

# Southern Ocean Dynamics Under Climate Change: New Knowledge Through Physics-Guided Machine Learning

NeurIPS 2023 Workshop: Tackling Climate Change with Machine Learning

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# The ocean and climate change

- The ocean, covering over 70% of the globe, has absorbed **more than 90%** of recent warming.
- Models predict changes in complex ocean systems.
- Example: shifts in location/strength of the Antarctic Circumpolar Current (ACC)
- However, the **physical drivers behind these changes are not well understood.**

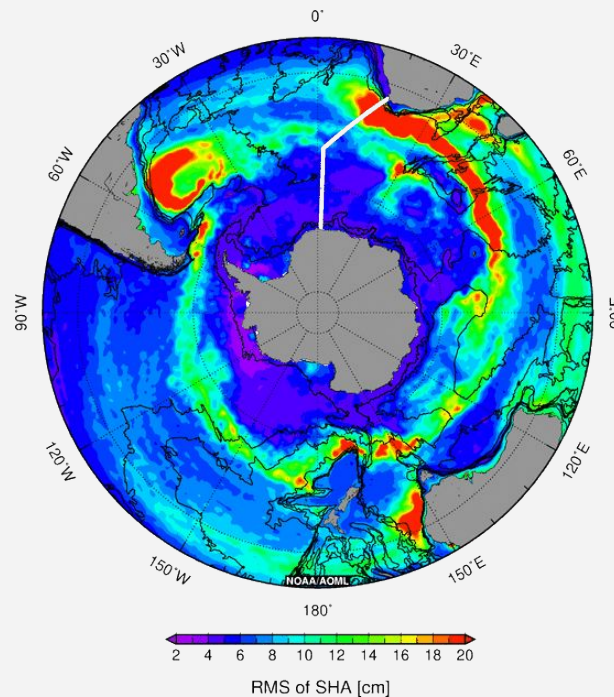
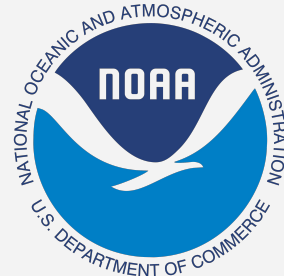


Image: NOAA/Atlantic Oceanographic & Meteorological Laboratory

Böning, C. W., Dispert, A., Visbeck, M., Rintoul, S. R., & Schwarzkopf, F. U. (2008). The response of the Antarctic Circumpolar Current to recent climate change. *Nature Geoscience*, 1(12), 864-869.

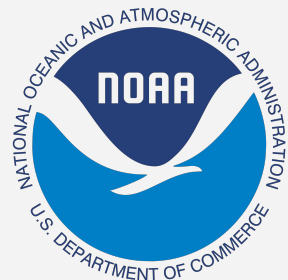


# Global climate modeling

- Coupled Model Intercomparison Project Phase 6 (CMIP6)
  - Standardized experimental design and distribution protocol
  - Massive amounts of data (23.4 PBs shared, still sparse)
- Hard to disseminate
  - Understanding how the **underlying physics** of the ocean is changing is difficult

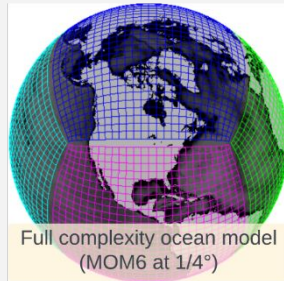


Image: Lawrence Livermore National Laboratory  
O'Neill, B. C., Tebaldi, C., Van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., ... & Sanderson, B. M. (2016). The scenario model intercomparison project (ScenarioMIP) for CMIP6. *Geoscientific Model Development*, 9(9), 3461-3482.

