Revealing the impact of global warming on climate modes using transparent machine learning

ClimateChangeAI Workshop, ICML 2021

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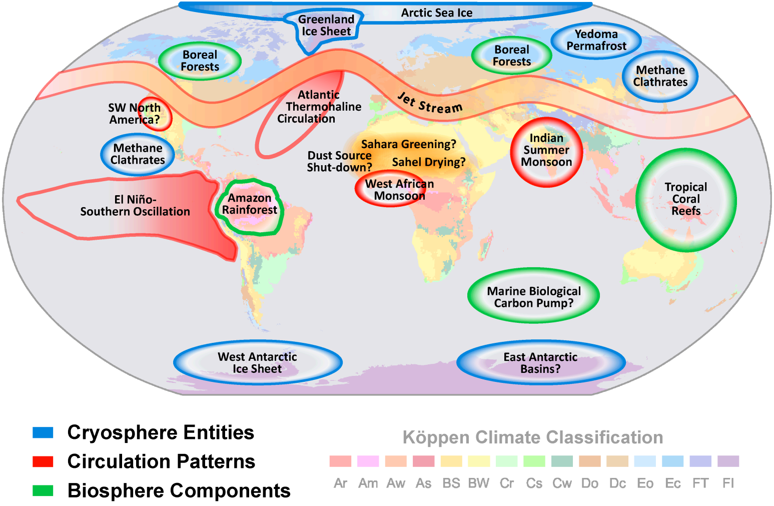
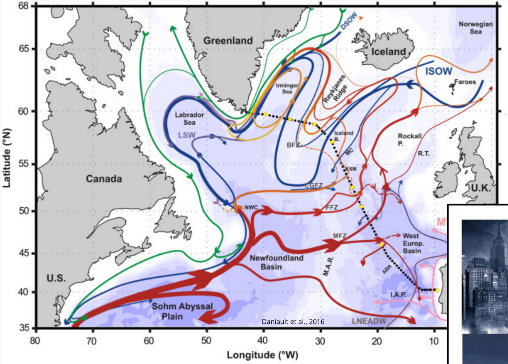
The ocean and global climate

The ocean, with its large heat capacity, has absorbed more than 90% of the heat gained by the planet between 1971 and 2010.

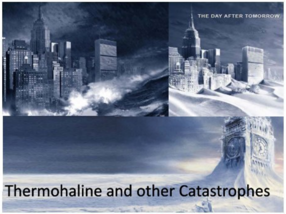


The ocean and global climate: Atlantic



Atlantic Meridional Overturning Circulation (AMOC):

- Thermohaline
- Heat transport to Europe
- Atmospheric patterns
- Drought in Europe
- Sea level USA East coast
- Hurricanes



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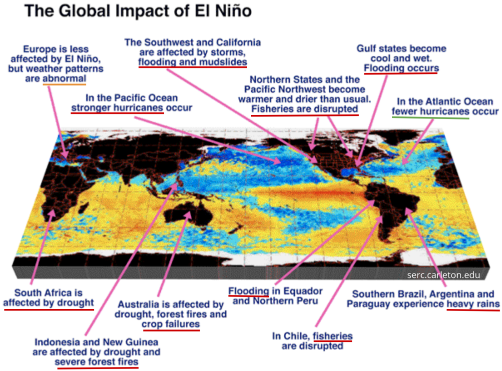
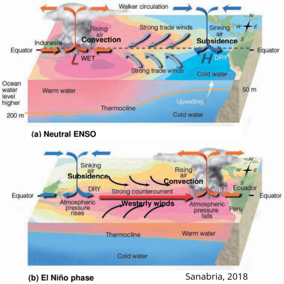
Often assessed with bulk metric:
One number to describe complex currents

