Identifying Southern Ocean fronts using unsupervised classification and edge detection

Simon Thomas[1], Dan Jones[2], Anita Faul[2], Erik Mackie[1], and Etienne Pauthenet[3]

[1]University of Cambridge
[2]NERC British Antarctic Survey
[3]Sorbonne Université, LOCEAN-IPSL, CNRS/IRD/MNHN

January 20, 2023

Abstract

Fronts are ubiquitous in the climate system. In the Southern Ocean, fronts delineate water masses, which correspond to upwelling and downwelling branches of the overturning circulation. A robust understanding of Southern Ocean fronts is key to projecting future changes in overturning and the associated air-sea partitioning of heat and carbon. Classically, oceanographers define Southern Ocean fronts as a small number of continuous linear features that encircle Antarctica. However, modern observational and theoretical developments are challenging this traditional framework to accommodate more localized views of fronts [Chapman et al. 2020]. In this work, we present two related methods for calculating fronts from oceanographic data. The first method uses unsupervised classification (specifically, Gaussian Mixture Modeling or GMM) and an interclass metric to define fronts. This approach produces a discontinuous, probabilistic view of front location, emphasising the fact that the boundaries between water masses are not uniformly sharp across the entire Southern Ocean. The second method uses Sobel edge detection to highlight rapid changes [Hjelmervik & Hjelmervik, 2019]. This approach produces a more local view of fronts, with the advantage that it can highlight the movement of individual eddy-like features (such as the Agulhas rings). The fronts detected using the Sobel method are moderately correlated with the magnitude of the velocity field, which is consistent with the theoretically expected spatial coincidence of fronts and jets. We will present our python GitHub repository, which will allow researchers to easily apply these methods to their own datasets. Figure caption Two methods for interpretable front detection. Solid lines represent classical fronts. (a) The "inter-class" metric, which indicates the probability that a grid cell is a boundary between two classes. The classes are defined by GMM of principal component values (PCs) derived from both temperature and salinity. The different colors indicate different class boundaries. (b) Sobel edge detection: approximately the magnitude of the spatial gradient of the PCs divided by each field's standard deviation, which highlights locations of rapid change.

Identifying Southern Ocean fronts using unsupervised classification and edge detection

AGU FALL MEETING

Online Everywhere | 1–17 December 2020

Simon Thomas[1, 2; †], Daniel Jones[1], Anita Faul[1], Erik Mackie[1, 3], Etienne Pauthenet[4]

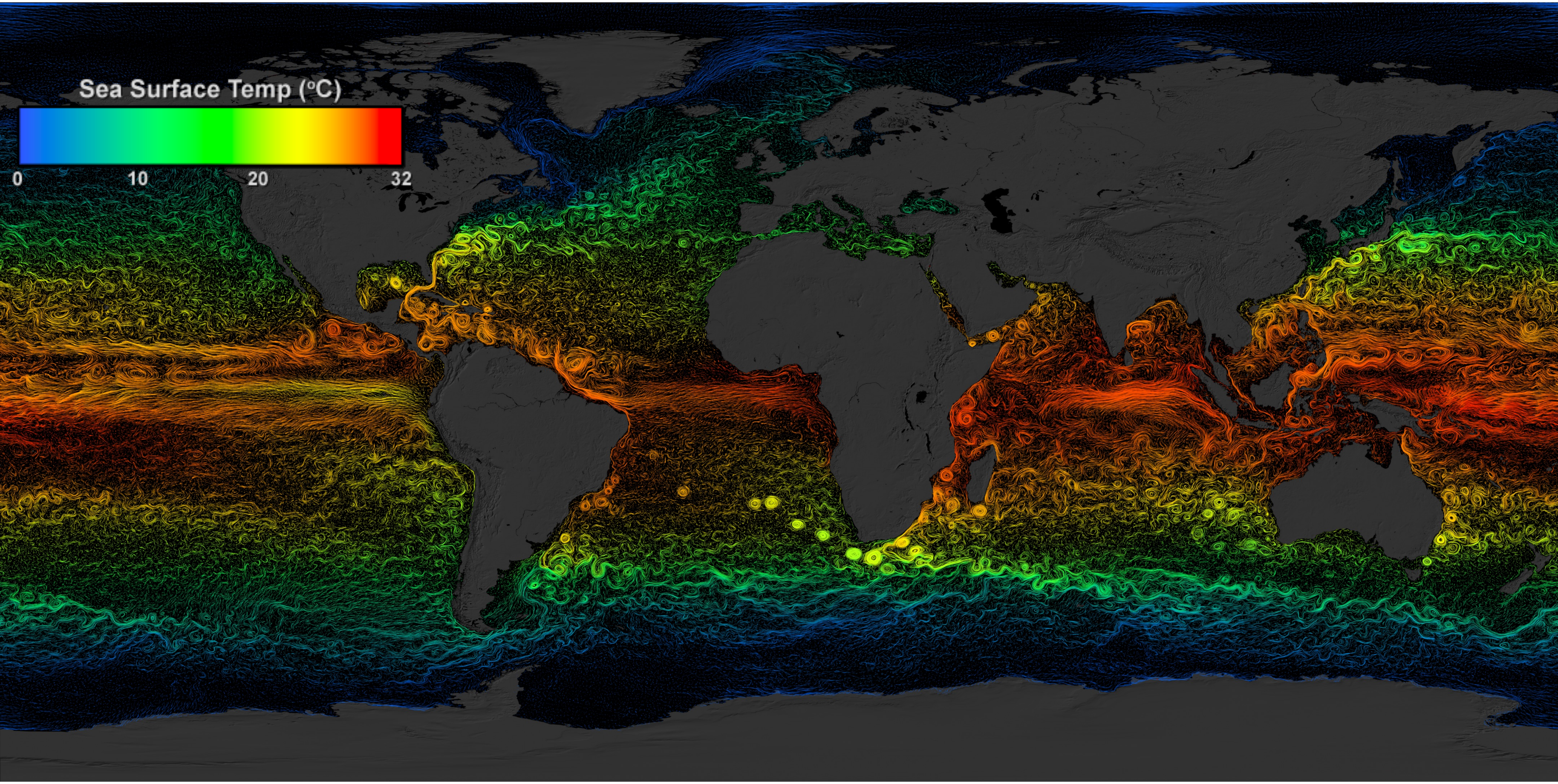
[1]British Antarctic Survey, Cambridge; [2]Department of Physics, University of Cambridge; [3]Cambridge Zero, University of Cambridge; [4]Sorbonne Universités, UPMC Université, L'OCEAN-IPSL, Paris.