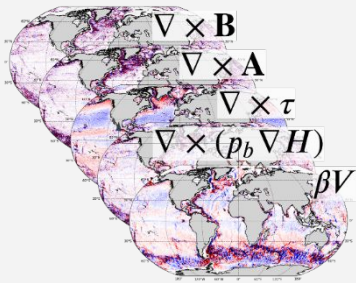


# Tracking global Heating with Ocean Regimes (THOR)

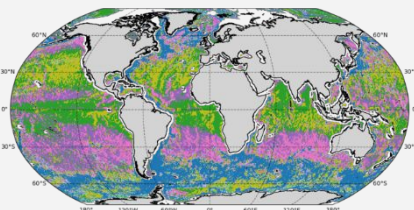
## 1) Cluster ocean dynamical regimes



Transform data to barotropic vorticity space

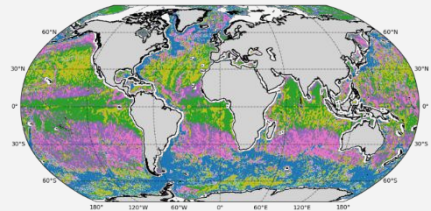
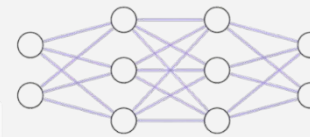
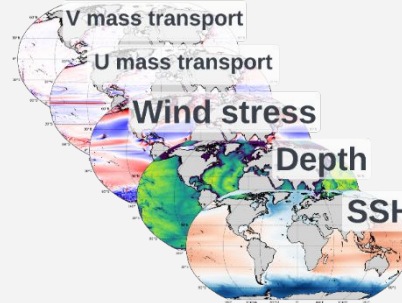


Native Emergent Manifold Interrogation (NEMI)



## 2) Supervised learning using labeled ocean dynamical regimes

With different inputs, train a neural network classifier using labels from Step 1

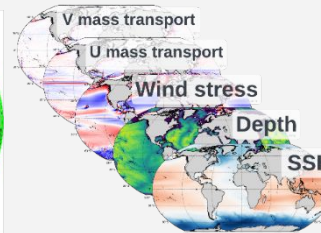


## 3) Tracking the effect of global Heating on Ocean Regimes (THOR)

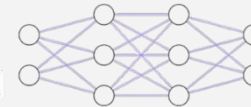
Predict ocean regimes of models with no access to in-depth ocean data



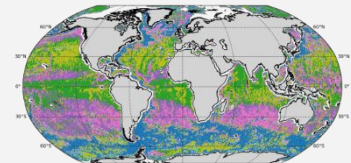
New ocean  
model of  
interest



Extract input data  
needed for  
classification



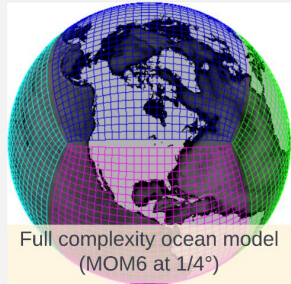
Run the trained  
classifier from **Step 2**



