Gaia: Global AI Accelerator:
Modeling MJO structures and tipping point analysis

Contractor's Name and Address:
Systems & Technology Research
600 West Cummings Park
Woburn MA 01801

Milestone 3:
Datasets and report on metrics to compare hybrid models over conventional models

Date of Report:
April 13, 2022

UNSW
Climate Change
Research Centre

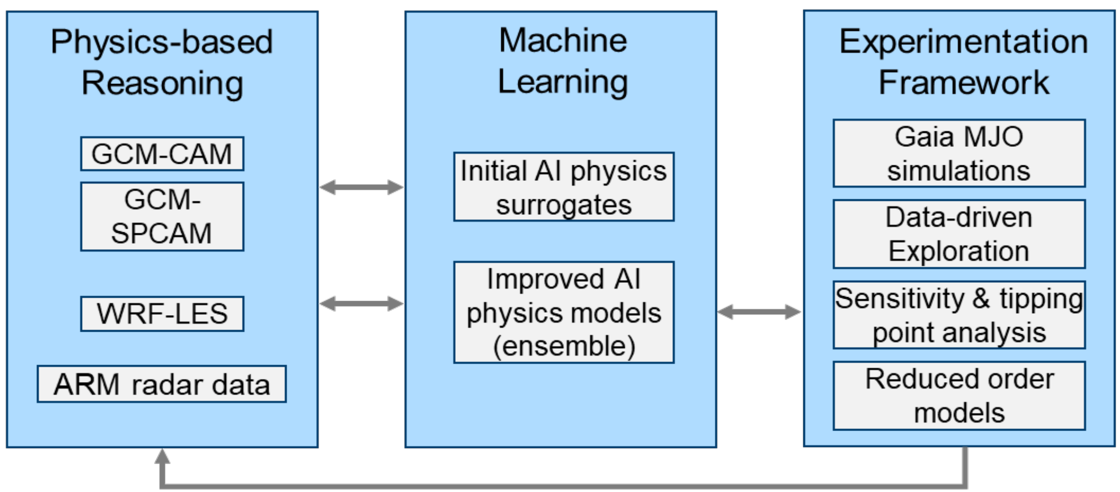
Gaia: Global AI Accelerator

str

UNSW
Climate Change
Research Centre

Problem: Global climate models (**GCMs**) are computationally expensive & lack resolution needed to model causally relevant local convection

Gaia Goal: Develop new hybrid AI tools and methods to accelerate models with improved cloud-resolving physics surrogates; test climate “tipping point” hypotheses, with focus on Madden Julian Oscillations (**MJO**)



GAIA Overview and Milestone 3

UNSW
Climate Change
Research Centre

Specific Objectives

1. Improve the overall computational efficiency of the GCM; and
2. Improve GCM performance and the ability to accurately predict self-organizing atmospheric wave phenomena; and
3. Exploit this improved model to explore previously unobserved regimes and to identify early warning signatures of large-scale changes to such self-organizing phenomena that could have large downstream global weather and climate impacts.

M3 Topic: Deliver prepared datasets for use in Phase I. Report on metrics to be used to compare the benefits of hybrid models of conventional models

GAIA Datasets

str

UNSW Climate Change Research Centre

Datasets generated so far

GCM/CAM4 (CESM1.0.6)

- Four years simulated data
- 30 minute timestep
- 2.5 deg grid (144 x 96)
- 30 levels
- Currently being extended to a ten-year run

GCM/SPCAM (super-parameterized CAM with Morrison microphysics, no CLUBB)

- Three years simulated data
- 20 minute timestep
- 16 SAM (the System for Atmospheric Modeling) columns
- 26 levels