[†]sithom@bas.ac.uk

British Antarctic Survey
NATURAL ENVIRONMENT RESEARCH COUNCIL

UNIVERSITY OF CAMBRIDGE

LOCEAN Laboratoire d'Océanographie et du Climat
Expérimentations et Approches Numériques

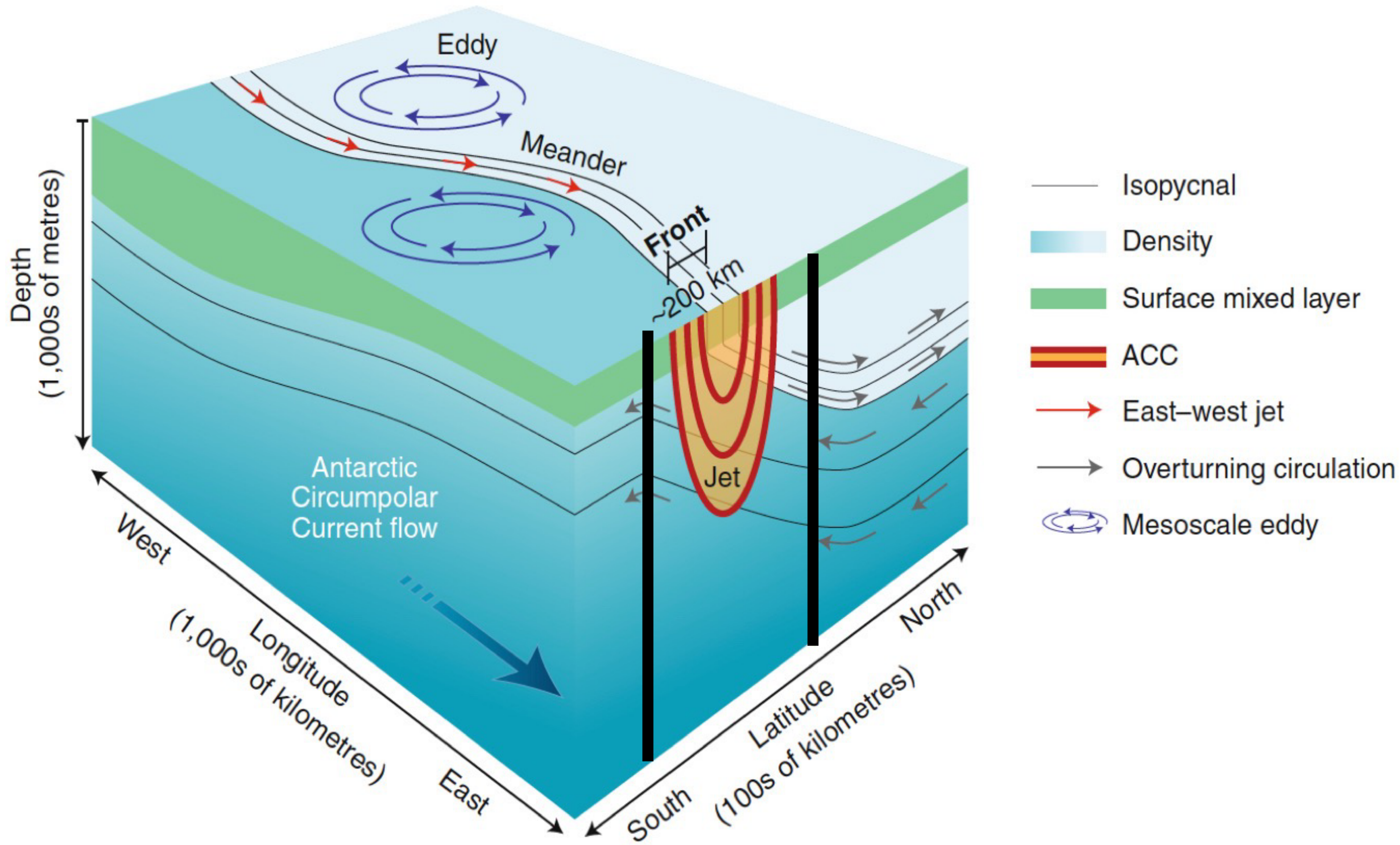


Global sea surface temperatures and currents

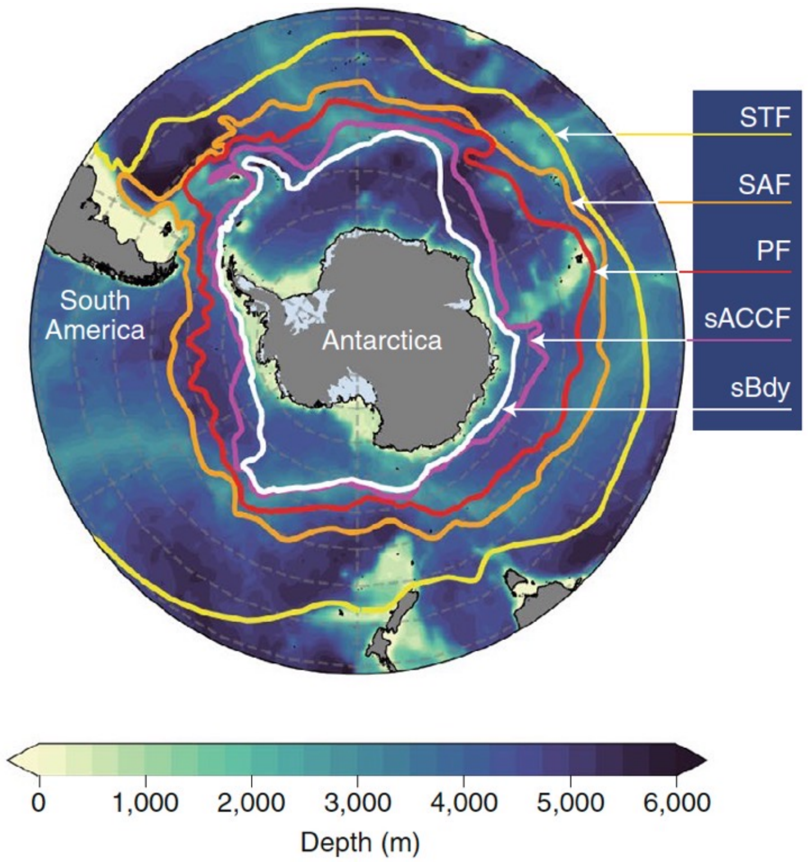
Credit: NASA

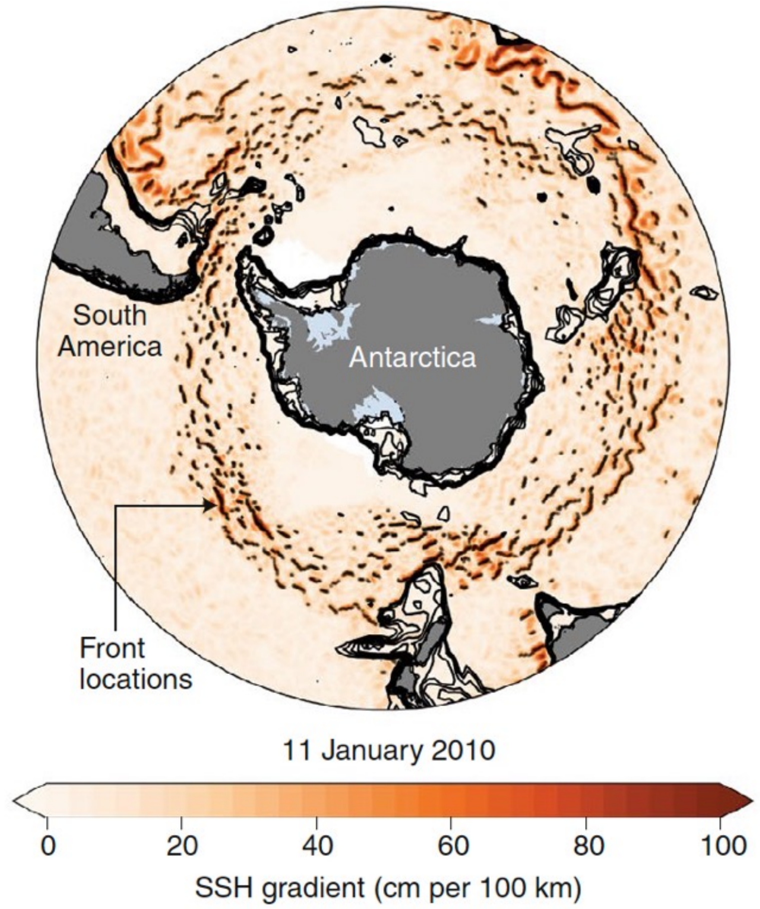
Motivation

- Chapman *et al.* 2020 challenged traditional views of fronts.



- The deep reaching jets of the Antarctic Circumpolar Current are expected to correspond to sharp gradients of temperature and salinity.

