Parameterizing the Subgrid-Scale Heat Flux at the Air-Sea Interface

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1 Introduction

Air-sea fluxes, including heat flux, are crucial in modeling climate systems. Coarse climate models (˜1°) exhibit significant heat flux biases, which can be as large as 10% of the true heat flux (Busecke et al., 2024). High-resolution models (˜1/10°) are computationally expensive, making them impractical for long-term simulations (U.S. Department of Agriculture, n.d.). This paper proposes a machine learning method using a convolutional neural network (CNN) to correct heat flux bias in low-resolution models, improving climate predictions without increasing computational cost.

2 Methodology

This method uses a CNN for super-resolution and bulk formulae, closed-form equations to calculate air-sea fluxes (Brodeau, n.d.). The method has four steps. The first is to calculate the low-resolution heat flux from low-resolution inputs by using the bulk formulae equations. The second is to super-resolve the input variables for the bulk formulae heat flux calculation. In other words, use a CNN turn low-resolution maps of variables to high-resolution maps. The third step is to calculate the high-resolution heat flux from the high-resolution bulk formulae inputs. The fourth step is the subtract the high-resolution heat flux and low-resolution heat flux to find the heat flux bias, also known as the subgrid-scale heat flux.

Currently, the project is on step two. The inputs to the bulk formulae equations are relative velocity, temperature at a reference height of 2 meters, specific humidity at a reference height of 2 meters, sea-surface temperature, and sea level pressure. Thus far, super-resolution for the relative velocity in the zonal and meridional direction and specific humidity at a reference height of 2 meters has been somewhat successful. Unfortunately, super-resolution efforts have yet to be successful for the rest of the variables.

3 Results

The results for super-resolution for the relative velocity in the zonal and meridional direction and specific humidity at a reference height of 2 meters are defined as somewhat successful because the predictions are able to pick up on local maxima/minima, major spatial features, and the correct range from the targets. Sample images that demonstrate this are included in Figure 1.

The training and validation loss curves for these variables are included in Figure 2. Note that the validation loss curves tend to mimic the pattern of the training loss curves. This

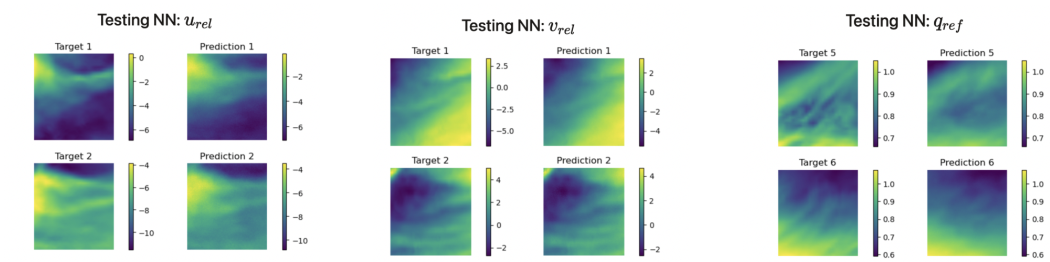

Figure 1: CNN Prediction and target comparisons of relative zonal velocity, relative meridional velocity, and specific humidity at 2m (left to right)

indicates the CNN is learning well, because it is performing similarly on the training data it has seen and validation data it has not seen before. Note that due to limited space, the super-resolution results and training loss curves for temperature at a reference height of 2 meters, sea-surface temperature, and sea level pressure will not be included.

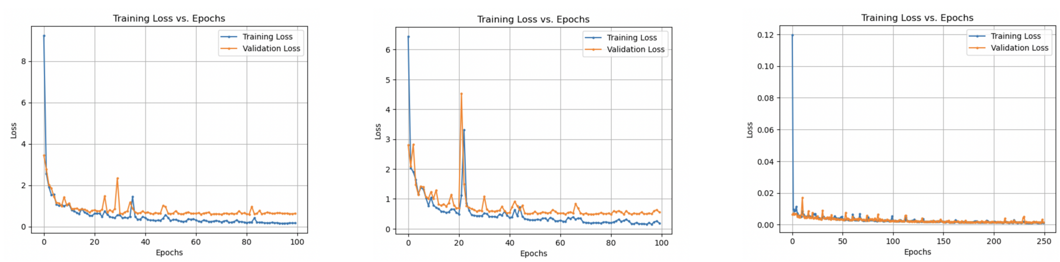

Figure 2: Training and validation losses for relative zonal velocity, relative meridional velocity, and specific humidity at 2m (left to right)

4 Future Work

In terms of near-term work, at the top of the list is improving CNN performance for sea-surface temperature, sea level pressure, and temperature at a reference height of 2m. Doing so will require hyperparameter tuning of the CNN and optimization of the CNN architecture. Steps three and four of the project should follow quite easily once this is accomplished.

5 References

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

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