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AIBEDO MILESTONE REPORT 6

Prepared by Kalai Ramea (PI)

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

Team (University of Washington): Phil Rasch

August 13, 2022

Problem statement

- Clouds modulate the Earth's radiation budget making them ideal for climate intervention techniques.
- 'Marine Cloud Brightening' is a technique to cool the climate by changing low clouds using sea spray aerosol injections in the boundary layer
- Designing such intervention experiments/scenarios are computationally expensive in conventional models (Earth System Models).

- Goal: Use AI to Construct a Clouds → Climate Response Function



$$\Omega(S) : \delta C(\vec{x}, h, \tau) \rightarrow \begin{cases} \delta \Psi_{atm}(\vec{x}) \\ \delta \Psi_{ocn}(\vec{x}) \\ \delta T_s(\vec{x}) \\ \delta P(\vec{x}) \end{cases}$$

A Perturbation in Low Clouds Global circulation and regional climate patterns

We develop a physics-informed machine learning model to emulate the response function. This is an order of magnitude faster than conventional models making them ideal for scenario generation, search of large parameters, etc.

Overview of Milestone 6

- Objective:

The objective of this milestone is to show the progress of the model and deliver the beta software (code).

- Updates Overview:

1. Model development update—we developed a better performing model ‘Spherical multi-layer perceptron network’ in addition to ‘Spherical U-Net’.
2. Physics constraints—we have incorporated physics constraints into our model and showed that the model conserves physics without losing accuracy
3. Phase 2 data providers (datasets, experiments)--UVic and UW teams have been developing experiments and showed initial results
4. AIBEDO Marine Cloud Brightening Experiments—We did preliminary MCB experiments with AIBEDO and showed promising results (Fluctuation Dissipation Theorem works!)
5. Comparison of AIBEDO prediction on different CMIP model ensembles—As an off-shoot, we are using the AIBEDO framework to compare how other Earth System Models perform against observational reanalysis data. This helps to decide the more reliable models for training AIBEDO V2.0
6. We now have an initial working version of our Visual Analysis System ([video link](#))—we will work with scientists to incorporate relevant features

Spherical Multi-Layer Perceptron

Salva Ruhling Cachay, Soo Kim, Kalai Ramea

ML model benchmarking

- As part of machine learning model benchmarking, we have been training the model using different ML frameworks (U-Net, Fourier Network, MLP, etc.). We found that Spherical MLP, i.e., an MLP network bolstered by Spherically transformed data performs best so far.
- We will be continuing our work in this direction to test more models and the goal is to produce a comparison paper of ML model benchmarking

Making the model 'hybrid' by incorporating physics

Peetak Mitra, Salva Ruhling Cachay

Constraints: overview

Constraint	Local (L) or Global (G)
Energy: Consistent Changes in Surface Temperature and Top of Atmosphere (TOA) Radiative fluxes	G
Enthalpy: Consistent Radiative fluxes at TOA, and Surface with Latent Heat Fluxes (precipitation)	G
Moisture: Consistent Precipitation and Evaporation Fluxes	G
Physical consistency: Non-negative precipitation	L
Mass: Consistent global surface pressure	G

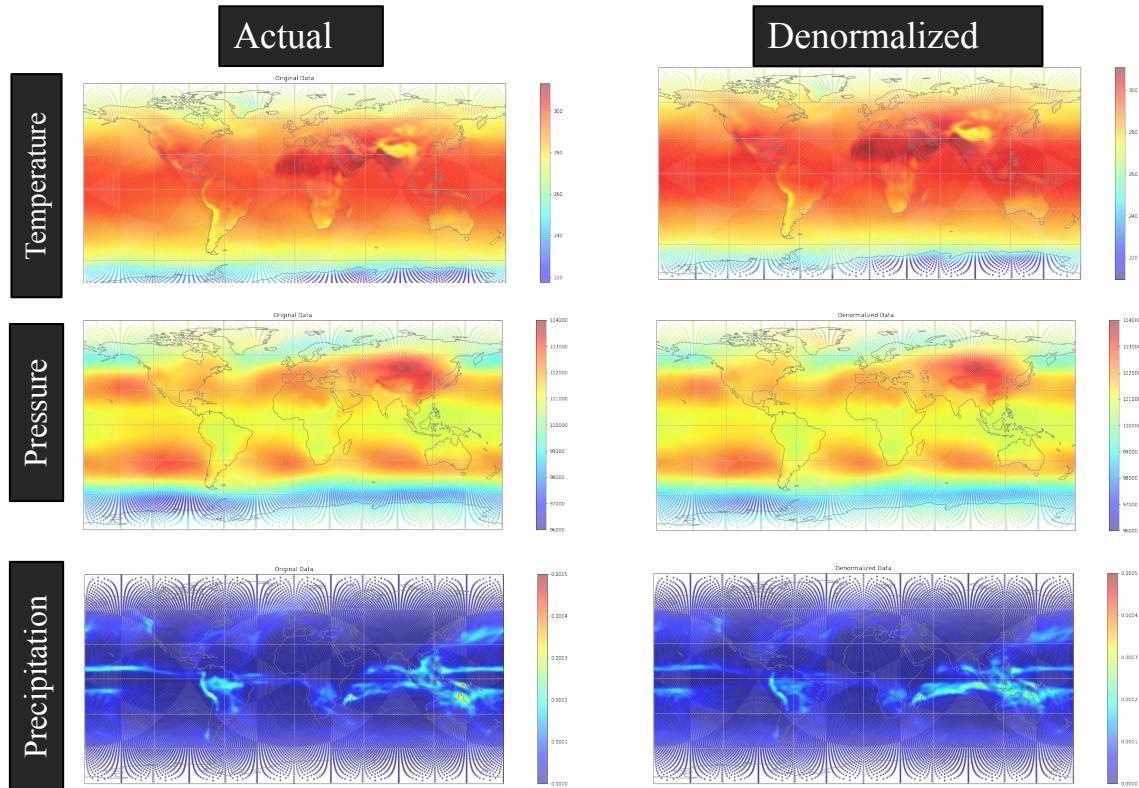
$$\begin{aligned}
 & \sum_t^{>1\text{yr}} \sum_{\text{spatial}} (\Delta R^{TOA} - \lambda_{ECS} \Delta T - \Delta A) = 0 \\
 & \sum_{\text{spatial}} (PL + SH + R_{TOA} - R_{SFC}) \Delta A - \epsilon_E \approx 0 \\
 & \sum_{\text{spatial}} (P - E) \Delta A - \epsilon_q \approx 0 \\
 & P \geq 0 \\
 & \sum_{\text{spatial}} (P_s) \Delta A - \epsilon_E \approx 0
 \end{aligned}$$

<i>TOA</i>	Top of the atmosphere
<i>SFC</i>	Surface
<i>A</i>	Area
<i>T</i>	Surface temperature
<i>P</i>	precipitation
<i>E</i>	evaporation
<i>P_s</i>	Surface pressure
<i>λ_{ECS}</i>	Feedback constant
<i>R</i>	Net radiation
<i>L</i>	Latent heat of vaporization
<i>SH</i>	Sensible heat flux
ϵ_E, ϵ_q	Correction factors

Denormalization

- Our preprocessing steps include ‘normalization’ of input and output variables
- This shifts the variables to a different space, hence to add physics constraints they had to be ‘denormalized’.
- We selected CMIP6 multi-ESM ensemble average climatology and variability for the denormalization
 - Single month or season used as basis for denormalization
 - This reference represents climatology and variability of the AiBEDO model
- We compared the actual and denormalized data to verify and confirmed that this method works well to map the data back and forth to normalized values

Actual vs. Denormalized values from CMIP6 multi-ESM ensemble average climatology and variability



- The reconstruction of normalized data using the CMIP-6 multi—ESM ensemble average climatology and variability works best for surface pressure, followed by surface air temperature.
- Denormalization of precipitation performs the worst among the three, specifically in tropics, although relative magnitudes are $\sim O(10^{-4})$