The ocean and global climate: ENSO



- Global climate mode
- Complex interplay of circulation
- Profound ocean impact



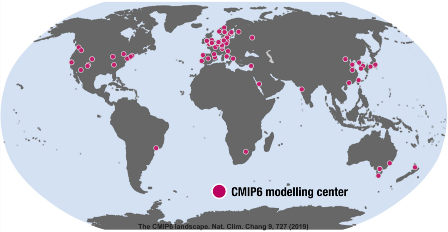
Sanabria, 2018

Often assessed with bulk metric:
One number to describe complex phenomena

Climate modelling

WCRP CMIP6

World Climate Research Programme



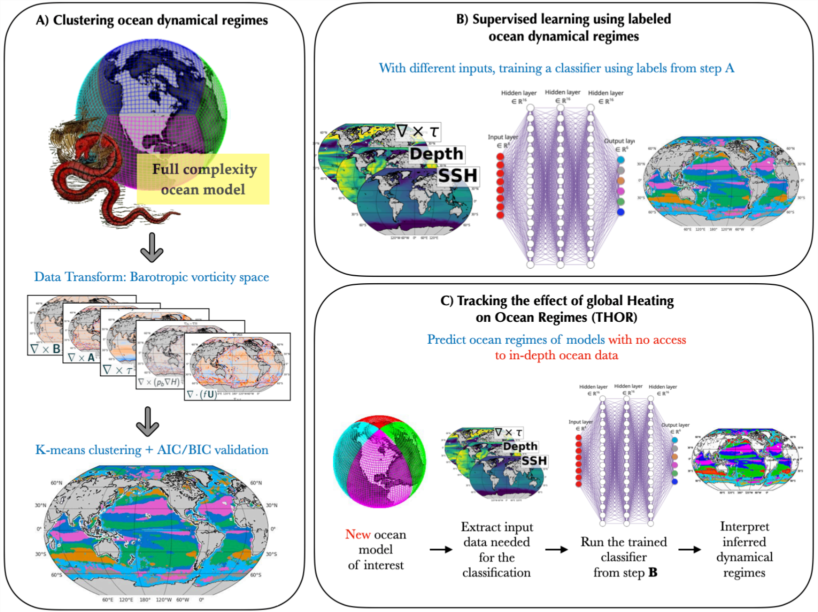
Coupled Model Intercomparison Project (CMIP)

- Standard experiment framework
- Comprehensive climate simulations
- Allows direct comparison of models
- Global participation

Lots of data; hard to store+disseminate; hard to analyze

Models used here: IPSL-CM6-LR [1], ESM4 [2], etc.

Tracking Global Heating with Ocean Regimes (THOR)



Tracking Global Heating with Ocean Regimes: A

Primitive equations

$$\frac{\partial u}{\partial t} + u\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y} + w\frac{\partial u}{\partial z} - fv = -\frac{1}{\rho_o}\frac{\partial P}{\partial x} + \frac{\partial}{\partial z}\left(K_m\frac{\partial u}{\partial z}\right) + F_u, \quad \text{Momentum (u component)}$$

$$\frac{\partial v}{\partial t} + u\frac{\partial v}{\partial x} + v\frac{\partial v}{\partial y} + w\frac{\partial v}{\partial z} + fu = -\frac{1}{\rho_o}\frac{\partial P}{\partial y} + \frac{\partial}{\partial z}\left(K_m\frac{\partial v}{\partial z}\right) + F_v \quad \text{Momentum (v component)}$$

$$\frac{\partial P}{\partial z} = -\rho g, \quad \text{density}$$

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z} = 0, \quad \text{continuity}$$

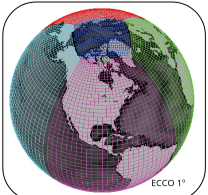
$$\frac{\partial \theta}{\partial t} + u\frac{\partial \theta}{\partial x} + v\frac{\partial \theta}{\partial y} + w\frac{\partial \theta}{\partial z} = \frac{\partial}{\partial z}\left(K_h\frac{\partial \theta}{\partial z}\right) + F_\theta, \quad \text{Advection of temperature}$$

$$\frac{\partial s}{\partial t} + u\frac{\partial s}{\partial x} + v\frac{\partial s}{\partial y} + w\frac{\partial s}{\partial z} = \frac{\partial}{\partial z}\left(K_h\frac{\partial s}{\partial z}\right) + F_s, \quad \text{Advection of salinity}$$

$$\rho = \rho(\theta, s), \quad \text{Density as a function of S and T}$$

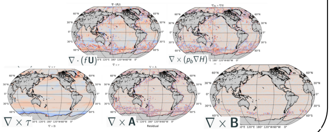
Ocean model that follows laws of physics

Huge number of 3D fields



Use theory to reduce dimensions and enhance interpretability

$$0 = \overbrace{\nabla \cdot (f\mathbf{U})}^{\text{Advection}} - \underbrace{\nabla \times (p_b \nabla H)}_{\text{Bottom Pressure Torque}} + \overbrace{\nabla \times \tau}^{\text{Wind and Bottom stress}} - \underbrace{\nabla \times \mathbf{A}}_{\text{Non-linear Torque}} + \overbrace{\nabla \times \mathbf{B}}^{\text{Lat. Visc.}}$$



