

Using ML to let modeling, theory and observations inform each other

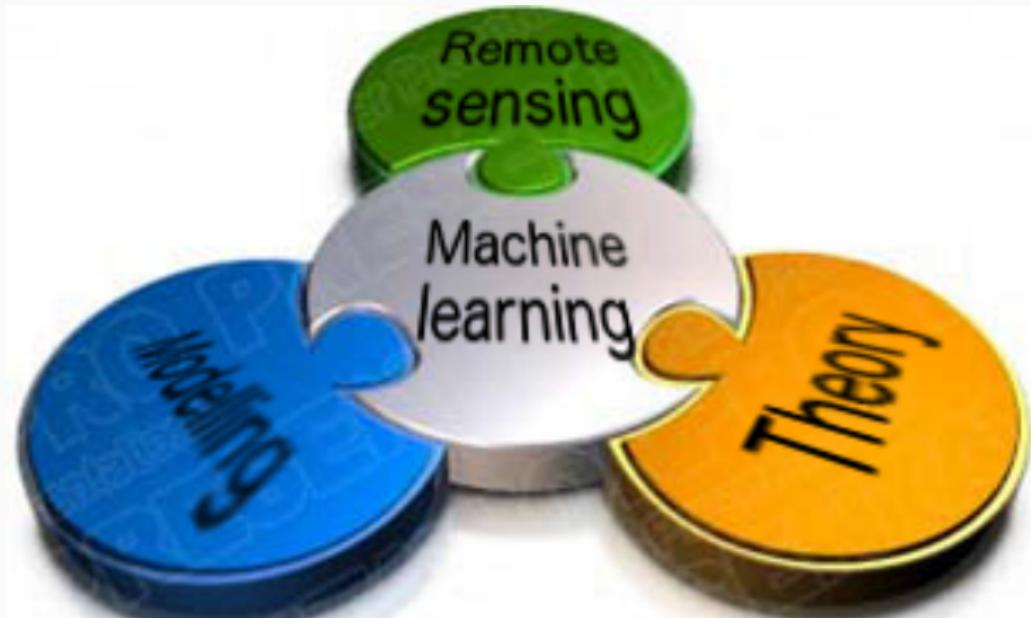
Maike Sonnewald^{1,2}

July, 2019

¹MIT & ²Harvard

Introduction

Why ML?



Goal of science/geoscience:
Have precise and accurate understanding of the natural world.

Motivation: My ocean bias

Ocean covers 70% of the Earth's surface

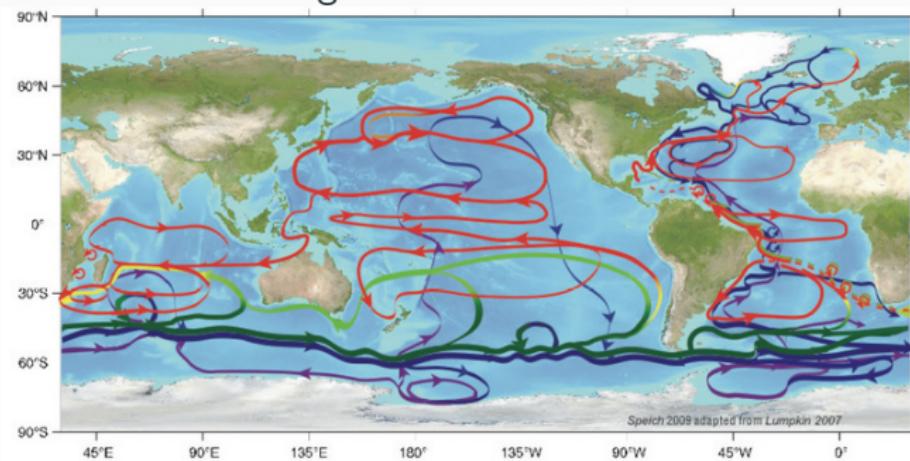
Heat capacity 1100 > times atmosphere

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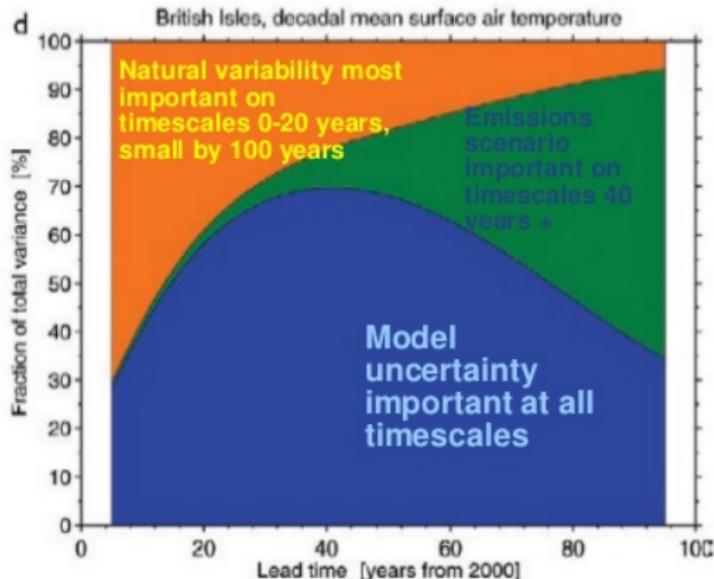
Heat capacity 1100 > times atmosphere

Since 1955, over 90% of excess heat from greenhouse gasses has
gone into oceans



The ocean takes up about 71% of Earth's space, but 95% of
the ocean remains unexplored. NOAA

Source of uncertainty in climate scenarios



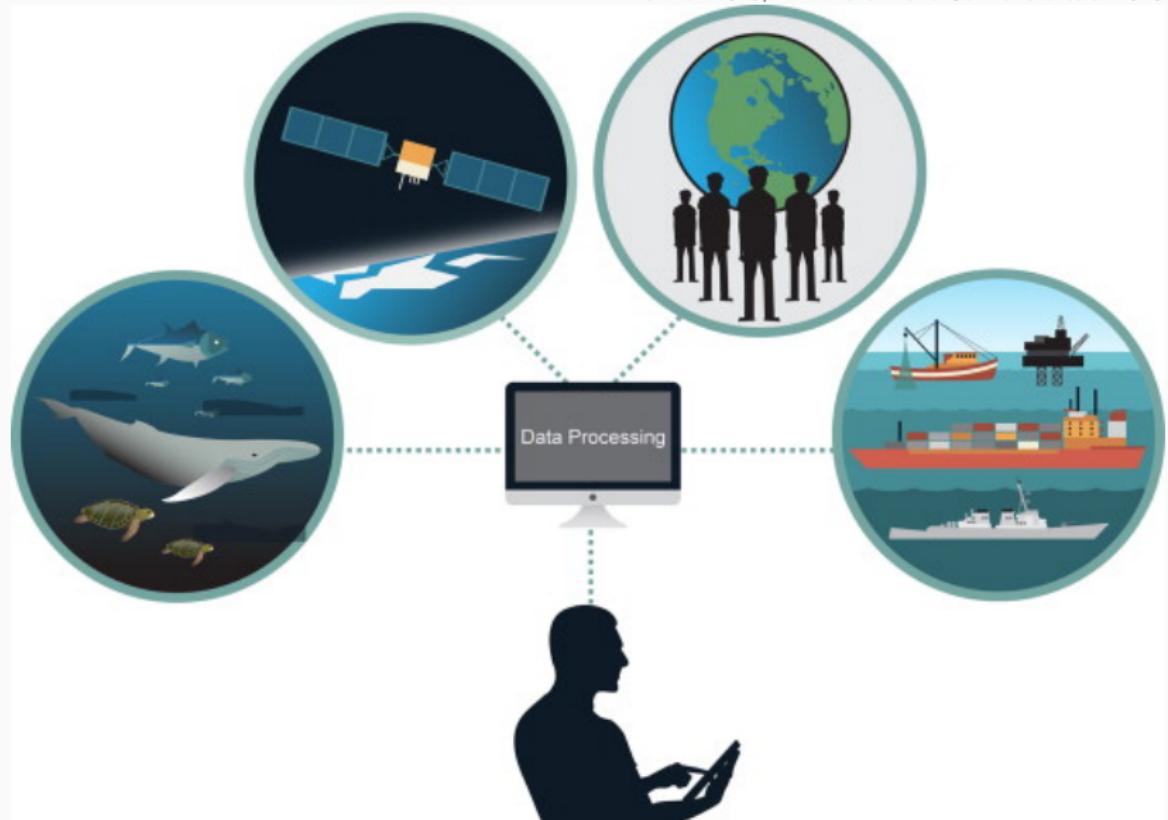
That depends on the timescale that we are looking at...

