Decoding Ecological Complexity: Unsupervised Learning determines marine eco-provinces

Maike Sonnewald, with Steph Dutkiewicz, Chris Hill and Gael Forget

Princeton University & NOAA/Geophysical Fluid Dynamics Laboratory
visitor University of Washington

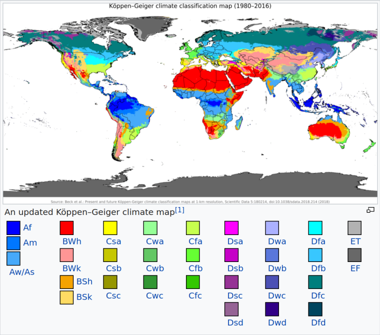
NOAA Geophysical Fluid Dynamics Laboratory

Utility of ocean ‘Provinces’

Question: How well can we see ocean biogeographic regions?

- Obs. data are sparse/complicated

- Ocean has liquid boundaries



- Compare locations
- Conservation/monitoring
- Assess base of food chain

Develop objective method to classify ocean ecology for both regional and global work

Longhurst et al. 1995, Zimmermann et al. 2018

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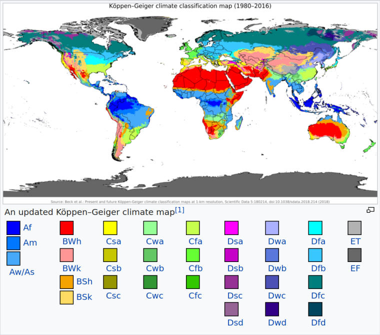

An updated Köppen–Geiger climate map[1]

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Longhurst et al. 1995, Zimmermann et al. 2018

