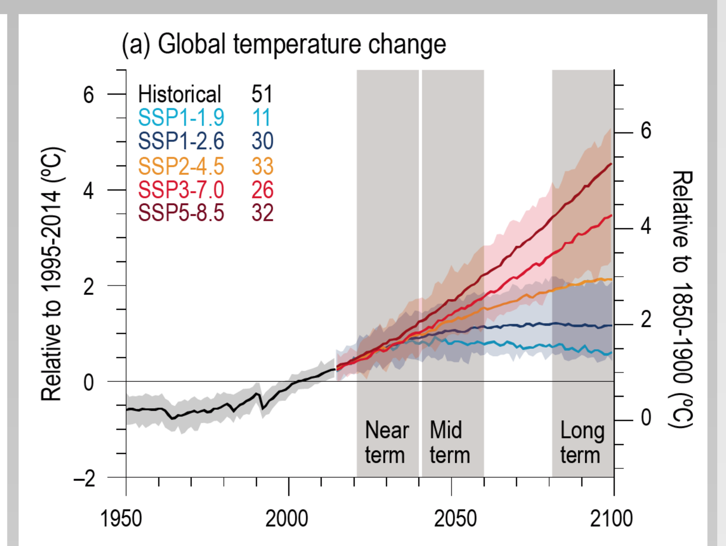


Figure 4. Global mean surface air temperature change for the different SSP scenarios (from Lee et al., 2021).

Lab Exercise: Create timeseries of emissions from different Representative Concentration Pathway (RCP) and Shared Socioeconomic Pathway (SSP) scenarios and quantify differences between the different scenarios.

Module 4: Quantifying Uncertainty in Climate Simulations

Learning Outcomes:

1. Explain the concepts of internal climate variability, model uncertainty and scenario uncertainty and how they contribute to uncertainty in future climate projections
2. Be able to select the appropriate type of model ensemble for quantifying uncertainty
3. Apply statistical methods to quantify different sources of uncertainty
4. Understand how emergent constraints can be used to reduce uncertainties in future climate projections