ipcc
INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE



We are becoming data rich in oceanography

Maxwell 2015, Kim Martini and Sonnewald et al 2013



We are becoming data rich in oceanography

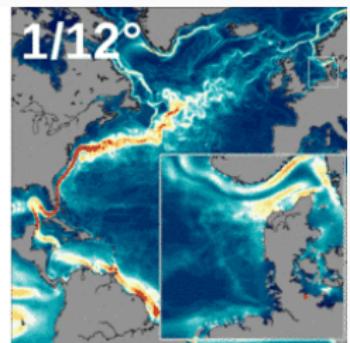
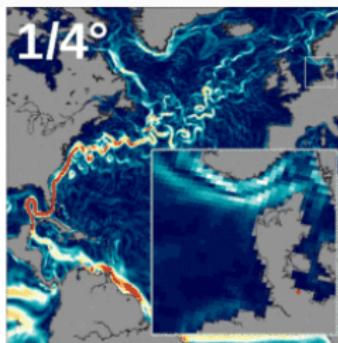
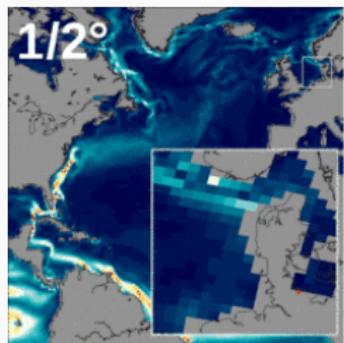
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Big data can be overwhelming

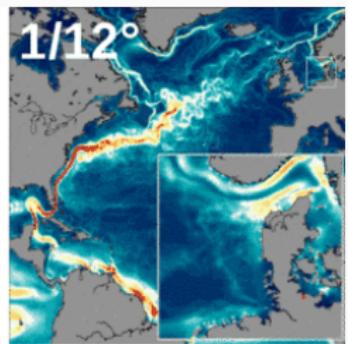
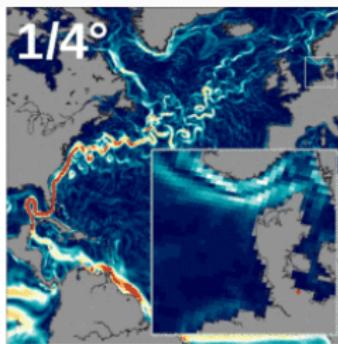
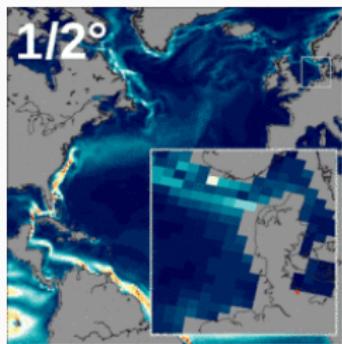


Observations are hard



NEMO (Geomar)

Observations are hard

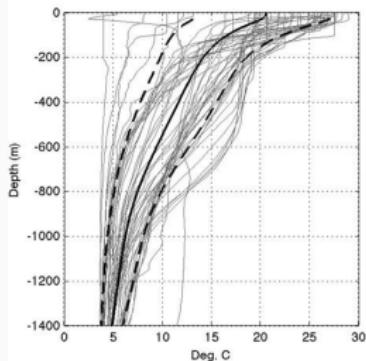


NEMO (Geomar)

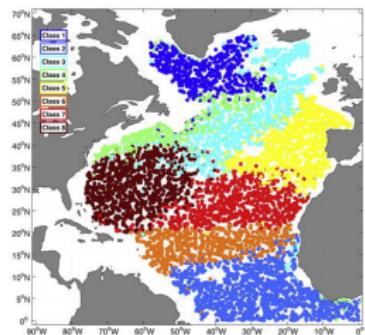
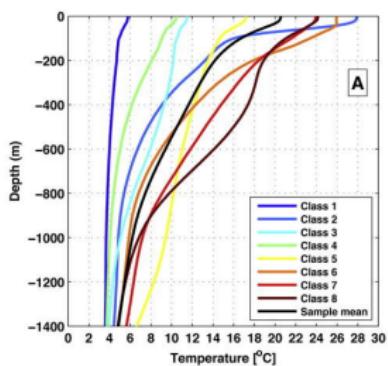
**The ocean is big with unquantified variance:
Huge+costly effort to gather data often relying on
serendipity**

Observations+ML

Complex distribution of heat in space



Data-driven model of heat content patterns



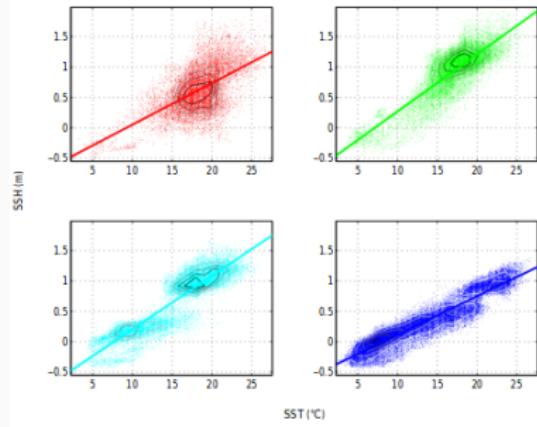
Random sample of Argo temperature profiles in the North Atlantic

Different groups of temperature profiles are identified automatically...

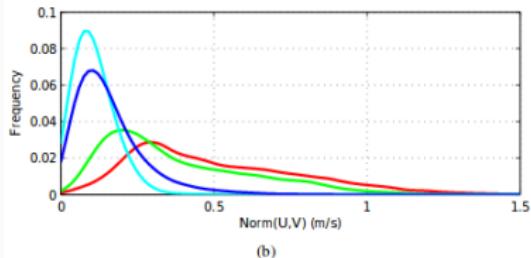
... that correspond to coherent regions of the ocean

unsupervised classification

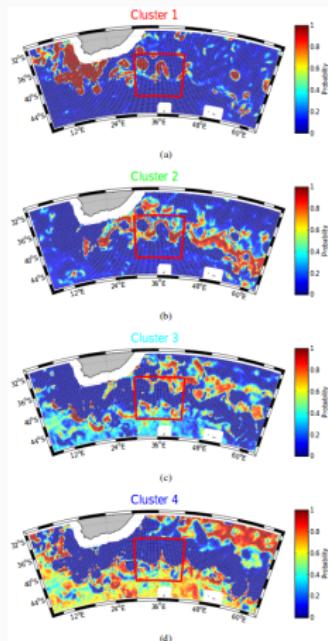
Observations+ML



(a)

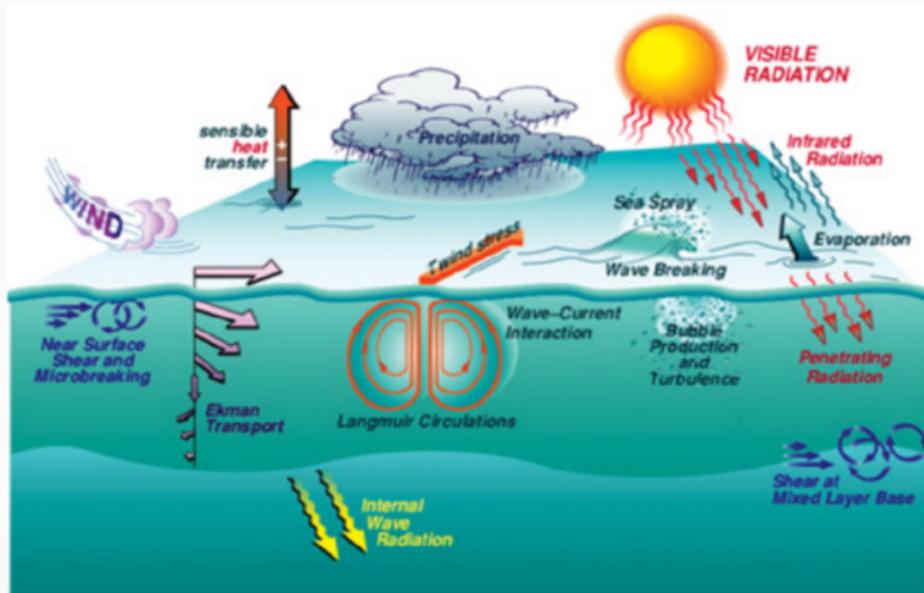


(b)



Tanedo, 2014 (IEEE)

Structural model uncertainty



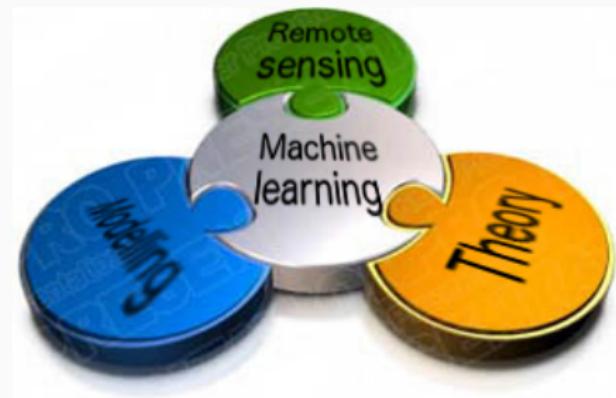
Weller, WHOI

Sources of uncertainty are many and varied:
Huge+constly efforts to improve “accuracy” even in the
absence of complete observational understanding.

Machine Learning to the rescue?

Can ML help?

- Find “emergent” patterns in models
- Group sparse observations
- Infer theoretical underpinning
- What can we do with these patterns?



