

In-Situ Observations Within The ECCO Reanalysis Framework

2024 IQuOD/GTSPP/SOOP/XBT/IODE meeting

Gaël Forget

Bologna, Italy

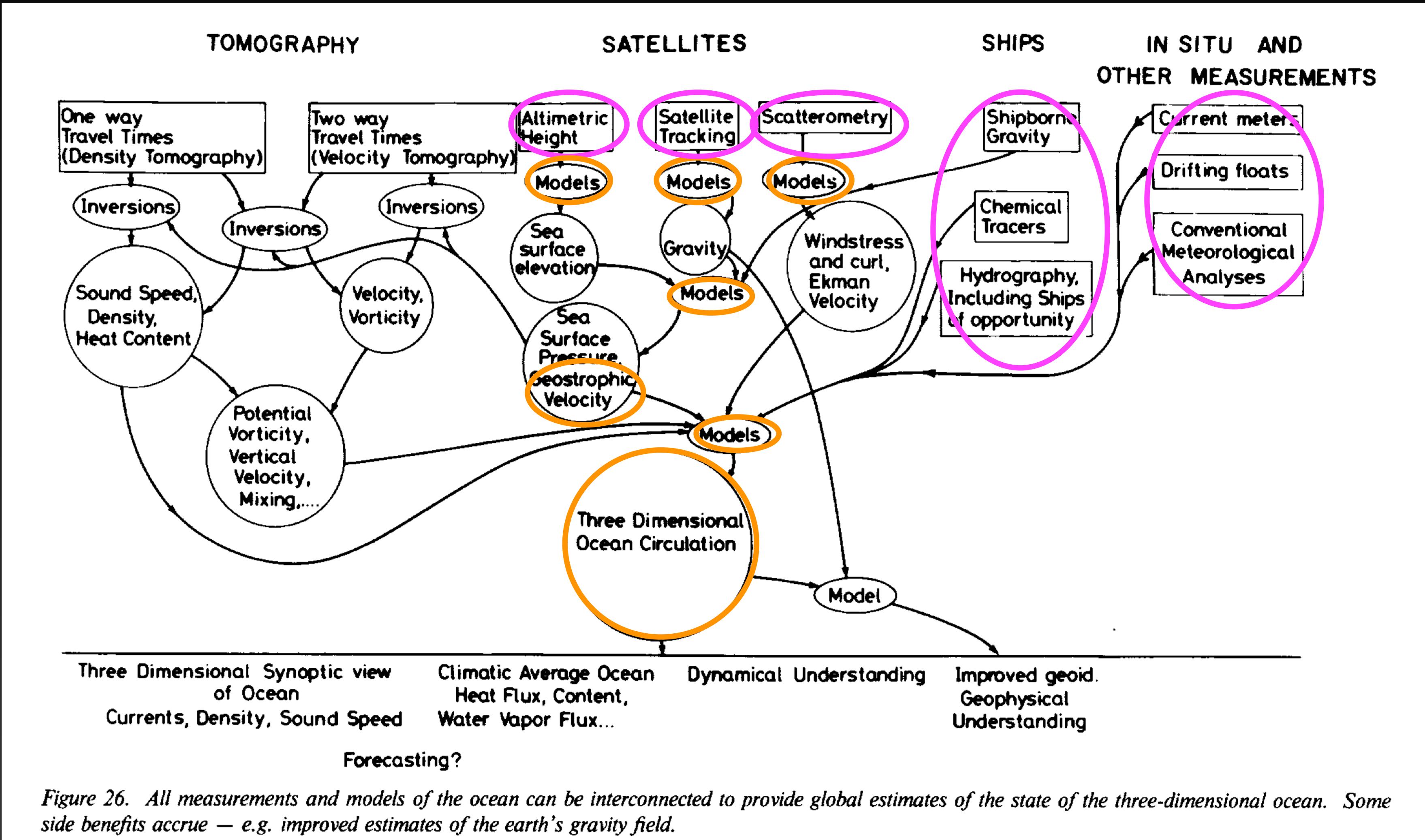
2024/11/13

Outline

- What's ECCO?
- In-situ data in ECCO
- The growing ECCO community

ECCO Version 0 : the concept

Carl Wunsch, 1982, Acoustic Tomography and Other Answers



ECCO version 4 : the implementation

An integrated framework for non-linear inverse modeling and global ocean state estimation
Forget, Campin, Heimbach, Hill, Ponte, Wunsch, 2015

Included Observational Data

Data set	<i>T</i> profiles	<i>S</i> profiles	
MDT	DNSC08 mean SSH minus EGM2008 geoid model	1993–2004	6.2×10^4
<i>T, S</i>	Blended monthly climatology OCCA WOA 2005 PHC 3.0	2004–2006 Unclear Unclear	$2 \times 5.7 \times 10^8$
SLA	Daily bin average of along-track altimetry	1992–2011	7.7×10^7
SST	Monthly maps	1992–2011	1.5×10^7
ICF	Monthly maps	1992–2010	1.4×10^7
Argo	833 033	800 269	
CTD	379 012	333 266	
XBT	597 009	0	
ITP	18 033	17 745	
SEaOS	103 117	87 806	
bobbers	7894	0	
CTD	161	161	

ECCO version 4 : the implementation

An integrated framework for non-linear inverse modeling and global ocean state estimation
 Forget, Campin, Heimbach, Hill, Ponte, Wunsch, 2015

Ocean Model	
$\frac{\partial \mathbf{v}}{\partial t} + (f + \zeta) \hat{\mathbf{k}} \times \mathbf{v} + \nabla_z^* \text{KE} + w \frac{\partial \mathbf{v}}{\partial z} + g \nabla_z^* \eta + \nabla_h \Phi'$	(1)
$= \mathbf{D}_{z^*, \mathbf{v}} + \mathbf{D}_{\perp, \mathbf{v}} + \mathcal{F}_{\mathbf{v}},$	
$\frac{\partial \Phi'}{\partial z} = g \frac{\rho'}{\rho_c},$	(2)
$\frac{1}{H} \frac{\partial \eta}{\partial t} + \nabla_z^*(s^* \mathbf{v}) + \frac{\partial w}{\partial z^*} = s^* \mathcal{F},$	(3)
$\frac{\partial(s^* \theta)}{\partial t} + \nabla_z^*(s^* \theta \mathbf{v}_{\text{res}}) + \frac{\partial(\theta w_{\text{res}})}{\partial z^*}$	
$= s^* (\mathcal{F}_\theta + D_{\sigma, \theta} + D_{\perp, \theta}),$	(4)
$\frac{\partial(s^* S)}{\partial t} + \nabla_z^*(s^* S \mathbf{v}_{\text{res}}) + \frac{\partial(S w_{\text{res}})}{\partial z^*}$	
$= s^* (\mathcal{F}_S + D_{\sigma, S} + D_{\perp, S}),$	

Included Observational Data

Data set	T profiles	S profiles
MDT	DNSC08 mean SSH minus EGM2008 geoid model	1993–2004 6.2×10^4
T, S	Blended monthly climatology OCCA WOA 2005 PHC 3.0	$2 \times 5.7 \times 10^8$ 2004–2006 Unclear Unclear
SLA	Daily bin average of along-track altimetry	1992–2011 7.7×10^7
SST	Monthly maps	1992–2011 1.5×10^7
ICF	Monthly maps	1992–2010 1.4×10^7
Argo	833 033	800 269
CTD	379 012	333 266
XBT	597 009	0
ITP	18 033	17 745
SEaOS	103 117	87 806
bobbers	7894	0
CTD	161	161

ECCO version 4 : the implementation

An integrated framework for non-linear inverse modeling and global ocean state estimation
 Forget, Campin, Heimbach, Hill, Ponte, Wunsch, 2015

Cost Function

$$J(\mathbf{u}) = \sum_i \alpha_i \times \left(d_i^T \mathbf{R}_i^{-1} d_i \right) + \sum_j \beta_j \times \left(\mathbf{u}_j^T \mathbf{u}_j \right)$$

$$d_i = \mathcal{P}(m_i - o_i),$$

$$m_i = \mathcal{SDM}(\mathbf{v}),$$

$$\mathbf{v} = \mathcal{Q}(\mathbf{u}),$$

$$\mathbf{u} = \mathcal{R}(\mathbf{u}'),$$

$$\frac{\partial \mathbf{v}}{\partial t} + (f + \zeta) \hat{\mathbf{k}} \times \mathbf{v} + \nabla_z^* \text{KE} + w \frac{\partial \mathbf{v}}{\partial z} + g \nabla_z^* \eta + \nabla_h \Phi' \\ = \mathbf{D}_{z^*, \mathbf{v}} + \mathbf{D}_{\perp, \mathbf{v}} + \mathcal{F}_{\mathbf{v}}, \quad (1)$$

$$\frac{\partial \Phi'}{\partial z} = g \frac{\rho'}{\rho_c}, \quad (2)$$

$$\frac{1}{H} \frac{\partial \eta}{\partial t} + \nabla_z^*(s^* \mathbf{v}) + \frac{\partial w}{\partial z^*} = s^* \mathcal{F}, \quad (3)$$

$$\frac{\partial(s^* \theta)}{\partial t} + \nabla_z^*(s^* \theta \mathbf{v}_{\text{res}}) + \frac{\partial(\theta w_{\text{res}})}{\partial z^*} \\ = s^* (\mathcal{F}_\theta + D_{\sigma, \theta} + D_{\perp, \theta}), \quad (4)$$

$$\frac{\partial(s^* S)}{\partial t} + \nabla_z^*(s^* S \mathbf{v}_{\text{res}}) + \frac{\partial(S w_{\text{res}})}{\partial z^*} \\ = s^* (\mathcal{F}_S + D_{\sigma, S} + D_{\perp, S}),$$

Ocean Model

Included Observational Data

MDT	DNSC08 mean SSH minus EGM2008 geoid model	1993–2004	6.2×10^4
T, S	Blended monthly climatology OCCA WOA 2005 PHC 3.0	2004–2006	$2 \times 5.7 \times 10^8$
SLA	Daily bin average of along-track altimetry	1992–2011	7.7×10^7
SST	Monthly maps	1992–2011	1.5×10^7
ICF	Monthly maps	1992–2010	1.4×10^7
Data set	T profiles	S profiles	
Argo	833 033	800 269	
CTD	379 012	333 266	
XBT	597 009	0	
ITP	18 033	17 745	
SEaOS	103 117	87 806	
bobbers	7894	0	
CTD	161	161	

ECCO version 4 : the implementation

An integrated framework for non-linear inverse modeling and global ocean state estimation
 Forget, Campin, Heimbach, Hill, Ponte, Wunsch, 2015

