HPC Accelerated Generative Deep Learning Approach towards Creating Digital Twins of Climate Models

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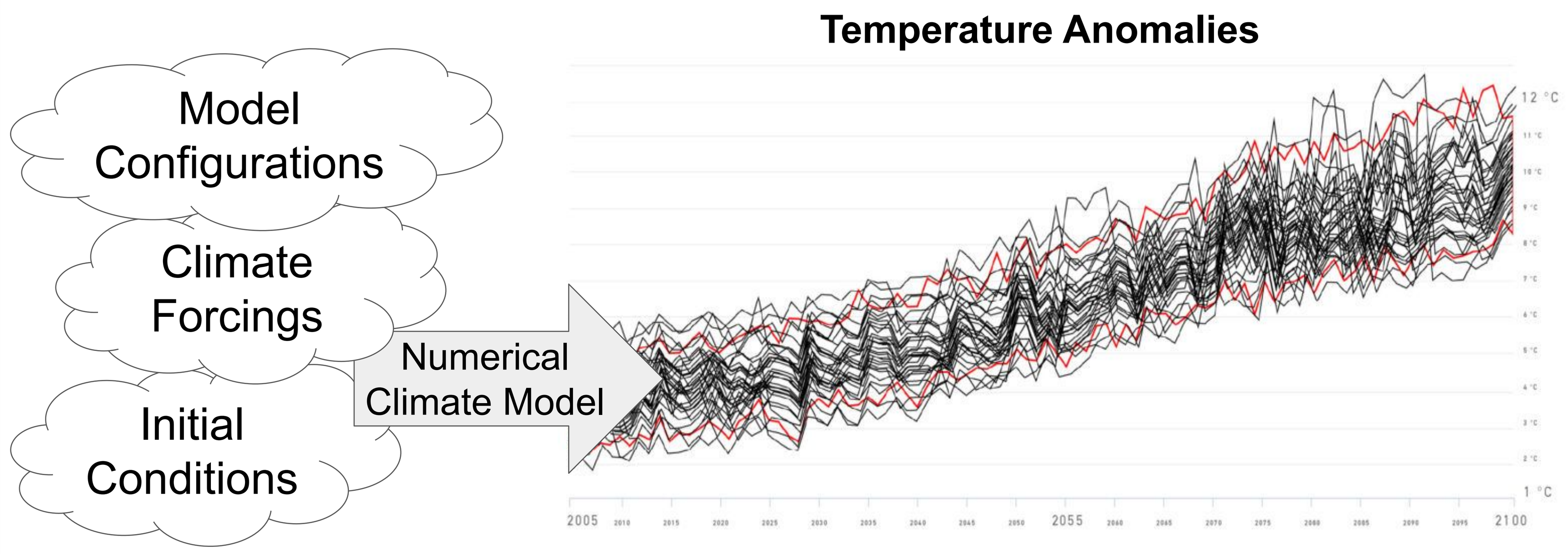
Introduction & Motivation

It is **IMPOSSIBLE** to perfectly simulate the real climate system. The solution for this are **MULTIPLE** climate model simulations that are used to provide a range of possible climate scenarios:



These are generated by running multiple simulations of climate models using different **initial conditions**, **forcings** and/or **model configurations**. The goal of generating ensembles is to capture the range of possible climate outcomes, given the uncertainties in both our **understanding** and the **potential impacts of human activities** on the climate system [1,2].

A problem that comes with this approach is the **SCALABILITY** of numerical climate models. Even though modern high performance systems provide great possibilities for climate modeling, the calculations remain hardware intensive and time consuming.