Case studies:

- 1: Physical Oceanography looking to improve understanding of western boundary currents
- 2: Ocean ecological compositions to understand long term monitoring

...Global dynamical regimes

Theory: Barotropic Vorticity equation

Momentum equations:

$$\partial_t \mathbf{u} + f \mathbf{k} \times \mathbf{u} = -\frac{1}{\rho_0} \nabla p + \frac{1}{\rho_0} \partial_z \tau + \mathbf{a} + \mathbf{b}, \quad \partial_z p = -g\rho, \quad \nabla \cdot \mathbf{v} = 0.$$

-Depth integrate, take curl

Barotropic Vorticity:

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

e.g. Sverdrup balance:

Wind stress curl and advection balance **locally**

$$\nabla \cdot (f \mathbf{U}) = \nabla \times \tau$$

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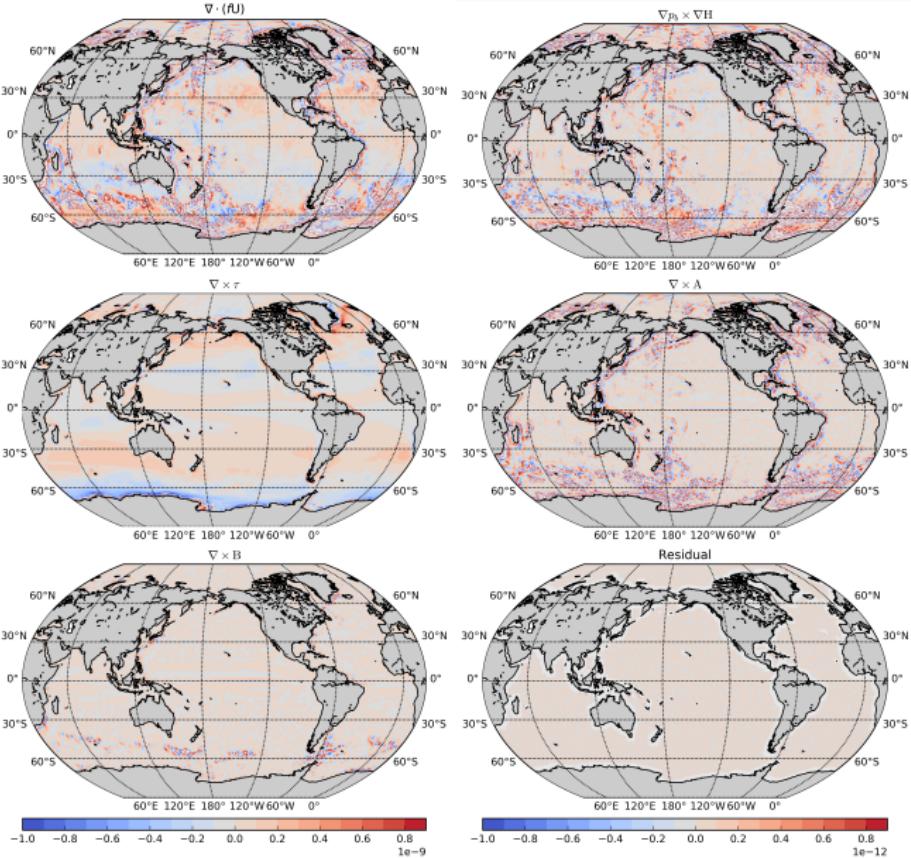
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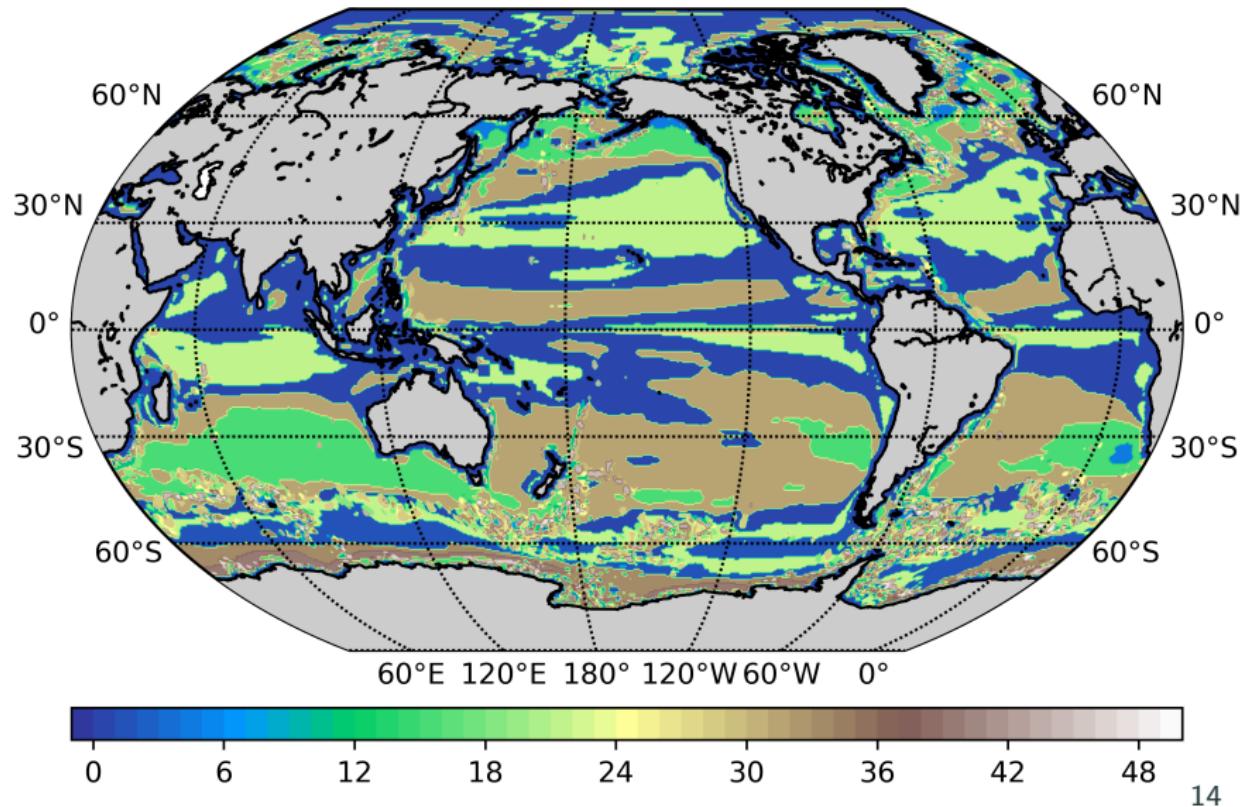
..Is this real? Is every location unique?

$$0 = \nabla \cdot (f\mathbf{U}) - \nabla \times (p_b \nabla H) + \nabla \times \tau - \nabla \times \mathbf{A} + \nabla \times \mathbf{B} \text{ (ms}^{-1}\text{)}$$