Making the model ‘hybrid’

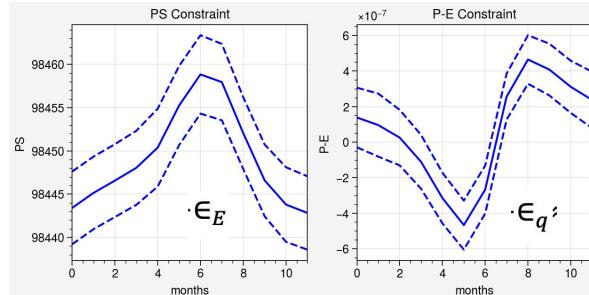
- Constraints are implemented as loss-regularizer, to the AIBEDO model, during model training process
 - Coefficients are included to 'enhance' or 'minimize' impact

```
overall_loss = model_loss + lambda * constraint_loss
```

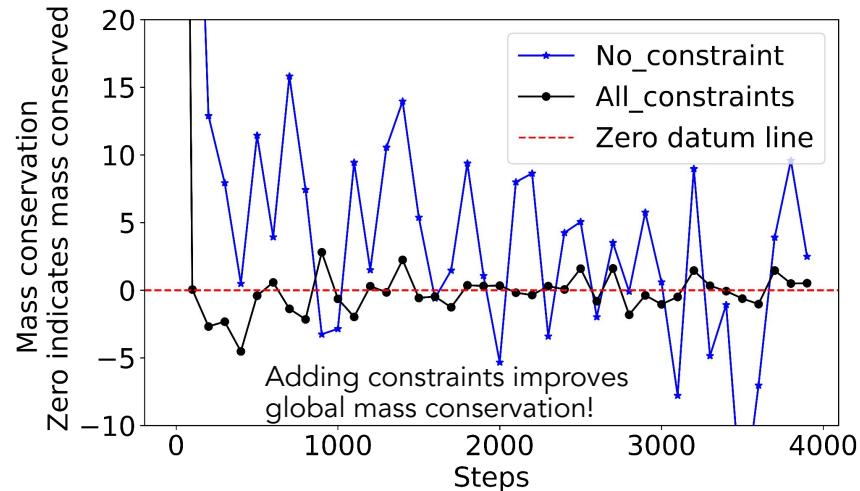
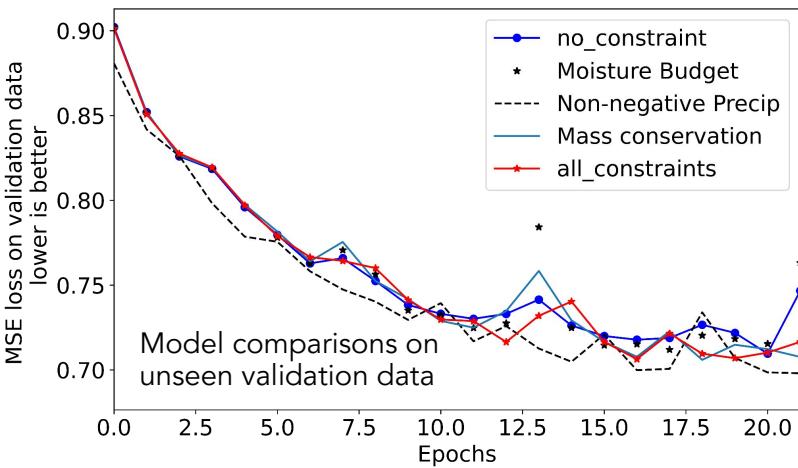
Applied at Local,
pixel level

**Applied at Global level,
only pixel level for non-negative precipitation**

- Applying loss on a *monthly scale*, introduces corrections.
 - Ex. for mass conservation (PS) and moisture Budget (P-E) constraints



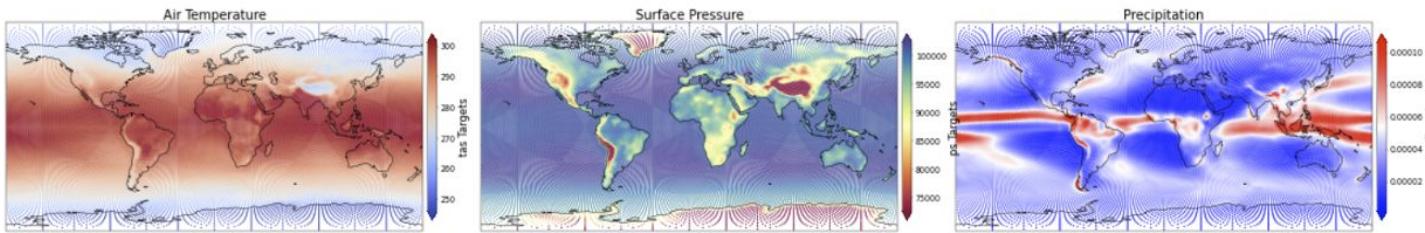
On-training performance



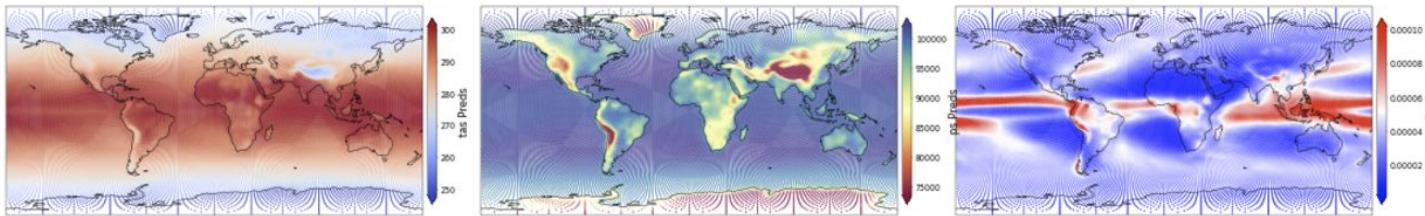
Key Takeaway: Adding constraints don't damage the rate of convergence, but they do improve the physical consistency of fields!