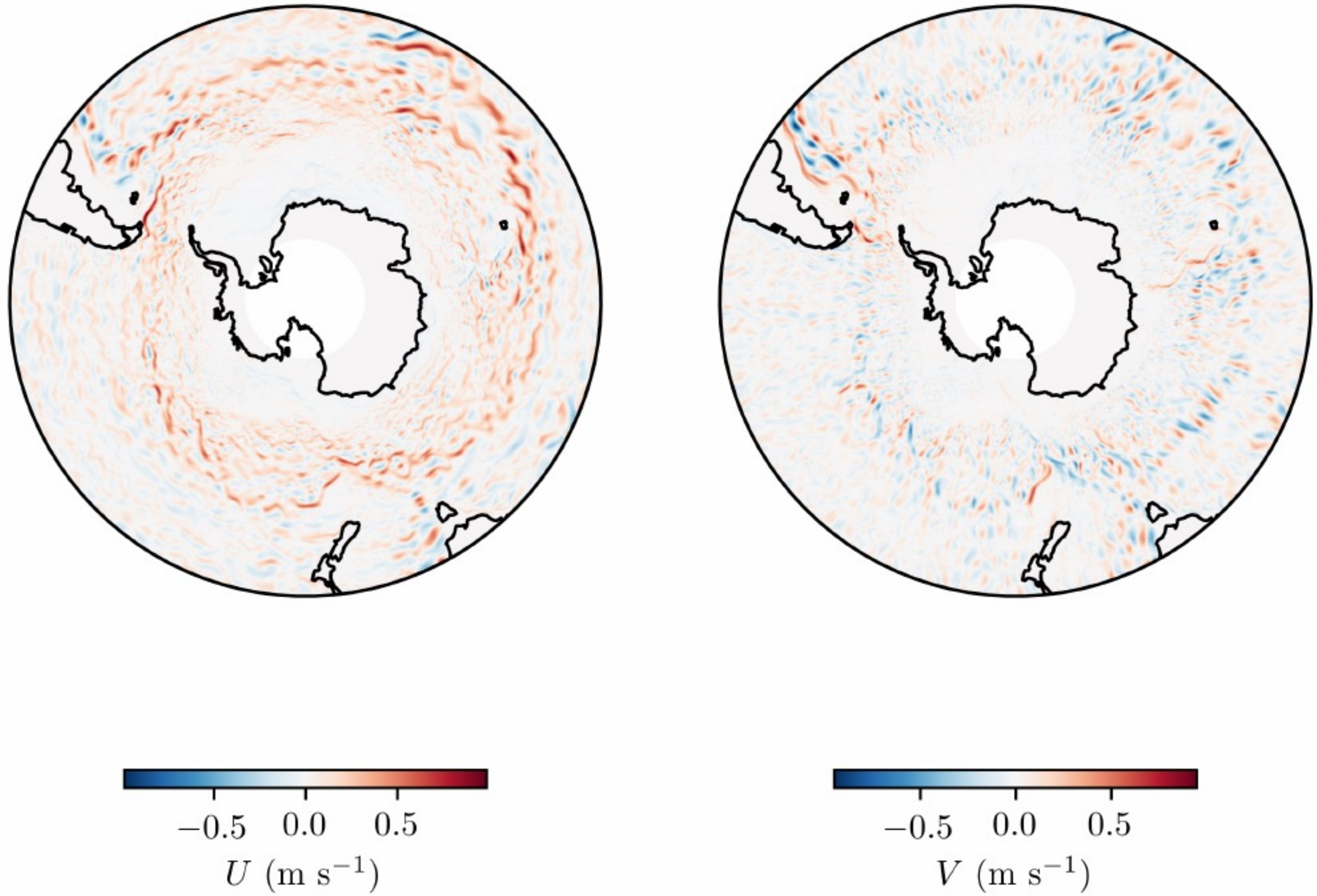




	Global	**Local**
Methods	Contours, Water mass criteria, GMM	Gradient thresholding, Sobel Edge, Skewness
Pro	Interpretable	Easy to define
Con	Hard to define	Hard to interpret

Table: A summary of Table 1 in Chapman *et al.* 2020.

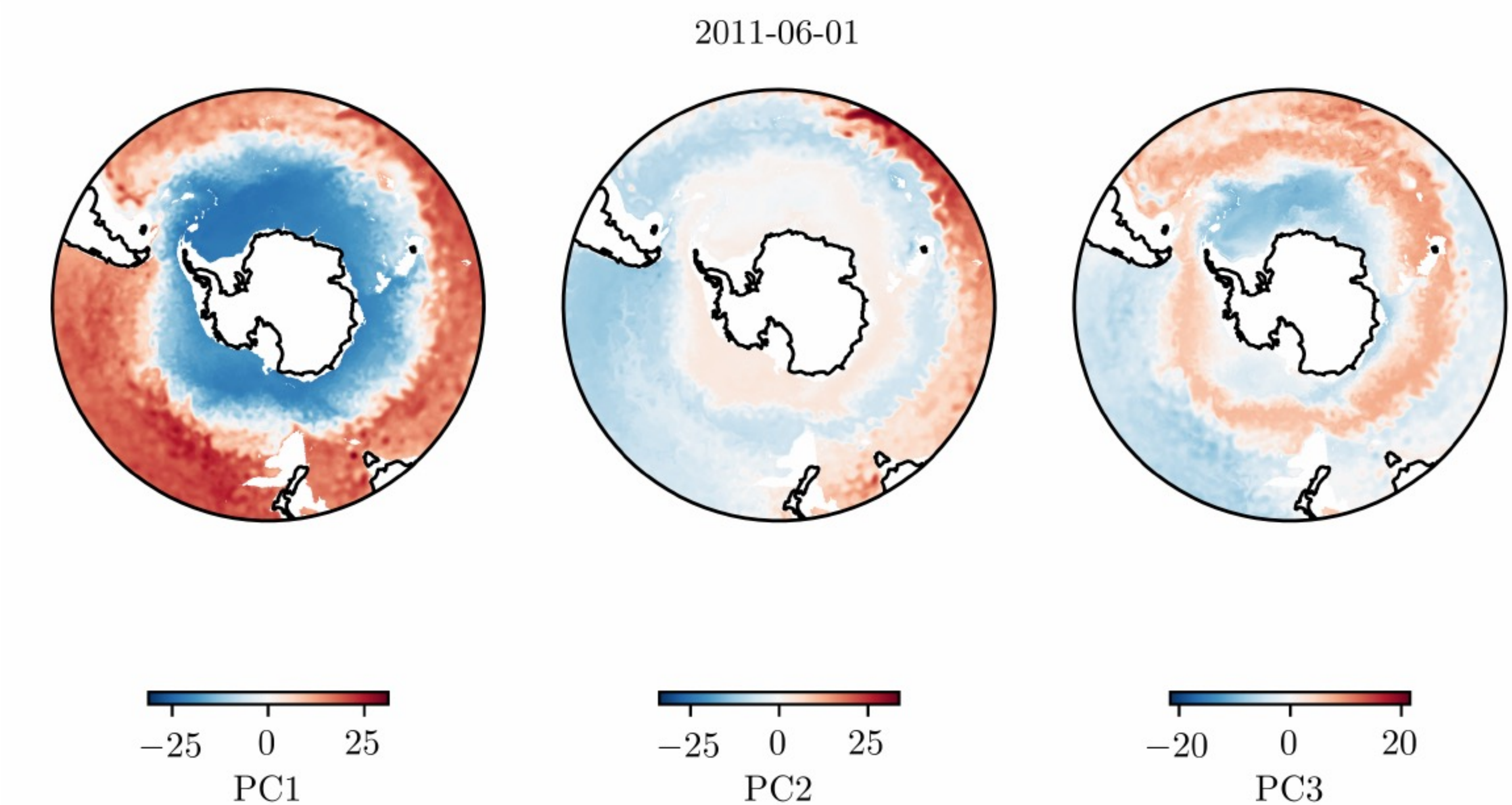
Dataset & Features: BSOSE-i106



- BSOSE-i106 state estimate (Verdy & Mazloff 2017).
- Monthly mean T and S profiles between 300m–2000m (Rosso *et al.* 2020).

