Parameterizing Air-Sea Heat Flux Biases in Climate Models

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1 Abstract

Air-sea fluxes refer to the transfer of energy, momentum, and chemical compounds across the air-sea interface. These phenomena heavily influence short-term weather systems and long-term climate variability (Woods Hole Oceanographic Institution, n.d.). Properly calculating air-sea fluxes is thus key to modeling the climate system. In this paper, we will be focusing specifically on the heat flux. Currently, coarse (˜ 1°) climate models are limited in their predictive ability because they make biased predictions of heat fluxes. Busecke et al. (2024) has demonstrated that this bias is significant, as it has a magnitude equivalent to 10% of the true heat flux. Unfortunately, simply running a high-resolution (˜ $\frac{1}{10}^{\circ}$) model is not a viable solution, as these simulations often require too much computational power to run for meaningful periods in simulation time (U.S. Department of Agriculture, n.d.). This paper aims to develop a machine learning-based method to correct the heat flux bias in climate models. This will ensure more accurate climate predictions without significantly increasing computational cost.

2 Introduction

This paper focuses on an approaches to address this problem. The proposed method leverages the bulk formulae, equations that can output the air-sea flux at a given resolution from a specific set of inputs at that resolution. This method involves training a convolutional neural network (CNN) to predict heat flux bias directly from low-resolution heat flux and low-resolution bulk formulae inputs. The paper will discuss the background, methodology, results thus far, and future work.

3 Background

3.1 Bulk Formulae

Our first approach to predicting the heat flux bias was by training a CNN to predict this bias from the low-resolution heat flux and low-resolution bulk formulae inputs. The bulk formulae used in this paper is defined below.

$$Q_L = -L_v \rho C_E [q_s - q_z] U_B \tag{1}$$

$$Q_H = \rho C_H C_P [\theta_z - T_s] U_B \tag{2}$$

$$Q_{tot} = Q_L + Q_H, \tag{3}$$

where Q_L is the latent heat flux, Q_H is the sensible heat flux, Q_{tot} is the total heat flux, ρ is the density of air, U_B is the bulk scalar wind speed at the reference height, θ_z is the potential temperature at the reference height, q_z is the specific humidity at the reference height, T_s is the temperature at the air-sea interface, q_s is the specific humidity at the air-sea interface, L_v is the latent heat of vaporization, C_D is the drag coefficient, C_E is the evaporation coefficient, and C_H is the sensible heat coefficient (Brodeau, n.d.). The last three values are specifically estimated using the European Centre for Medium-Range Weather Forecasts (ECMWF) Integrated Forecasting System (IFS) version CY40R1 (European Centre for Medium-Range Weather Forecasts, n.d.).

It is important to note that some of the variables above are related. Thus, it is not necessary to have data for all aforementioned variables in order to calculate an accurate heat flux. A minimum set of independent inputs was taken to be the input set for the bulk formulae calculation in AeroBulk, a Fortran-based library that calculates air-sea fluxes according to the equations above. AeroBulk takes inputs of temperature and specific humidity at a reference height, sea-level pressure, sea-surface temperature, and relative velocity at the air-sea interface (Brodeau, n.d.). We assume a fairly flat ocean, so sea-level pressure becomes constant, and is thus discarded from the above set.

3.2 Multi-scale Processes and Modeling in Climate Systems

Before discussing the methodology of this project, it is important to understand some key concepts about multi-scale climate modeling. Most processes in the Earth system occur across a continuum of scales, and these scales interact with each other. This holds true for heat fluxes at the air-sea interface. In order to be accurate, climate models must capture the behavior at and interaction between each of these scales. In practice, this is quite challenging: a model at a certain resolution can only capture behavior at its resolution scale and above. The model will not account for behavior at scales smaller than its resolution. As a result, the model is inherently biased because it does not capture small-scale, or "sub-grid" scale (SGS), processes (Christensen & Zanna, 2022). This sub-grid scale forcing is the heat flux bias mentioned in the introduction. Developing a method to account for the SGS heat flux will allow low-resolution climate models to reduce their bias (Christensen & Zanna, 2022).

4 Methodology

4.1 Datasets

This project uses data from the National Oceanic and Atmospheric Administration's Geophysical Fluid Dynamics Laboratory (NOAA GFDL). The specific climate model is the GFDL Coupled Model version 2.6 (GFDL CM2.6). This model is a coupled atmosphere-ocean planetary-scale general-circulation model (NOAA Geophysical Fluid Dynamics Laboratory, n.d.). The dataset contains nineteen years of daily-averaged data at a high resolution. Our low-resolution data could have been taken from a low-resolution run of the same model, but we instead chose to simply filter down the high-resolution data using the package GCM-Filters, which filtered out any phenomena below an inputted spatial scale (GCM-Filters Documentation, n.d.). Lastly, the low-resolution heat flux was calculated by inputting the low-resolution data filtered through GCM-filters into the aforementioned AeroBulk code. For the CNN training, which is discussed more in depth later in the paper, about 75% of data was used for training, and the rest for testing.

