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AIBEDO MILESTONE REPORT 8

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

December 13, 2022

Overview of Milestone 8 (Phase I final deliverable)

1. Our team delivered a comprehensive hybrid model components for mapping cloud properties with regional climate and global circulation elements. We developed data-driven components and several domain constraints to ensure that the model retains the physics of the system.
2. We also performed several Marine Cloud Brightening simulations in Earth Systems Models (CESM2) to understand the extent of changes due to cloud perturbations
3. We did Earth Systems Model intercomparison using AIBEDO—to assess the quality of cloud perturbation outcomes
4. We performed MCB experiments using AIBEDO for different time lags and compared the results with ESM simulations. Our model performs as well as ESM at a fraction of the computational need.
5. We developed an interactive visualization board for performing MCB experiments for pre-defined locations, which helps stakeholders to understand the regional impacts and on known tipping points

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.

AIBEDO Phase-I Hybrid Model Summary

Soo Kim, Kalai Ramea, Peetak Mitra, Salva Ruhling Cachay

Hybrid Model

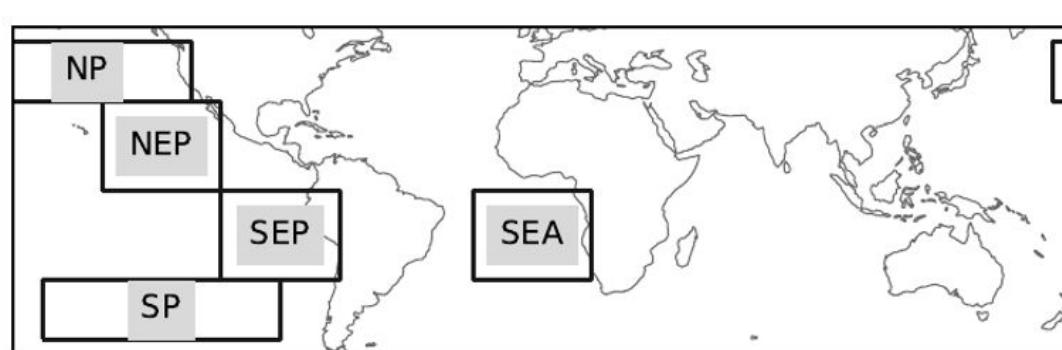
- We developed three model architectures: Spherical-UNet, Spherical-MLP and Spherical-FNO (Fourier Neural Operator) networks for AIBEDO
- During development we experimented with preprocessed CESM2 dataset. Full training is being done with sub-selected, aggregated ESM model data
- We preprocess the data to perform deseasonalizing and detrending to remove any cyclical trends and thus capture responses to cloud perturbations
- The input and output mapping can be run for simultaneous timelines and with lag. We observed that cloud perturbation response is captured better in lagged models.

Marine Cloud Brightening Experiments

Haruki Hirasawa, Phil Rasch

CESM2 MCB Experiments

- UVic is contributing CESM2 and E3SM 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

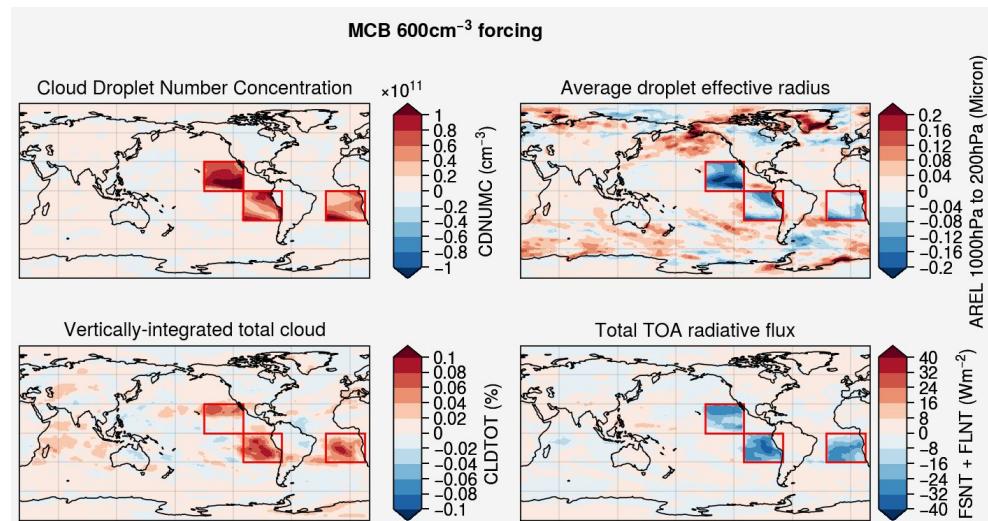


Completed Experiments

ID	Simulation	Model Configuration	Description	Length
1	MCB Calibration R1 + R2 + R3	Fixed-SST (CAM6)	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	CESM2 Control	Fully Coupled	Control SSP2-4.5 experiments	2015 to 2100 x 17
3	CESM2 NEP	Fully Coupled	SSP2-4.5 experiments with NE Pac CDNC Forcing	2015 to 2065 x 2
4	CESM2 SEP	Fully Coupled	SSP2-4.5 experiments with SE Pac CDNC Forcing	2015 to 2065 x 2
5	CESM2 SEA	Fully Coupled	SSP2-4.5 experiments with SE Atl CDNC Forcing	2015 to 2065 x 2
6	CESM2 Three region	Fully Coupled	SSP2-4.5 experiments with CDNC forcing applied in the NE Pac, SE Pac, and SE Atl	2015 to 2065 x 3