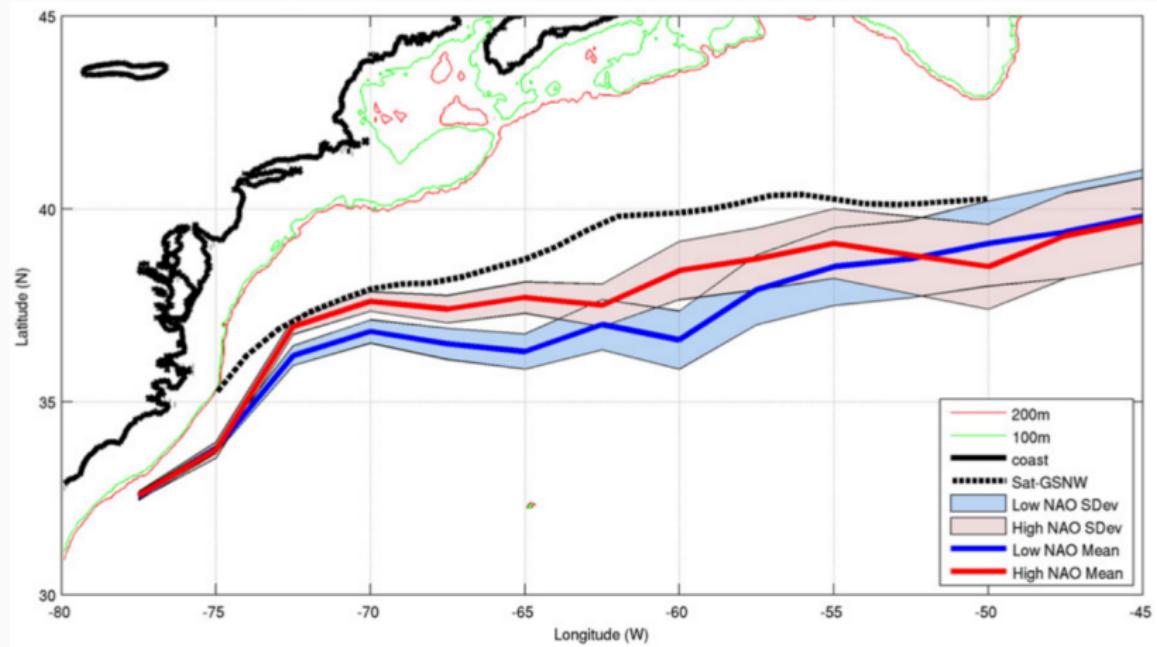


Dynamical regions

K-Means with 50 clusters, scaled data

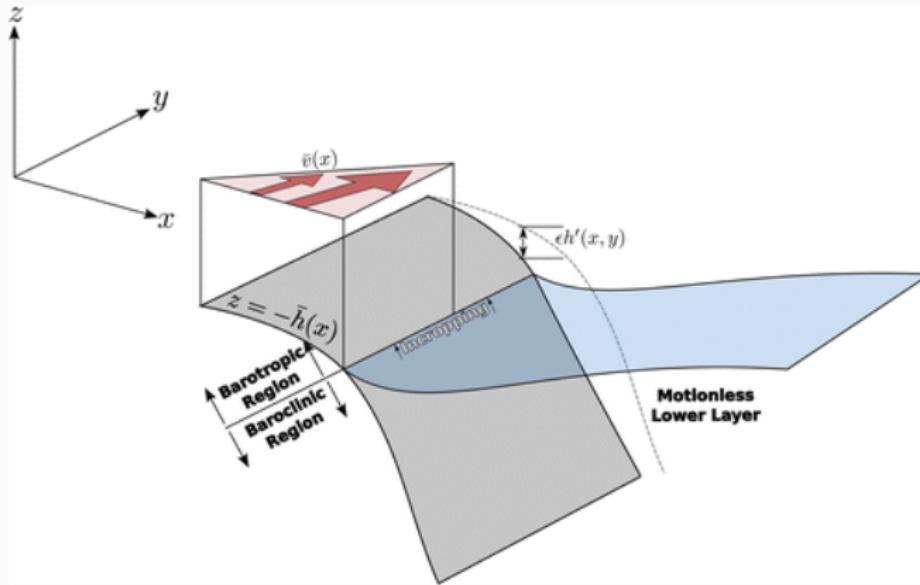


The thing about Gulf Stream separation



Schoonover 2017

The thing about Gulf Stream separation



Schoonover 2017

Somewhat ad-hoc parameterization

Bathymetric interaction tuning

Knowing what the real ocean is doing+how variable this is

The thing about Gulf Stream separation

The depth integrated (Barotropic) vorticity:

$$0 = \nabla \cdot (f\mathbf{U}) + \frac{1}{\rho_0} \nabla \times (p_b \nabla H) + \frac{1}{\rho_0} \nabla \times \tau + \nabla \times \mathbf{A} + \nabla \times \mathbf{B} \quad (\text{Eq 1})$$

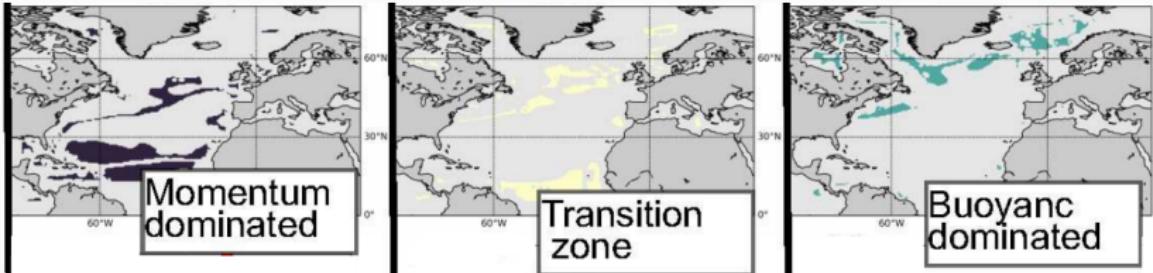
The diagram illustrates the components of the vorticity equation. The first term, $\nabla \cdot (f\mathbf{U})$, is labeled 'Planetary vorticity advection'. The second term, $\frac{1}{\rho_0} \nabla \times (p_b \nabla H)$, is labeled 'Bottom Pressure Torque'. The third term, $\frac{1}{\rho_0} \nabla \times \tau$, is labeled 'Wind and bottom stress'. The fourth term, $\nabla \times \mathbf{A}$, is labeled 'Non-linear torque'. The fifth term, $\nabla \times \mathbf{B}$, is labeled 'Viscous torque'.

Following Mertz and Wright (1992) we distinguish a momentum driven torque of the depth averaged pressure, and the baroclinic Joint Effect of Baroclinicity and Relief (JEBAR) term:

$$\frac{1}{\rho_0} \nabla \times (p_b \nabla H) = \frac{1}{\rho_0} \nabla \times (\bar{p} \nabla H) - \nabla \times \left[\frac{\chi \nabla H}{H} \right] \quad (\text{Eq 2}) \quad \chi = \frac{g}{\rho_0} \int_H^z z \rho dz \quad (\text{Eq 3})$$

The diagram shows the decomposition of the pressure torque term. The term $\frac{1}{\rho_0} \nabla \times (p_b \nabla H)$ is split into two parts: 'Torque of depth averaged pressure' and 'JEBAR'.

The theory that could help



Area, name	Leading terms	Boyancy vs Momentum
12.2%, Quasi-Sverdrupian	$0 \approx \nabla \times \tau_{sb} + \nabla \cdot (f\mathbf{U})$	NA
15.7%, Momentum Dominated	$0 \approx \nabla \cdot (f\mathbf{U}) + \nabla \times \tau_{sb} + \frac{1}{\rho_0} \nabla \times (p_b \nabla H)$	$JEBAR < \frac{1}{\rho_0} \nabla \times (\bar{p} \nabla H)$
61.1%, Transition Zone	$0 \approx \nabla \times \tau_{sb} + \nabla \cdot (f\mathbf{U}) - \frac{1}{\rho_0} \nabla \times (p_b \nabla H)$	$JEBAR \approx \frac{1}{\rho_0} \nabla \times (\bar{p} \nabla H)$
3.6%, Buoyancy Dominated	$0 \approx \nabla \times \tau_{sb} + \nabla \times \mathbf{A} - \frac{1}{\rho_0} \nabla \times (p_b \nabla H)$	$JEBAR >> \frac{1}{\rho_0} \nabla \times (\bar{p} \nabla H)$
≈5.7%, Dominantly non-linear	$0 \approx \nabla \cdot (f\mathbf{U}) + \nabla \times \tau_{sb} + \frac{1}{\rho_0} \nabla \times (p_b \nabla H) - \nabla \times \mathbf{A}$	$JEBAR >> \frac{1}{\rho_0} \nabla \times (\bar{p} \nabla H)$

The theory that could help

Free-slip: BPT is uphill-flow, no-slip: BPT is viscous stress divergence (Hughes & de Cuevas 2001)



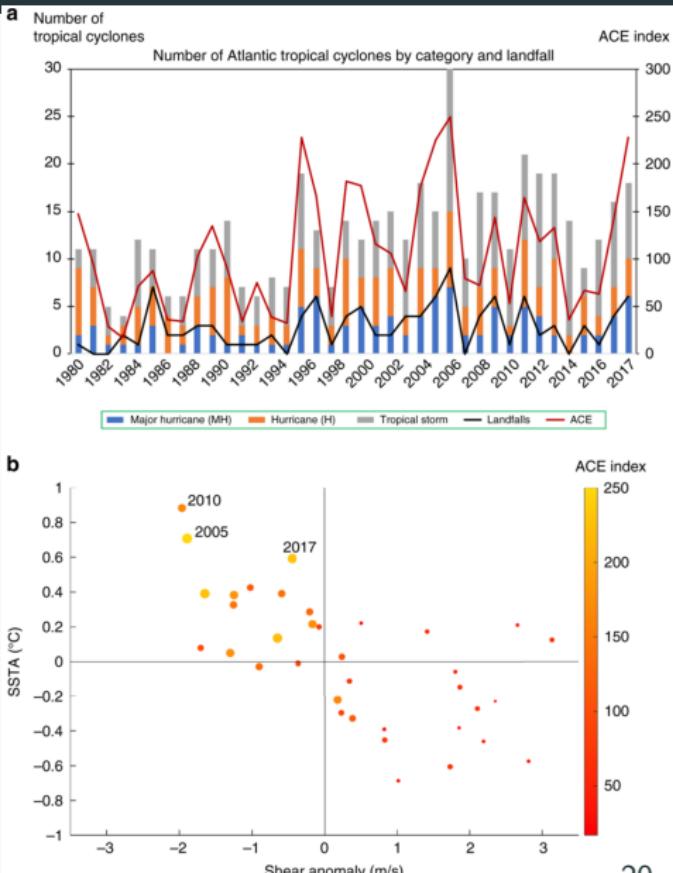
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Improve hurricane forecast?

Motivation:

“Extreme weather events cost the lives of 246 lives in the US alone since 2018 alone and 5000 world wide.”