Time averaged spatial distribution

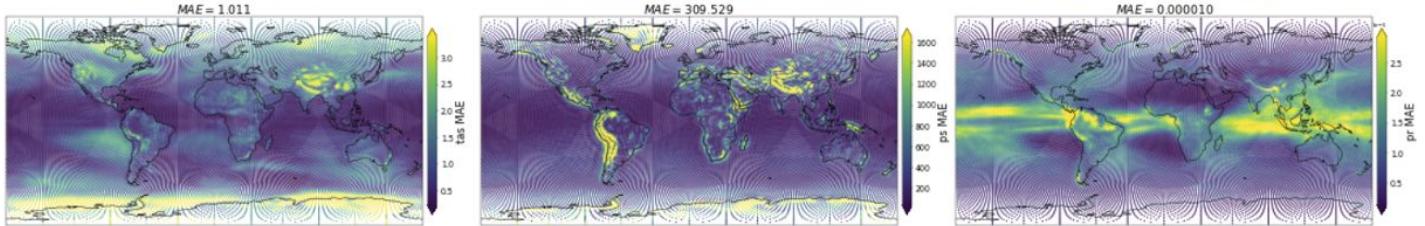
Ground Truth



Predictions



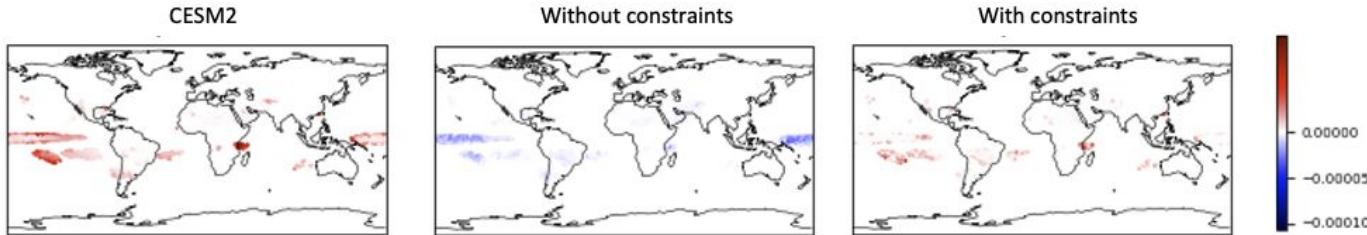
Error



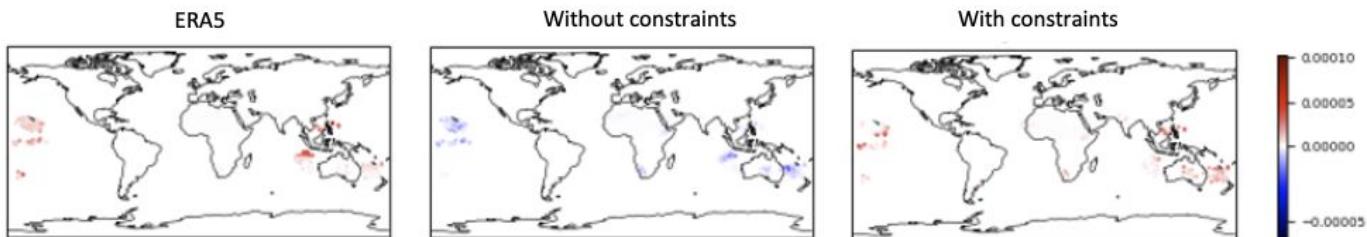
Improvements in predictions

Precipitation

In-distribution



Under-distributional shift



Ongoing work

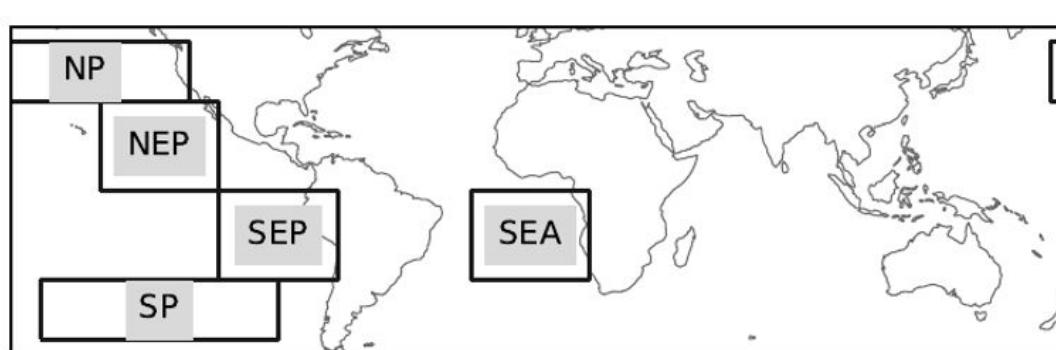
- Coefficient (lambda) for the constraints, represents a significant source of uncertainty to model predictions
- Explore conditional probability/Bayesian optimization based approaches to inform ideal set of parameterization for lambda.
- Evaluating energy conservation at a global, and zonal (ex. tropics, midlatitudes) level using spatio-temporal information and joint probabilities.

Marine Cloud Brightening Experiments

Haruki Hirasawa, Phil Rasch

Phase 2 Plans: CESM2 MCB Experiments

- UVic is contributing CESM2 simulations to a MCB model intercomparison lead by Prof. Rasch using computing resources courtesy of AWS
- MCB perturbations will be applied to marine stratocumulus regions by fixing Cloud Droplet Number Concentration to specified values



Planned Experiments

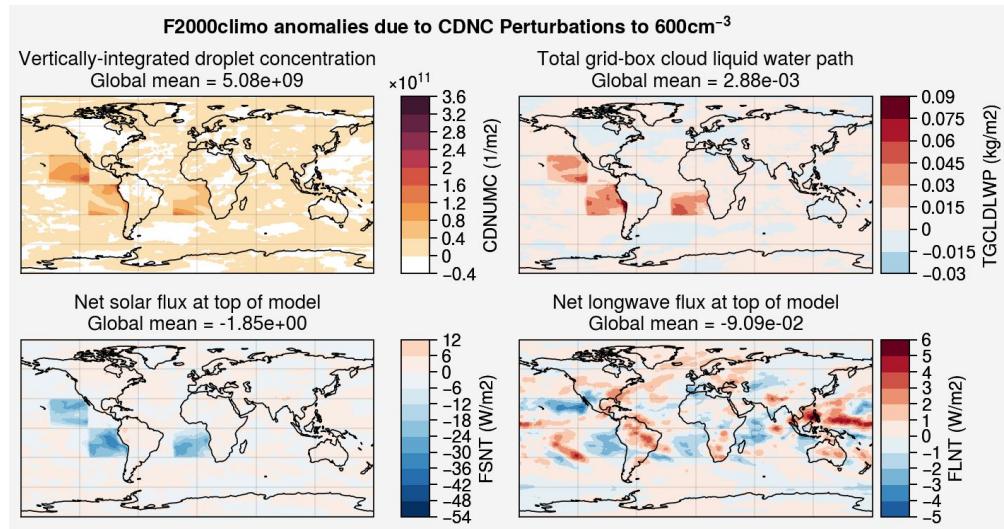
ID	Simulation	Model Configuration	Description	Length
1	MCB Calibration R1 + R2 + R3	Fixed-SST	Short atmosphere-only experiments aimed at identifying CDNC values in NE Pac (R1), SE Pac (R2), and SE Atl (R3) required to achieve -1.8Wm ⁻² forcing	10 x 5
2	E3SM Control	Fully Coupled	Control SSP2-4.5 experiments	2015 to 2070 x 10
6	E3SM Control	Fully Coupled + CDNC Fixed R1 + R2 + R3	SSP2-4.5 experiments with CDNC forcing applied in the NE Pac, SE Pac, and SE Atl	2015 to 2070 x 10

Scientific questions to be addressed

- What are the climatic consequences of increasing the albedo in regions of the planet known for persistent marine cloud distributions?
- Can one “optimize” the MCB to achieve particular climate goals, such as avoid tipping points?
 - AiBEDO will allow for rapid exploration of MCB scenarios to generate potential forcing patterns.

GCM Marine Cloud Brightening Experiments

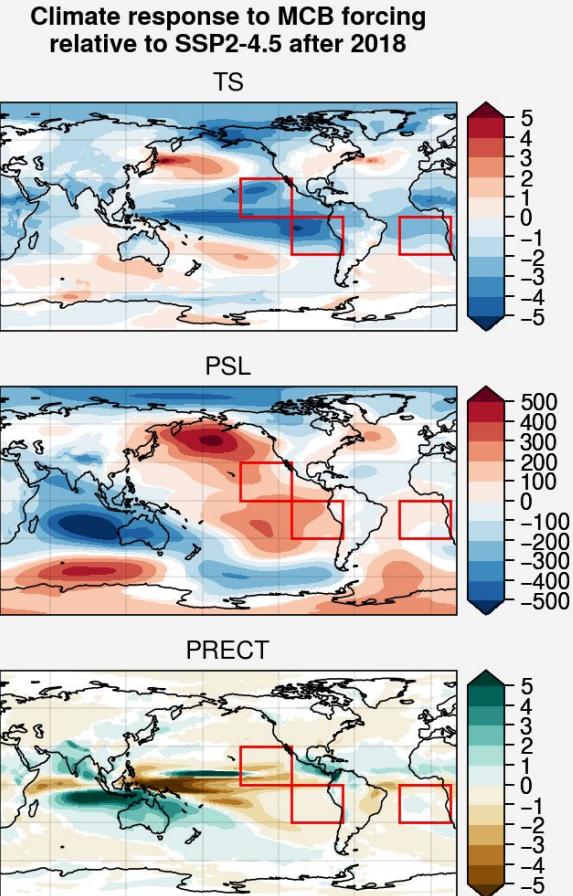
- Preliminary prescribed-SST simulations quantifying forcing have been completed
- Large values (600cm^{-3}) required to achieve target forcing of -1.8Wm^{-2}