GCM/SPCAM with CLUBB (unified cloud parameterisation) and Morrison microphysics

- Three years simulated data
- 20 minute timestep
- 16 SAM columns
- 26 levels

GAIA Datasets

UNSW Climate Change Research Centre

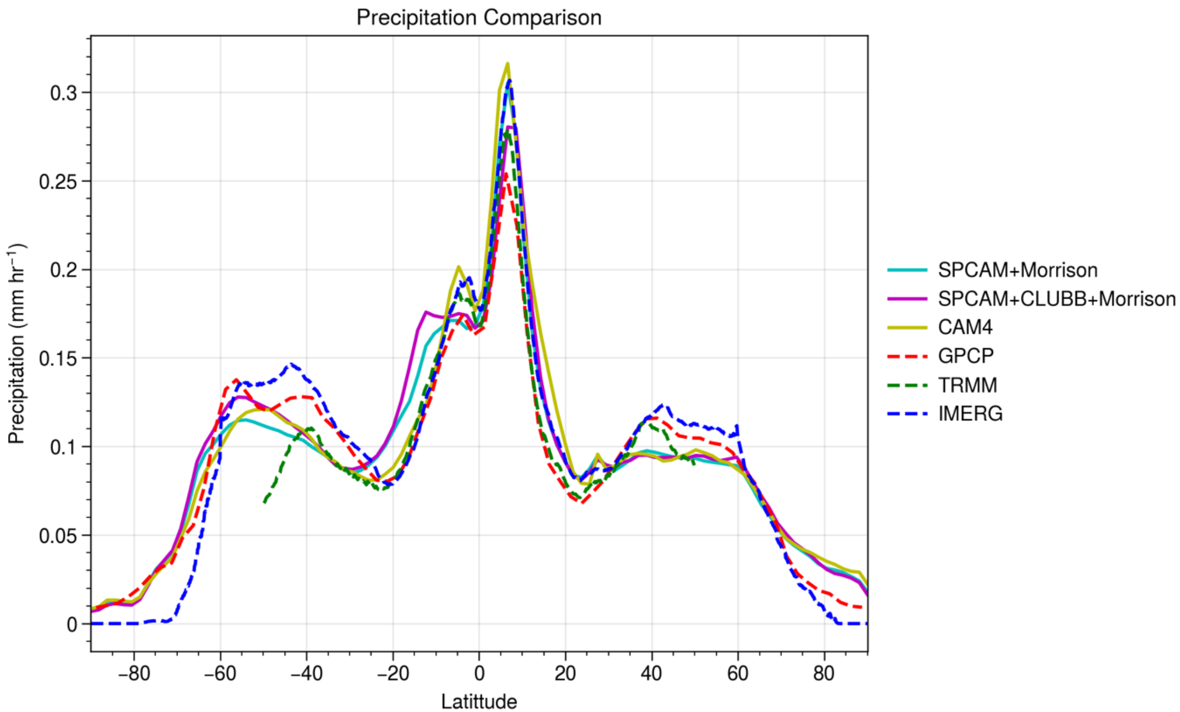
The model output is available every three hours with an additional model time step to account for memory. Note that all simulations include the following key variables:

- Total (convective and large-scale) precipitation rate (liq + ice), PRECT
- Convective precipitation rate (liq + ice), PRECC
- Q total physics tendency, PTEQ
- T total physics tendency, PTTEND
- Specific humidity, Q
- Temperature, T
- Zonal wind, U
- Meridional wind, V
- Vertical velocity, OMEGA
- Sea Level Pressure, SLP
- Solar Insolation, SOLIN
- Sensible Heat Flux, SHFLX
- Surface Latent Heat Flux, LHFLX
- Net Solar Flux at Surface, FSNS
- Net Longwave Flux at Surface, FLNS
- Net Solar Flux at the Top of Model, FSNT
- Net Longwave Flux at the Top of Model, FLNT

GAIA Model Evaluation, (1)

All simulations evaluated zonally for Precipitation and Outgoing Longwave Radiation (OLR) from satellite observations

