Influence of the Deep NINJA float data on a deep ocean state estimation

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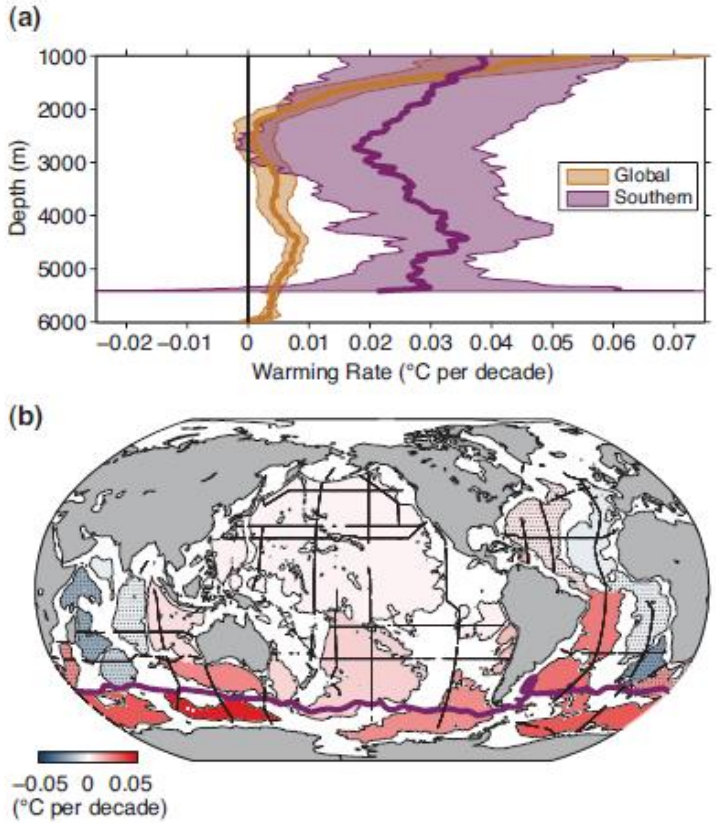
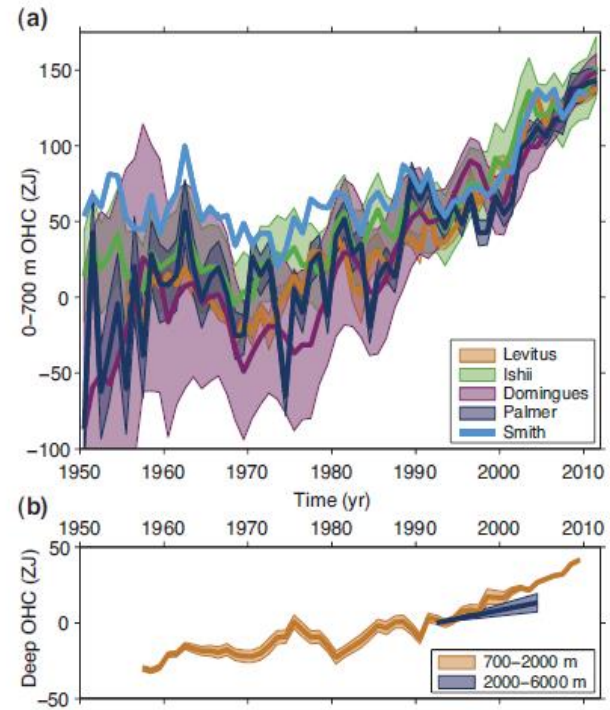
Climate changes in deep ocean

Areal mean warming rate



Mean warming rate below 4,000 m

Observation-based estimates of annual global mean upper OHC



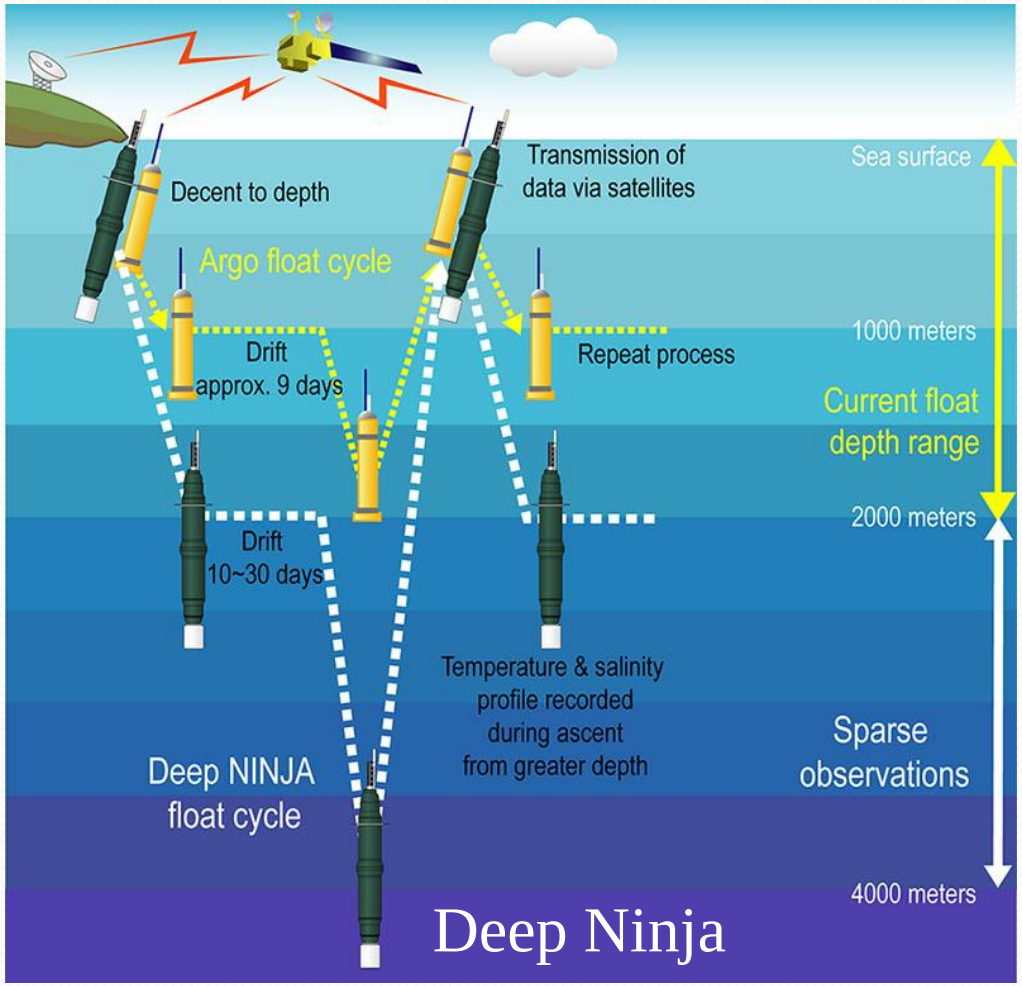
The estimates of annual global mean mid-depth/deep OHC (5y-rm)