Unsupervised Learning: Find structure

Supervised

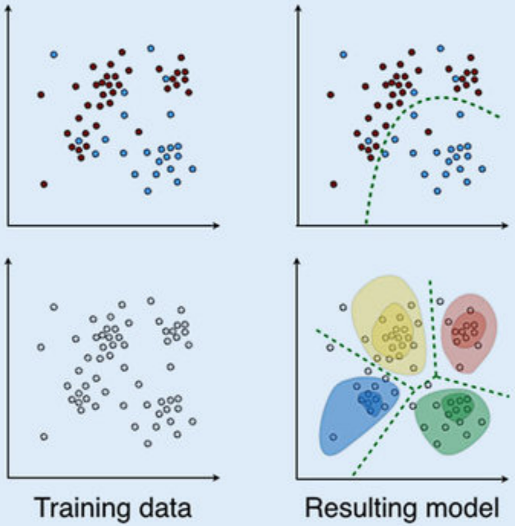
-Labeled data

-Decision boundary

Unsupervised

-No labels

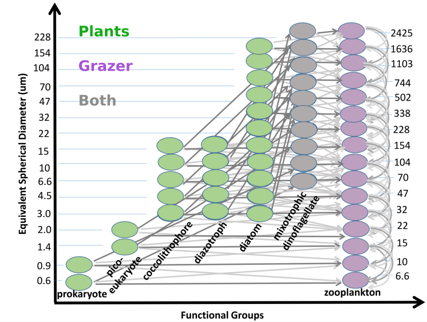
-Identify structures

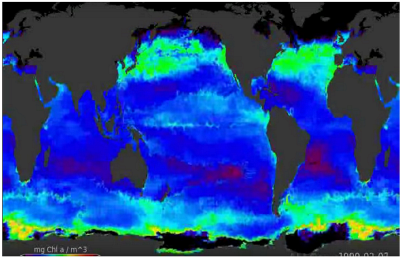


Langs et al. 2018

Darwin: Global biogeochemical ecosystem model

Physical model (ECCO)+biogeochemistry+trait based ecology

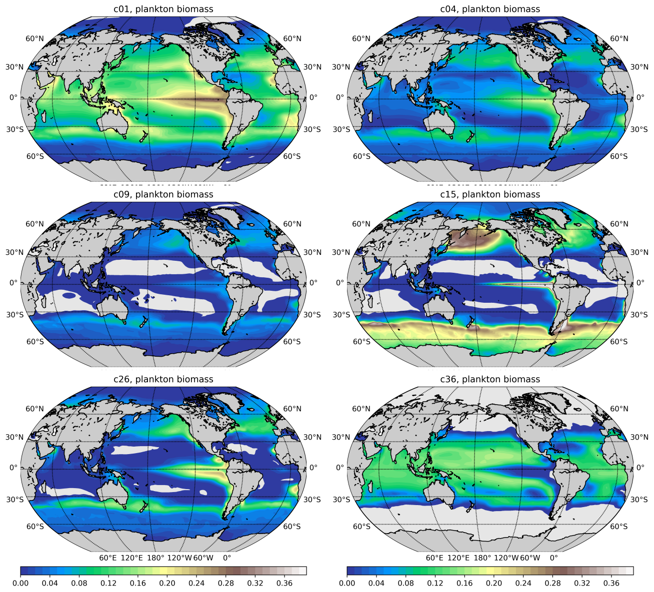




mg Chlorophyll a/m^3

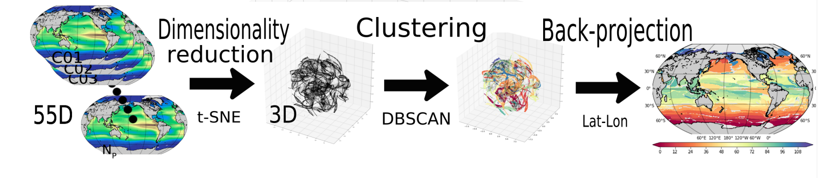
Dutkiewicz et al., 2015

51 species (biomass) and 4 nutrients (concentration)

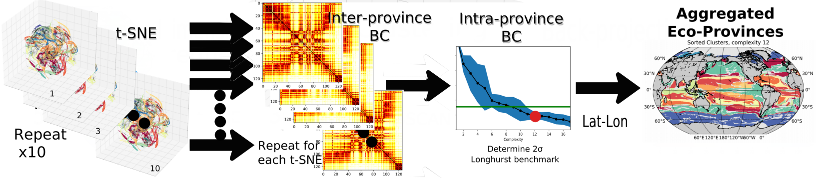


SAGE: Systematic AGgregated Eco-province method

Eco-Provinces



Aggregated Eco-Provinces (AEPs)



Sonnewald et al., Science Advances, 2020

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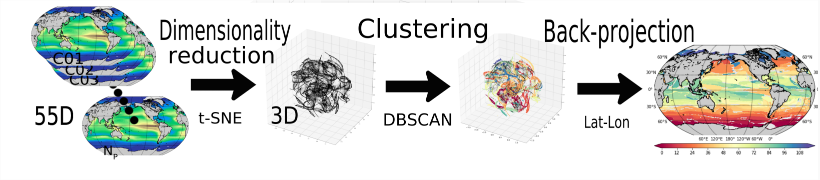

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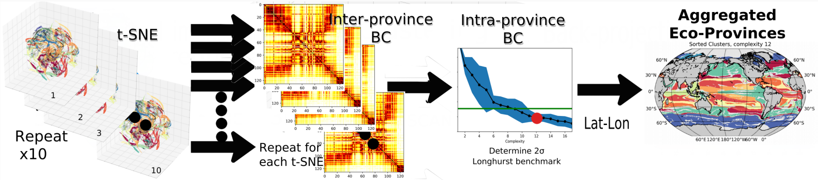
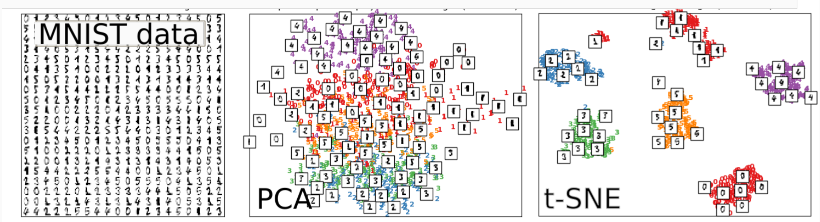