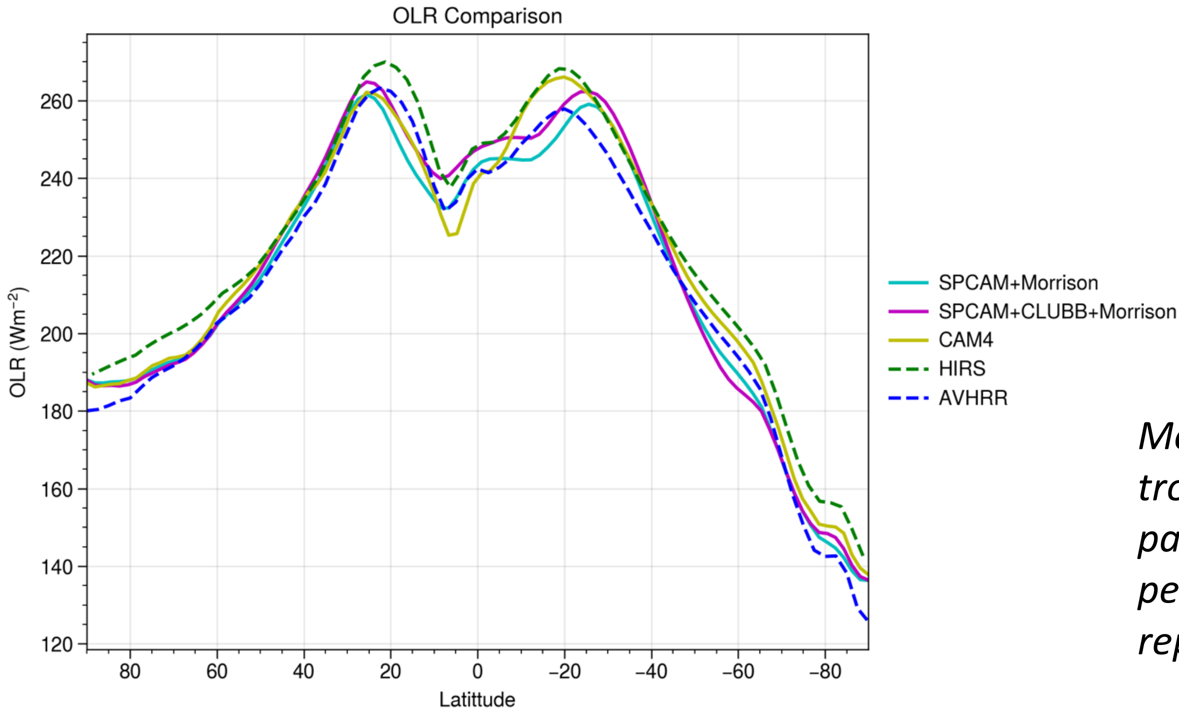
UNSW
Climate Change
Research Centre



Zonal distribution of precipitation using model runs (solid lines) and satellite observations (dashed lines)

GAIA Model Evaluation, (2)

UNSW Climate Change Research Centre



Zonal distribution of Outgoing Longwave Radiation (OLR) using model runs (solid lines) and satellite observations (dashed lines)

Modelled OLR is mostly underestimated in the tropics, but SPCAM with CLUBB (unified cloud parameterisation) and Morrison microphysics perform better, likely due to the representation of deeper clouds

AI Surrogate

str

UNSW
Climate Change
Research Centre

- We trained both a baseline and a memory-based model on the larger SPCAM dataset (3 years). We observed meaningful improvement in skill when incorporating memory
- We trained a baseline model on the larger CAM4 dataset (4 years) and performed ablation studies on the input variables. As previous studies observed, temperature, humidity and omega have the most impact on skill

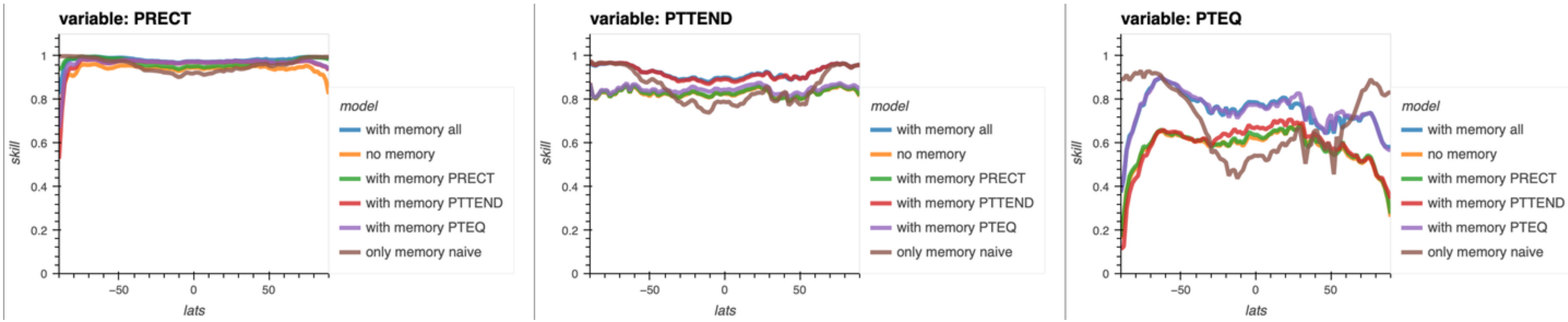
To quantify impact of memory, we trained several model configurations on the SPCAM data covering 4 years. We used first three years to training and validation and the last year to test, training four different models:

- *No memory*: baseline model consisting of 7 FCN (fully connected layers)
- *With memory all*: baseline model architecture with additional inputs of PRECT (total precipitation), PTTEND (temperature tendency), PTEQ (humidity tendency)
- *Only memory naïve*: naïve model that simply predicts the previous timestep
- *With memory [VAR]*: model using only a single output variable from previous timestep as additional input

AI Surrogate – assess skill with added memory

str

UNSW
Climate Change
Research Centre



Figures above show skill averaged over levels and longitudes as a function of using output from the previous timestep as memory. Each panel shows skill for predicting a different variable. Each curve represents a model with different memory configurations.