Cloud and Radiative effects of Cloud Droplet Number Perturbations from prescribed-SST CESM2 experiments

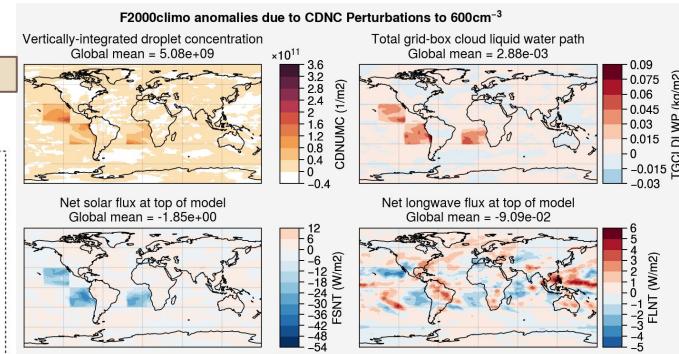
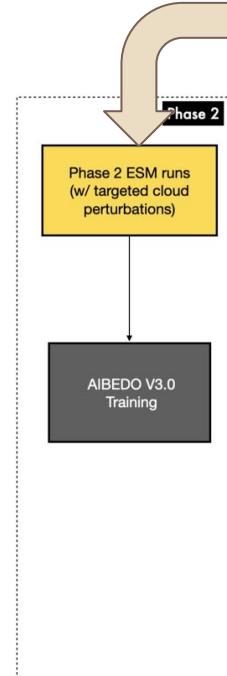
Climate Response to MCB forcing

- Global mean cooling of ~1.2K in response to the 600cm^{-3} CDNC perturbation
- Strong regional cooling signals emerge in the Tropics and Arctic
- Precipitation declines in tropical Pacific, increases in NH African and South Asian monsoon regions



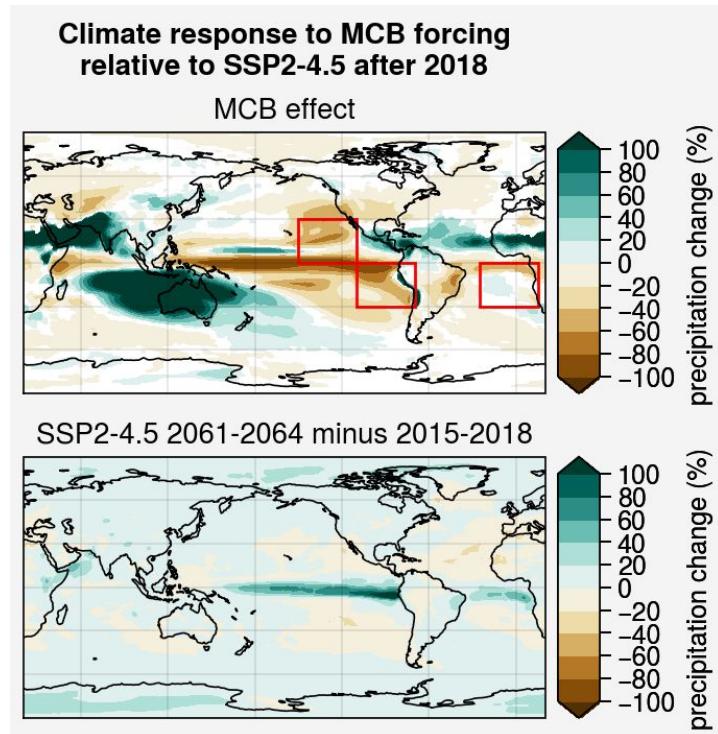
Future Work: Using CESM2 simulations to evaluate AiBEDO

- Data from coupled atmosphere-ocean CESM2 and E3SM experiments will serve as out-of-sample validation of AiBEDO response



Future Work: Using AiBEDO to optimize MCB interventions

- MCB interventions can have negative consequences if applied incorrectly
- For example, we see a reduction in California and Amazon rainfall
- This depends on the pattern of MCB forcing, thus we will use AiBEDO to optimize MCB interventions

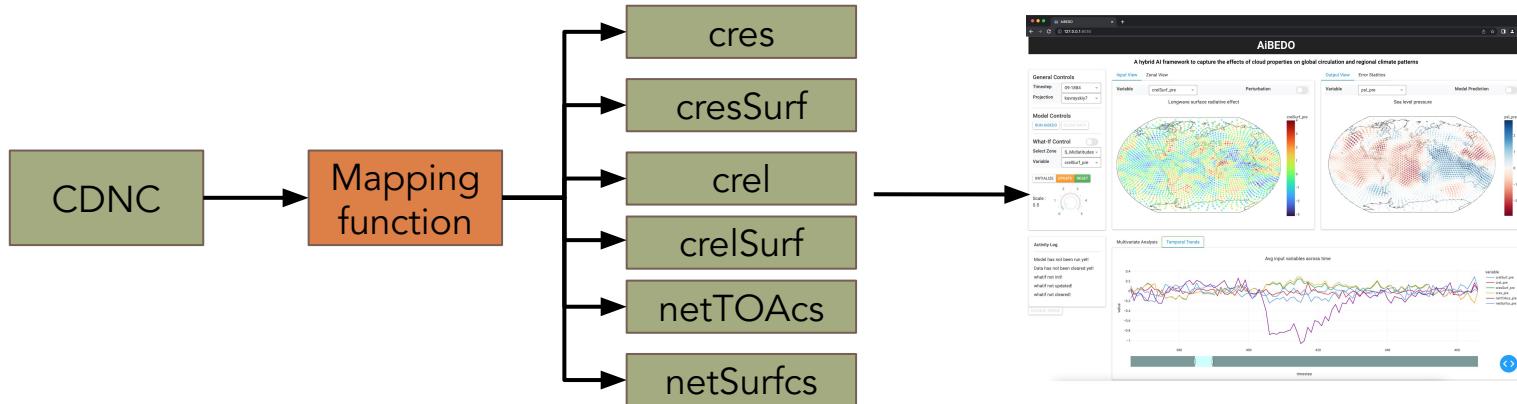


Marine Cloud Brightening Perturbations in AIBEDO

Dipti Hingmire, Hansi Singh

Perturbations in ESM vs. AIBEDO

- Cloud droplet number concentrations (CDNC) used for MCB in Earth Systems Models is not a direct input to AIBEDO
- Ideally, we would develop a 'mapping function' between CDNC and input variables to assess the impact of MCB

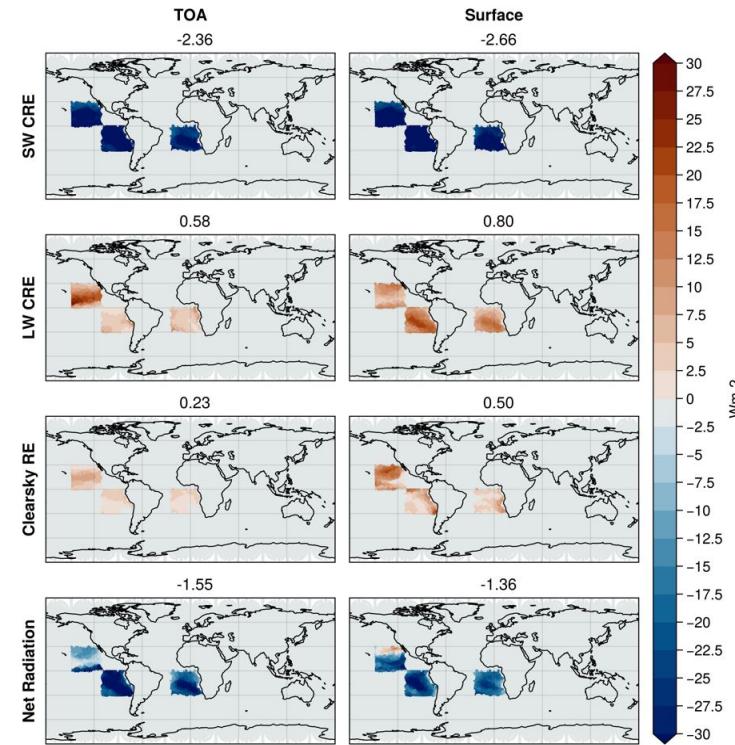
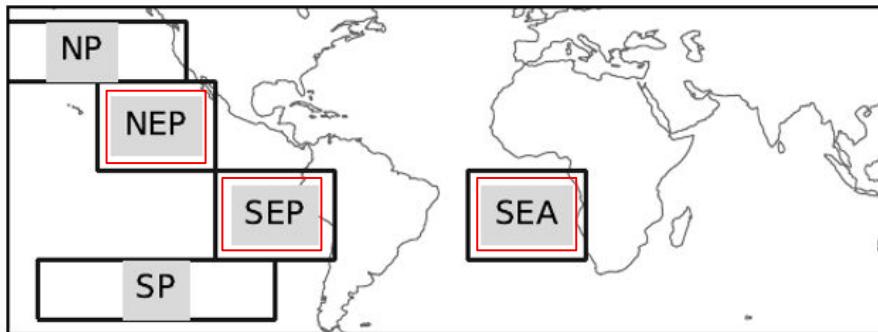


