Ocean data assimilation and analysis

DA training course 2023

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With inputs from M Chrust, P Browne, M A Balmaseda, K Mogensen, E de Boisseson, R Buizza and many others

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Outline

- Ocean system and ocean observations
- NEMOVAR ocean data assimilation system
- Bias correction in ODA
- Assimilation of Sea-Level data
- Assimilation of SST data
- Assimilation of Sea-Ice data
- Ocean (re)analysis system and its applications

Why do we do Ocean DA?

- **Forecasting: initialization of coupled models**
  - NWP, monthly, seasonal, decadal
  - Seasonal forecasts need calibration
- **Towards coupled DA system (weakly -> quasi-strong -> strong …)**
  - **See Phil's presentation**
- **Climate application: reconstruct & monitor the ocean *(re-analysis)***
- ***Verification/evaluation/co-design of Global Ocean observing network (OSE/OSSE)***
- **Other applications**
  - Commercial applications (oil rigs, ship route …), safety and rescue, environmental (algii blooms, spills)

Ocean versus Atmosphere

Spatial/time scales The radius of deformation in the ocean is small (~30km) compared to the atmosphere (~3000km). Time scales varies from hours (mixing) to decades (overturning circulations).

Ocean is a data sparse system, in-situ observation is limited and mostly covers upper ocean only, satellite observation only covers ocean surface and is only available for a relatively short period.

The ocean is forced at the surface and land boundary, by the wind/waves, heating/cooling and fresh-water fluxes

Uncertainty in forcing fluxes contributes to uncertainty in model results.

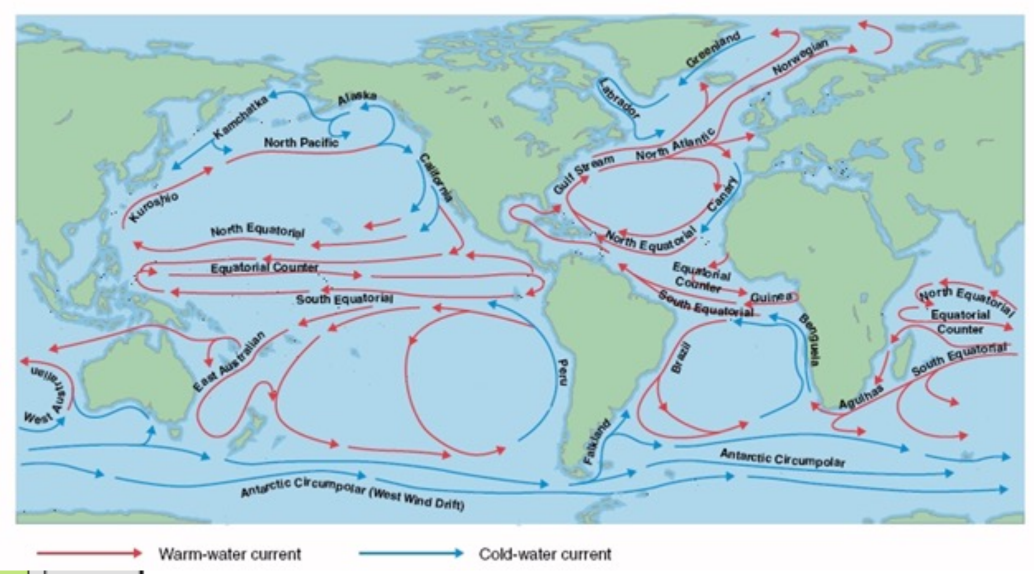
The ocean is strongly stratified in the vertical, especially near the surface. Although deep convection also occurs

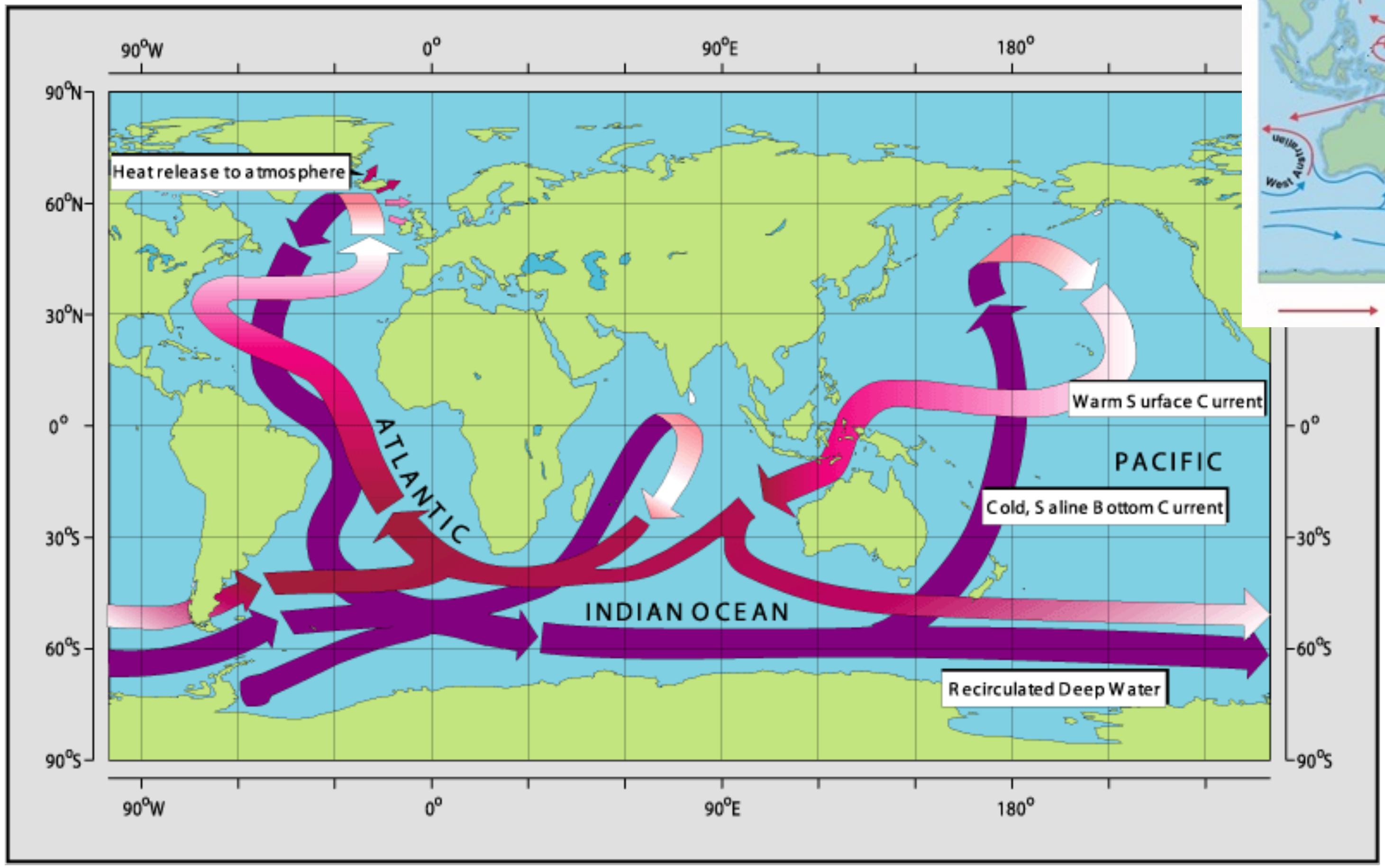
Density is determined by Temperature and Salinity

The ocean has continental boundaries; dealing with them is not trivial in data assimilation

Ocean time scales: from hours to centuries

Wind Driven: Gyres, Western Boundary Currents, Upwelling regions (coastal, equatorial), Ekman pumping and subduction →





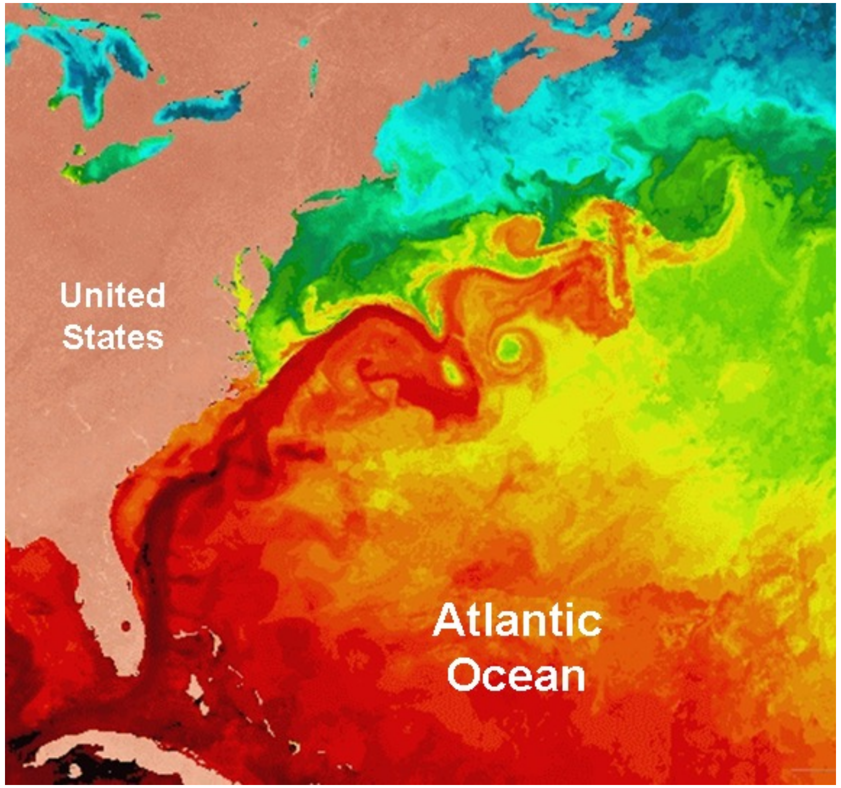
← **Density Driven:**

Thermohaline Circulation

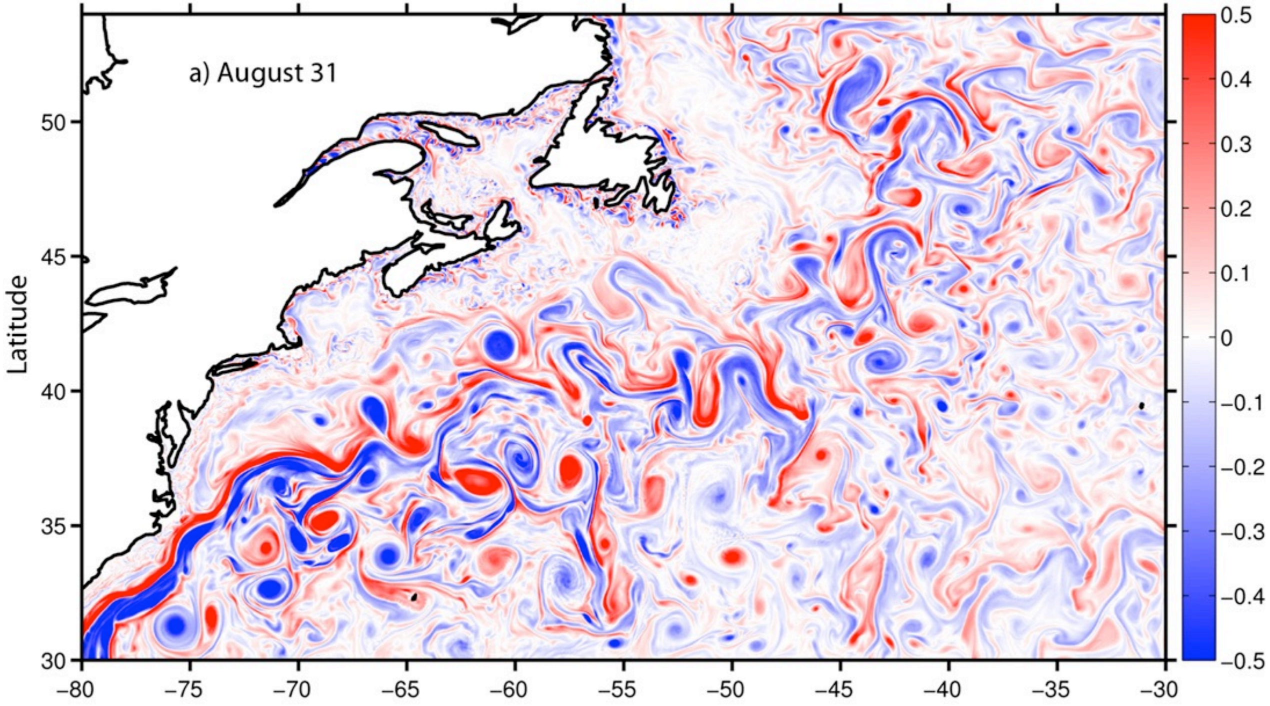
Ocean is a system with much longer memory but slow response compared to the Atmosphere

Ocean spatial scales

Satellite image of SST in the North Atlantic Ocean (from NOAA)



1/50 degree Ocean surface relative vorticity (CHASSIGNET and Xu, 2017)



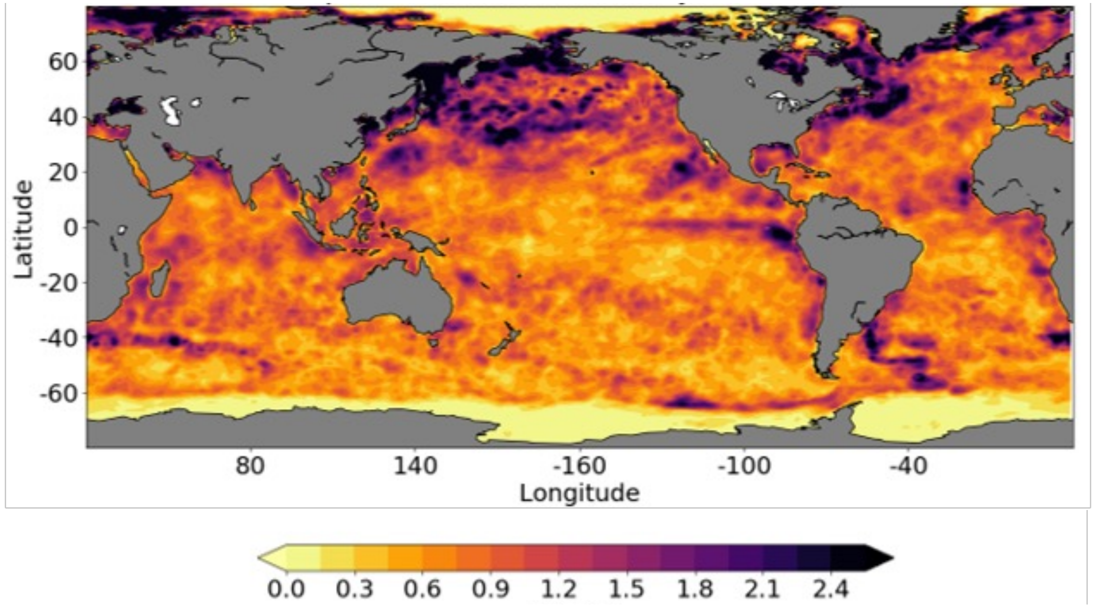
mesoscale and submesoscale eddies

Ocean variables with various spatial scales: from hundred meters to hundreds of km

