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

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***Abstract*—In climate modeling, it is impossible to perfectly model the real world due to our incomplete understanding of the highly complex climate system. However, by running climate models multiple times with small variations in input parameters or model configurations, it is possible to explore the range of possible climate scenarios and estimate the uncertainties associated with these. This is especially important for investigating extreme climate events such as the response to volcanic eruptions where these ensembles are used for impact assessments and policy-making. However, generating ensembles of high-resolution climate runs using these models requires a significant amount of computational resources and time, which can be especially crucial in the context of risk assessments and decision makings. This dissertation addresses this challenge by applying machine learning techniques to generate high-resolution ensemble members of climate models. The procedure is divided in two steps. The first addresses the generation of low resolution ensemble runs using a generative adversarial network (GAN) in comparison with a deep diffusion model (DDM). The second step investigates downscaling of low resolution ensemble runs using convolutional neural network (CNN) approach. Finally, the study investigates the combination of the ensemble generation and super-resolution approaches to generate high-resolution ensemble runs. Since the overall goal is to provide time-efficient ways to generate high-resolution ensemble members, this study further implements different parallelization techniques to accelerate the performance to a maximum and minimize computation time. This study will allow further investigations into climate modeling that were previously not possible due to time and resource constraints.**

***Index Terms*—Machine Learning, Generative Deep Learning, Parallelization, Machine Learning in Climate, Digital Twin, Earth System Modeling**

I. INTRODUCTION

The Earth's climate is a complex system composed of several interconnected parts [1]. Because there are many uncertainties in how these components interact and respond to changes in greenhouse gas concentrations, aerosols, and other factors, climate models are unable to perfectly simulate the real climate system. Therefore, climate ensembles refer to a set of climate model simulations that are used to provide a range of possible outcomes. These are generated by running multiple simulations of climate models using different initial conditions and/or different model configurations. The goal of generating ensembles is to capture the range of potential climate outcomes, given the uncertainties in both our understanding of the climate system and the potential impacts of human activities on the climate. There are different methods for generating climate ensembles, with the most common approaches being a set of global climate models (GCMs) [2] or Earth System Models (ESMs) [1] to simulate potential climate scenarios. These models are based on a complex set of mathematical equations that describe the physical, chemical, and biological processes that govern the Earth's climate system. To generate an ensemble of simulations, small changes are made to the initial conditions or model parameters in each simulation. For example, varying the initial concentration of greenhouse gases, the amount of solar radiation, or the ocean temperature in each simulation. Alternatively, different versions of the same model, or different models altogether, can be used.

Even though multiple climate model runs can be scaled and parallelized given the right hardware, it remains a highly computationally expensive and time consuming task. This can limit the horizon of potential climate outcomes which is especially important for investigating extreme climate events like the climate response to volcanic eruptions. Machine learning approaches are known for their ability to create fast predictions and generalize well on different applications. Specifically, generative machine learning approaches have proven to achieve astonishing results in creative applications such as image or

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text generation [3]–[6]. In a way, the generation of multiple climate model runs can be seen as a creative task, where the exact correctness is of less importance and more the range of possible outcomes. Hence, we propose a state-of-the-art generative machine learning approach that addresses the task of simulating climate models in a creative manner.

II. Objective and Methods

We frame our objective as a generative spatio-temporal challenge. Beginning with n initial climate states, presented as global monthly mean data grids, our aim is to produce n sequences of monthly global grids. To enable the generation of arbitrarily lengthy sequences and to work around hardware constraints, we adopt an iterative approach. In this approach, the model forecasts the next state, which is then utilized as input to predict the subsequent state. However, a drawback of this approach is that errors introduced by the model accumulate with each iteration, potentially leading to significant deviations from accurate values. To address this issue, we introduce a supporting climate member that spans the entire time range to be forecasted and serves as a guiding reference for the model. We introduce two generative deep learning models to generate ensembles of climate simulations, a conditional deep diffusion model [7] and a conditional GAN [8]. In specific, this study investigates the Max Planck Institute Earth System Model (MPI-ESM) LR [9], from which the historical runs are used, consisting of a set of 200 calculated members, ranging from 1850-2005. This provides a large set of global climate fields from different variables. Independently from the generative models, a convolutional neural network (CNN) is trained for down-scaling on low-resolution data, using the HR version of the MPI-ESM. For further performance acceleration, two distributed deep learning techniques are implemented. In order to speed up the training process, data parallelization splits the input training batch across multiple GPU devices. For the forward pass during training, the model is replicated on each device. Then, each input split is separately forwarded on the devices. For the backward pass, the gradients from the replicated model of each device are summed. For model parallelization, the model is distributed onto different GPUs such that each GPU calculates the weight updates of at least one complete layer in the model. This allows to train large scale models, that exceed the graphical memory of a single GPU.