Introducing perturbations in AIBEDO (process)

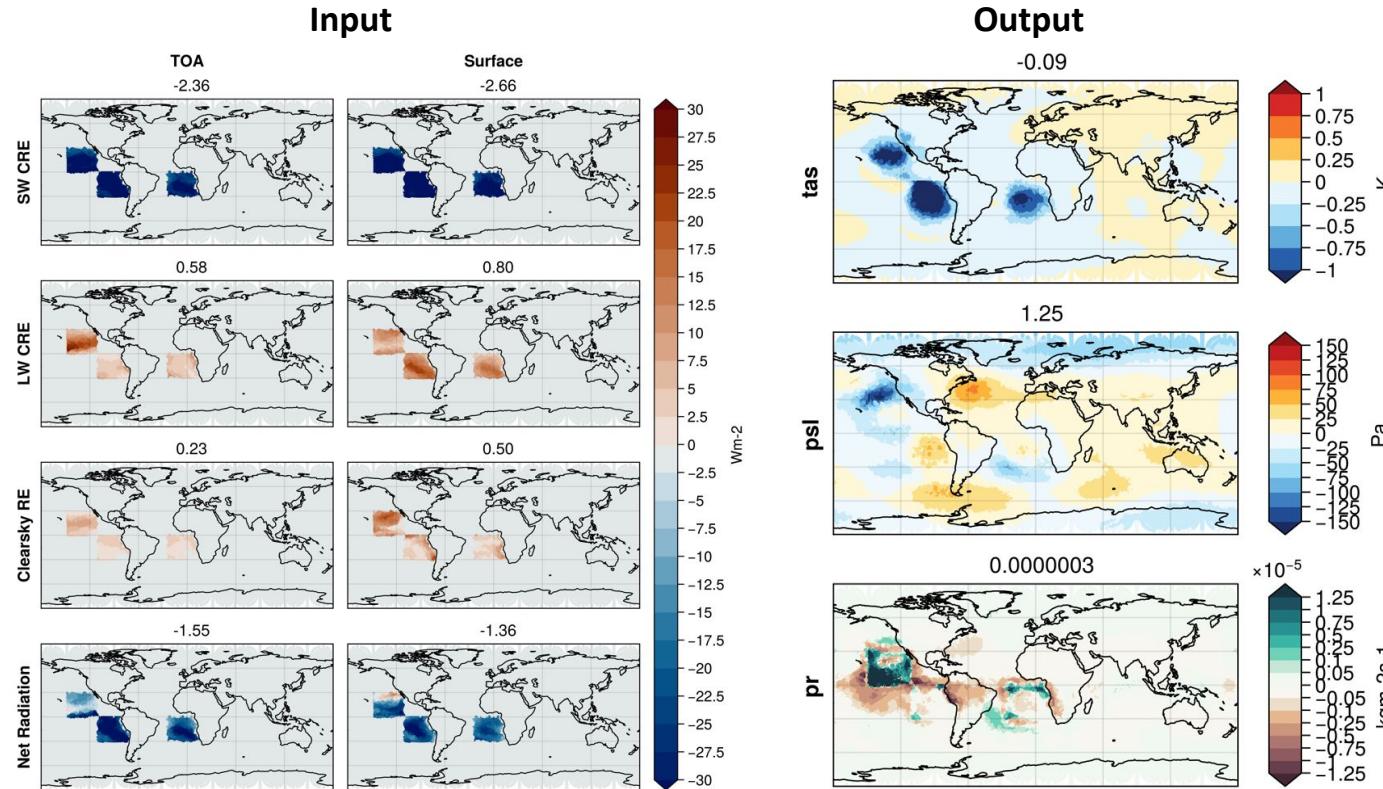
- Cloud brightening ‘sites’ are introduced as perturbations in input radiation variables
- However, input variables are interdependent and cannot be changed independently
- Our method to introduce perturbations:
 - Regress all input variables on *cres* linearly at each grid point
 - Set preprocessed *cres* as prescribed value over the MCB region
 - Using regression coefficients and intercepts construct other input variables corresponding to *cres* perturbation

MCB like perturbation inputs to AiBEDO

- Increase in albedo over three MCB regions corresponds to changes in surface and TOA radiation



AiBEDO response to MCB like perturbations

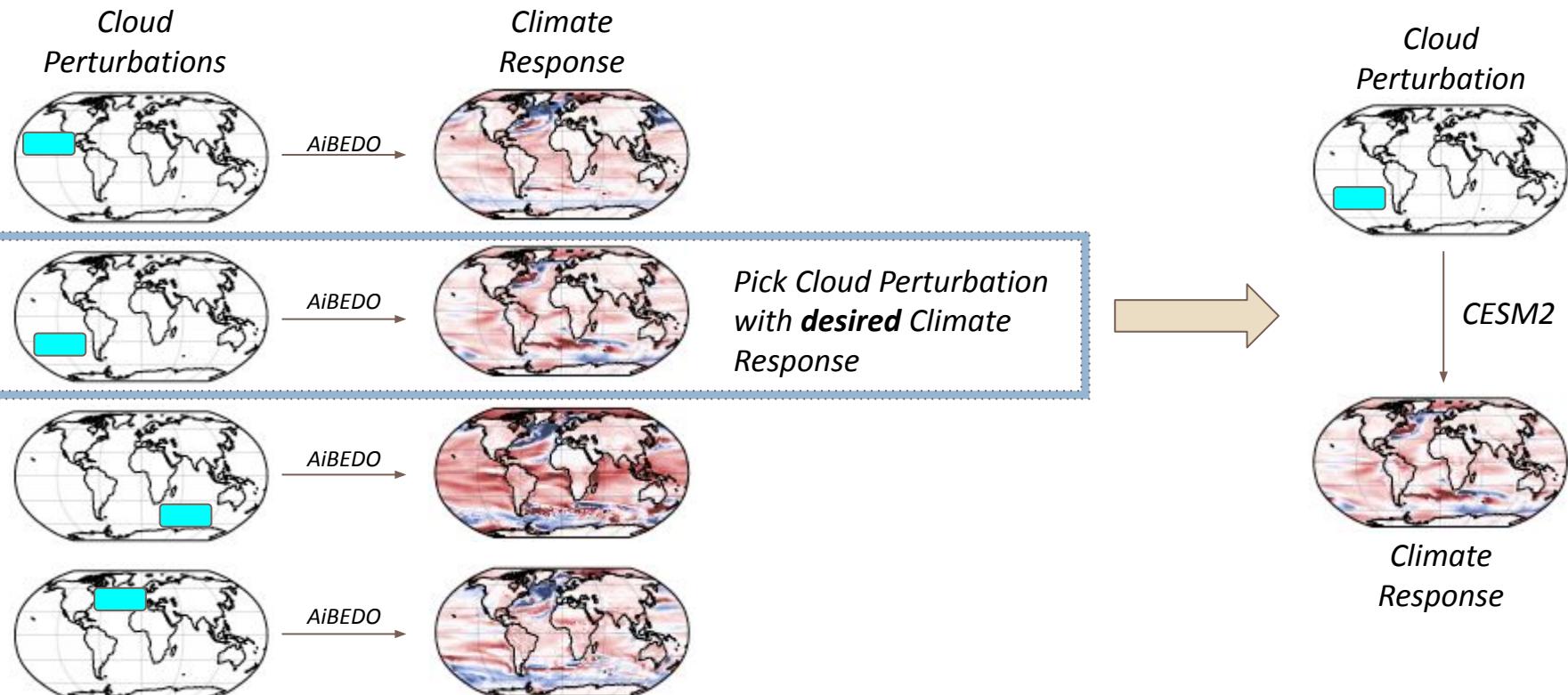


AiBEDO is able to predict appropriate temperature response to cloud brightening perturbations