Preprocessing: Principal Component Analysis

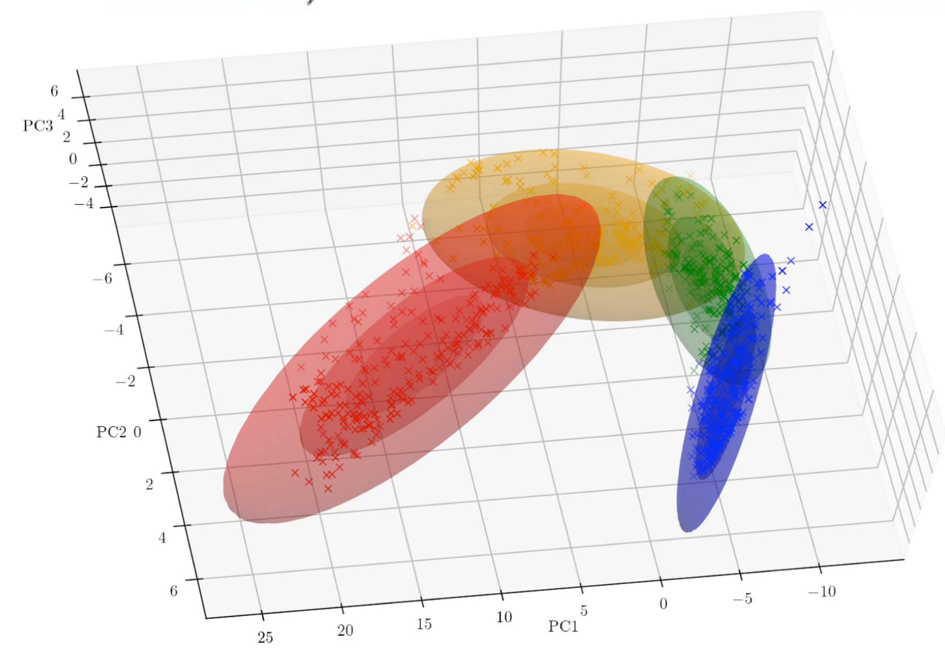
- Take coefficients from 3 principal components (North *et al.* 1982; Pauthenet *et al.* 2017).



Explained Variance: 75% 16% 7%

Global Model: Gaussian Mixture Modelling

- Using GMM (Maze *et al.* 2017; Jones *et al.* 2019).
- K clusters.



- Posterior probabilities:

$$\mathbb{P}\left(c_n = c_k\right) = \frac{\lambda_k\,\mathcal{N}\left(\vec{x}_n\,;\;\vec{\mu}_k\,,\Sigma_k\right)}{\sum_{k=1}^{K}\lambda_k\,\mathcal{N}\left(\vec{x}_n\,;\;\vec{\mu}_k\,,\Sigma_k\right)} \tag{1}$$

- We define (thanks to A.F.):

$$\mathcal{I}\left(\vec{x}_n\right) = 1 - \left(\mathbb{P}\left(c = c_k\right)_{\mathrm{max}} - \mathbb{P}\left(c = c_l\right)_{\mathrm{runner-up}}\right), \tag{2}$$

where $\vec{x}_n$ is the n^{th} profile's principal component values.

Global: $\mathcal{I}$-metric

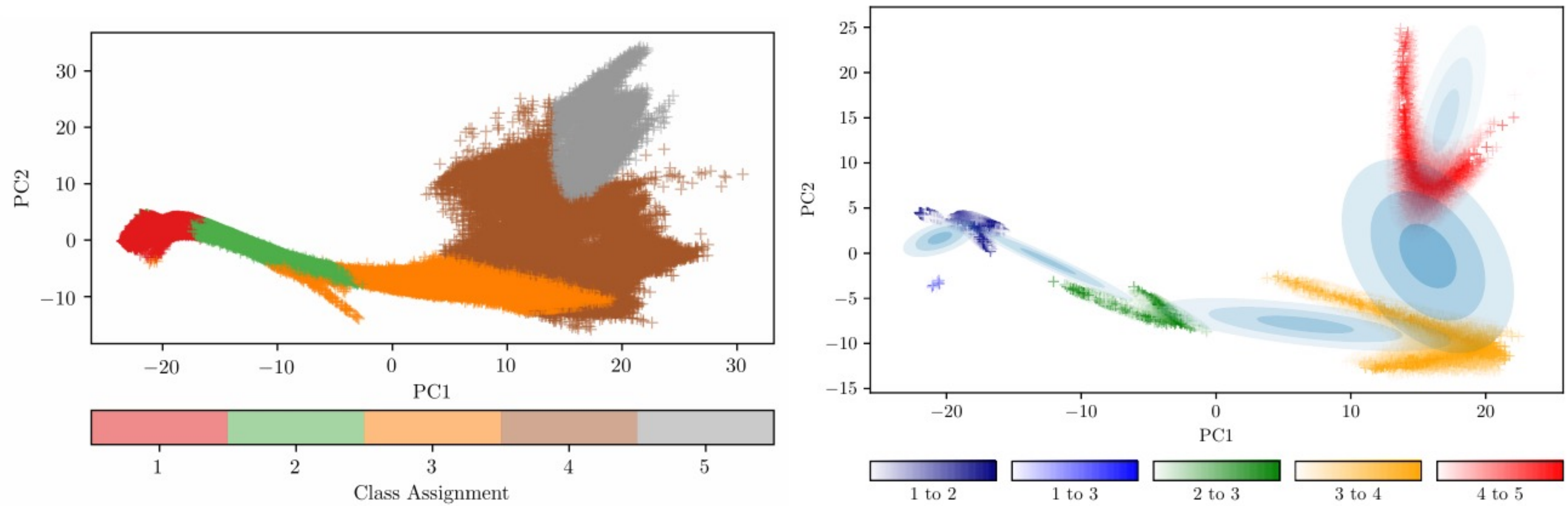


Figure: GMM and $\mathcal{I}$-metric with $K = 5$ in 2PC space.