Ocean is forced by external forcings

Impact of Atmospheric forcing

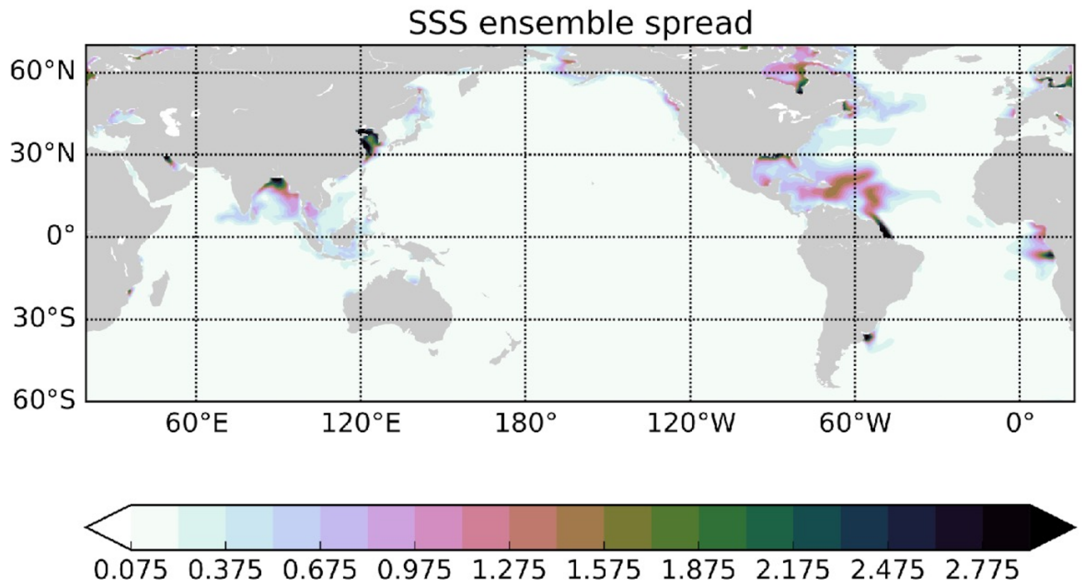
SST spread due to atmospheric forcing perturbation



de Boisséson et al., 2020

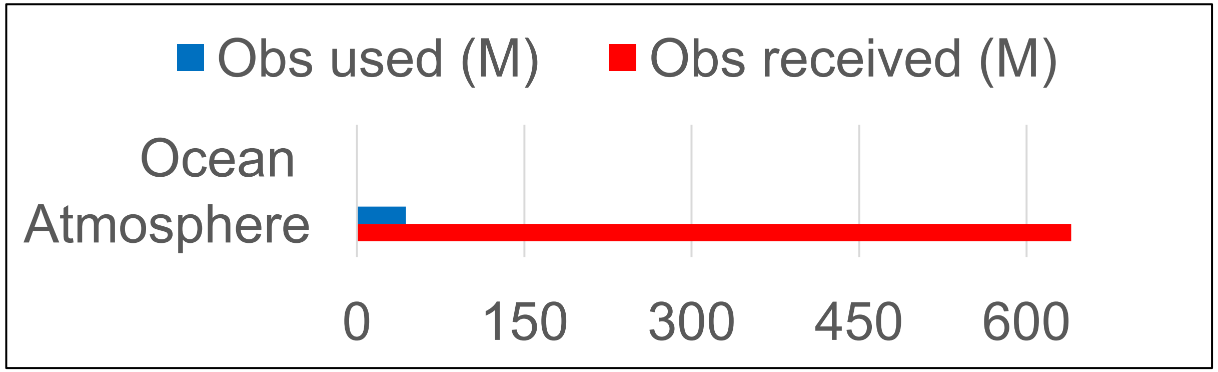
Impact of land freshwater input

SSS spread due to land freshwater input perturbation



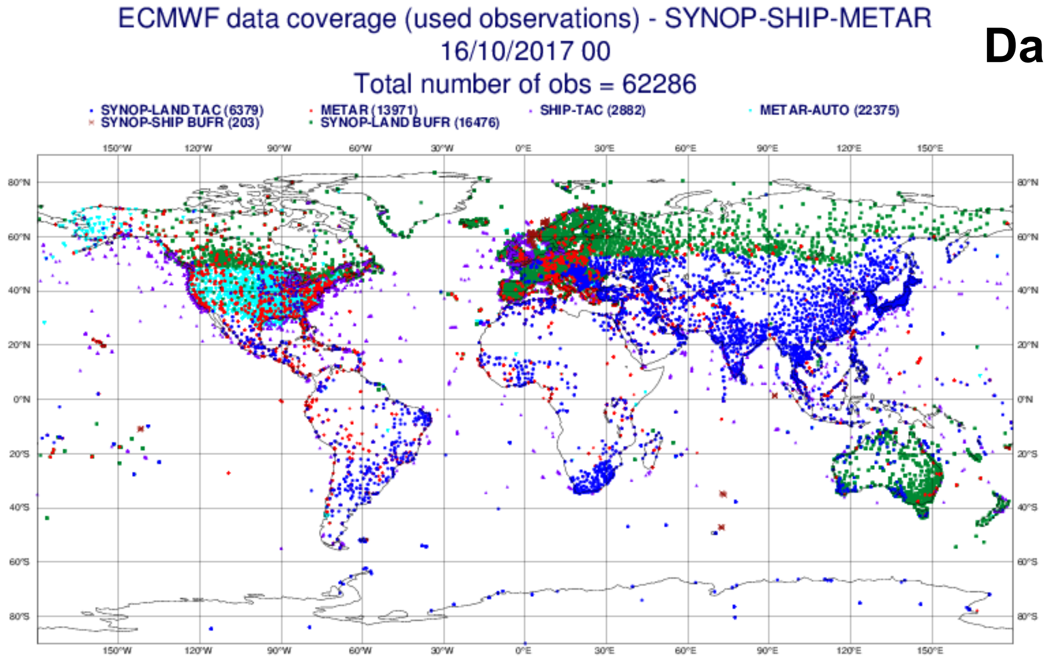
Zuo et al., 2020

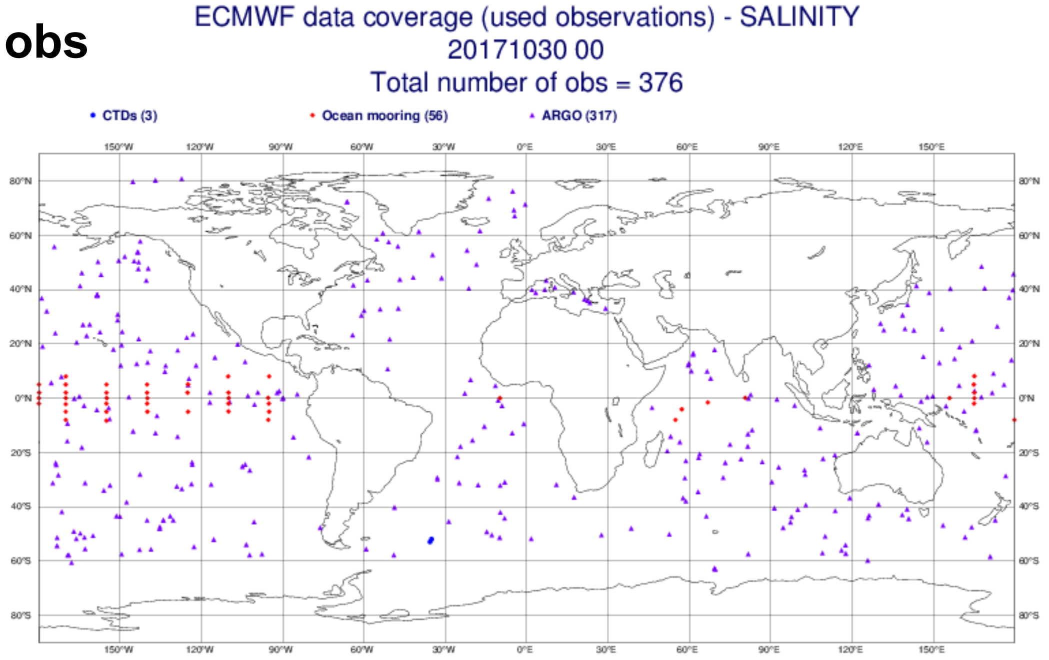
Ocean is a data sparse system



Ocean observation is about 1/1000 to 1/10000 smaller than Atmospheric observation

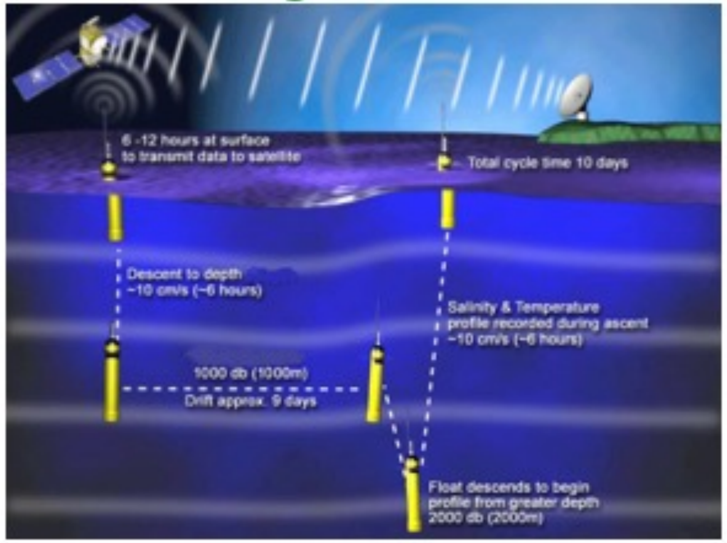
Daily obs





Ocean in-situ observations

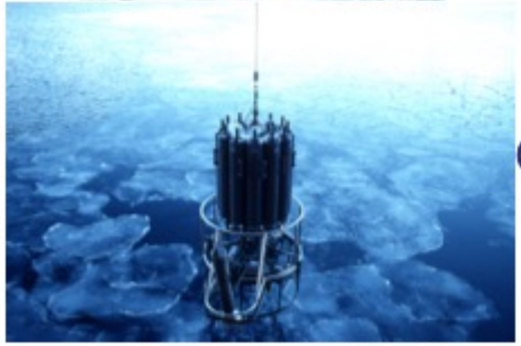
Argo floats



Argo operational cycle.
[Argo 2018]

Ship based observations

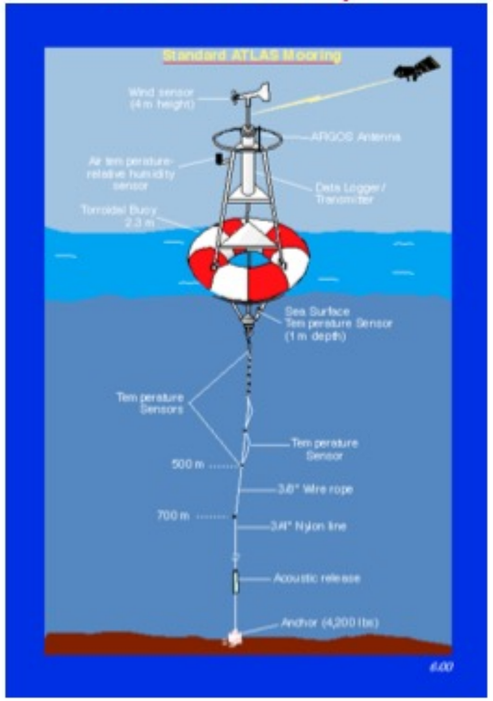
XBT



CDT

[CSIRO 2001]

Moored buoys



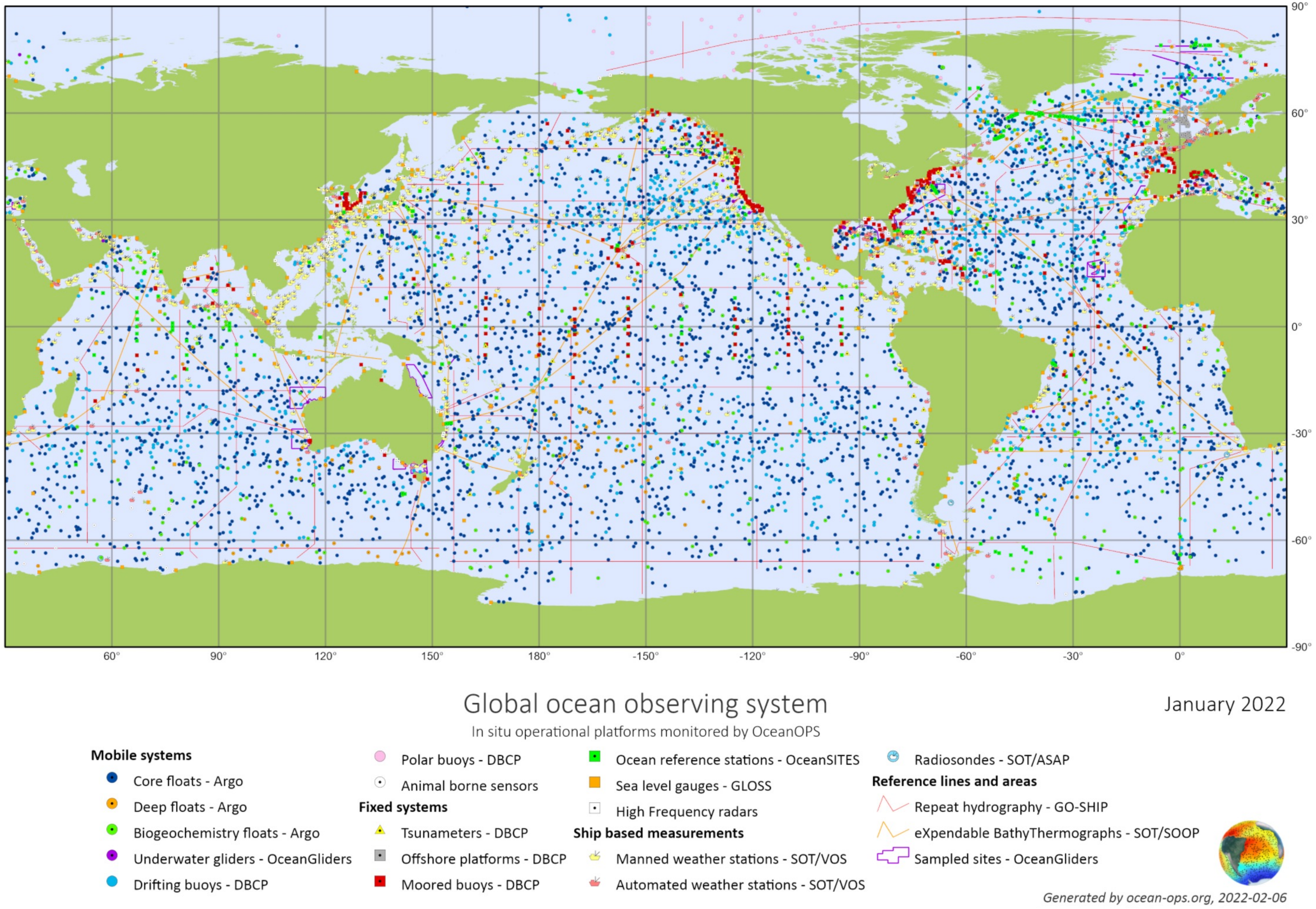
[PMEL 2018]

Mammals!

[MEOP et al. 2015]

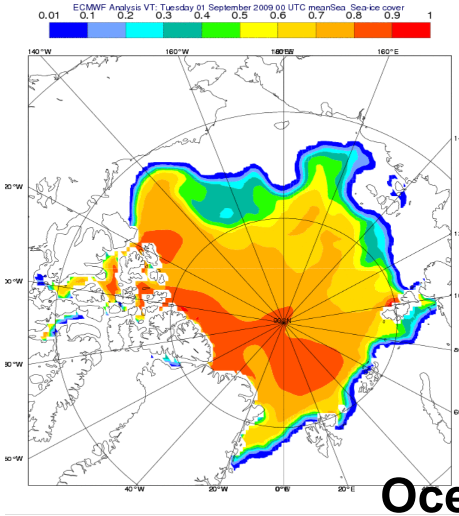
New observations types are emerging: gliders, Deep Argo, BioArgo, drifter, saildrone …

The Global Ocean Observing System (GOOS)

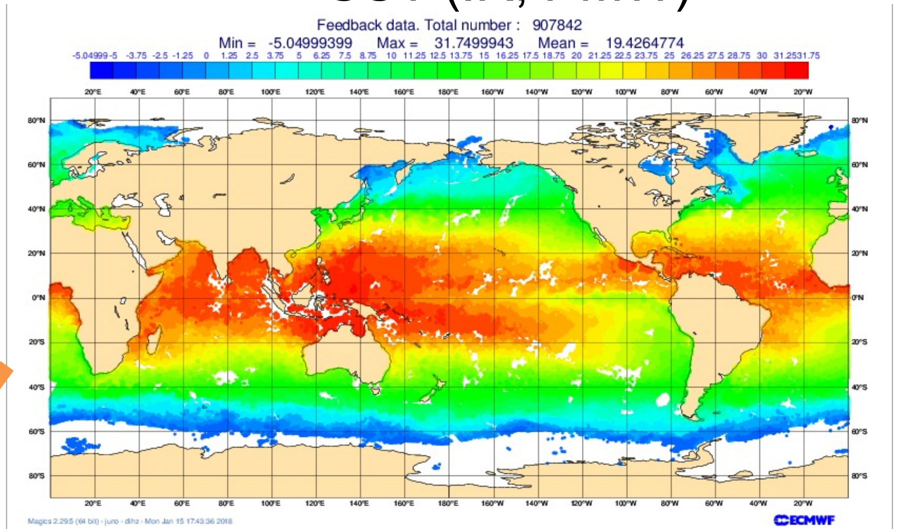


Satellite ocean surface observations

Sea-ice concentration

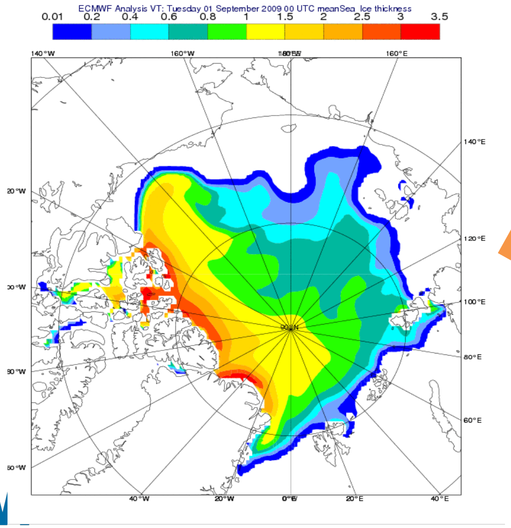


SST (IR, PMW)

