The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery Milestone 12 Report

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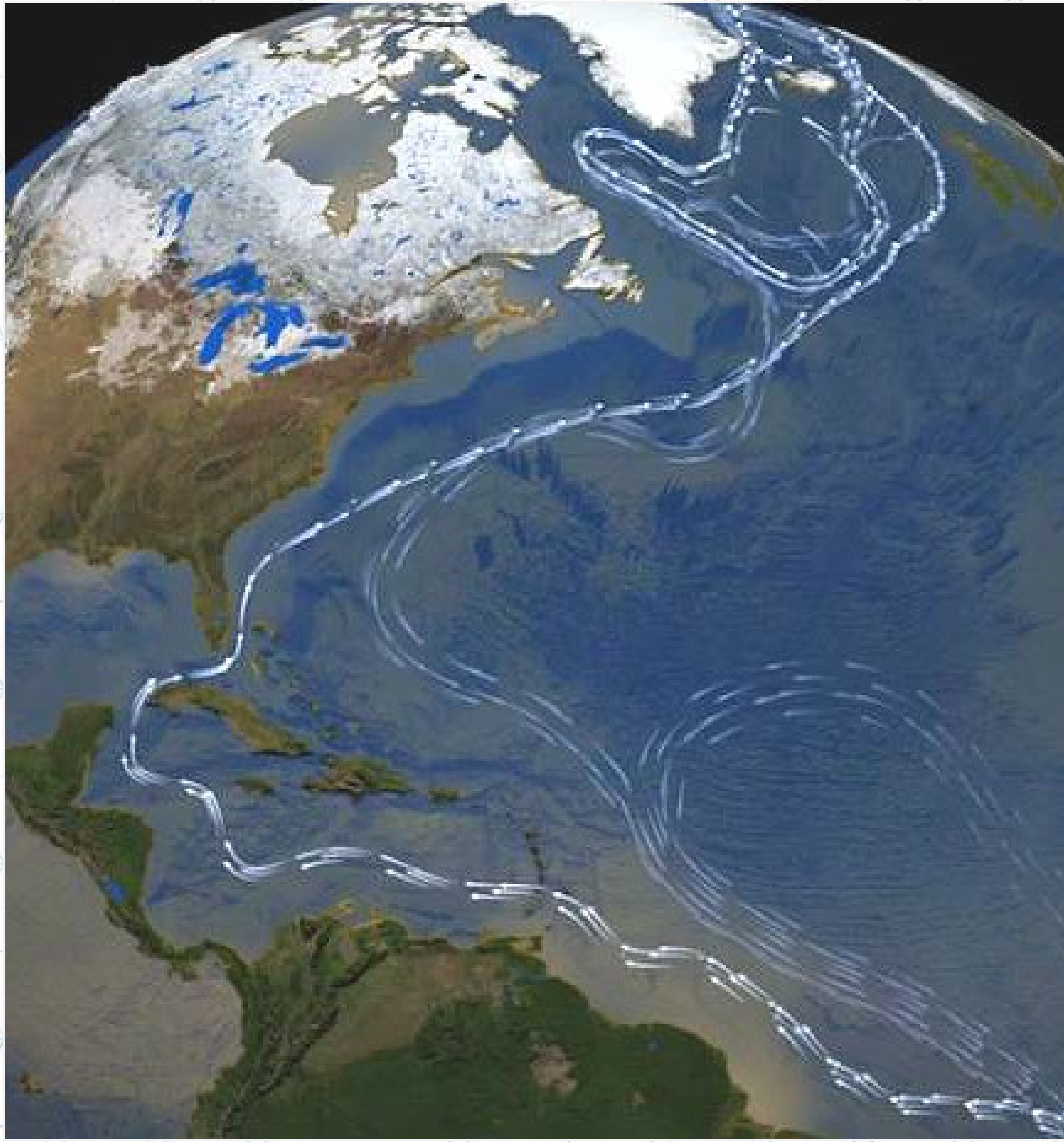

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Team

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

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Overview

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- This technical report covers the period of April 10, 2023, through June 15, 2023.
- The deliverable for this milestone is this report.

Team Resources

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- Code
  - https://github.com/JHUAPL/PACMANs - Public to all (Up to date with all code from start to MS 3 deliverables)
  - https://github.com/JHUAPL/PACMANs_internal - Public to DARPA, JHU, and APL (Hold until internal approvals)
- Documentation
  - https://pacmans.readthedocs.io/en/latest/
- Datasets
  - https://data.idies.jhu.edu/PACMANS/

Goals and Impact

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

The goal for this milestone includes:

- Deliver final Phase 2 report on comparison of results with conventional models, documenting the established benefits and new capabilities of hybrid models.

Task 1.6 Use Case Ocean Modeling Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Subtask Description: We will report final details of the use case.

- In this report we describe use case modeling related to the global circulation under forcing mechanisms.

- We also describe the research related to CESM2 and GISS box model calibration efforts and its impact on model disagreement research.

Task 1.6 Use Case Ocean Modeling Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Our use cases involve the shutoff of the global overturning circulation under a range of forcing mechanisms associated with global warming. Within the box model this has generated several interesting results.

1. **Identification of the role of polar amplification in driving shutoff of the overturning**. In the box model, if all latitudes warm at the same rate and freshwater fluxes increase at a rate of 7% the overturning remains stable at very high levels of warming (8-10K). However, when the observed Northern Polar amplification is included in the model, the same physics produces overturning collapse at a much lower value of warming (3-4K). A key here is that as the climate warms, it requires less of a difference in temperature between low and high latitudes to produce the same density difference.

Task 1.6 Use Case Ocean Modeling Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

2. **Identification of mechanisms that allow the overturning to restart.** We have found that the deepening of the pycnocline and increasing lateral diffusive salt flux to high latitudes represents a potential mechanism for restarting the overturning not previously recognized in the literature.

3. **Interbasin tipping points.** Our six box model results demonstrate a complicated structure of tipping points between the basins. We find three states of overturning in each basin: a shallow, reversed circulation where the water in the high latitudes is lighter than the low-latitudes due to a freshwater cap, an intermediate circulation similar to the modern Pacific where water sinks in the northern latitudes but returns to low latitudes as intermediate water, and the situation we find in the North Atlantic where water becomes sufficiently dense to sink into the deep. We find that our baseline box model exhibits transitions from a Deep Atlantic/Intermediate Pacific to a Deep Atlantic/Reversed Pacific to a Reversed Atlantic/Intermediate Pacific to a Reversed Atlantic/Reversed Pacific state.

Task 1.6 Use Case Ocean Modeling Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- We have identified a particular use case in which some versions of a full coupled model under global warming see an overturning collapse and rapid recovery, while others do not.

- This result is reported by our collaborators at GISS in Romanou et al. (in press).

- As shown in Figure 1, under the scenario of greenhouse gas forcing shown in the top panel, the depth of mixing in the Labrador Sea collapses over the course of the 21st century, but recovers at very different times during the following century. The overturning stream function follows a similar range of paths.

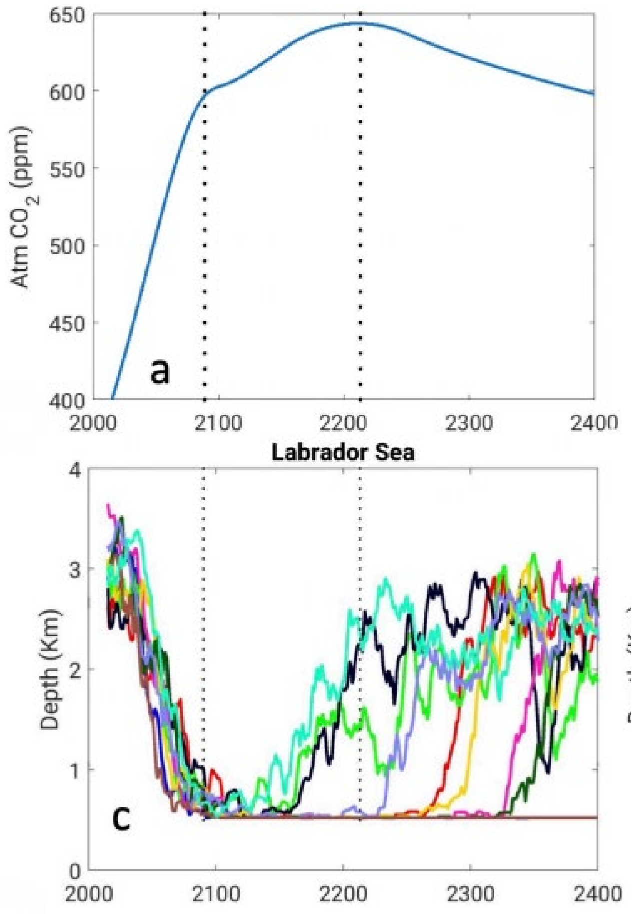


Figure 1: *Bifurcation in the re-establishment of convection in the Labrador Sea under the SSP2.6 scenario (top panel shows CO2). Bottom panel shows depth of mixing in Labrador Sea from 10 ensemble members. (From Romanou et al., in press).*

Task 1.6 Use Case Ocean Modeling Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- We have also begun CESM simulations, but they have not run out far enough to yield robust results – further scientific questions remain.

- An important recognition from our work is that this re-establishment of the overturning under constant conditions is not predicted by the classic fold bifurcation theory.

- Under fold bifurcation theory, the forcing must reverse in order to re-establish an overturning. However, this re-establishment behavior is frequently found in our box model results (and indeed represented one of the challenges in exploring the resulting phase space of the box model).

Task 1.6 Use Case Ocean Modeling Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- We are approaching analysis of this use case in two ways. The first is by fitting a box model to the use case and examining whether it produces similar behavior.

- The second is to use modal decomposition to reduce the dimensionality of the space and examine whether the dynamics change as we move into global warming.

- This work has resulted in the finding that one can develop an oscillator mechanism whereby positive anomalies in one mode produce positive tendencies in a second mode, which then produces negative tendencies in the first mode.

Task 1.6 Use Case Ocean Modeling Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- This oscillator is illustrated in Figure 2, which shows the structure of the two modes in the preindustrial climatology.
- A positive value of mode 1 (cooling/freshening in the Labrador Sea) produces a positive trend in mode 2 (southward extension of the subpolar gyre).
- However, positive mode 2 produces a negative trend in mode 1 (warming, salinification of the Labrador Sea).

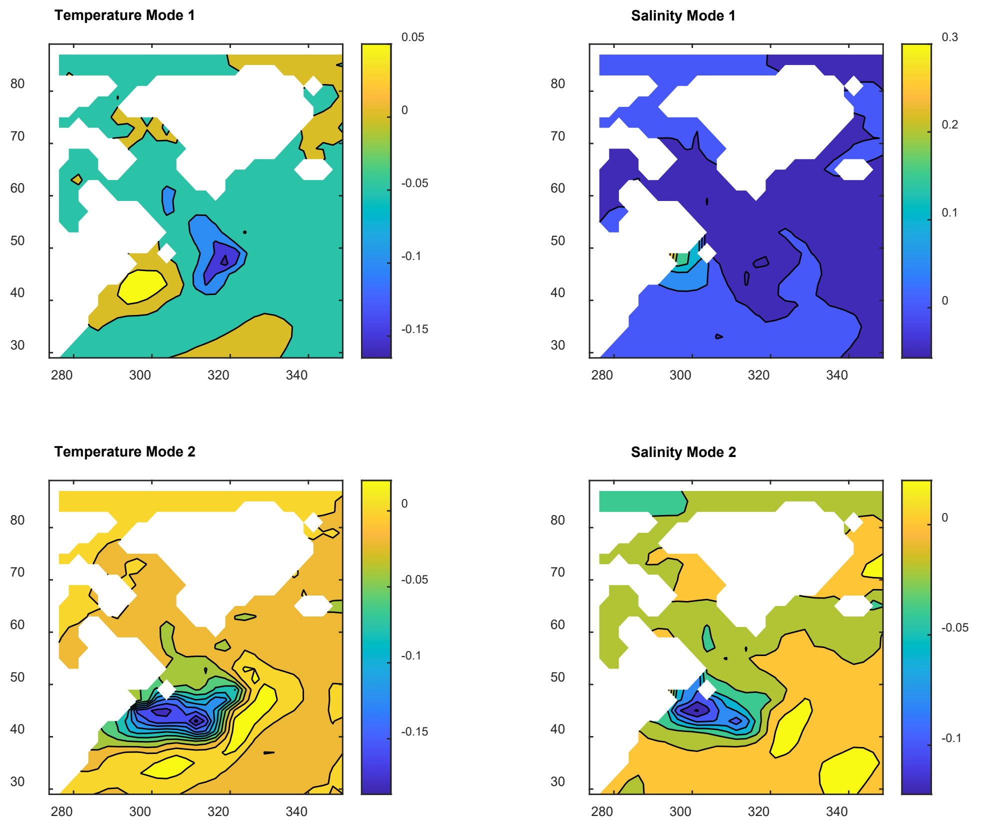


Figure 2: *Modal decomposition of SST (left) and SSS (right) modes of variability for model in previous figure. Variability in mode 1 is associated with overturning.*

Task 1.6 Use Case Ocean Modeling Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

There are two major items which we have learned from this analysis:

1. While the linear analysis is capable of producing an oscillation, the time scales involved are too slow, suggesting an opportunity to use more **nonlinear techniques** such as Koopman operators.

2. There **are** changes in the modal structure as we look at simulations under global warming.

Task 1.6 Use Case Ocean Modeling Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- In particular, in the preindustrial case, changes in the overturning do not result in salinity changes in the Arctic.
- However, as the Arctic warms and more of it melts each summer, it becomes more sensitive to the changes in overturning.
- This change in modal structure may be critical to coupling, as Romanou et al. (2023) suggest that it is freshwater anomalies emanating from the Arctic that determine the timing of shutoff and re-establishment of convection.

Task 1.6 Use Case Ocean Modeling - CMIP model disagreement

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Sample of time series for multiple global climate models

- 4 CMIP models' SSP5-85 runs processed, showing model disagreement.
  - MPI-ESM1-2-LR: Max Planck Institute for Meteorology Earth System Model
  - ACCESS-CM2: Australian Community Climate and Earth System Simulator
  - CESM2: USA, Community Earth System Model
  - CAN-ESM5: Canadian Earth System Model
- 3 of 4 models show strong decrease in AMOC strength, but pycnocline depth changes are inconsistent shown in Figure 3.

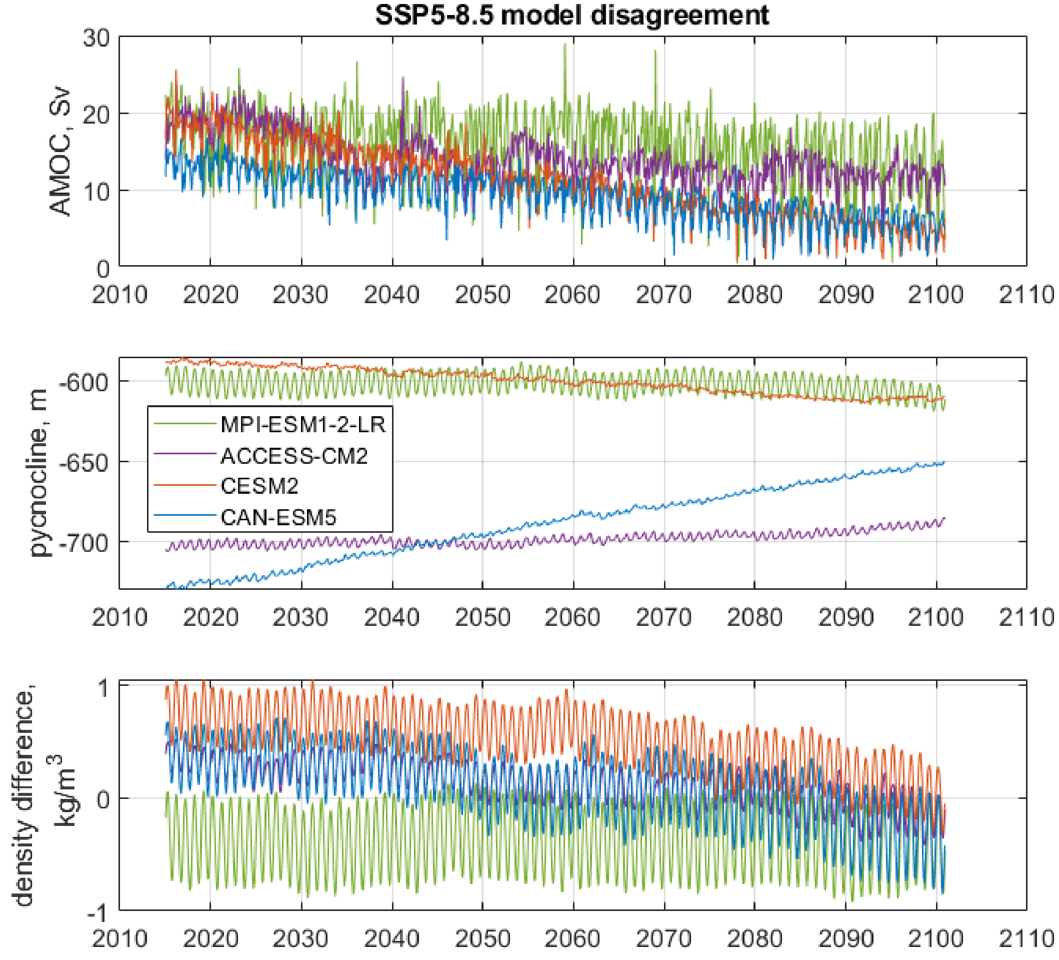


Figure 3: *SSP5-8.5 Model disagreement across ensemble members.*

Task 1.6 Use Case Ocean Modeling

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

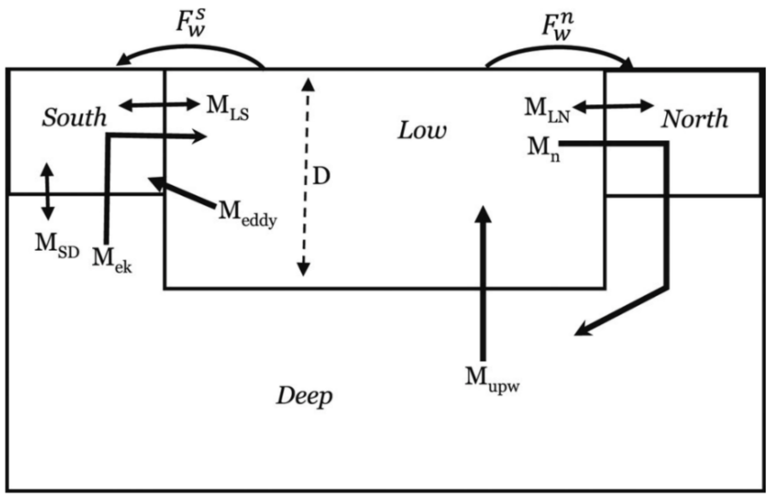


Figure 4. *Four box model*

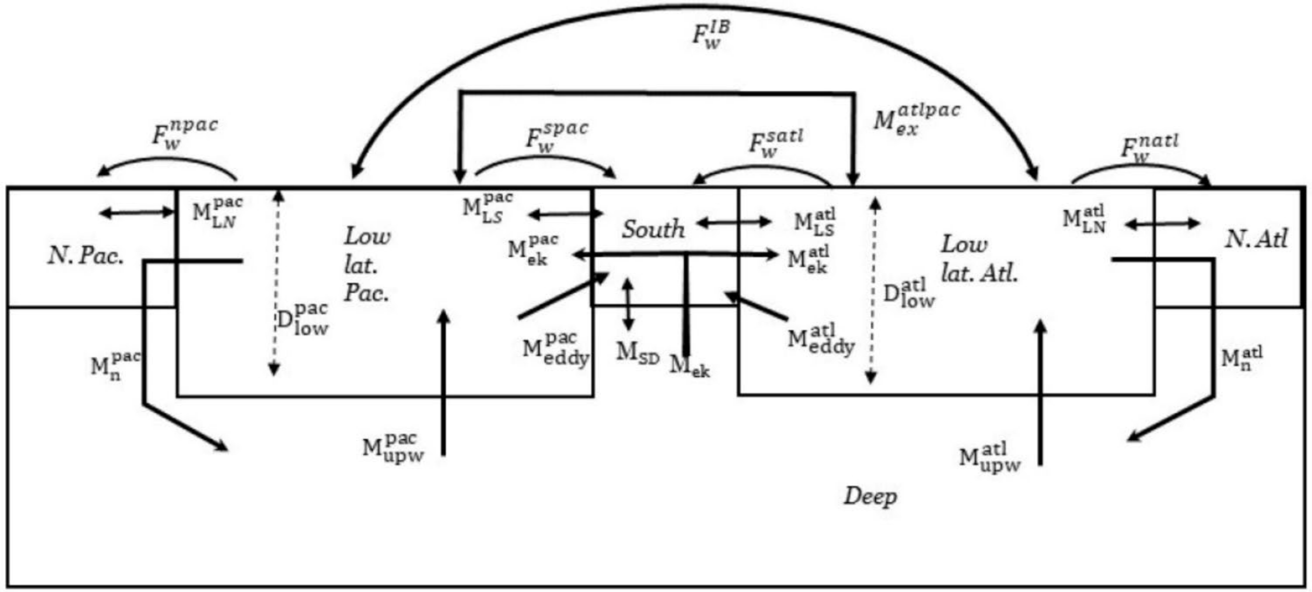


Figure 5. *Six box model*

- Four box model has been demonstrated to well represent CESM2 dynamics. (Figure 4)
- Six box model has been developed and analyzed. (Figure 5)

Task 1.6 Use Case Ocean Modeling - Fitted CESM2 to Four Box

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Fitting Method

- Depth of high-latitude boxes chosen to be 327m for CESM2 and 300m for GISS-E2.1.
- Fit ϵ from least-squares for AMOC.
- Fit the Gent-McWilliams diffusivity AI, from least-squares for the eddy flux.
- Vertical diffusivity K_v is fit to have the mean upwelling flux match between the theory and the volume flux balance for the low-latitude box.
- Figure 6 shows 11 members simulated using parameters from 1st member.