Cost Function

$$J(\mathbf{u}) = \sum_i \alpha_i \times \left(d_i^T \mathbf{R}_i^{-1} d_i \right) + \sum_j \beta_j \times \left(\mathbf{u}_j^T \mathbf{u}_j \right)$$

$$d_i = \mathcal{P}(m_i - o_i),$$

$$m_i = \mathcal{SDM}(\mathbf{v}),$$

$$\mathbf{v} = \mathcal{Q}(\mathbf{u}),$$

$$\mathbf{u} = \mathcal{R}(\mathbf{u}'),$$

$$\frac{\partial \mathbf{v}}{\partial t} + (f + \zeta) \hat{\mathbf{k}} \times \mathbf{v} + \nabla_z^* \text{KE} + w \frac{\partial \mathbf{v}}{\partial z} + g \nabla_z^* \eta + \nabla_h \Phi' \\ = \mathbf{D}_{z^*, \mathbf{v}} + \mathbf{D}_{\perp, \mathbf{v}} + \mathcal{F}_{\mathbf{v}}, \quad (1)$$

$$\frac{\partial \Phi'}{\partial z} = g \frac{\rho'}{\rho_c}, \quad (2)$$

$$\frac{1}{H} \frac{\partial \eta}{\partial t} + \nabla_z^*(s^* \mathbf{v}) + \frac{\partial w}{\partial z^*} = s^* \mathcal{F}, \quad (3)$$

$$\frac{\partial(s^* \theta)}{\partial t} + \nabla_z^*(s^* \theta \mathbf{v}_{\text{res}}) + \frac{\partial(\theta w_{\text{res}})}{\partial z^*} \\ = s^* (\mathcal{F}_\theta + D_{\sigma, \theta} + D_{\perp, \theta}), \quad (4)$$

$$\frac{\partial(s^* S)}{\partial t} + \nabla_z^*(s^* S \mathbf{v}_{\text{res}}) + \frac{\partial(S w_{\text{res}})}{\partial z^*} \\ = s^* (\mathcal{F}_S + D_{\sigma, S} + D_{\perp, S}),$$

Ocean Model

Optimized Parameters

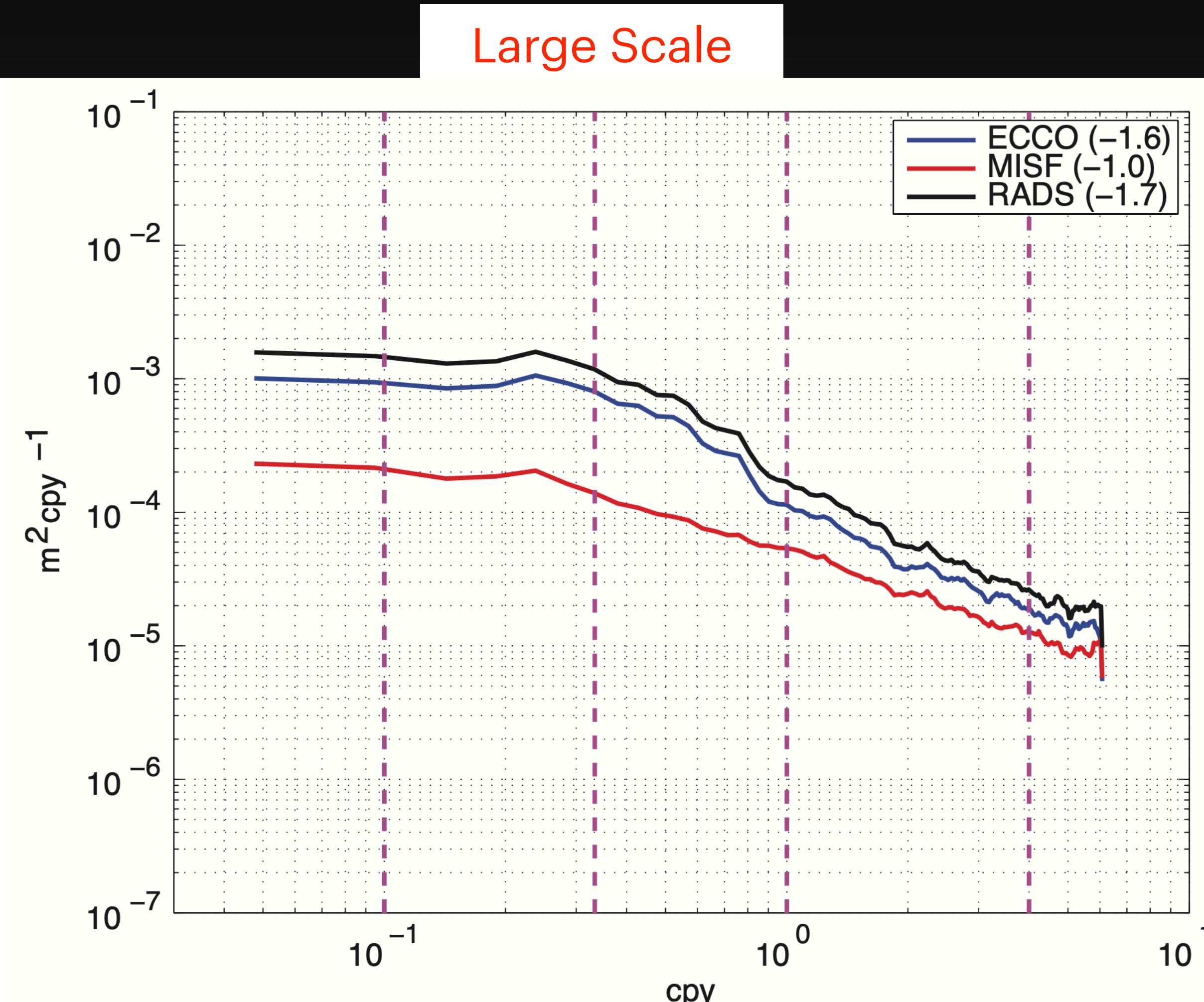
Initial condition for temperature	N/A	2.4×10^6
Initial condition for salinity	N/A	2.4×10^6
Diapycnal diffusivity	Time mean	2.4×10^6
Isopycnal diffusivity	Time mean	2.4×10^6
GM intensity	Time mean	2.4×10^6
Atmospheric temperature at 2 m	Bi-weekly	3.2×10^7
Specific humidity at 2 m	Bi-weekly	3.2×10^7
Precipitation	Bi-weekly	3.2×10^7
Downward longwave radiation	Bi-weekly	3.2×10^7
Downward shortwave radiation	Bi-weekly	3.2×10^7
Zonal wind stress	Bi-weekly	3.1×10^7
Meridional wind stress	Bi-weekly	3.1×10^7

Included Observational Data

MDT	DNSC08 mean SSH minus EGM2008 geoid model	1993–2004	6.2×10^4
T, S	Blended monthly climatology OCCA WOA 2005 PHC 3.0	2004–2006	$2 \times 5.7 \times 10^8$
SLA	Daily bin average of along-track altimetry	1992–2011	7.7×10^7
SST	Monthly maps	1992–2011	1.5×10^7
ICF	Monthly maps	1992–2010	1.4×10^7
Data set	T profiles	S profiles	
Argo	833 033	800 269	
CTD	379 012	333 266	
XBT	597 009	0	
ITP	18 033	17 745	
SEaOS	103 117	87 806	
bobbers	7894	0	
CTD	161	161	

The partition of regional sea level variability

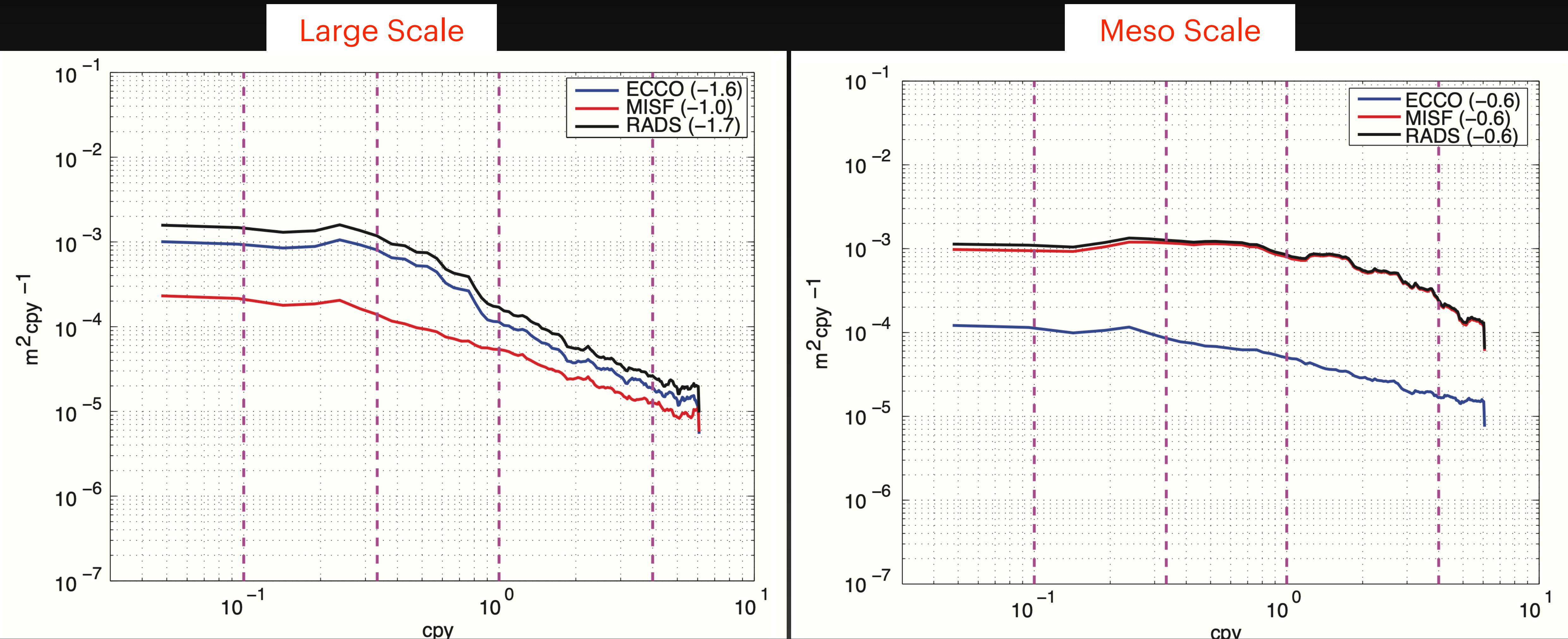
Forget and Ponte, *progress in oceanography*, 2015



1. Compute local frequency spectra; 2. Global average of frequency spectra

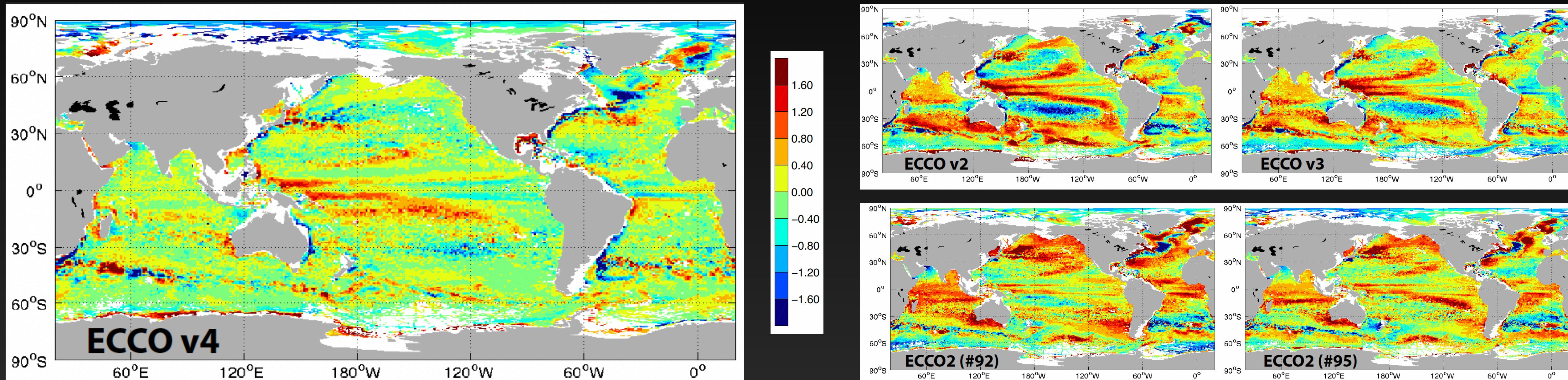
The partition of regional sea level variability