GCM Marine Cloud Brightening Experiments

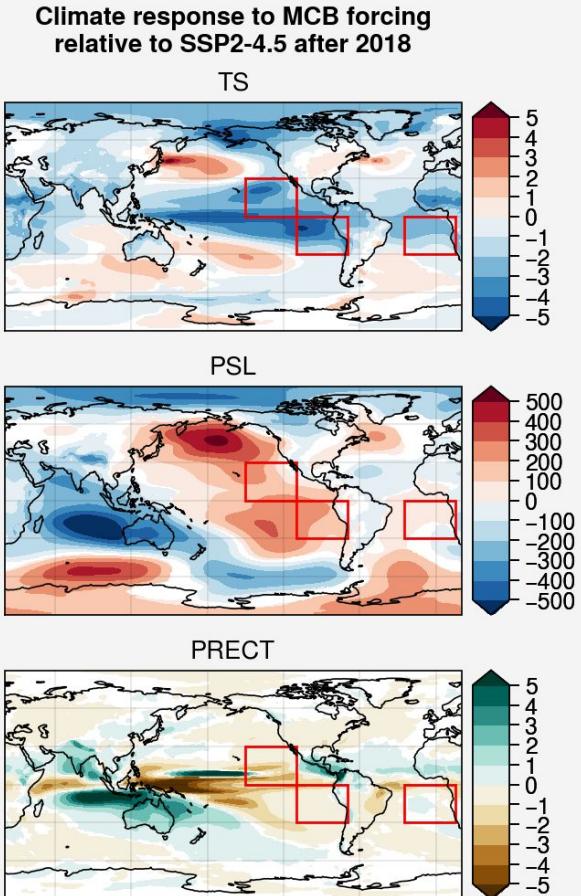
- Preliminary prescribed-SST simulations quantifying forcing have been completed
- Large values (600cm^{-3}) required to achieve target forcing of -1.8Wm^{-2}



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

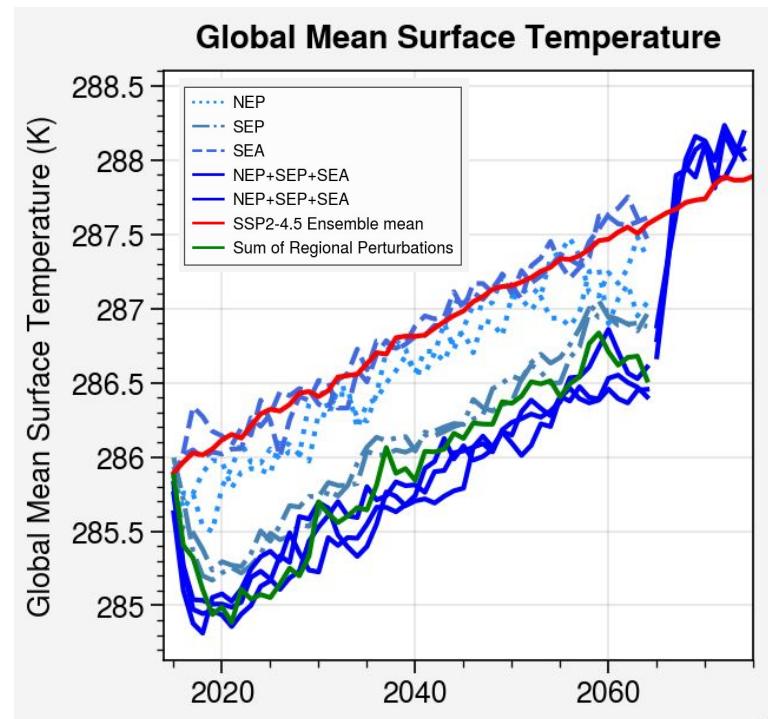
Climate Response to MCB forcing

- 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



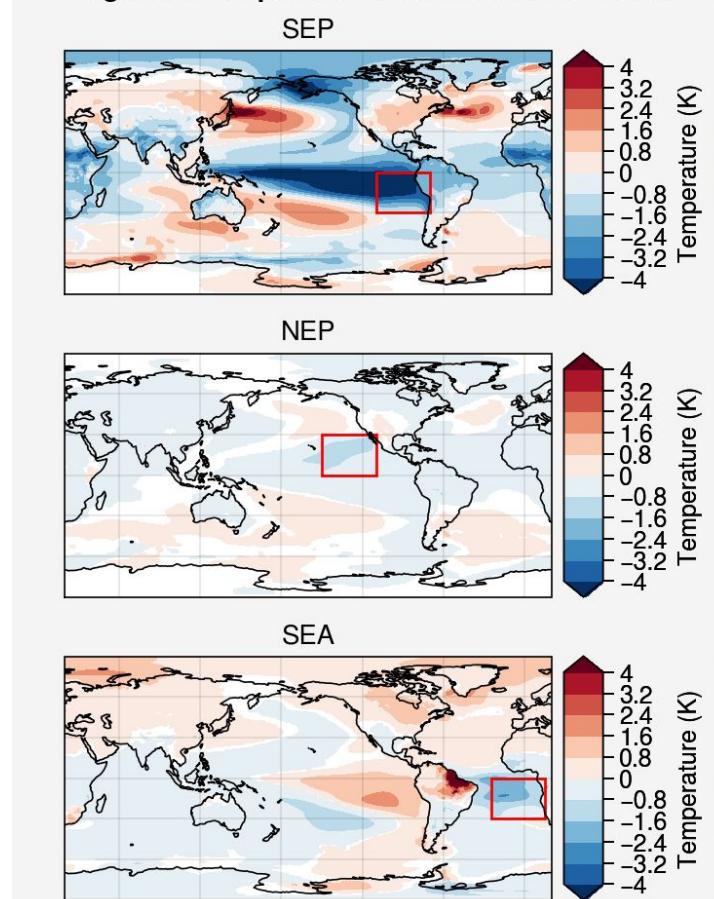
Global cooling effect of MCB forcing

- We find large difference in the sensitivity of global mean temperatures to MCB forcing depending on the location of the forcing
- Southeast Pacific forcing is the most impactful
- South Atlantic forcing has negligible global mean impact