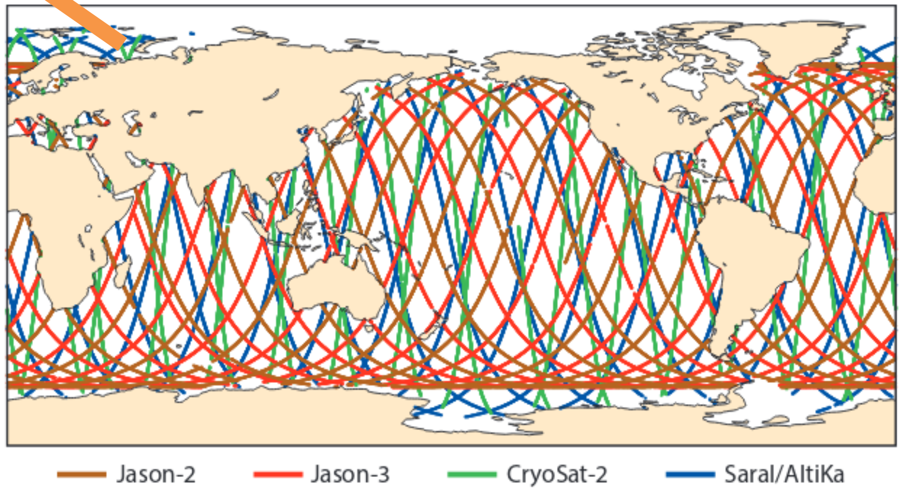


Ocean and sea-ice model

Sea-ice thickness



Sea-Level Anomaly (Altimeter)

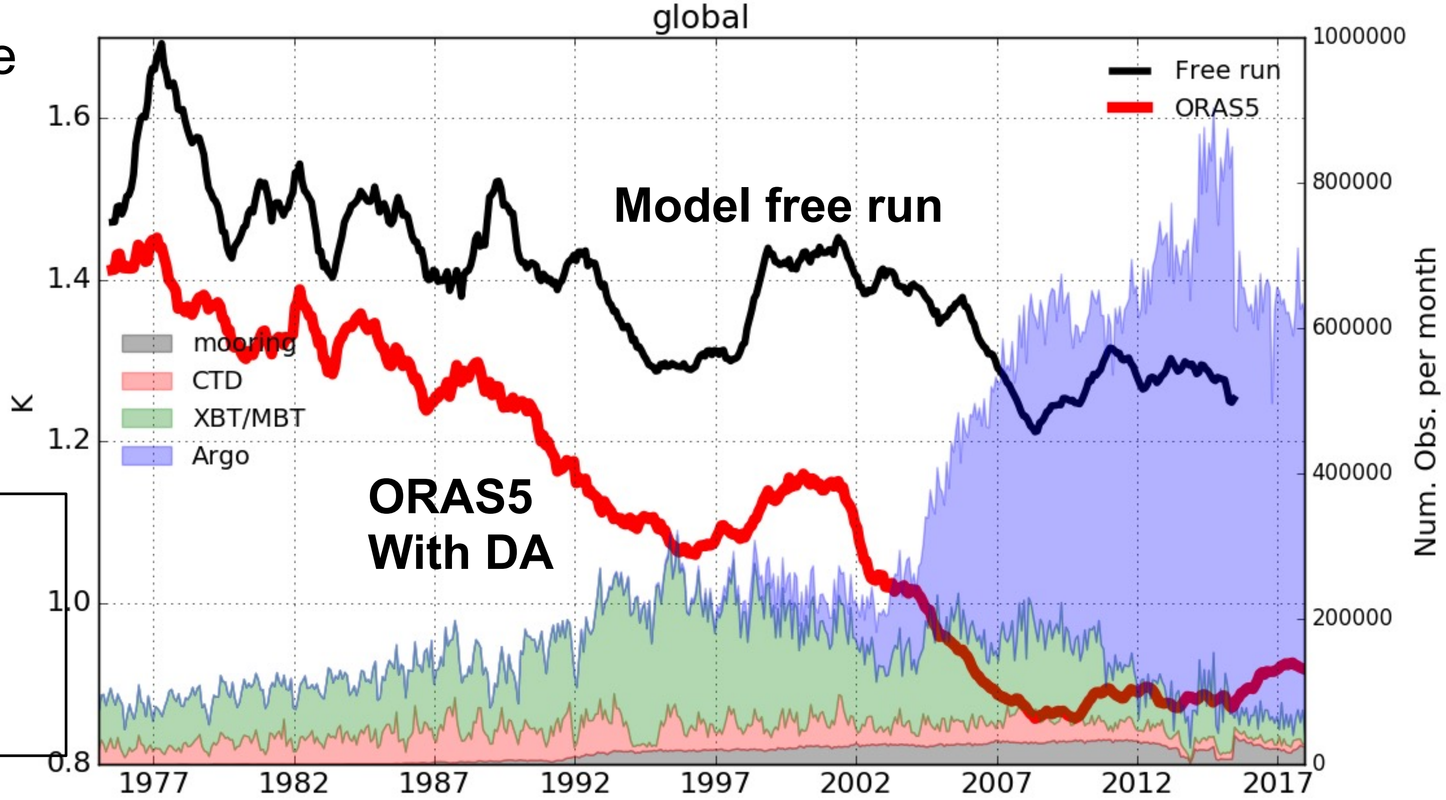


ECMWF

Observations impact on the ocean state estimation

Observations are essential for improving initialization

Temperature RMSE: 0-1000m



MRB: moored buoy
OSD: CTD sonde
XBT: Expendable bathythermograph
PFL: Argo float

Assimilation of ocean in-situ observations helps to constrain the 3D ocean, therefore providing better estimation of the ocean initial condition for the coupled forecasting system

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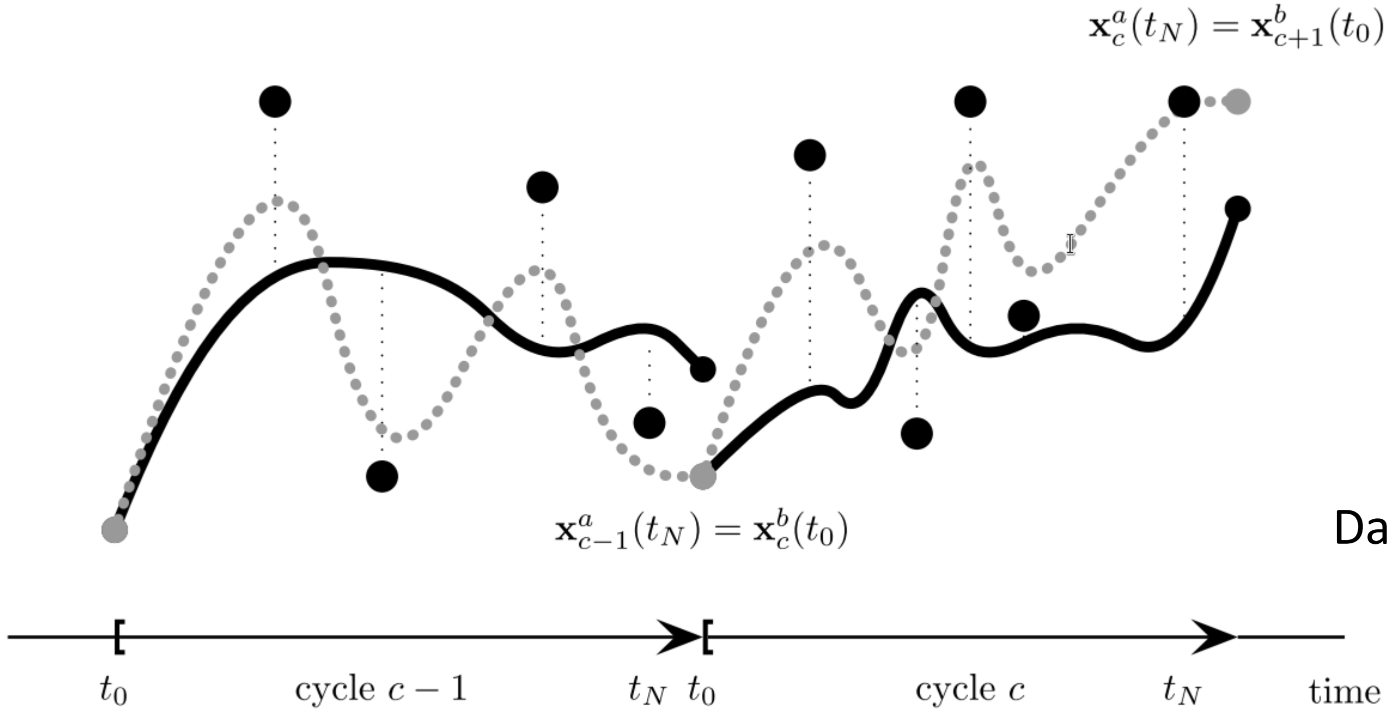
Ocean DA at ECMWF: NEMOVAR

- **The "NEMOVAR" assimilation system used in ECMWF.**
  - En Variational DA system as a collaborative project among **CERFACS**, **ECMWF**, **INRIA** and the **Met Office** for assimilation into the **NEMO** ocean model.
    - Solves a linearized version of the full non-linear cost function.
    - Incremental **3D-Var FGAT** running operational, 4D-Var in research model
  - Background correlation model based **diffusion operators**
  - Background errors are correlated between different variables through **balance operator**
- To avoid initialization shock increments are typically applied via Incremental Analysis Update (**IAU**) which applies the increments as a forcing term over a period of time.

NEMOVAR: 3D-Var FGAT



Daget et al 2009

Figure 1: Schematic illustration of the procedure used to cycle 3D-Var. On each cycle c, the model is integrated from t_0 to t_N starting from a background initial condition $\mathbf{x}_c^b(t_0)$ (grey dots) to produce the background trajectory $\mathbf{x}_c^b(t_i)$ (black solid curve). The difference between the observations $\mathbf{y}_{c,i}^o$ (black dots) and their background counterpart $(\mathbf{H}_{c,i}\mathbf{x}_c^b(t_i))$ is computed (represented by the vertical thin dotted lines) for use in the 3D-Var FGAT minimization. After minimization, the model integration is repeated from the same initial condition $(\mathbf{x}_c^b(t_0))$ but with the analysis increment applied using IAU. This produces the analysis trajectory $\mathbf{x}_c^a(t_i)$ (grey dashed curve). The updated model state $\mathbf{x}_c^a(t_N)$ at the end of cycle c is then used as the background initial condition for the next cycle $c+1$ (grey dots).

NEMOVAR: Linearized Cost function

Weaver et al 2003,2005
Daget et al 2009
Mogensen et al 2012
Balmaseda et al 2013

$$J[\delta \mathbf{w}] = \frac{1}{2}\delta \mathbf{w}^{\mathrm{T}}\mathbf{B}^{-1}\delta \mathbf{w} + \frac{1}{2}(\mathbf{G}\delta \mathbf{w} - \mathbf{d})^{\mathrm{T}}\mathbf{R}^{-1}(\mathbf{G}\delta \mathbf{w} - \mathbf{d})$$

$\mathbf{y}^{\mathrm{o}} = \{(\mathbf{y}_0^{\mathrm{o}})^{\mathrm{T}} \cdots (\mathbf{y}_i^{\mathrm{o}})^{\mathrm{T}} \cdots (\mathbf{y}_N^{\mathrm{o}})^{\mathrm{T}}\}^{\mathrm{T}}$ $\longrightarrow$ 4D observation array

$\delta \mathbf{w} = \mathbf{w} - \mathbf{w}^{\mathrm{b}}$ $\longrightarrow$ w is the control vector

$\mathbf{d} = \mathbf{y}^{\mathrm{o}} - G(\mathbf{w}^{\mathrm{b}})$ $\longrightarrow$ Departure vector

$$G(\mathbf{w}) = \begin{pmatrix} \vdots \\ G_i(\mathbf{w}) \\ \vdots \end{pmatrix} = \begin{pmatrix} \vdots \\ H_i[M(t_i, t_0)\{K(\mathbf{w})\}] \\ \vdots \end{pmatrix}$$

- **Balance operator**: convert to w space, B becomes block diagonal, representing the spatial covariance model.
- **Diffusion operator**: The spatial covariances is specified by diffusion operator (Weaver and Courtier 2001)

Balance operator

$$\mathbf{w}^{\mathrm{b}} \equiv K^{-1}\{\mathbf{x}^{\mathrm{b}}(t_0)\}$$

$$(T, S_{\mathrm{U}}, \eta_{\mathrm{U}}, u_{\mathrm{U}}, v_{\mathrm{U}})^{\mathrm{T}} \longleftarrow (T, S, \eta, u, v)^{\mathrm{T}}$$

linearly independent

Solution:

$$\delta \mathbf{w}^{\mathrm{a}} \approx \mathbf{B}\,\mathbf{G}^{\mathrm{T}}\left(\mathbf{G}\,\mathbf{B}\,\mathbf{G}^{\mathrm{T}} + \mathbf{R}\right)^{-1}\mathbf{d}.$$

$$\delta \mathbf{x}^{\mathrm{a}} = K\left(\mathbf{w}^{\mathrm{b}} + \delta \mathbf{w}^{\mathrm{a}}\right) - K\left(\mathbf{w}^{\mathrm{b}}\right) \approx \mathbf{K}\,\delta \mathbf{w}^{\mathrm{a}}$$

$$\mathbf{x}^{\mathrm{a}}(t_i) = M(t_i, t_{i-1})\left[\mathbf{x}^{\mathrm{a}}(t_{i-1}), F_i\,\delta \mathbf{x}^{\mathrm{a}}\right]$$

IAU,Bloom et al 1996

NEMOVAR: Linearized Balance Operator

Define the balance operator symbolically by the sequence of equations

$$
\begin{array}{llcllllllll}
\text{Temperature} & \delta T & = & \delta T & & & & & & & \\
\text{Salinity} & \delta S & = & \mathrm{K}^{\mathrm{b}}_{S,T}\,\delta T & + & \delta S_{\mathrm{U}} & = & \boxed{\delta S_{\mathrm{B}}} & + & \delta S_{\mathrm{U}} & \\
\text{SSH} & \delta \eta & = & \mathrm{K}_{\eta,\rho}\,\delta \rho & + & \delta \eta_{\mathrm{U}} & = & \delta \eta_{\mathrm{B}} & + & \delta \eta_{\mathrm{U}} & \\
\text{u-velocity} & \delta u & = & \mathrm{K}_{u,p}\,\delta p & + & \delta u_{\mathrm{U}} & = & \delta u_{\mathrm{B}} & + & \delta u_{\mathrm{U}} & \\
\text{v-velocity} & \delta v & = & \mathrm{K}_{v,p}\,\delta p & + & \delta v_{\mathrm{U}} & = & \delta v_{\mathrm{B}} & + & \delta v_{\mathrm{U}} &
\end{array}
$$

Treated as approximately mutually independent without cross correlations

$$
\begin{array}{lllll}
\text{Density} & \delta \rho & = & \mathrm{K}^{\mathrm{b}}_{\rho,T}\,\delta T & + \mathrm{K}^{\mathrm{b}}_{\rho,S}\,\delta S \\
\text{Pressure} & \delta p & = & \mathrm{K}_{p,\rho}\,\delta \rho & + \mathrm{K}_{p,\eta}\,\delta \eta
\end{array}
\Bigg\}.
$$