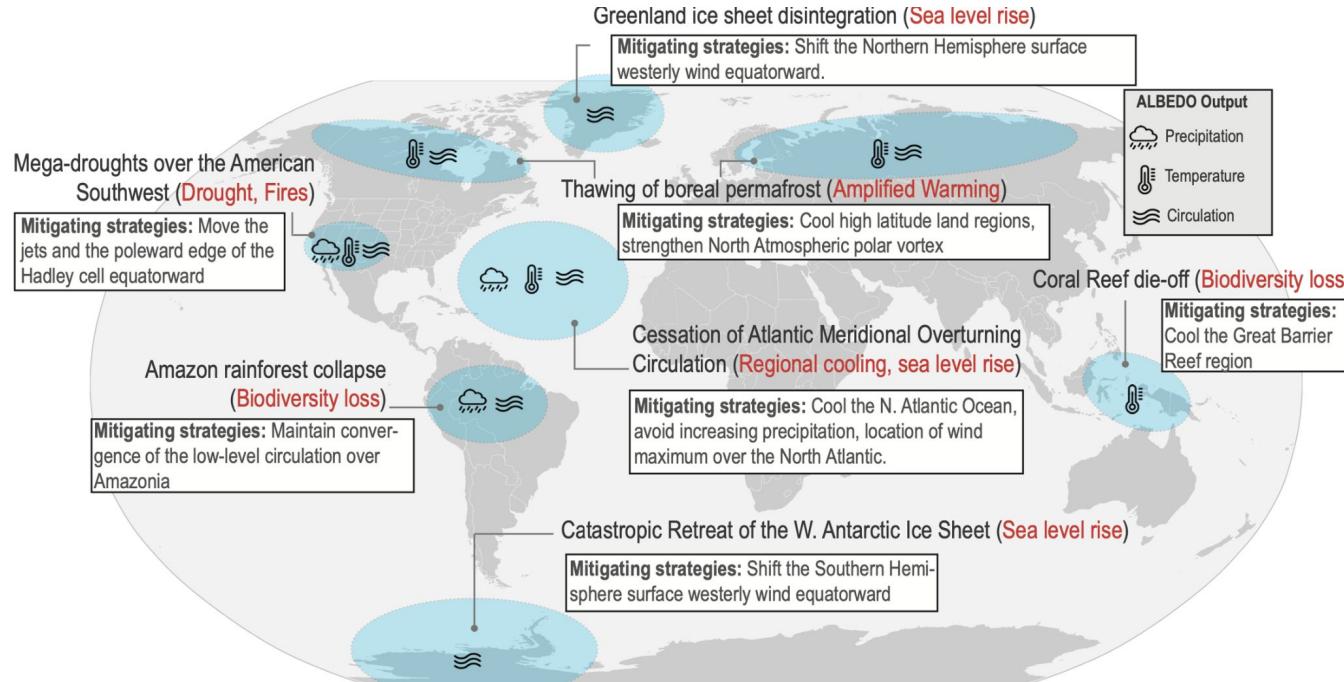
Ongoing work

- AlBEDO model is trained on natural variability of cloud changes, and our hypothesis is FDT would capture these forced radiative changes
- We want to know the limits of AlBEDO/FDT in predicting the right responses for Marine Cloud Brightening perturbations.
- We will continue to perform 'patch tests' to identify the limits of the model, as well as perform 'zonal perturbations', 'multiple patch tests', and document the same
- We will be comparing the results with the CESM2 and E3SM runs that are being run by the UW team
- Knowing the limits of the model will help us determine Phase 2 runs, and "new data" that is generated from Phase will be used for finetuning the model.