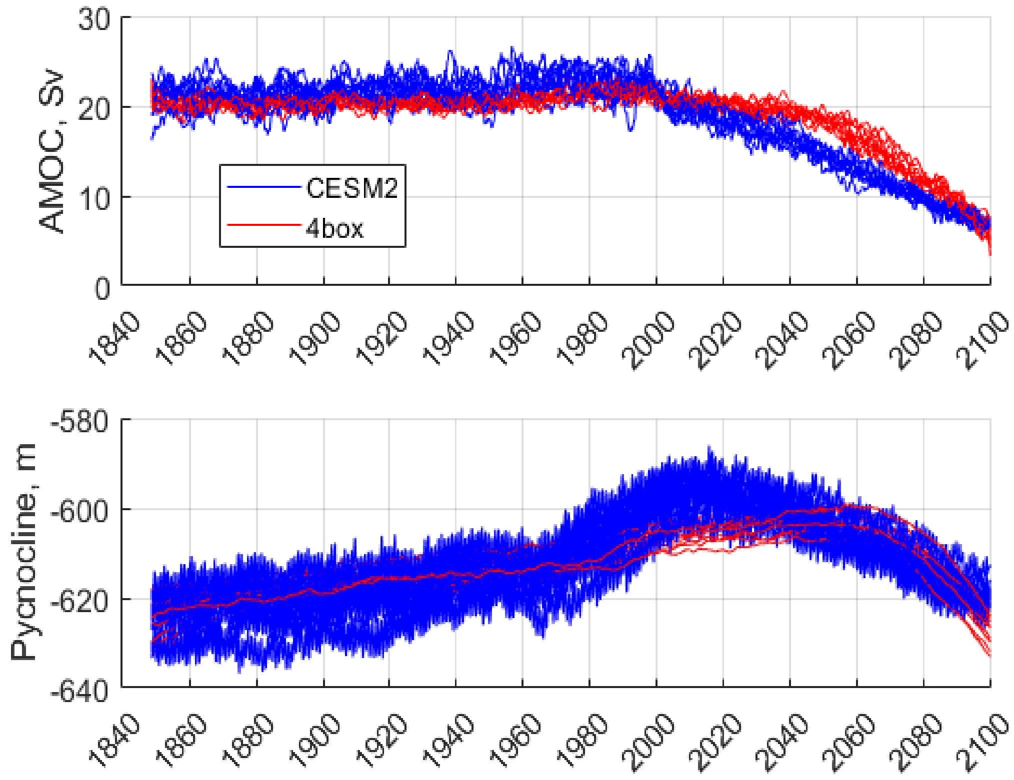


Figure 6: *Comparing the CESM2 data with the fitted four box model. General shape/trend is correct for both AMOC strength and pycnocline depth.*

Task 1.6 Use Case Ocean Modeling - Fitted CESM2 to Four Box

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- Depth of high-latitude boxes chosen to be 327m for CESM2 and 300m for GISS-E2.1.
- Fit ϵ from least-squares for AMOC.
- Fit the Gent-McWilliams diffusivity AI, from least-squares for the eddy flux.
- Vertical diffusivity K_v is fit to have the mean upwelling flux match between the theory and the volume flux balance for the low-latitude box.
- Figure 7 shows variation in parameters as fitted across 11 members. This represents the uncertainty in the value of these parameters, and is small (2-7%).

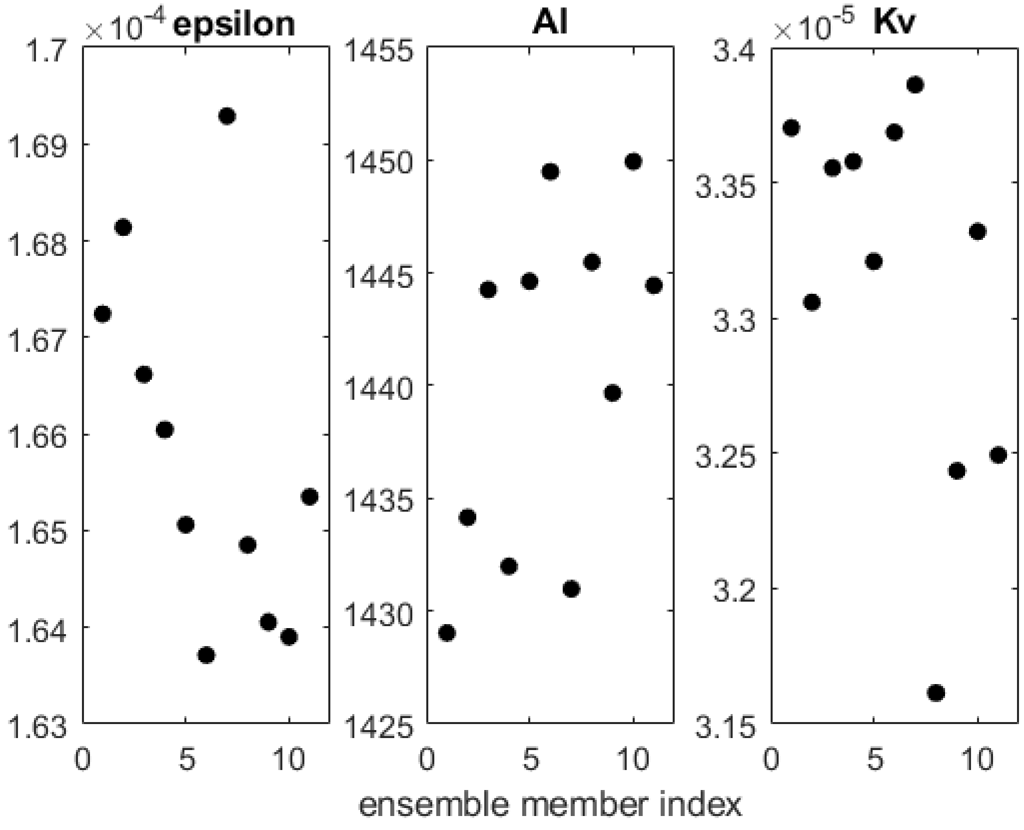


Figure 7: *Variation in the fitted the four box model parameters across the CESM2 ensemble members.*

By fitting multiple ensemble members, we get a measure of uncertainty on their values for CESM (helpful for model disagreement analysis – see next slide)

Task 1.6 Use Case Ocean Modeling - Fitted CESM2 and GISS-E2.1 to Four Box

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Fitting one member of each

- First ensemble member of CESM2 Large Ensemble.
- Historical and SSP3-7.0 run of GISS-E2.1.
- Table 1 below shows the values.

	CESM2	GISS-E2.1
ϵ	1.74e-4	1.49e-4
AI	1430	1610
K_v	3.37e-5	3.27e-5

Table 1. *Comparison between CESM2 and GISS parameter where epsilon and AI for GISS are outside of the uncertainty range of CESM2 values.*

Question: can these emergent parameters help explain inter-model differences in AMOC projections under a warming climate?

Approach: Examine separatrix of the two for AMOC on/off.

Task 1.6 Use Case Ocean Modeling Final Report - Differences in AMOC for 2 surrogates

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

GISS-E2.1

CESM2

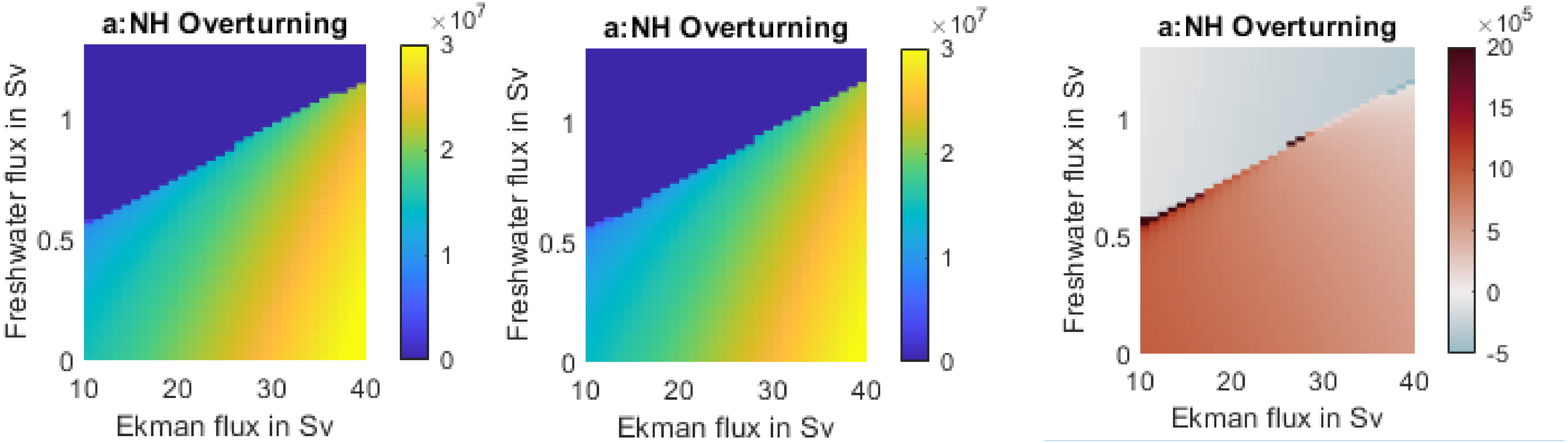


Figure 8. *GISS and CESM2 as a function of Ekman flux and Freshwater flux.*

Both represent the same world, both look similar

Difference of 0.2Sv Fwn or 0.5Sv Mek in shutoff
GISS AMOC 0.7Sv stronger in 'on' state

Task 2.7 Phase 2 Data Final Delivery

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Subtask Description: We will document updates and deliver any new datasets.

- In this report we describe the new datasets that have been developed and shared for both the box models and calibrated CESM2 and GISS models.

Task 2.7 Phase 2 Data Final Delivery

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Four box processed CMIP global model data:

11 members of CESM2 large ensemble-- USA, Community Earth System Model.

1 each of:

- GISS-E2.1, USA, NASA Goddard Institute for Space Science
- MPI-ESM1-2-LR: Max Planck Institute for Meteorology Earth System Model
- ACCESS-CM2: Australian Community Climate and Earth System Simulator
- CESM2: CAN-ESM5: Canadian Earth System Model

Task 2.7 Phase 2 Data Final Delivery

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Box model datasets used for machine learning:

- Python package of the box models allows one to specify initial conditions and parameter values.
- Produces datasets in netcdf format.

Four box model ML dataset:

- Recreates the Gnanadesikan experiments (in Matlab code).
- Generates the same plots.
- Enables creation of labeled training data for training machine learning algorithms and temporal training data for training the AI surrogates.

Six box model ML dataset:

- Created using a grid search approach.
- Enables creation of labeled training data for training machine learning algorithms and temporal training data for training the AI surrogates.

Task 3.8 AI Physics-Informed Surrogate Model Phase 2 Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Subtask Description: We will report final details of perceived benefits and capabilities based on the evaluations and benchmarks.

- In this report we highlight the benefits of using the hybrid models and describe the latest results in the bifurcation analysis applied to the six box model.

Task 3.8 AI Physics-Informed Surrogate Model Phase 2 Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- The AI/Hybrid model approach has been **extremely effective** in generating new hypotheses which we expect to be the focus of future modeling work.
- In particular, the process of dimensionality reduction forced us to grapple with key shortcomings of theory.
- We describe these shortcomings of theory.

Task 3.8 AI Physics-Informed Surrogate Model Phase 2 Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

1. We had to reconcile the work in the literature about the competing roles of density contrasts between high and low latitudes and northern vs. southern latitudes.

    - Doing this has generated a significant series of hypotheses that can be tested using idealized models.

2. The fold bifurcation theories that have dominated discussions of overturning shutoff and collapse do not **spontaneously produce recovery**, which is seen in both the coupled models and the box models.

    - We have framed a number of theories for how such recovery might occur, which will focus future exploration of the CMIP6 models.

Task 3.8 AI Physics-Informed Surrogate Model Phase 2 Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

3. The AI-based hybrids **focus attention on models near tipping points**, which is a very different approach than previously taken in climate modeling.

    - It motivated us to design new experimental designs and model suites.

4. The development of a **wider suite of tipping points** than previously recognized offers interesting opportunities from a dynamical systems point of view.

Task 3.8 AI Physics-Informed Surrogate Model Phase 2 Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

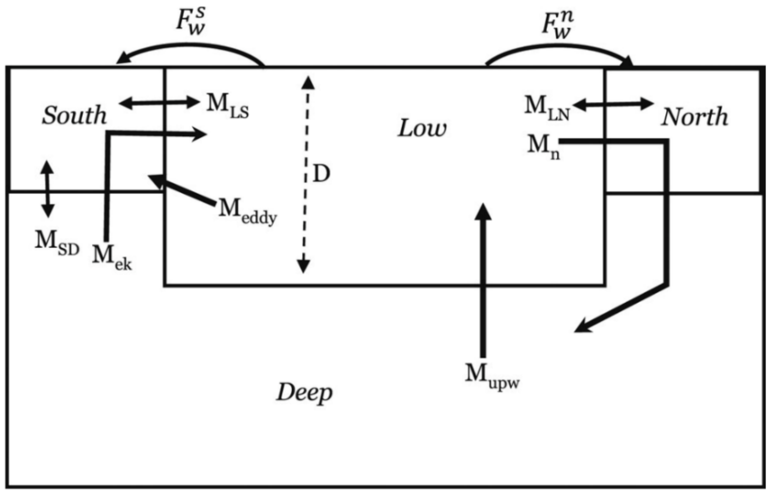


Figure 9. *Four box model*

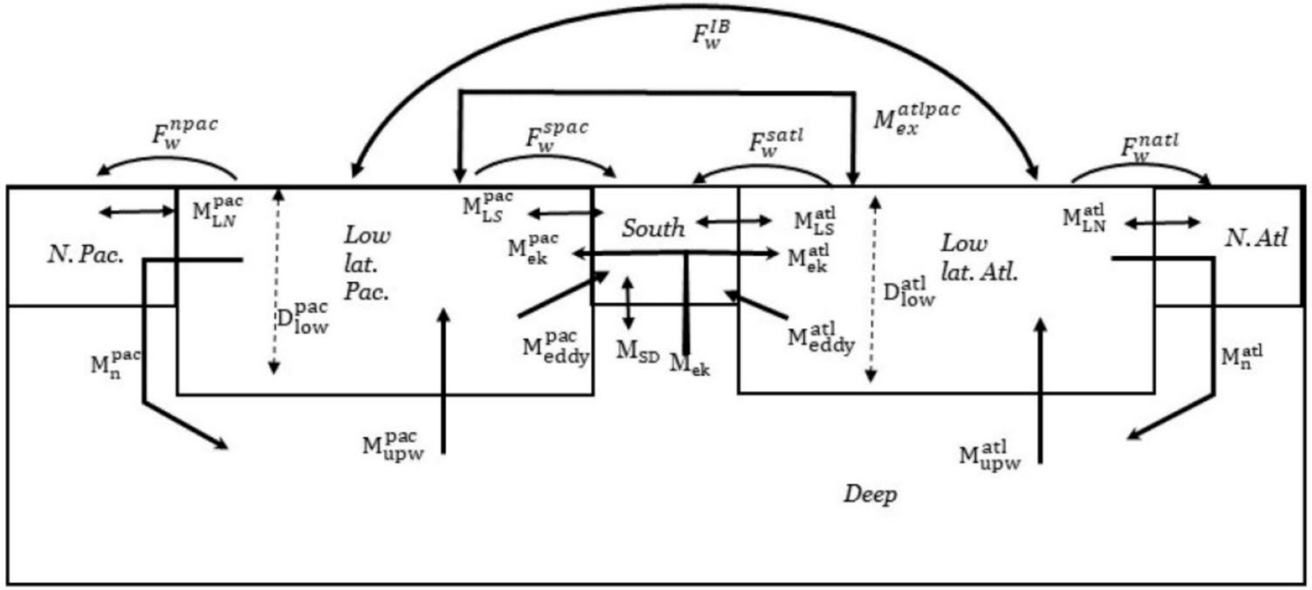


Figure 10. *Six Box Model*

- Recall, this effort began with bifurcation analysis of the four box model shown in Figure 9, with the goal of learning escape times.
- To support continued climate modeling efforts we have also begun bifurcation analysis of the six box model, shown in Figure 10.

Task 3.8 AI Physics-Informed Surrogate Model Phase 2 Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- The bifurcation diagram was analyzed with respect to the nondimensional north freshwater flux.
- Figures 11(a) and 11(b) show the NH overturning M_{n^*} while Figures 11(c) and 11(d) show the nondimensional depth D_*.
- The Hopf at $T_{r}{}^{n}{}_{FW}$ =0.0384 is subcritical. The value where the limit cycle seems to "go vertical" is 0.0375. It approaches an unstable homoclinic orbit.