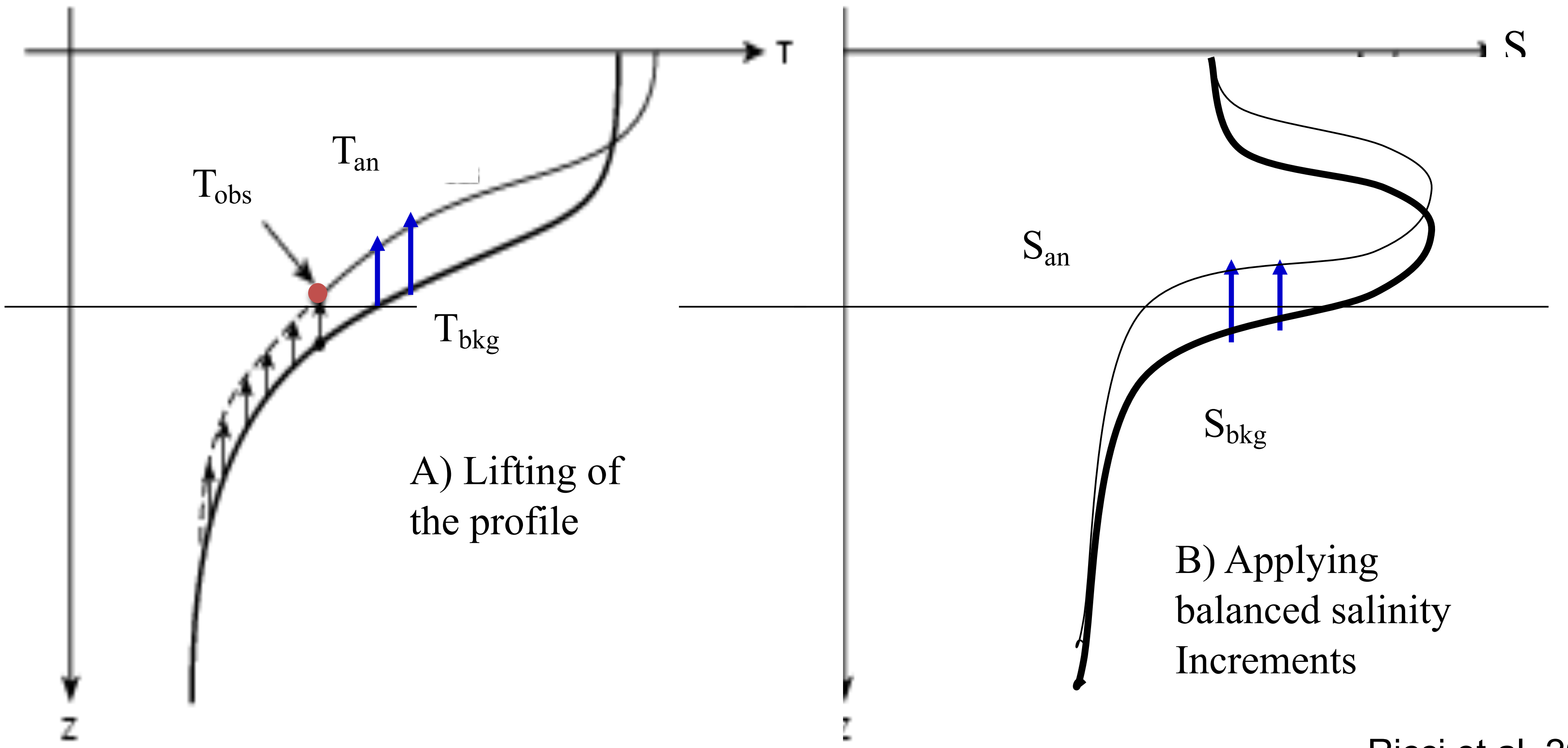
Weaver et al., 2005, QJRMS

NEMOVAR: balance operator

Salinity balance
(approx. T-S conservation
To preserve the water mass properties
following Troccoli and Haines (1999))

$$\delta S_{\mathrm{B}} = \gamma_S^{\mathrm{b}} \left(\frac{\partial S}{\partial z}\right)^{\mathrm{b}} \delta z \qquad \delta z = \left(\frac{\partial z}{\partial T}\right)^{\mathrm{b}} \delta T.$$

γ_S^{b} is 0 unless T-S is weakly correlated



Ricci et al. 2005

T/S/SSH balance: vertical displacement of the profile.

NEMOVAR: Background-error covariances

General B formulation in NEMOVAR

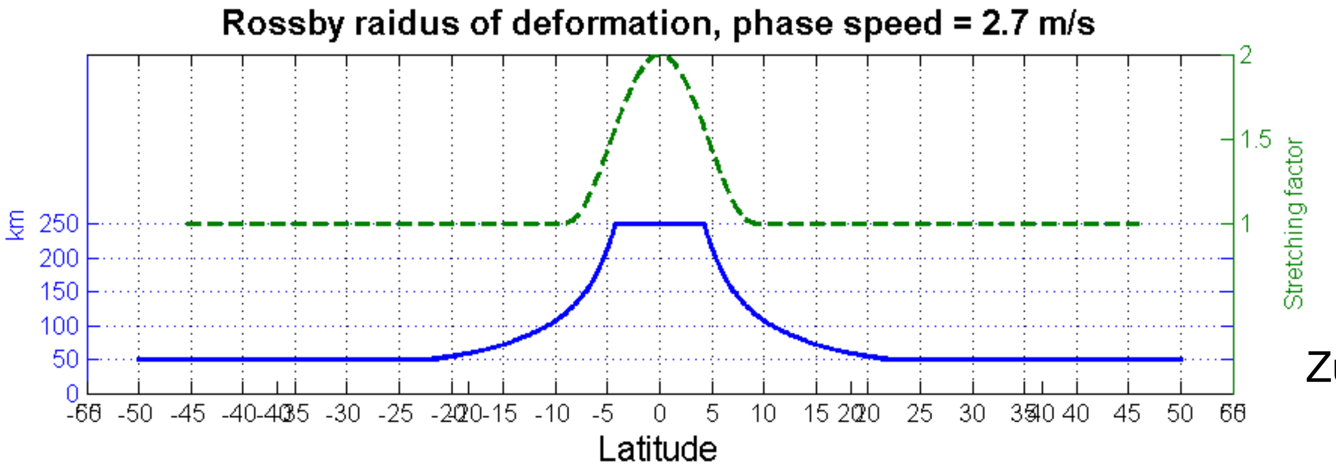
$$\mathbf{B} = \beta_m^2\left(\mathbf{B}_{\mathrm{m}_1} + \mathbf{B}_{\mathrm{m}_2} + ..\right) + \beta_e^2 \mathbf{B}_{\mathrm{e}} + \beta_E^2 \mathbf{B}_{EOF}$$
$$\mathbf{B}_{\mathrm{m_i}} = \mathbf{K}_{\mathrm{b}} \mathbf{D}_{\mathrm{i}}^{1/2} \mathbf{C}_{\mathrm{m_i}} \mathbf{D}_{\mathrm{i}}^{1/2} \mathbf{K}_{\mathrm{b}}^{\mathrm{T}}$$

- $\boldsymbol{B_m}$ is modelled covariance matrix (can use multiple model to represent different scales)
- $\boldsymbol{B_e}$ is a localized ensemble-based covariance matrix
- $\boldsymbol{B_{EOF}}$ is a EOF-based covariance matrix
- $\boldsymbol{C_m}$ is correlation matrix (including diffusion operator)
- $\boldsymbol{D_m}$ is a diagonal matrix of variances (block-diagonal).

$$\mathbf{C}_X^{1/2} = \mathbf{\Gamma}_X^{1/2} \boxed{\mathbf{L}_X^{1/2}} \mathbf{W}_X^{-1/2}$$

diffusion operator use diffusion tensor $\boldsymbol{\kappa_m}$ to represent a particular de-correlation length-scales

Horizontal correlation length-scales used in ORAP5



Zuo et al., 2015

Ensemble Var DA with hybrid B

A cost-effective way is to use only a single **modelled covariance** matrix $\boldsymbol{B_m}$, but use ensemble to estimate both variances ($\boldsymbol{D_m}$ -> $\boldsymbol{D_e}$) and the local correlation tensor ($\boldsymbol{\kappa_m} \rightarrow \boldsymbol{\kappa_e}$ in $\boldsymbol{C_m}$)

$$\mathsf{B}_{\mathrm{m}} = \mathsf{K}_{\mathrm{b}}\, \mathsf{D}_{\mathrm{m}}^{1/2}\, \mathsf{C}_{\mathrm{m}}\, \mathsf{D}_{\mathrm{m}}^{1/2}\, \mathsf{K}_{\mathrm{b}}^{\mathrm{T}}$$

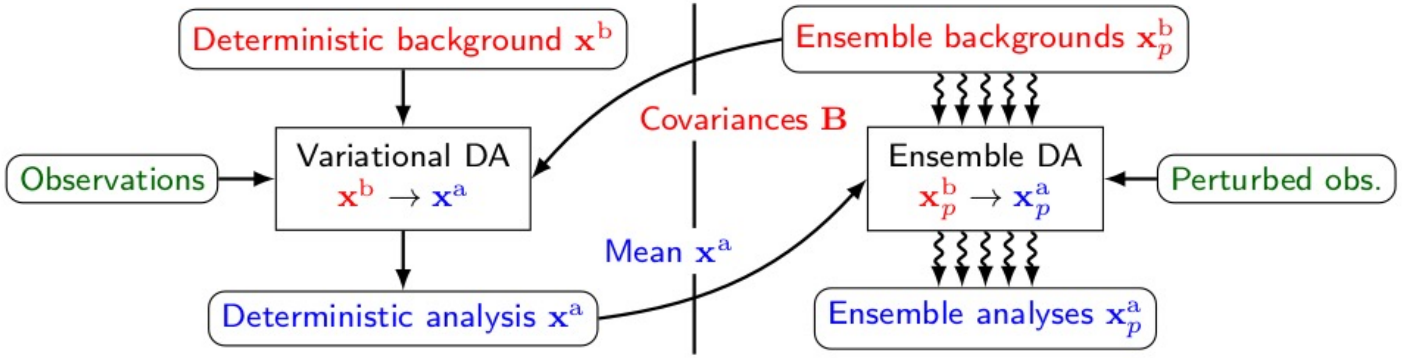
Or even take a hybrid approach when estimate $\boldsymbol{D_m}$ and $\boldsymbol{C_m}$ in $\boldsymbol{B_m}$

$$\begin{aligned} \mathsf{D} &= \alpha_{\mathrm{m}}^2\, \mathsf{D}_{\mathrm{m}} + \alpha_{\mathrm{e}}^2\, \mathsf{D}_{\mathrm{e}} \\ \boldsymbol{\kappa} &= \gamma_{\mathrm{m}}^2\, \boldsymbol{\kappa}_{\mathrm{m}} + \gamma_{\mathrm{e}}^2\, \boldsymbol{\kappa}_{\mathrm{e}} \end{aligned}$$

Where $\boldsymbol{D_m}$ and $\boldsymbol{\kappa_m}$ are modelled (static) components, and $\boldsymbol{D_e}$ and $\boldsymbol{\kappa_e}$ are ensemble (flow-dependent) estimations, $\boldsymbol{\alpha_{m,e}}$ and $\boldsymbol{\gamma_{m,e}}$ are constant weights.

Ensemble Var DA with hybrid B

Generate an ensemble of analyses from an ensemble of background states and perturbed observations



- Ensemble DA perturbations simulate errors for the deterministic system;
- 3D-Var analysis for both deterministic and ensemble system;
- Observation and surface forcing perturbations as in ORAS5 (Zuo et al. 2017);
- Implementation of stochastic physics in NEMO (A. Storto, CMRE).

BGE variances ($\boldsymbol{\sigma}^2$) in hybrid B

A hybrid background error variances $\boldsymbol{\sigma}^2$ in $\boldsymbol{D_m}$ contains modelled variances $\boldsymbol{\sigma_m^2}$ (parameterized $\boldsymbol{\sigma_p^2}$ + climatology $\boldsymbol{\sigma_c^2}$) and “error-of-the-day” estimated from ensemble spreads ($\boldsymbol{\sigma_e^2}$)

Parameterized $\boldsymbol{\sigma_p^2}$ | Climatology $\boldsymbol{\sigma_c^2}$ | Hybrid $\boldsymbol{\sigma^2}$

Temperature

Unbal. Salinity

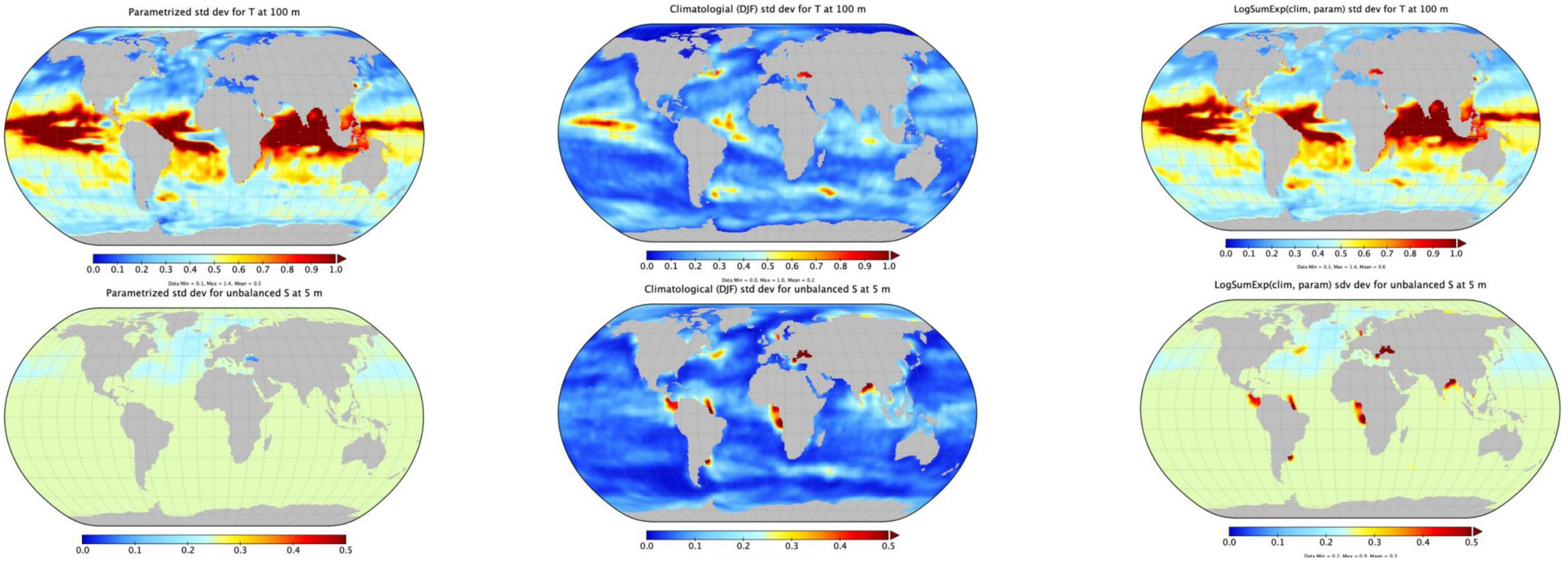


Figure by Anthony Weaver

Diffusion tensor ($\boldsymbol{\kappa}$) in hybrid B

A hybrid diffusion tensor $\boldsymbol{\kappa}$ in $\boldsymbol{C}_m$ contains a static diffusion tensor $\boldsymbol{\kappa}_m$ (parameterized $\boldsymbol{\kappa}_p$ + climatology $\boldsymbol{\kappa}_c$) and a flow-dependent tensor $\boldsymbol{\kappa}_e$

Parameterized $\boldsymbol{\kappa}_p$ | Climatology $\boldsymbol{\kappa}_c$ | Hybrid $\boldsymbol{\kappa}$