Sonnewald et al., Science Advances, 2020

Accounting for nonlinearities matters

ML benchmark: Classify 70k hand written digits (MNIST data)



- PCA assumes underlying normal distribution
- t-Statistic Neighborhood Embedding makes no assumptions
  - $\rightarrow$ more appropriate for geoscience data

scikit-learn.org

t-Statistic Neighbourhood Embedding

t-Statistic Neighbourhood Embedding helps 'flatten' the data.

We minimize 'distance' between lat+lon points in 11D and a low dimensional projection using the Kullbach-Leibner (KL) divergence.

If x_i is the i-th object in 11D, and y_j is the j-th object low-dim: space

$$p_{j|i} = \frac{\exp(-\|\mathbf{x}_i - \mathbf{x}_j\|^2 / 2\sigma_i^2)}{\sum_{k \neq i} \exp(-\|\mathbf{x}_i - \mathbf{x}_k\|^2 / 2\sigma_i^2)},$$

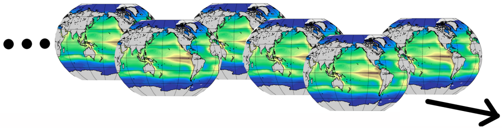
and the same for a reduced dimensional set:

$$q_{ij} = \frac{(1 + \|\mathbf{y}_i - \mathbf{y}_j\|^2)^{-1}}{\sum_{k \neq l} (1 + \|\mathbf{y}_k - \mathbf{y}_l\|^2)^{-1}}.$$

This is done as:

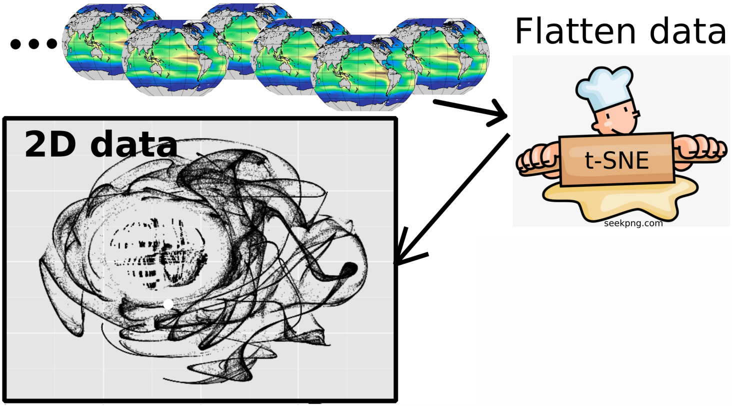
$$KL(P||Q) = \sum_{i \neq j} p_{ij} \log \frac{p_{ij}}{q_{ij}}$$

