AIBEDO MILESTONE 4 REPORT

Prepared by Kalai Ramea (PI)

Team (PARC): Sookyung Kim, Peetak Mitra, Subhashis Hazarika

Team (University of Victoria): Hansi Singh, Dipti Hingmire, Haruki Hirasawa

Team (University of Washington): Phil Rasch

Overview of Milestone 4

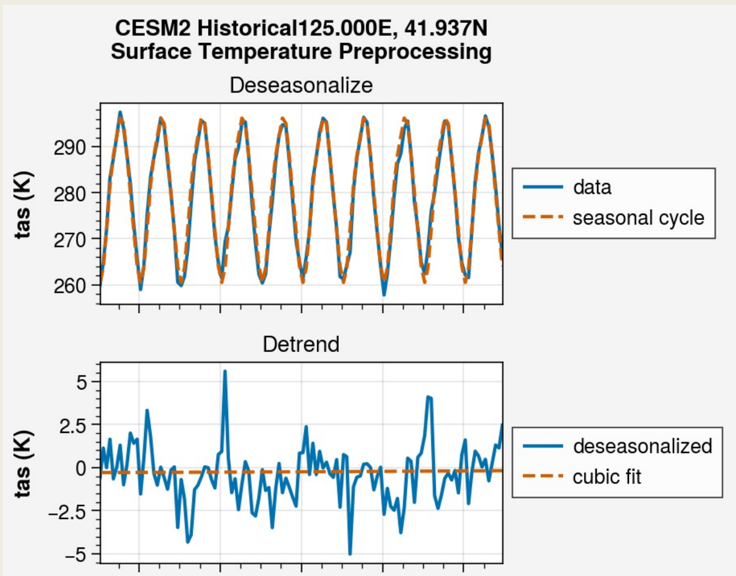
- *Objective:* Report preliminary analysis on new mathematical insights from the model and data analysis
- Updates Overview:
  - Additional observational reanalysis datasets for 'benchmarking'
  - Initial results from the spatial model (Spherical-U-Net)
  - Region-wise analysis
  - Details on modeling lag response and initial results of spatiotemporal model (Temporal Spherical U-Net)
  - Details of how physics constraints are being included in the model
  - Conferences/Publications
  - Ongoing work

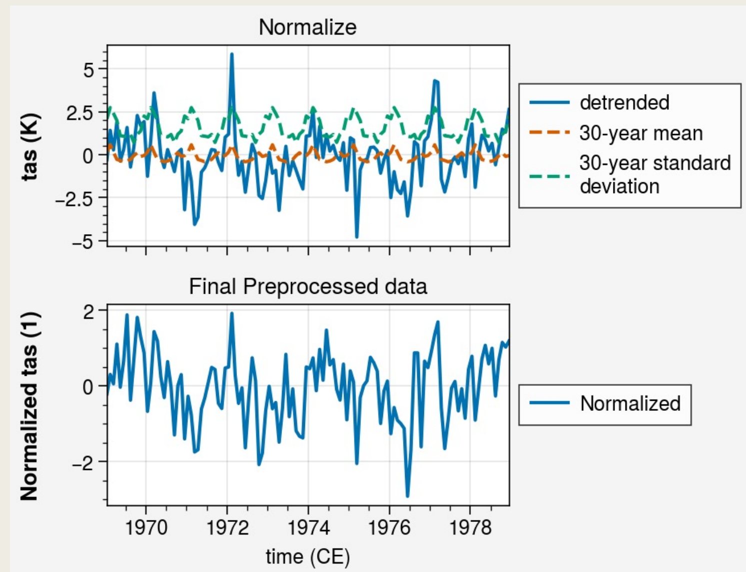
Observational Reanalysis Data

- In milestone 3 we mentioned a list of preprocessed CMIP6 model ensembles
- We will be testing these ensembles against observational reanalysis data to perform data quality checks
- To that end, we preprocessed the following observational reanalysis data:
  - *MERRA2 (0.5 degree resolution)*
  - *ERA-5 (0.25 degree resolution)*
- We will be sub-selecting the model ensembles that produce results that are close to observational data