III. Results

The training data comprised 99 ensemble members from the MPI historical data set. One of these members was selected as the support member, while the others served as input for training. During training, a random point in time was selected and the models were given the task to predict the subsequent time step. For evaluation, the remaining 100 ensemble members were used. Here, the initial state of 99 members were used as the input to the model, while the remaining was selected as support member. It took 12 hours to train both models. The GAN produced member outputs much more quickly, generating them in just a few seconds, whereas the diffusion model required a span of two days. In Figure 1, a comparison is presented between the spread of the monthly mean temperature fields for all the generated members and the original ones. The diffusion model (top row) exhibits a slight low bias towards the end, while the GAN demonstrates a highly robust spread and ensemble mean. Both models are able to reconstruct the temperature decreases after volcanic eruptions in 1883, 1902, 1963, 1982 and 1991. However, when investigating climate events such as ENSO cycles, the diffusion model was able to produce much more realistic results. Furthermore, the diffusion model produced consistent results within the whole generated time range, whereas the results from the GAN model featured jumps inbetween predicted time steps of the same member.

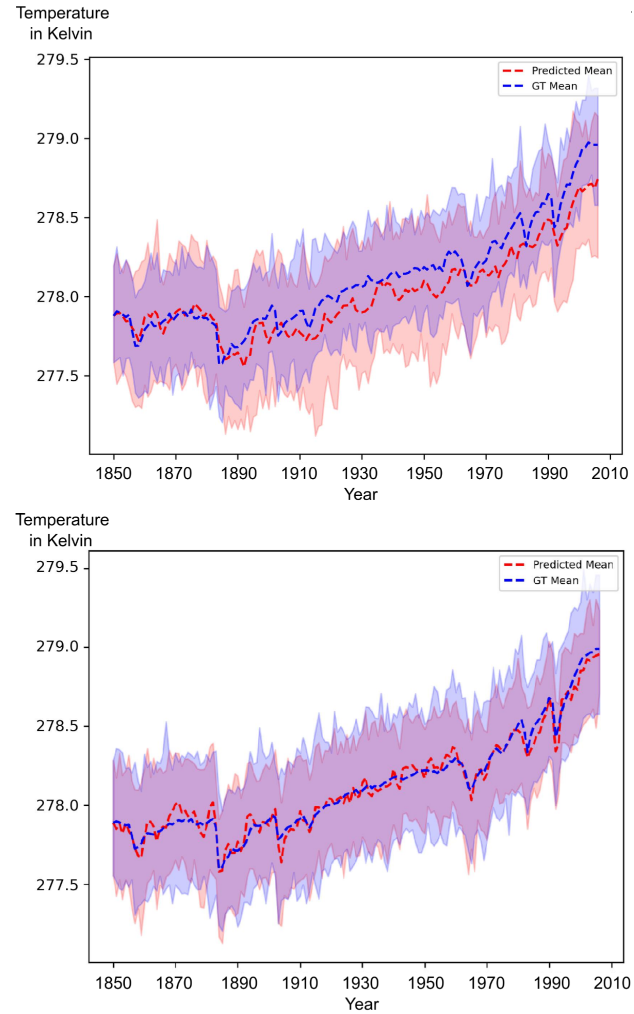

Fig. 1. Field mean spread and mean of the original ensembles and the results of the diffusion model (top row) and GAN (bottom row).

IV. Conclusion and Future Work

We developed two generative machine learning approaches that are able to create ensembles of climate simulations using a single simulation as input. So far, the models are able to create a realistic ensemble of low-resolution surface temperature fields over a long time period (150+ years) at a monthly temporal resolution. Furthermore, our super-resolution CNN is able to produce good results for the task of down-scaling low-resolution temperature fields to high-resolution temperature fields on a global scale. The performance of combining these two approaches still needs to be investigated. In future work, we want to look at not only temperature fields but also more dynamic climate variables such as precipitation, surface pressure and wind.

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