Our Planned Workflow for Designing MCB Perturbations

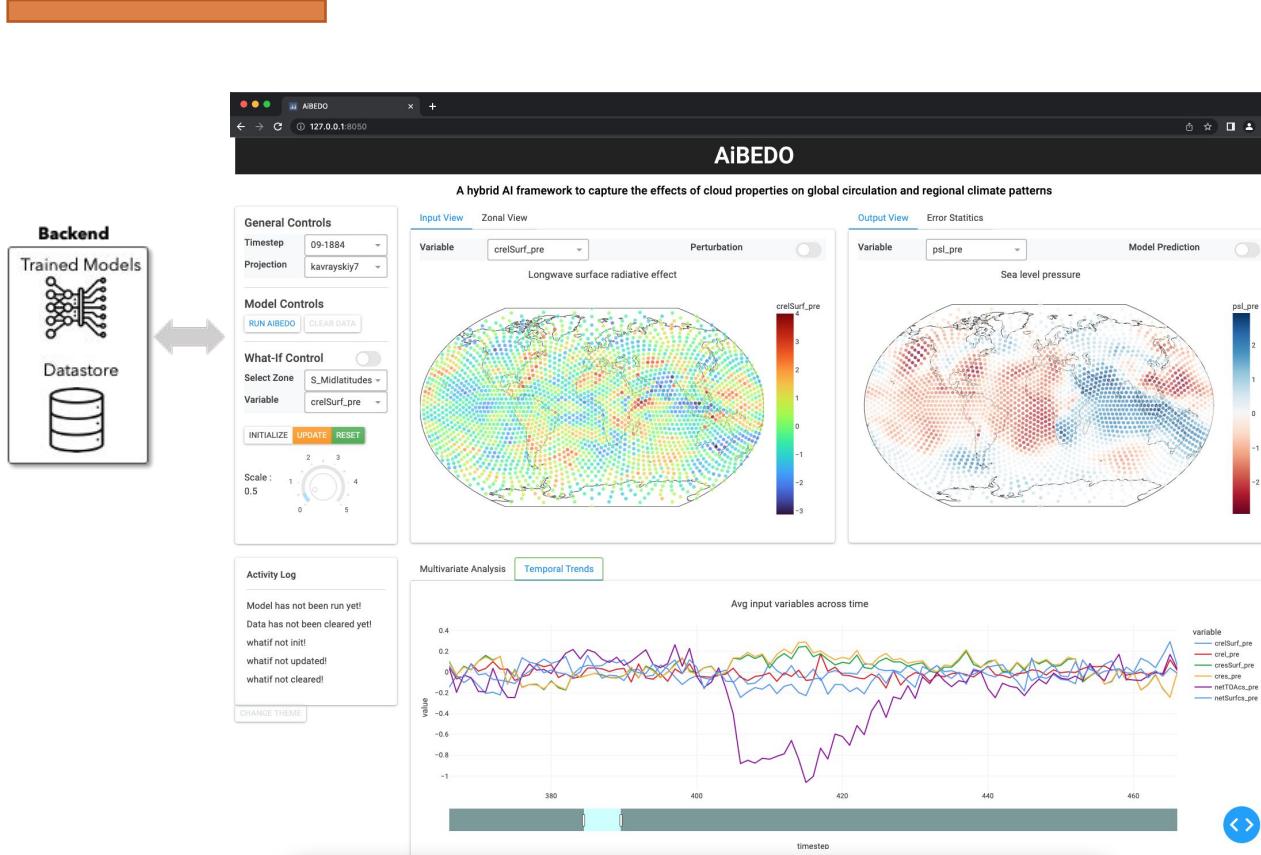


Our Goal: to use AiBEDO to Design MCB Interventions to Avoid Tipping Points



AIBEDO Visual Analysis System

Subhashis Hazarika



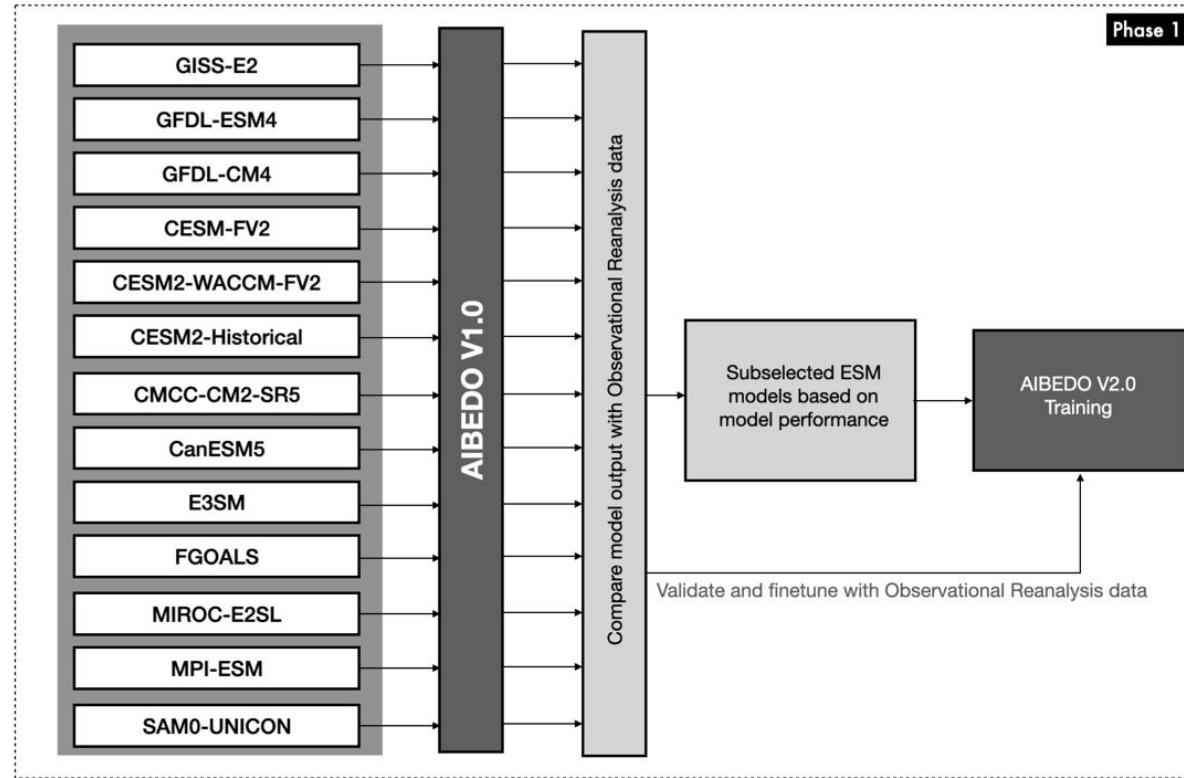
- We are developing an interactive AiBEDO visual analysis framework w/ input from climate modelers
- This will incorporate tools for post-hoc analysis: model diagnosis, attribution maps, sensitivity analysis
- Modelers/policy makers can quickly perform 'what-if' scenarios of targeted cloud perturbations

Click this link to see the working demo: <https://www.youtube.com/watch?v=ZV4GmTniZIQ>