Preprocessing Steps

- Our preprocessing steps include: Deseasonalizing, Detrending, and Normalizing.
- We generated plots to illustrate these steps more clearly



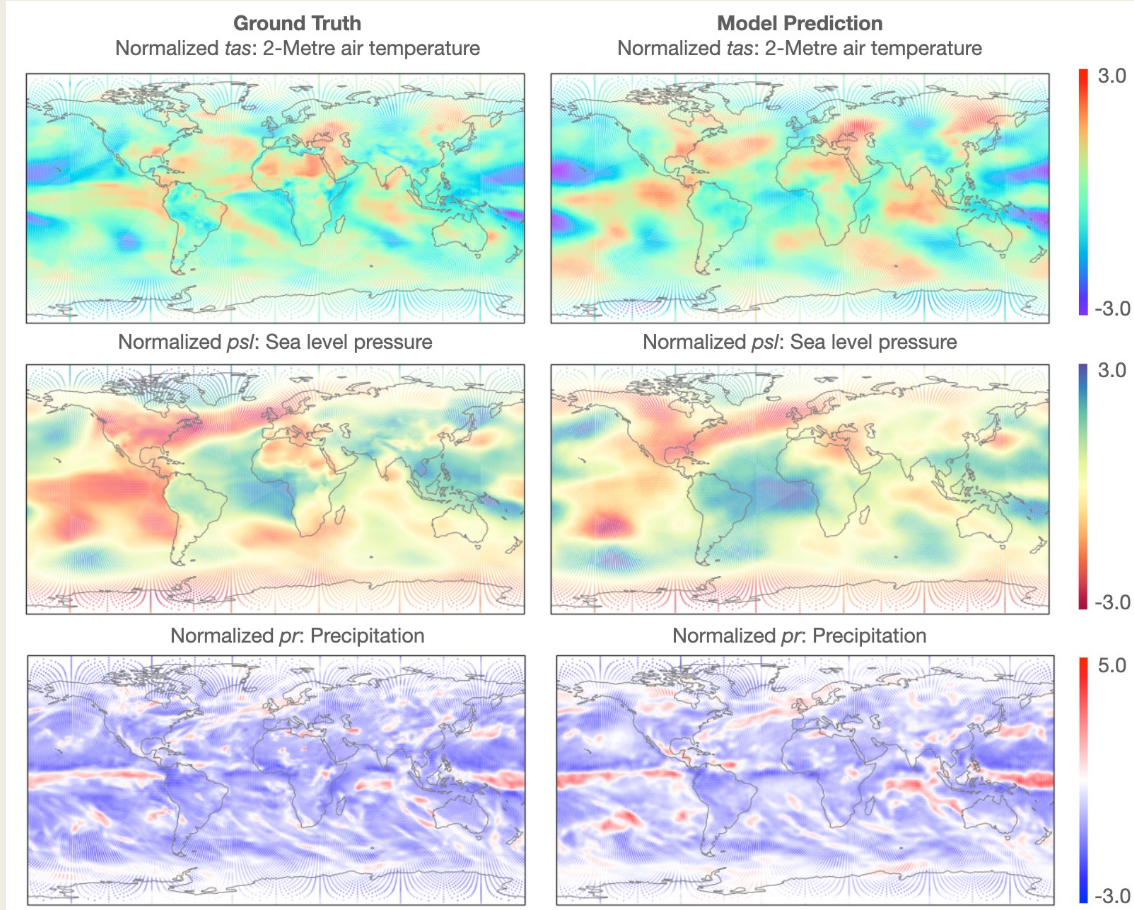


Preliminary Results

6-layered Spherical U-net trained on CESM2 model ensemble

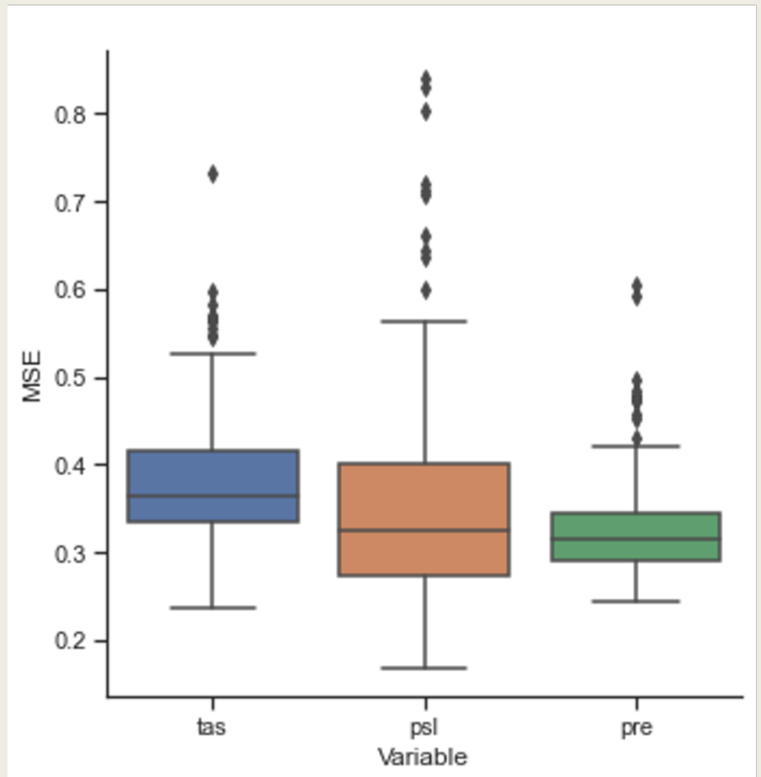
Icosahedral sampling with level=6 (resolution: 110 km, 40962 vertices)

Model	Overall MSE