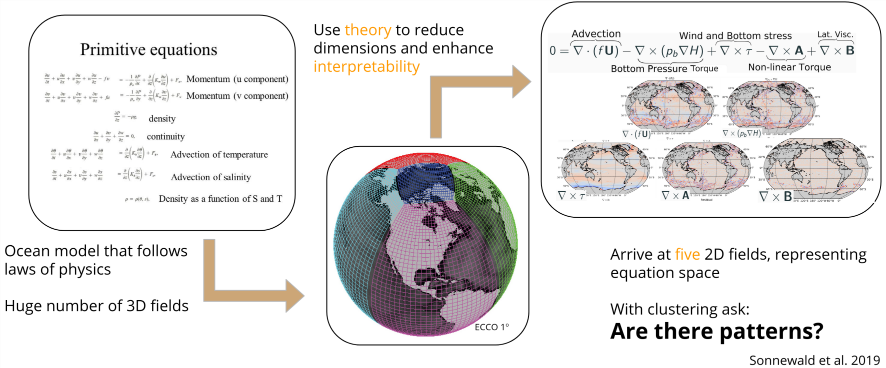
Arrive at five 2D fields, representing equation space

With clustering ask:

Are there patterns?

Sonnewald et al. 2019

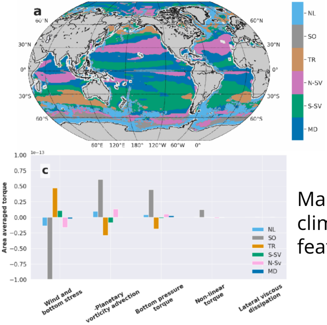
Tracking Global Heating with Ocean Regimes: A



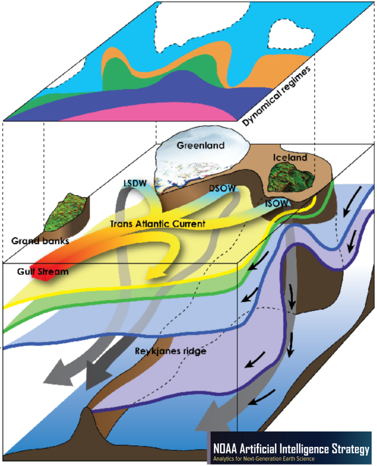
Interpretable AI [5]

Tracking Global Heating with Ocean Regimes: A

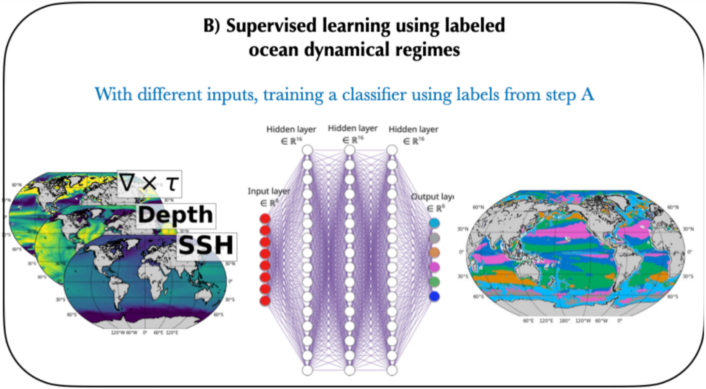
K-means+
strict statistical and
geoscientific criteria



Map onto
climatically key
features



Tracking Global Heating with Ocean Regimes: B



Engineer dataset

Input theory informed:

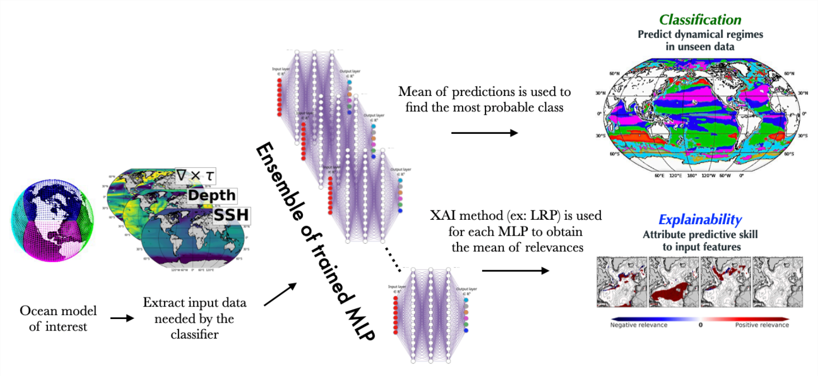
1. Wind stress
2. Sea surface height+grads
3. Depth+grads