4.2 Convolution Neural Network Architecture and Training

A convolutional neural network is used to find the SGS forcing, or heat flux bias. The choice to use a CNN was primarily influenced by the fact that there are spatial patterns in maps of the variables we have discussed in this paper. CNNs are particularly adept at learning such patterns (MathWorks, n.d.).

For inputs, the CNN took low-resolution fields of relative ocean-atmosphere velocity, sea-surface temperature, specific humidity at a reference height of 2 meters above the air-sea interface, and atmospheric temperature at the same reference height. This is the minimum set of independent variables for a bulk formula calculation that we discussed in the Bulk Formulae section above. The CNN also takes the low-resolution heat flux as an input. The output of the CNN is the heat flux bias. The CNN has an architecture that involves three convolutional layers, three pooling layers, and two fully connected layers. The architecture is detailed in the diagram below.

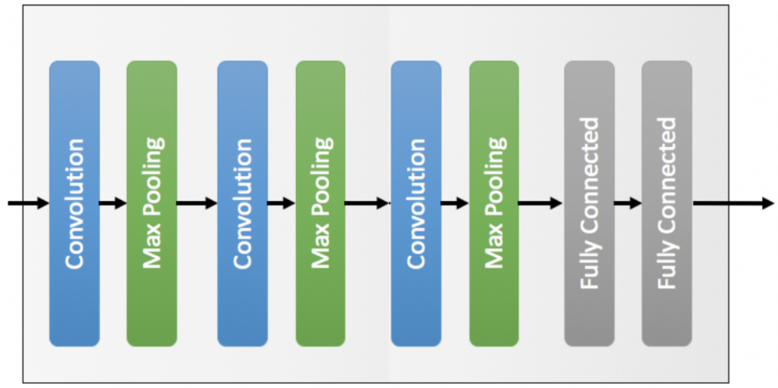

Figure 1: CNN architecture

Additionally, several hyperparameter combinations were examined via grid testing. The optimizer options were stochastic gradient descent (SGD) and Adam. The learning rate choices were 0.1, 0.001, and 0.0001. And, the number of epochs options were 20, 50, 100, 500, and 1000. The loss function, chosen to be mean square error, was kept the same for all trials. The combination of hyperparameters that produced the best output was a learning rate of 0.001, mean squared error loss function, the Adam optimizer, and training over 1000 epochs. The training loss curve for this case is included below.

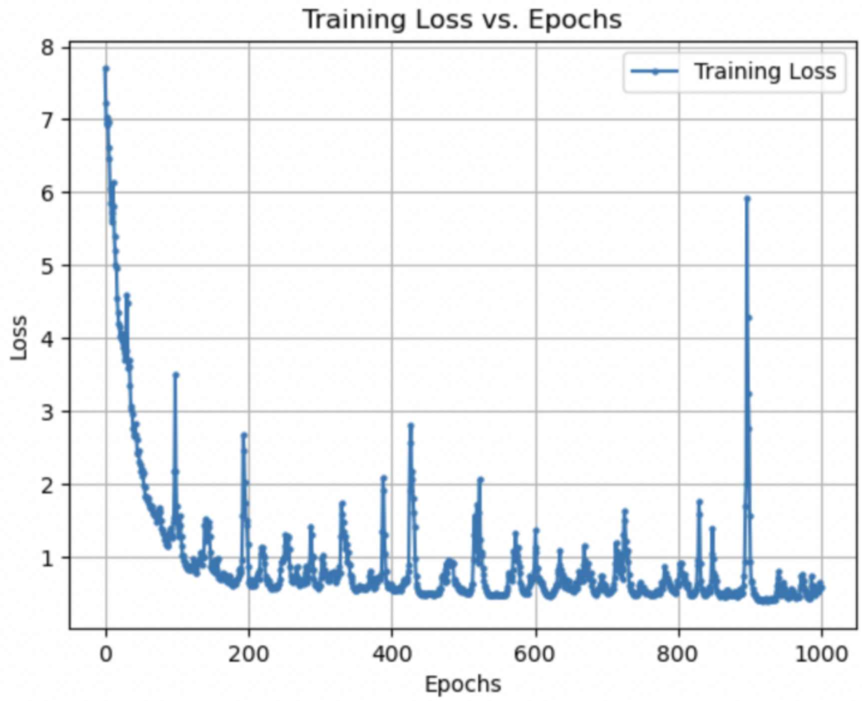

Figure 2: Training loss

5 Results

As seen by the CNN in Figure 2, the losses decreased to below 1 by the end of training. This indicated that the CNN learned how to predict the heat flux bias very well, since the target images had values between -10 and 5. However, when testing the CNN, the root mean square error (RMSE) between predictions and targets ranged from two to five, which is 13.33% to 33.33% of the magnitude of the targets (see Figure 3). This large error indicates the CNN did not learn well. This case of having low training losses but fairly inaccurate testing predictions indicates that overfitting may have happened. This is when CNN learns the patterns in the training data too precisely, and is thus unable to generalize to data outside the training set.