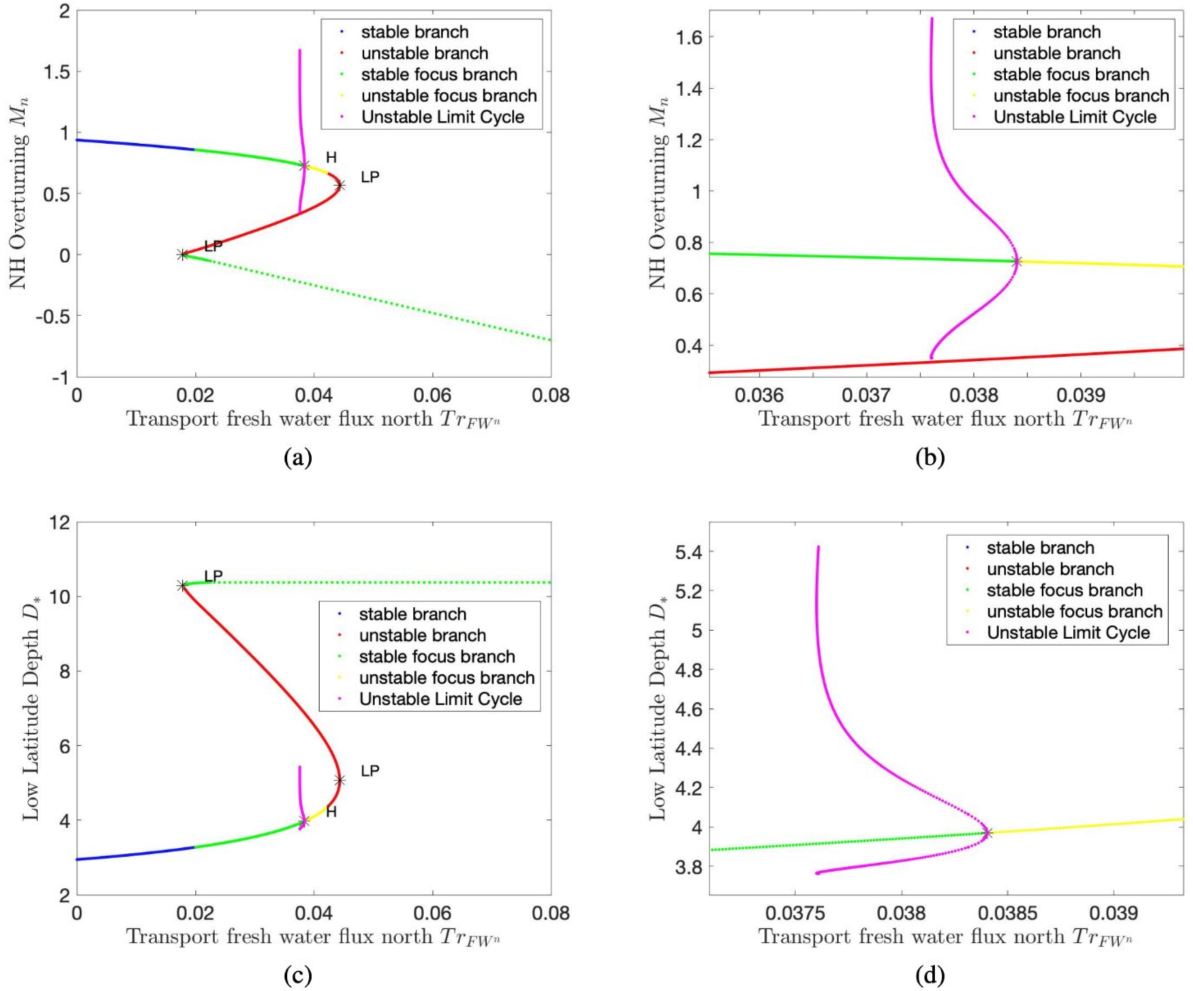
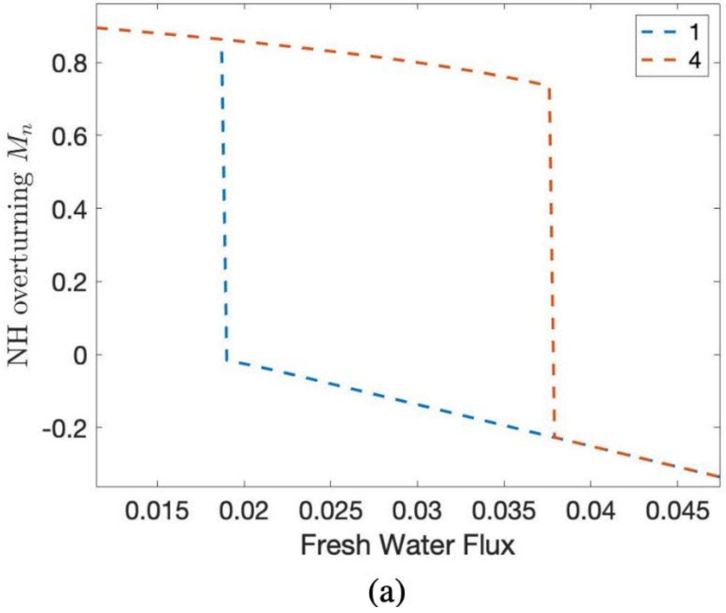


Figure 11. *a) NH overturning M_{n^*} b) Nondimensional depth D_* c-d) Zoom-in close to the Hopf bifurcation point for M_{n^*} and for D_*, respectively*

Task 3.8 AI Physics-Informed Surrogate Model Phase 2 Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- The bifurcation diagrams seems to reflect the behavior observed in the paper (Gnanadesikan et al. 2018) where initial conditions with D=1 are attracted by the upper branch because there is an early switch activation.
- The “blow up” is given by the upper limit point LP. For D=4 the “blow up” is close to the subcritical Hopf. The solution loses stability before the exact Hopf point because the initial conditions may start outside the unstable limit cycle. Hysteresis behavior is shown below.



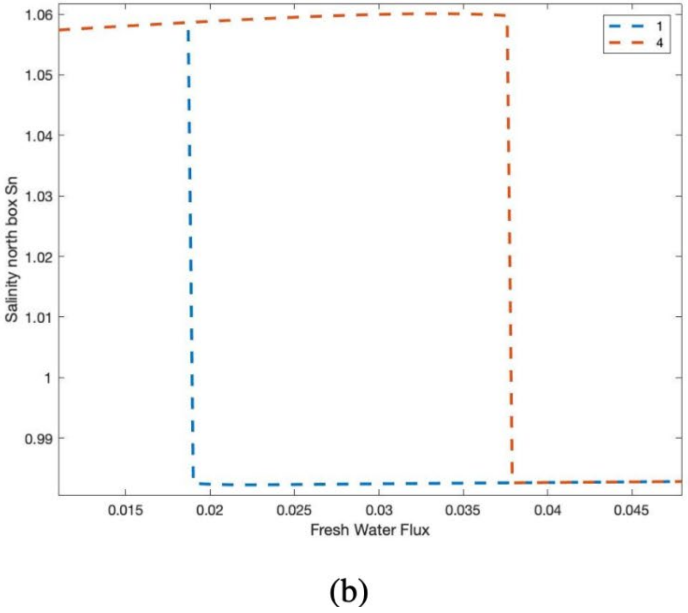


Figure 12. *a) Hysteresis diagram as* M_{n*} *varies; b) Hysteresis diagram as* D_* *varies*

Task 3.8 AI Physics-Informed Surrogate Model Phase 2 Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Additional Dynamics Results:

- The limit cycle approaches an homoclinic bifurcation, with the period blowing up vertically.
- Additional visualizations of this behavior are shown in Figure 13.

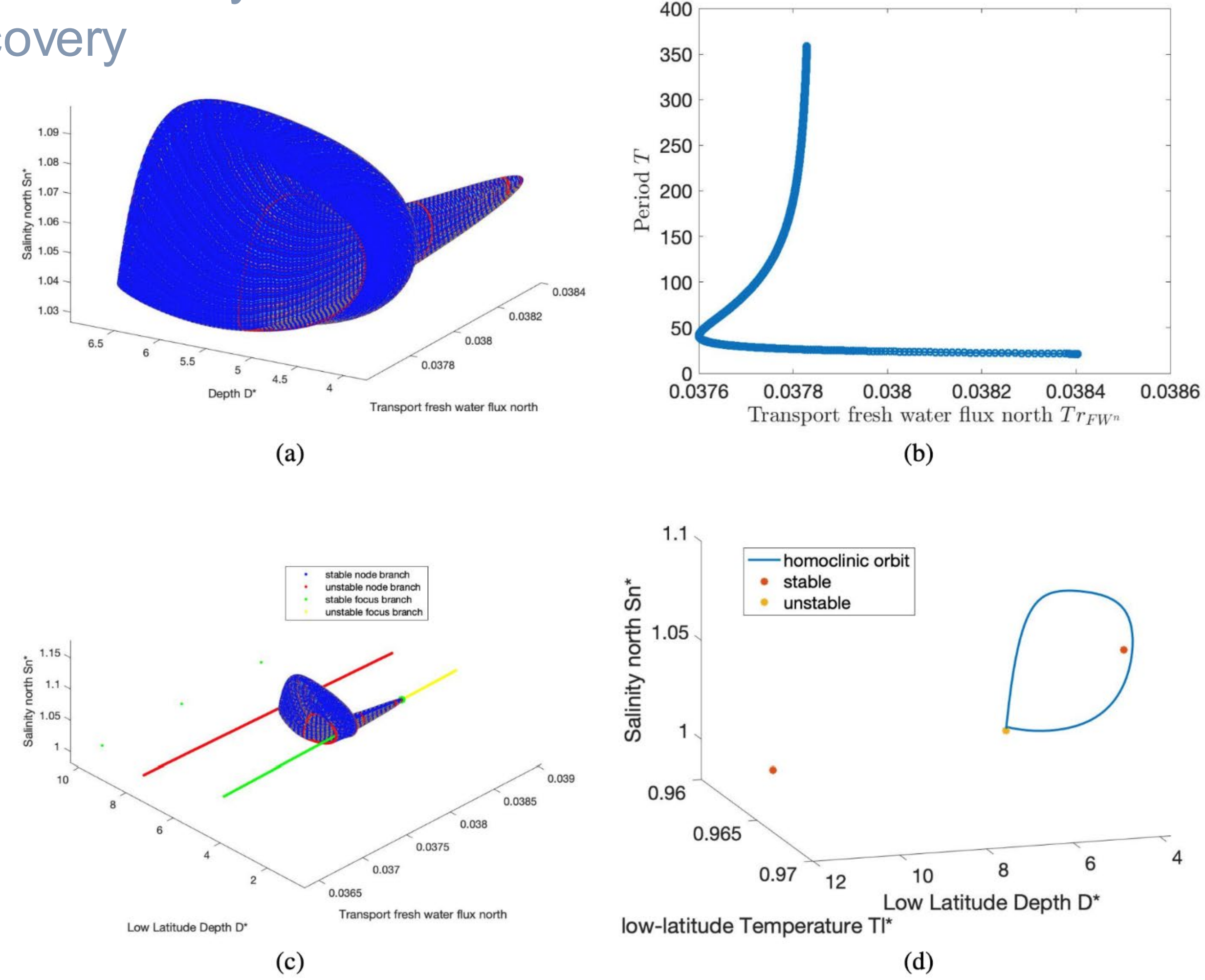


Figure 13. *a) Limit cycle continuation; b) Blow-up of the period of the limit cycle; c) Limit cycle on the bifurcation diagram; d) Homoclinic orbit in a three-dimensional state variable projection.*

Task 3.8 AI Physics-Informed Surrogate Model Phase 2 Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Schematic of three types of circulation in high latitudes:

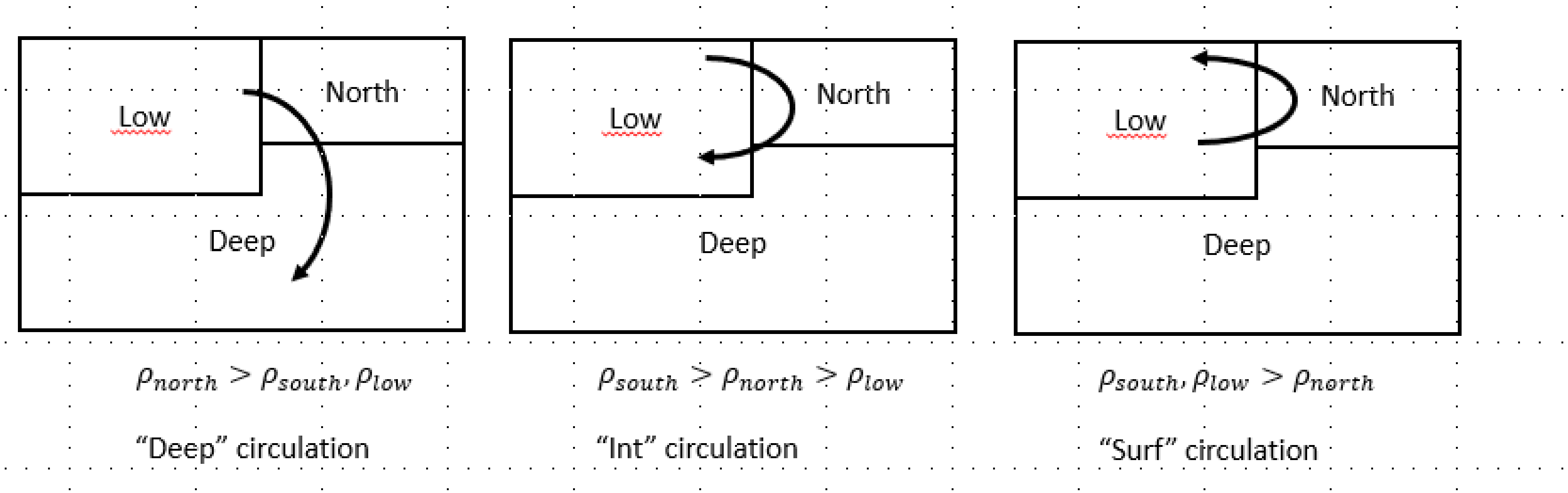


Figure 14. *Schematics of three types of circulation patterns.*

- Modern ocean can be described as "DeepNA-IntNP"
- Stommel model, Gnanadesikan et al., 2018 show a transition between DeepNA and SurfNA.
- What about the six box model?

Task 3.8 AI Physics-Informed Surrogate Model Phase 2 Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- After review/obtaining results, we found it was much more complicated

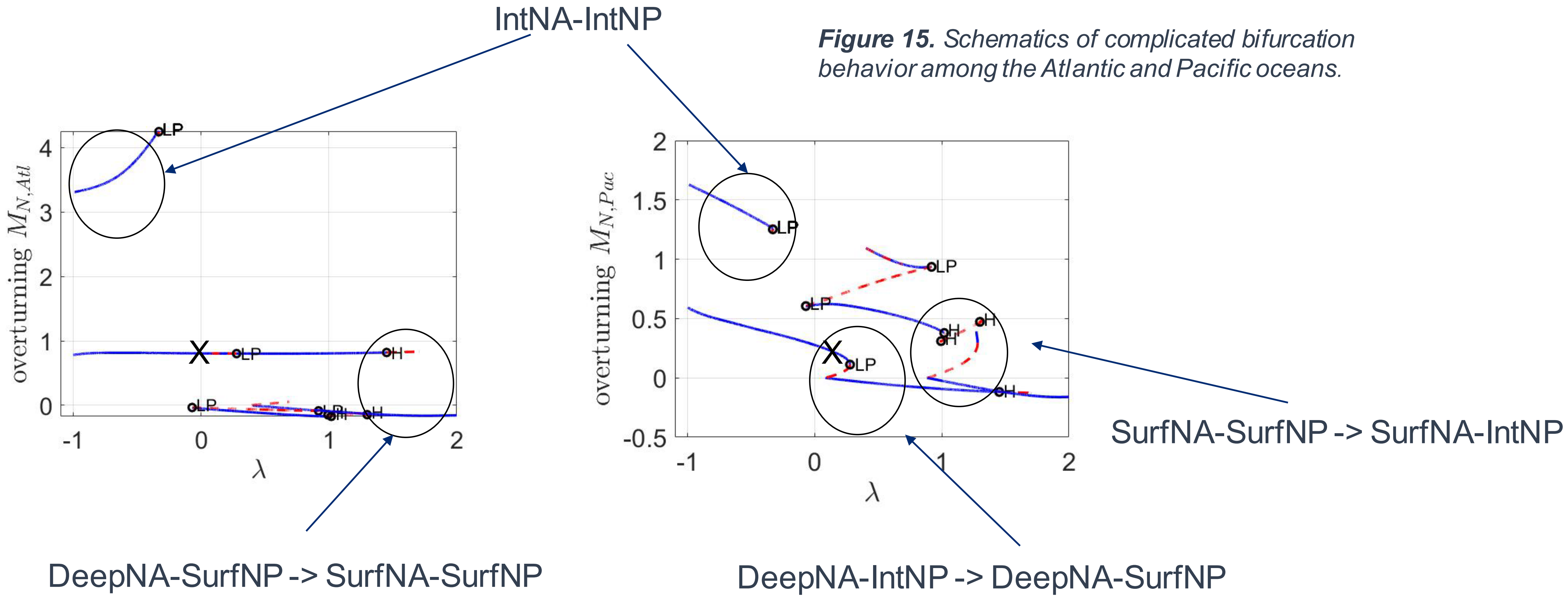


Figure 15. *Schematics of complicated bifurcation behavior among the Atlantic and Pacific oceans.*

Task 3.8 AI Physics-Informed Surrogate Model Phase 2 Final Report – Continued Work

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

1. We used a recently developed deep-learning framework [Dietrich et al., 2021] that identifies effective stochastic differential equations (eSDEs) from data. By using this deep-learning framework we will continue this work to learn a parameter-dependent eSDE for parameter values λ before and after the tipping point.
2. We may use the deterministic (drift) component of the eSDE to construct the bifurcation diagram based on this surrogate model. We will illustrate that the drift component of the surrogate eSDE model is capable of discovering the bifurcation point.
3. Furthermore, we will then use the surrogate eSDE model to perform rare event computations (exit time/stopping time computation). We start from the identified stable steady state and integrate the eSDE, for a specific value of the parameter, until the first time we reach (and surpass) the saddle. The latter can be performed by using the surrogate models and performing (a) kinetic Monte Carlo (kMC) simulation, (b) solving a partial differential equation boundary value problem arising from the Feynman-Kac formula, (c) and computing the mean exit time numerically with quadrature integration. We also perform kMC simulations of the full model (with added noise) to estimate the mean exit time.
4. We will then estimate the total time needed for the escape time computations. Preliminary results, on similar complex systems for epidemiological networks [Gross and Kevrekidis, 2008], suggest that the kMC computations of the surrogate eSDE model need 18 minutes whereas the escape time computation of the full model needs ~ 200 times more. This also takes into account the time needed to sample the data and train the network.
5. In the immediate future, we will finalize the six box model computations and obtain targeted tipping point models close to (a) the saddle-node tipping point and (b) the subcritical Hopf tipping point discovered.

Task 4.8 AI Simulation Phase 2 Final Report

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Subtask Description: We will report final details of perceived benefits and capabilities based on the evaluations and benchmarks, including the effectiveness of the tipping point causality model as part of conventional workflow and shortcomings/constraints of a simulated approach and necessary constraints.

- In this section we will describe the benefits of using the AI simulation for tipping point discovery. We will describe the role of causality and how it will improve the overall workflow. We will describe shortcoming and constraints of TIP-GAN, the neuro-symbolic model, and the causal model.

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- New type of generative adversarial network - **TIP-GAN** for tipping point discovery is able to learn bifurcations in parameter space.
  - Showed we could recreate the Gnanadesikan 2018.
  - Have been able to use the TIP-GAN to make new discoveries and learn more about parameter sensitivities .
- Newly developed **neuro-symbolic deep learning architecture** for scientific discovery using natural language question/answer
  - Have been able to show that the neuro-symbolic model has strong performance translating questions to questions and questions to programs and reasonable performance translating programs to questions.
  - Latest version trained on 2nd version of AMOC questions shows similar performance.
- TIP-GAN and neuro-symbolic integration shows tremendous speed-up in scientific discovery process and strong performance answering AMOC-shutoff question.
- The causal model uncovered interesting correlations between parameters. It was not integrated into the process flow with TIP-GAN and the neuro-symbolic model, as it is still being independently evaluated.

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

- Recall the TIP-GAN and neuro-symbolic flow as seen in Figure 16.

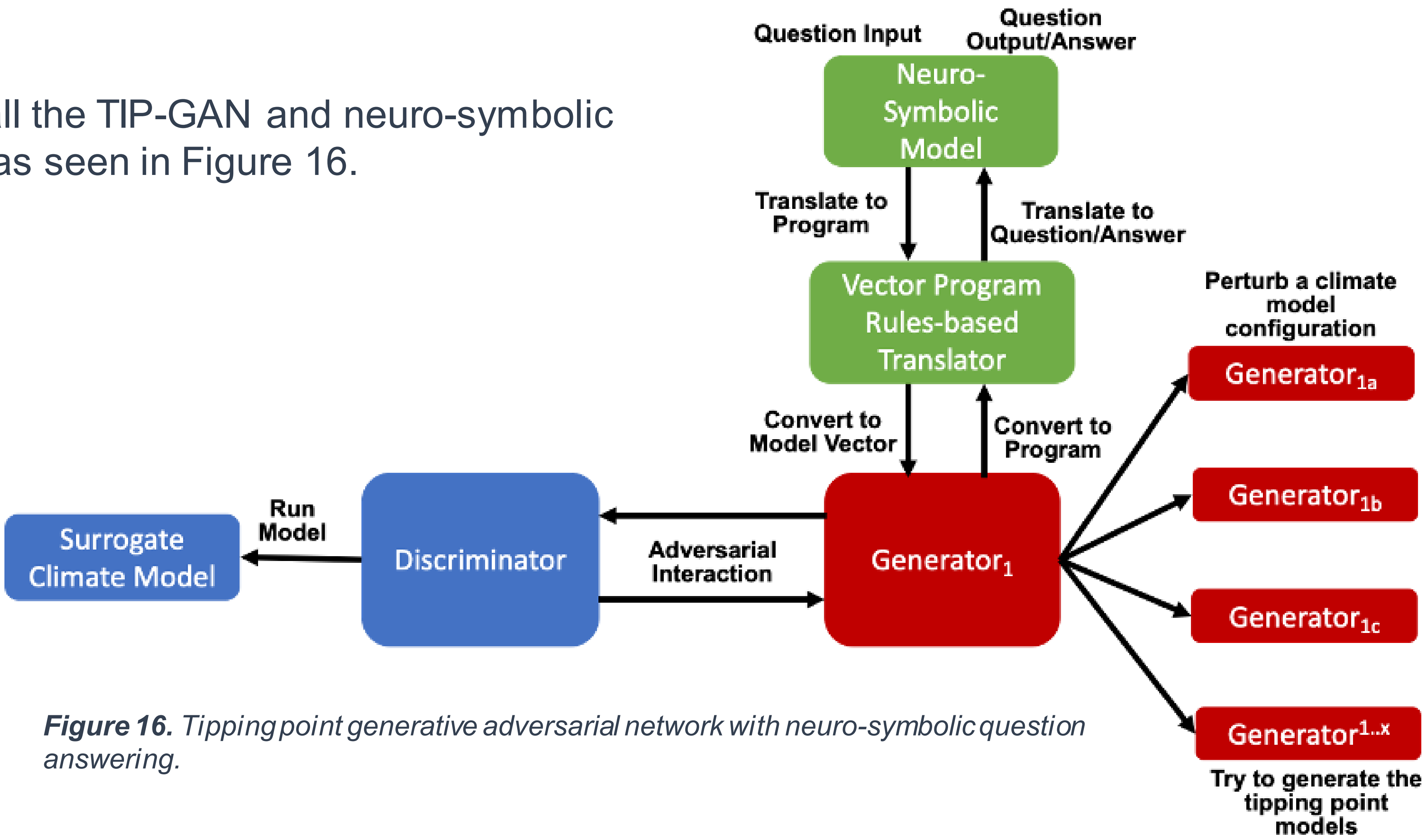


Figure 16. *Tipping point generative adversarial network with neuro-symbolic question answering.*

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

VQE70 – The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- Showed that the GAN could be used to exploit the area of uncertainty consistent with the separatrix as seen in Figure 17.
- Also showed compelling classification precision, recall, F1 scores.