Purkey and Johnson (2010)

Bottom-water warming

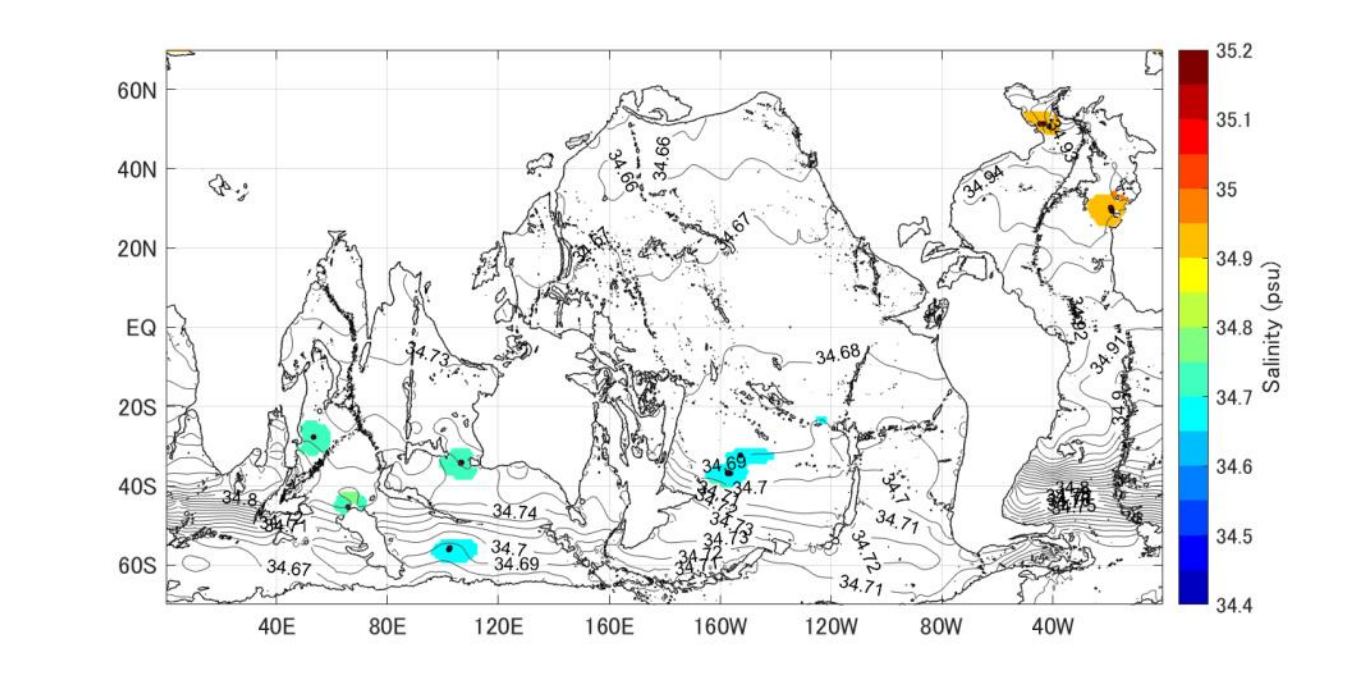
http://www.ipcc.ch/(IPCC 5th assessment report)

Continuous deep ocean monitoring is required



Along with GO-SHIP, deployment of deep floats is promising to explore the deep ocean climate change.

At present, a small number of deep floats have been deployed in the world.



Here we show an approach to utilize available float data to improve a deep ocean state estimation. The impact of the deep float is examined by a twin experiment on the basis of 4D-VAR adjoint ocean data synthesis system.