Forget and Ponte, *progress in oceanography*, 2015



1. Compute local frequency spectra; 2. Global average of frequency spectra

Improved fit to Argo in ECCO4 by optimizing *mixing* parameters



Temperature Misfits (ECCO minus Argo+)

- Forget et al 2015a , <https://doi.org/10.5194/gmd-8-3071-2015>
- Forget et al 2015b , <https://doi.org/10.5194/os-11-839-2015>

Mapping Ocean Observations in a Dynamical Framework: A 2004–06 Ocean Atlas

Forget, JPO, 2010

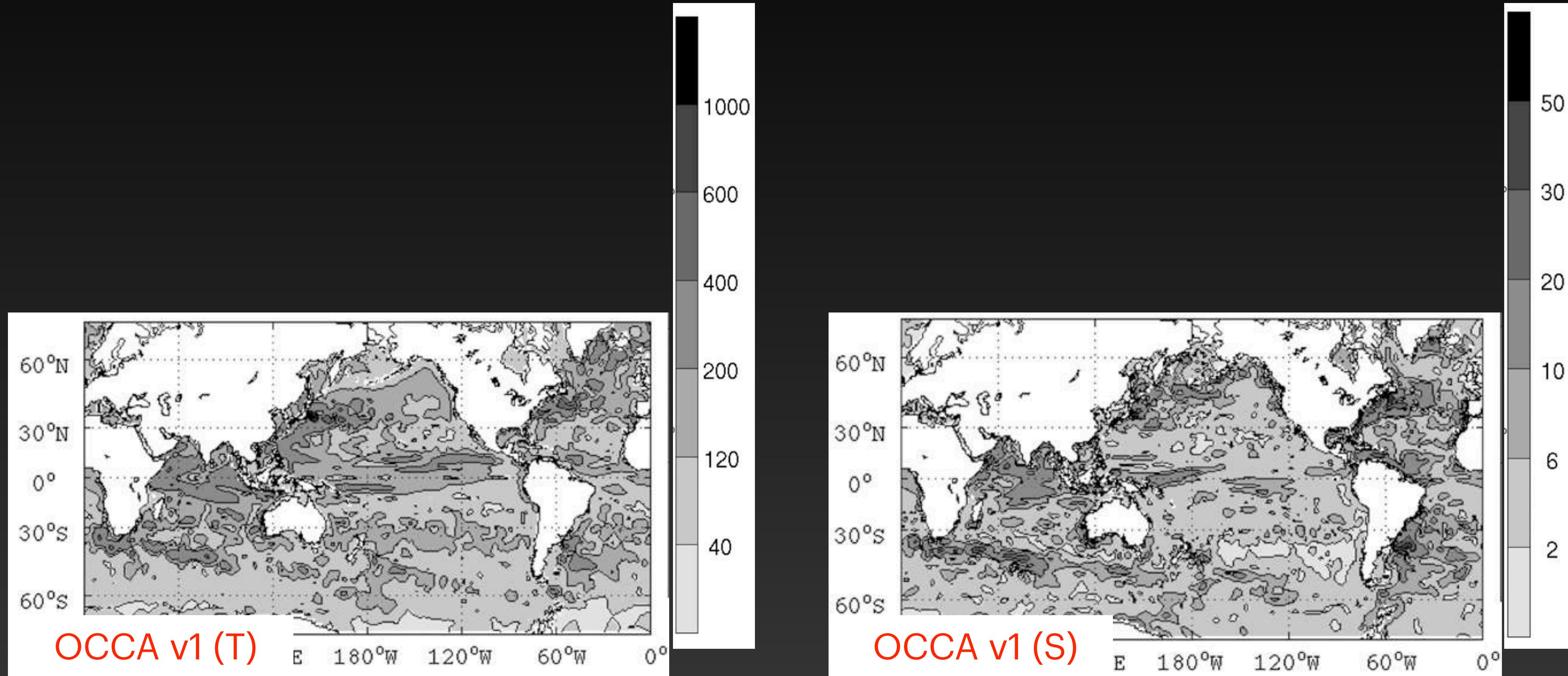


FIG. 14. Magnitude of the flux divergence fluctuation that is implied by the seasonal cycle of the vertically integrated (left) heat (W m^{-2}) and (right) freshwater (mm day^{-1}) content, for (top) *WOA01*, (middle) Fourier truncated *WOA01* (see appendix A), and (bottom) OCCA. The implied fluxes diagnostic computation is $\|\Delta\mathcal{H}/\Delta t\|$, where $\Delta\mathcal{H}$ is the content difference from one month to the next, Δt is

Mapping Ocean Observations in a Dynamical Framework: A 2004–06 Ocean Atlas

Forget, JPO, 2010

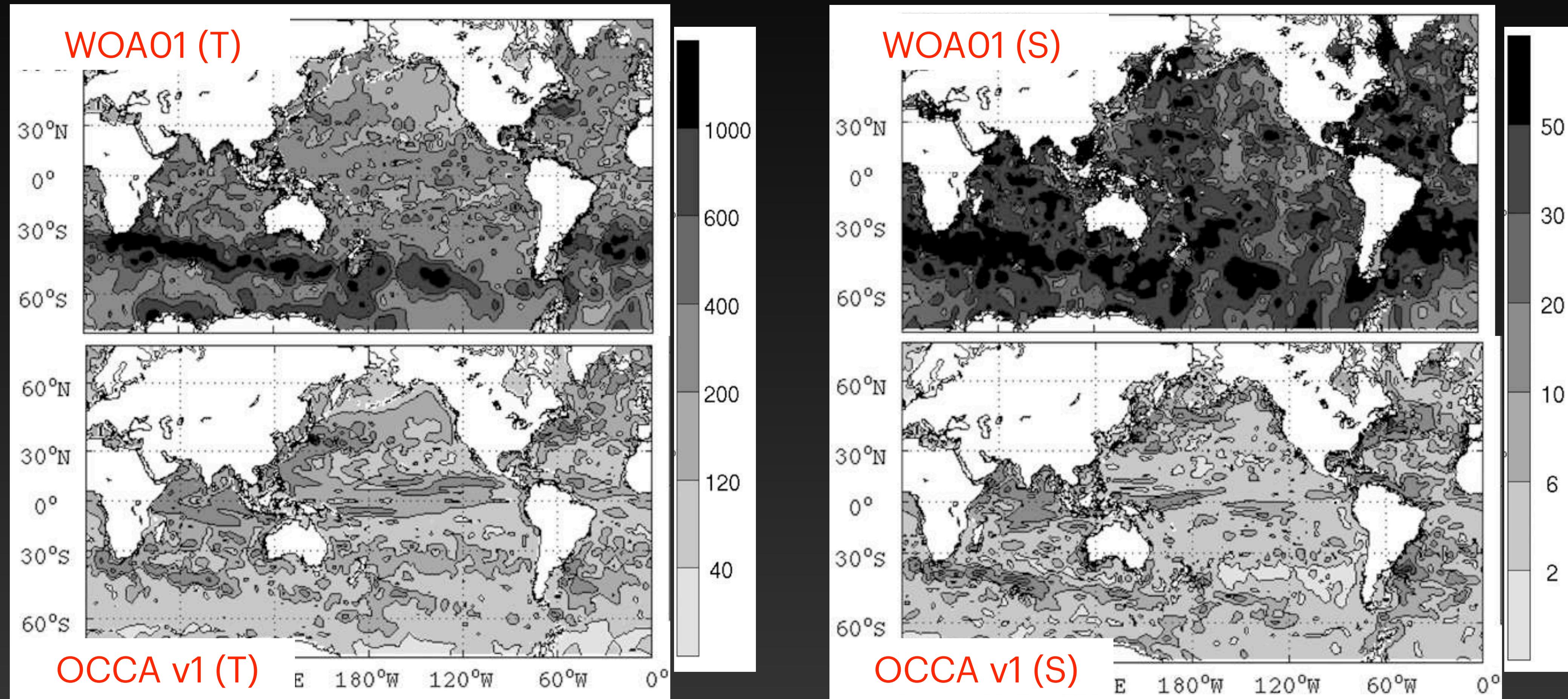


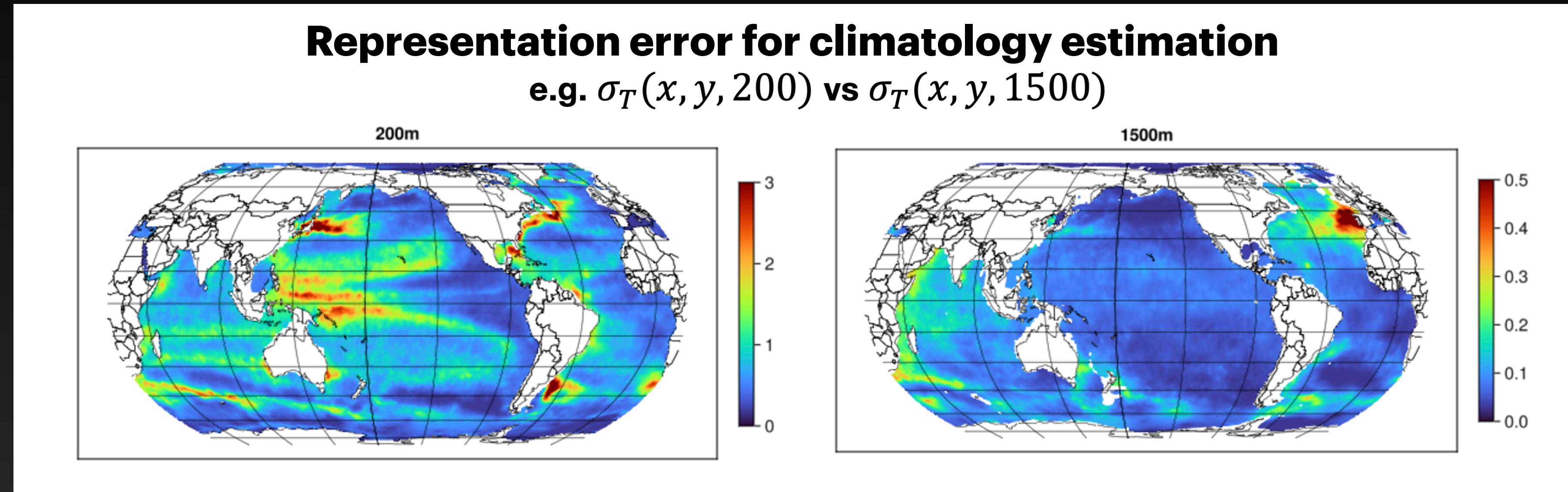
FIG. 14. Magnitude of the flux divergence fluctuation that is implied by the seasonal cycle of the vertically integrated (left) heat (W m^{-2}) and (right) freshwater (mm day^{-1}) content, for (top) *WOA01*, (middle) Fourier truncated *WOA01* (see appendix A), and (bottom) *OCCA*. The implied fluxes diagnostic computation is $\|\Delta\mathcal{H}/\Delta t\|$, where $\Delta\mathcal{H}$ is the content difference from one month to the next, Δt is