Labels: Dynamical regimes (Step A)

Train Ensemble MLP

- Ensemble of 50 MLPs: same architecture, different initialization
- MLP: 4 layers, 24-24-16-16 neurons
- Keras-tuner for Hyperparameters
- Class prediction: Average softmax probabilities of the Ensemble MLP

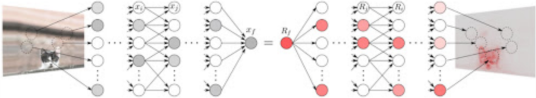
Tracking Global Heating with Ocean Regimes: B



Sonnewald and Lguensat 2021 [3]

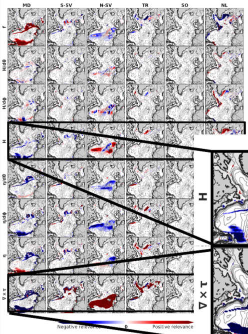
Tracking Global Heating with Ocean Regimes: B

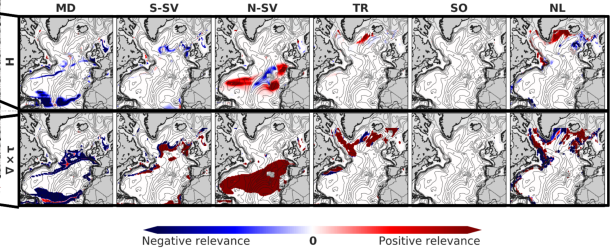
Additive Feature Attribution:
Explainable AI (XAI)



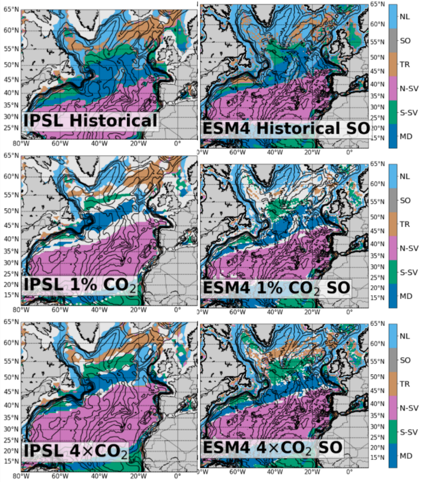
Layerwise Relevance Propagation (LRP)

- Dynamical regime (horizontal) by input feature (vertical)
- Relevance mean of ensemble LRP estimation
- Pos/Neg regions conform with expectations from theory
- Avoid underspecification (D’Amour et al., 2020)
- Confidence in out-of-sample prediction ⇐ All climate simulation





Tracking Global Heating with Ocean Regimes: C



Circulation is known to weaken with climate change: Mechanisms?

Two example IPCC climate models:

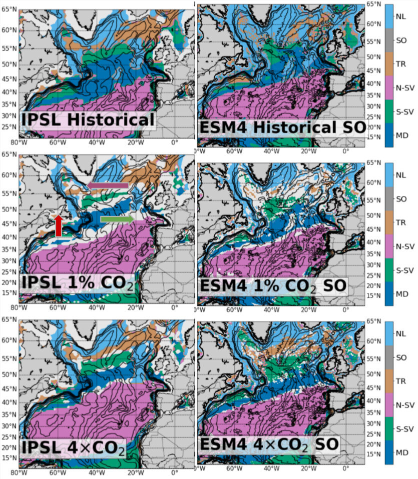
- IPSL (Fr.) and GFDL-ESM (USA)
- Perturbation from 'historical'
- Moderate pace increase: 1% CO_2
- Abrupt increase: 4xAbrupt CO_2

THOR reveals:

- USA east coast current shift (Gulf Stream)
- Heat delivery not as far north (Trans Atlantic Current)
- Areas of waters sinking shift
- Stronger in IPSL
- 4xAbrupt CO_2 bigger change