Response to Regional perturbations

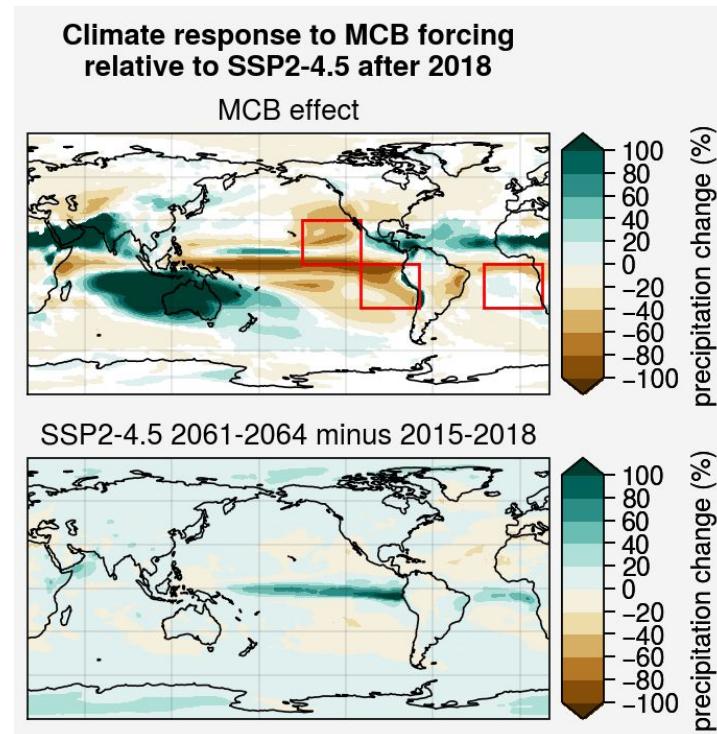
- Strong dependence of climate response on location of MCB forcing
- Opposing effect of forcing in different regions (e.g. in Amazon rainfall)
- Supports the need for a means to rapidly explore MCB forcing scenarios



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

This work was originally slated to be completed under Phase 2. However, as AiBEDO team is not moving forward to Phase 2, so this is considered as future opportunity to expand Phase 1 models.



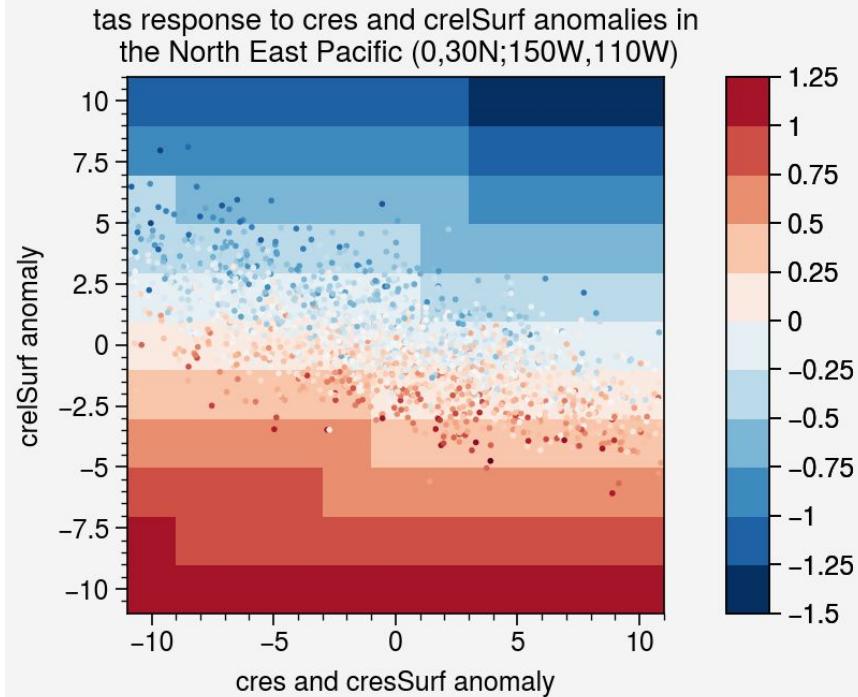
Marine Cloud Brightening Perturbations in AIBEDO

Haruki Hirasawa, Dipti Hingmire, Hansi Singh

Confounded Causality

- We expect the ML model to produce a negative temperature response to a reduction in downwelling shortwave radiation
- Early versions of the model produced the inverse relationship
- Consistent with tas anomalies causing negative cloud feedbacks instead of cloud radiation effect on tas

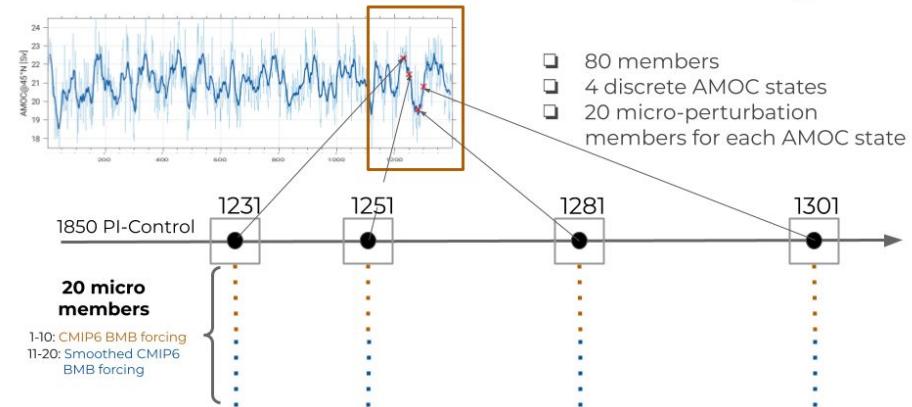
Heatmap of local surface temperature response to cloud SW and LW anomalies in the North East Pacific
Showing negative correlation between cres and tas



Training Datasets

- After extensive testing of different ML models, training datasets, and input variable sets we obtain expected behaviour when a time-lagged model is trained on a single ESM dataset with a sufficiently large pool of non-normalized data
- We use the Community Earth System Model 2 (CESM2) Large Ensemble smoothed biomass burning emission simulations
 - 50 ensemble members x 165 years x 12 months ~ 100,000 months of data