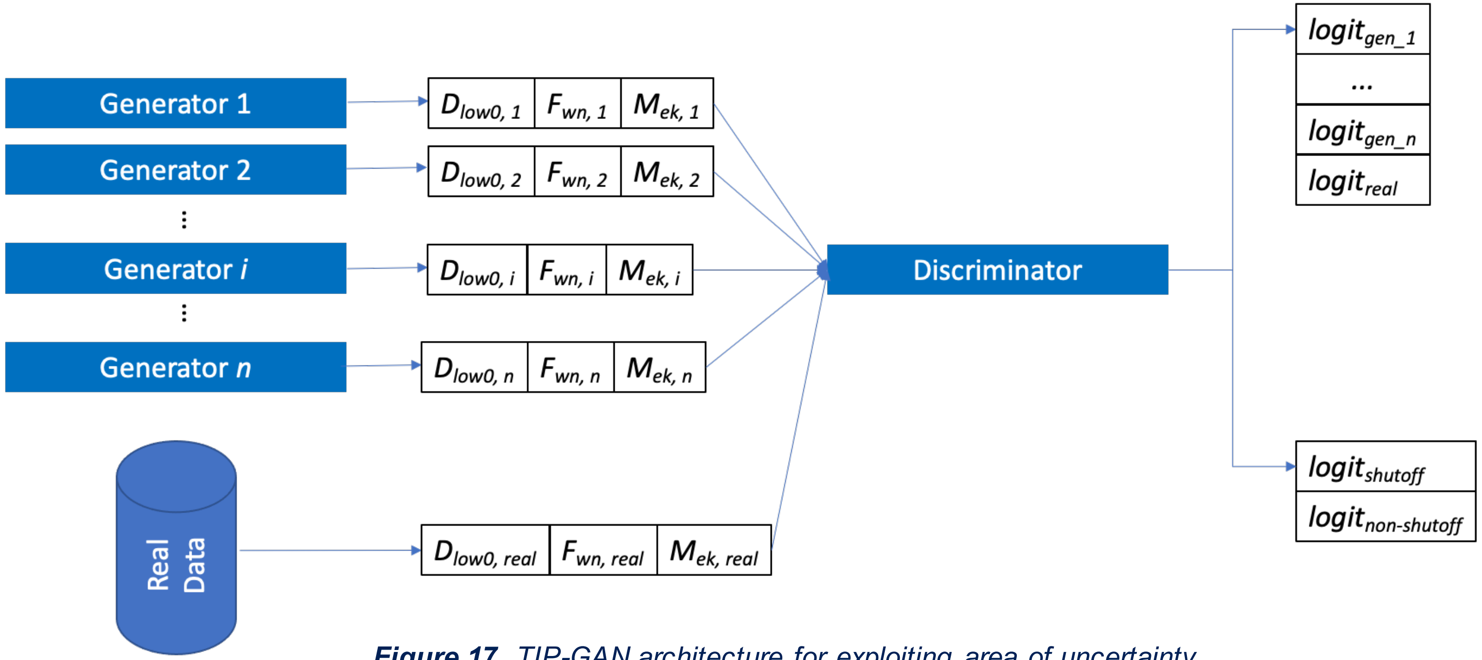


Figure 17. *TIP-GAN architecture for exploiting area of uncertainty.*

Dlow0 - Thermocline depth of lower latitudes
Mek - Ekman flux from the southern ocean
Fwn - Fresh water flux (North)

Sleeman, Jennifer, David Chung, Chace Ashcraft, Jay Brett, Anand Gnanadesikan, Yannis Kevrekidis, Marisa Hughes et al. "Using Artificial Intelligence to aid Scientific Discovery of Climate Tipping Points." AAAI Fall Symposium – Knowledge Guided ML (Nov 2022), arXiv preprint arXiv:2302.06852 (2023)

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

VQE70 – The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Training samples: 10,774
Test samples: 2,694
GAN samples: 2,694
N = number of generators

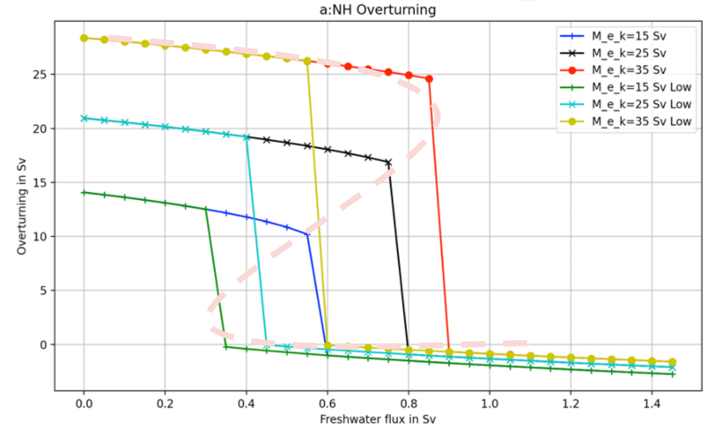


Figure 18. *Recreated collapses using Python-generated tools for machine learning dataset creation from the four box model (Gnanadesikan 2018)*

Dataset	F1 Discriminator Score	% in uncertainty region
Test		35.5
1 Generator GAN	.971	67.4
2 Generator GAN	.927	91.4
3 Generator GAN	.925	98.7

Table 2. *F1 scores and % of uncertainty region.*

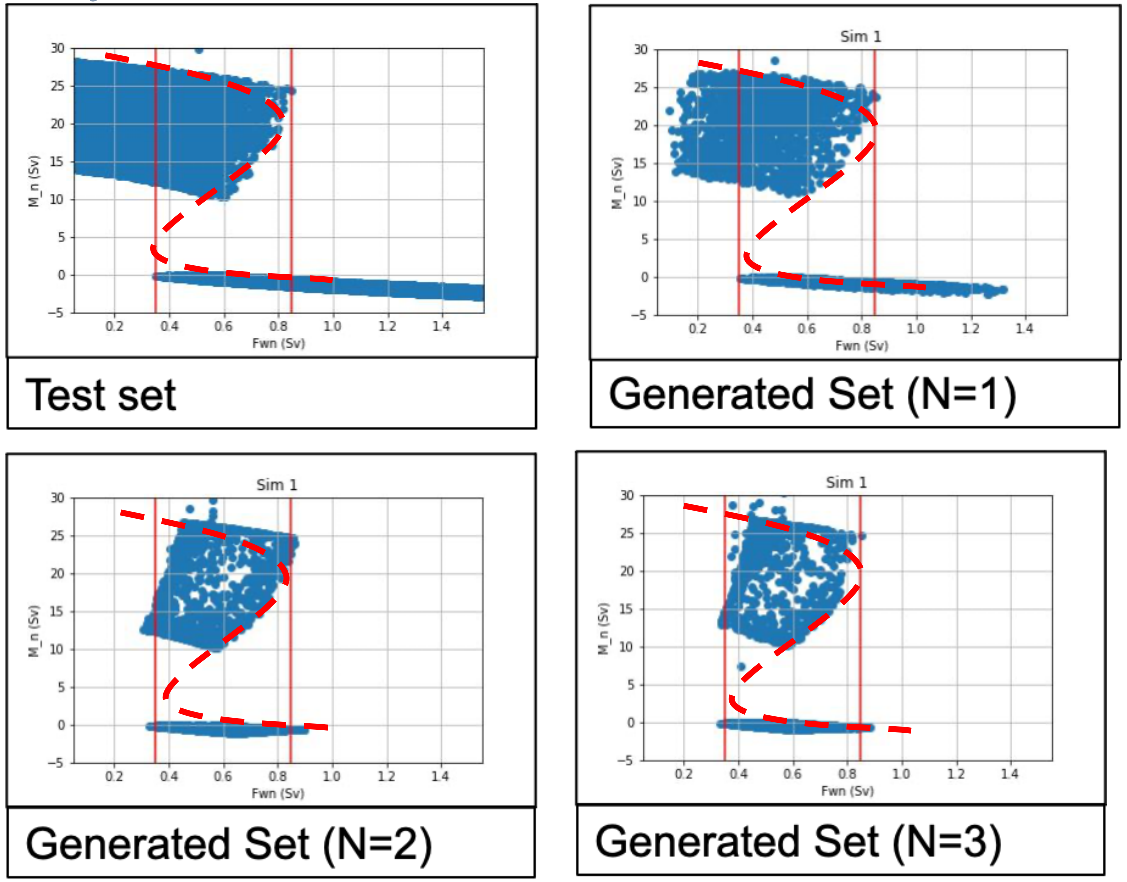


Figure 19. *Comparing GAN-generated results for N = (1,2,3) with the test set.*

By increasing the number of generators, the GAN is better able to target the area of the bifurcation consistent with the 2018 experiments.

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- TIP-GAN is also able to learn AMOC recoveries as shown in Figures 20-22.

Discriminator Prediction AMOC ON

Discriminator Prediction of Recovery

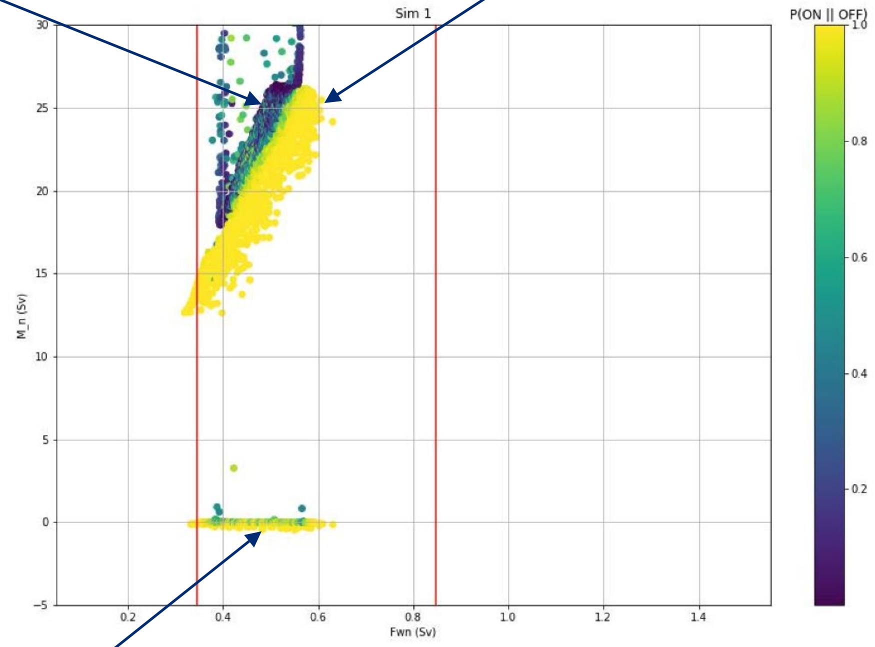


__Figure 20.__ GAN-generated output – with three labels.

Discriminator Prediction AMOC OFF

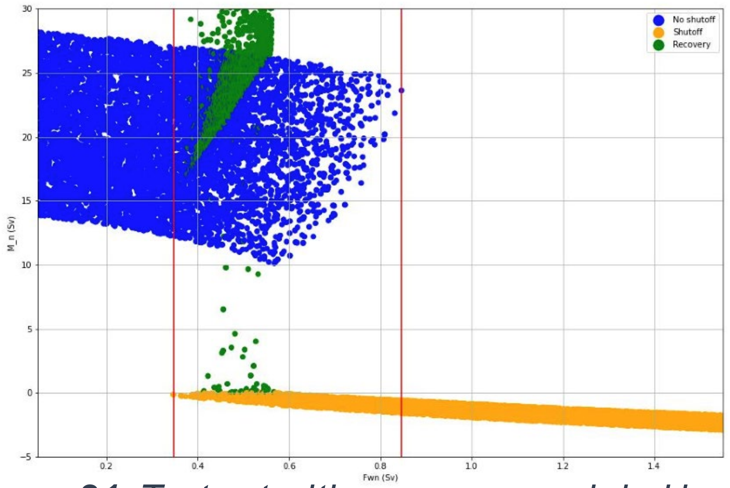


__Figure 21.__ Test set with new recovery label included.

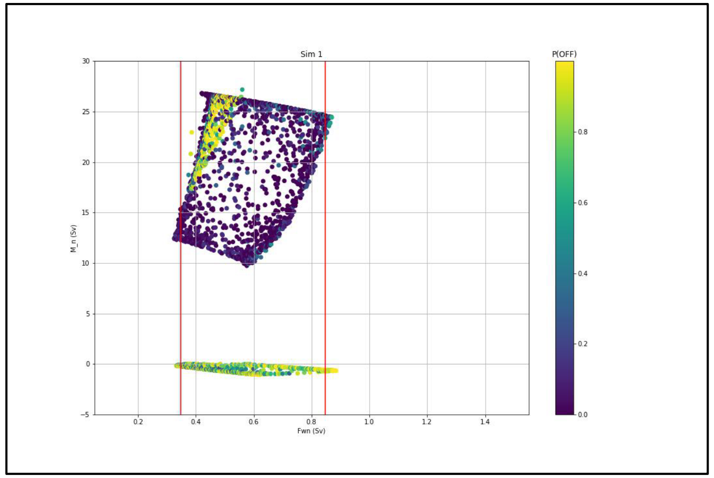
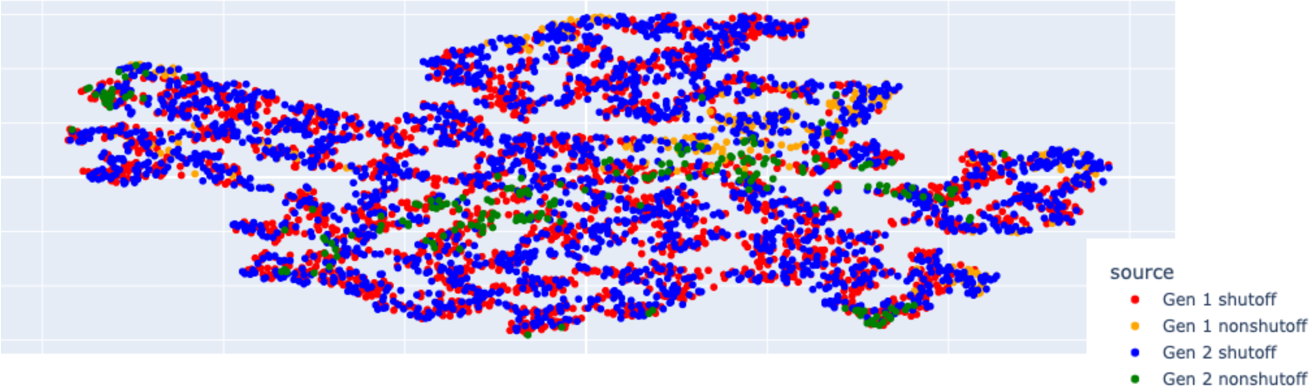


__Figure 22.__ TIP-GAN with the inclusion of recovery labeling.

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Figure 26. *t-SNE TIP-GAN (n=2) generator embeddings Timestep 40.*



t-SNE embeddings shows TIP-GAN learning more structure over time and in particular becoming more biases towards AMOC models with shutoffs consistent with the training loss function objectives

Figure 23. *t-SNE TIP-GAN (n=2) generator embeddings Timestep 0.*

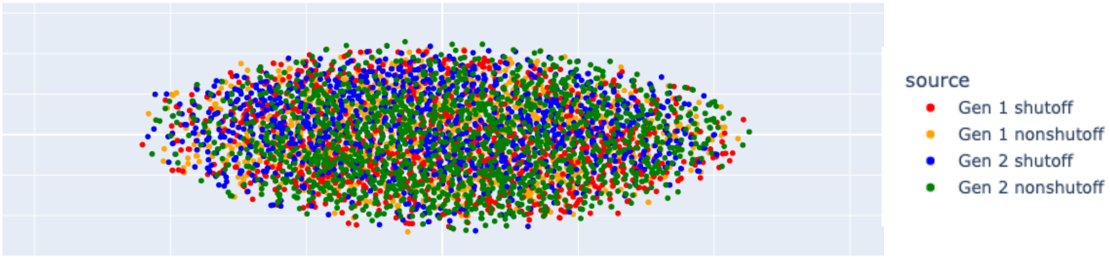


Figure 24. *t-SNE TIP-GAN (n=2) generator embeddings Timestep 10.*

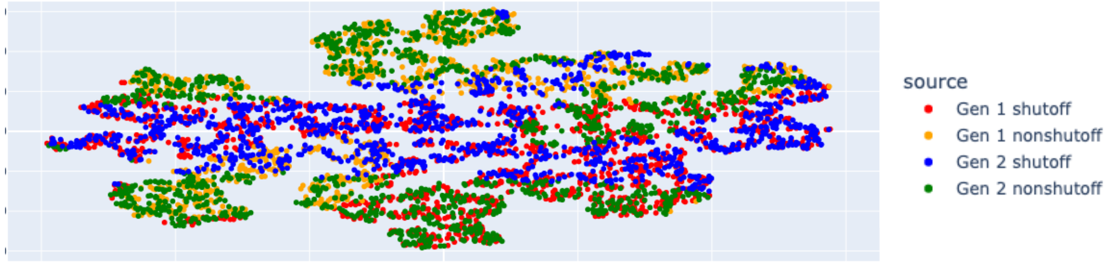
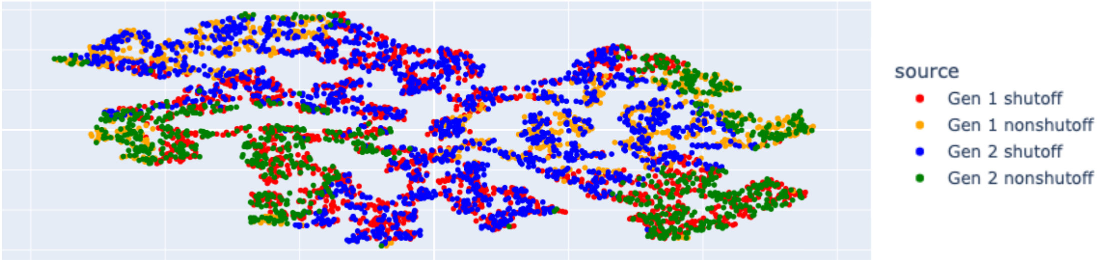


Figure 25. *t-SNE TIP-GAN (n=2) generator embeddings Timestep 20.*



Task 4.8 AI Simulation Phase 2 Final Report - Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Figure 27. *t-SNE TIP-GAN (n=2) generator embeddings Timestep 40 for GISS Calibrated Model.*

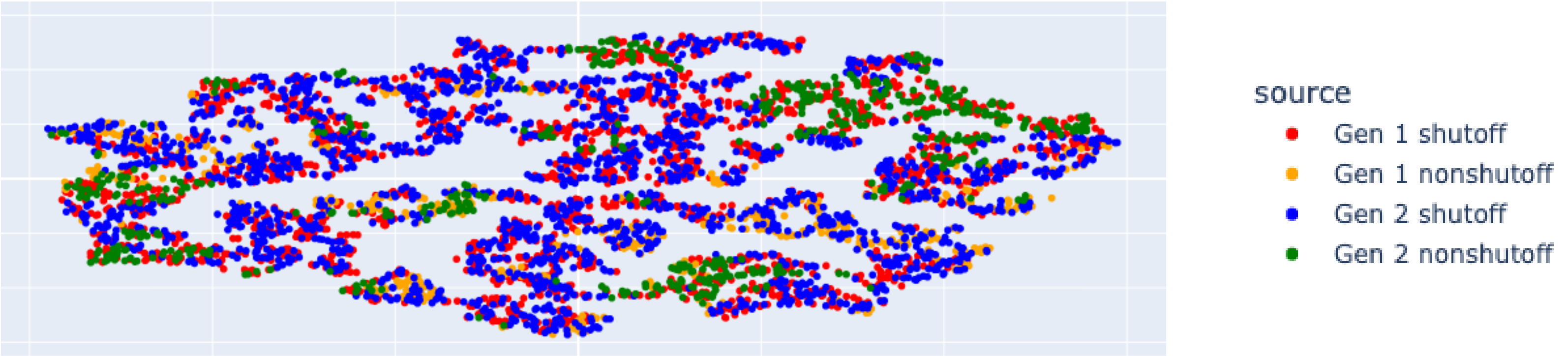
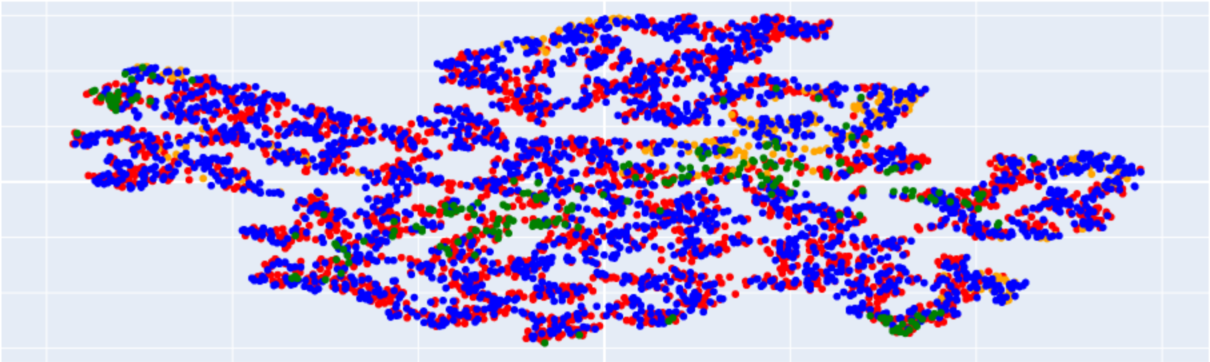


Figure 28. *t-SNE TIP-GAN (n=2) generator embeddings Timestep 40 for CESM2 calibrated model.*



t-SNE embeddings of the GISS calibrated and CESM2 calibrated show that TIP-GAN finds fewer shutoffs for GISS than CESM2.