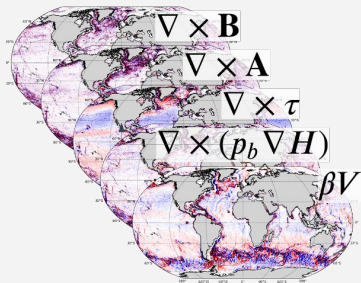
Interpret inferred  
dynamical regimes

# Step 1: Mesoscale unsupervised clustering

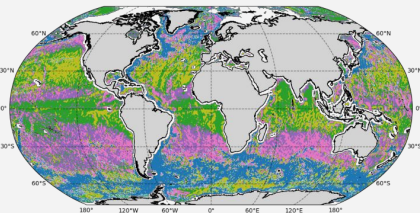
## 1) Cluster ocean dynamical regimes



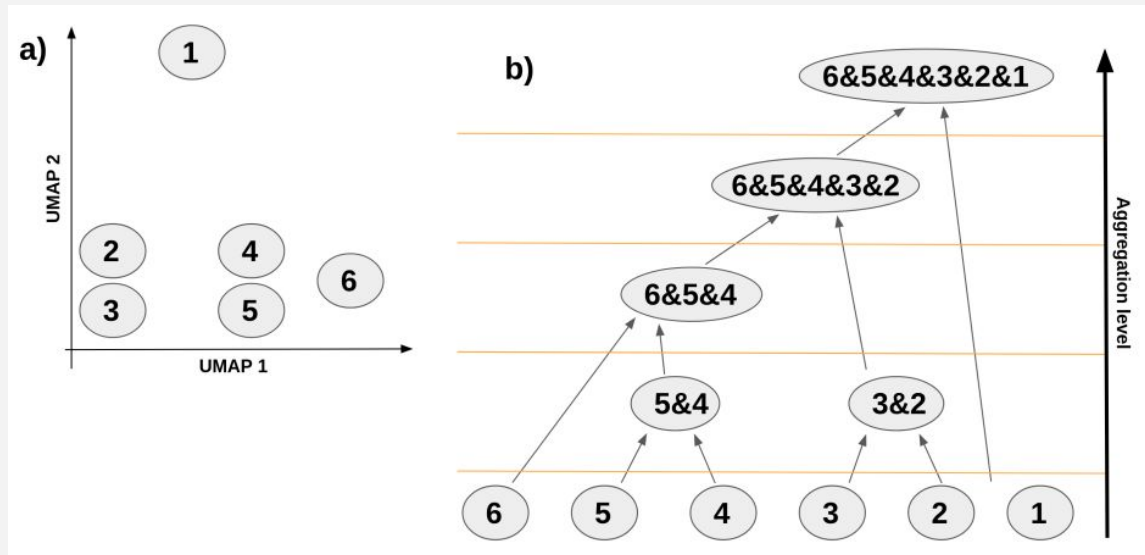
Transform data to barotropic vorticity space



Native Emergent Manifold Interrogation (NEMI)



- **Native Emergent Manifold Interrogation (NEMI)**  
utilizes Uniform Manifold Approximation and Projection (UMAP) paired with **agglomerative clustering**



- Partitions the ocean grid cells into clusters (**dynamical regimes**) based on their physics

McInnes, L., Healy, J., & Melville, J. (2018). Umap: Uniform manifold approximation and projection for dimension reduction. *arXiv preprint arXiv:1802.03426*.  
Sonnewald, M. (In review). A hierarchical ensemble manifold methodology for new knowledge on spatial data: An application to ocean physics. *JAMES*.

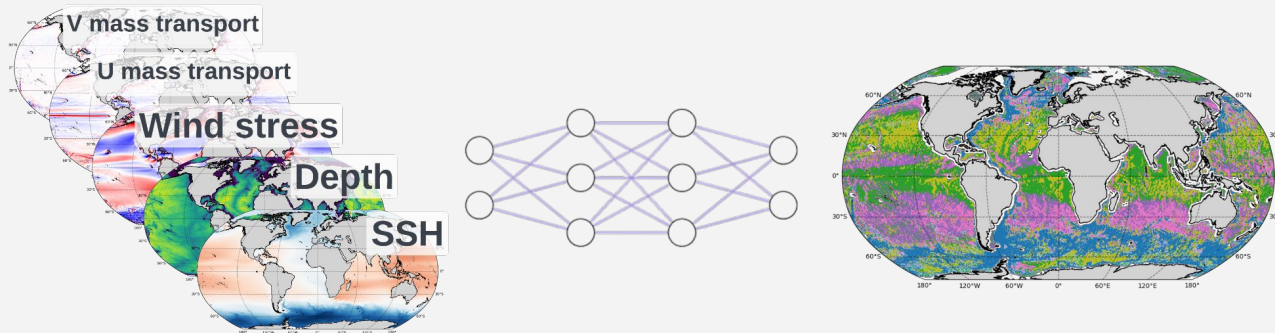




# Step 2: Learning regimes from readily available fields

## 2) Supervised learning using labeled ocean dynamical regimes

With different inputs, train a neural network classifier using labels from Step 1



