Climate Model Emulation Through Machine Learning

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Abstract

The sentiment for climate change and its disastrous consequences have evidently come to fruition in the last 15 years. A chain of events, mistakenly heavily politicized yet firmly backed by scientific evidence, climate change has become our present reality. Figuring out the trends, gaps, and opportunities in our earth's climate is essential to lead a safer socioeconomic future and climate modeling has become a forefront for this effort. However, utilizing Earth System Models has become too computationally expensive and become an inefficient process to simulate different climate indicators. In this paper we aim to replicate the ClimateBench v1.0 (Watson-Parris et al. 2022) paper, in efforts to see the robustness in climate model emulation using different machine learning concepts. Part of the CIMP6 datasets, our team will be looking specifically at the data from the NorESM2 Earth system simulation to build our models. We aim to predict annual mean global temperature, annual mean global precipitation, and the 90th percentile of daily precipitation every year. Our features will be climate change forcers like carbon dioxide, methane and aerosols and see its effects over certain periods of time. Additionally, we will discuss our model performance and use key accuracy metrics to understand and interpret our findings. Lastly, we want to compare our results with the ClimateBench paper and provide new scenarios/ideas to understand certain aspects of our socioeconomic future that have not been emulated or simulated.

Website: TBA
Code: https://github.com/lemoncastle/Capstone-Q1

1 Introduction

1.1 Overview

Based on the works of ClimateBench(Watson-Parris et al. 2022), we aim to develop and replicate the models from its findings. The idea is to understand how the ClimateBench Models perform through various model selections. Our focus will primarily be on implementing the Random Forest Regressor and other ML models utilized in the paper. The main goal is to see how the results when replicated can compare to other emulations. We want to see how close the accuracy and performability of the emulations will guarantee its reliability. This will give us the opportunity to utilize these simulations to understand other key climate indicators in certain parts of the world that have not been previously simulated. Deciphering climate change is evidently a requirement and experimenting with climate data through machine learning is necessary to bring global change.

1.2 Prior Works

A work that inspired the ClimateBench v1.0 is a paper formulated by (Rasp et al. 2020) titled WeatherBench. This paper is similar to ClimateBench as they are both benchmarks that allow direct comparisons between models that differ vastly. WeatherBench provides a benchmark for a 3 to 5 day range of weather forecasting. The dataset is from ERA5 reanalysis and is used due to being one of the best in forecasting atmospheric states and contains decades of data between 1979 to 2018. The data was regridded to lower resolutions to relax the GPU memory constraints. The baselines used in WeatherBench are CNN, Linear Regression, ECMWF IFS and an IFS with coarser horizontal resolutions. These are evaluated by using the year 2017 and 2018, with the metric to evaluate error being root-mean-square error. The IFS perform with the lowest RMSE, followed by direct CNN, linear regression, and iterative CNN performing the weakest. (Rasp et al. 2020) ClimateBench builds upon WeatherBench by using its main premise to apply it towards long-term effects of global warming, allowing different scenarios to be evaluated against a guideline.

ClimateBench's training data comes from NorESM2 which was developed by (Seland et al. 2020) is an Earth System Model that is built upon another model titled CESM2. ESMs primarily simulate conditions of NorESM2 differs from other models because it was developed using varied oceans and ocean biogeochemistry models. In addition, there were improvements in energy conversion between dry and moist,as well as using different modules for aerosol physics and chemistry that affect interactions with clouds and radiation. To elaborate, the atmosphere model changes include greenhouse gases such as CO2,CH4, N2O, emissions from aerosols and aerosol precursors and human caused emissions (Black Carbon, Sulfur Dioxide) being used for a vertical distribution. The ocean biogeochemistry upgrade consists of using an updated module compared to NorESM1 and the land model difference between previous modules is a new limitation of nitrogen-carbon (Seland et al. 2020) ClimateBench utilizes NorESM2 because the updates the model presents is more accurate making it a better basis for training data to understand long term effects of climate change.

1.3 Description of Data

The ClimateBench dataset is constructed from a curated selection of climate simulations run through the NorESM2 Earth System Model as part of the CMIP6 archive. It includes three types of experiments: historical runs that simulate the observed climate from 1850–2014, future emissions scenarios from ScenarioMIP (ssp126, ssp370, ssp585) that model low to high-emission pathways, and single forcing experiments from DAMIP (hist-GHG and hist-aer) that isolate the effects of greenhouse gases and aerosols. These are all used for training machine learning emulators, while the medium-emissions scenario ssp245 is held out entirely as the test set to evaluate generalization. A description of each above mentioned scenario is provided in the table below:

Protocol	**Experiment**	**Period**	**Notes**
ScenarioMIP (O'Neill et al. 2016)	ssp126	2015–2100	A high ambition scenario designed to produce significantly less than 2° warming by 2100.
ScenarioMIP (O'Neill et al. 2016)	ssp245	2015–2100	Designed to represent a medium forcing future scenario. This is the test scenario to be held back for evaluation.
ScenarioMIP (O'Neill et al. 2016)	ssp370	2015–2100	A medium-high forcing scenario with high emissions of near-term climate forcers (NTCF) such as methane and aerosol.
ScenarioMIP (O'Neill et al. 2016)	ssp585	2015–2100	Represents the high end of the range of future pathways and leads to a forcing of 8.5 Wm^{-2} in 2100.
CMIP6 (Eyring et al. 2016)	historical	1850–2014	A simulation using historical emissions of all forcing agents designed to recreate the historically observed climate.
DAMIP (Gillett et al. 2016)	hist-GHG	1850–2014	A historical simulation with varying concentrations for CO_2 and other long-lived greenhouse-gases (only)
DAMIP (Gillett et al. 2016)	hist-aer	1850–2014	A historical simulation only forced by changes in anthropogenic aerosol(only)

Our output variables consist of annual global maps of key climate variables such as temperature, diurnal temperature range, precipitation, and extreme precipitation which are aggregated to annual mean values and kept at their native spatial resolution (approximately 2°). Dinural temperature range is calculated as the annual mean of the difference in daily maximum and minimum surface air temperatures. Additionally, our input variables consist of carbon dioxide, methane, sulfur dioxide, and black carbon.

To Be continued...

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