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Using TIP-GAN we perturbed both together and separate:

- the initial depth of the pycnocline D_low
- the Northern Hemisphere freshwater flux F_wn
- Ekman flux

<u>Research discovery</u>:

- Ekman flux appears to create states that are more spread out and not all collapsing to the manifold as shown in Figure 29.
- Tells us there is still more work to be done to understand how southern ocean fluxes are influencing the AMOC.

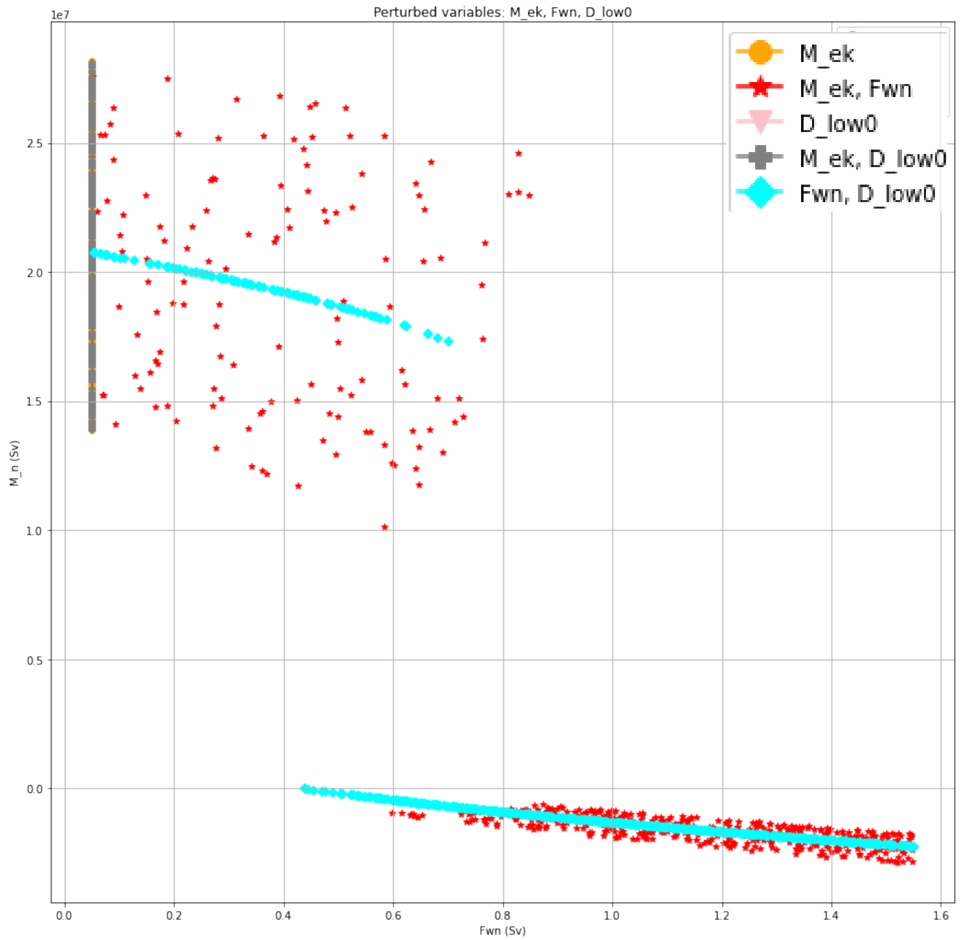


Figure 29. *Shows AMOC on/off as a function of Freshwater Flux and Overturning color-coded in terms of parameters that were generated a-priori where a single parameter was randomly generated in isolation or two parameters were randomly generated together.*

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Using TIP-GAN we perturbed both together and separate:

- the initial depth of the pycnocline D_low
- the Northern Hemisphere freshwater flux F_wn
- Eddy Mixing Coefficient A_Redi

<u>Research discovery</u>:

- By varying the initial conditions and eddy mixing coefficient together, we can extend the “off” state to much lower levels of freshwater flux than if we vary only one of the parameters as shown in Figure 30. This has implications for how easily the overturning recovers from shutoff.

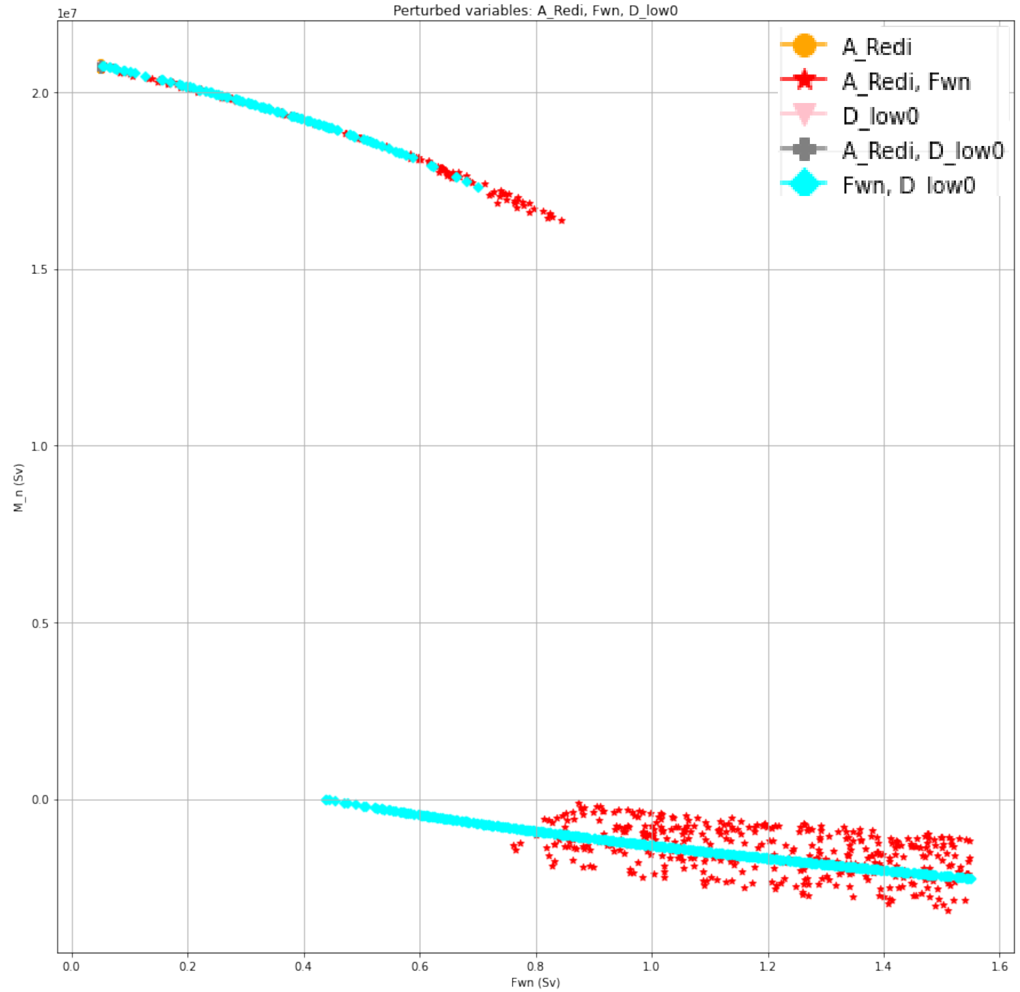


Figure 30. *Shows AMOC on/off as a function of Freshwater Flux and Overturning color-coded in terms of parameters that were generated a-priori where a single parameter was randomly generated in isolation or two parameters were randomly generated together.*

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Findings: High temperatures in the northern high latitude box can shut off AMOC, consistent with the expected density dependence. Interestingly, a link to the southern ocean is suggested by a more moderate ***Tnorth*** temperature and high ***Ssouth*** salinity shown in Figure 31. This suggests that AMOC shutoff could be affected by density differences between the north and south high-latitude boxes rather than just the direct north and low-latitude box density difference from the governing equations.

GENERATOR 2 (red off)
Tnorth being high is a shutoff; clear vs Dlow0 and S_south, where it is insensitive to them. Also, Tnorth high and Tlow low is a shutoff; that's the density difference we'd expect.Generator 1 (blue off) shows up in high Tnorth and Dhigh and medium Tnorth high Ssouth

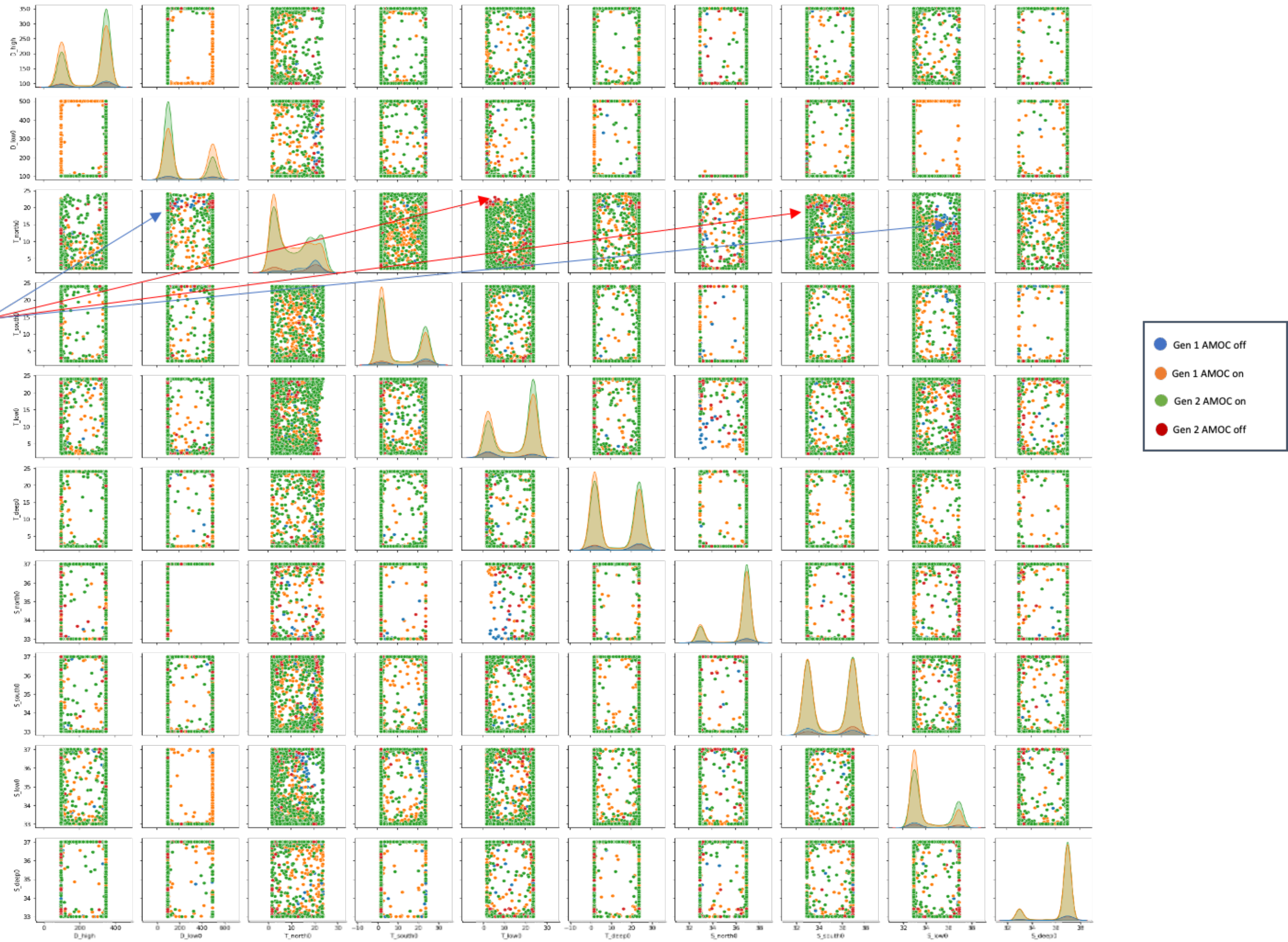


Figure 31. *Shows a pair plot of CESM2 model parameters for understanding relationships between pairs of parameters.*

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Findings: Although we find many shutoffs at high ***Fwn*** in human exploration, the GAN has also found many shutoffs at low ***Fwn*** shown in Figure 32*.* These are a new area for future exploration by scientists.

Surprising and intriguing that the low Fwn shutoffs (in Gen 2)

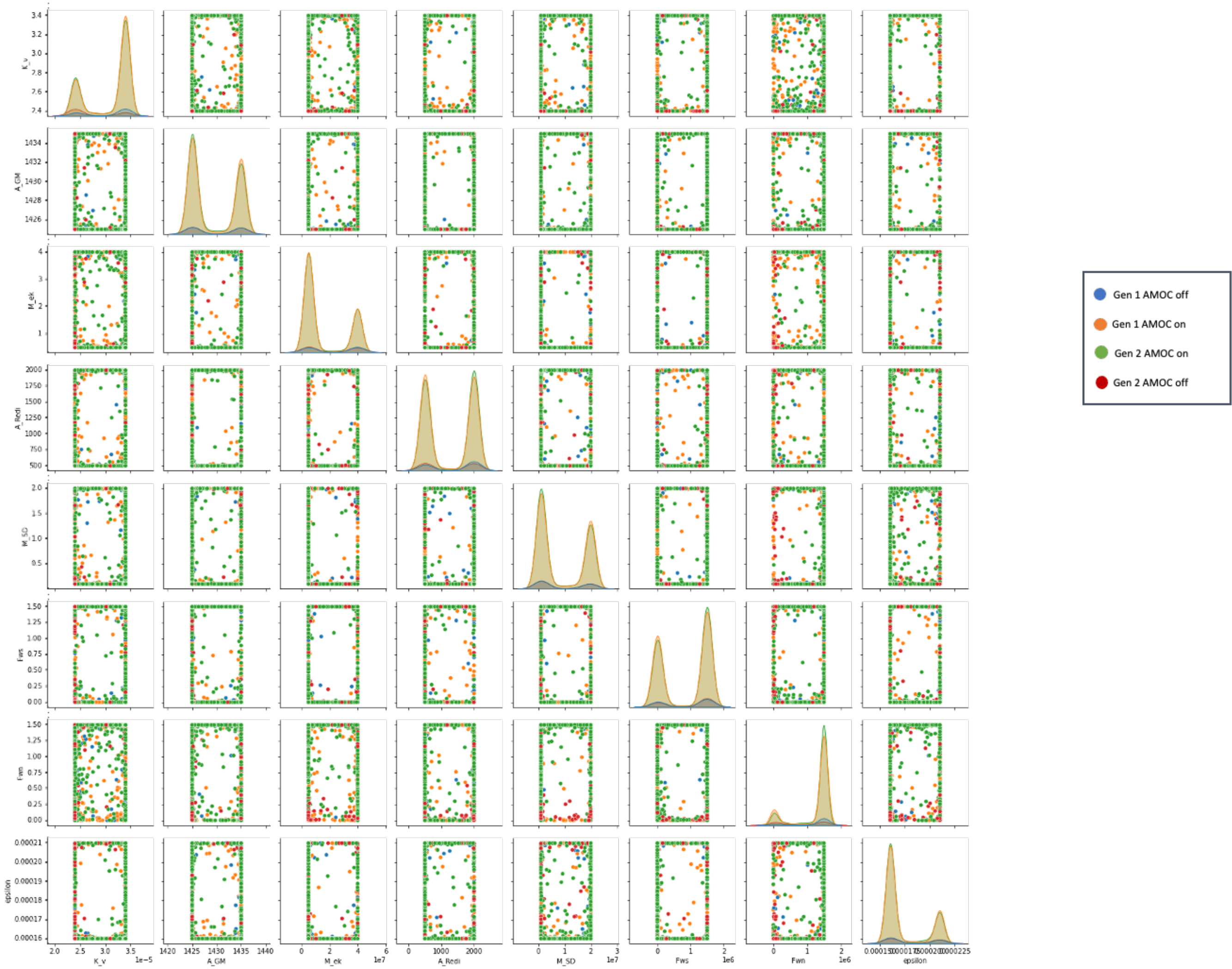


Figure 32. *Shows a pair plot of CESM2 model parameters for understanding relationships between pairs of parameters.*

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Findings: ***Aredi***, the along-isopycnal mixing coefficient controlling ***MLS*** and ***MLN***, covaries with ***Dlow*** (flux between Low and highlat boxes, makes dynamical sense) and ***Snorth*** (suggests isopycnal mixing important for salinity in the north box, interesting that this shows up more clearly than for **Slow**, ***Tnorth***, or ***Tlow***) shown in Figure 33.