AI Surrogate – ablation study

str

UNSW Climate Change Research Centre

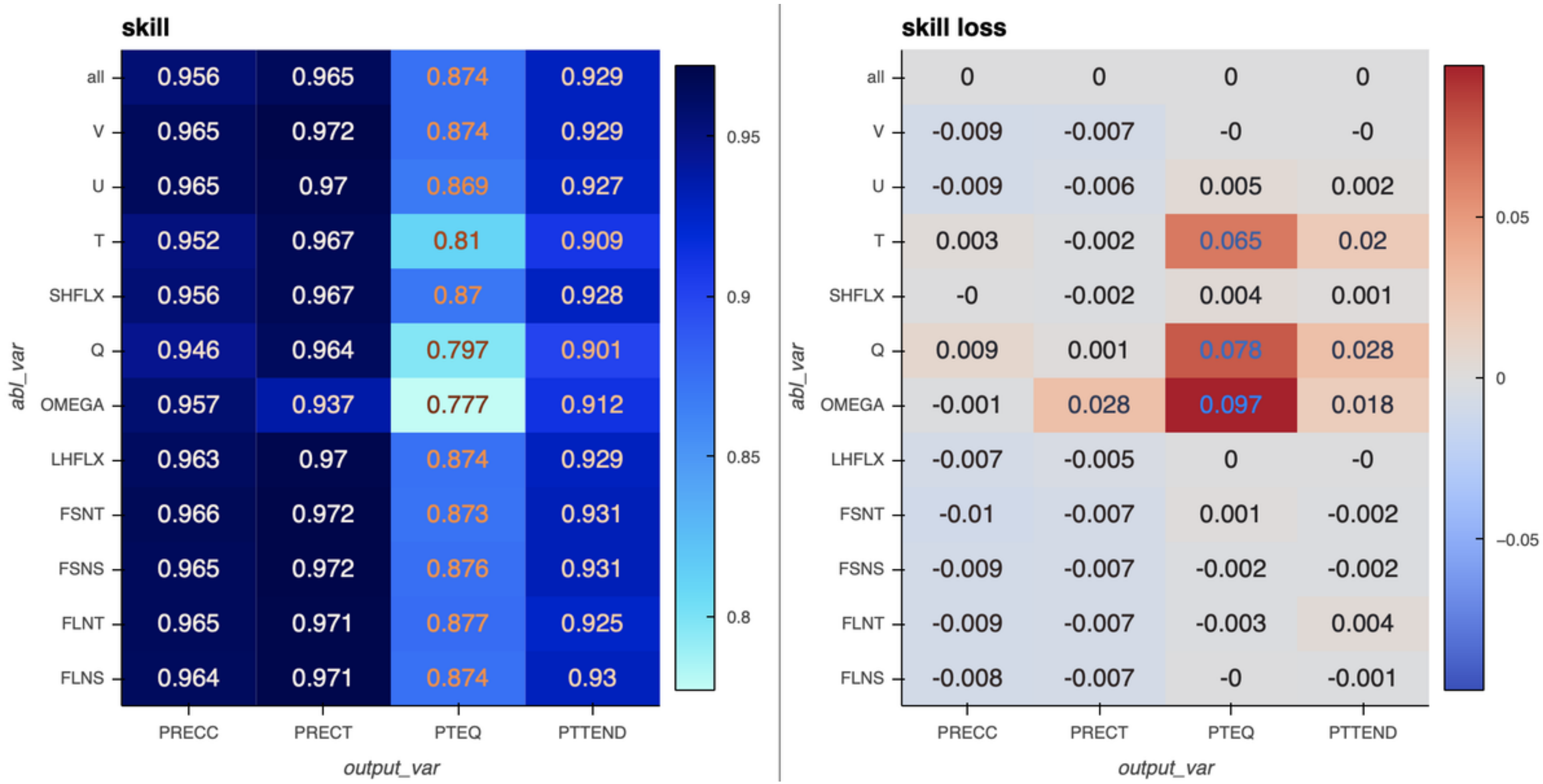


Figure above is Ablation of input variables for baseline model trained on CAM4 data. Left panel shows skill. Right panel shows decrease in skill if an input variable is removed (rows); Temperature (T), humidity (Q) and vertical velocity/pressure (Omega) have the greatest impact.

Step for next month

str

UNSW
Climate Change
Research Centre

- Develop tools to export pytorch model into a torchscript C++ model to be compatible with running inside the GCM
- Develop techniques to identify input space regions that achieve maximal disagreement between surrogate predictions. This will serve as a means to select candidate input regimes when running the more computationally expensive LES simulations