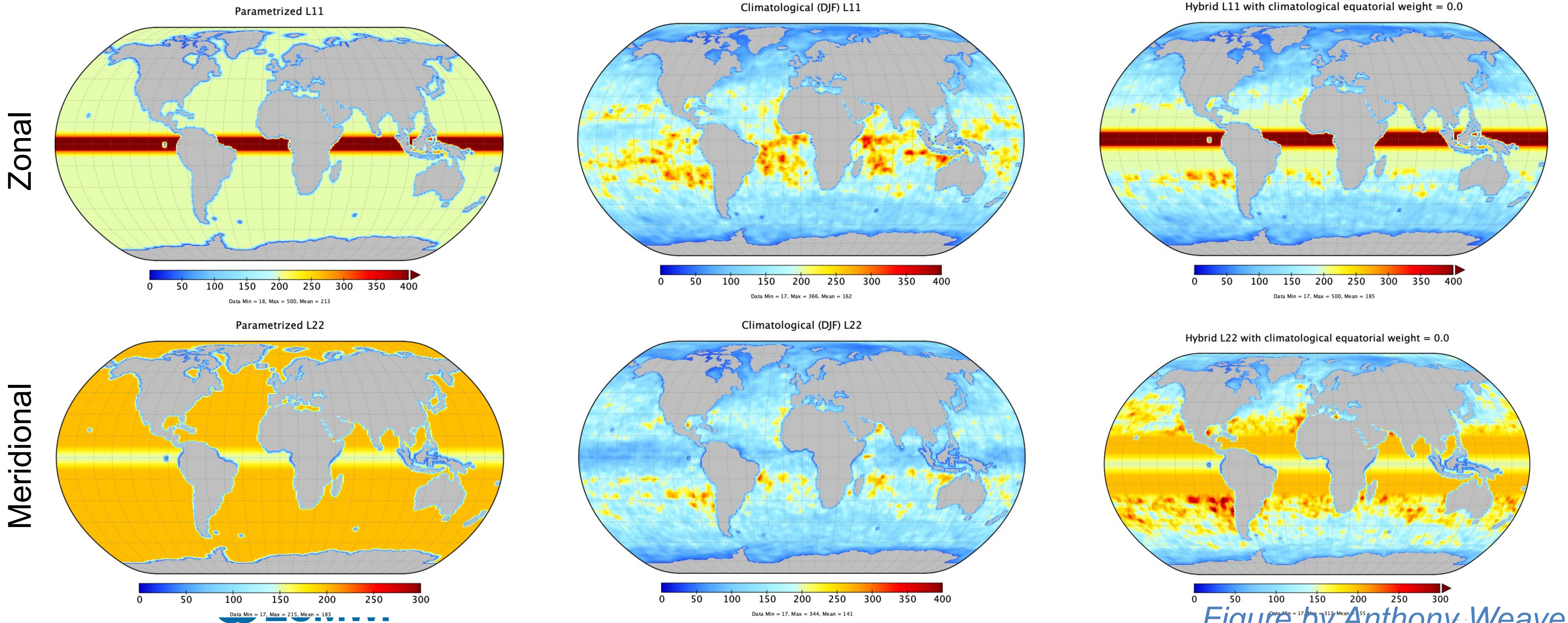


Figure by Anthony Weaver

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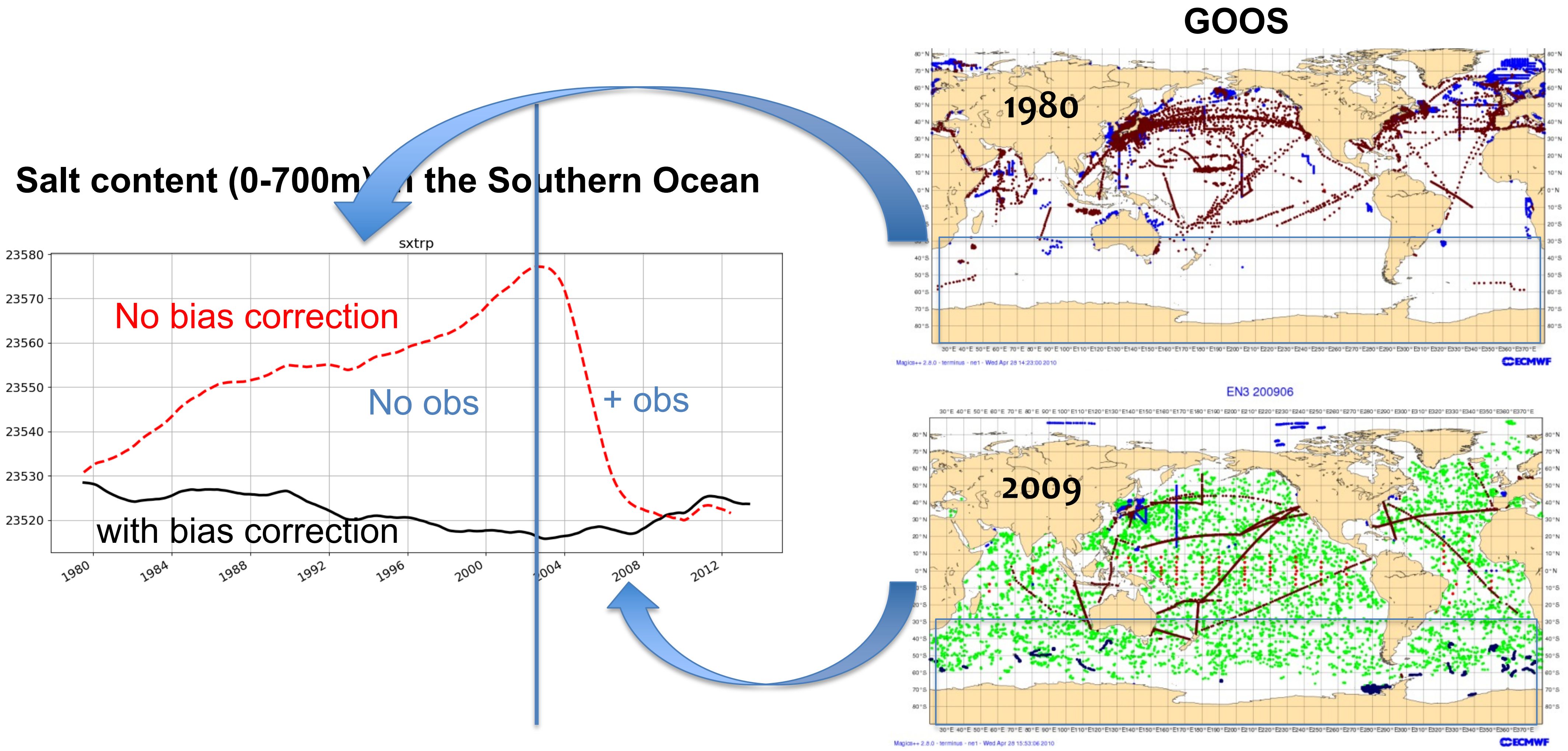
Why do we need bias correction in ODA

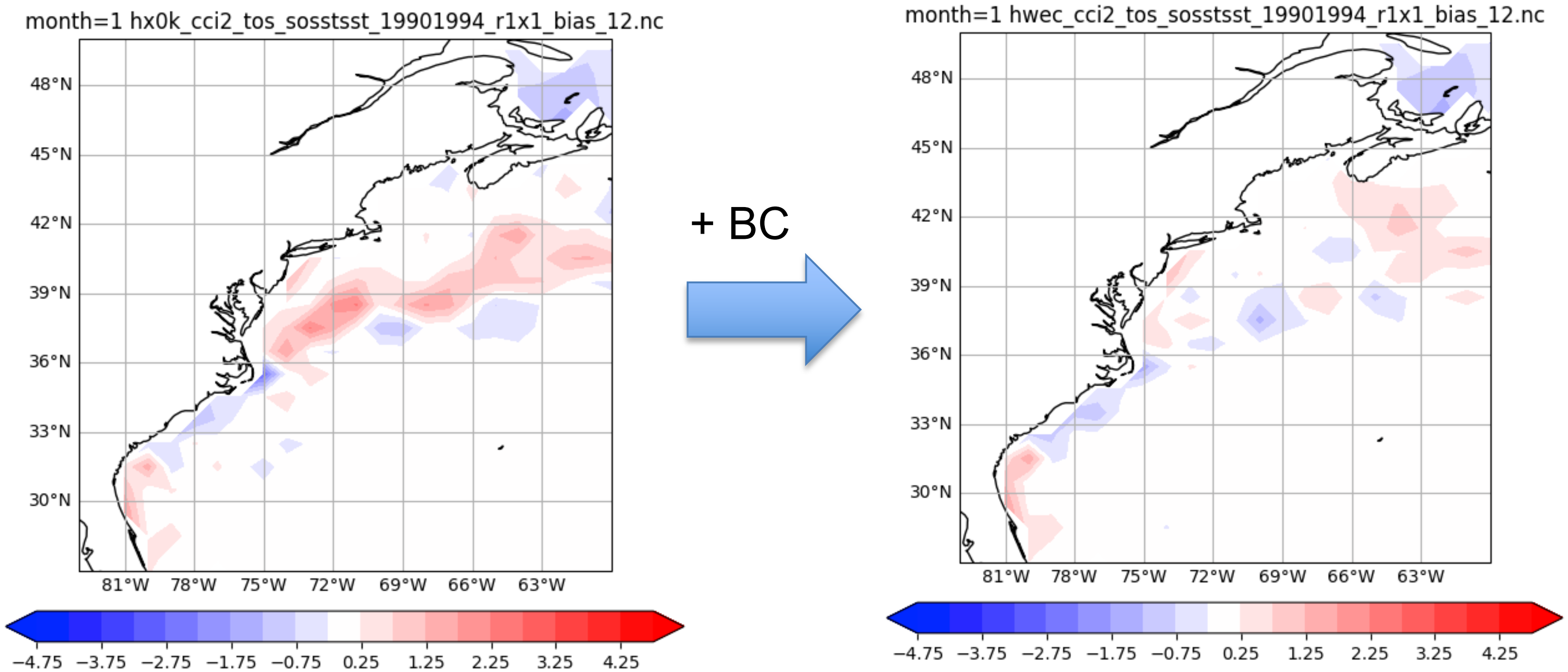
To mitigate changes in the observing system. E.g. salt content drift in the Southern Ocean during pre-Argo period due to lack of in-situ observations.



Why do we need bias correction in ODA

To correct systematic errors in models/forcing/boundary conditions, and biases introduced by DA system. E.g. add BC can greatly reduced SST biases, especially in the Gulf Stream regions where the ¼ degree NEMO model has persistent bias.

SST biases (February) in the Gulf Stream Extensions



Bias Correction scheme

Bias term include two parts, (a) a-priori bias ($\overline{b}_i$) for systematic errors, and (b) a temporal evolution bias term (b'_c) for slow evolving signals (Balmaseda et al, 2007)

$$b_c = \overline{b}_i + b'_c$$

Slow varying term, estimated online from assimilation increments

Seasonal term, estimated offline from data-rich period

$$b'_c = \alpha b'_{c-1} - A\delta x^a_{c-1}$$

A is a Linear transformation matrix from the state vector increment (δx^a_c) to bias control vector; α is the memory factor

$$\overline{b}_i = \overline{b}_{i-1} + \overline{\delta x^a_i}$$

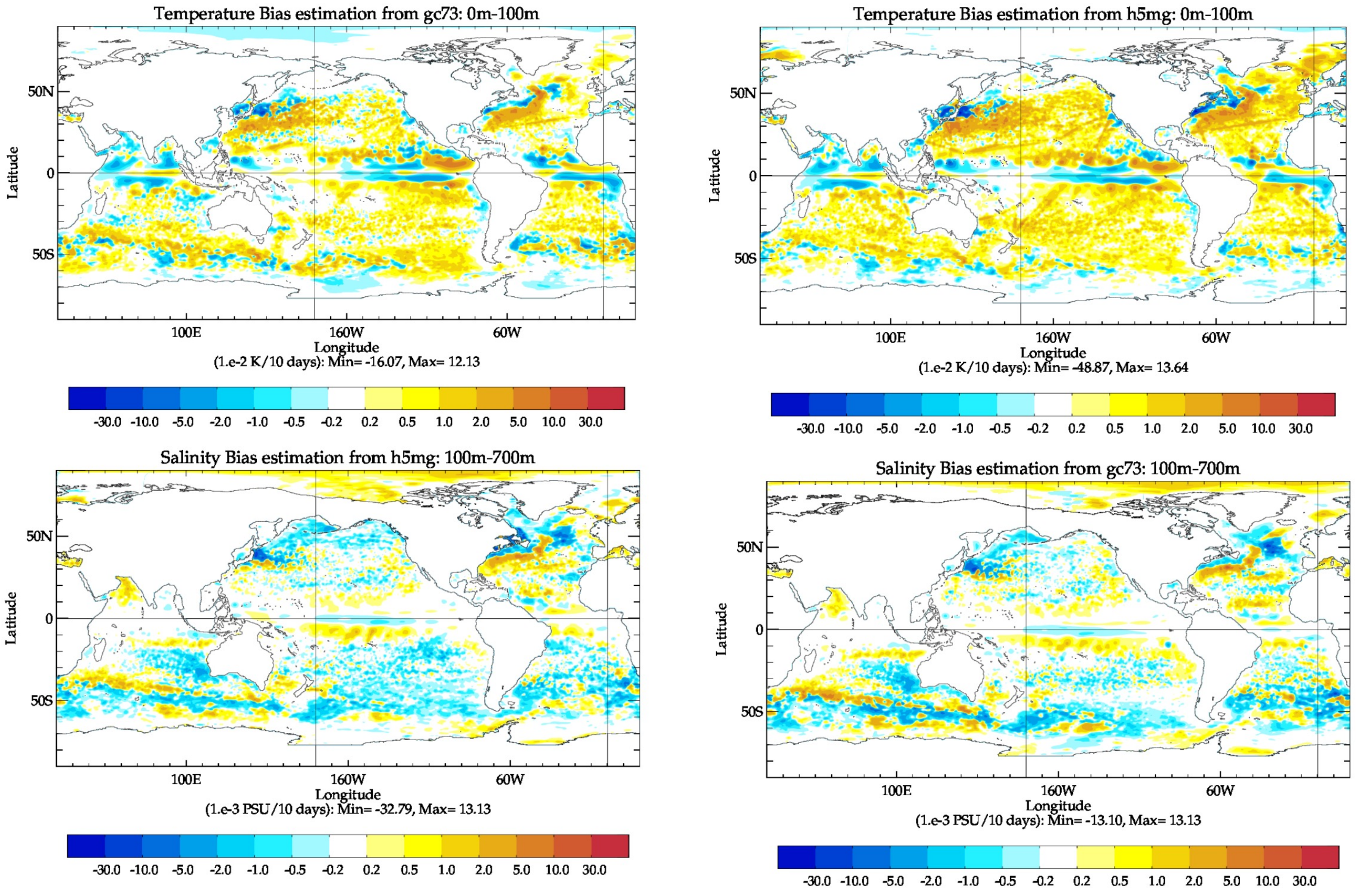
A-priori bias term can be estimated with iterative approach, where $\overline{b}_0 = 0$, and $\overline{\delta x^a_i}$ is averaged increments from the i_{th} iteration, which should approach to zero with i increases

The bias correction is used to modify the tendencies of the nonlinear model used in the background and analysis outer loops, so the time evolution of the background and analysis states can be expressed as

$$\mathbf{x}^{\mathrm{b}}_c(t_i) = M(t_i, t_{i-1})\left[\mathbf{x}^{\mathrm{b}}_c(t_{i-1}), \mathbf{b}_{c-1}\right],$$
$$\mathbf{x}^{\mathrm{a}}_c(t_i) = M(t_i, t_{i-1})\left[\mathbf{x}^{\mathrm{a}}_c(t_{i-1}), \mathbf{b}_{c-1}, F_i\,\delta\widetilde{\mathbf{x}}^{\mathrm{a}}_c\right]$$

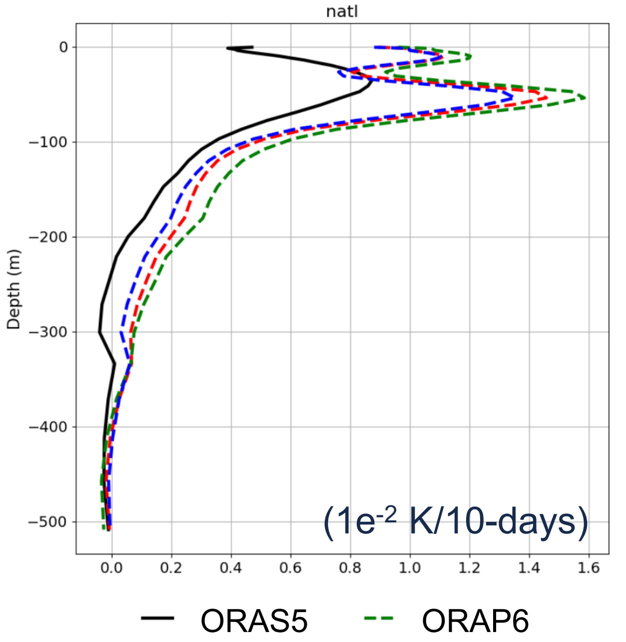
A-priori bias term for different systems

A-priori biases ($\bar{b}_1$) in (left) ORAS5 and (right) ORAP6



Among other differences, ORAS5 uses ERA-int forcing while ERA5 forcing is used in ORAP6