Model mechanism intercomparison is facilitated

Tracking Global Heating with Ocean Regimes: C



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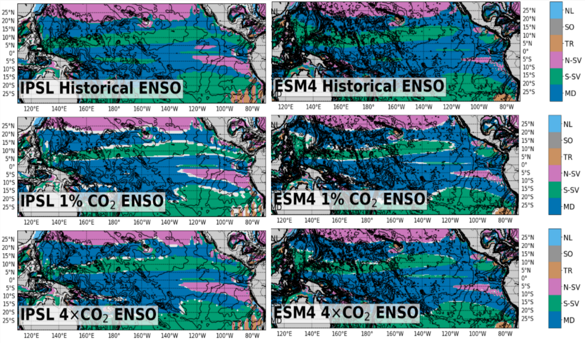
Tracking Global Heating with Ocean Regimes: C



Change less clear:
Mean state brings variability

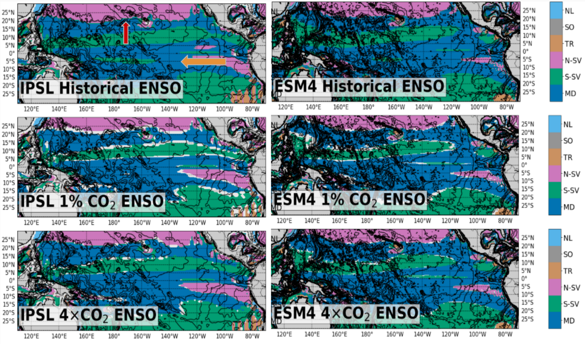
THOR reveals:

- Widening of upwelling by Peru: Cold water delivery
- Expansion of wind-driven polewards transport

Model comparison:

- Bigger difference in dynamics
- Reflection of model configuration?
- IPSL largest change

Tracking Global Heating with Ocean Regimes: C



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Summary + open questions

THOR strives for transparency:

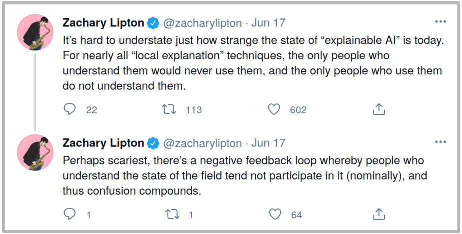
- 1: Has interpretable AI first step with equation transform and clustering
- 2: Engineers labeled dataset grounded in oceanographic theory and utility
- 3: Dataset allows an Ensemble MLP to be verified for theoretical conformance

Climate analysis appropriate:

- THOR's theory conformance boosts confidence in out-of-sample application
- Avenue for CMIP6 data dissemination+analysis?
- Blueprint for other analysis: Monsoon, marine biogeochemistry

Open questions for the ML community:

- XAI methods are ***sometimes unreliable*** (adversarial attacks, design choices..)
- An Ensemble MLP can be replaced by other ML techniques, but need an estimate of ***uncertainty*** too



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arXiv:2104.12506v1 [physics.ao-ph] 26 Apr 2021

Topical Review

Bridging observation, theory and numerical simulation of the ocean using Machine Learning

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Abstract.
Progress within physical oceanography has been concurrent with the increasing sophistication of tools available for its study. The incorporation of machine learning (ML) techniques offers exciting possibilities for advancing the capacity and speed of established methods and also for making substantial and serendipitous discoveries. Beyond vast amounts of complex data ubiquitous in many modern scientific fields, the study of the ocean poses a combination of unique challenges that ML can help address. The observational data available is largely spatially sparse, limited to the surface, and with few time series spanning more than a handful of decades. Important timescales span seconds to millennia, with strong scale interactions and numerical modelling efforts complicated by details such as coastlines. This review covers the current scientific insight offered by applying ML and points to where there is imminent potential. We cover the main three branches of the field: observations, theory, and numerical modelling. Highlighting both challenges and opportunities, we discuss both the historical context and salient ML tools. We focus on the use of ML in situ sampling and satellite observations, and the extent to which ML applications can advance theoretical oceanographic exploration, as well as aid numerical simulations. Applications that are also covered include model error and bias correction and current and potential use within data assimilation. While not without risk, there is great interest in the potential benefits of oceanographic ML applications; this review caters to this interest within the research community.

Keywords: Ocean Science, physical oceanography, machine learning, observations, theory, modelling, supervised machine learning, unsupervised machine learning.
Submitted to: *Environ. Res. Lett.*

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Review on ML for ocean science
Preprint https://arxiv.org/abs/2104.12506

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HRMES

NOAA

Sonnewald et al. [4]

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