Aredi covaries with Dlow and Snorth
This is on and off in both generators

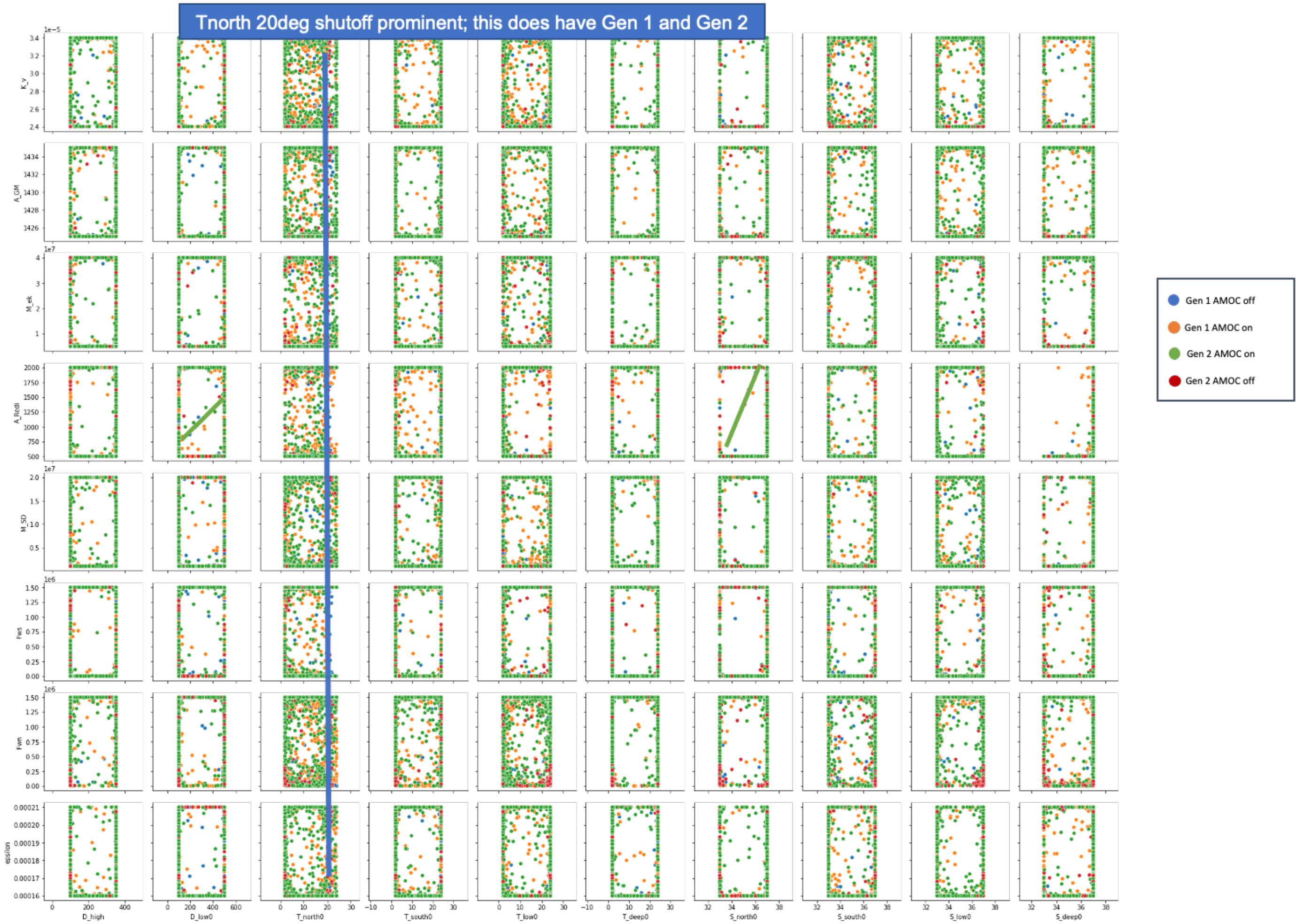


Figure 33. *Shows a pair plot of CESM2 model parameters for understanding relationships between pairs of parameters.*

Task 4.8 AI Simulation Phase 2 Final Report - Early Causal Results Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Generator 1

Generator 1: ***Mn*** and ***Mek*** have linear relationship. This has been observed in the GCMs and in the four box model. The ***Dlow Mek*** off state linear relationship is interesting and novel. The low ***Fwn*** off states tend to have low ***Mek*** and moderate ***Dlow***—that's a great **hypothesis** to be tested in the future.

Hypothesis: There is an AMOC-off condition that can occur with low ***Mek***, moderate ***Dlow***, and low-to-moderate ***Fwn***. Test with global ocean model.

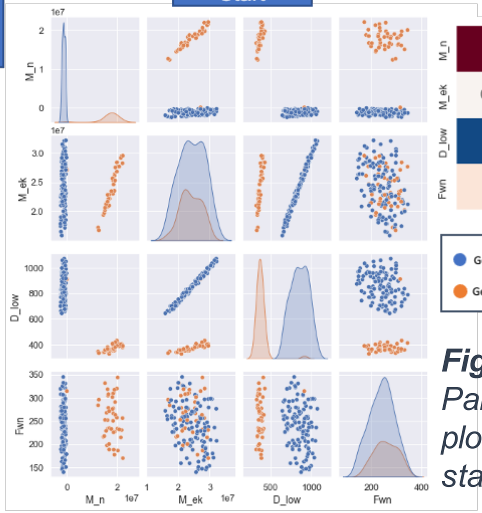
Generator 2: Found fewer AMOC-off states at high ***Fwn*** than generator 1.

Correlation plots show stronger correlations between ***Mn*** and ***Mek*** in Generator 2 than Generator 1.

Generator 2

Start

End



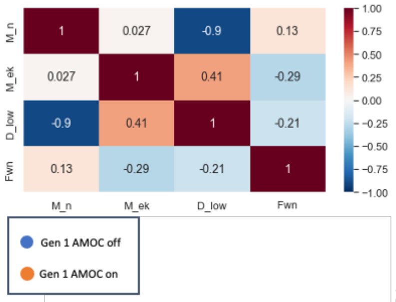
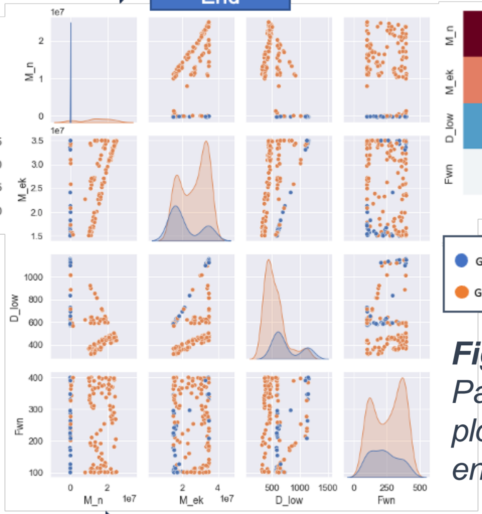


Figure 34. Generator 1 *Pair plot and correlation plot of Four box model at start timestep.*



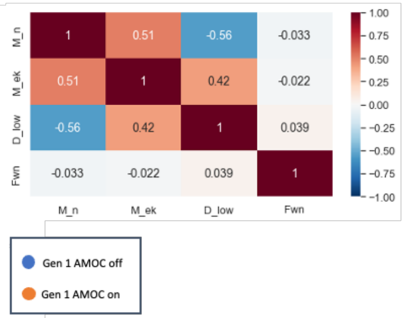
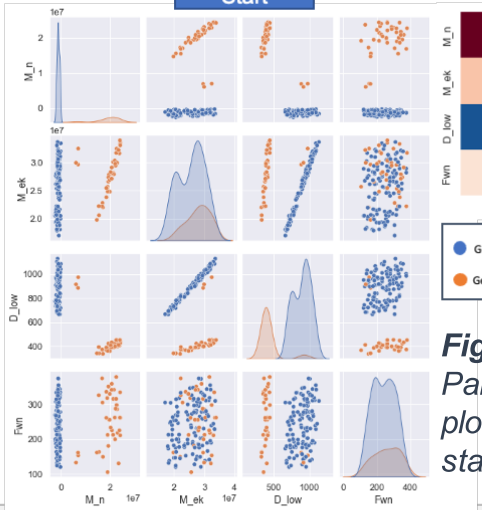


Figure 35. Generator 1 *Pair plot and correlation plot of Four box model at end timestep.*

Start

End



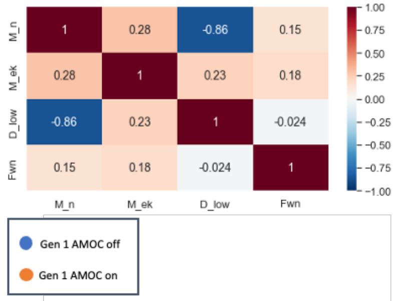
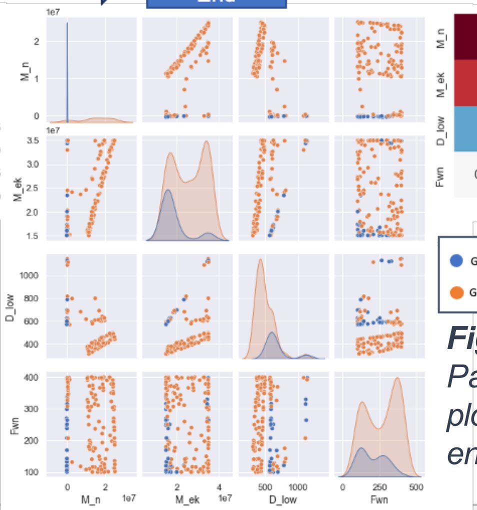


Figure 36. Generator 2 *Pair plot and correlation plot of Four box model at start timestep.*



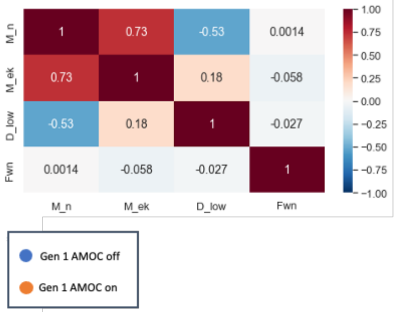


Figure 37. Generator 2 *Pair plot and correlation plot of Four box model at end timestep.*

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

General TIP-GAN discoveries:

- TIP-GAN is more sensitive to freshwater flux changes as opposed to temperature changes.
- TIP-GAN shows that varying the eddy mixing coefficient would make sense when moving from the box models to the global models.

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- Neuro-symbolic translation final findings.

- Using the bi-directional translations enables scientific discovery by allowing scientists to ask questions of the trained TIP-GAN.

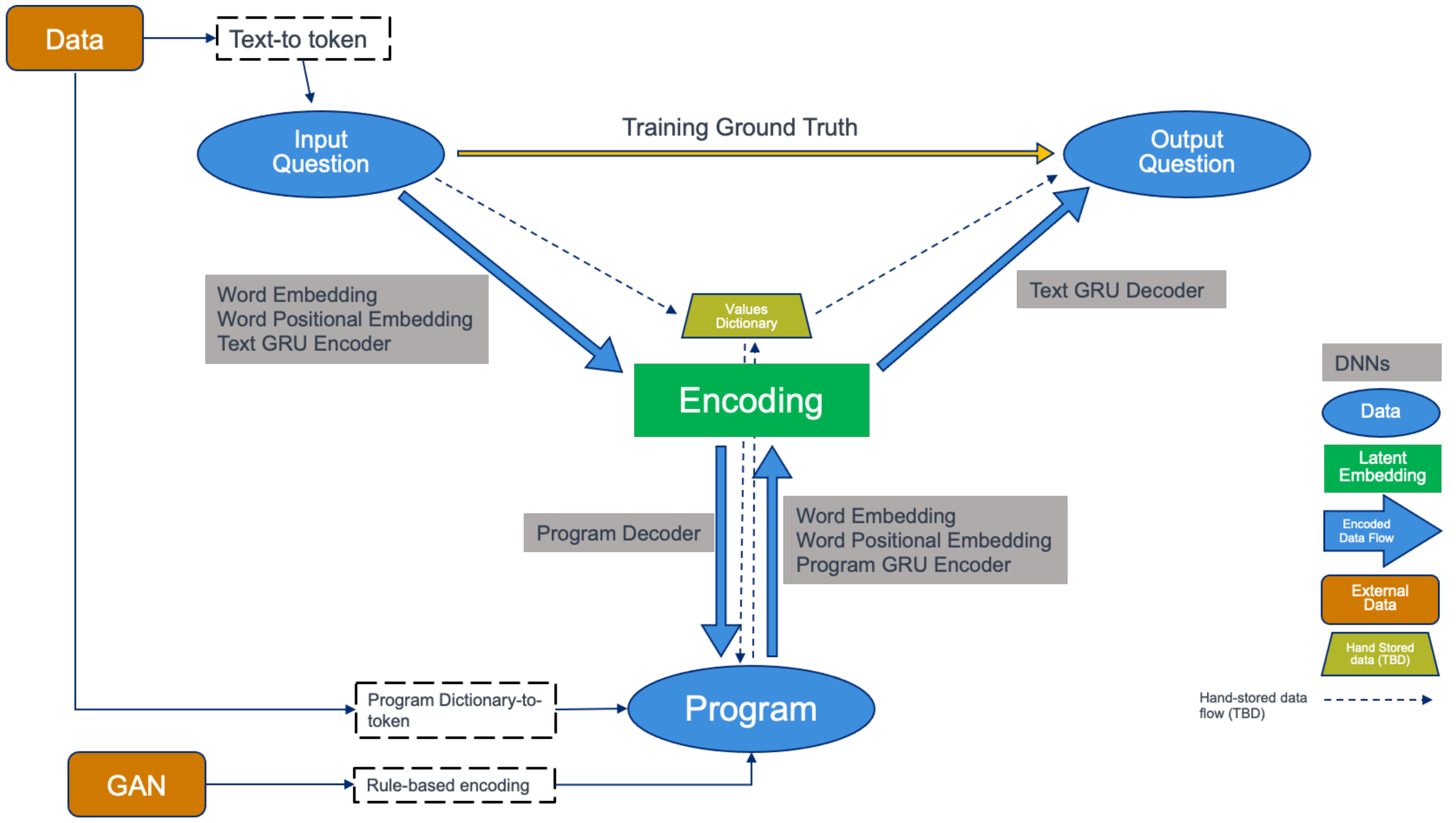


Figure 38. *Neuro-symbolic translation questions to programs for GAN consumption and GAN output to NL questions for human consumption – *first of its kind**

Task 4.8 AI Simulation Phase 2 Final Report - Benefits

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- Early work evaluated using a well-known benchmark – CLEVR.
- Adapted to evaluate our model with promising results.

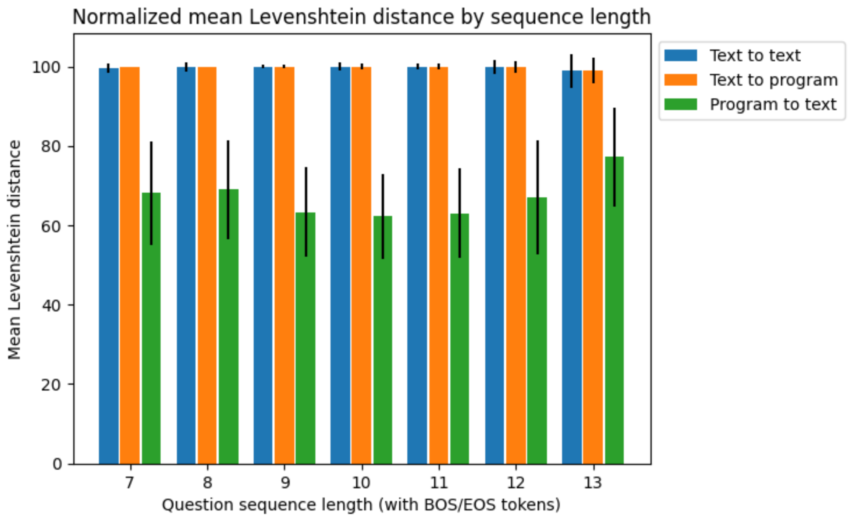


Figure 39. *Normalized mean Levenshtein distance by sequence length. Great performance on all three translations.*

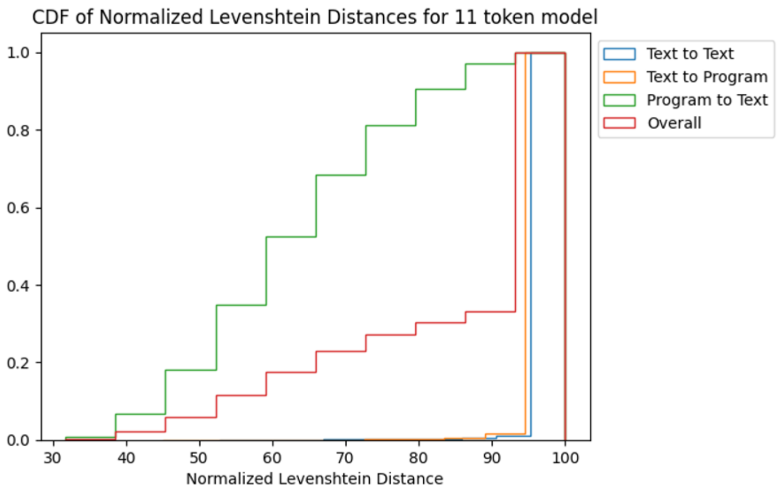
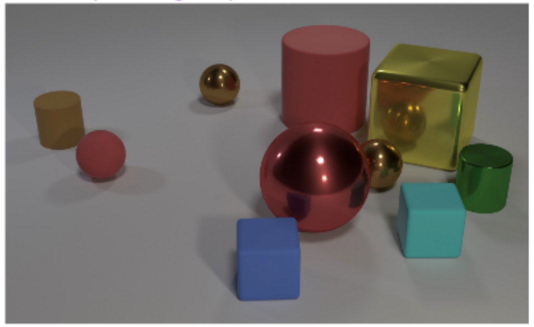


Figure 40. *CDF of normalized mean Levenshtein distance by sequence length. Great performance on all three translations.*

	Quest to Question	Question to Program	Program to Question	Overall
Distance	99.78	99.78	66.10	88.55

Table 3. *Levenshtein results - using CLEVR dataset*

Questions in CLEVR test various aspects of visual reasoning including **attribute identification**, **counting**, **comparison**, **spatial relationships**, and **logical operations**.



Q: Are there an **equal number** of **large things** and **metal spheres**?
Q: **What size** is the **cylinder** **that is left of** the **brown metal** thing **that is left of** the **big sphere**?
Q: There is a **sphere** with the **same size as** the **metal cube**; is it **made of the same material as** the **small red sphere**?
Q: **How many** objects are **either** **small cylinders** or **red** things?

Figure 41. *Example questions from the CLEVR dataset.*

$$
\operatorname{lev}_{a,b}(i,j) = \begin{cases} \max(i,j) & \text{if } \min(i,j)=0, \\ \min \begin{cases} \operatorname{lev}_{a,b}(i-1,j)+1 \\ \operatorname{lev}_{a,b}(i,j-1)+1 \\ \operatorname{lev}_{a,b}(i-1,j-1)+1_{(a_i \neq b_j)} \end{cases} & \text{otherwise.} \end{cases}
$$

Levenshtein Distance Used to Measure Performance

Task 4.8 AI Simulation Phase 2 Final Report – Shortcomings/Constraints

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

TIP-GAN:

- There are challenges in using a full GCM with TIP-GAN.
  - Models tend not to have AMOC collapse.
  - No real ground truth.
- TIP-GAN becomes unstable without thorough analysis of bounding parameter values.
- Proving the TIP-GAN made new discoveries is hard to quantify due to the high dimensional space.
- Moving from a deterministic to a stochastic model also proves to be challenging as TIP-GAN is trained with the surrogate model as the oracle, so the question with a stochastic model is, "Given the stochasticity, how many runs of the model is enough to calculate an accurate probability of the likelihood of a shut-off?"
  - We don't see this as a limitation, but more as an interesting extension to the current TIP-GAN.

Task 4.8 AI Simulation Phase 2 Final Report – Shortcomings/Constraints

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Neuro-symbolic Translations:

- Bi-directionally translating scientific questions and programs is challenging.
  - Question to program translation is straightforward, newer complex questions yielded results that were comparable with the simpler question.
  - However, program to question translation is challenging due to the one-to-many relationship and the consideration of semantics.
  - Again, we see this as an opportunity to really push the research into this area of AI-assisted scientific discovery by using GPT and other large language models to help reduce question complexity and to perform automatic question generation.

Causal Learning:

- Is showing causal paths across TIP-GAN generators enough for explainability?
- Causal graphs to represent generative learning were hard to construct and interpret.
  - Establishing causality is challenged by feedback loops across parameters.

Task 5.3 Phase 2 Evaluation

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Subtask Description: We will evaluate the full AI hybrid approach and benchmark with conventional models comparing performance of tipping point identification. We will evaluate new capabilities in terms identifying locations of importance and processes that differ shapely between models, motivating the requirement for more direct measurements and additional observable data.

- In this report we describe a study used to evaluate and benchmark the AI hybrid approach with conventional models.
- Part of this study is to understand the effects of global warming using the AI-Simulator, which may inform the need for additional observational data.
- We also include final results related to the performance integration.

Task 5.3 Phase 2 Evaluation – Warming Scenario

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- In this study, we understand the effects of global warming using the AI-Simulator to assist with better understanding the outcomes given a set of scenarios. We run the same scenarios using the box model and compare the outcomes.

Experiment 1: Starting from an AMOC-on condition and following a warming and hydrologic cycle increasing pattern, when does AMOC turn off? In this case, we include more warming at high latitudes, representative of polar amplification.

Parameter Setup for AMOC On Model: T0n=2; T0s=4;T0d=3; T0l=17; Fws=1e6 (1Sverdrup) Fwn 0.5e6

Warming Scenario 1: T0n=4; T0s=6;T0d=3; T0l=18; Fws=1.07e6 (1Sverdrup) Fwn 1.07*0.5e6
Warming Scenario 2: T0n=6; T0s=8;T0d=3; T0l=19; Fws=1.14e6 (1Sverdrup) Fwn 1.14*0.5e6
Warming Scenario 3: T0n=8; T0s=10;T0d=3; T0l=20; Fws=1.21e6 (1Sverdrup) Fwn 1.21*0.5e6

Task 5.3 Phase 2 Evaluation – Warming Scenario

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- TIP-GAN with high confidence predicts no shut-off for all scenarios, warming 3 resulted in a shut-off for warming 3 using the box model.