Combined model	0.3523
tas-only	0.3604
psl-only	0.4229
pr-only	0.2855



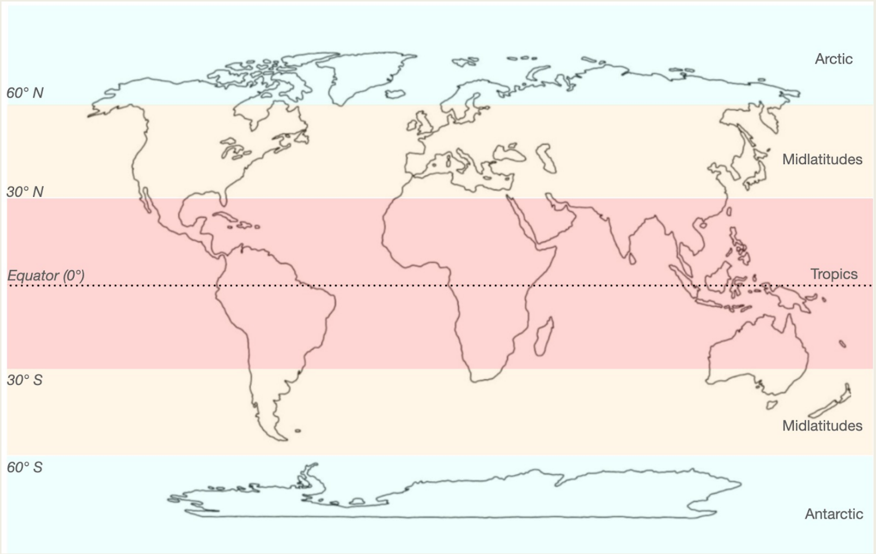
Preliminary Results

- The plot illustrates the distribution of MSE over all the points in the globe
- While all the variables have tail end (a series of outliers) distribution, Sea level pressure (*psl*) seems to have more variability
- Overall, the prediction of *tas* is poorer than the rest of the variables