Deep NINJA: A deep float measurable in the deeper ocean upper 4,000m

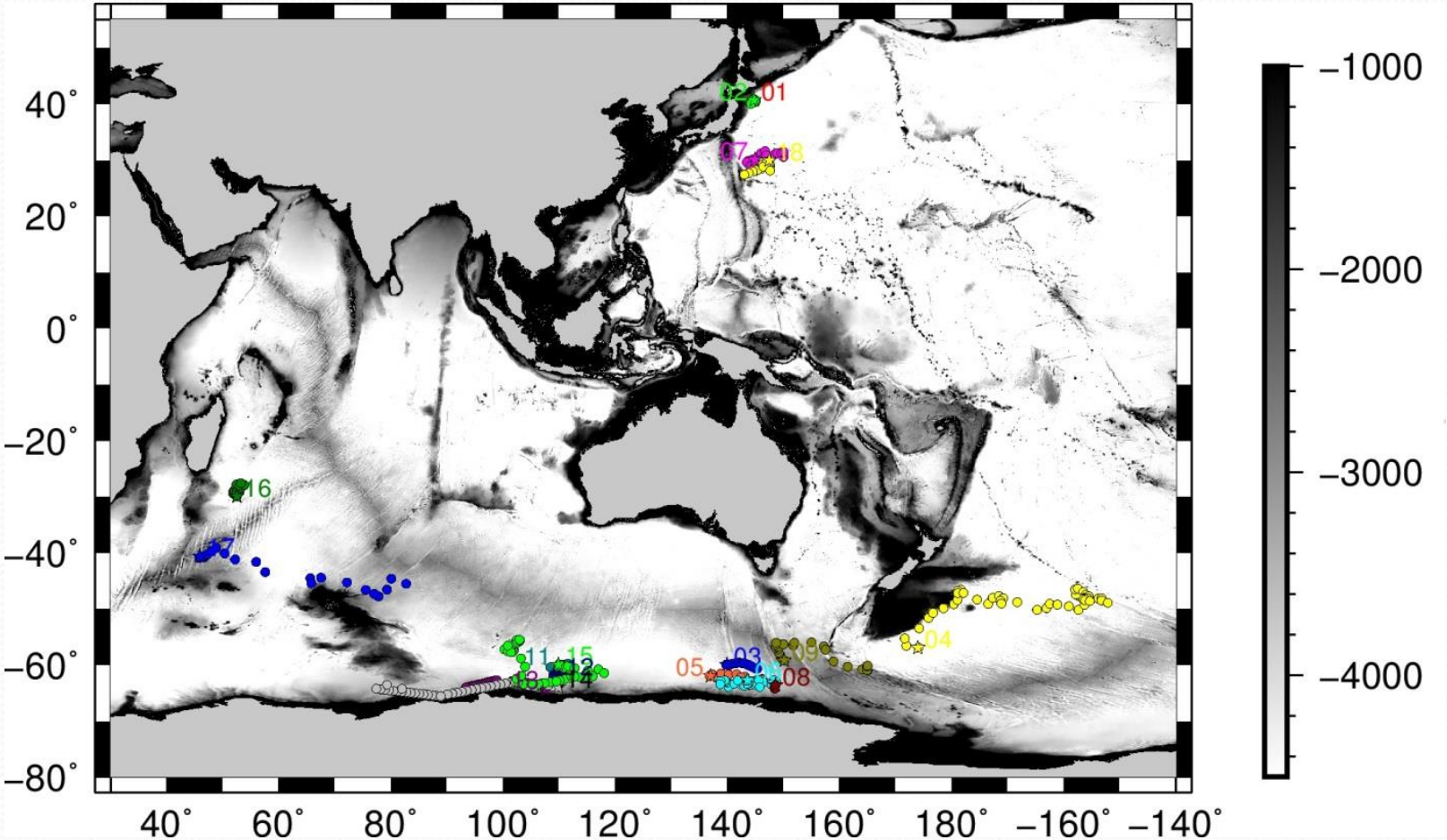
Specification of Deep NINJA

- Max. profile depth: 4000 dbar
  - Available from the tropics to the high-latitudes with seasonal ice
  - About 90% of the ocean's volume is measurable
- Pressure hull: Aluminum alloy
- Sensor: SBE 41CP
  - Enough capacity for additional sensors
- Communication: Iridium SBD, two-way
- Position fixing: GPS
- Est. lifetime: (more than) 1 year (by Lithium battery)
- Functions: Avoidance of surface sea ice
  Avoidance of groundings

We have deployed 21 Ninjas until July 2017.

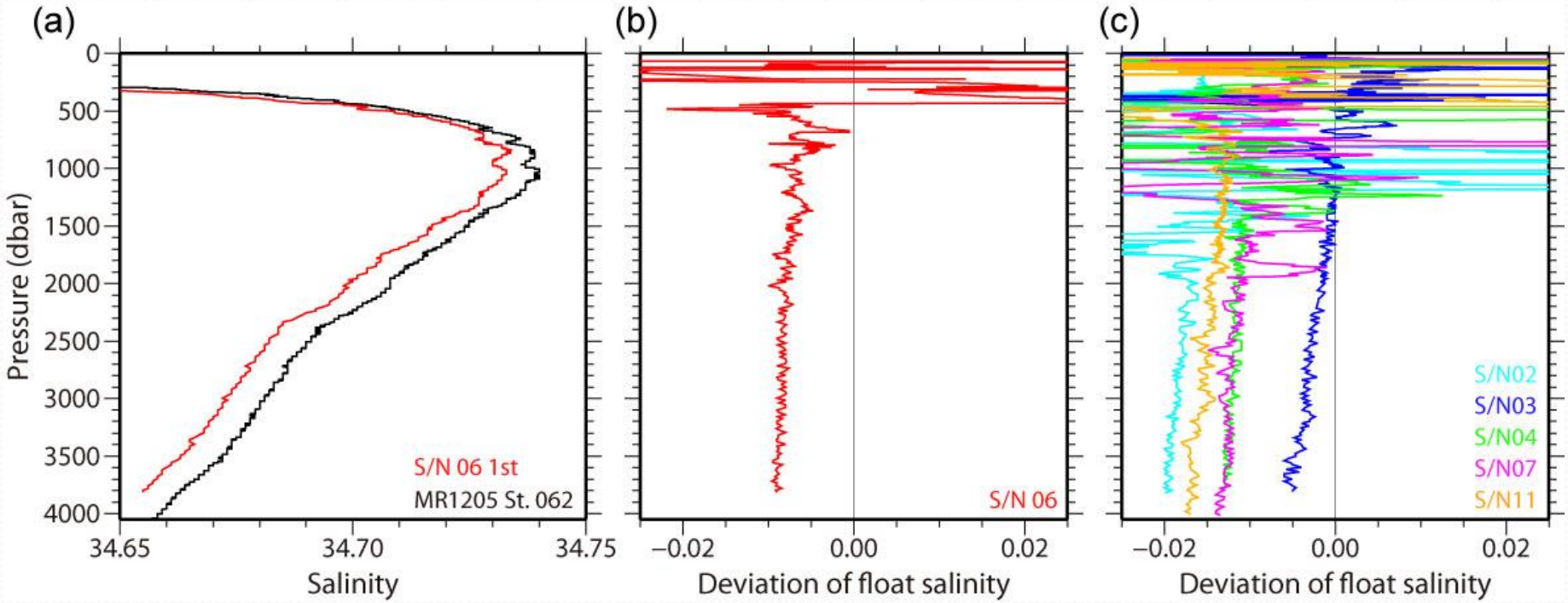
courtesy of Dr. T. Kobayashi

Trajectories of the deployed DeepNINJAs



Southern Ocean is our main target.

Problem in data synthesis



Float salinity measurements were deviated from shipboard reference.
The salinity bias, besides an offset component for some floats, had a pressure dependence component which makes the deeper measurements fresher.
The fresher-ward pressure dependency was found at the salinity of all floats, and its rate was around -0.5 to -2.5 x 10^{-6} $dbar^{-1}$: the well-calibrated CTD sensor on a deep float yields fresher salinity than the truth at 4000 dbar by 0.002 to 0.01.

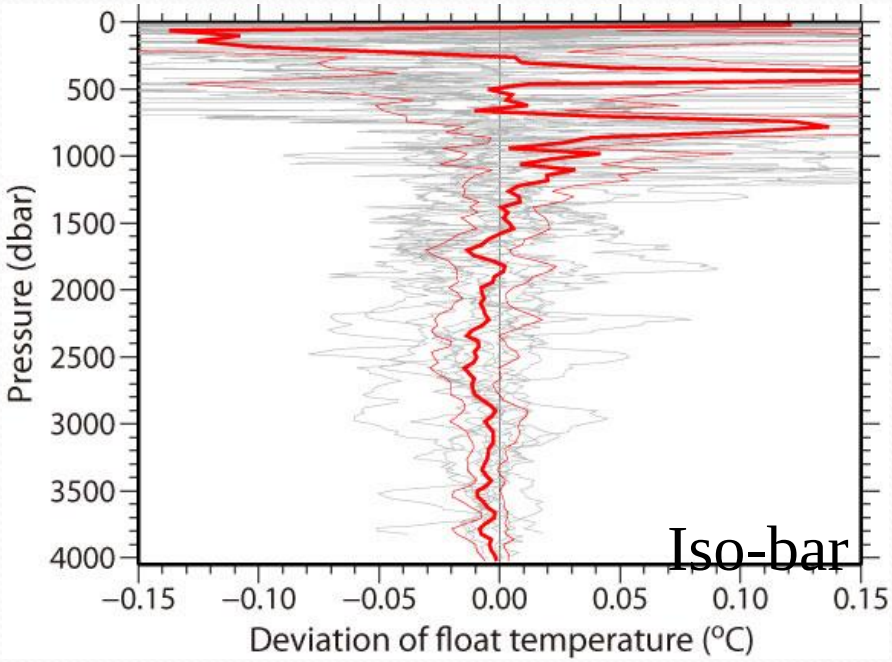
Kobayashi et al. (in preparation)