LENS2 - Macro/Micro Perturbation Design



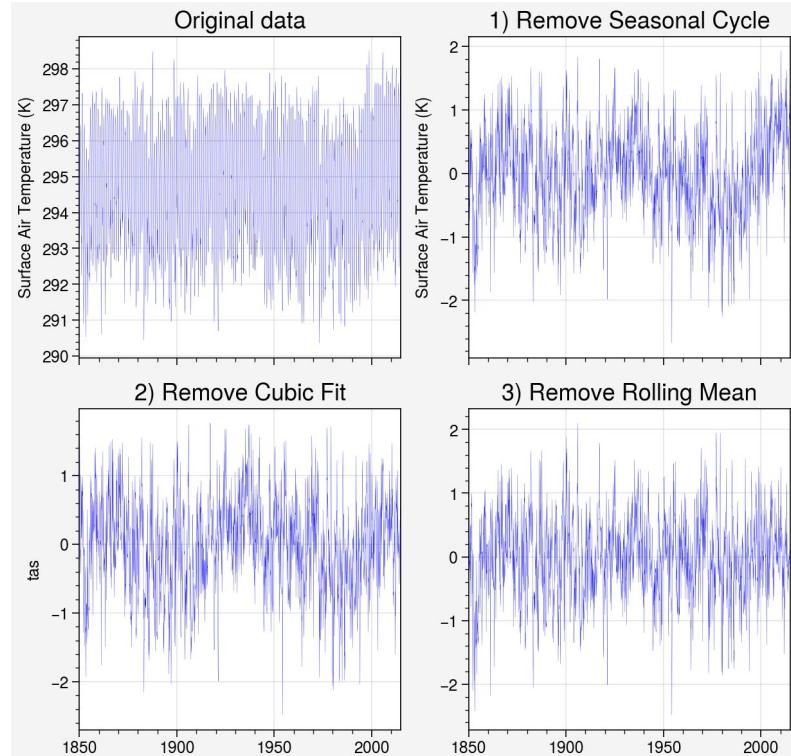
Aug 2021

Revised preprocessing

After some testing, we find that we must update our preprocessing to get the desired ML model behaviour.

We use “no-normalization” preprocessing:

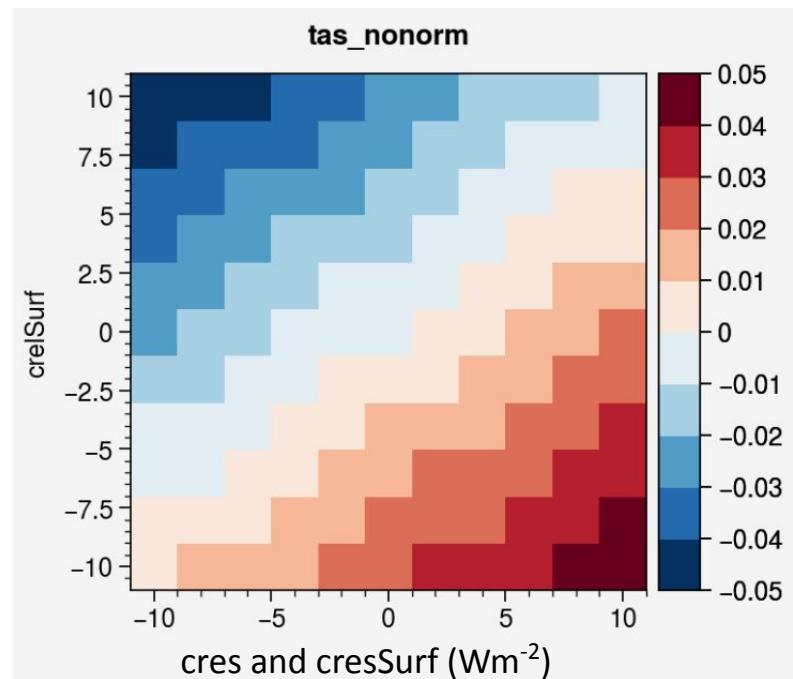
- Deseasonalize
- Detrend
- Remove rolling average
- Convert output variable units so they are $O(1)$
 - Temperature (K); precipitation (mm/day); surface pressure (hPa)



Corrected Causality?

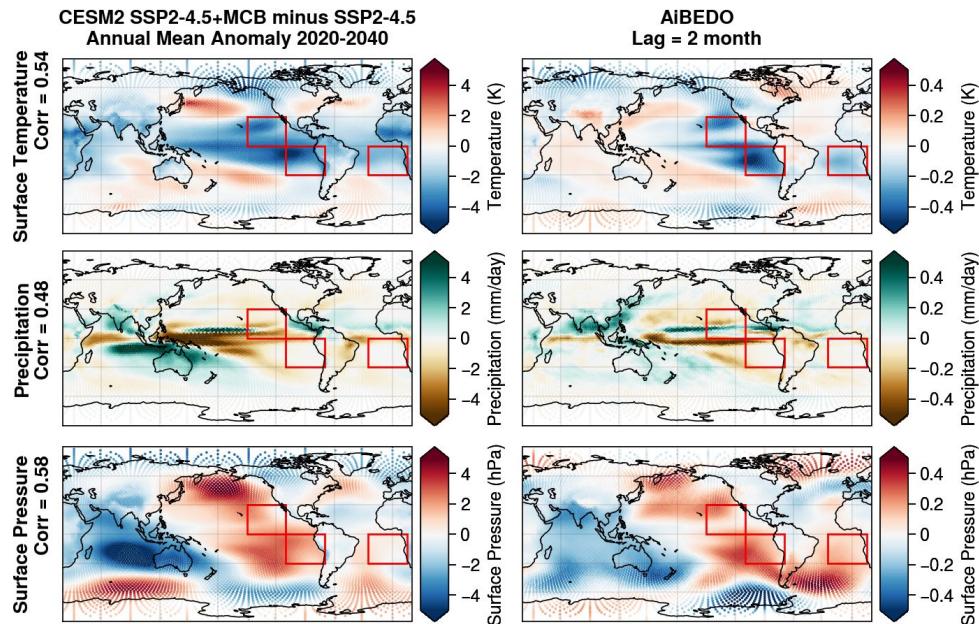
- The CESM2 piControl MLP model projects cooling due to negative cres anomaly
- Thus, the local temperature responds as expected, but what about remote responses to MCB-like forcing?