Global: $\mathcal{I}$-metric

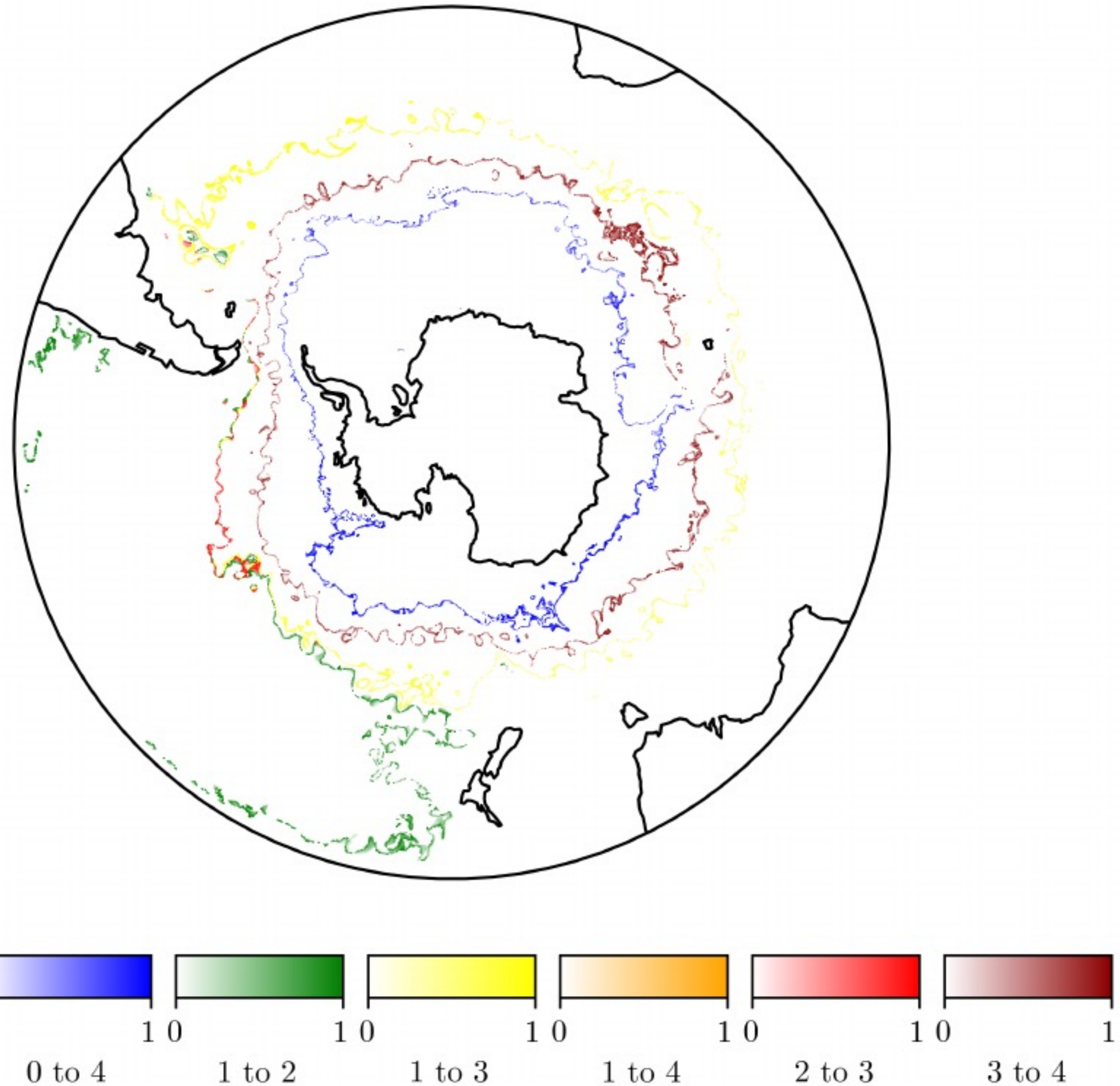


Figure: $\mathcal{I}$ of GMM with $K = 5$.