Learning: Understanding the data



Flatten data

Learning: Understanding the data



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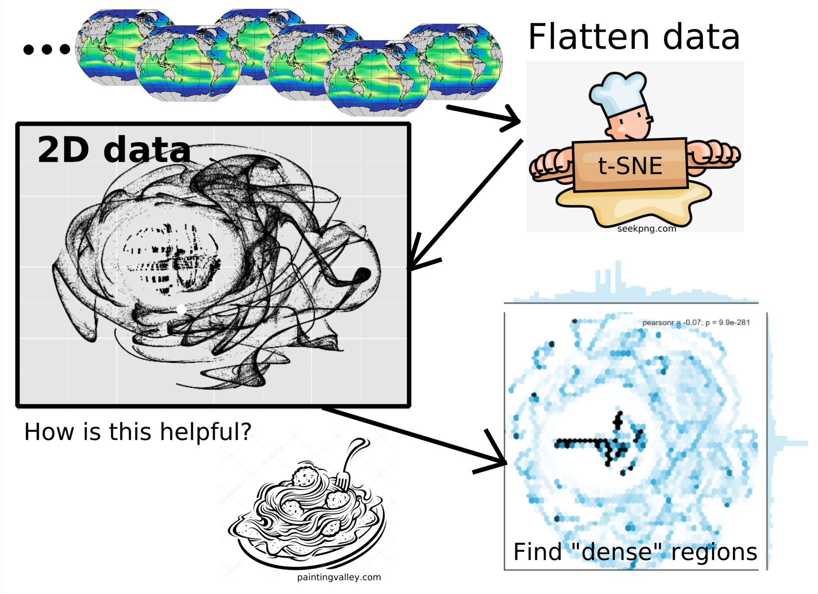
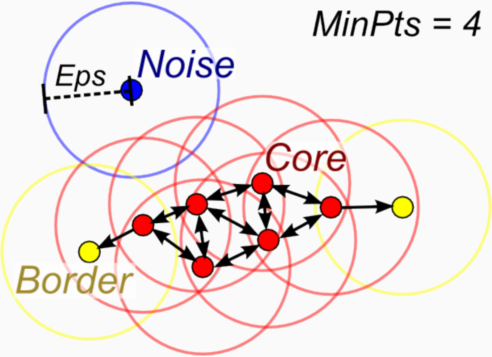


Density-based spatial clustering of apps with noise

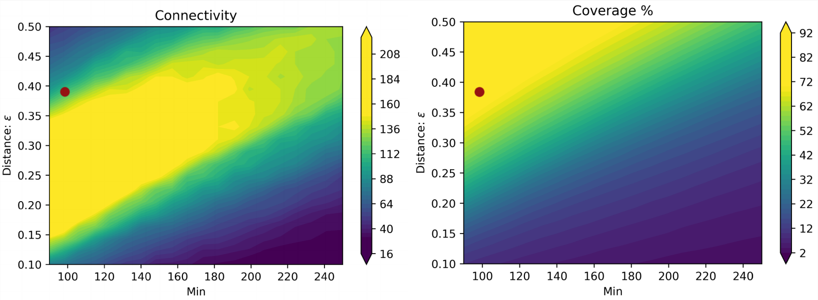


stackexchange.org

- Parameters: distance ‘Eps’ and minimum points ‘MinPts’