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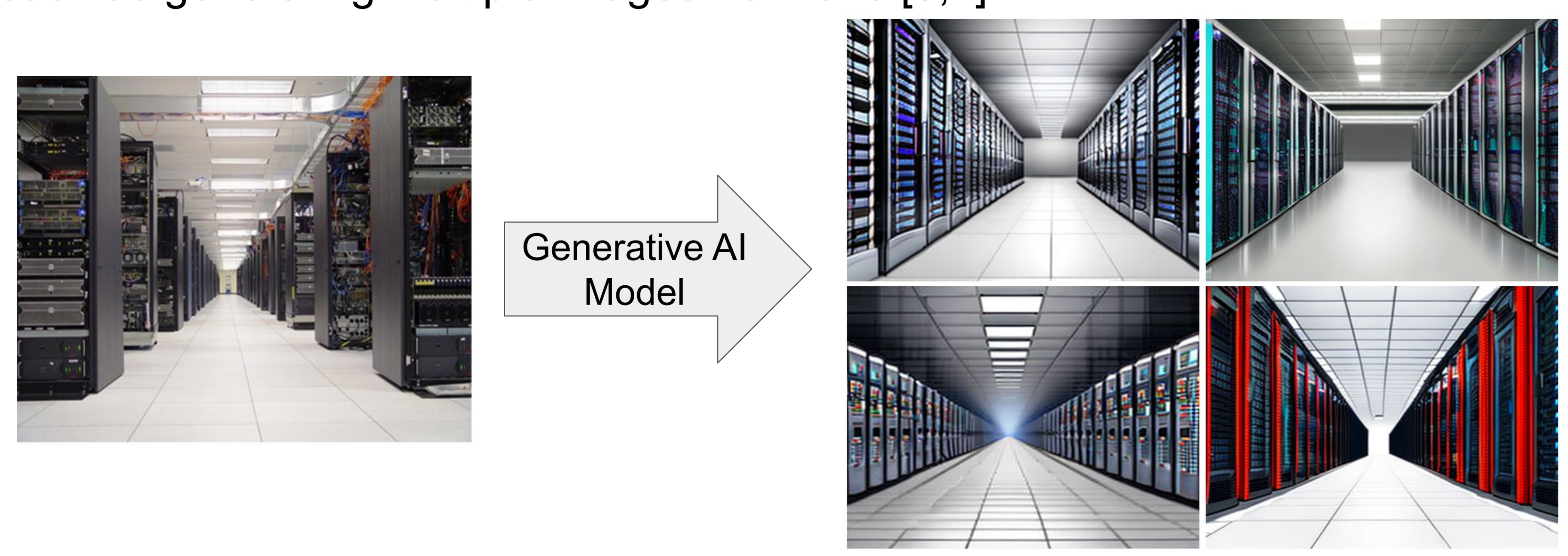
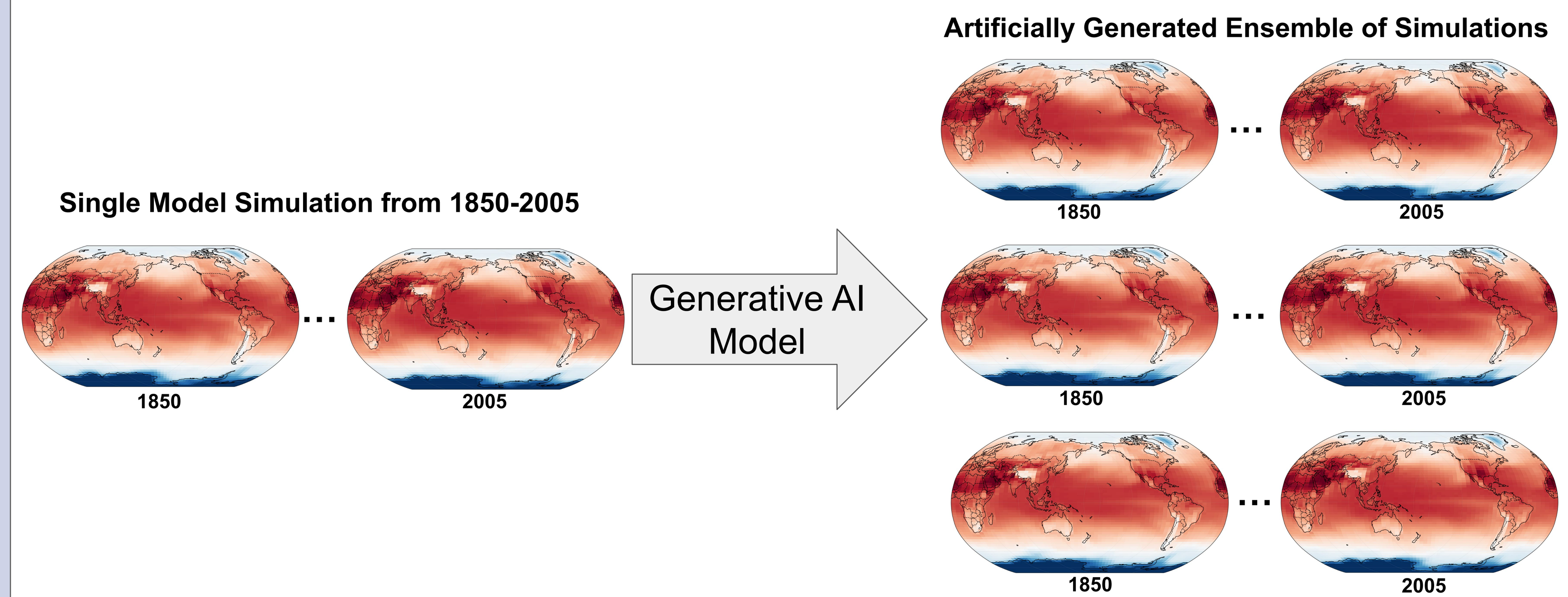
Methods