Temperature and Pressure are not "biased"

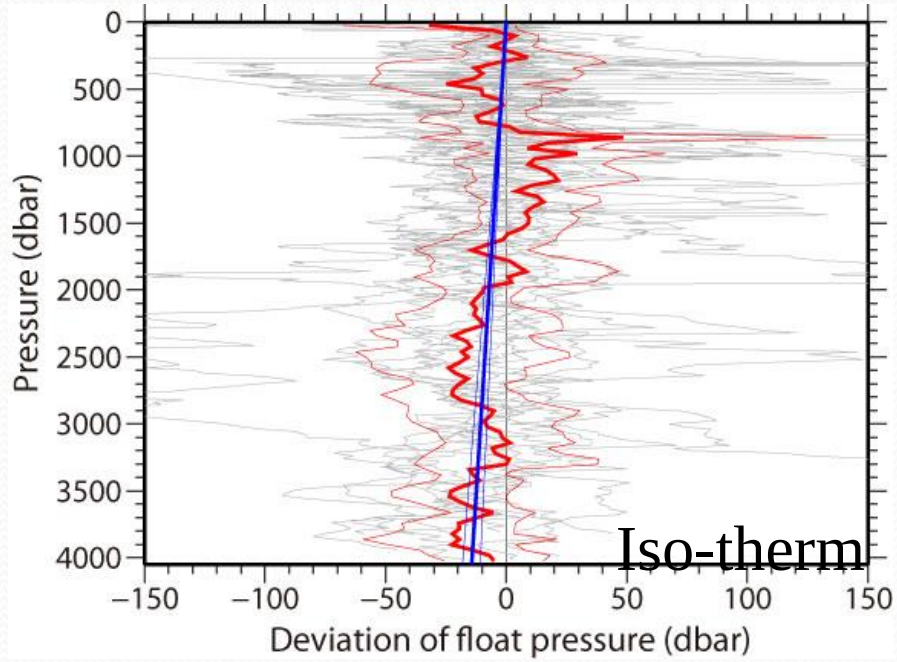
Average of 11 comparisons (gray) to remove heaving effects

Thick/thin red: Average and upper/lower limit of 95% confidence interval

in-situ temperature



Pressure



Float temperature and pressure were deviated negatively from shipboard reference in average (N=11), especially in the depth below 2000 dbar. However, it was not concluded statistically that they were "biased" (95% confidence level).

Kobayashi et al. (in preparation)

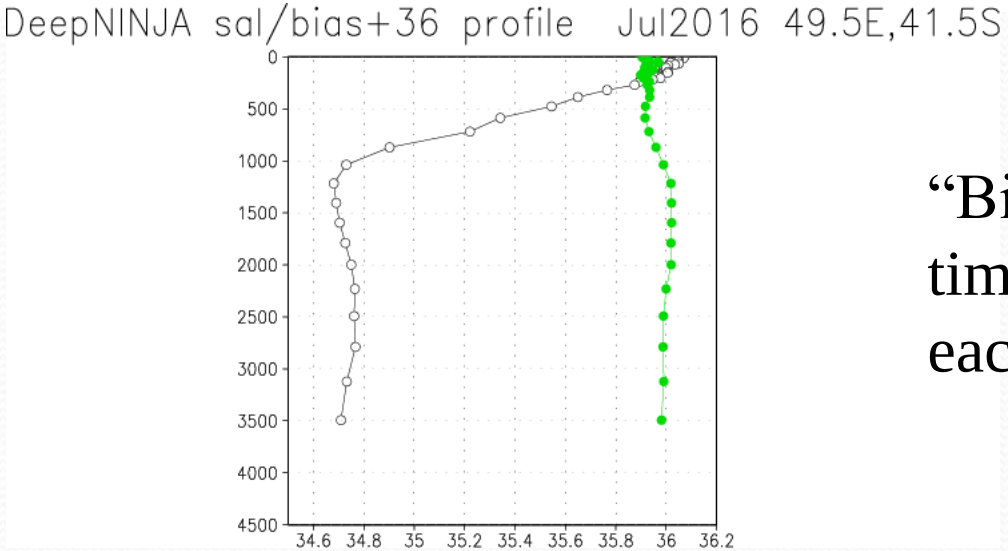
Pre-process for bias correction

Mean value of the difference between float profiles and 4-d EN4 data is assumed to be "bias" of the float.

- Estimated bias : $b(n,k)$, float observation : y, EN4 climatology : $\overline{y(i,j,k,m)}$

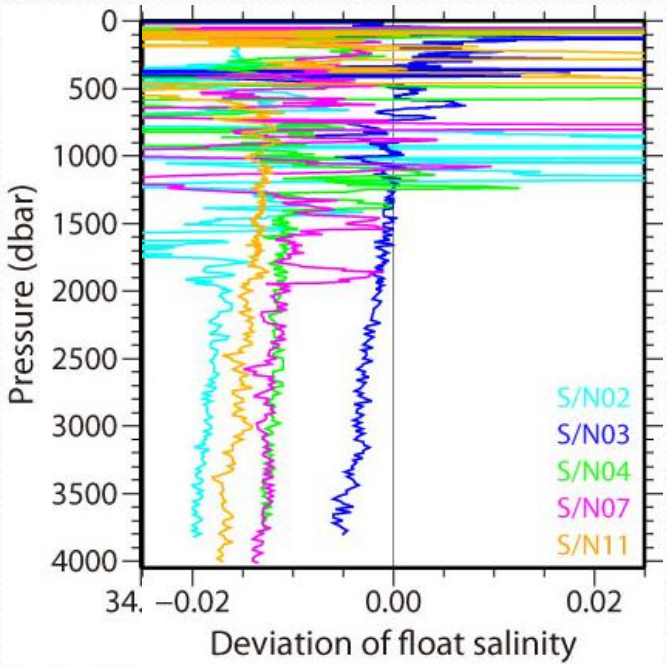
$$b(n,k) = \overline{y - \overline{y(i,j,k,m)}}$$