MLP CESM2 piControl lag=1
Surface temperature anomaly due to radiation anomalies in the NEP



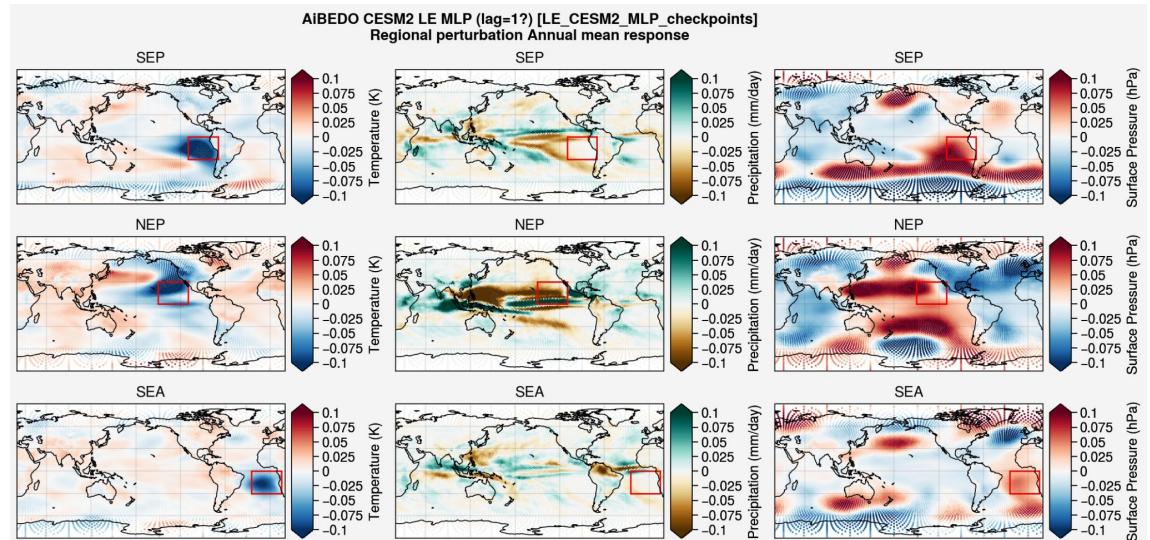
Shortwave cloud radiative effect in AiBEDO

- We test the effect of a radiative perturbations estimated from CAM6 in AiBEDO and compare to CESM2
- AiBEDO projections have good performance in reproducing the pattern of climate response



AiBEDO response to forcing in different regions

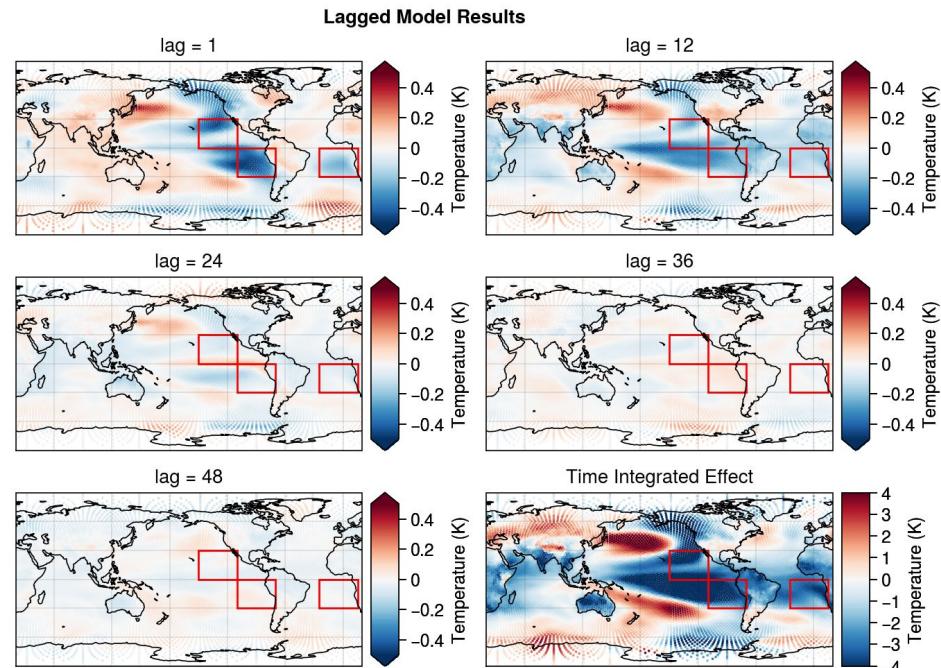
- Responses to regional perturbations resemble CESM2 responses as well
- SEP is not as sensitive to MCB relative to NEP as in CESM2



Model trained at different lags

We plan to resolve the issues with too-small magnitudes in the AiBEDO response by using FDT method

Thus, we train different versions of AiBEDO at different time lags and integrate the outputs.



ESM Intercomparison using AiBEDO

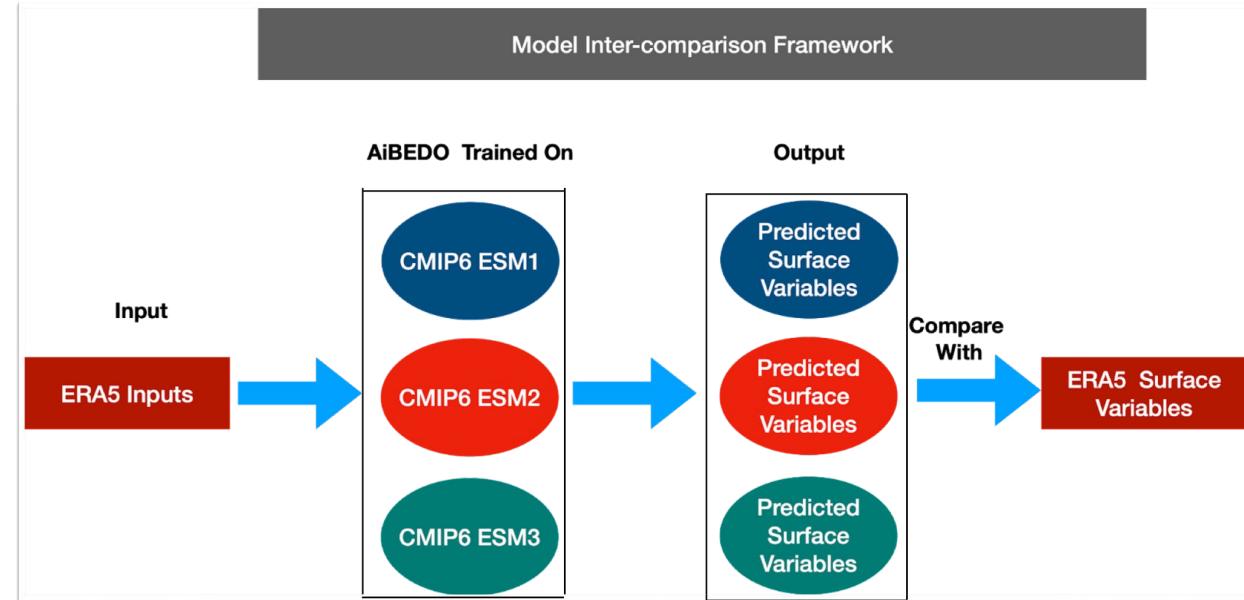
Dipti Hingmire, Keighan Gemmell, Haruki
Hirasawa, Hansi Singh