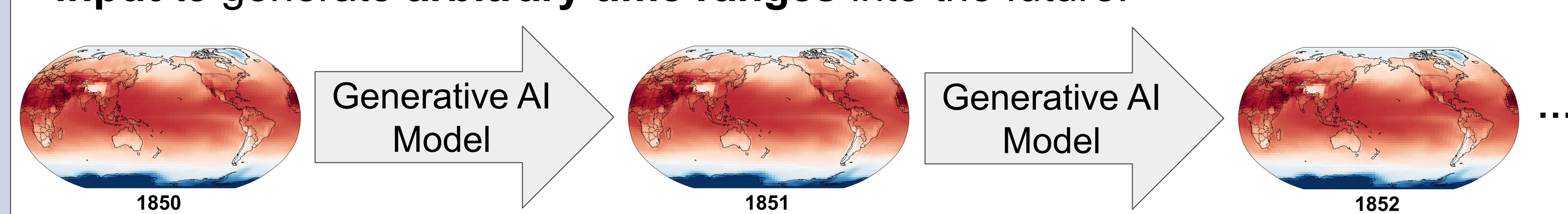
Generative Machine Learning approaches can be used for creative tasks, such as generating multiple images from one [3,4]:



From the same input, these models are able to produce similar outputs with slight variations. Sounds like the **PERFECT** model for creating ensembles of climate model simulations, right?
Instead of giving text prompts, we can provide **a single climate model run as an input** and let our model create an **ENSEMBLE** of similar model runs:



We further define our objective as a **generative spatio-temporal problem**. Therefore, we adopt an **iterative** prediction approach, that predicts a time step based on the previous. This enables the model to take its **own output as input** to generate **arbitrary time ranges** into the future:



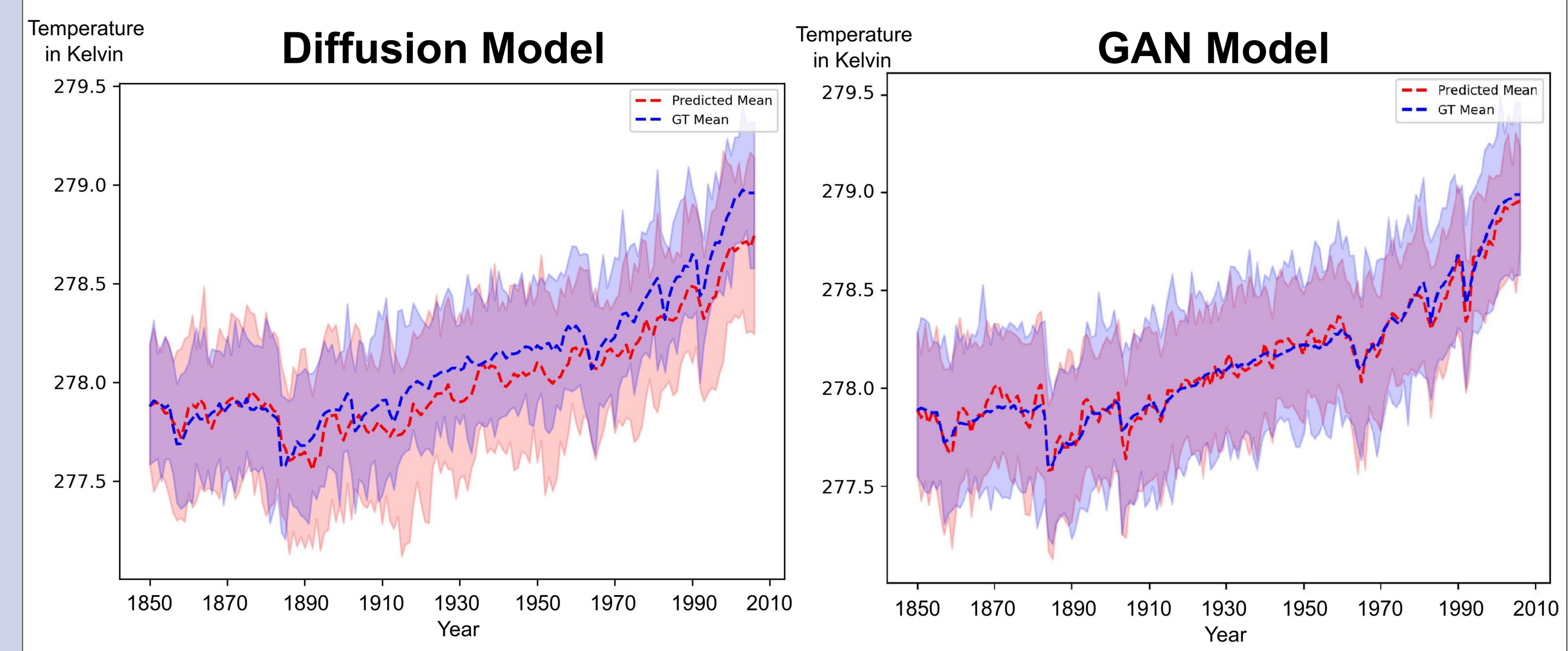
We implement two different generative models, a generative adversarial network (**GAN**) [5] and a **deep diffusion model** [6]. Both models implement similarly complex **U-Nets** with **4 encoding and 4 decoding layers**.