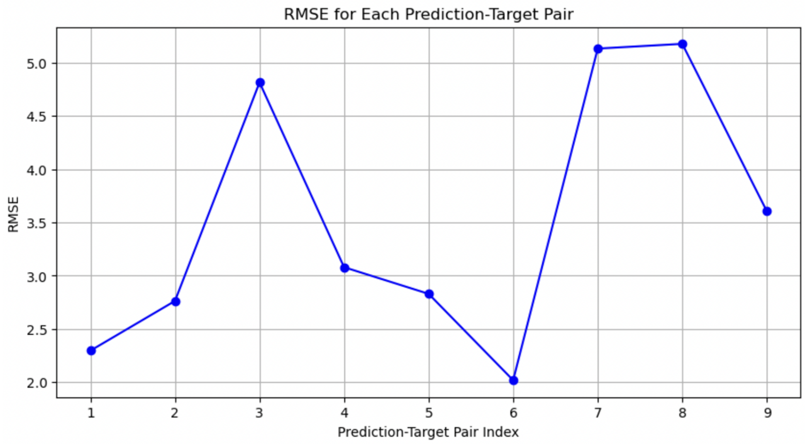

Figure 3: Root mean square error of testing data

Another possibility is that the CNN architecture and training process need to be altered. In Figure 4, we see that the predictions from the CNN are able to pick up on local minima/maxima, some general spatial patterns, and the correct range for the data. This indicates that it may be possible to find heat flux bias from the current inputs to the CNN, and that alterations to the CNN could help accomplish this goal. These alterations can include adding a dropout rate, weight decay, or adaptive learning rate.

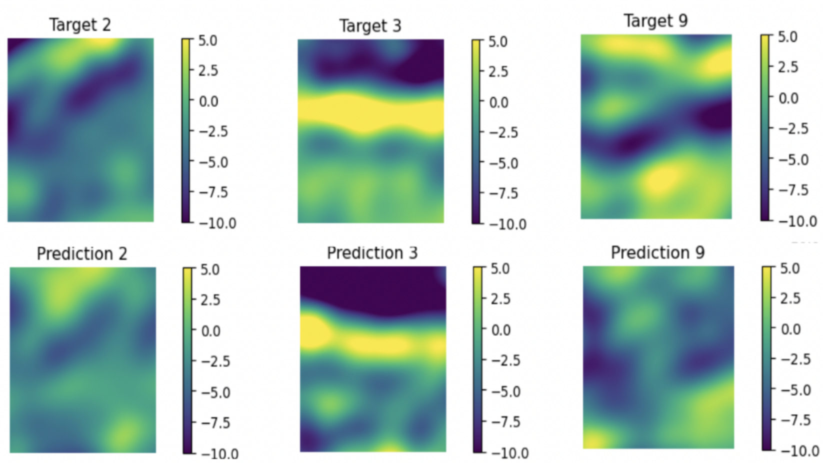

Figure 4: Select target-prediction pairs from CNN

6 Future Work

The approach in this paper to find heat flux bias is simply one of many possible approaches, and is my first attempt to solve this problem. For this attempt, it is important to optimize the CNN architecture and training to determine if there is a threshhold for the accuracy of this approach. If the desired accuracy is unable to reached, other methods may offer better results. One possibility is super-resolving low-resolution heat flux data to find high-resolution heat flux, then subtracting the two to find the heat flux bias. Another possibility is using different machine learning methods to solve this problem, such as artificial neural networks or equation discovery.

7 Bibliography

Brodeau, L. (n.d.). Aerobulk. GitHub. Retrieved December 19, 2024, from https://github.com/brodeau/aerobulk?tab=readme-ov-file

Busecke, J., et al. (2024). Missing sub-grid air-sea flux in climate models. ArXiv. https://doi.org/10.31223/X5WQ47

Christensen, H., & Zanna, L. (2022). Parameterization in weather and climate models. Oxford University Press.

European Centre for Medium-Range Weather Forecasts. (n.d.). IFS documentation. Retrieved December 19, 2024, from https://www.ecmwf.int/en/publications/ifs-documentation

GCM-Filters Documentation. (n.d.). GCM-filters. Retrieved December 19, 2024, from https://gcm-filters.readthedocs.io/en/latest/

MathWorks. (n.d.). Introduction to deep learning: What are convolutional neural networks? Retrieved December 19, 2024, from https://www.mathworks.com/videos/introduction-to-deep-learning-what-are-convolutional-neural-networks–1489512765771.html

NOAA Geophysical Fluid Dynamics Laboratory. (n.d.). High-resolution climate modeling. Retrieved December 19, 2024, from https://www.gfdl.noaa.gov/high-resolution-climate-modeling/

U.S. Department of Agriculture. (n.d.). Basics of global climate models. Northwest Climate Hub. Retrieved December 19, 2024, from https://www.climatehubs.usda.gov/hubs/northwest/topic/basics-global-climate-models

Woods Hole Oceanographic Institution. (n.d.). Center for Advanced Scientific Inquiry and Marine Autonomous Systems. Woods Hole Oceanographic Institution. Retrieved on December 18, 2024, from https://www2.whoi.edu/site/casimas/