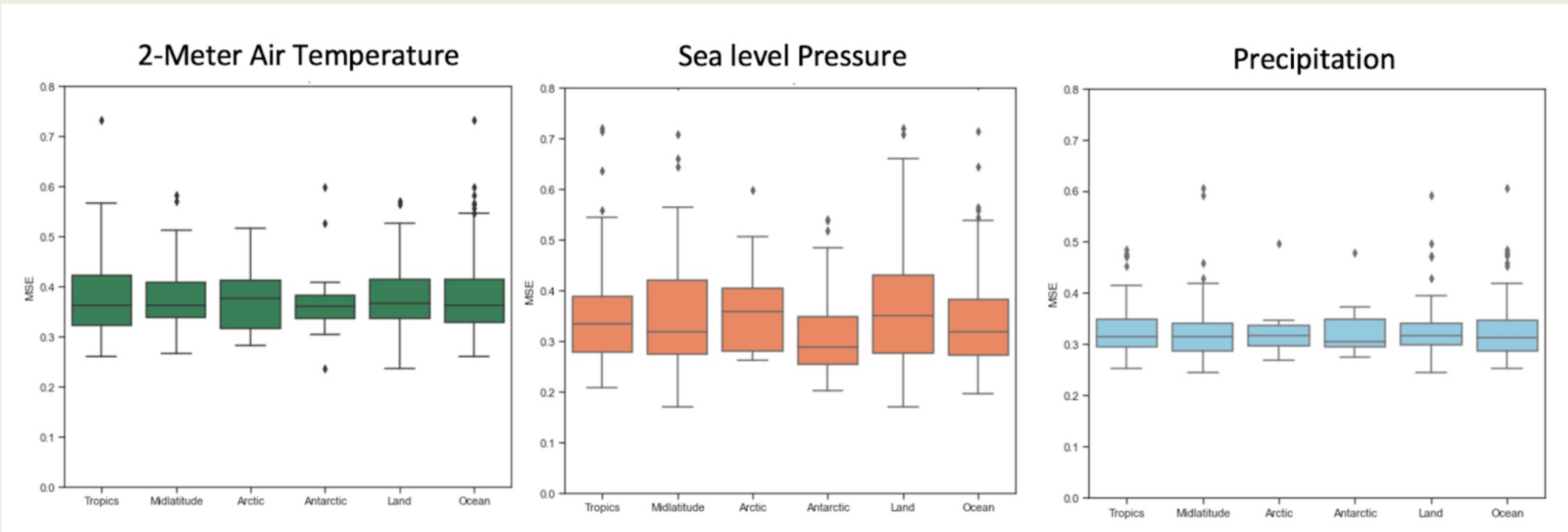


Region-wise Metrics

Helps investigate where exactly the model is underperforming → physics constraints can be incorporated accordingly.



Preliminary Results (region-wise errors)



- The plots show the distribution of MSE for each zonal region (Tropics, Midlatitudes, Arctic, Antarctic), as well as for land and oceanic regions.
- These region-wise distribution is helpful once we start incorporating physics constraints (specifically the ones dedicated for regions) to understand model performance.