To even accelerate the performance of our models, we introduce **3** additional optimizations:

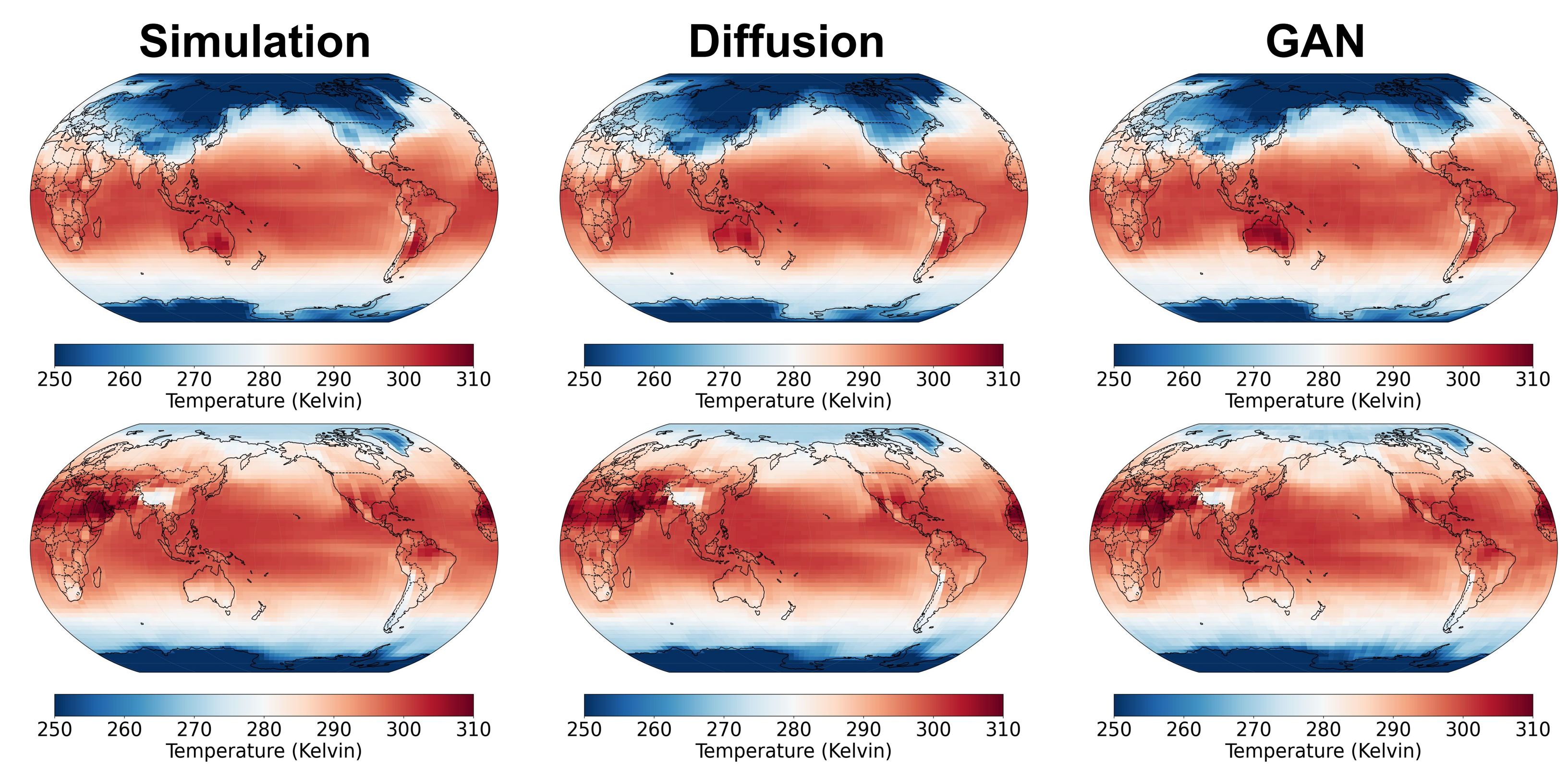
1. A **Super-Resolution** CNN, allowing us to generate low-resolution runs, which are then **downscaled** to higher resolutions
2. **Data Parallelization** to accelerate parallel computations of l**arge training batches**
3. **Model Parallelization** to enable training of **large** machine learning models to accommodate more **complex climate model runs**