Outline

- What's ECCO?
- In-Situ data in ECCO
- The growing ECCO community

In-situ T/S profiles in ECCO

Forget and Wunsch 2007 (updated)

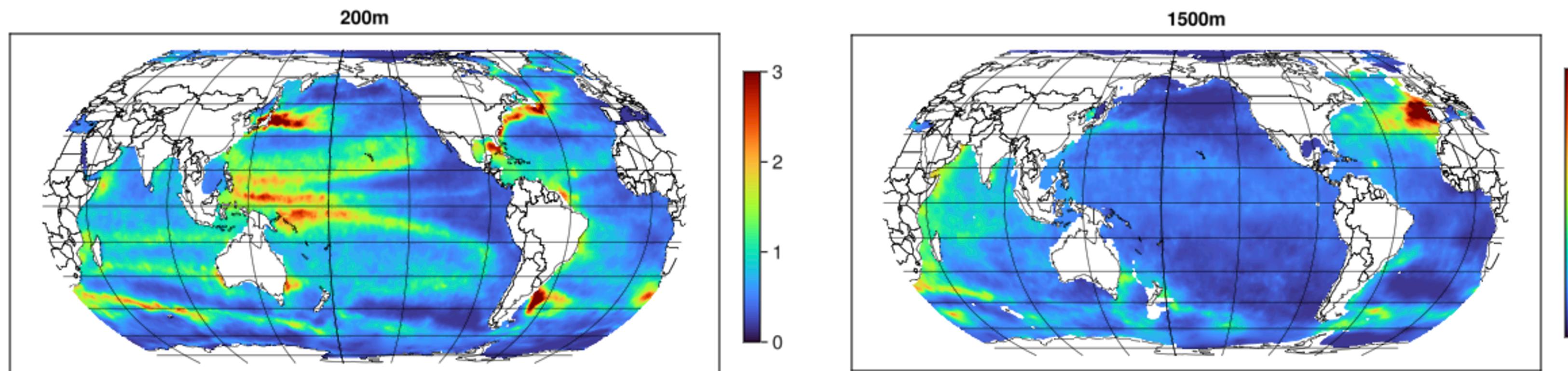


In-situ T/S profiles in ECCO

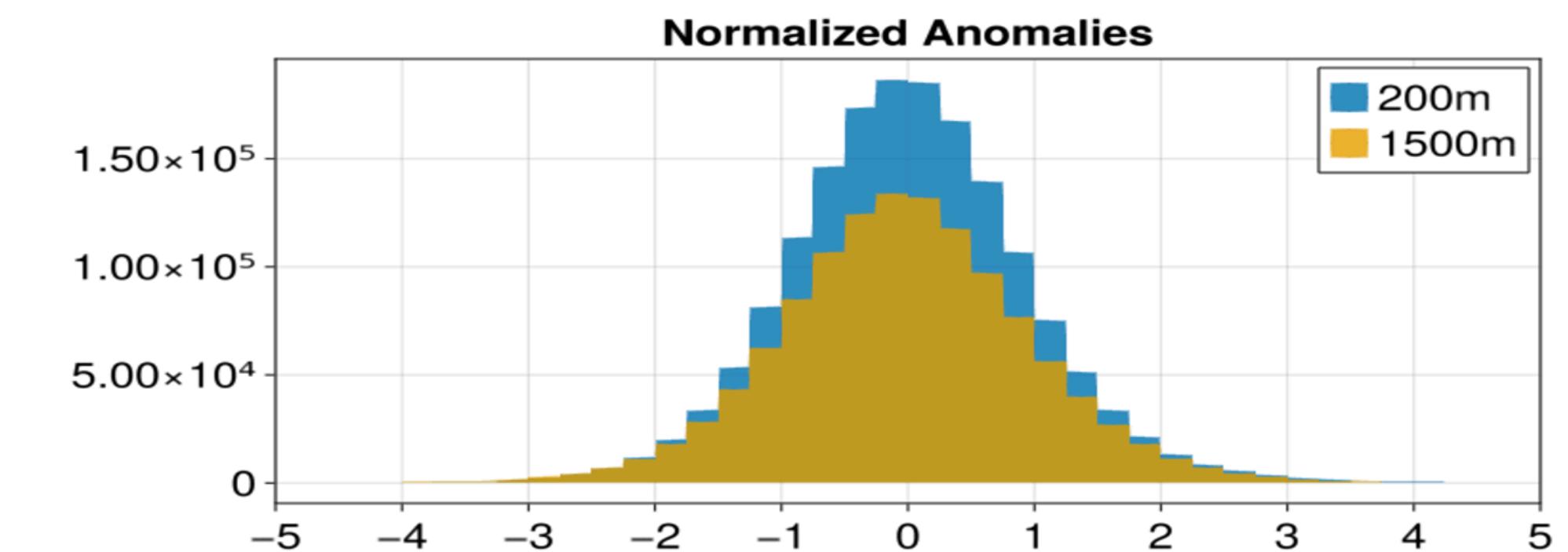
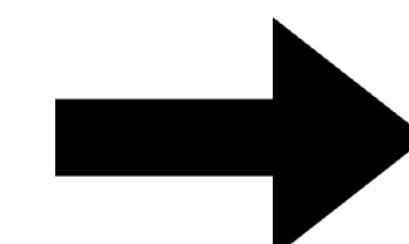
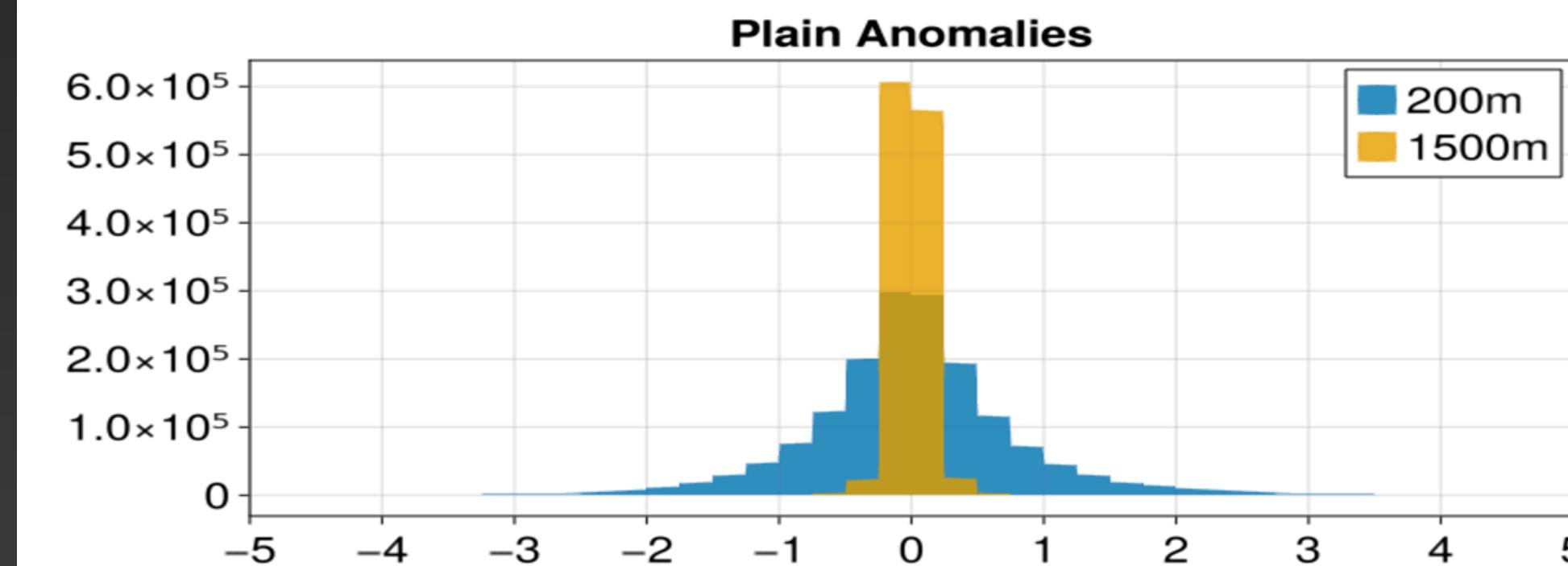
Forget and Wunsch 2007 (updated)