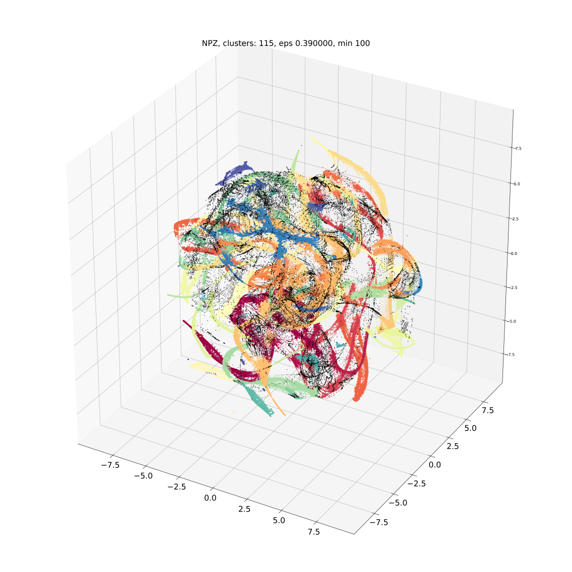
Ester et al. 1996

Densitybased spatial clustering of apps with noise



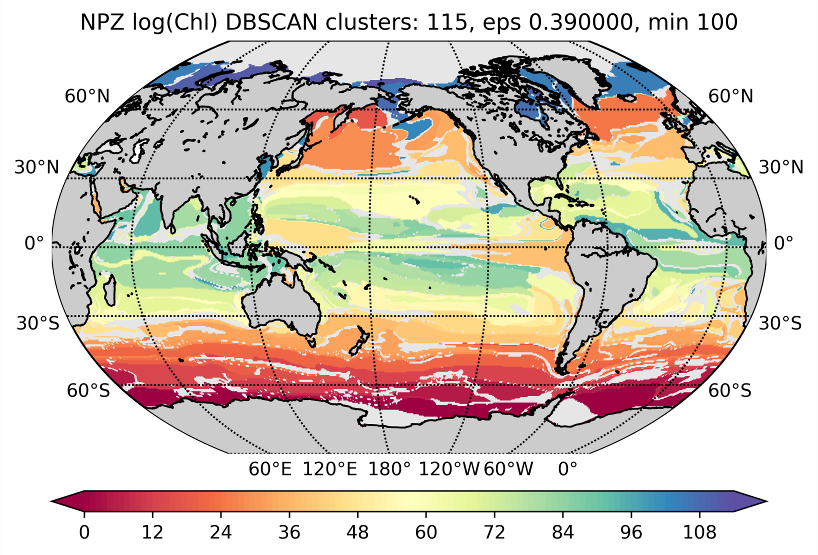
2D ‘elbow’ check in connectedness+cover

Density-based spatial clustering of apps with noise



Clustering nutrients, phytoplankton and zooplankton (NPZ)

Eco-Provinces



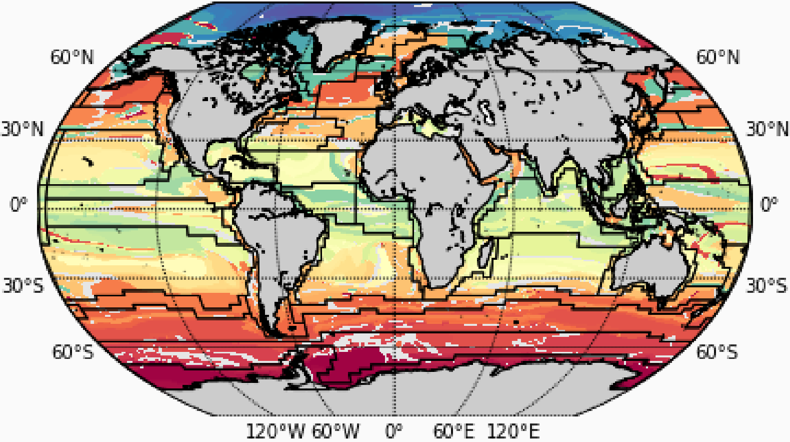
Clustering nutrients, phytoplankton and zooplankton (NPZ)

Aggregated Eco-Provinces: AEPs

Global utility of eco-provinces

Goal: Aggregation/nesting for regional to global insight

Current: Longhurst provinces are 'gold standard'

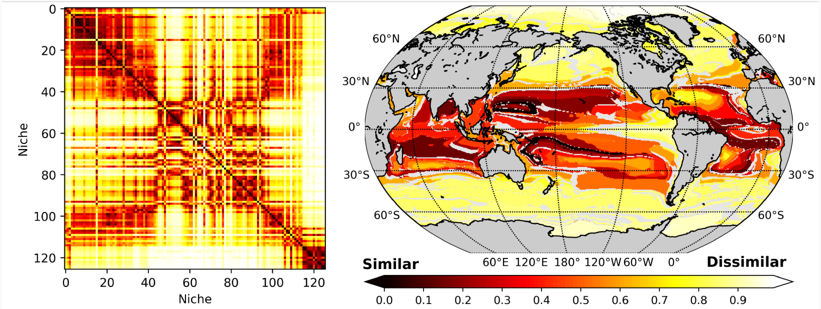


Longhurst provinces on eco-provinces (Longhurst et al. 1995)

Quantifying ecological "distance"