Global: $\mathcal{I}$-metric

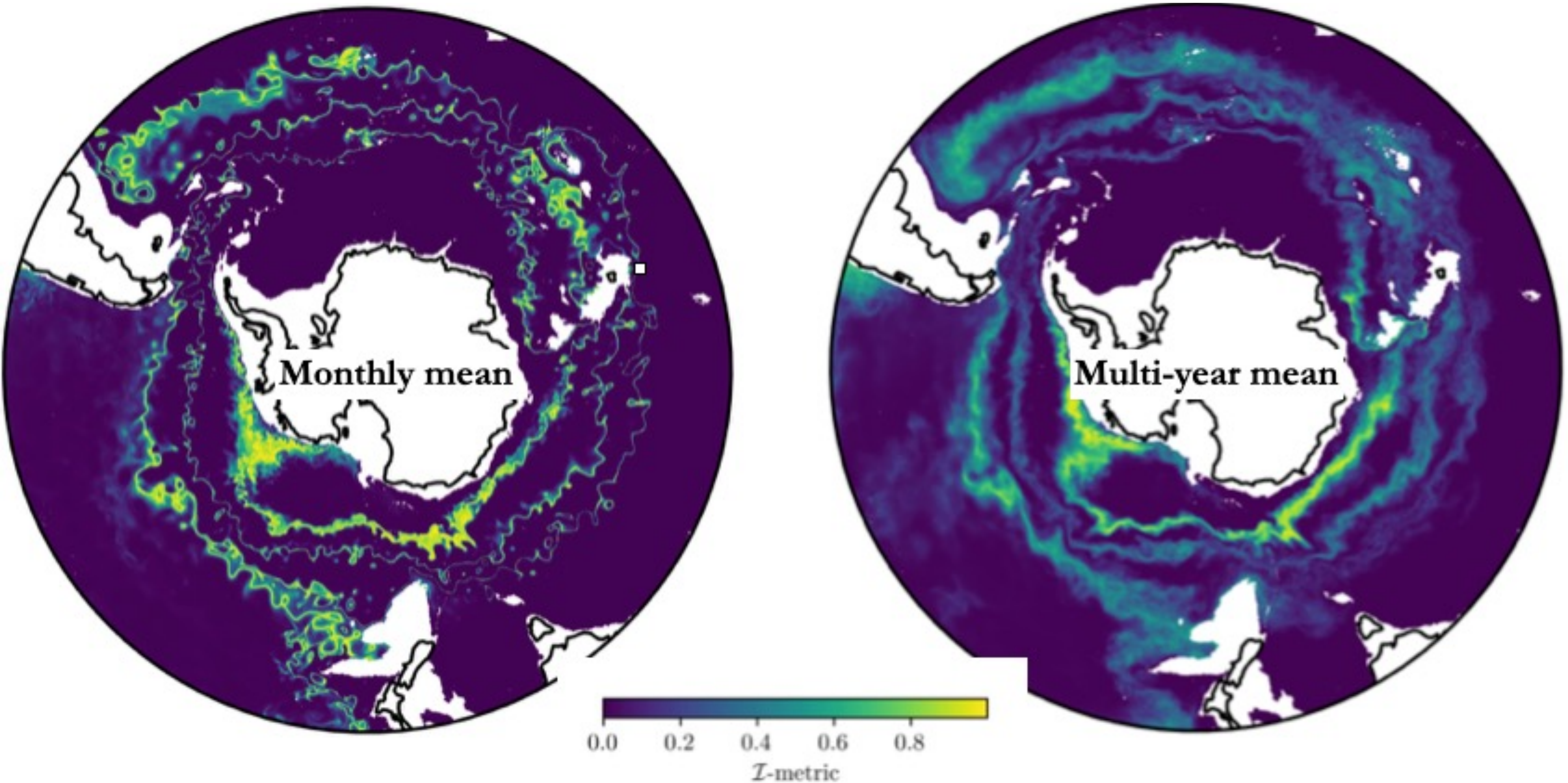


Figure: $\mathcal{I}$ of GMM with $K = 5$.

Local: Sobel Edge Detection

- We build on a Sobel edge detection method (Hjelmervik & Hjelmervik 2019) on the 3 PC-fields.
- Approximately the smoothed PC 2D gradient.