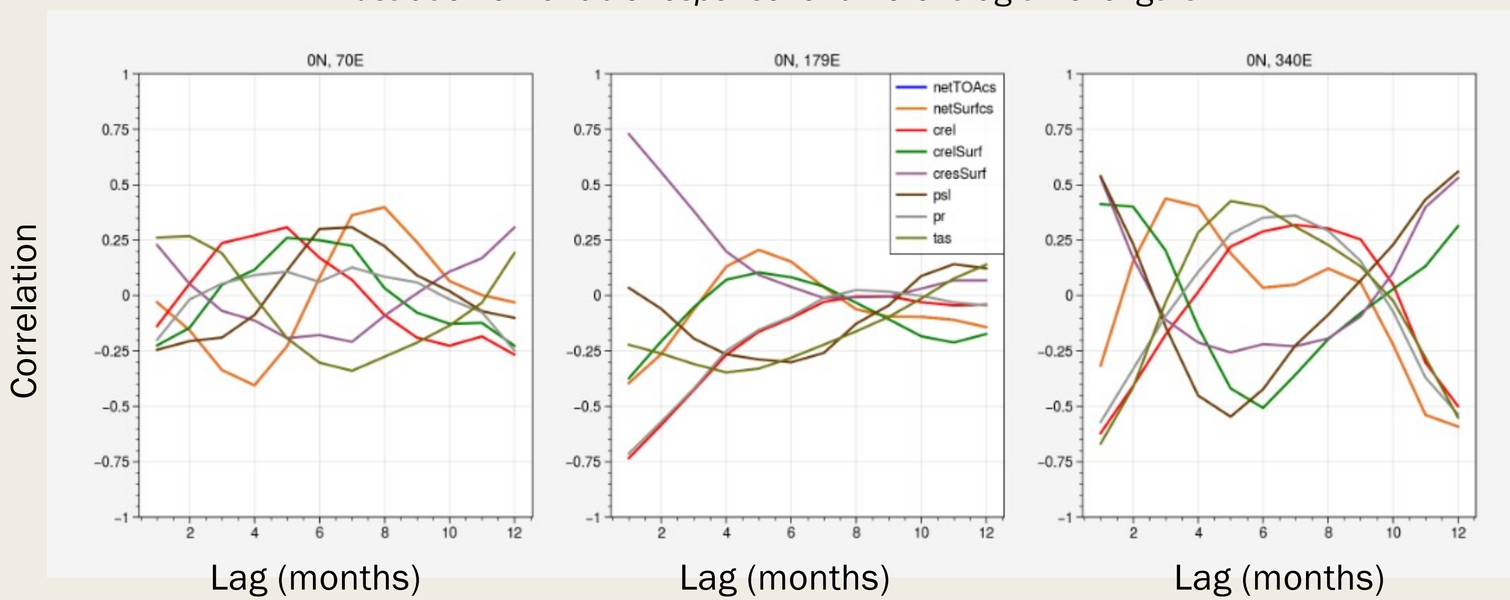
Lag response modeling

- A response in a climate system is rarely spontaneous as it consists of complex convections and teleconnections
- In our application, we are testing the possible response of global circulation and regional climate outcomes arising from changes in cloud properties
- To understand the response length, we ran simple lag correlations between input variables and output variables for different lag time lengths.

Lag response modeling

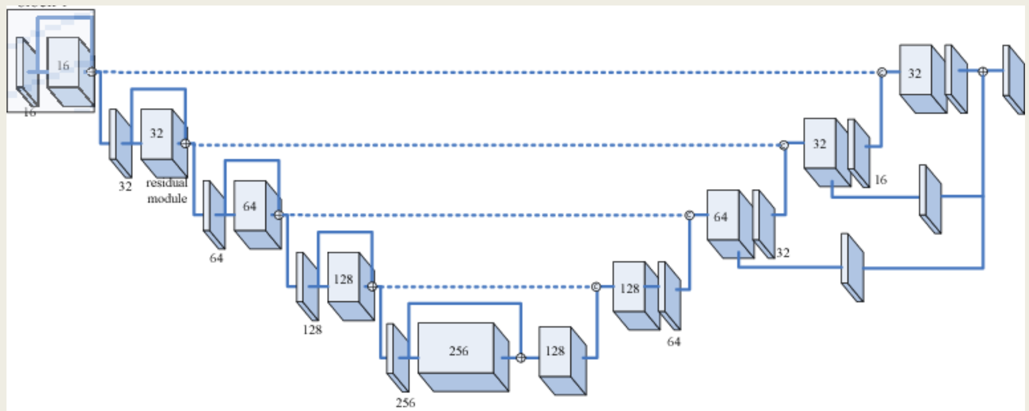
- While the response at different locations may differ, we observed from this simple test that we start to see the highest correlation around 3-6 months timeframe.