Bray-Curtis dissimilarity:

$$BC_{ij} = 1 - \frac{2C_{ij}}{S_i + S_j}$$

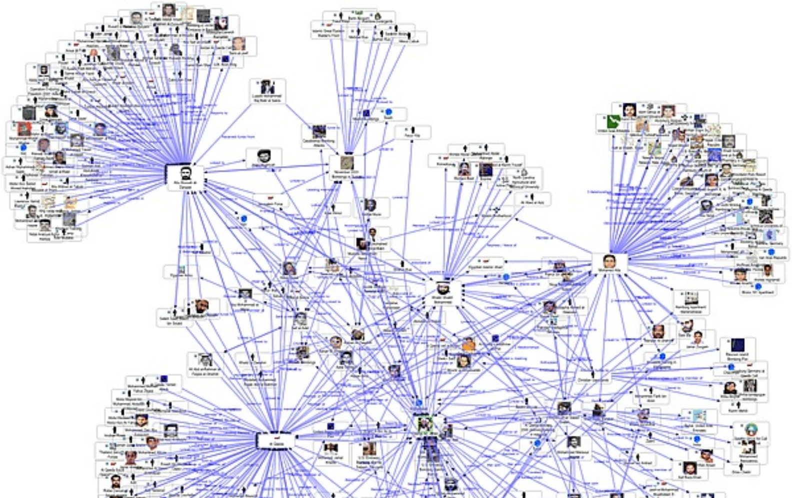


Sonnewald et al., Science Advances, 2020, Bray and Curtis, 1957

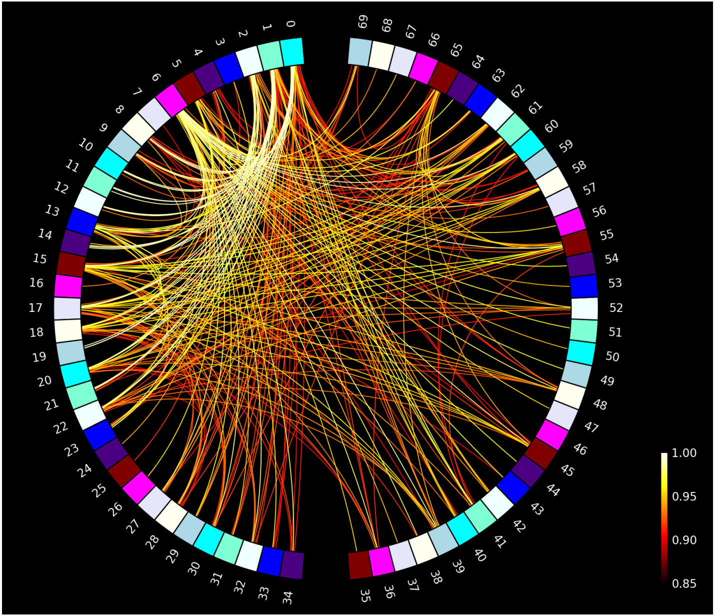
Leveraging complexity: Graph Theory

"A branch of mathematics used to represent relations and networks. Widely used in network analysis. A graph consists of a set of points (nodes or vertices) and the pairwise links between them (arcs or lines)."