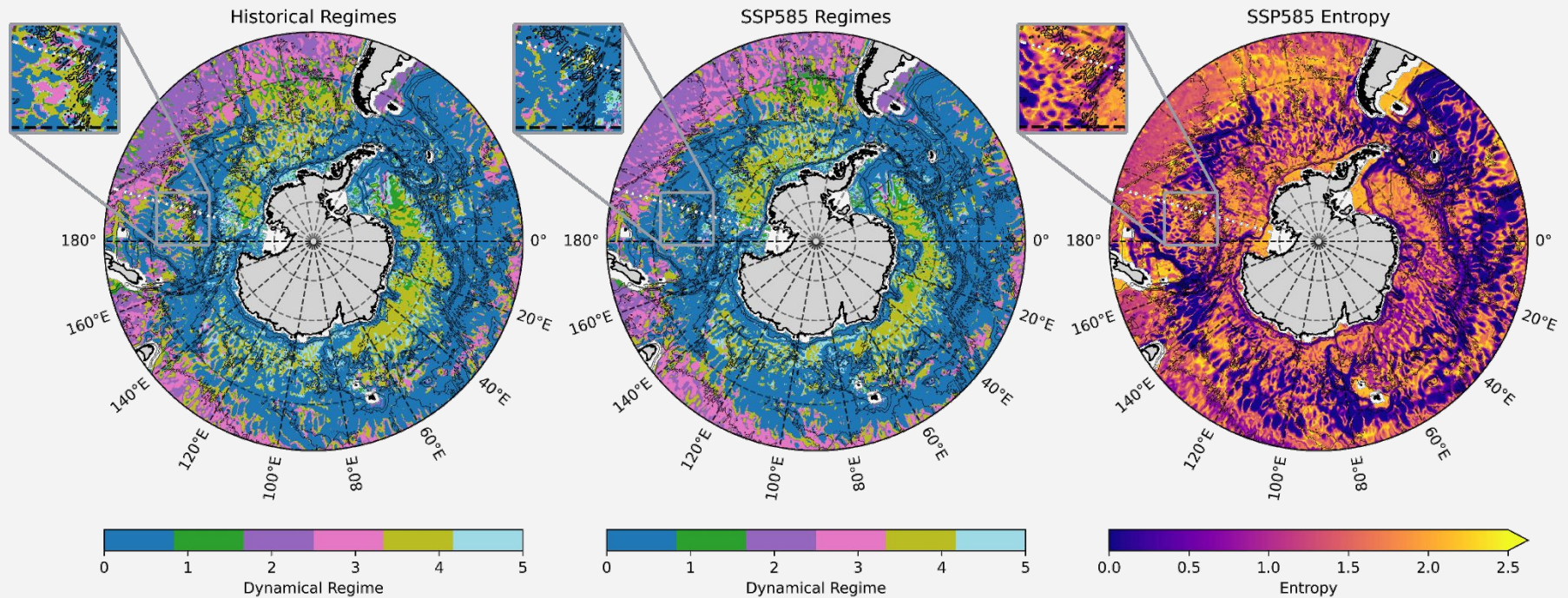
### - Inputs

- Sea surface height (ZOS) + x/y gradients
- Depth (column height) + x/y gradients
- Wind stress curl ( $\nabla \times \tau$ )
- Depth summed monthly mass transport (umo\_2d + vmo\_2d)
- Coriolis parameter (f)