Understanding interactions between clouds, radiation and surface climate in different ESMs

- The state-of-the-art Earth System Model (ESM) projections of the circulation response to increasing atmospheric greenhouse gas involve large uncertainties at the regional level, mainly attributed to cloud-radiation-climate interactions.
- We are developing a novel framework to test fidelity of ESMs in simulating observed interactions between clouds, radiation and surface climate employing AiBEDO.

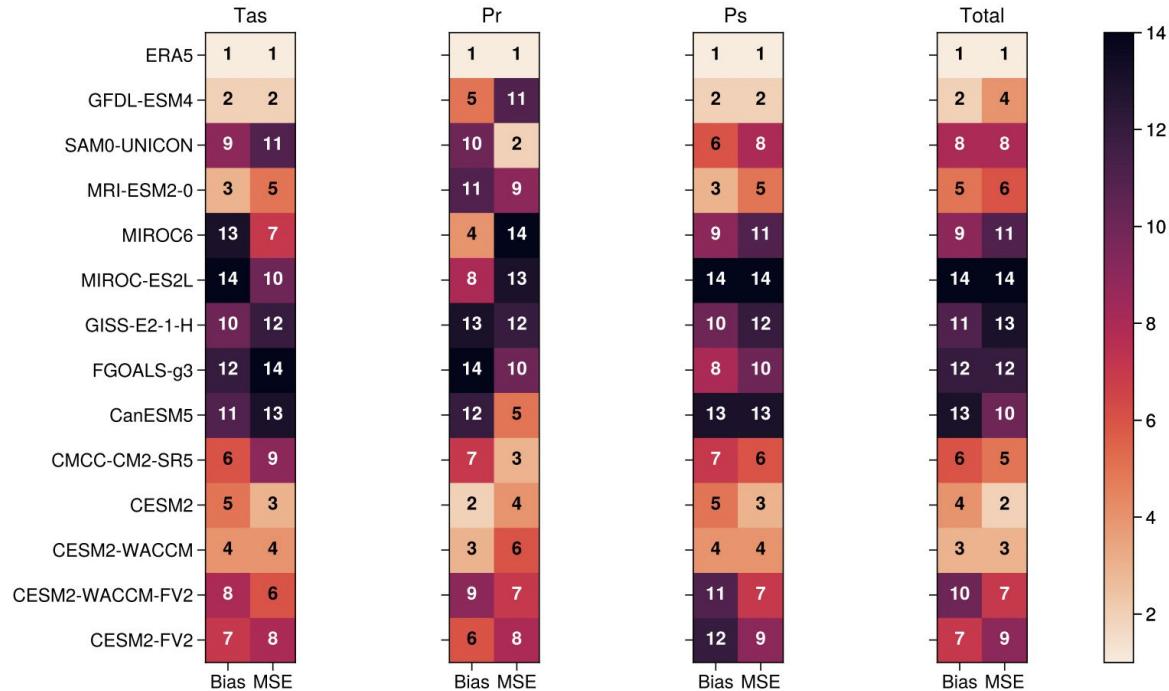
Procedure

- We train AiBEDO on various CMIP6 ESMs. Subsequently, we test the performance of AiBEDO on ERA5 reanalysis.
- The performance of AiBEDO trained on an ESM in predicting ERA5 inputs is a means for assessing how well a given ESM simulates cloud-radiation-climate interactions



ESM Rankings based on ability to simulate the observed interactions between clouds, radiation and surface climate

- Total rankings of ESMs are similar by both the methods, however for individual variable the rankings differ by two methods.
- For precipitation and temperature rankings by both methods differ by large values, e.g. highest difference between two rankings is observed for precipitation for MIROC6