Representation error for climatology estimation

e.g. $\sigma_T(x, y, 200)$ vs $\sigma_T(x, y, 1500)$

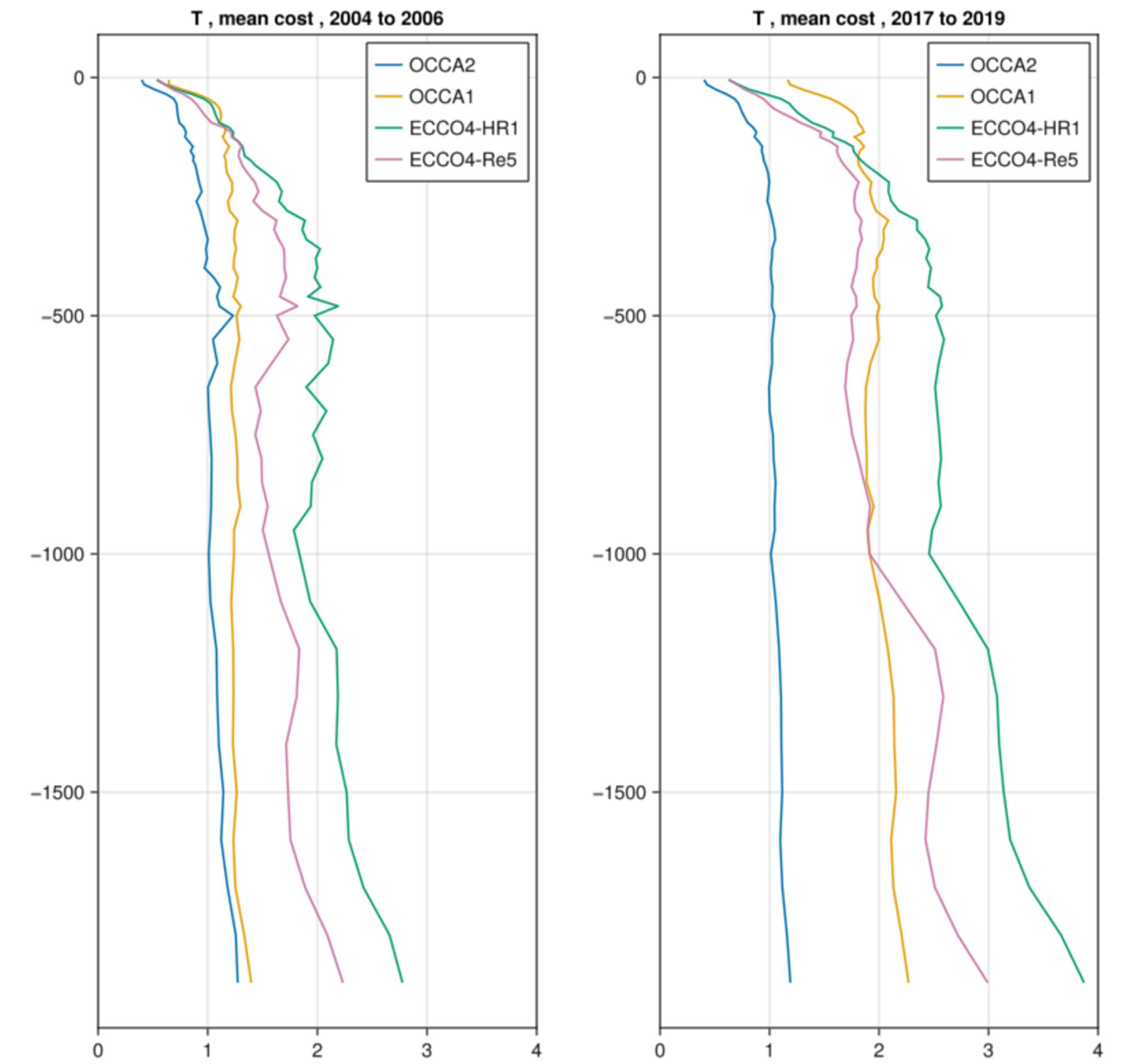


Normalizing Anomalies
PDF of Climatology minus Argo



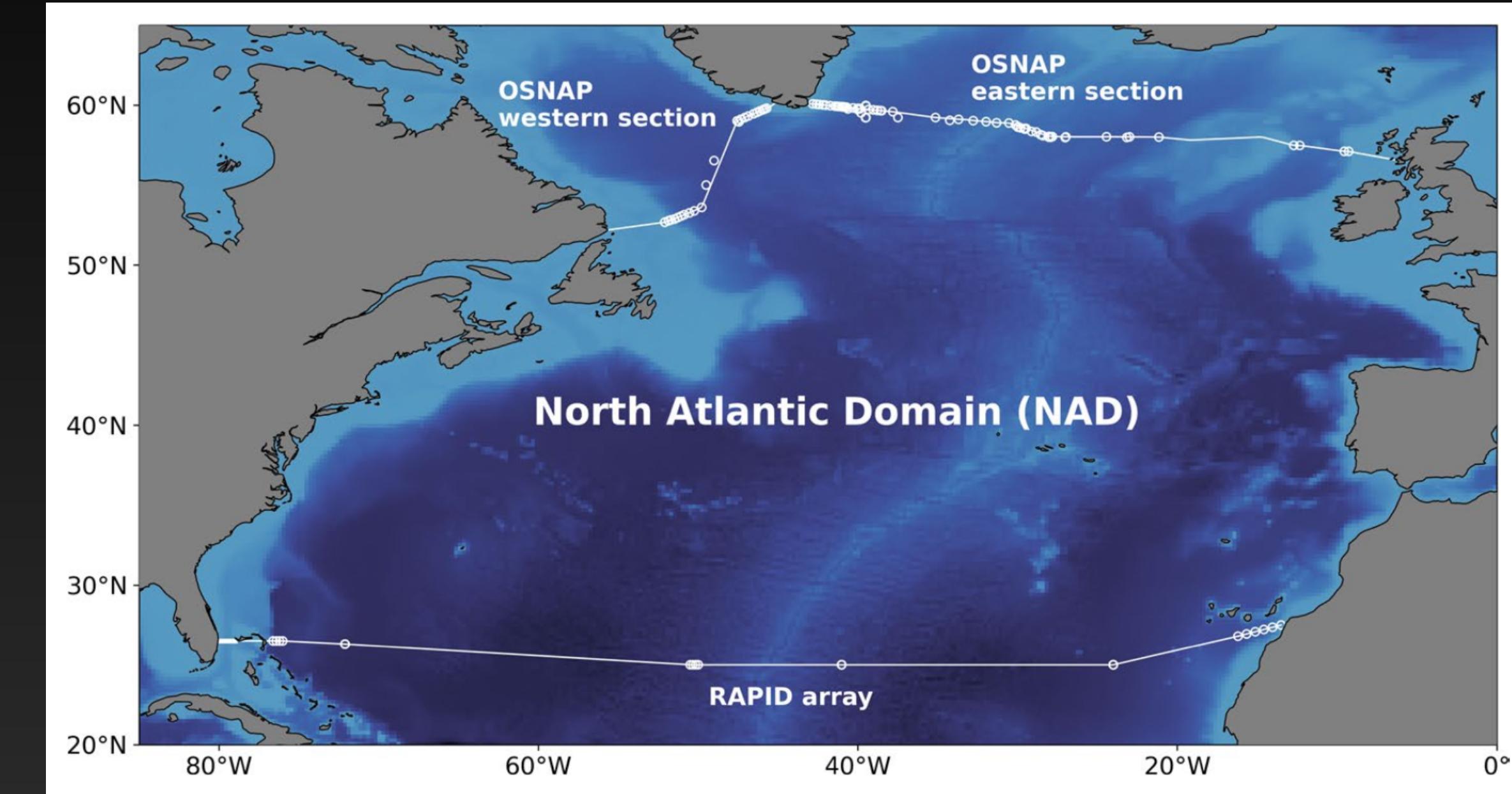
In-situ T/S profiles in ECCO representation error and cost function for climatology estimation

- Goal : define normalized data-to-estimate distance (i.e., cost function)
- Representation Error = signal NOT well resolved by data or estimate
 - e.g., meso- and submeso-scale signals in Argo (3 degree resolution)
 - same signals in Argo objective mapping like IAP, NCEI, or ECCO
- Forget and Wunsch 2007 (Argo, or any T/S profile) :
 - estimate $\sigma_T^2 = \overline{(T_{obs} - T_{est})^2}$ via sample variance
 - Map out $\sigma_T^2(x, y, z)$ via objective mapping
 - Cost function = $\overline{(T - T_{obs})^2 / \sigma_T^2}$
- Other example : Forget & Ponte 2015 (altimetry)
- Use Cases : Forget 2011 (OCCA), Forget et al 2015 (ECCO4)
- Work in Progress :
 - Monthly mapping $\sigma_T^2(x, y, z, t)$ for 0-2000m
 - Subtract ECCO, rather than climatology, as T_{est}



Uncertainty Quantification via Ensembles

Ocean Heat Transport Estimates



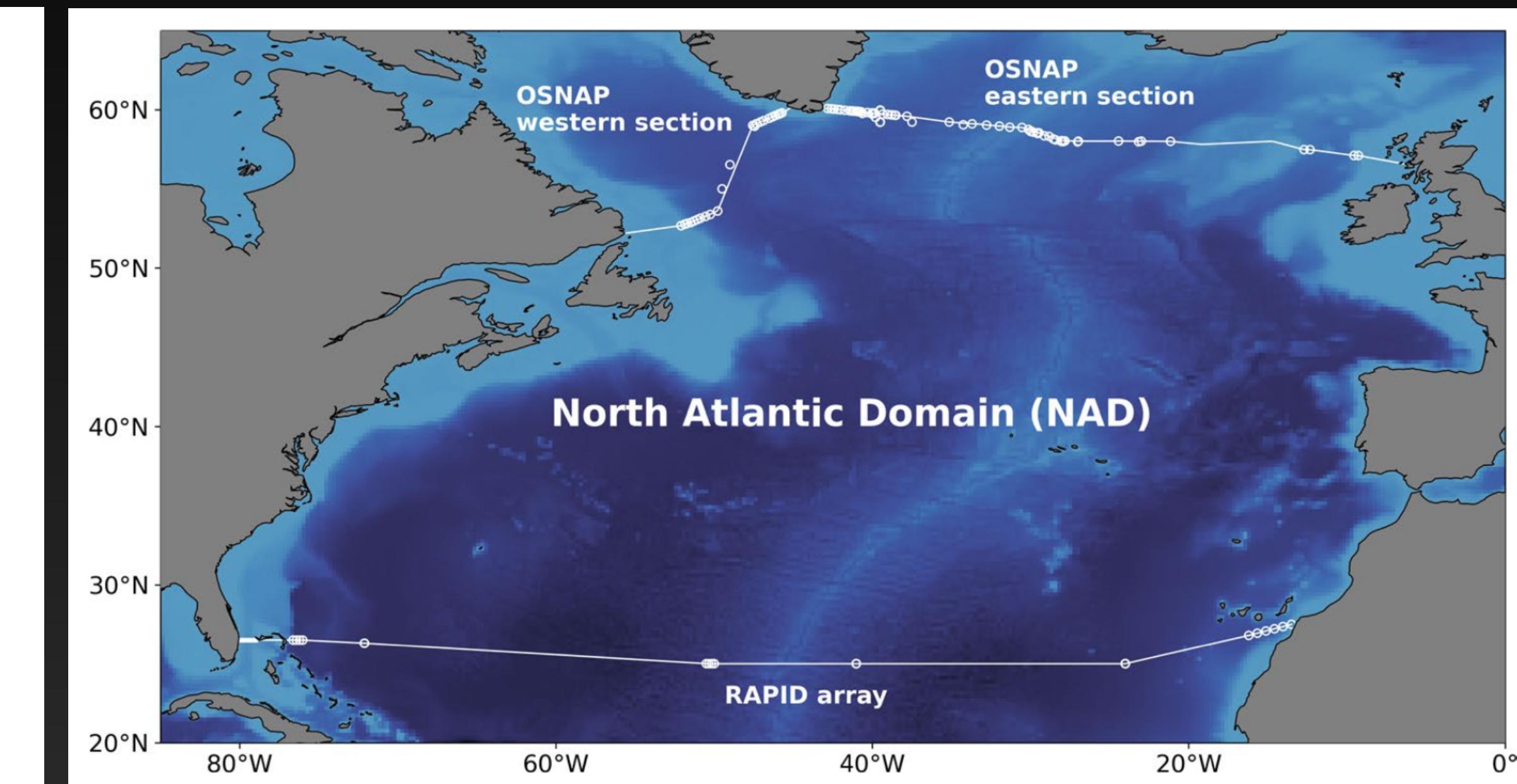
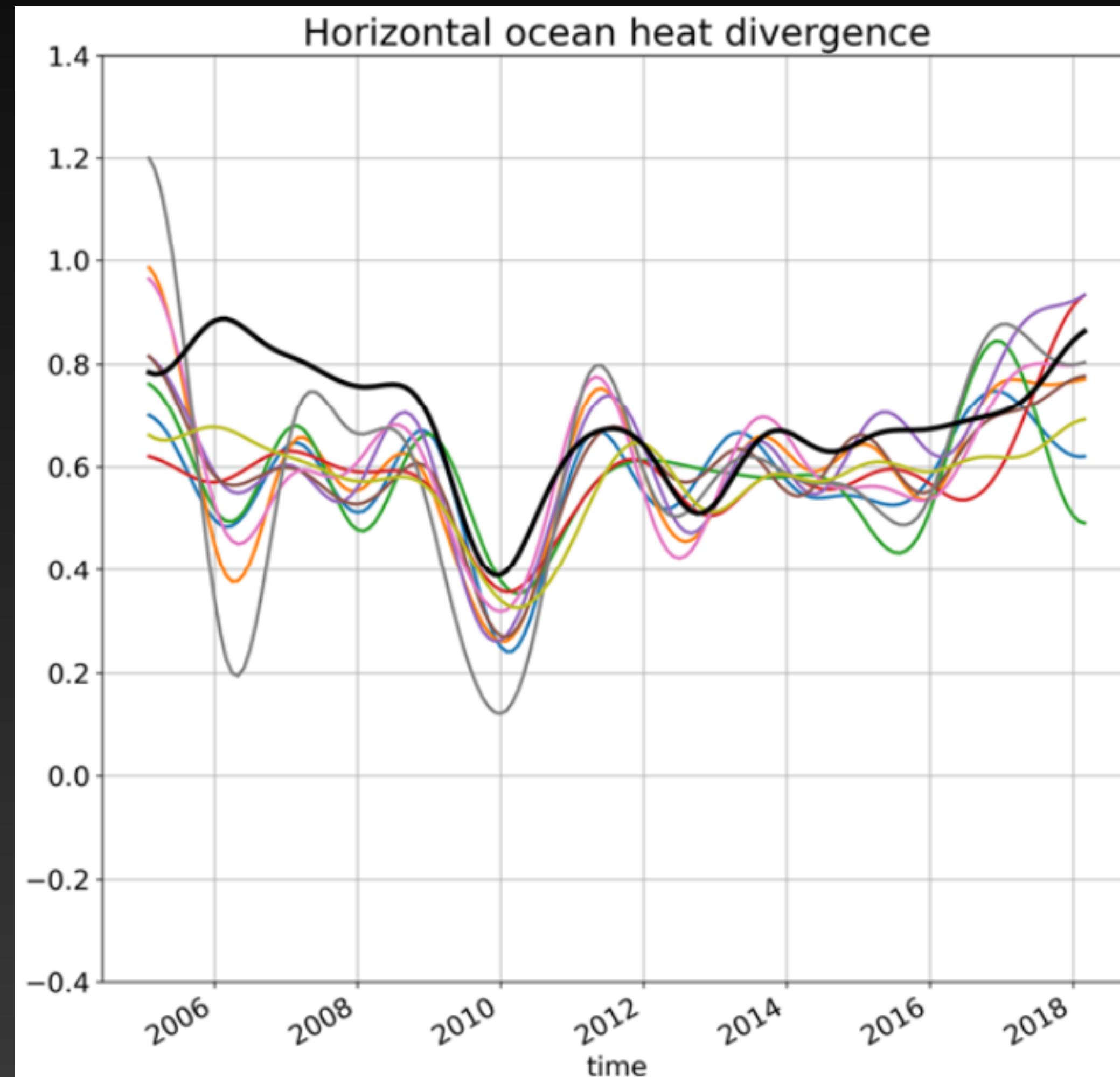
Meyssignac, B., S. Fourest, Michael Mayer, et al.