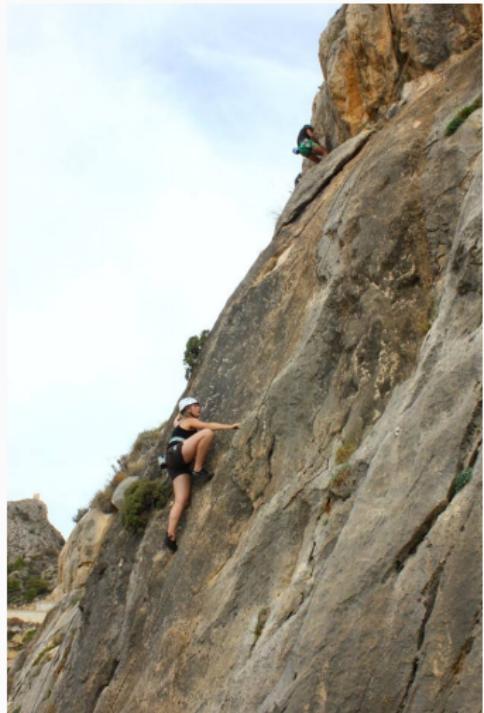
(NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2019)



Cliff hanger:

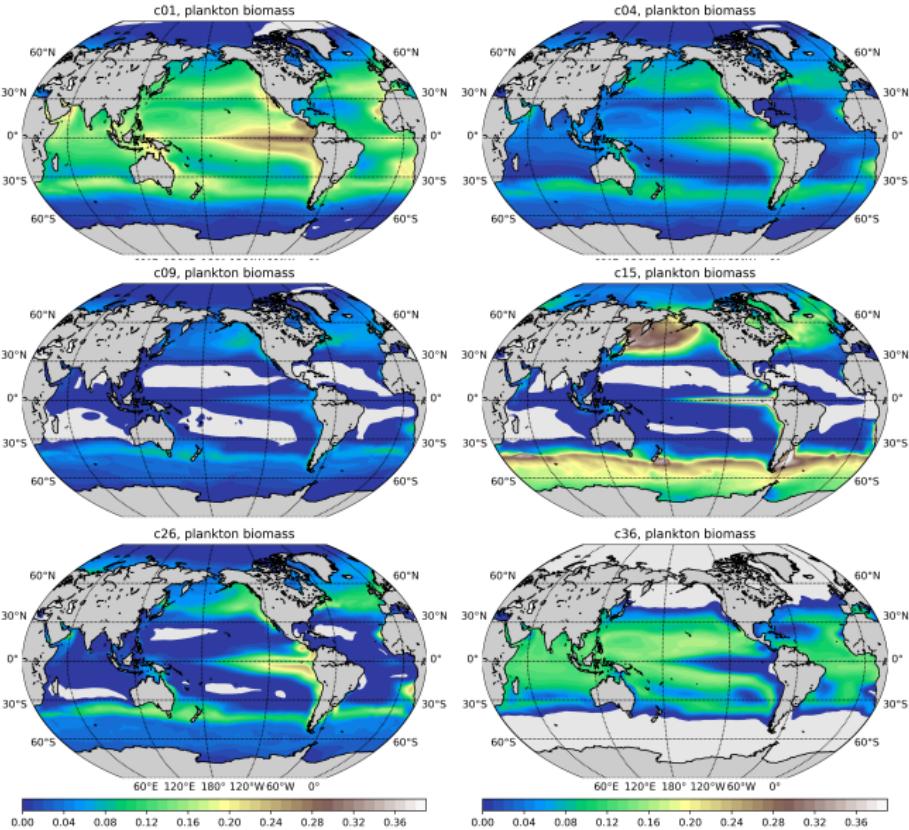
Edge computing

- Recognize key lacking data
- Target using clusters/regions
- Infer where to sample
- Inform modeller

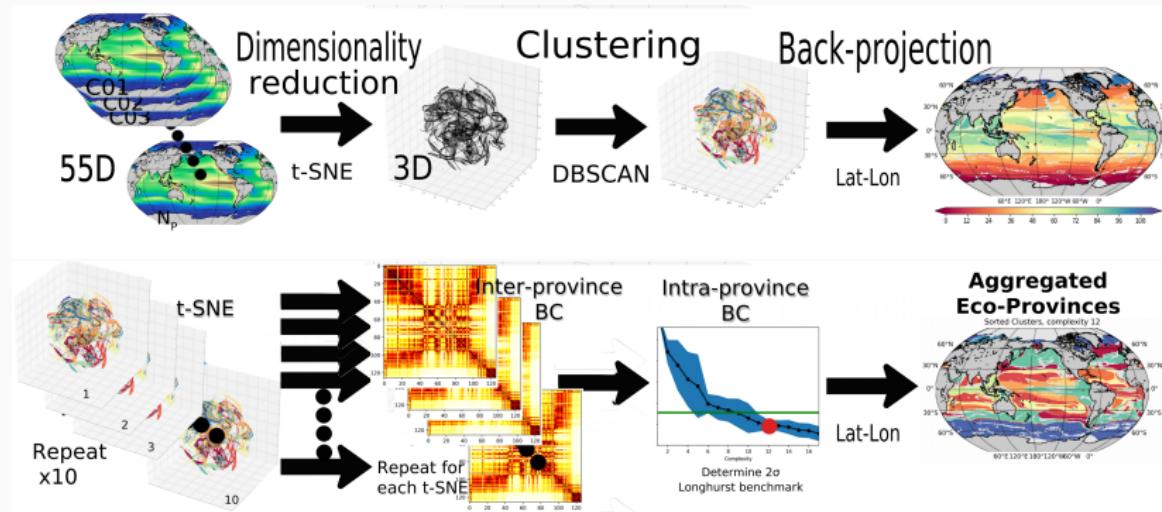


...Global ecological regimes

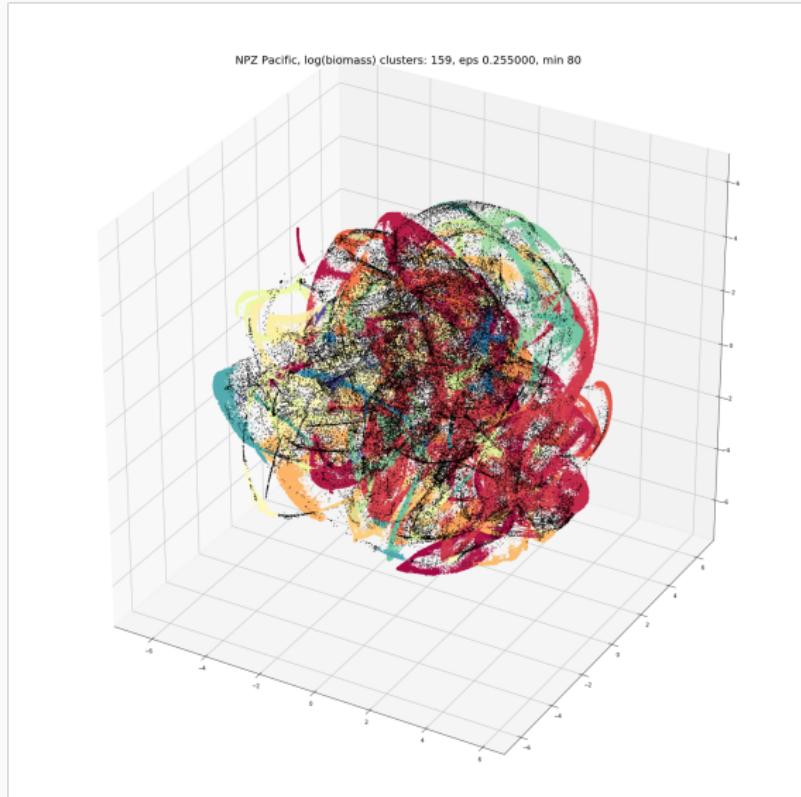
Complicated: 51 species (biomass) and 4 nutrients