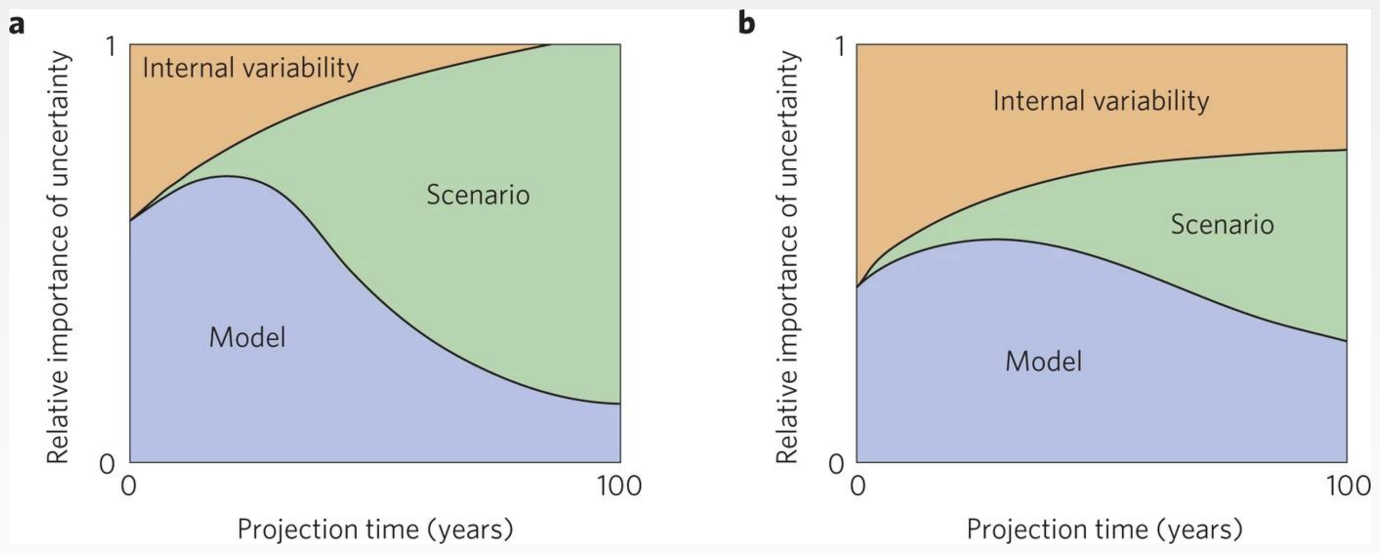


Figure 5. The relative importance of the three sources of uncertainty (internal variability, model uncertainty and scenario uncertainty in long-term projections of (a) global mean surface air temperature, and (b) regionally-averaged dynamic sea level (from Yin, 2015).

Lab Exercise: Create a Hawkins and Sutton (2009) type figure to quantify the relative contributions of uncertainty from internal variability, scenario uncertainty and model uncertainty for global mean surface air temperature and precipitation. Discuss how these differ by variable and over time.

Module 5: Role of AI in Climate Modeling: Statistical Emulation

Learning Outcomes:

1. Understand what a perturbed parameter ensemble is, and how they can be used to reduce uncertainty in model physics
2. Explain how ML based approaches can be used to calibrate model parameters