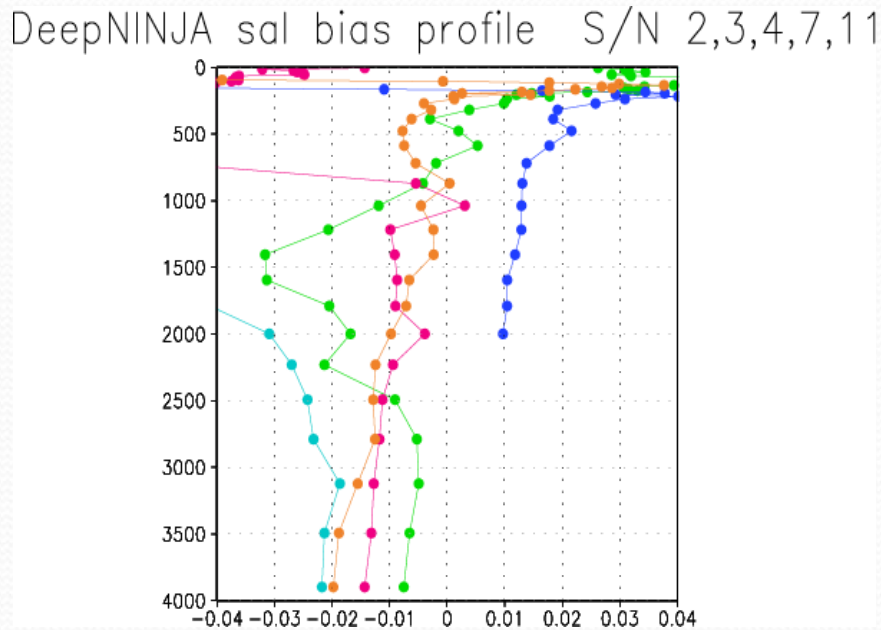
- n: Float ID , (i,j,k): 3-d position , (m,y): month,year

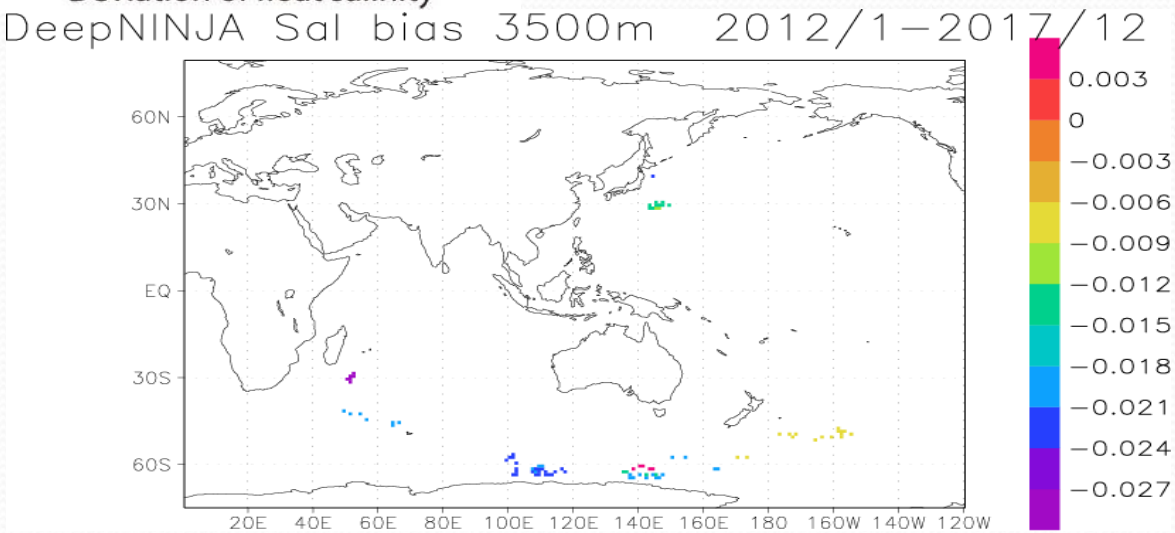


"Bias" is defined as a 1-d time-independent profile for each float.

Estimated salinity biases







Estimated STate of Ocean for Climate research (ESTOC)

OGCM:

GFDL MOM3, quasi-global 75°S-80°N (Osafune et al., 2015, Doi et al., 2015)
horizontal res: 1°x1°, vertical res:45 levels

Spinup：

1. 3000-year with a climatological forcing (accelerated method)
2. 120-year as climatological seasonal march.
3. 10-year with interannual forcings from NCEP/DOE.

Biogeochemical model:

NPDZC model **(Off Line)**

Data synthesis for physical parameters：

method: strong constraint 4D-VAR adjoint.
adjoint coding: by TAMC with some modifications.
assimilation window: 17 years (2000-2017)
control variables: initial T, S, 10-daily surface fluxes
first guess: executed form the last of Spinup 3
assimilated elements: OISST, T, S （Ensembles ver.4）, AVISO SSH anomaly, GMSL.

Data synthesis for biogeochemical parameters:

method: 4D-VAR without adjoint (Green's function)
control variables: model parameters
assimilated elements: Nitrate (WOA climatology), Phytoplankton (SeaWiFS) Chl-a (WOA climatology as Detritas)

Anomaly assimilation in data synthesis

Since mean states of models have inevitable biases such as those related to parameterizations of subgrid processes, an attempt to eliminate the biases forcibly can cause an initial shock and thus prevent the model reproducing the temporal variations that we are interested in, including the bottom-water warming. In order to overcome these drawbacks, this system includes a unique method for anomaly assimilation. Suppose that we optimize the ocean state using two separate observational terms for the mean state and the temporal variation. If the mean state and the temporal variation are denoted by an overbar and prime, the observational term of the cost function is written as

$$J_o = \frac{1}{2}\sum_{i,j,k,t}\left[\left(\frac{\bar{z}_{i,j,k} - \bar{y}_{i,j,k}}{a_k}\right)^2 + \left(\frac{z'_{i,j,k,t} - y'_{i,j,k,t}}{b_k}\right)^2\right]\Delta V_{i,j,k}, \tag{2}$$

where i, j, and k denote grid indices (two horizontal and one vertical), t denotes a time index, and $\Delta V_{i,j,k}$ is the volume for each grid cell. This takes the form

$$J_o = \frac{1}{2}\sum_{i,j,k,t}\left(\frac{z_{i,j,k,t} - y^*_{i,j,k,t}}{b_k}\right)^2 \Delta V_{i,j,k}, \tag{3}$$

using bias-corrected observational data, $y^*_{i,j,k,t} \equiv y_{i,j,k,t} - (1 - b_k a_k^{-1})(\bar{y}_{i,j,k} - \bar{z}_{i,j,k}) = y_{i,j,k,t} - \Delta y_{i,j,k}$. We use this form of cost function, in which we can evaluate the two statistical parameters b_k and $\Delta y_{i,j,k}$ from the model field $\mathbf{z}$ in the spin-up run as follows,