Results

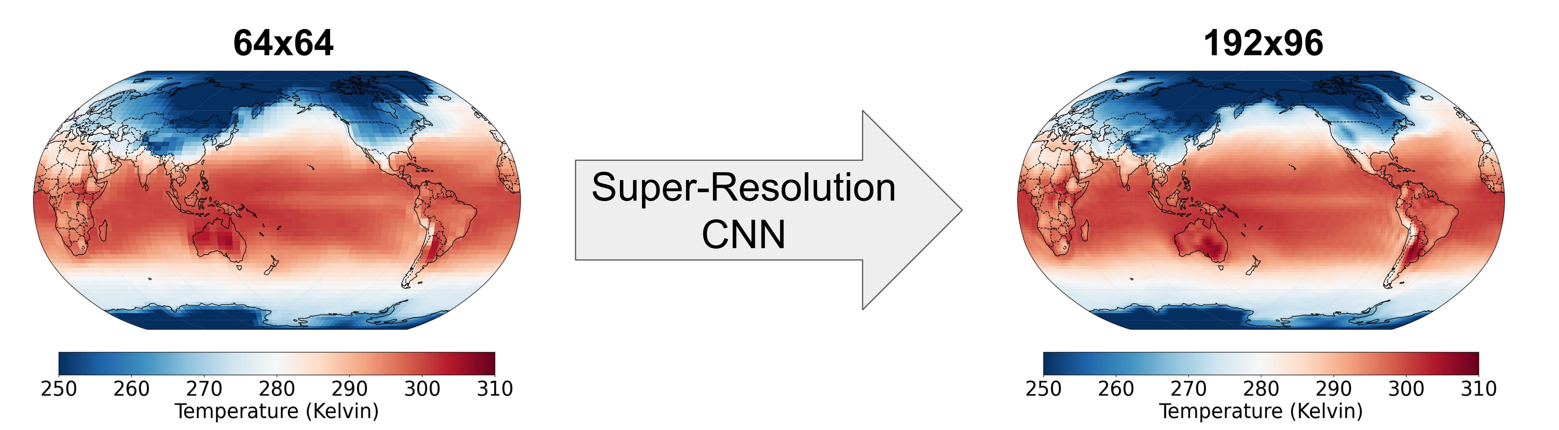
We trained the two generative models with **100 members** from the MPI-Grand Ensemble (**MPI-GE**). After training, we created 100 members with each model, ranging from **1850-2005** with a **monthly** temporal resolution. Then, we compared it to the remaining 100 members from the MPI-GE [2]. The plots show the the average temperature fields of the generated and original members.



Now, we take a look at a visual comparison between generated results and the simulation. The images below show January 2005 (top row) and August 2005 (bottom row).



The models were trained on temperature grids of **64x64**. Hence, the results shown so far are 64x64 grids. Now, we want to take this a step further and apply our **super-resolution CNN** in order to obtain the original resolution of the MPI-GE. Below is an example of the result of the diffusion model from January 2005.



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