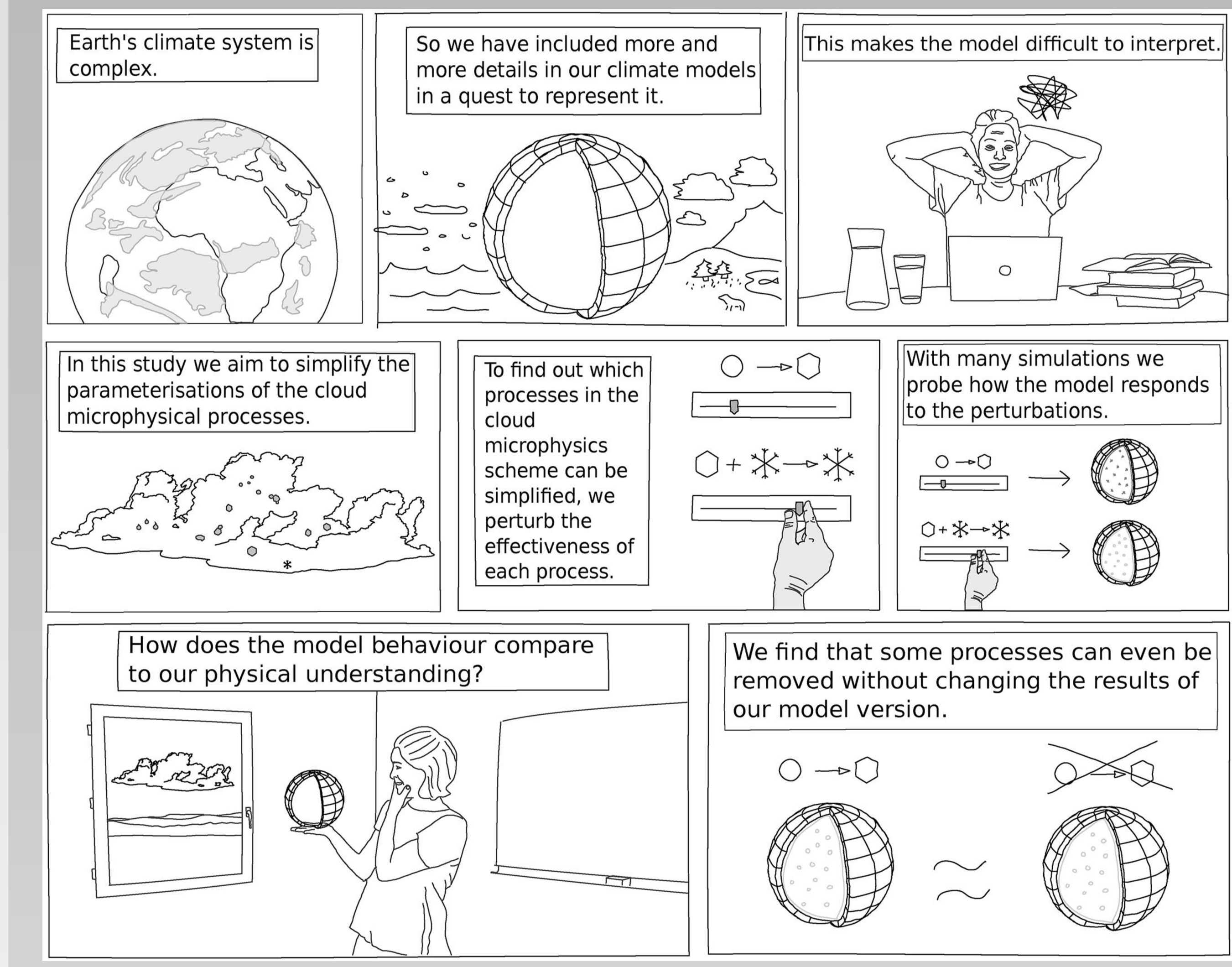


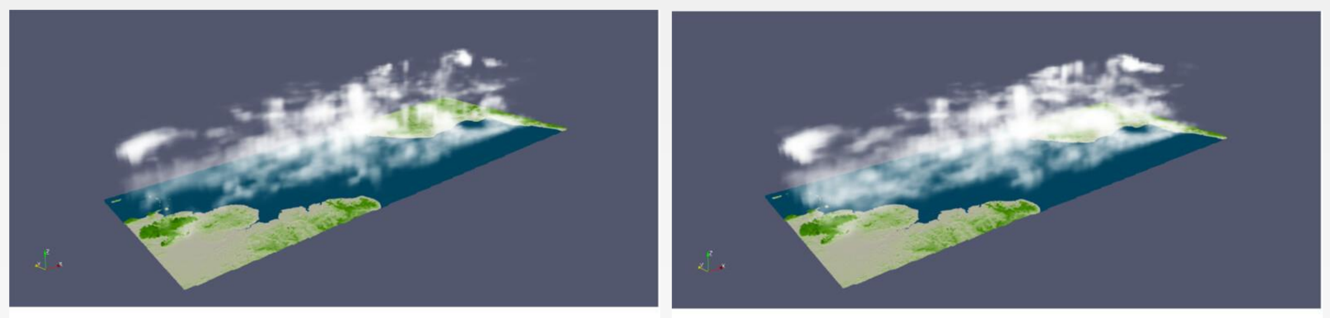
Figure 6. A comic outlining the motivation for and methodology surrounding statistical emulation of cloud microphysics in the ECHAM-HAM climate model (from Proske et al., 2023).

Lab Exercise: Explore the impact of perturbed parameter ensemble experiments on Earth's climate sensitivity using a Gregory et al. (2004) type regression and output from statistical emulations of the CESM2 model.

Module 6: Role of AI in Climate Modeling: Physical Parameterization

Learning Outcomes:

1. Explain how structural uncertainty differs from parametric uncertainty in climate models
2. Understand the causes of structural uncertainty and approaches to its quantification
3. Become familiar with examples of physical parameterizations being replaced by AI models in ESMs



(a) NN cloud cover (b) Ground Truth

Figure 7. Comparison of cloud cover from a neural network (NN) compared with ground truth data (from Grundner et al., 2022) .

Lab Exercise: Compare the performance of CMIP6 model precipitation globally, and over tropical regions with that of a model which incorporates AI-based cloud parameterization schemes.

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