Scenario	Box Model	Tip-GAN Prediction	Confidence
On Point	No	No	.985
Warming 1	No	No	.983
Warming 2	No	No	.979
Warming 3	Yes	No	.972

Table 4. *Results of the three warming scenarios comparing the box model with TIP-GAN predictions. TIP-GAN and the box model are in disagreement for warming scenario 3.*

Task 5.3 Phase 2 Evaluation – CESM-2 Warming Scenario

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- Running the same example, but instead using CESM-2 Calibrated Model and removing polar amplification, there was even higher confidence that warming 3 will not result in a shutoff. This is consistent with the box model results.

Warming Scenario 1: T0n=3; T0s=5;T0d=3; T0l=18; Fws=1.07e6 (1Sverdrup) Fwn 1.07*0.5e6
Warming Scenario 2: T0n=4; T0s=6;T0d=3; T0l=19; Fws=1.14e6 (1Sverdrup) Fwn 1.14*0.5e6
Warming Scenario 3: T0n=5; T0s=7;T0d=3; T0l=20; Fws=1.21e6 (1Sverdrup) Fwn 1.21*0.5e6

Scenario	Shutoff?	Prediction	Confidence
Warming 1	No	No	.996
Warming 2	No	No	.993
Warming 3	No	No	.987

Table 5. *Results of the three warming scenarios for CEMS2 Calibrated model comparing the box model with TIP-GAN predictions. TIP-GAN and the box model are in full agreement.*

Task 5.3 Phase 2 Evaluation – GISS Warming Scenario

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- Ran the same examples, but instead used the GISS Calibrated Model. Both result in similar predictions. Removing polar amplification did not result in higher confidence that warming 3 will not result in a shutoff, but it was still consistent with the box model results.
- When increasing ***Fwn*** and keeping ***Fws*** and temperatures constant, TIP-GAN predicts an off state when ***Fwn*** is ~3x the default value (0.5e6).

Scenario	Shutoff?	Prediction	Confidence
Default	No	No	.987
Warming 1	No	No	.990
Warming 2	No	No	.992
Warming 3	Yes	No	.994

Table 6. *Results of the three warming scenarios for the GISS calibrated model, comparing the box model with TIP-GAN predictions. TIP-GAN and the box model are in agreement.*

Scenario	Shutoff?	Prediction	Confidence
Warming 1	No	No	.994
Warming 2	No	No	.993
Warming 3	No	No	.992

Table 7. *Results of the three warming scenarios with polar amplification removed for the GISS calibrated model, comparing the box model with TIP-GAN predictions. TIP-GAN and the box model are in agreement.*

Task 5.3 Phase 2 Evaluation – Conclusions

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- In the CESM-2 model TIP-GAN predicts a shutoff when ***Fwn*** is nearly double (1.91x) the default value (0.5e6).

- If ***T*** and ***Fwn*** are incrementally increased to produce a shutoff prediction, TIP-GAN still does not predict a shutoff when ***Fwn*** is fixed and temperature is steadily increased.

- TIP-GAN's decision boundary is significantly more sensitive to changes in ***Fwn*** than temperature.

- TIP-GAN was trained on temperatures bounded from 2-24 Celsius. The GAN doesn't identify an off state for the warmest case (***T_low0*** = 20) or for any cases where ***T_low0*** approaches 25 C.

Task 5.3 Phase 2 Evaluation – AI Simulation Integration

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

In this experiment:

1. 2000 natural language questions were randomly generated pertaining to the AMOC collapsing based on the value of 3 changing parameters (using a uniform distribution for each parameter).
2. Questions were translated into TIP-GAN programs.
3. TIP-GAN answered programs based on trained models (previously trained using the four box model).
4. Answers were returned to simulated researcher.
5. Process was compared to an actual researcher.
6. Total time was computed for each process.
7. Performance on question to program translations were computed.
8. Performance on answers to questions were computed.

Task 5.3 Phase 2 Evaluation – AI Simulation Integration

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- The neuro-symbolic translation from question to program was evaluated on translating the 2000 questions. The neuro-symbolic translation was able to translate every question correctly shown in Table 8. Example questions shown in Table 9.

Note: The questions were similar in structure, with ***D_low0***, ***Fwn***, and ***M_ek*** as the parameters that could be involved in the question (all other parameters held constant). Any combination of 1 to 2 parameters formulated the question.

	Precision	Recall	F-Measure
AMOC Off	100%	100%	100%
AMOC ON	100%	100%	100%

Table 8. *Neuro-symbolic performance in translating natural language questions to programs. Evaluated on how accurately it translated the question to the correct program structure - it appears to have performed very well.*

Example Question	Program Translation
if D_low0 is 142.2005075375089 and Fwn is 1020814.0505557163, does the AMOC collapse?	ChangeSign(four_box_model(SetTo(D_low0,142.2005075375089),SetTo(Fwn,1020814.0505557163)),M_n)

Table 9. *Example question and TIP-GAN Program Translation. (Note:* ***D_low0*** *is the parameter for thermocline depth of the lower latitudes and* ***Fwn*** *is the parameter for freshwater flux in the North.*

Task 5.3 Phase 2 Evaluation – AI Simulation Integration

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- The TIP-GAN was trained using the four box model. The trained TIP-GAN was then used to answer the questions provided by the neuro-symbolic model.
- Results are shown in Table 10 and Figure 42.

	Precision	Recall	F-Measure
AMOC Off	99.602%	100%	99.8%
AMOC ON	100%	99.600%	99.8%

Table 10. *TIP-GAN Prediction Performance for the 2000 questions translated into programs.*

Note: The programs were used to directly predict AMOC On/Off for each question, as opposed to running the four box model to obtain the answer.

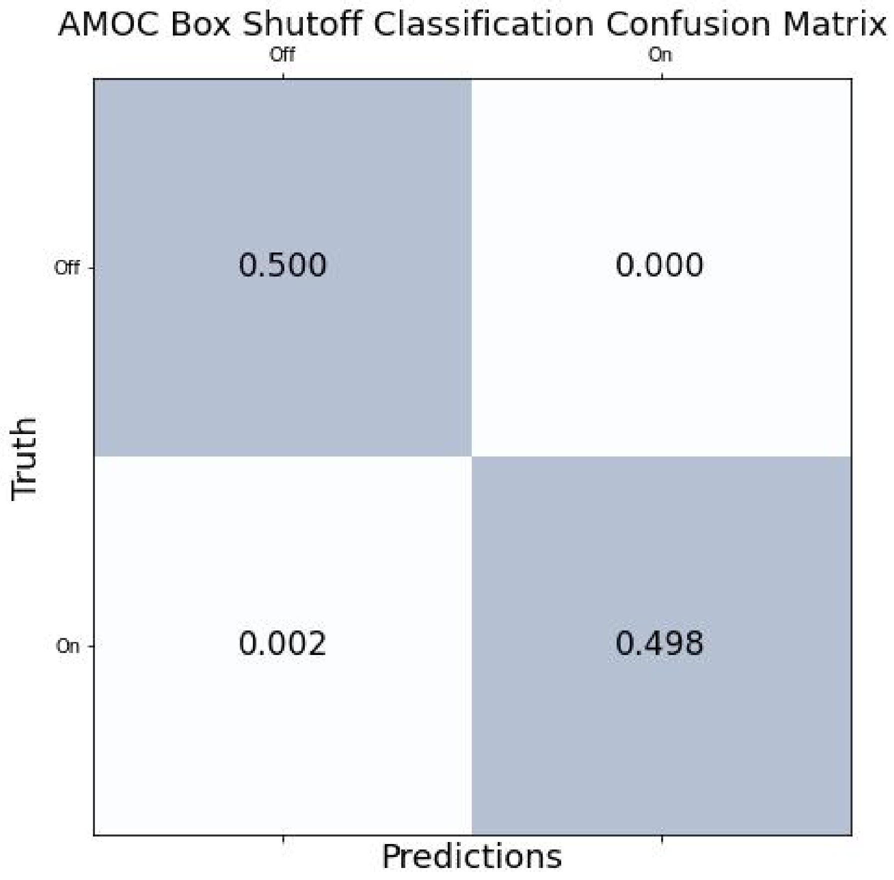


Figure 42. *TIP-GAN Prediction Performance Confusion Matrix for the 2000 questions translated into programs.*

Task 5.3 Phase 2 Evaluation – AI Simulation Integration

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

	Neuro-symbolic Translation	TIP-GAN Prediction	Full AI Simulation
Total Average Time in seconds	0.04	0.0000054	0.045

Table 11. *In this table we show the average time in seconds to perform the translation from question to program and to obtain an answer to the program. The final column is the overall AI Simulation total time.*

	Four Box Model Run (Python)	TIP-GAN Prediction
Total Average Time in seconds	0.96	0.0000054

Table 12. *In this table we show the average time in seconds, comparing running the four box model to obtain an answer to a question as opposed to getting the prediction from the TIP-GAN.*

Task 5.3 Phase 2 Evaluation – AI Simulation Integration

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

Oceanographer simulating answering a question.

***Question**: If Ekman Flux is 28226923.55 and Northern Hemisphere Freshwater Flux is 840575.51, does the AMOC collapse?*

***Answer**: Yes*

	Human Question to Program translation	Running the Four Box Model in Matlab	Human Interpretation of answer
Total Time in seconds	360	0.32	180

***Table 13.** Estimated Time Performance for a single example question to program translation and execution of four box model to obtain an answer.*

Task 5.3 Phase 2 Evaluation – New Question Performance

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- We extended the complexity of the questions used and generated 19 different question types.

- We performed a 90/10 split for training and test sets
  - 250,000 train samples
  - 12,500 test samples

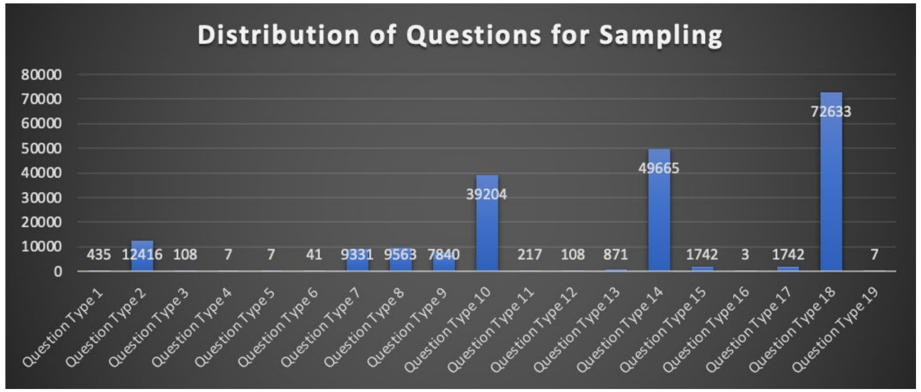


***Figure 43.** Distribution of Questions Used for Training the Neuro-symbolic Networks.*

Question Type	Example
1	What is the value of the overturning in the north latitudes at time step 3441 if the freshwater flux in the north latitude is 54785.814174809064?
2	If the Redi coefficient is 966.1041715067744 and the lower latitude initial thermocline depth is 367.03168813434985, does the AMOC collapse?
3	What is the final value of the AMOC when the initial salinity of the northern box is 31.90016602053442?
4	What is the nearest point to the current configuration with the AMOC off?
5	Find the nearest point to the current configuration with the AMOC off.
6	Does Fwn collapse the AMOC at 47887.43025295444?
7	Find the nearest point to the current configuration with the AMOC on, only varying the following parameters: the value of epsilon, the interface height diffusion coefficient, the initial temperature of the shallow ocean, the initial salinity of the shallow ocean, the initial salinity of the deep ocean, the area of the northern box.
8	If I set M_SD to 16376895.649532888, the freshwater flux in the southern latitude to 998459.5946592593, and the total model area to 371951331002107.25, will the overturning in the north latitudes increase?
9	If I decrease the initial temperature of the deep ocean by 0.42685610126021595, will the north atlantic deep water formation rate decrease?
10	By increasing the initial temperature of the northern box by 0.20513786641511758, will salinity in the southern latitudes decrease?
11	Given the starting vector, with Fws now allowed to vary from 0.0 to 1500000.0, does increasing Fws increase AMOC according to the GAN?
12	Find the nearest 4 points to the current configuration with the AMOC on.
13	Given the starting vector, vary epsilon between 0.00017769398928617632 and 0.00018038463322936978. For what values is AMOC "OFF"?
14	Given the starting vector, vary the initial temperature of the southern ocean between 2.5798667083604157 and 11.195587818693213, and the freshwater flux in the southern latitude between 500565.1088961287 and 871885.0115239422. For what values is AMOC "ON"?
15	Given the starting vector, vary the resistance to overturning between 0.0001860342067503932 and 0.00019679077103575926. For what values is AMOC "ON"? What are the largest 29 values for which the AMOC is on?
16	From the given point, what fraction of the neighbors within plus or minus 55 percent of each variables current value have AMOC off.
17	From the nearest point to the starting vector where the AMOC is on, find the nearest point increasing M_SD where the AMOC is on. Use the GAN to determine AMOC state.
18	From the starting vector, and according to the GAN, does decreasing the initial salinity in the north or decreasing the time step produce a closer AMOC on state?
19	From the nearest point to the starting vector where the AMOC is off, and according to the four box model, does hosing or climate warming get us to a AMOC on point closer to the starting vector?

***Table 14.** Example Questions Based on Templates Used for Training the Neuro-symbolic Networks.*

Task 5.3 Phase 2 Evaluation – New Question Performance

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

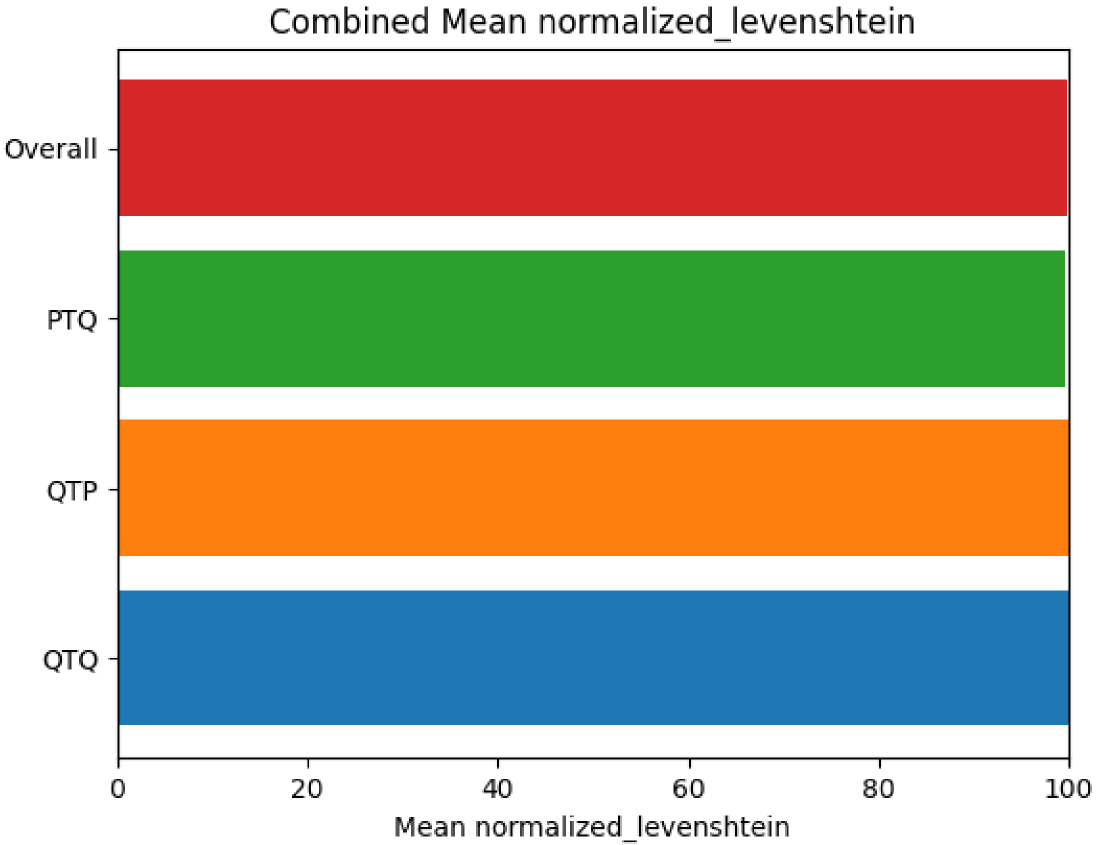


Figure 44. *Normalized mean Levenshtein distance by translation type. Great performance on all three translations.*

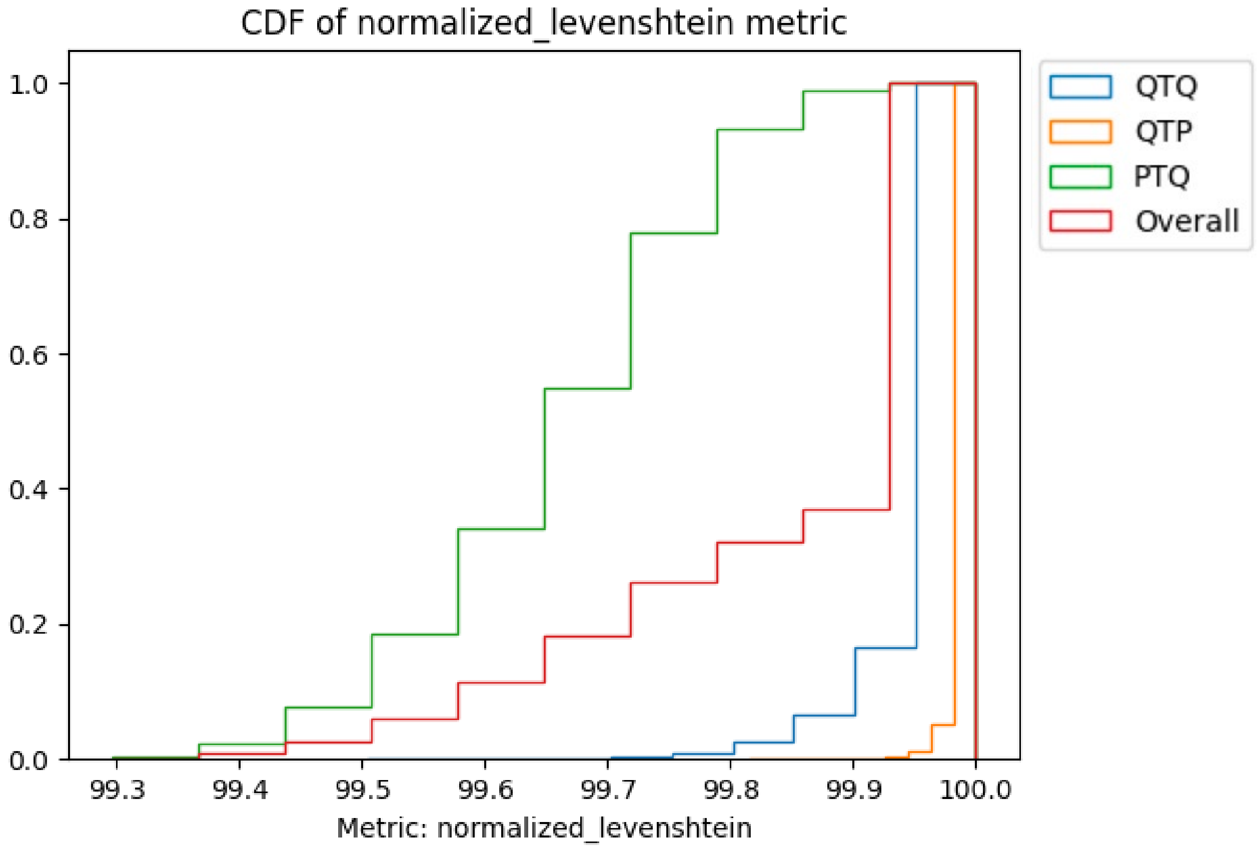


Figure 45. *CDF of normalized mean Levenshtein distance by translation type. Great performance on all three translations.*