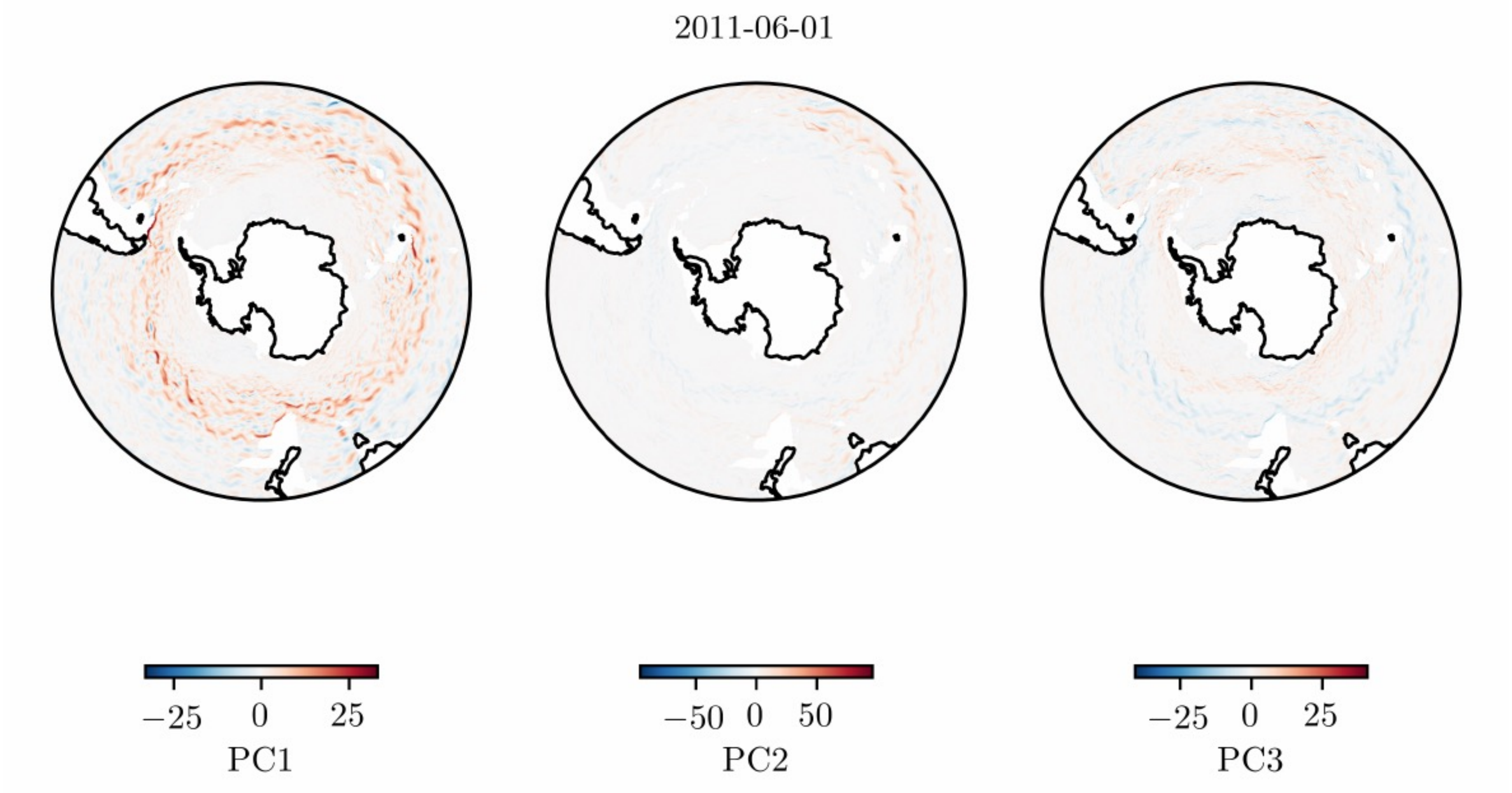
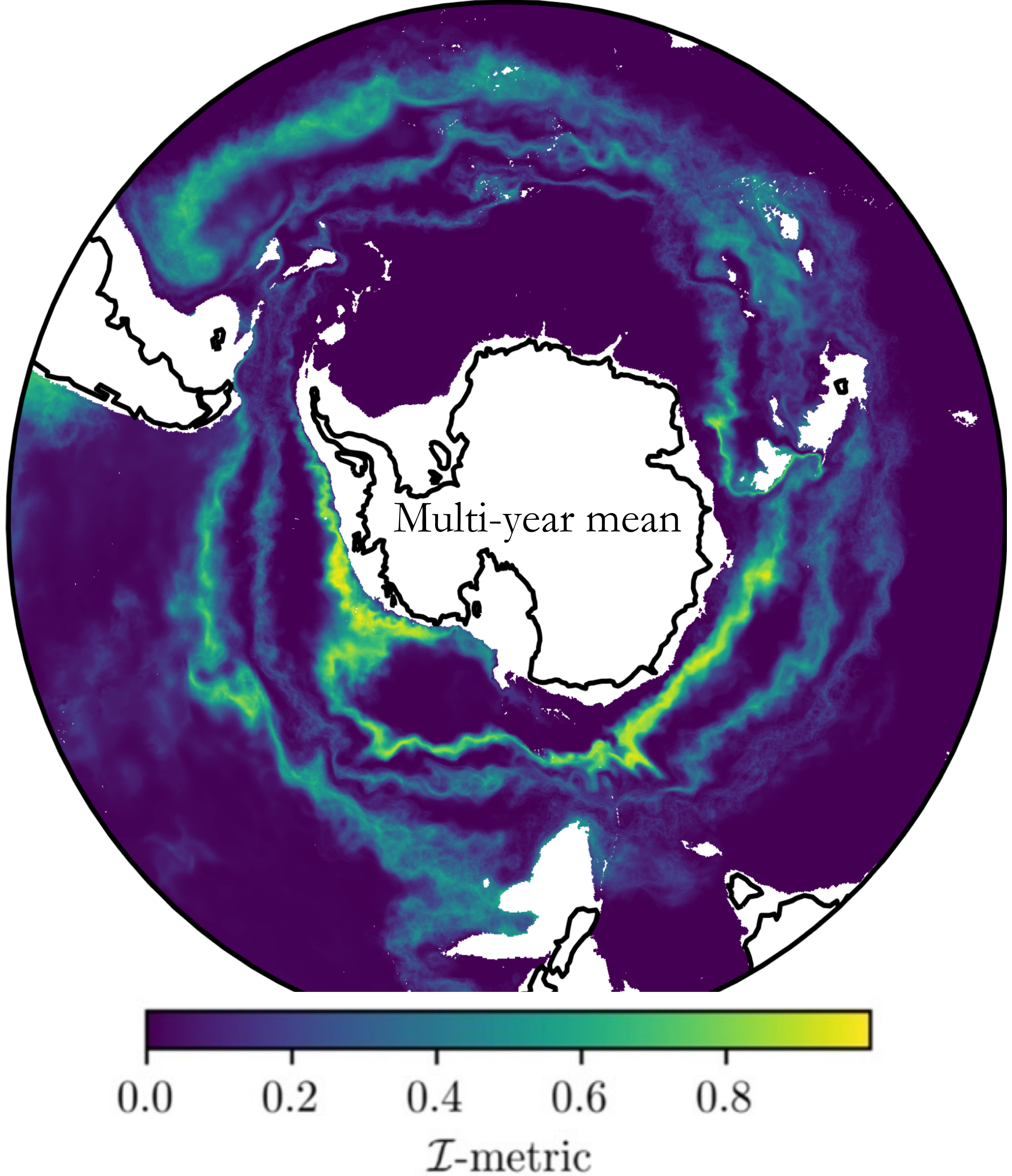


Figure: Sobel edge fronts in latitude direction.

Conclusion



- We propose a probabilistic metric for defining water mass boundaries. Use a depth range, not surface information.
- This expands on the classical, time-averaged view of fronts and water mass boundaries, following Chapman *et al.* 2020.
- Paper and a GitHub repository in prep.

References I

1. Chapman, C. C., Lea, M.-A., Meyer, A., Sallée, J.-B. & Hindell, M. Defining Southern Ocean fronts and their influence on biological and physical processes in a changing climate. *Nature Climate Change* (2020).
2. Verdy, A. & Mazloff, M. R. A data assimilating model for estimating Southern Ocean biogeochemistry. *Journal of Geophysical Research: Oceans* (2017).
3. Rosso, I. *et al.* Water Mass and Biogeochemical Variability in the Kerguelen Sector of the Southern Ocean: A Machine Learning Approach for a Mixing Hot Spot. *Journal of Geophysical Research: Oceans* **125,** e2019JC015877 (2020).
4. North, G. R., Bell, T. L., Cahalan, R. F. & Moeng, F. J. Sampling errors in the estimation of empirical orthogonal functions. *Monthly weather review* (1982).
5. Pauthenet, E., Roquet, F., Madec, G. & Nerini, D. A linear decomposition of the Southern Ocean thermohaline structure. *Journal of Physical Oceanography* (2017).

References II

6. Maze, G. *et al.* Coherent heat patterns revealed by unsupervised classification of Argo temperature profiles in the North Atlantic Ocean. *Progress in Oceanography* (2017).
7. Jones, D. C., Holt, H. J., Meijers, A. J. & Shuckburgh, E. Unsupervised clustering of Southern Ocean Argo float temperature profiles. *Journal of Geophysical Research: Oceans* (2019).
8. Hjelmervik, K. B. & Hjelmervik, K. T. Detection of oceanographic fronts on variable water depths using empirical orthogonal functions. *IEEE Journal of Oceanic Engineering* (2019).