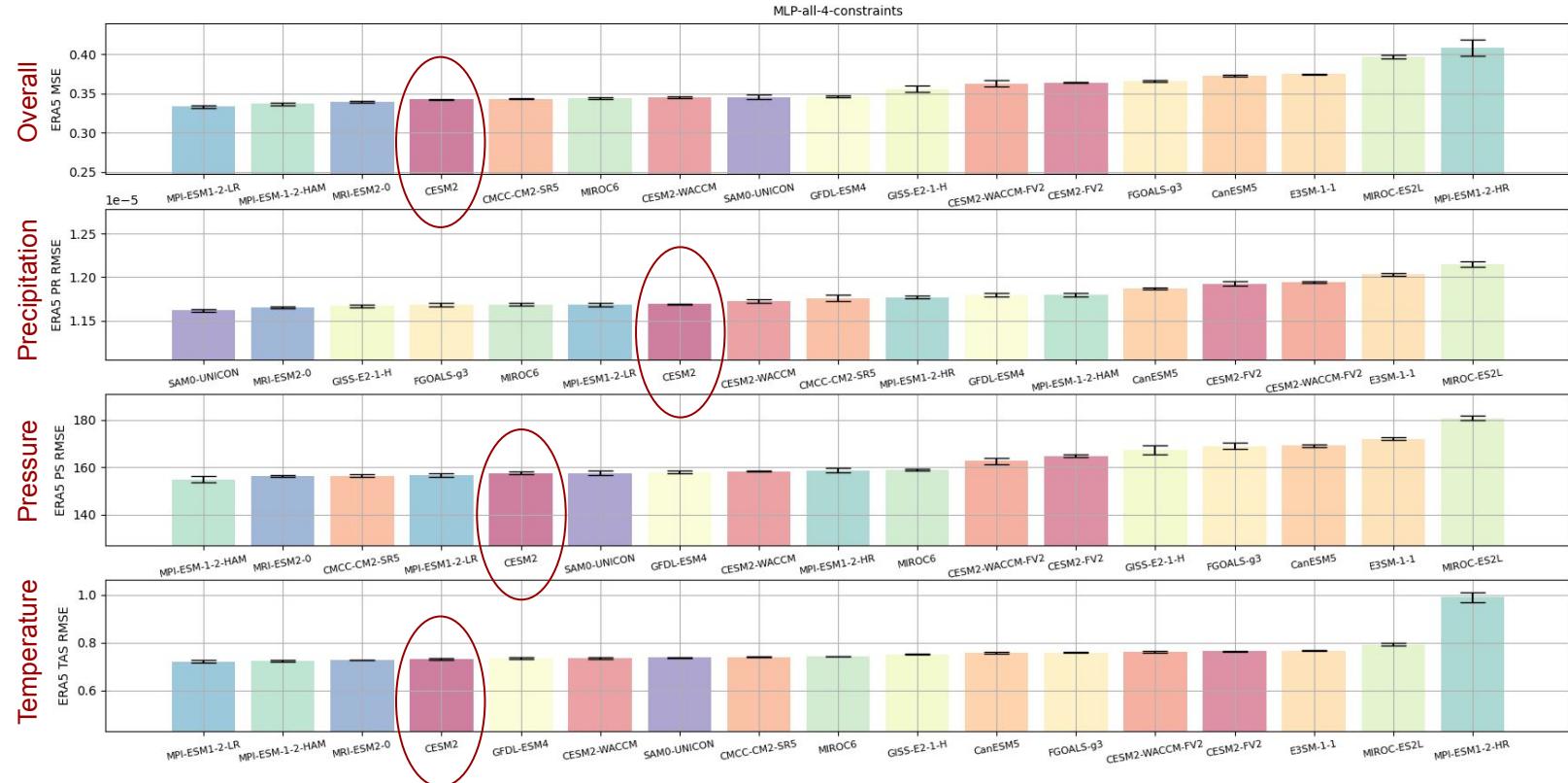
Model Intercomparison

Kalai Ramea, Soo Kim, Salva Ruhling Cachay

Model training in stages: benchmarking, full training, validation

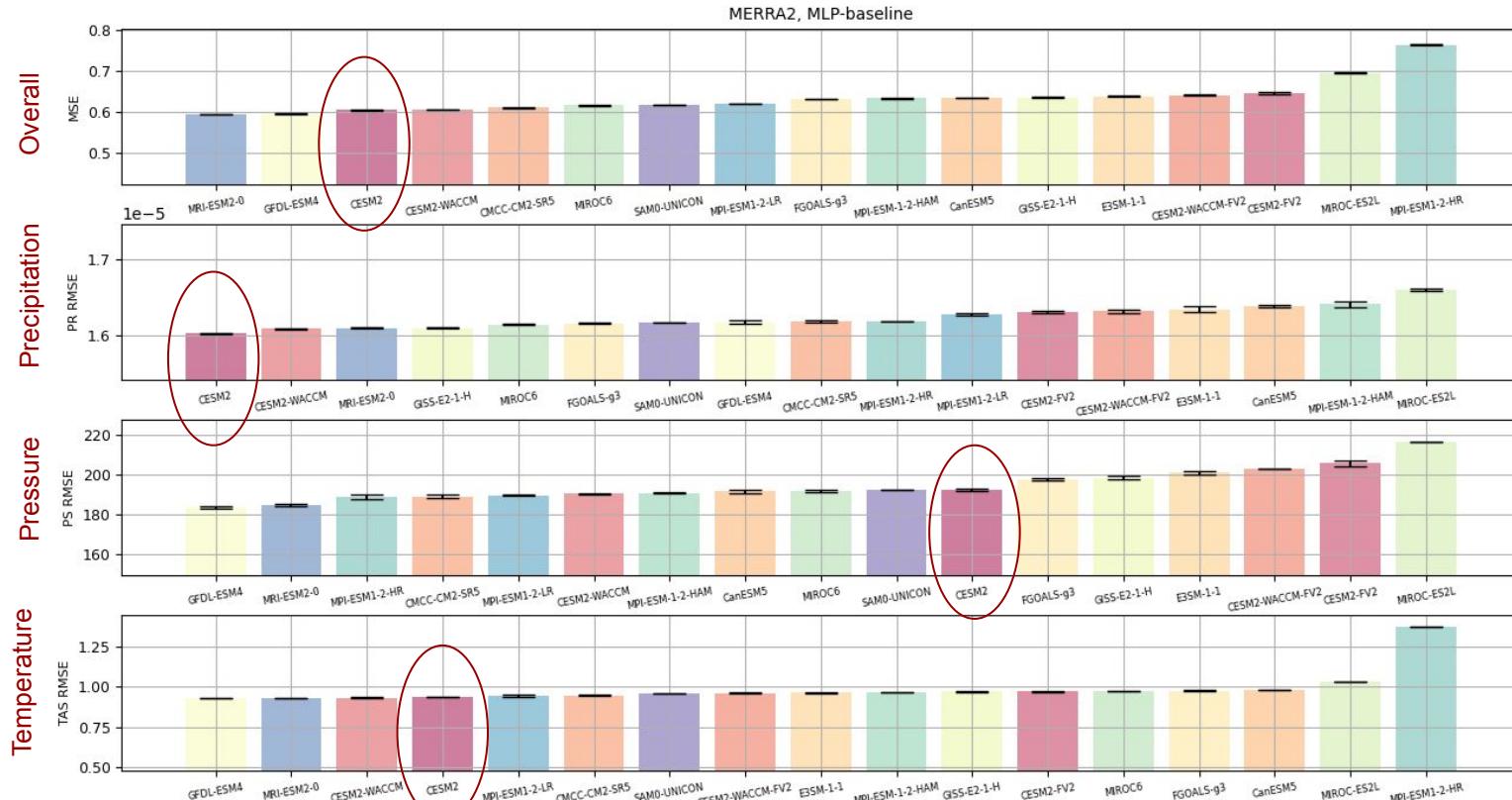


Benchmarking against ERA-5 (preliminary results)



Smaller MSE → Closer to observational data (ERA-5).

Benchmarking against MERRA-2 (preliminary results)



Smaller MSE → Closer to observational data (MERRA-2).

Initial Reflections on Model Intercomparison

- We trained on individual ESMs and tested on two observational reanalysis data (ERA-5 and MERRA-2).
- Our initial results suggest that, in the overall metric, we can see an agreement between the two set of results for most ESMs. For eg, CESM2 is closer to observational data vs. MIROC-E2SL in both
- We will set a threshold and select ESMs for combined model training for AIBEDO V2.0.



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AIBEDO: a hybrid AI framework to capture the effects of cloud properties on global circulation and regional climate patterns.

[Edit on GitHub](#)

AIBEDO: a hybrid AI framework to capture the effects of cloud properties on global circulation and regional climate patterns.

Note

This project is under active development.

Concept

Clouds play a vital role both in modulating Earth's radiation budget and shaping the coupled circulation of the atmosphere and ocean, driving regional changes in temperature and precipitation. The climate response to clouds is one of the largest uncertainties in state-of-the-art Earth System Models (ESMs) when producing decadal climate projections. This limitation becomes apparent when handling scenarios with large changes in cloud properties, e.g., 1) presence of greenhouse gases->loss of clouds or 2) engineered intervention like cloud brightening->increased cloud reflectivity.

Climate intervention techniques—like marine cloud brightening—that need to be fine-tuned spatiotemporally require thousands of hypothetical scenarios to find optimal strategies. Current ESMs need millions of core hours to complete a single simulation. AIBEDO is a hybrid AI model framework developed to resolve the weaknesses of ESMs by generating rapid and robust multi-decadal climate projections. We will demonstrate its utility using marine cloud brightening scenarios—to avoid climate tipping points and produce optimal intervention strategies.

- Datasets
 - Training data
 - Preprocessing
 - Data required for Physics Constraints
- Hybrid AI Model Architecture
 - Spatial Data-Driven Component
 - Spherical U-Net Architecture

We will be developing a 'landing page' for the project in addition to the detailed documentation page

AIBEDO documentation page:
<https://aibedo.readthedocs.io/>

Past Publications and Conferences

- Past presentations/submissions
 - Climate Informatics 2022
 - Gordon Research Conference
 - re:MARS
 - IEEE Viz4Climate (submitted Jul 22)
- Abstract submissions to American Geophysical Union (AGU)
 - Several abstracts are submitted to AGU (August 3, 2022)
 - Focus areas: ML/AI, Climate dynamics, Interventions, Uncertainty analysis

AGU submission titles (August 2022)

- Interactive Visual Analytics to Study the Impacts of Cloud Radiative Properties on Climate Patterns
- AiBEDO: A hybrid AI model to capture the effects of cloud properties on global circulation and regional climate patterns
- On incorporating first principles based physical conservation laws into global climate emulators
- ClimFormer: building an attention-based climate emulator
- MCB Forcing and Climate Response in the Community Earth System Model 2
- AI assisted evaluation of ESMs in simulating observed cloud climate interactions
- Marine Cloud Brightening Intervention Optimization using a Hybrid AI Approach
- Will correcting cloud radiative biases over the Southern Ocean improve precipitation biases over the Indian subcontinent in CESM2 simulations?

Summary and Ongoing work

- We have completed the data-driven spatiotemporal modeling of AiBEDO and in the process of integrating physics constraints
 - Accelerated predictions: Our preliminary inference time to generate short-term predictions is ~0.5 seconds for an output timestep (monthly)
 - Metrics will be generated to compare with ESM runtime and we are also developing a ‘simple’ conventional model to compare AiBEDO’s performance
- We are benchmarking AIBEDO trained on CMIP6 models against observational reanalysis data
 - These sub-selected datasets will be used for training AIBEDO v2.0
- We are performing model intercomparison using AiBEDO trained on a CMIP6 model against other CMIP6 models (to understand deviations in variability across ESMs)
- We are fine-tuning MCB experiments for Phase 2 dataset generation