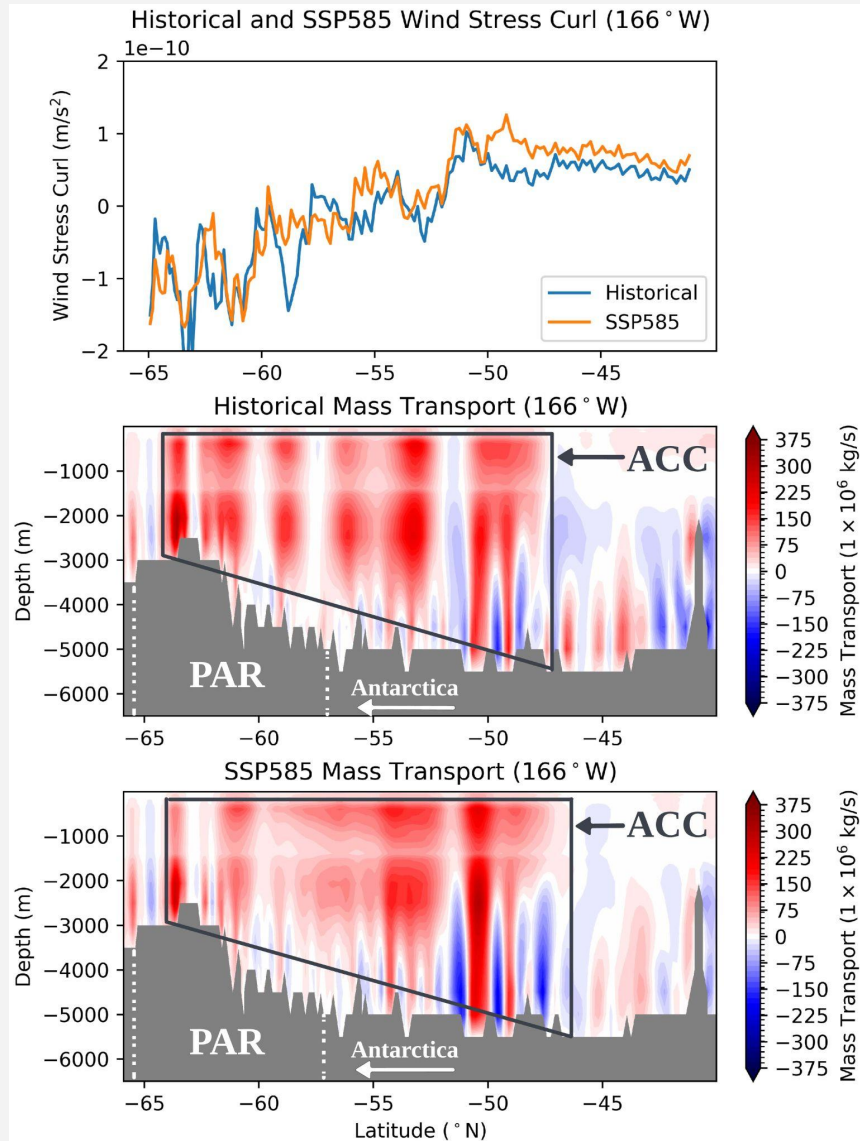
- Labels: 6 dynamical regimes identified by NEMI
- Ensemble of 50 feedforward MLPs for uncertainty quantification

# Step 3: Predicting regimes under climate change

**THOR reveals a shift in physics** where the Antarctic Circumpolar Current (ACC) meets the Pacific Antarctic Ridge (PAR).



# Key contributions



- **Mesoscale inference** of subsurface dynamical regimes
- **THOR guides further exploration** where the Antarctic Circumpolar Current (ACC) meets the Pacific-Antarctic Ridge (PAR)
- **THOR reveals a shift in dynamics**
- Due to increased wind stress, the ACC moves away from the rough surface of the PAR into a flatter region where it **flows more freely**



# Future directions and conclusion

- Comparing CMIP models could give insight into how different representations of ocean physics affect predictions
- Predicting dynamical regimes with spatially aware neural networks, **without trading off with explainability**
- Questions? Contact [wyik@hmc.edu](mailto:wyik@hmc.edu)

Read our paper! →



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