North Atlantic Heat Transport Convergence
Derived from a Regional Energy Budget Using
Different Ocean Heat Content Estimates

Surveys in Geophysics, 2024

Uncertainty Quantification via Ensembles

Ocean Heat Transport Estimates



Meyssignac, B., S. Fourest, Michael Mayer, et al.
North Atlantic Heat Transport Convergence
Derived from a Regional Energy Budget Using
Different Ocean Heat Content Estimates
Surveys in Geophysics, 2024

Uncertainty Quantification via Ensembles

Ocean Heat Transport Estimates

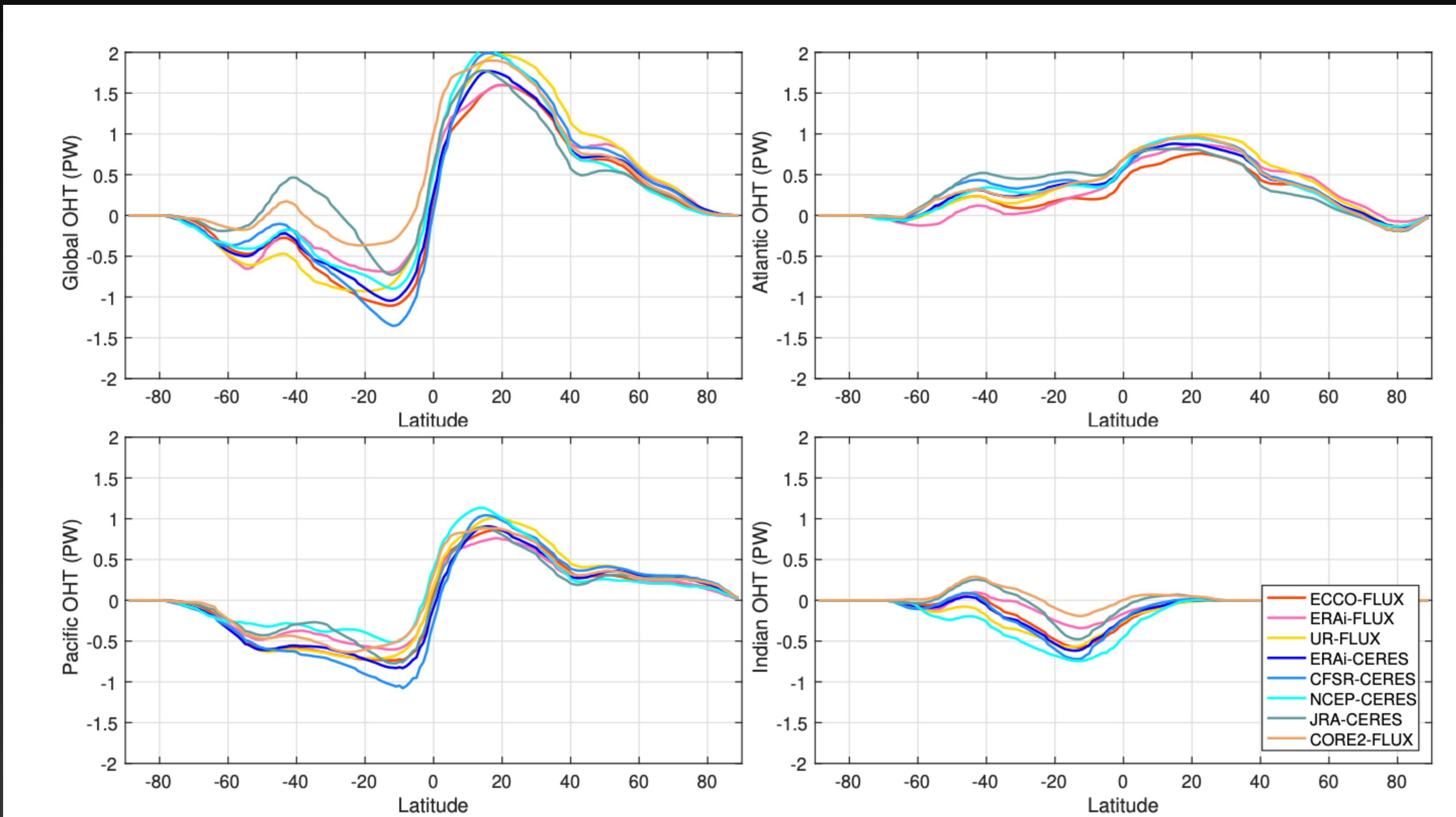


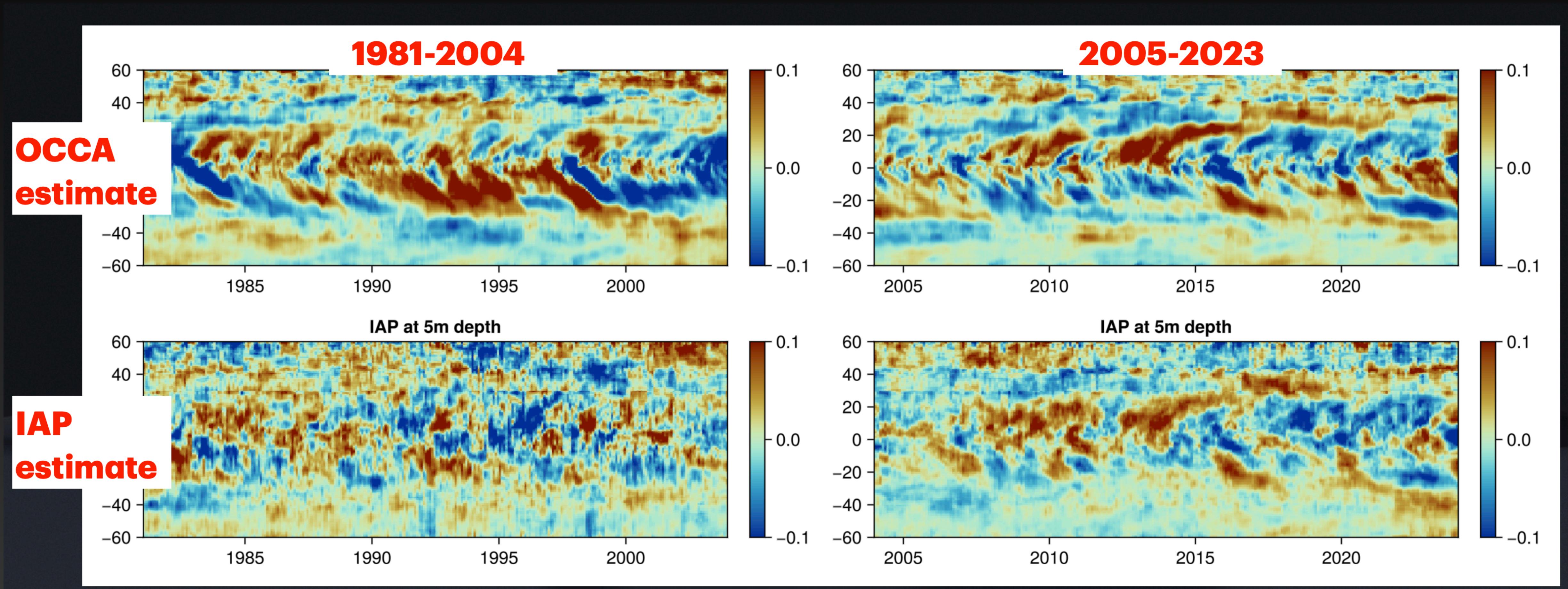
Figure S7: Meridional ocean heat transports (in PW) for the Global Ocean (top left), Atlantic (top right), Pacific (bottom left), and Indian (bottom right) inferred from various air-sea heat flux



See Supplementary of
Forget & Ferreira 2019
Global ocean heat transport
dominated by heat export from
the tropical Pacific.
Nat. Geosci. **12**, 351–354 (2019)