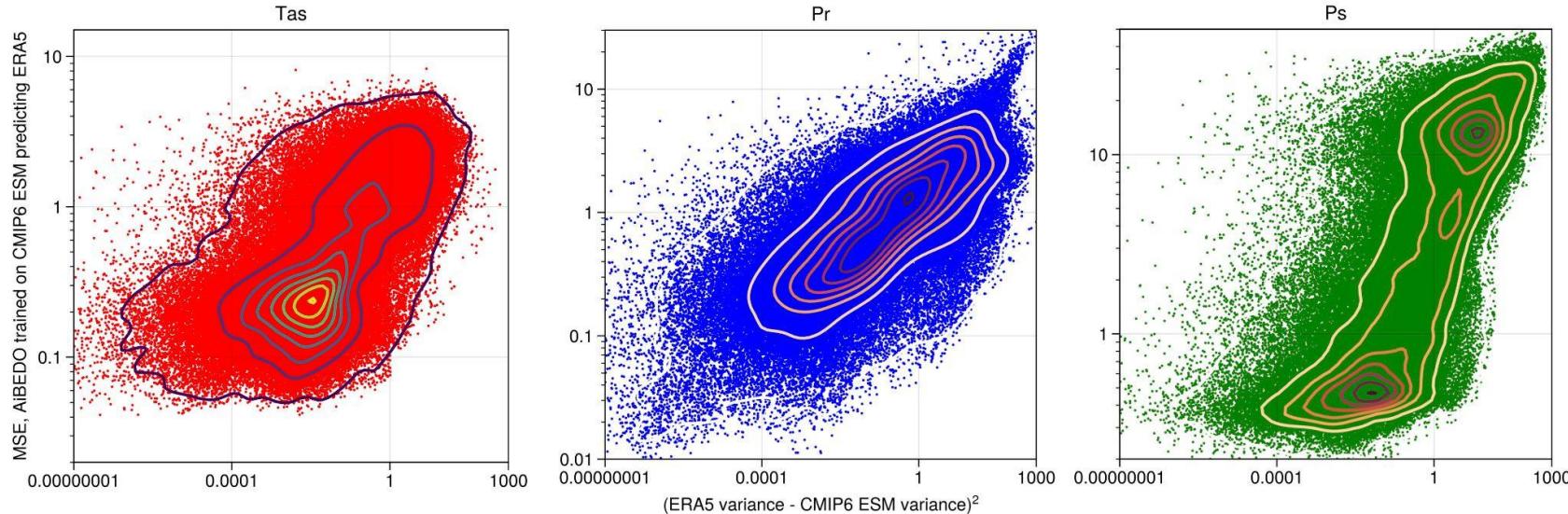


BIAS : Rank based on ESM Bias with ERA5

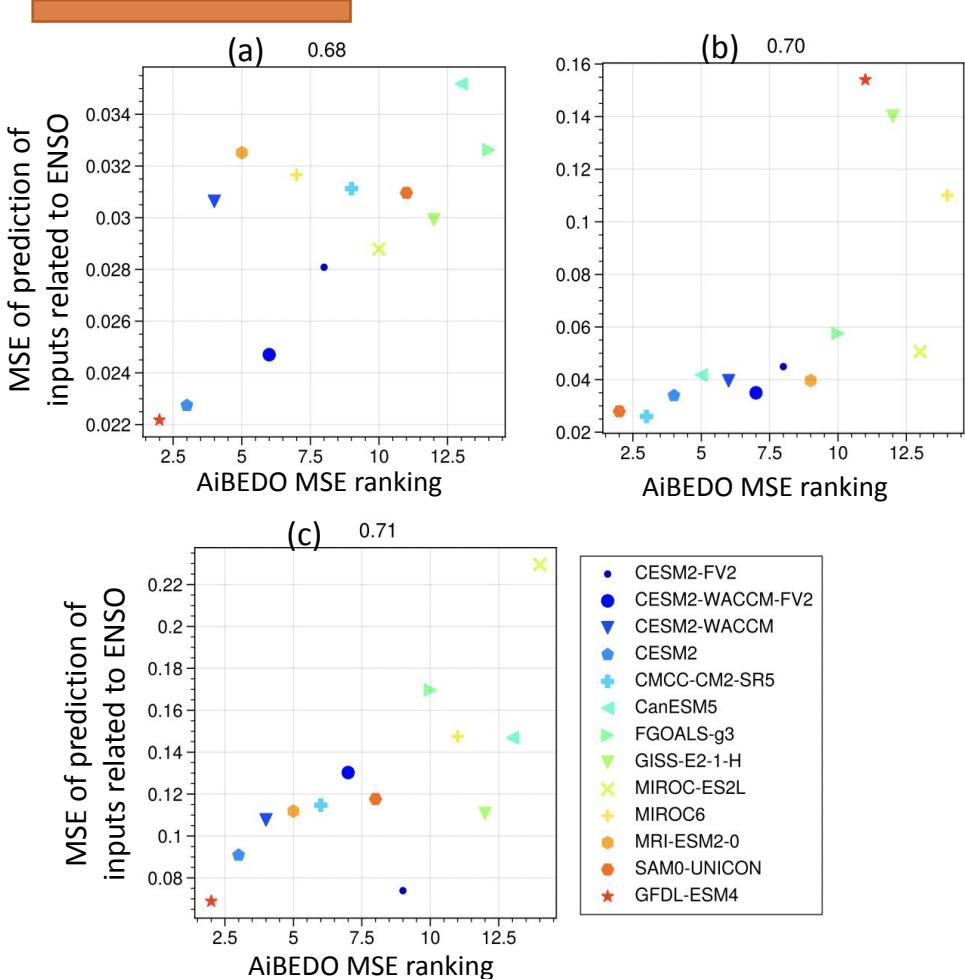
MSE : Rank Based on MSE from AiBEDO trained on ESM predicting ERA5

AiBEDO MSE is higher where variance of ESM used for training differs from variance of ERA5

Scatter plots of square of difference between observed variance (ERA5) and CMIP6 ESMs against MSE for predicting each output variable using AiBEDO trained on respective ESM.



- When ESMs regional variance is similar to ERA5 then AiBEDO trained on that ESM better predicts ERA5 surface variables



ENSO related cloud radiation climate interaction representations in ESMs

- ESMs showing large errors in association of cloud radiation and surface climate interaction related to ENSO (as inferred from MSE of AiBEDO trained on ESM to predict inputs regressed on ENSO index) have large AiBEDO MSE rankings .

Scatter plot of MSE of prediction of inputs related to ENSO by AiBEDO trained on different ESMs and AiBEDO MSE rankings of ESMs for (a) Tas, (b) Pr and (c) Ps



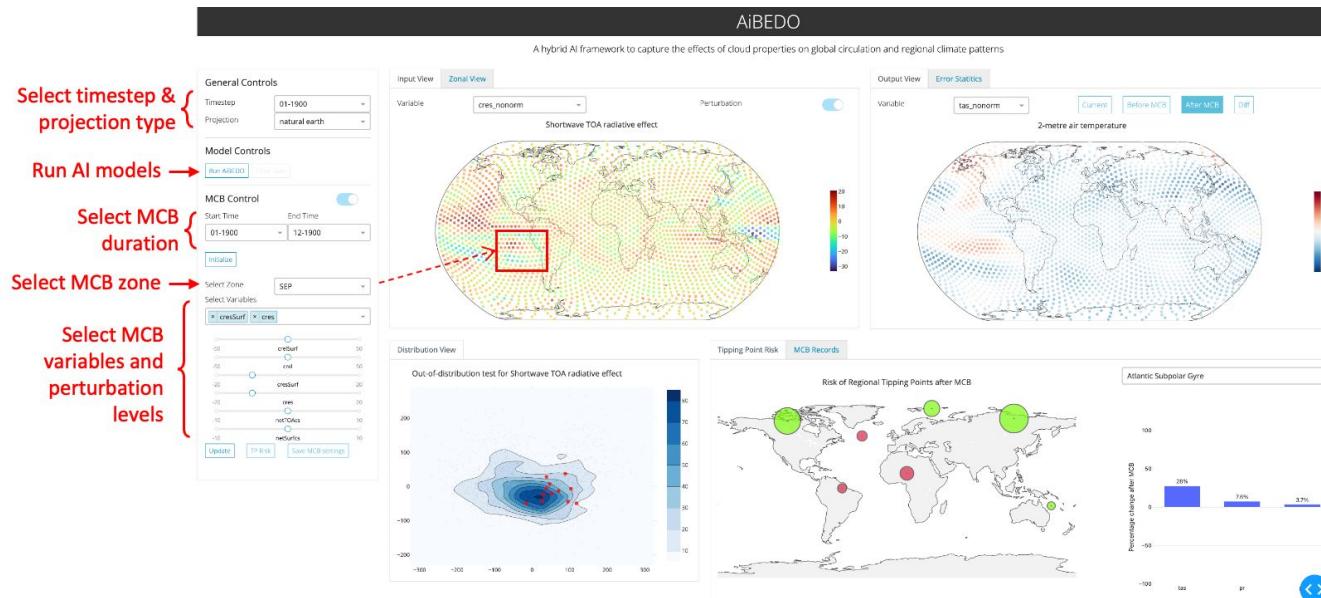
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AIBEDO Visual Analysis System