Finding clusters → Aggregated Eco-Provinces

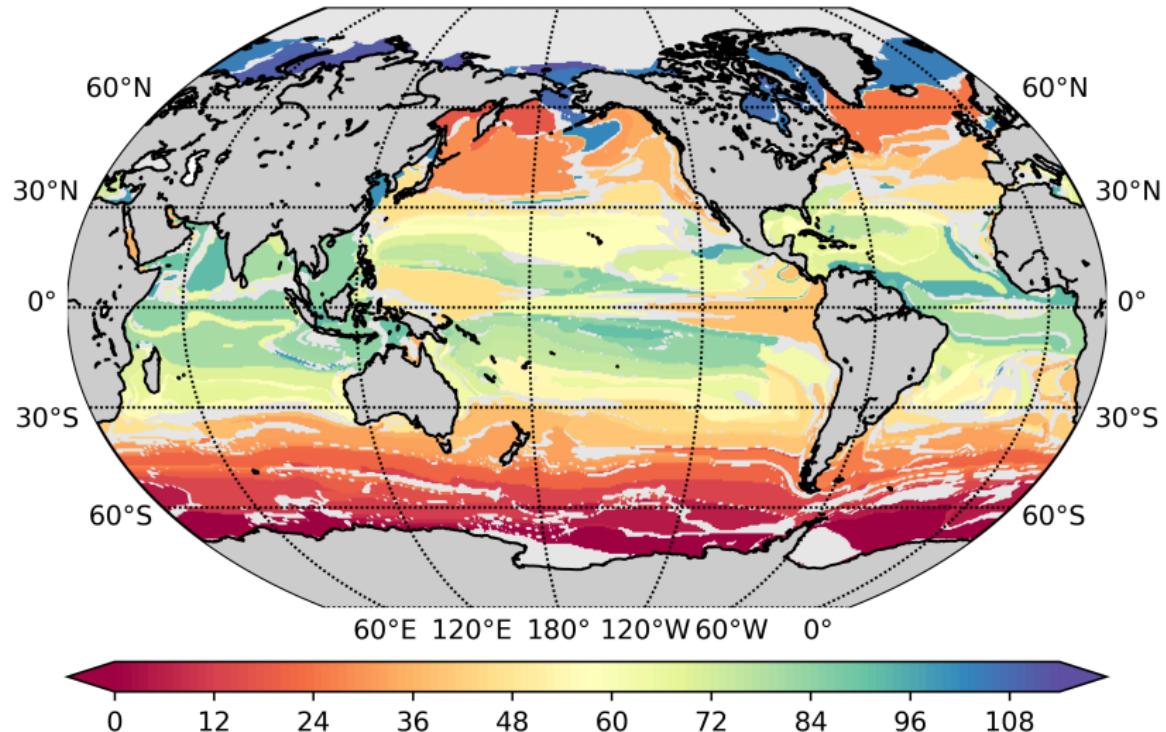


Unsupervised learning: DBSCAN

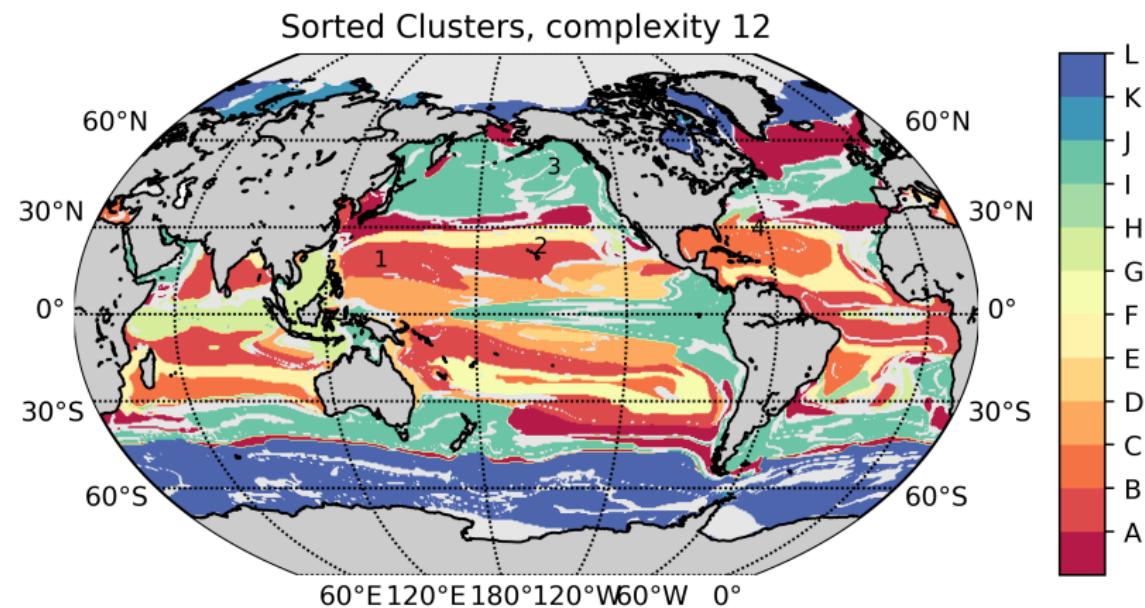


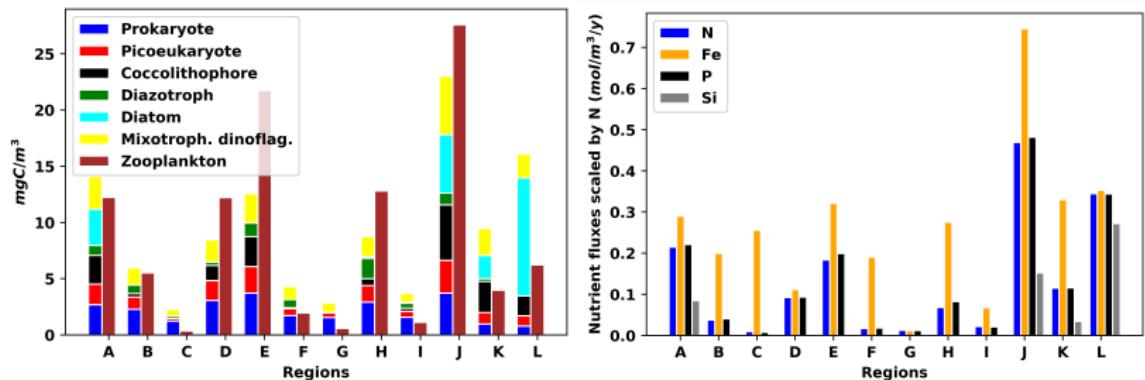
Eco-Provinces

NPZ log(Chl) DBSCAN clusters: 115, eps 0.390000, min 100



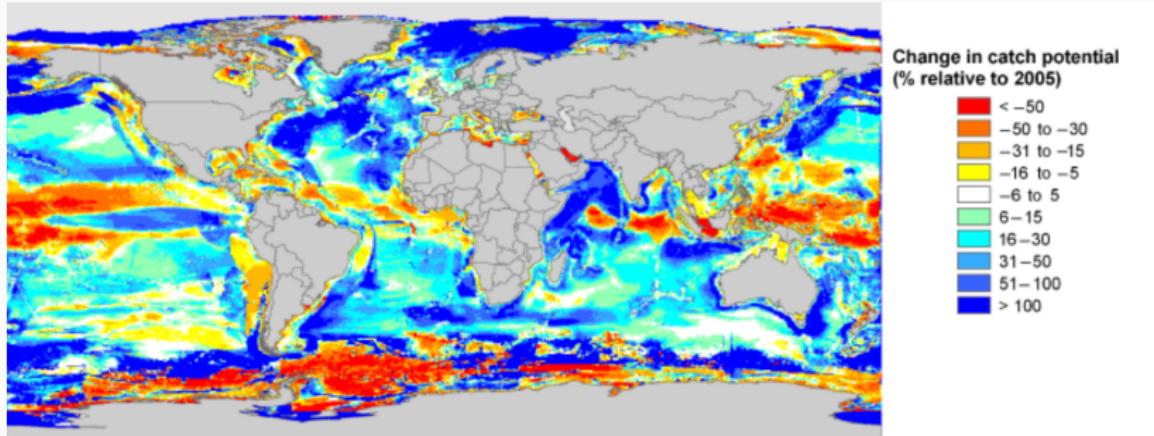
Aggregated Ecological Provinces





- Similar biomass/chl but different community structure
- Biomass is poor predictor of zooplankton: Trophic cascades?

Fisheries: Where is the zooplankton?



Around 85% of global fish stocks are over-exploited, depleted, fully exploited or in recovery from exploitation

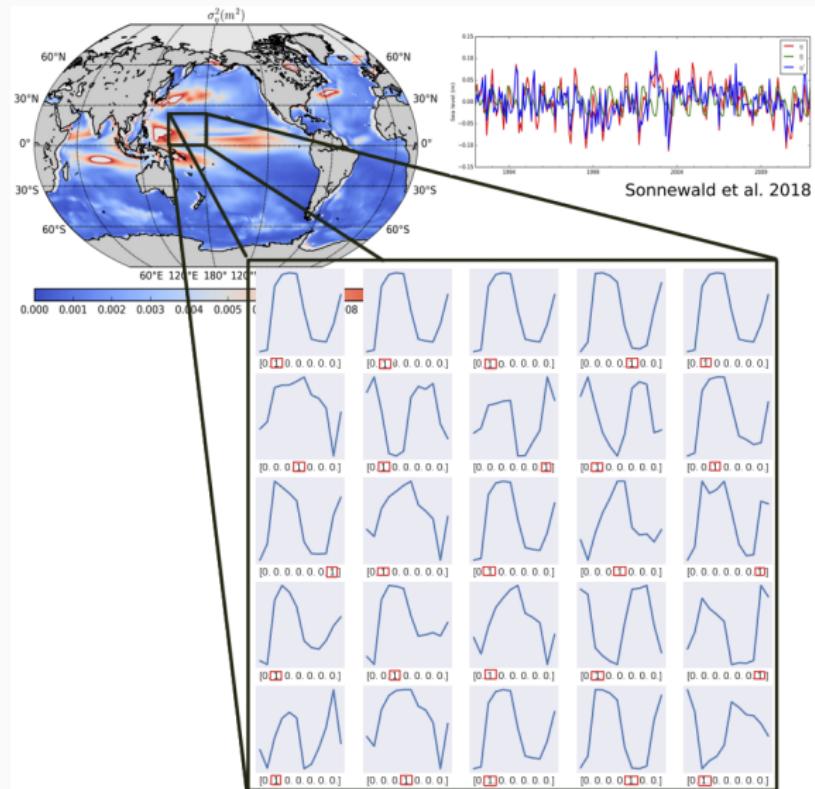
All West African coastal fisheries have declined 50% in just 30 years.