Uncertainty Quantification via Ensembles

Surface Salinity Anomaly Estimates



(from my presentation at GEWEX Meeting, 2024)

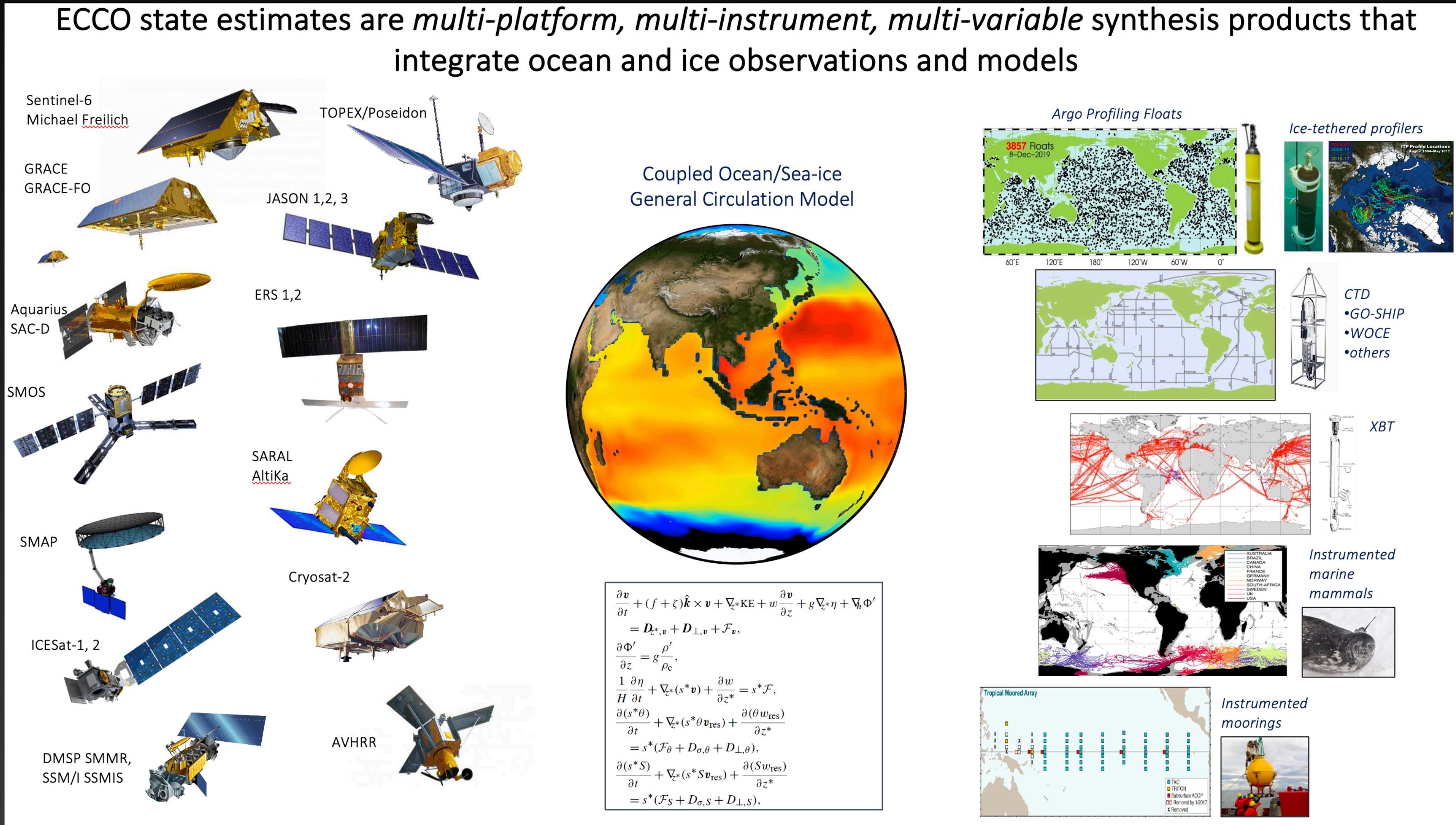
Outline

- What's ECCO?
- In-Situ data in ECCO
- The growing ECCO community

ECCO central production at JPL

Wang, Fenty, Fukumori, Forget, et al

ECCO state estimates are *multi-platform, multi-instrument, multi-variable* synthesis products that integrate ocean and ice observations and models



ECCO : community at large

- Use of ECCO state estimates :
 - *~ 2000 papers listed @ ecco-group.org*
- Use of the ECCO estimation framework :
 - *(MIT, JPL,) SIO, UT Austin, WHOI, NCAR, U Washington*
 - *AWI, U Hamburg, BAS, Oxford, ...*

ECCO : the next generation

<https://ecco-hackweek.github.io/ecco-2024/>



Search ⌘ + K

Welcome to ECCO HackWeek!

Details

- Event Logistics
- Schedule ↗
- Team ↗
- Participant Conduct

Preparation

- What to Expect
- Checklist
- Intro to Open Science Studio and

Digital Twins for Ocean Robots

▼ Data (Julia)

- [Climatology.jl](#) : accessing, reading, displaying, and analyzing climate data sets stars 15
- [OceanRobots.jl](#) : analysis and simulation of data generated by ocean robots stars 23
- [ArgoData.jl](#) : Argo data processing and analysis stars 18

▼ Data (Julia, 2)

- [OceanColorData.jl](#) : Ocean color data processing and analysis stars 10
- [Marine Ecosystems](#) : marine ecosystem observations and models github 403
- [Dataverse.jl](#) : interfaces to Dataverse APIs, collections, datasets, etc stars 7

▼ Models (Julia)

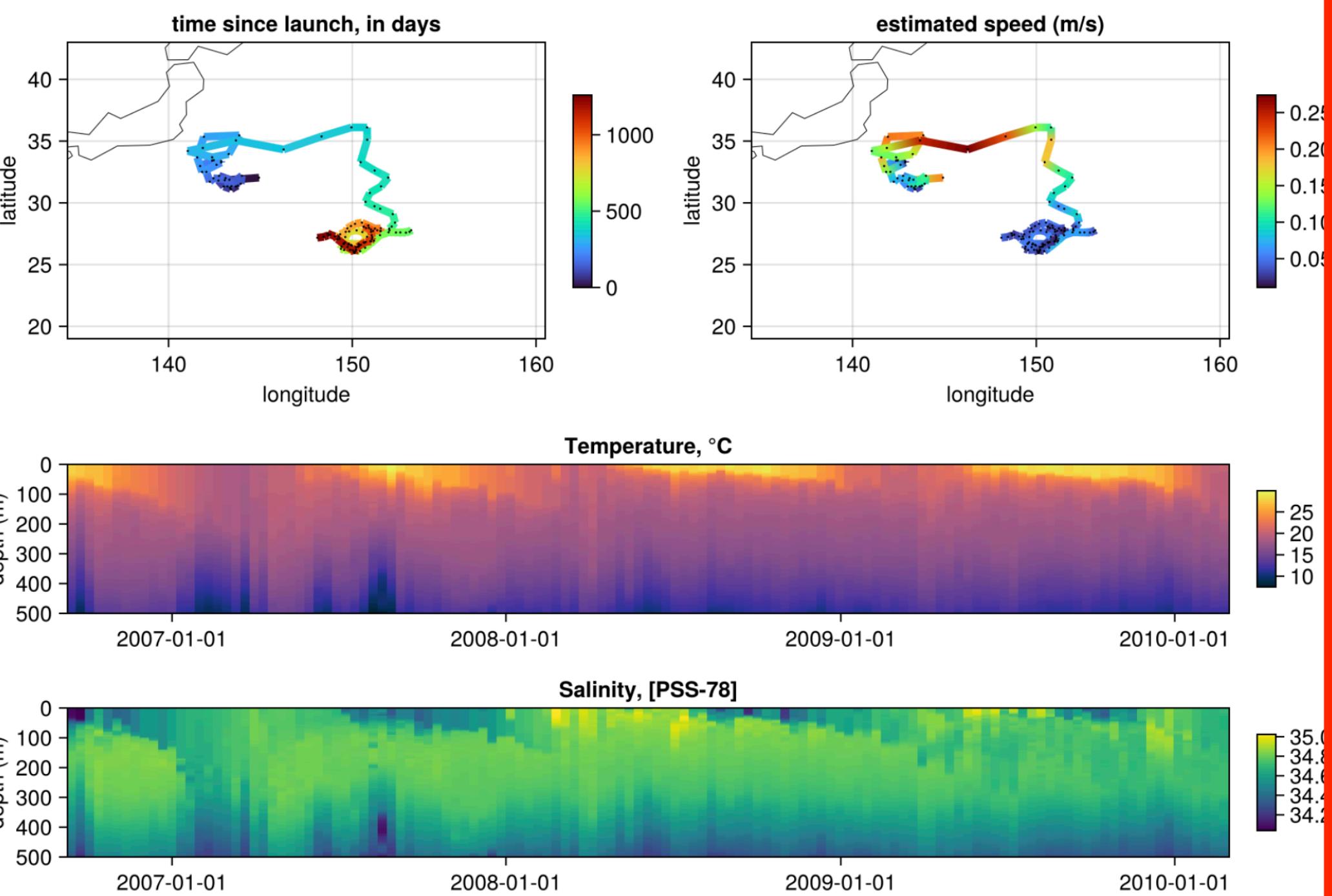
- [ClimateModels.jl](#) : uniform interface to climate models of varying complexity stars 43
- [MITgcm.jl](#) : framework to interact with MITgcm (setup, run, output, plot, ...) stars 31
- [MeshArrays.jl](#) : gridded Earth variables, global domain decomposition, and C-grid support stars 42

▼ Models (Julia, 2)

- [ECCO.jl](#) : package enables with automatic differentiation and optimization packages stars 7
- [Drifters.jl](#) : trajectory simulations for point particles in the Ocean and Atmosphere stars 36
- [PlanktonIndividuals.jl](#) : simulation of plankton communities and their interaction with environmental factors stars 30

Code 1: Download and visualize one Argo float data as in Fig. 4.

```
1  using OceanRobots, ArgoData, CairoMakie
2
3  lst=GDAC.files_list(); wmo=6900900
4  argo=read(ArgoFloat(), wmo=wmo, files_list=lst)
5
6  fig=plot(argo, option=:standard)
```