Illustration of variable response for different lag time lengths



Temporal Spherical U-Net

- We are augmenting the Spherical U-Net architecture to incorporate the temporal dimension (concatenated along the variable vector axis) as shown in the figure below:



- Our initial investigation for testing the lag response suggests that a lag response of **3 months** works best (mainly resulting from the prediction of surface air temperature). Other output variables such as precipitation and sea level pressure work best to predict at simultaneous (sub-monthly) scales, which could be a result of the choice of input variables that do not account non-cloud properties.

“Denormalizing” data for Physics Constraints

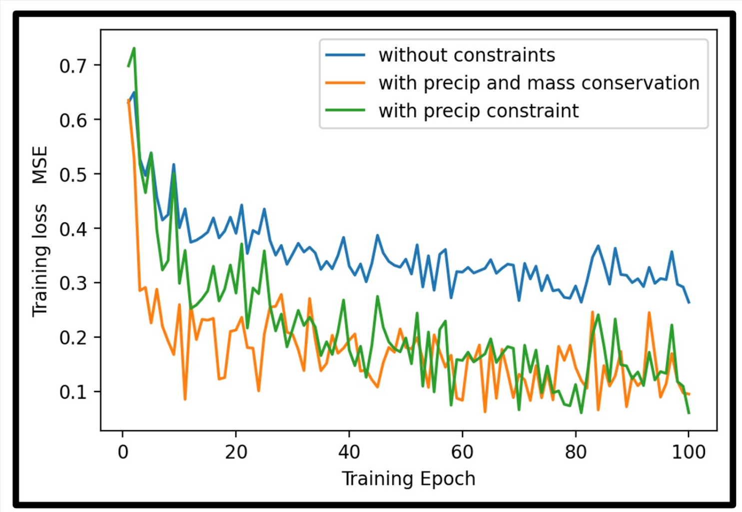
- As the AiBEDO model deals with normalized variables while the constraint require the variables in their original units (and with physically realistic spatial variations), we must “denormalize” the model output to apply the constraints.
- The training data fed into the model is detrended and deseasonalized, thus filtering out all low frequency information. However, the climatology and variability change as anthropogenic climate change intensifies.
- Furthermore, the data is derived from a range of models with differing mean climatology and interannual variability patterns.
- Thus, passing through the climatology and variability associated with the model and time period of training time step provides additional information about model uncertainty and GHG forced climate change that is undesirable when training in a Fluctuation Dissipation framework.

“Denormalizing” data for Physics Constraints (contd.)

- We select a single reference climatology and variability with which to denormalize the model output for calculating constraints. This reference can thus be thought to represent the climatology and variability of the AiBEDO model.
- We select the **CMIP6 multi-ESM ensemble average climatology and variability** for the denormalization (though we might equally consider using reanalysis data).
- The average variability is computed as the square root of the average of the interannual variances across the ESMs.
- Note that we must still deal with a seasonal cycle in the climatology. A simple approach is to use a single month or season as the basis for the denormalization. More sophisticated methods of incorporating seasonal information is part of ongoing work.

Preliminary results after adding physics constraints

- We started with incorporating the simplest of physics constraints:
  - *Non-negative precipitation (i.e. precipitation values should be >= 0)*
  - *Mass conservation*
- Our initial results show drastic improvement in accuracy and speed of convergence after the physics constraints are added.



Conferences/Publications

- We presented our work as a poster at Climate Informatics, 2022
- Kalai Ramea will be speaking at re:MARS about AIBEDO (June 2022)
- Haruki Hirasawa will be presenting AIBEDO at Gordon Research Conference (June--July 2022)

Ongoing work and next steps

- We are continuing to incorporate denormalized physics constraints
- We will perform investigative runs of model ensemble members against observational reanalysis data. The model ensembles that resemble the reanalysis data the most will be sub-selected for model training
- We are investigating how we can utilize the input variables for designing Marine Cloud Brightening (MCB) experiments—possibilities may include narrowing the list of input variables
  - We are working with Dr. Rasch to identify scenarios for MCB interventions
- We are developing a methodology plan for post-hoc visual analysis module