Synergy

ML in its many flavours



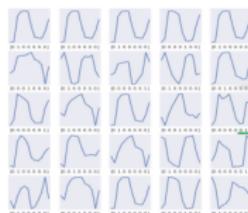
Input?



Can we develop a predictive model?

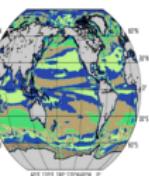
Model.png

Data



Input
(features)

Answers



Output
(prediction)

Hidden Layers
lots of layers ~ "deep learning"

Predictive model

Momentum equations:

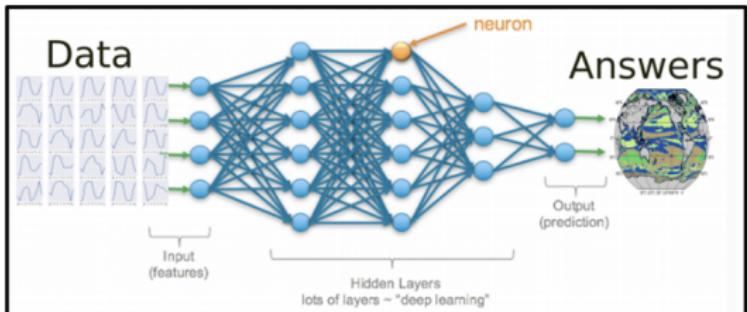
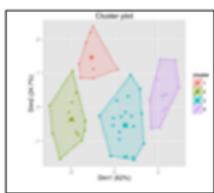
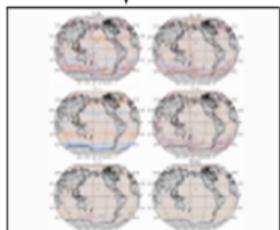
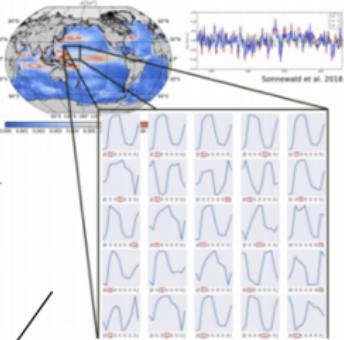
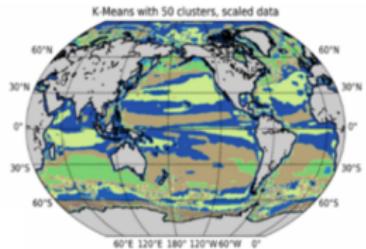
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Depth integrate, take curl

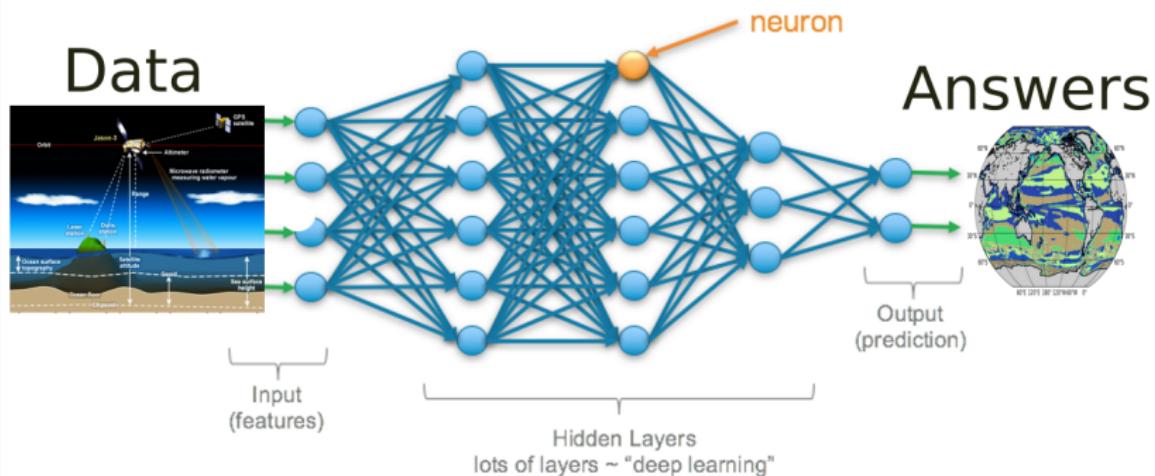
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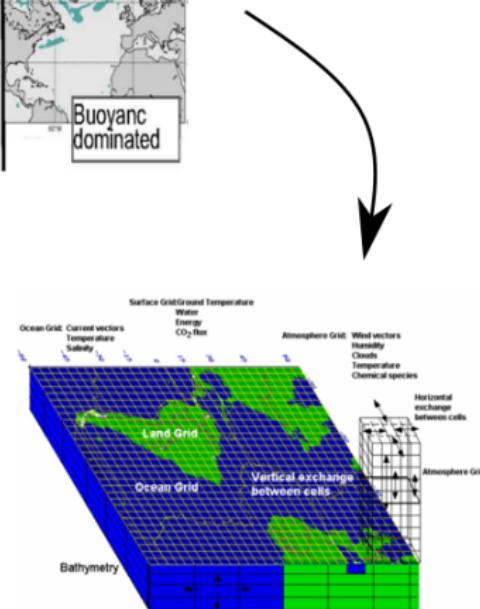
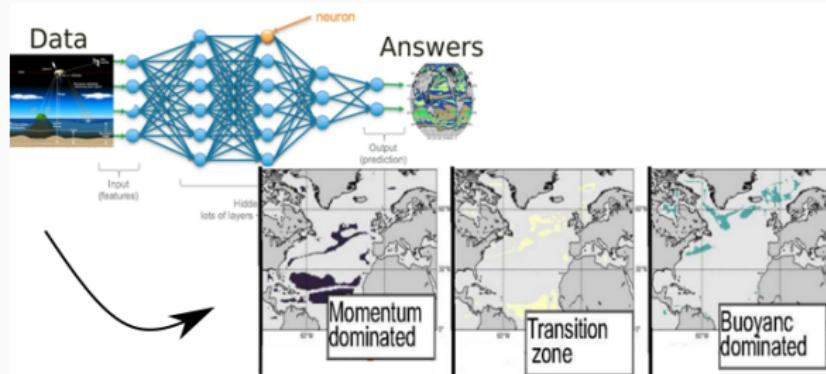
Addition: Wind and Bottom stress Lat. Hc
Bottom Pressure Tissue Non-Divergent Torque



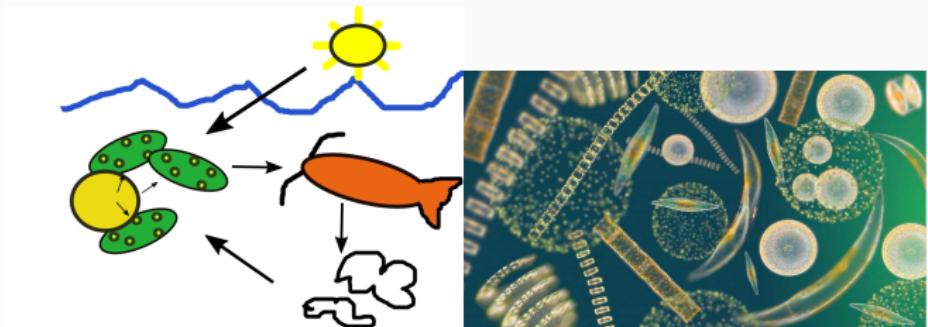
Can use observations to improve models?



Can use observations to improve models?

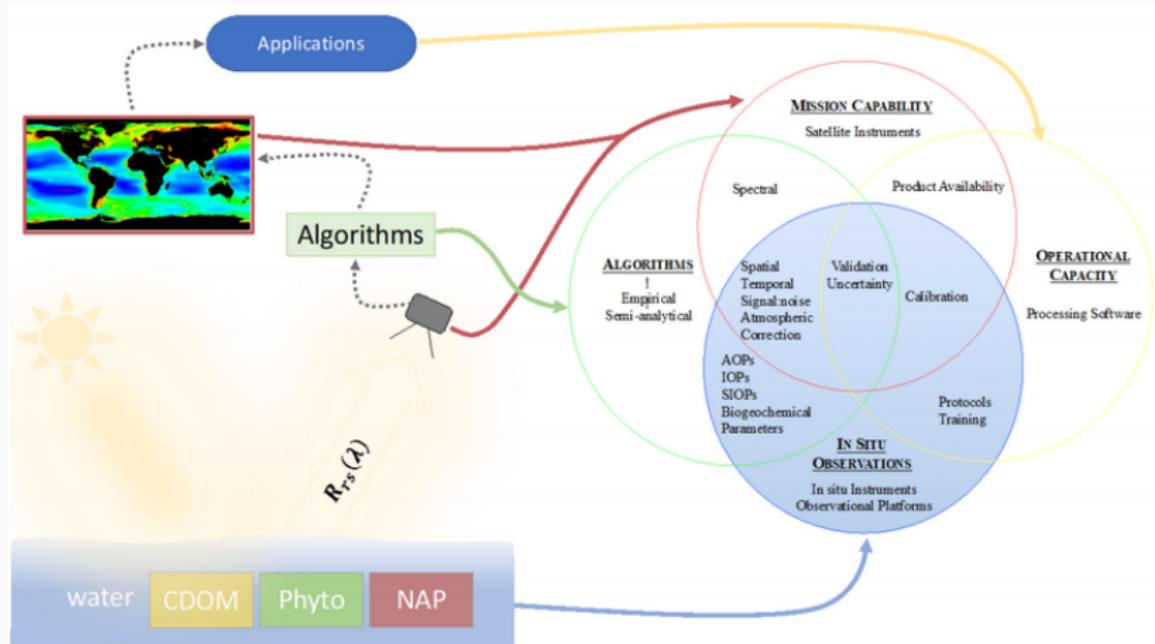


Can ML improve ecosystem models?