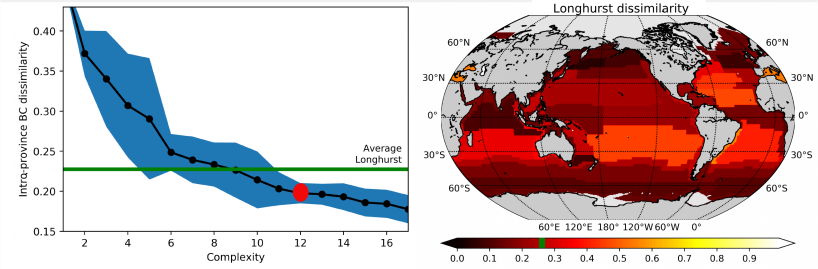
Oxfordreference.com



Complexity: Eco-province graph

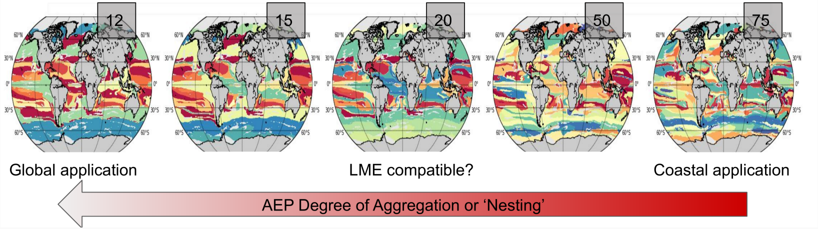


Complexity: Global application benchmark

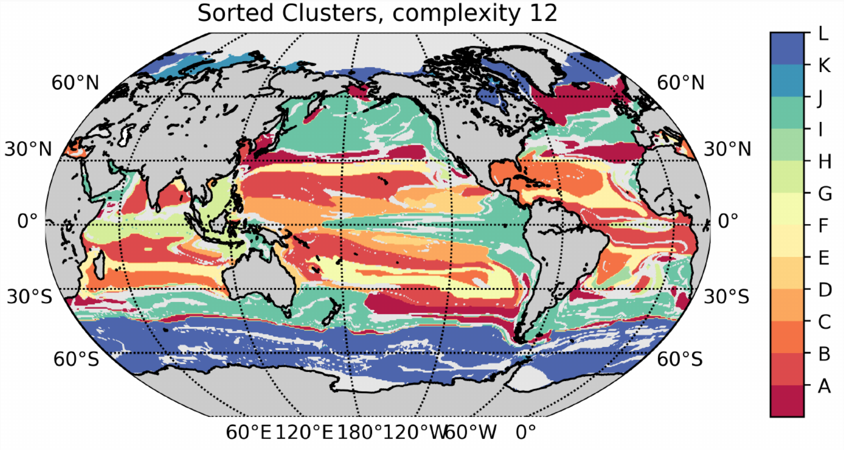


Sonnewald et al. Science Advances, 2020

Complexity: Choosing aggregation level



Aggregated Ecological Provinces



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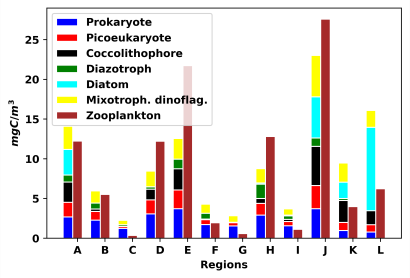
Interpret patterns



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

Model 'cartoon' of real ecosystem: Combine with in-situ observations?

Sonnewald et al. Science Advances, 2020

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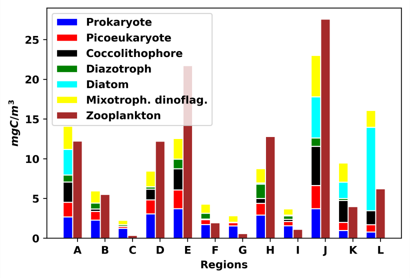

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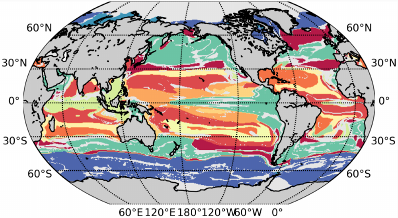
Sonnewald et al. Science Advances, 2020

Global biochemical provinces

Objectively uncovered eco-provinces in global ocean.

→ Aggregation for global to regional applications.

- Method:
    - Probabilistic t-SNE and DBSCAN
    - AEP: Graphs and dissimilarity
- Similar Chl;different ecology
- Ecological impact on zoolankton abundance



Systematic AGregation of Eco-provinces method:
github.com/maikejulie/plottingAEPs

Sonnewald et al. Science Advances, 2020

Thank you!