Subhashis Hazarika

AiBEDO Visual Analysis System

- Interactive visualization system to *load different ESM data, run trained hybrid models and analyze different MCB experiments and their effects*



AiBEDO Visual Analysis System

- Key highlights:
 - Set different MCB scenarios
 - Access their impacts on different regional climate tipping points
 - Monitor out-of-distribution effects
 - Progressively save interesting MCB settings



The screenshot shows a table titled "MCB Records" with a red border around the data area. The table has columns for MCB ID, Start Time, End Time, Latitudes, Longitude, and various perturbation parameters. The data rows are numbered 1 through 4.

MCB ID	MCB Duration (mm-yyyy)		MCB Site (Bounding Box)		Perturbations					
	Start Time	End Time	Latitudes	Longitude	crelSurf	crel	cresSurf	cres	netTOacs	netSurfaces
X 1	01-1900	12-1900	-30.00, 0.00	-110.00, -70.00	0.00	0.00	-10.00	-10.00	0.00	0.00
X 2	01-1900	12-1900	-30.00, 0.00	-110.00, -70.00	0.00	0.00	-10.00	-10.00	0.00	0.00
X 3	01-1900	12-1900	-30.00, 0.00	-110.00, -70.00	-15.50	11.00	-10.00	-10.00	0.00	0.00
X 4	01-1900	12-1900	-30.00, 0.00	-110.00, -70.00	-7.00	-24.50	-2.00	4.50	0.00	0.00

Saved MCB experiment settings

- Demo Video: <https://youtu.be/3dmqYqkSLOo>



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ACTM and AIBEDO documentation

Kalai Ramea

Datasets

Hybrid AI Model Architecture

Climate dynamics

Marine Cloud Brightening

Code usage and tutorials

AIBEDO Reports



Your entire MLOps stack in one open-source tool Get Started in 2 Minutes [See how](#)

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

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



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

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

TUTORIALS AND CODE SNIPPETS

Code Snippets

HYBRID MODELS

Gallery of Hybrid Models



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Welcome to ACTM Gallery

ACTM Program Overview and Performers

Climate change, whether natural or human-driven, has huge potential impacts on geopolitical and economic stability, food and water security, and DoD missions and operations. Current climate models of highly complex, underlying physical processes are computationally intensive and provide limited actionable guidance to policy makers, especially on the risks and causes of sudden tipping-points, runaway feedback loops, and the strategic implications of potential adversarial activity. Third wave AI methods (e.g., neuro-symbolic hybrid AI models that can incorporate context and can extract causal factors and internal structure) have the potential to improve the accuracy of climate forecasts as well as improve the predictability of tipping points and to provide actionable guidance on new data when predictability remains poor. Faster learned models, particularly when used in conjunction with full-scale physics models for validation, will enable policy makers to better explore the climate impacts and risks of policy decisions. Quantifying climate risks is essential to prepare for a range of scenarios such as those related to DoD planning and decision support (e.g., arctic strategy/defense, regional destabilization, global power/economic realignment, base/force locations, and extreme weather threats) and to identify new potential high-value observations (e.g., stratospheric vs. ocean surface vs. deep ocean vs. arctic, etc.) to enhance confidence in forecasts.

The objective of ACTM program is to explore AI-assisted modeling of complex processes related to climate. The specific goals of this effort are to:

- Explore the use of third wave AI methods to enhance models of complex interconnected processes. In particular, to develop hybrid AI models of the climate and Earth system that capture missing physical, chemical, or biological processes with sufficient computational efficiency to explore decadal scale effects and characterize tipping points and bifurcations.
- Develop methods to assimilate diverse data into models and estimate the “value of new data” to enhance confidence in target-specific forecasts relative to state-of-the-art (SOTA) techniques.

Here is a list of projects in ACTM program and their official documentation links:

AIBEDO documentation page:
<https://actm-gallery.readthedocs.io/>

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)
 - Eight abstracts are submitted to AGU (August 3, 2022)
 - Focus areas: ML/AI, Climate dynamics, Interventions, Uncertainty analysis
 - Four accepted for oral presentation, four accepted for poster presentation

AGU Presentations 2022

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

Invited Talks

- Lawrence Livermore National Lab (Kalai)--August 2022
- CU Boulder (Hansi)--September 2022
- University of Waterloo (Hansi)--October 2022
- NASA (Hansi)--October 2022

Summary of Phase 1 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 benchmarked AIBEDO trained on CMIP6 models against observational reanalysis data
 - These sub-selected datasets are used for training AIBEDO v2.0
- We performed model intercomparison using AiBEDO trained on a CMIP6 model against other CMIP6 models (to understand deviations in variability across ESMs)
- We compared MCB experiments using AIBEDO and those that were simulated using ESMs. Our results agree very well, and AIBEDO took only a fraction of the computation power that ESMs need to produce these outcomes.
- Our visualization dashboard shows how the MCB experiments can be run interactively, and its impact on regional climate and tipping points.