Extra Slides

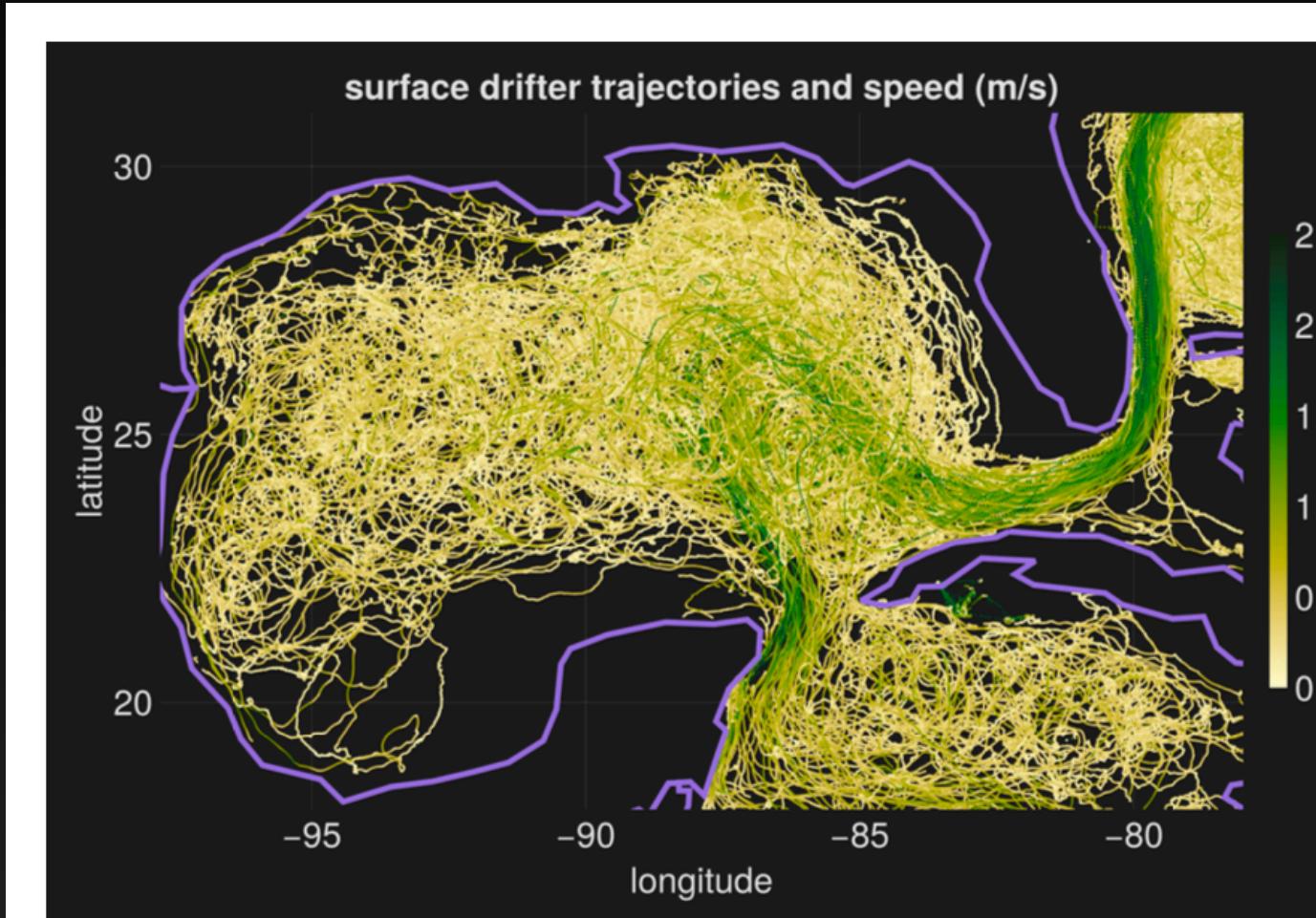


Fig. 6: Drifter trajectories in the Gulf of Mexico region. Large velocities highlight the path of the Gulf Stream, being fed by the loop current.

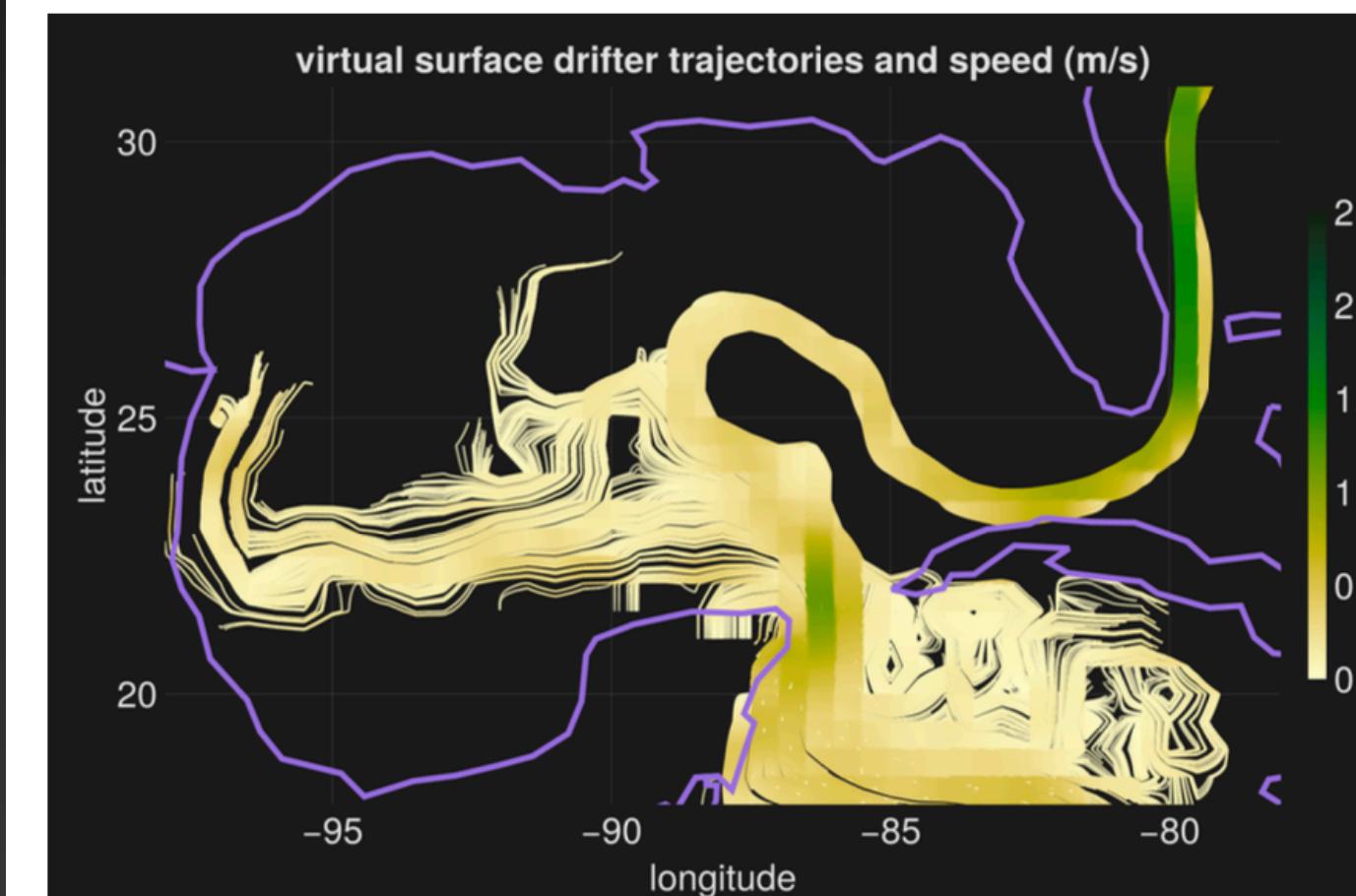


Fig. 7: Virtual drifter trajectories predicted using (1) just the climatological mean flow field estimated from drifters (Fig. 3, and the northward component) and (2) DRIFTERS.JL to calculate trajectories.

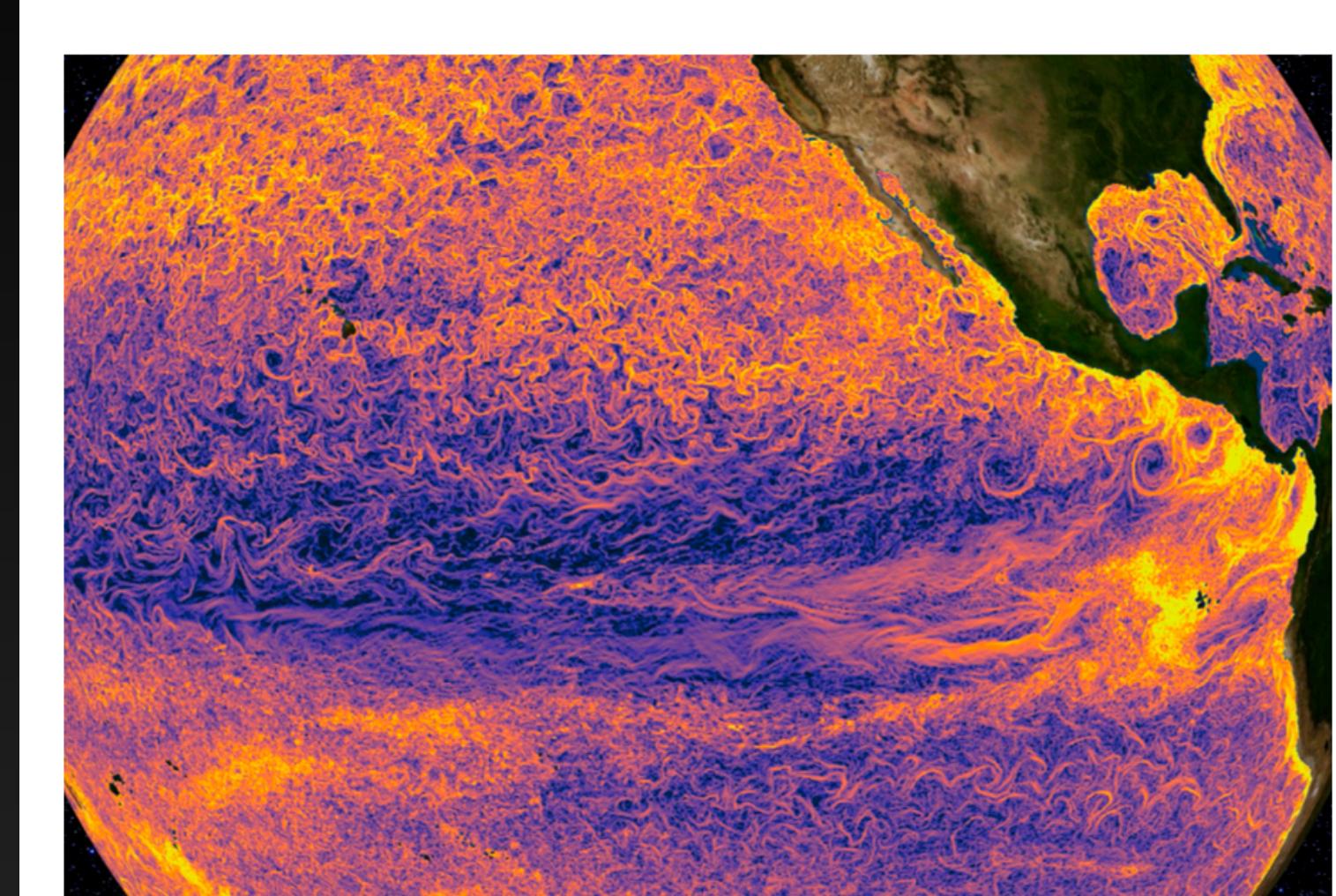


Fig. 8: Temperature fronts in a global km-scale MITgcm simulation. Plotted is the logarithm of the spatial gradient of a temperature snapshot.