Vertical profile of $\bar{b}_T$ in ORAS5 and ORAP6 in the North Atlantic Ocean



Temporal variable bias term

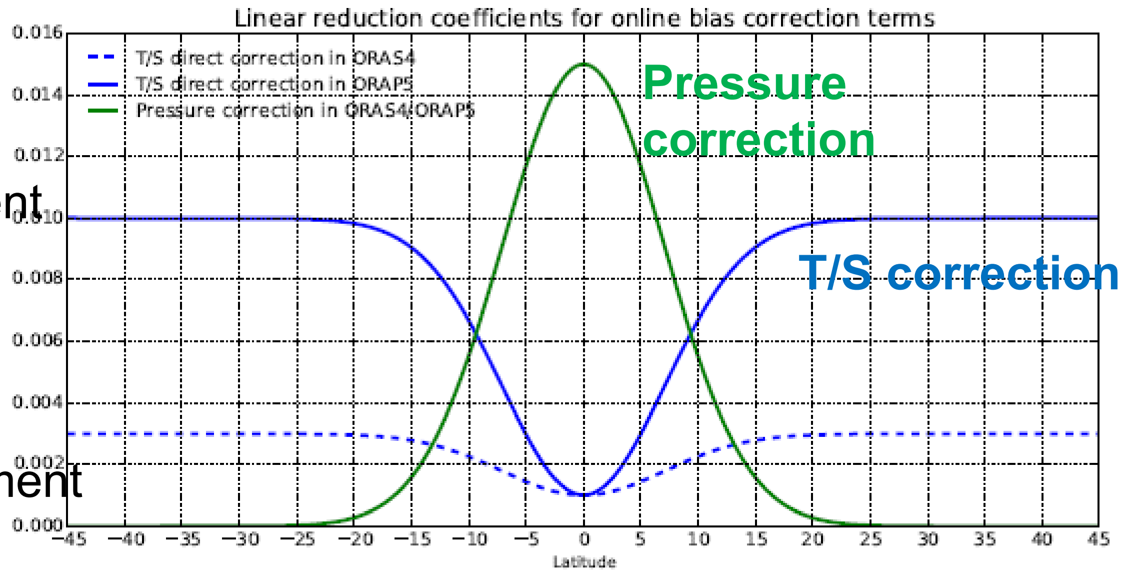
The latitude dependent partition coefficients determine the proportion of online bias corrections applied directly on T/S, and on pressure term. These values ensure that at low latitude the dominant bias term is pressure correction.

$$\mathbf{A} = \begin{bmatrix} a^{tr,T} & 0 & 0 & 0 & 0 \\ 0 & a^{tr,S} & 0 & 0 & 0 \\ a^{p,T} & 0 & 0 & 0 & 0 \\ 0 & a^{p,S} & 0 & 0 & 0 \end{bmatrix}$$

A: Partition matrix, The coefficients in A is latitude dependent in NEMOVAR

1 % increment

0.1 % increment

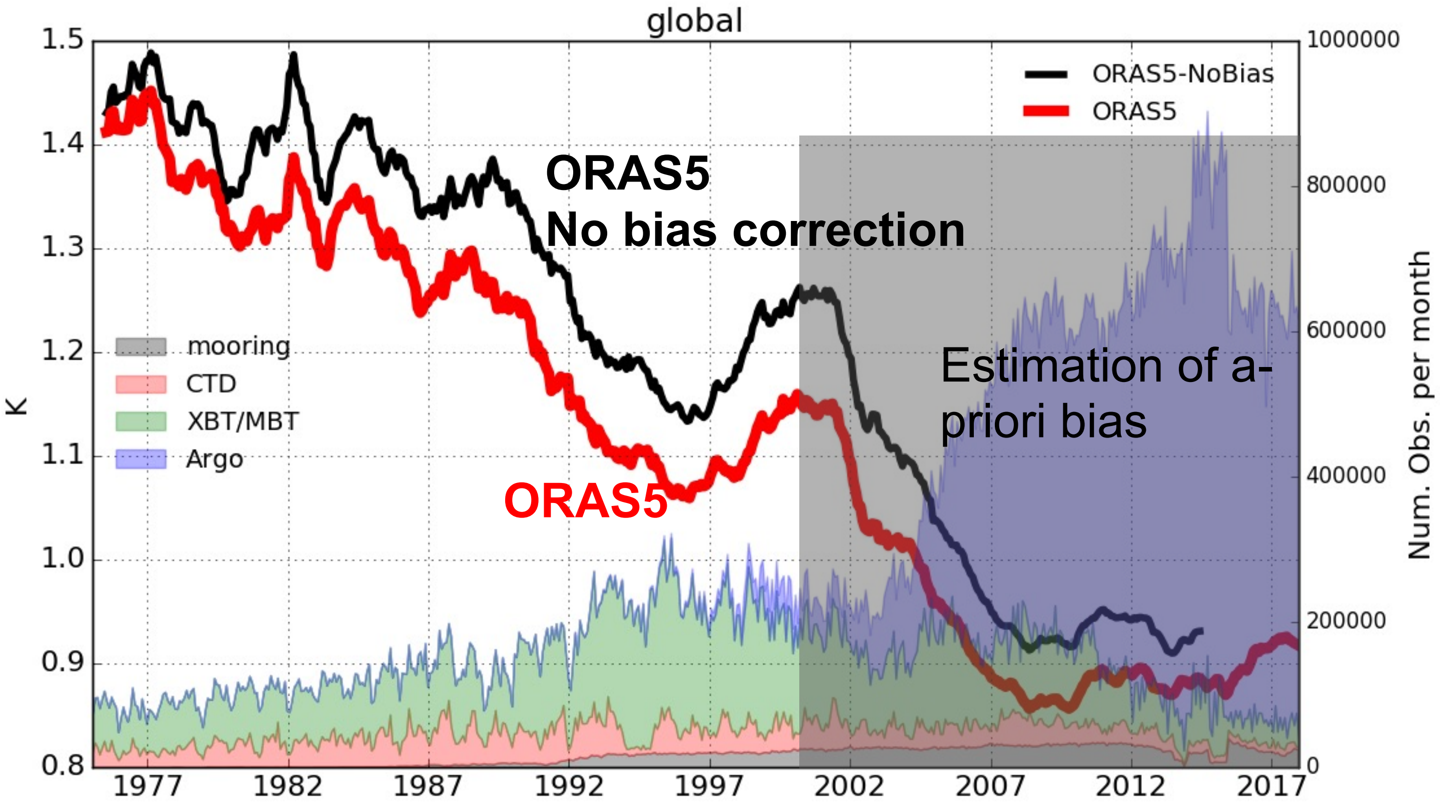


Zuo et al., 2015

Figure 3: Latitude-dependent linear reduction coefficients as applied on online bias correction terms in equations 6 and 7: blue line - $a^{tr,T/S}$, reduction coefficients that apply to direct temperature and salinity corrections (different for ORAS4 and ORAP5); and green line - $a^{p,T/S}$, reduction coefficients that apply to pressure bias correction.

Impact of bias correction on ocean reanalysis

Temperature RMSE: 0-1000m



Mean: 2005-2014

	T RMS reduction	S RMS reduction
In-situ	65%	90%
Bias-corr.	14%	10%

Bias correction in ODA is essential, and in particular important for mitigating spurious signals introduced due to changes in the observing system

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- Assimilation of SST data
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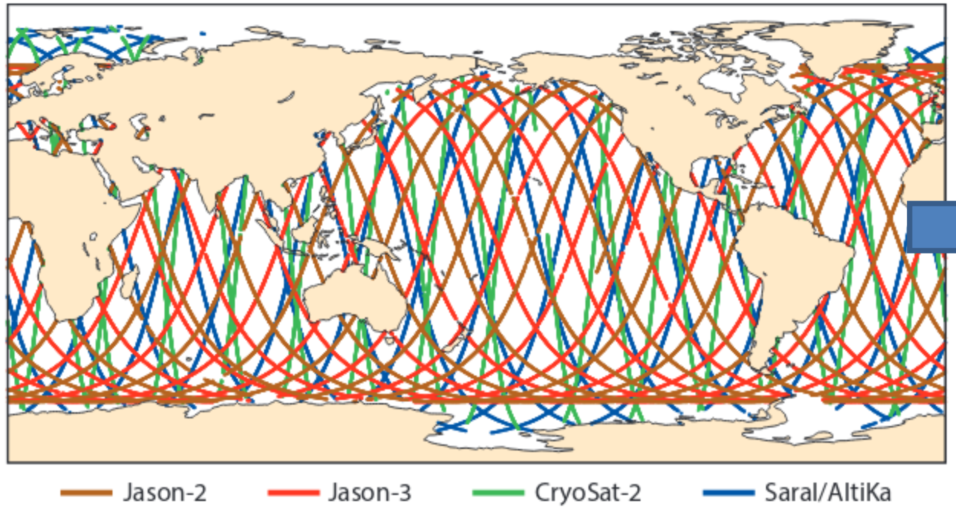
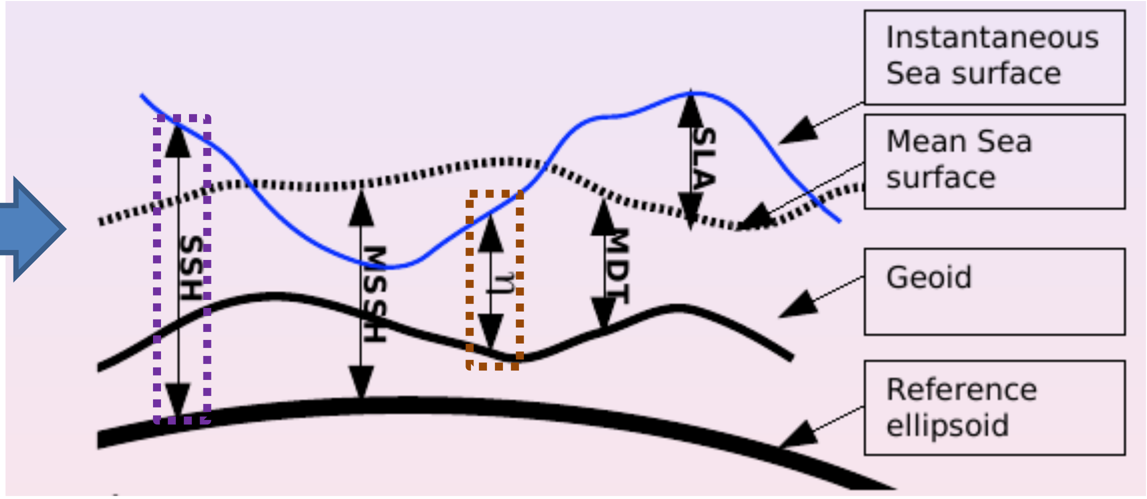
- Ocean (re)analysis system and its applications

Assimilation of Sea Surface Height (SSH)





Altimeter measures SSH (respect reference ellipsoide)
Model represents η (ssh referred to the Geoid)

SSH-Geoid= η

Geoid was poorly known (until recent years)

Alternative: Assimilate Sea Level Anomalies (SLA) respect a time mean

Obs: SSH anomalies = SSH-MSSH = Obs SLA
Mod: η anomalies = η – MDT = Mod SLA

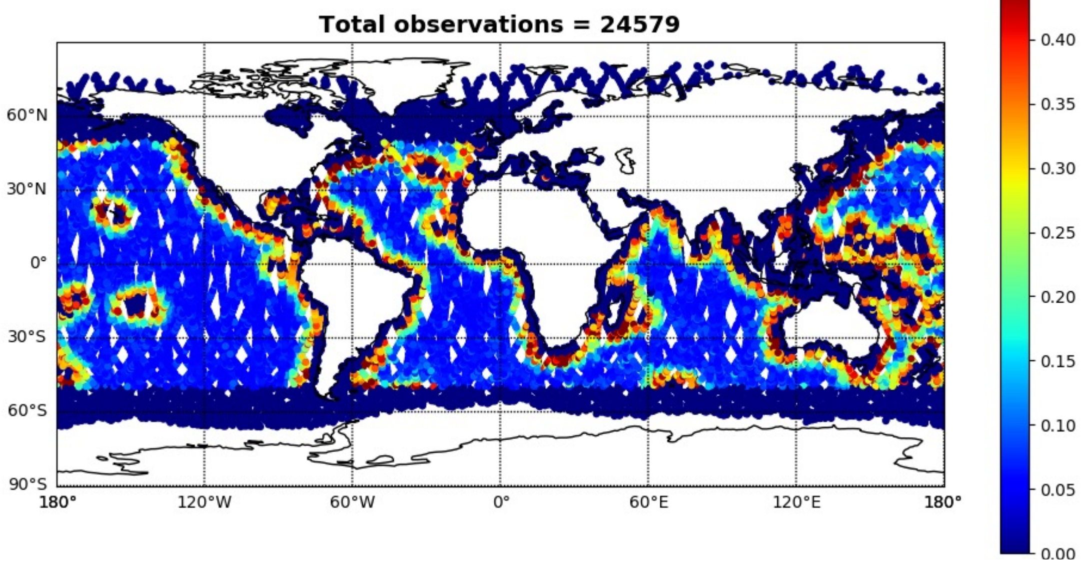
Where: MSSH= Temporal Mean SSH ;
MDT = Temporal Mean of model SL Mean Dynamic Topography

MSSH – Geoid = MDT

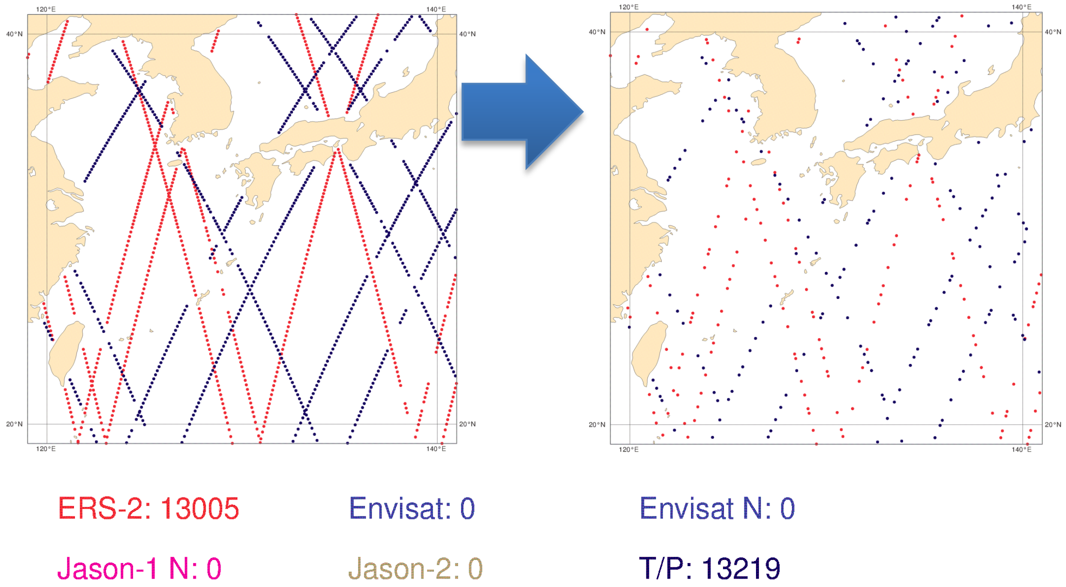
Assimilation of SSH: pre-processing

- **The SLA along track data has very high spatial (9-14km) resolution for the operational ocean assimilation systems.**
  - Features in the data which the model can not represent
  - "Overfitting" to SLA obs
- **This can be dealt with in different ways:**
  - Inflate the observation error
  - Construction of "superobs" or thinning

Inflate OBE std dev of SSH



Thinning of SLA obs

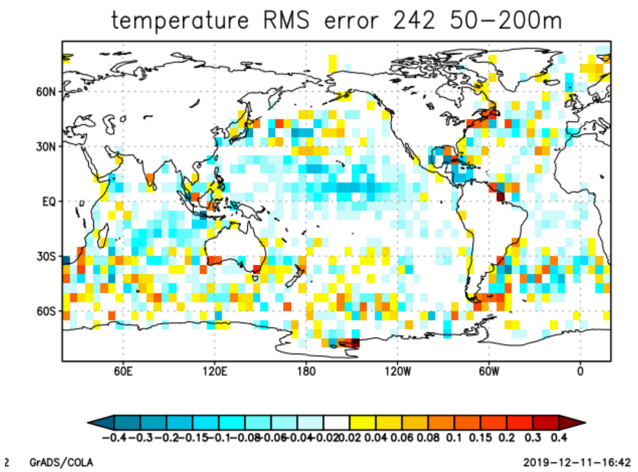


Assimilation of SSH: impact on ocean states

Assimilation of SSH improves simulated ocean states

- Global mean sea-level changes
- Regional sea-level changes
- Subsurface temperature and salinity
- Large-scale ocean circulations