Task 5.3 Phase 2 Evaluation – New Question Performance

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

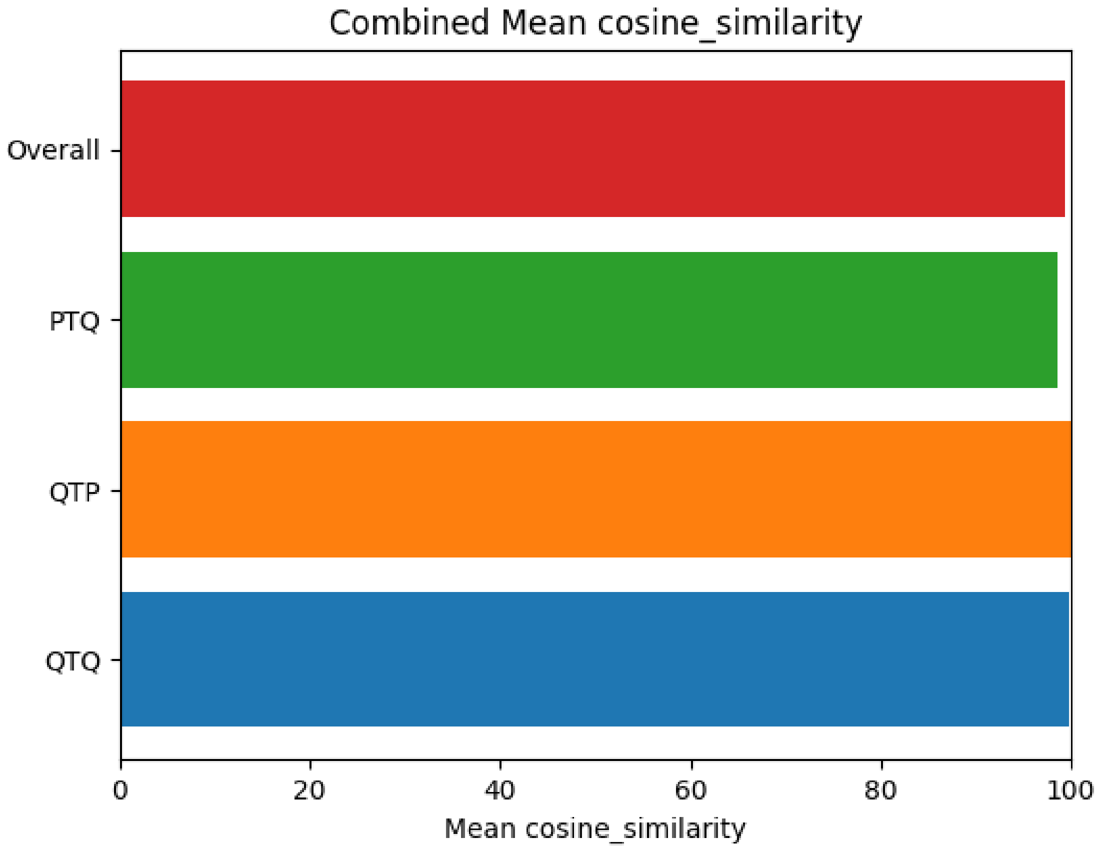


Figure 46. *Combined mean cosine similarity by translation type. Great performance on all three translations.*

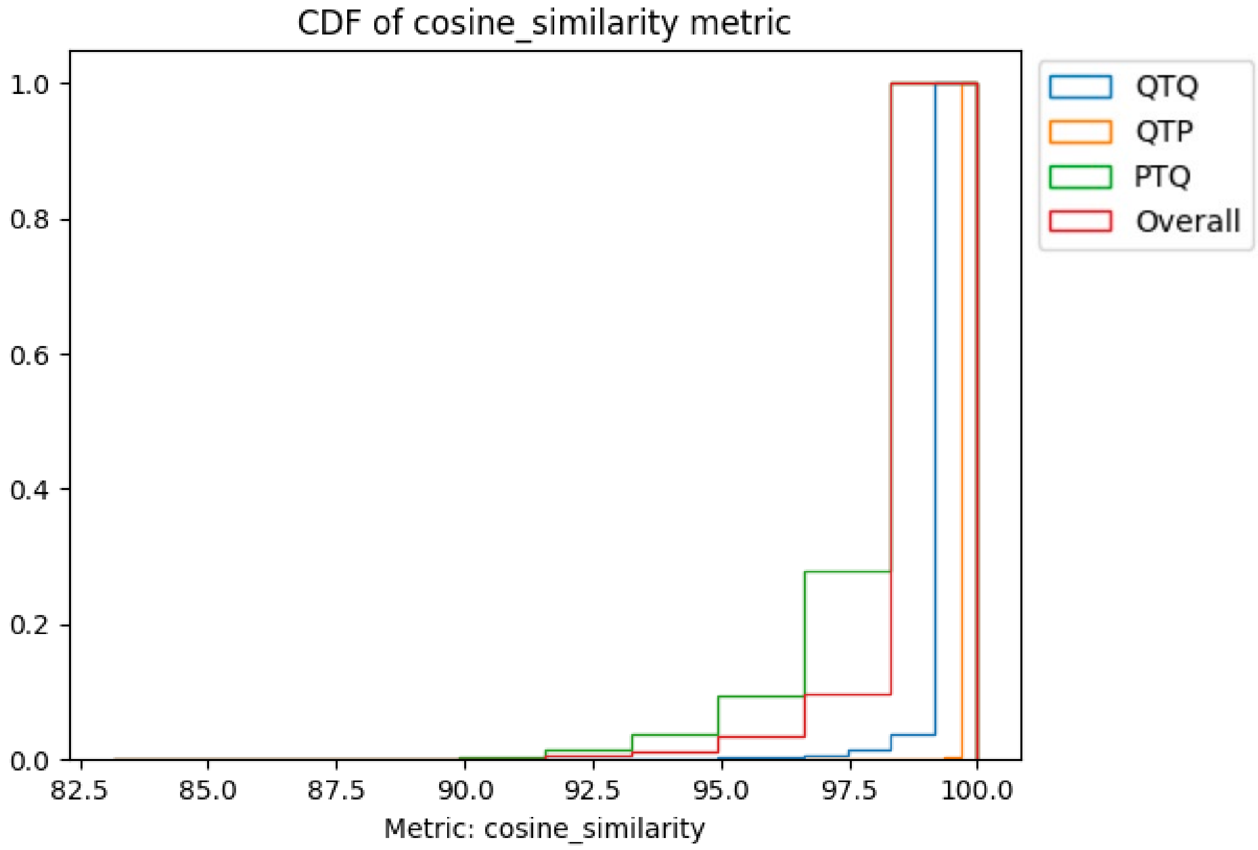


Figure 47. *CDF of combined mean cosine similarity by translation type. Great performance on all three translations.*

Task 5.3 Phase 2 Evaluation – New Question Performance

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

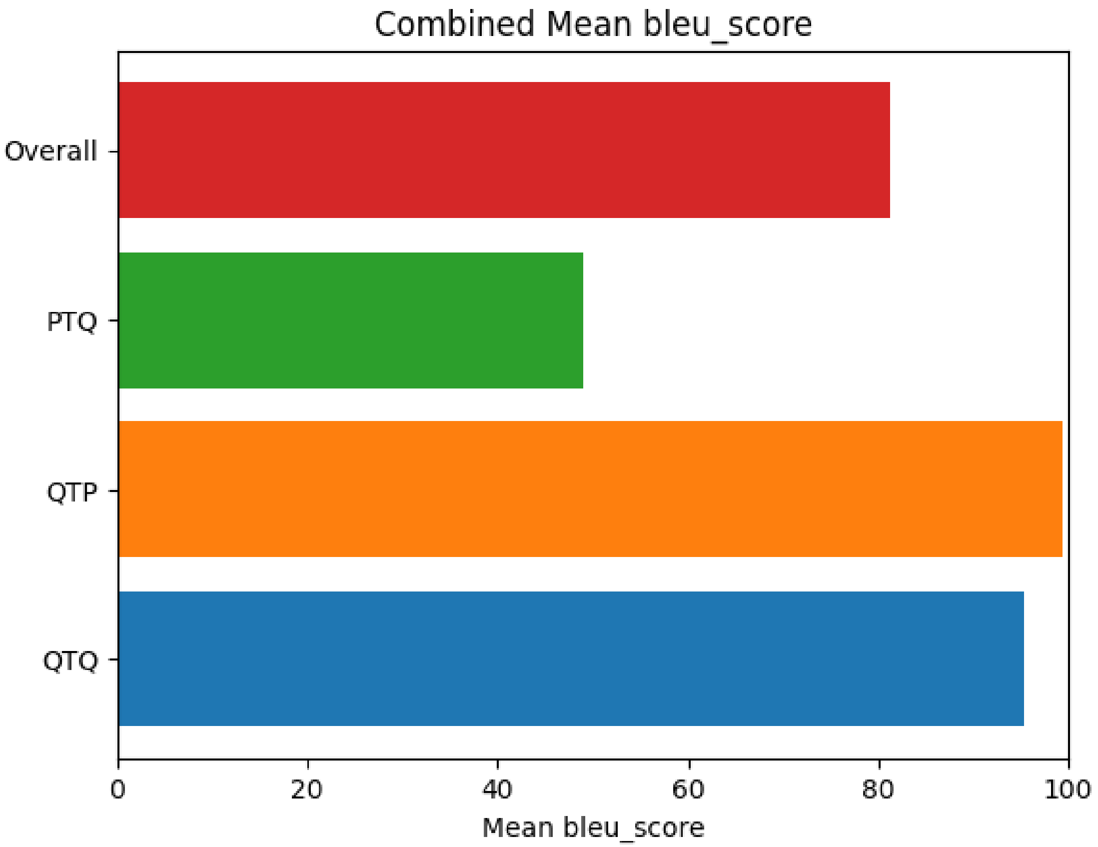


Figure 48. *Combined mean Bleu score by translation type. Great performance on all three translations.*

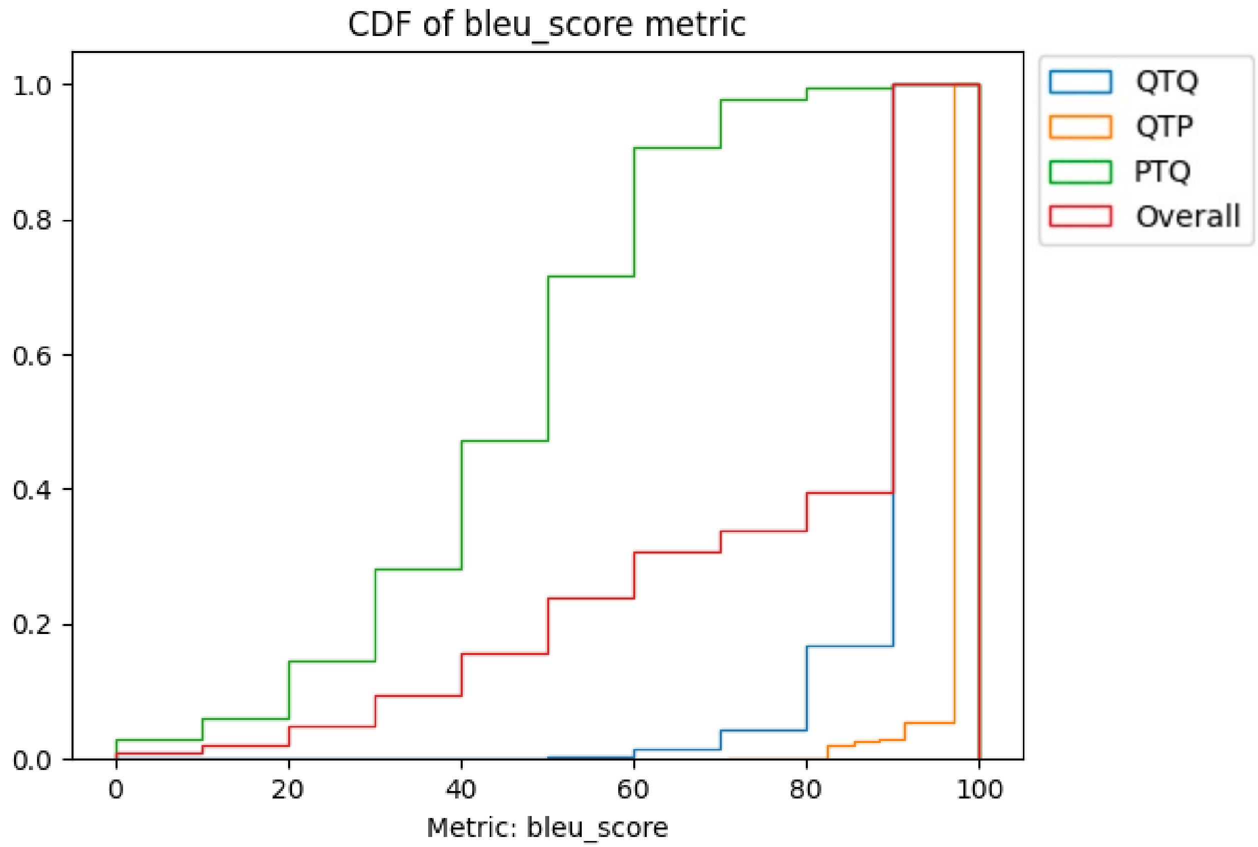


Figure 49*. CDF of combined mean Bleu score by translation type. Great performance on all three translations.*

Task 5.3 Phase 2 Evaluation – New Question Performance

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

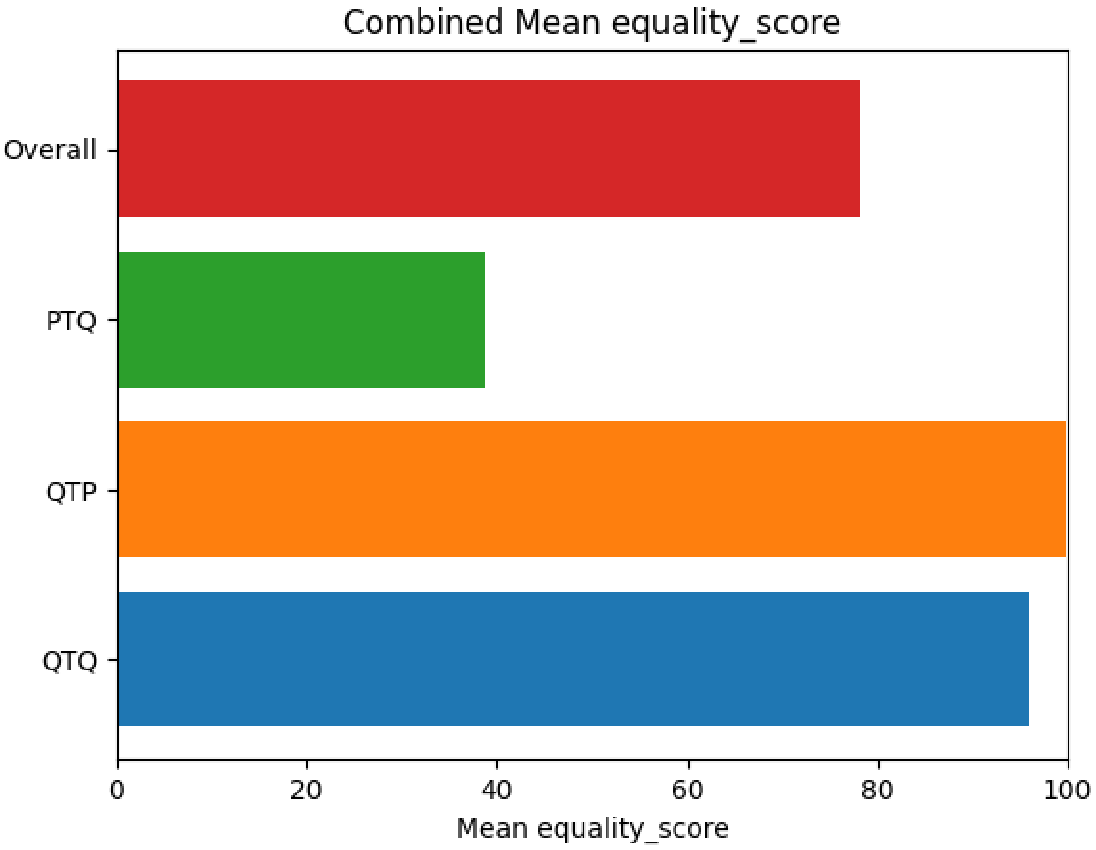


Figure 50. *Combined mean equality score by translation type. Great performance on all three translations.*

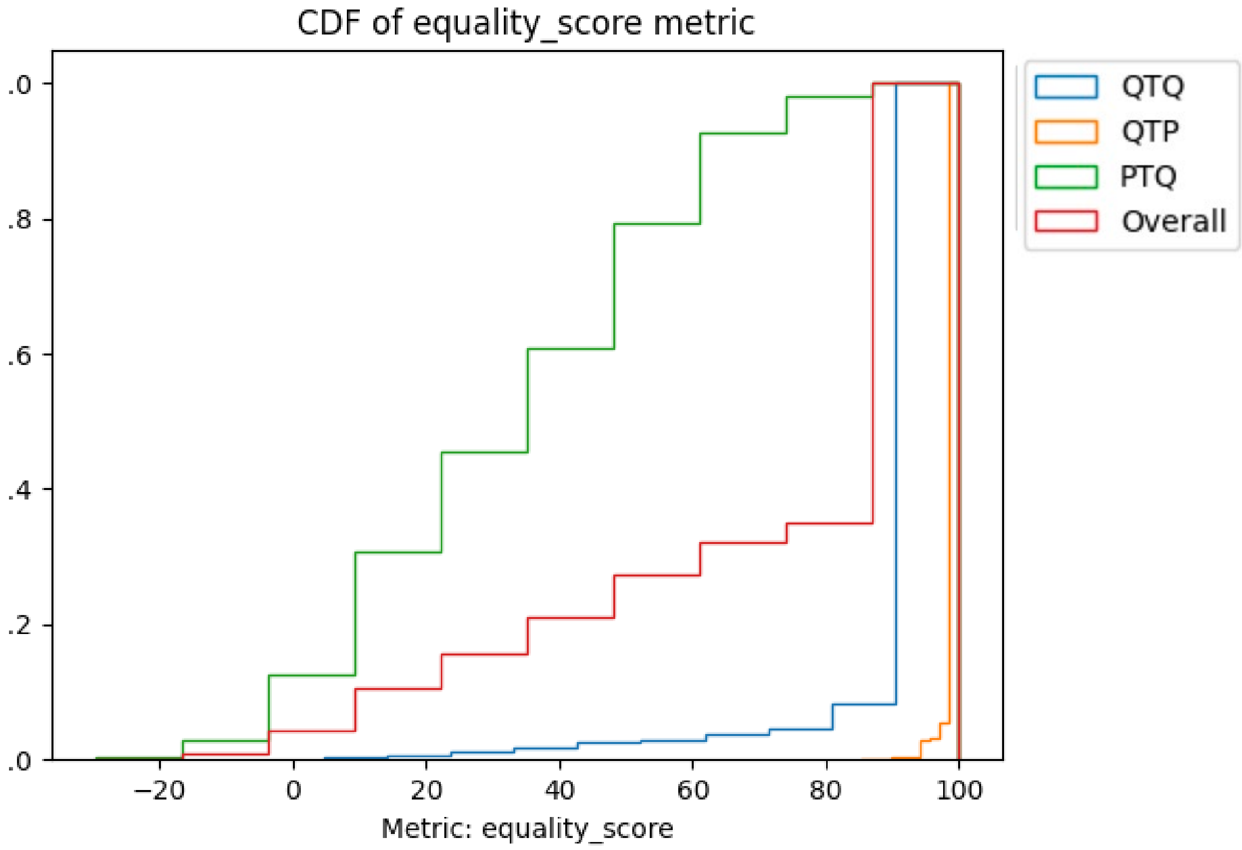


Figure 51. *CDF of combined mean equality score by translation type. Great performance on all three translations.*

Final Remarks and Conclusions – TIP-GAN

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- In a short period of time we formed a **multi-disciplinary team** that had never worked together prior to this effort.

- We developed a new **TIP-GAN** AI-based assisted climate modeling approach that includes a **neuro-symbolic translatio**n model for translating between natural questions and programs.

- We showed that the TIP-GAN **can in fact learn bifurcations** in parameter space and that together a **substantial speedup** can be obtained when compared with a typical scientific discovery process flow both in converting questions to programs and in answering questions.

Final Remarks and Conclusions - Insights and Six Box Model

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- We showed how TIP-GAN could be trained using the four box model as an oracle, and that the **AI approach to discovering tipping points can lead to new insights** and shortcomings in existing models. This motivated the effort to develop the **six box model**.

- The six box model models the overturning behavior in terms of the Atlantic and Pacific. It reflects more of the **complexities of the AMOC** than in the four box model.

- Bifurcation analysis applied to six box model show **high degrees of complexity** in terms of the bifurcations.

Final Remarks and Conclusions – Large GCMs

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- By **calibrating box models to large GCMs,** there is a path forward in applying PACMANs to the large GCMs.

- We showed that the box models reasonably represent the **dynamics of the CESM2** model when calibrated to the box model.

- We were able to obtain a **measure of uncertainty** regarding the ensemble member spread across three key parameters. This will provide additional insights of model disagreement.

Final Remarks and Conclusions – AI Simulator

The Physics-informed AI Climate Model Agent Neuro-symbolic Simulator (PACMANS) for Tipping Point Discovery

- Evaluations shows that the AI Simulator is **both efficient and accurate** in terms of predicting AMOC collapse.
- Benchmarks shows that the AI Simulator uncovers **interesting sensitivities to model parameters** that could inform how large modeling efforts should be conducted.
- **Causal models** showed correlations between parameters that warrant further investigation.

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