$$\Delta y_{i,j,k} = \left(1 - \frac{b_k}{a_k}\right)\left(\bar{y}_{i,j,k} - \bar{z}_{i,j,k}\right), \tag{4}$$

$$a_k{}^2 = \sum_{i,j}\left[\left(\bar{z}_{i,j,k} - \bar{y}_{i,j,k}\right)^2 \Delta V_{i,j,k}\right] / \sum_{i,j}\Delta V_{i,j,k}, \tag{5}$$

and

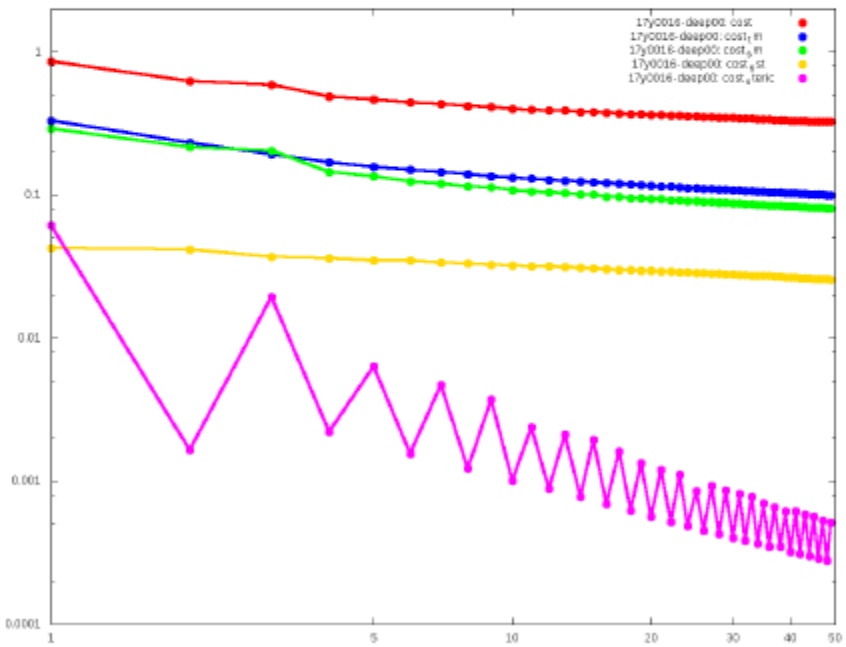
$$b_k{}^2 = \sum_{i,j,t}\left[\left(z'_{i,j,k,t} - y'_{i,j,k,t}\right)^2 \Delta V_{i,j,k}\right] / \sum_{i,j,t}\Delta V_{i,j,k}. \tag{6}$$

Osafune et al., (2015)

Tentative results of identical twin experiment

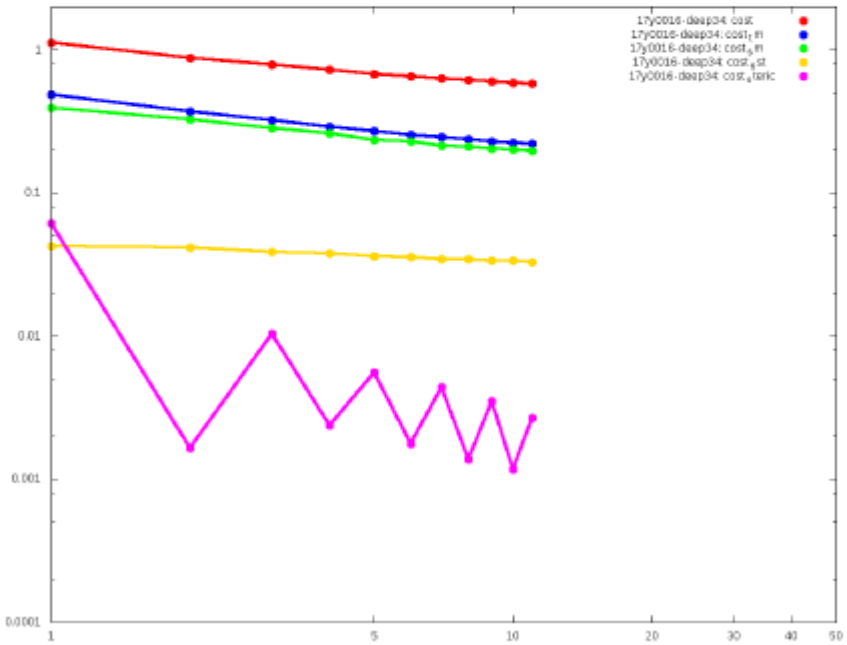
No DeepNINJA

test-deep00:



DeepNINJA synthesis

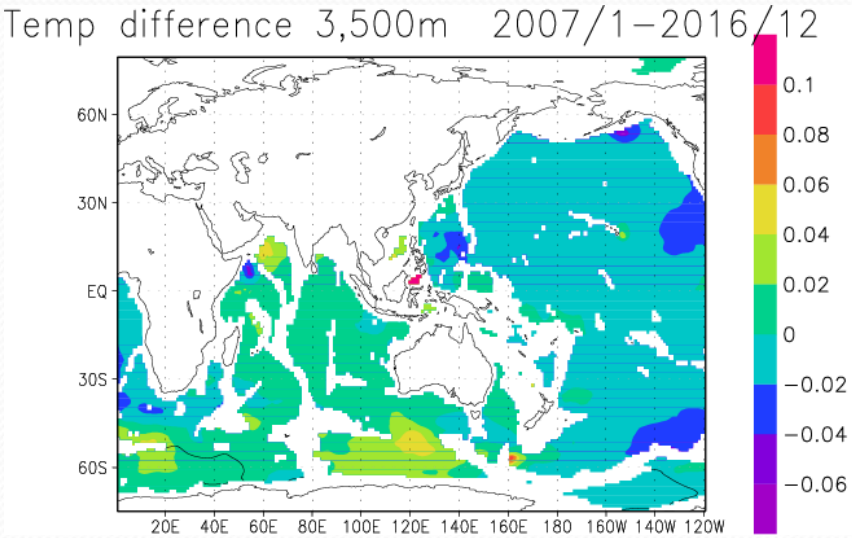
test-deep34:

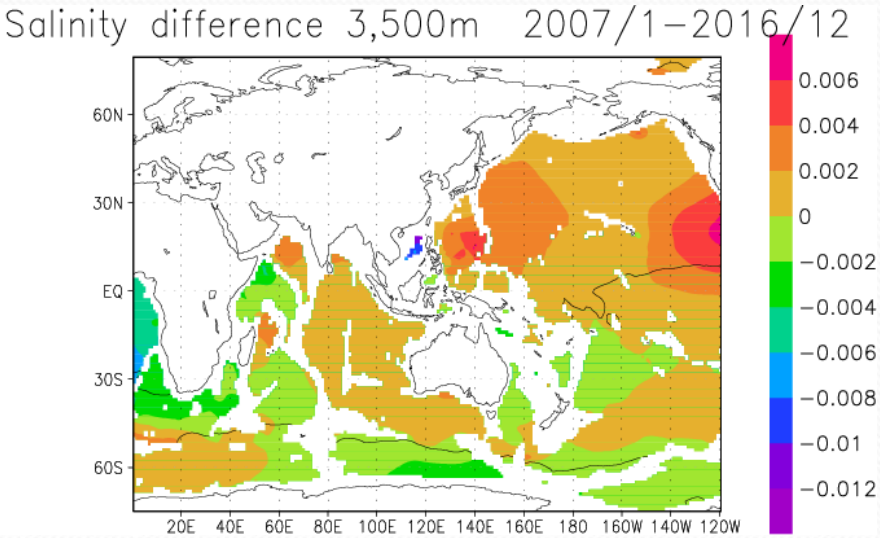


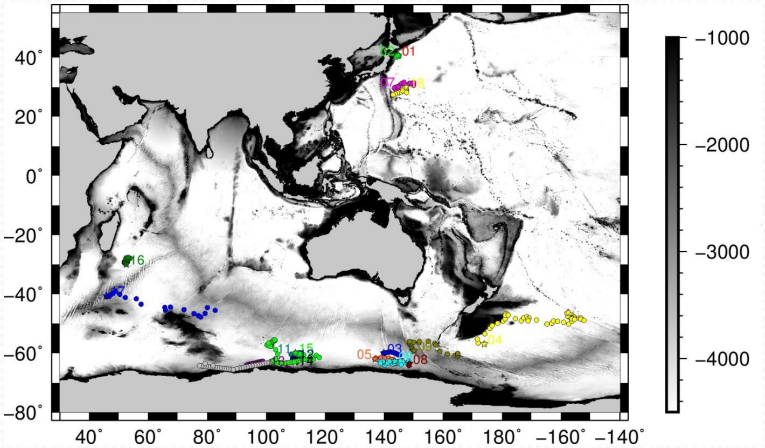
Time changes of costs

Tentative Results

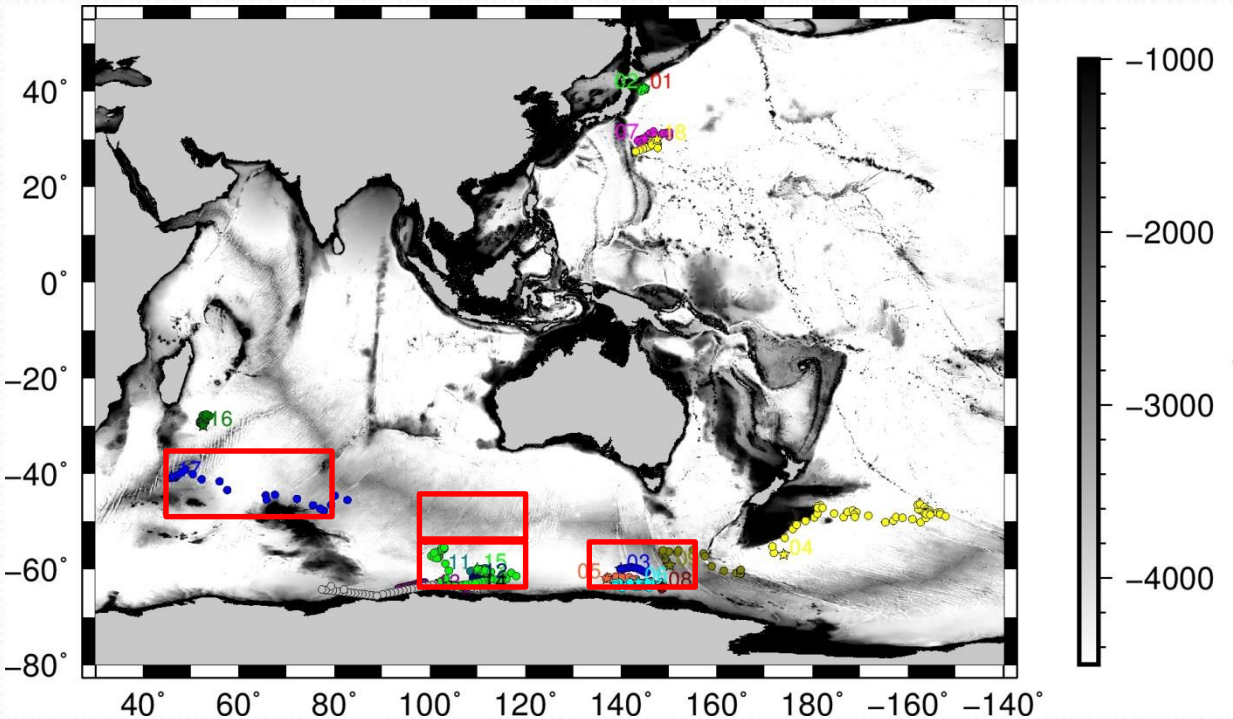
Including differences of progress of optimization ……







Influence of DeepNINJA (3,500-m salinity)



	Natural std	difference mean
S Sigma	0.00042	-0.00019
	0.00039	-0.00022
	0.00017	-0.0019
	0.00057	-0.0019

Summary

- *We try correcting DeepNINJA bias by using EN4 climatology as a pre-process before data assimilation. Estimated bias looks by and large acceptable. Along this line, data from deep floats deployed alone without deep cast (high-quality CTD observation) could be utilized for deep ocean state estimate*
- *Identical twin experiment may show some implications about float density. => We will continue careful investigation improving the scheme.*
- *Many future works remain….*

Future works

- Is special processing for other deep floats needed?
- Is there time-dependent bias?
- Is EN4 climatology valid as reference?
- How about assimilation for other variables (DO, ocean turbulence)?
- Data assimilation in the deep ocean should be carefully improved.
- Development of robust/stable sensor should be needed.
- More deployment with deep cast helps improve the pre-processing.
- Retrieve of deployed float helps get more bias information on each float.