T ∆RMSE (O-B):
assim. SSH – not assim. SSH

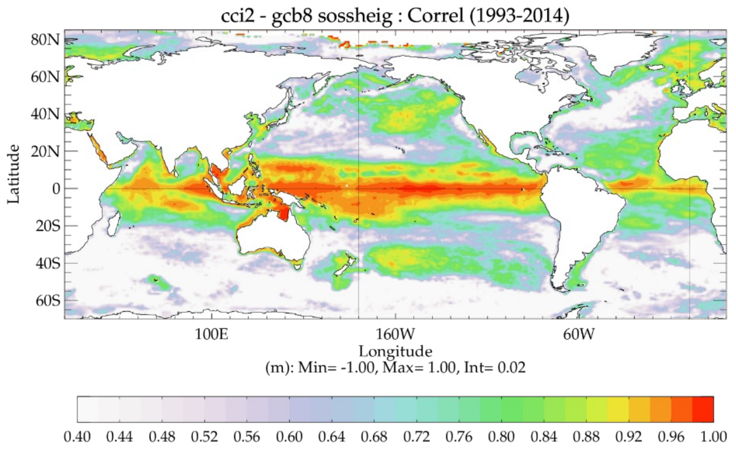


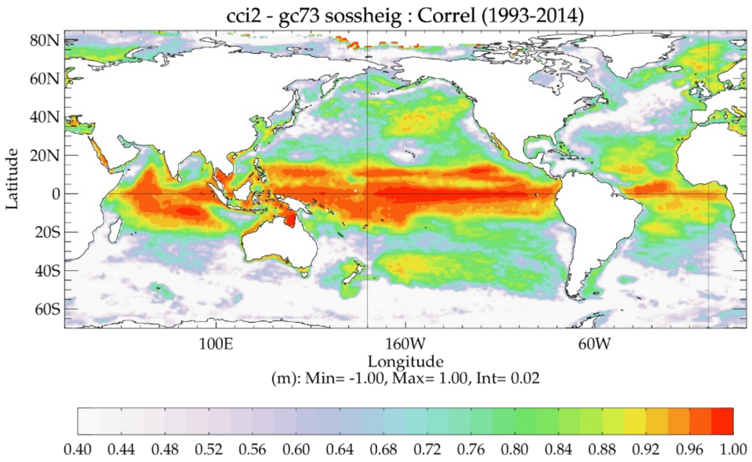
Temporal correlation (monthly) to AVISO data

ORAS5-NoAlti

Zuo et al., 2018

ORAS5





- Ocean system and ocean observations
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Assimilation of SST: nudging

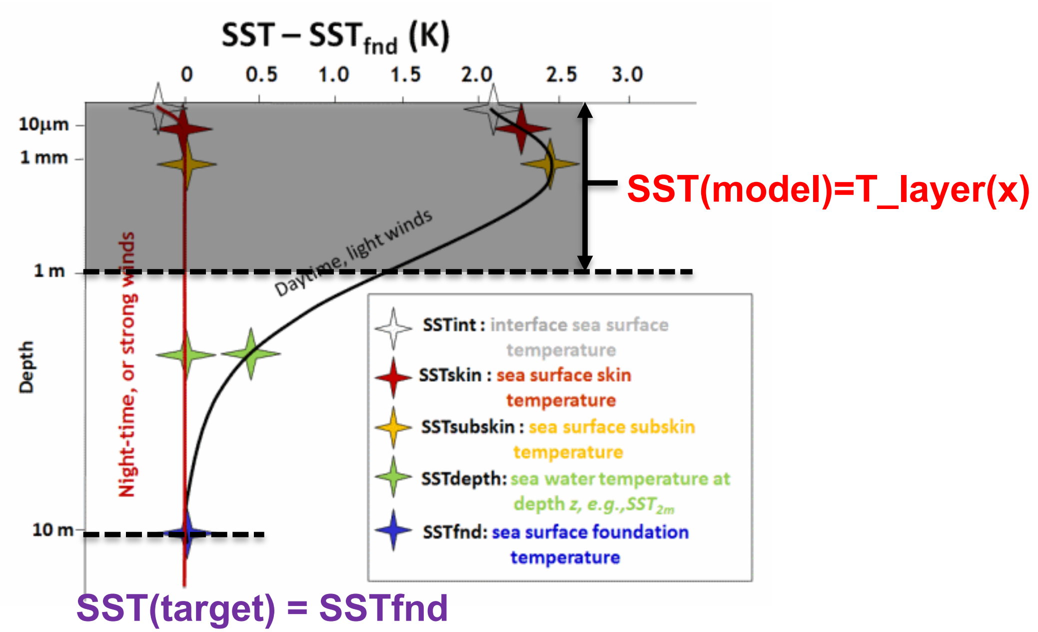
A simple nudging scheme to L4 objective analysis data (e.g. OSTIA)

$$Q_{ns} = Q_{ns}^{o} + \frac{dQ}{dT}(SST_{MODEL} - SST_{TARGET})$$

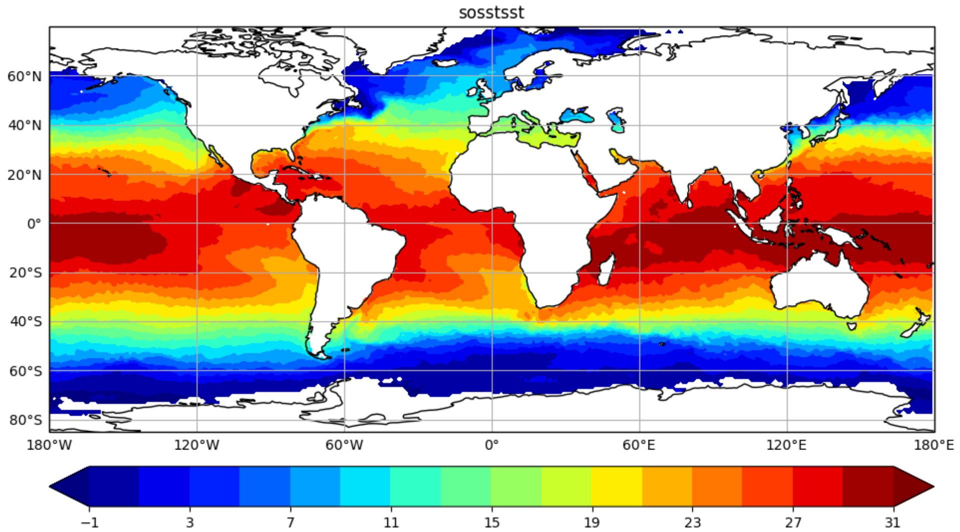
Haney 1917

non-solar total heat flux

Fixed negative feedback coefficient



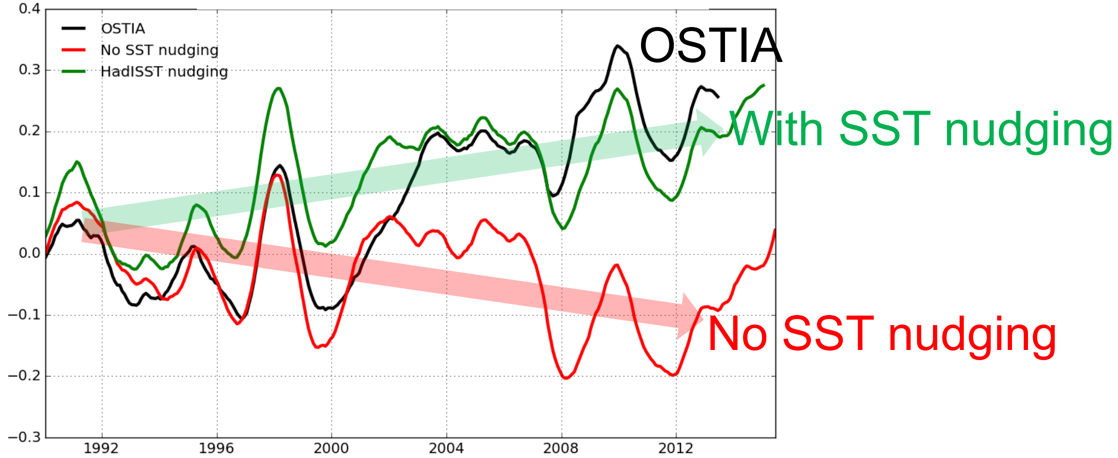
ESA CCI2 SST data (Jan 2016)



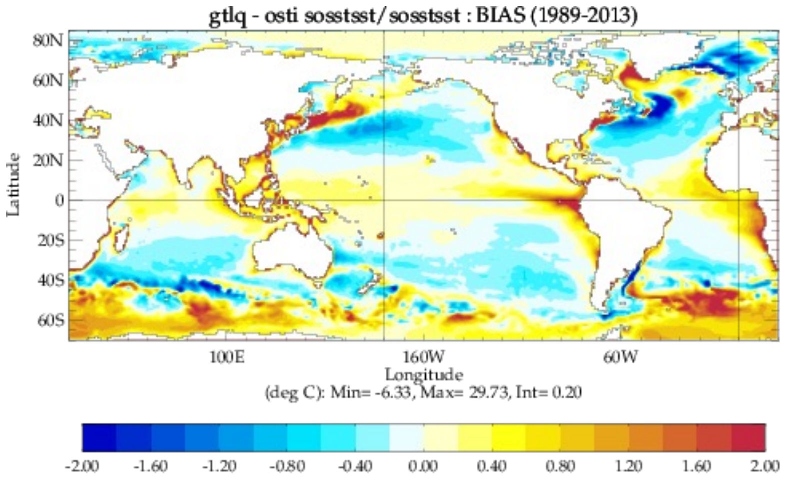
Impact of SST nudging

- Overall very effective except for some areas with weak vertical stratification
- Not accounting complicated error characteristics in the L4 SST analysis
- Not accounting vertical correlation when apply SST constrain in the surface

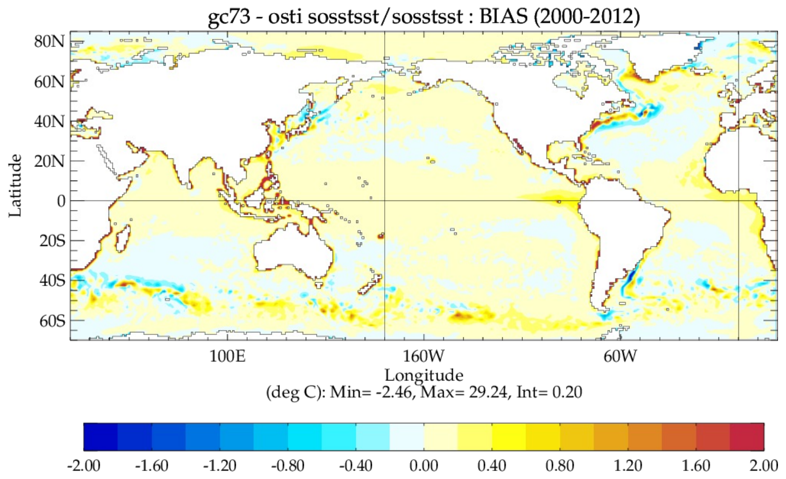
Global mean SST



SST bias: free run - OSTIA



SST bias: ORAS5 - OSTIA



Assimilation of L4 SST with NEMOVAR

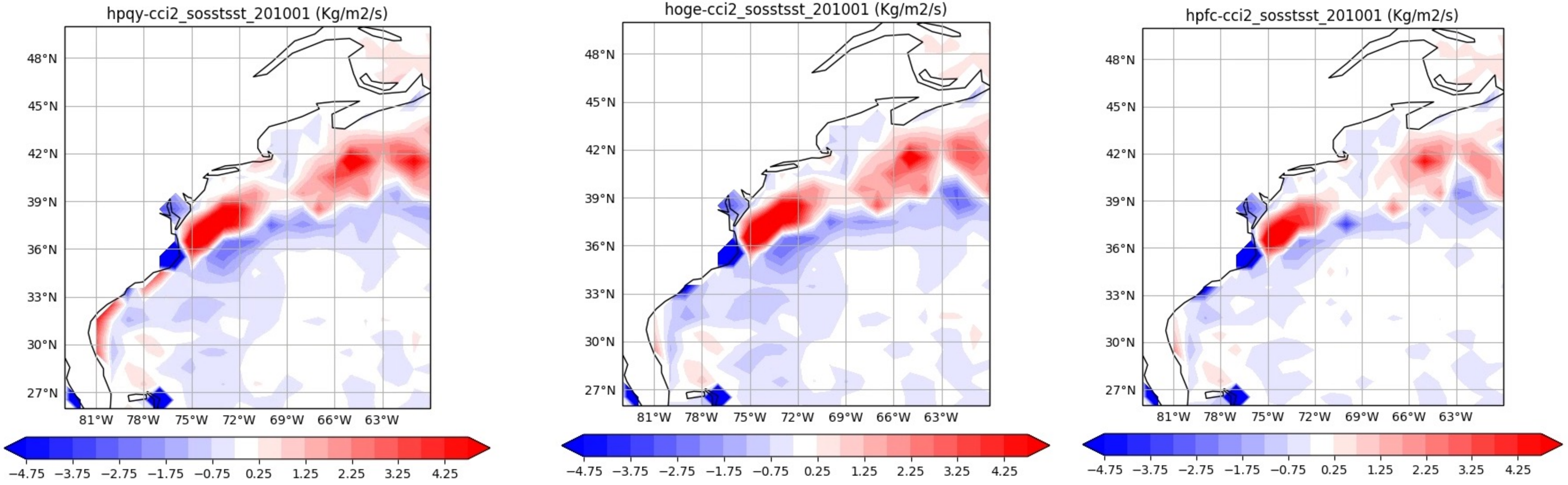
- Assimilation of L4 SST (OSTIA) with Ens. 3DVar and hybrid-B approach
- SST DA leads to reduced SST biases on the Gulf Stream extensions w.r.t nudging method
- Hybrid-B with a MLD dependent vertical tensor is essential in SST DA

Biases in SST

Nudging SST

SST DA (parameterized B)

SST DA (hybrid-B)



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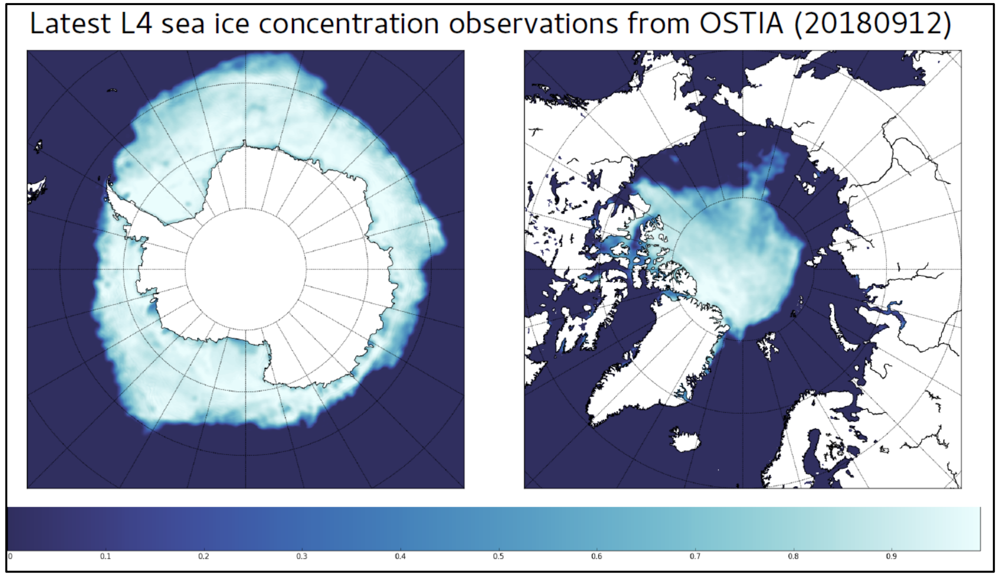
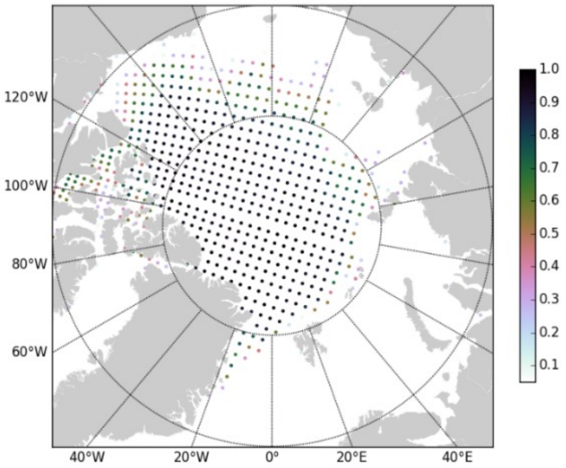
Sea-ice DA with single-category LIM2 model