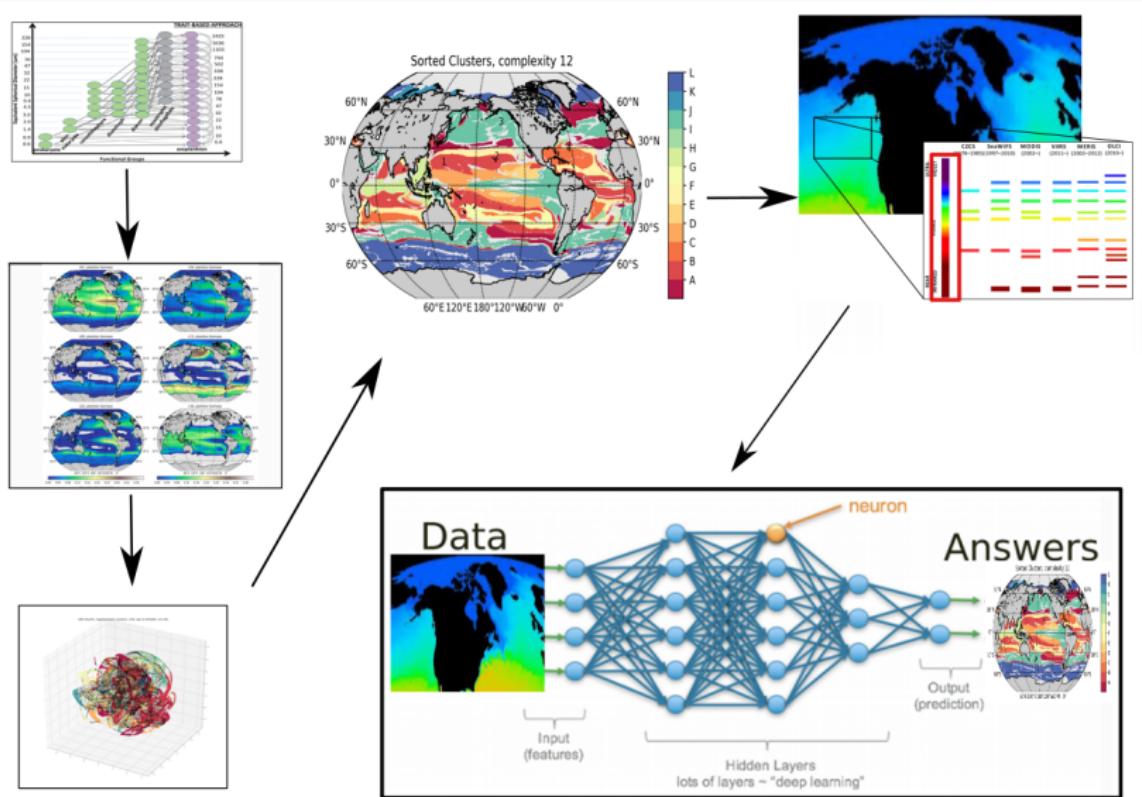
It's complicated

Can ML improve ecosystem models?

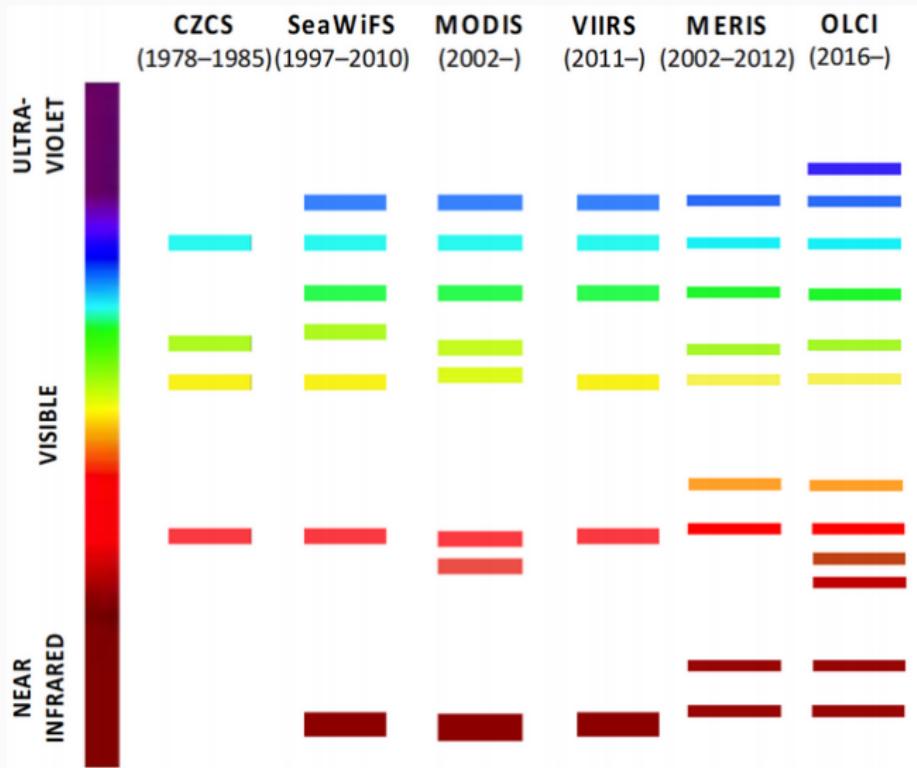


Real world may be instructive

Ecoprovinces are again... complicated...



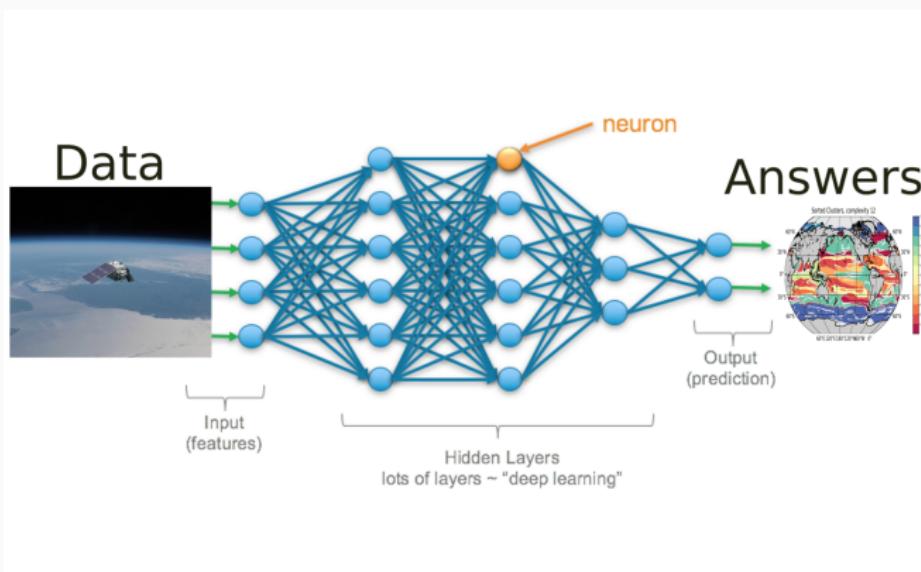
Future looks colourful!



Future looks colourful: PACE



Future looks colourful: Predictive model

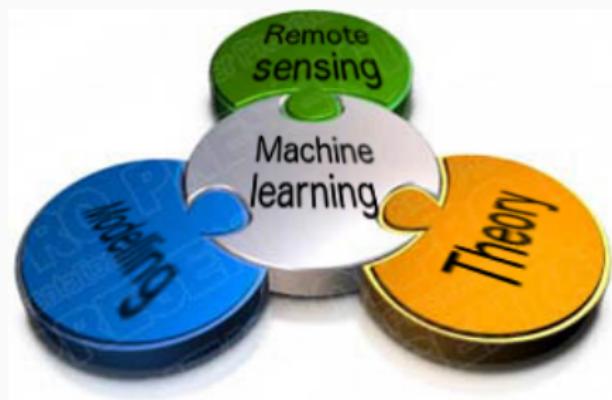


Summary

...Can unsupervised learning give system insight?

Can ML help?

- Make complicated data complex
- Allows insight to parameterize and simplify
- Create synergy between models, theory and observations



ML towards the goal of science/geoscience:
Have precise and accurate understanding of the natural world.