Fin

Cost function

$$J = [x - x_0]^T B_1^{-1} [x - x_0] + [H(x) - y^*]^T R^{-1} [H(x) - y^*]$$
$$+ [\nabla \cdot (x - x_0)]^T B_2^{-1} [\nabla \cdot (x - x_0)],$$

$$here,\ y^* : observations\ (\text{inc. model bias}),\ x : \text{control variable},$$

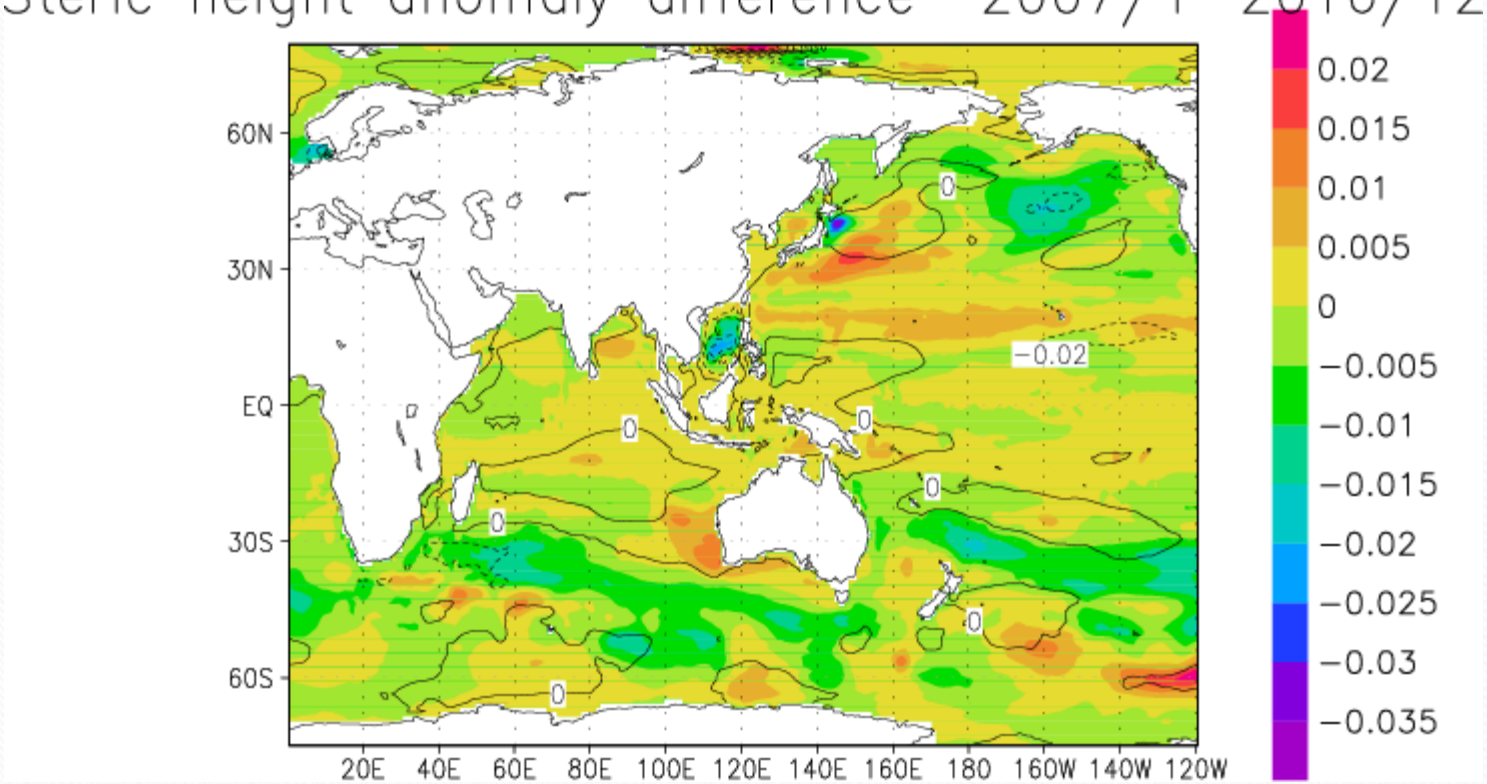
$$H : observation\ matrix,$$

$$R : observation\ error\ (\text{inc. representativeness error}).$$

Assimilated elements: Temperature, Salinity (ENSEBLES v.3+JAMSTEC observations),
SST (reconstructed Reynolds+OISST ver.2),
SSH anomaly data (AVISO).

First guess is generated from
momentum, net heat, shortwave, latent heat flux of NCEP/DOE .

Steric height anomaly difference 2007/1–2016/12



Model improvement

Based on ESTOC

(Estimated STate of global Ocean for Climate research)

more details can be seen in Osafune et al. (2015, GRL)

- OGCM : GFDL/MOM3 (75°S-80°N, 1°×1°×45 levels)
- assimilation window: 1957-2014 (58 years)
- assimilation method: 4D-VAR (strong constraint)
  - dynamically consistent without artificial source/sink
- control variables:

  initial conditions, atmospheric forcings,

  parameters for tidal mixing (Γ, q_{sub}, q_{sup}, h, a, b)
- assimilating data: subsurface TS (EN4), OISST, ε

- Two tidally induced vertical mixing schemes are implemented in addition to the surface mixing scheme of Noh (2004), and double diffusion
  - $\kappa_z = \kappa_{noh} + \kappa_{dd} + \kappa_{NEAR} + \kappa_{FAR}$
- ε is diagnosed from model κ and N^2 with Γ=0.2, and add the new cost function $J_\varepsilon = \Sigma\,(\log(\varepsilon)-\log(\varepsilon_{obs}))^2\,w$

Tidally Induced vertical mixing

Near Field Mixing: St. Laurent et al. (2002)

$$\kappa_{NEAR} = \sum_{i=1}^{4} \frac{\Gamma q E_g^i(x,y) H(z)}{\rho N^2} \qquad q = \begin{cases} q_{sub} = 1 & \text{for subinnertial} \\ q_{sup} = 0.3 & \text{for superinnertial} \end{cases}$$

$$H(z) = \frac{e^{-(z_b - z)/h}}{h(1 - e^{-z_b/h})}$$

Far Field Mixing: Hibiya et al. (2006)

$$\kappa_{FAR} = (F(\theta,\phi) + b) * \frac{\phi}{20} \qquad \text{for } 0 \le \phi < 20$$

$$\kappa_{FAR} = F(\theta,\phi) + b \qquad \text{for } 20 \le \phi < 30$$

$$\kappa_{FAR} = F(\theta,\phi) * \frac{35-\phi}{5} + b \qquad \text{for } 30 \le \phi < 35$$

$$\kappa_{FAR} = b \qquad \text{for } 35 \le \phi$$

with

$$F(\theta,\phi) = a * \log_{10}(E_{internal}(\theta,\phi)/0.1) \qquad \text{for } E_{internal}(\theta,\phi) \ge 0.1\,Jm^{-3}$$

$$F(\theta,\phi) = 0 \qquad \text{for } E_{internal}(\theta,\phi) < 0.1\,Jm^{-3}$$