Sea-Ice Concentration data from L4 analysis is assimilated through 3DVar scheme in the OCEAN5 system

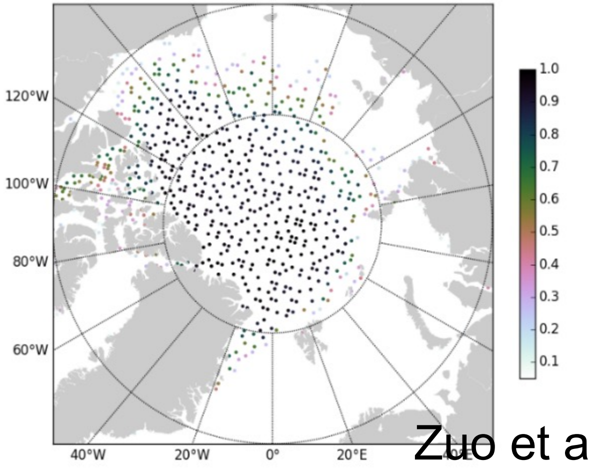
- Treated as univariate
- Pre-thinned via regular or stratified random sampling
- Assimilated through outer-loop coupling in NEMO-LIM2



Regular thinning



random thinning



Zuo et al., 2017

Sea-ice DA with multi-category SI3 model

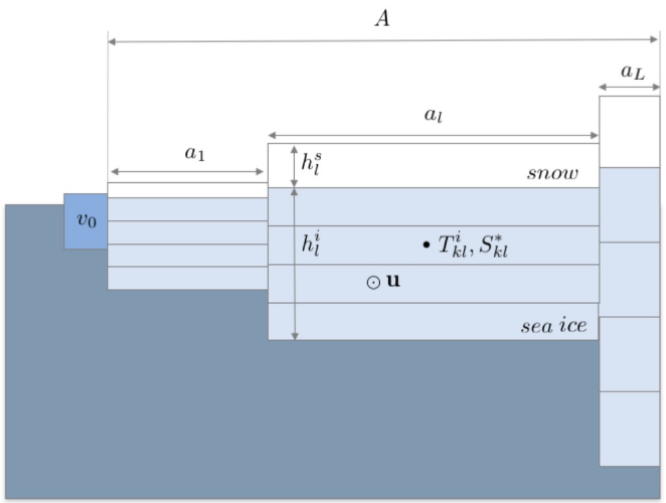
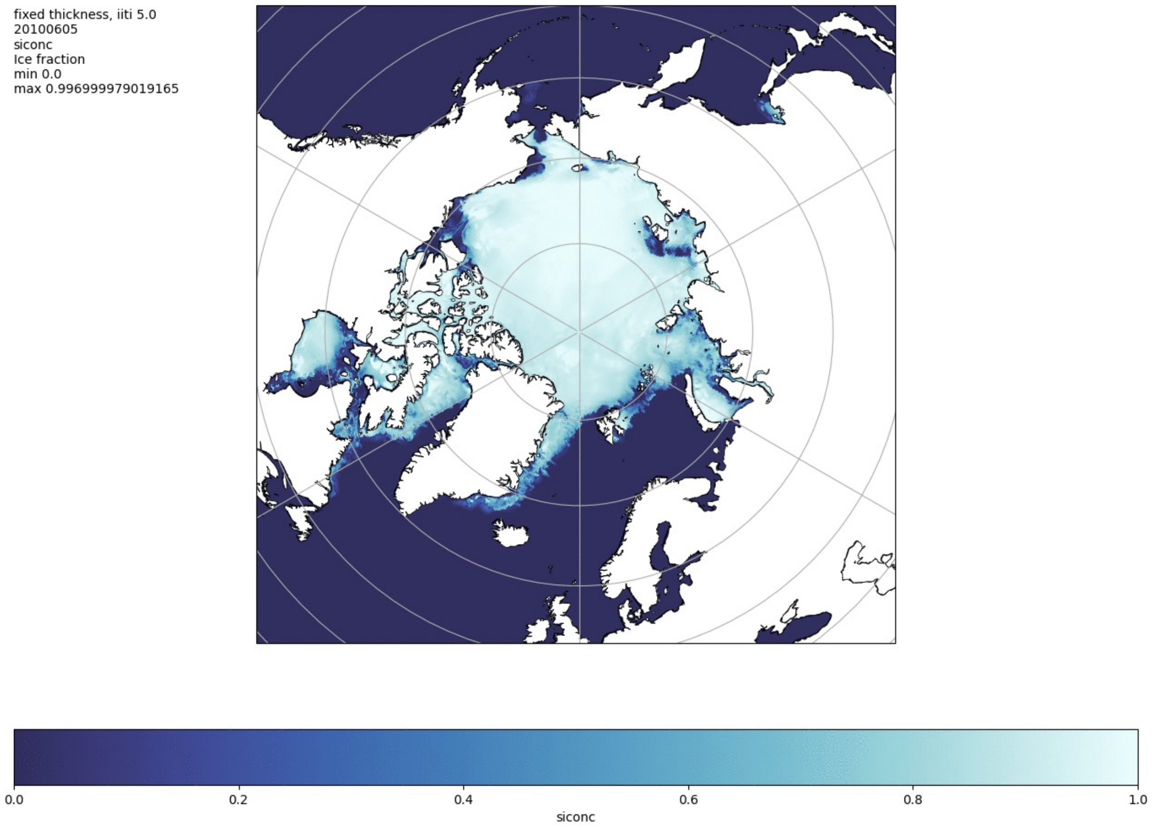


Figure 1.1.: Representation of the ice pack, using multiple categories with specific ice concentration ($a_l, l = 1, 2, ..., L$), thickness (h_l^i), snow depth (h_l^s), vertical temperature and salinity profiles (T^i_{kl}, S^*_{kl}) and a single ice velocity vector (u).

ORAS6 prototype daily sea-ice concentration



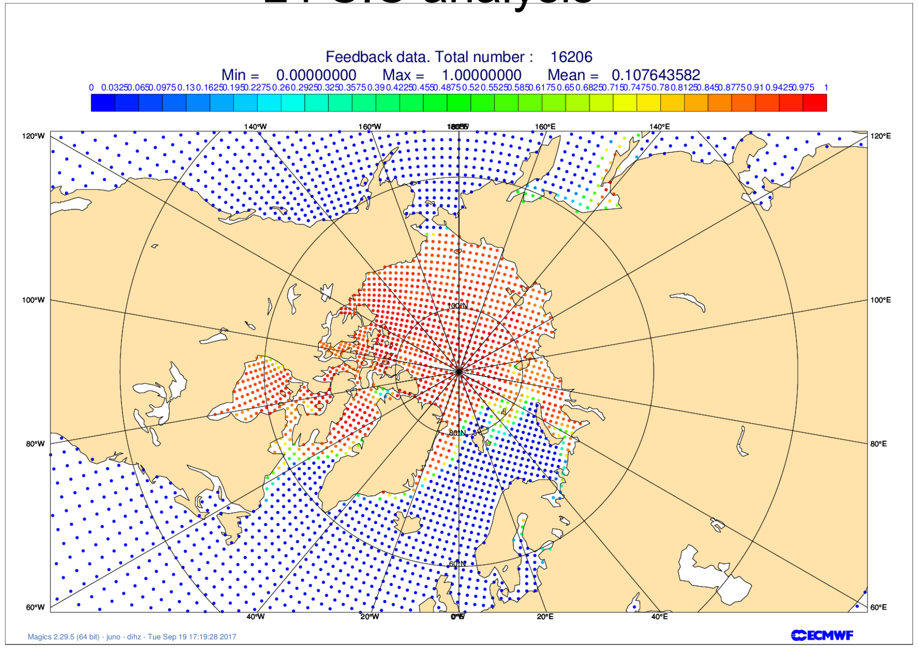
Considerations with SIC DA in SI3 (multi-category sea-ice model with melt ponds)

- How to distribute increments among different thickness categories
- Where to apply sea-ice increments in the ice time-stepping scheme
- Introduce thermodynamic balance between sea-ice and ocean state variables
- Grow sea-ice from open water with DA increment
- Interaction between sea-ice increment and ice advection

Assimilation of L3 sea-ice data

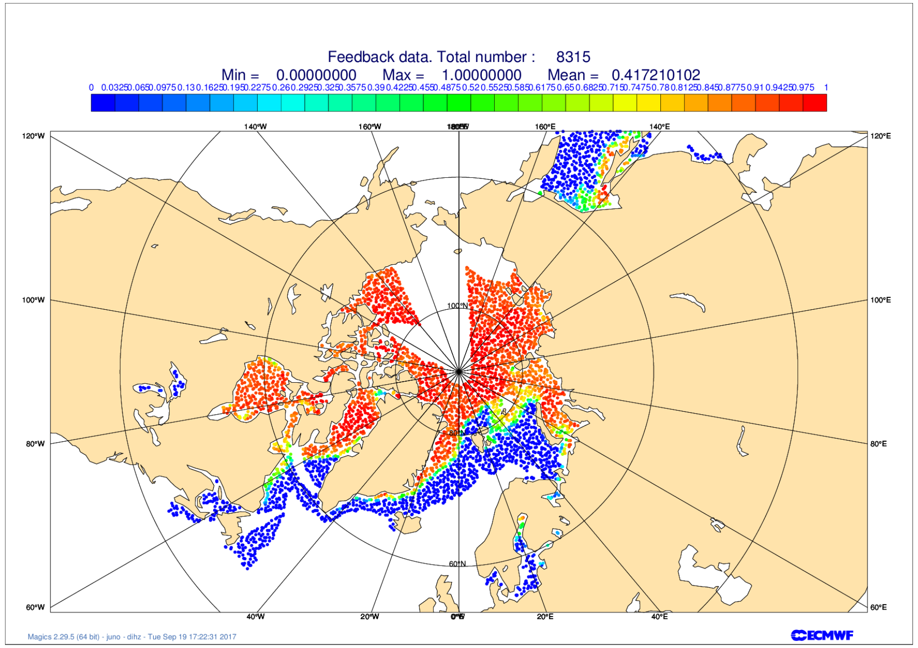
Daily SIC on 20130118

L4 SIC analysis



L4 analysis: with filtering, masking, infilling to produce a gap-free product

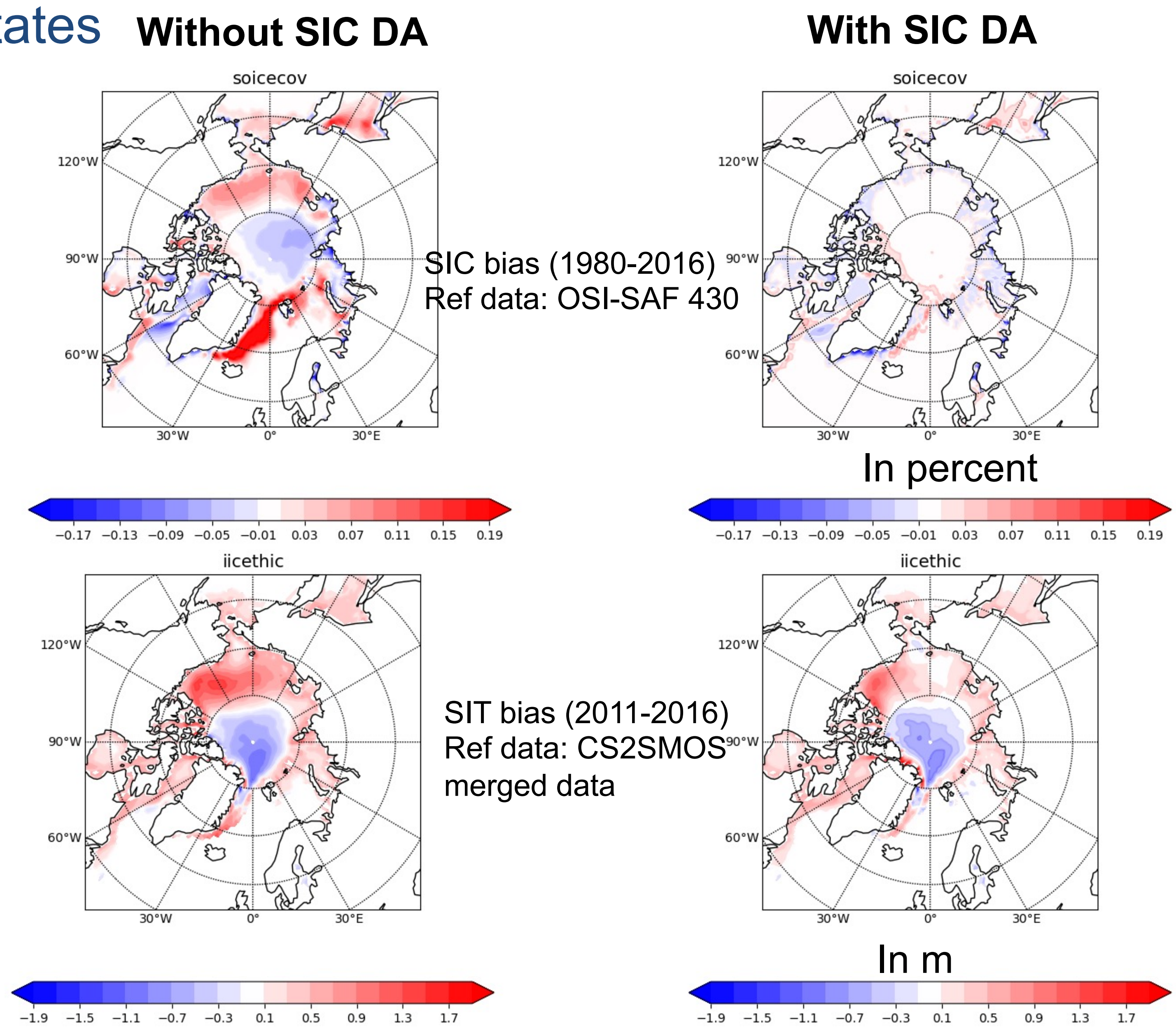
L3 SIC data



with 10km resolution there is ~1 milion obs per day from L3 OSI-SAF, with no infilling created observation

Positive impact on sea-ice states

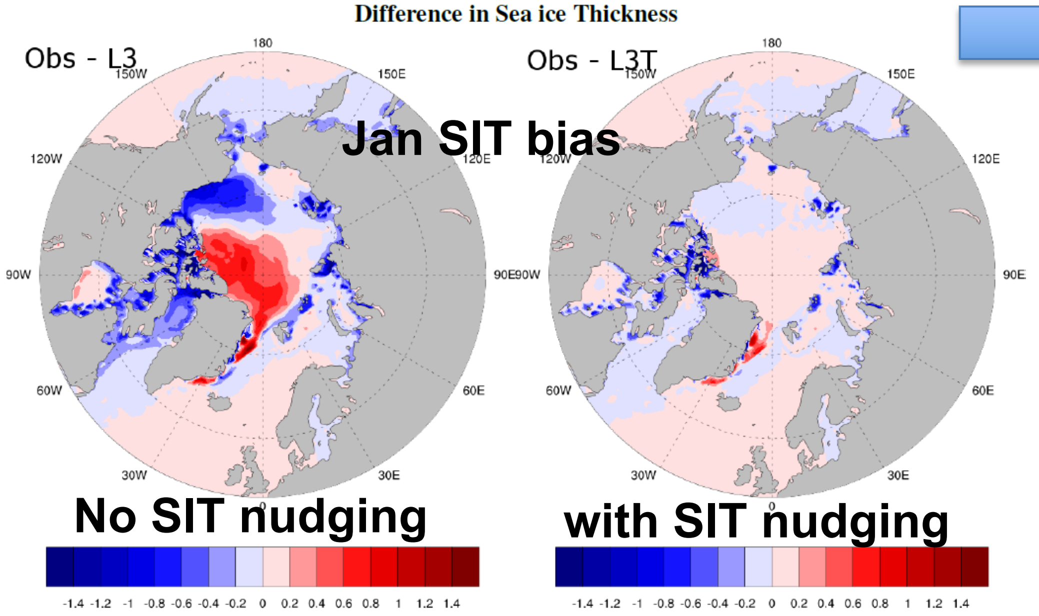
Assimilation of SIC data in ORAS5 leads to improved sea-ice state performance in both sea-ice concentration and sea-ice thickness



Nudging sea-ice thickness (SIT)

$$SIT^n = SIT^m - [\frac{\Delta t}{\tau}(SIT^m - SIT^o)]$$

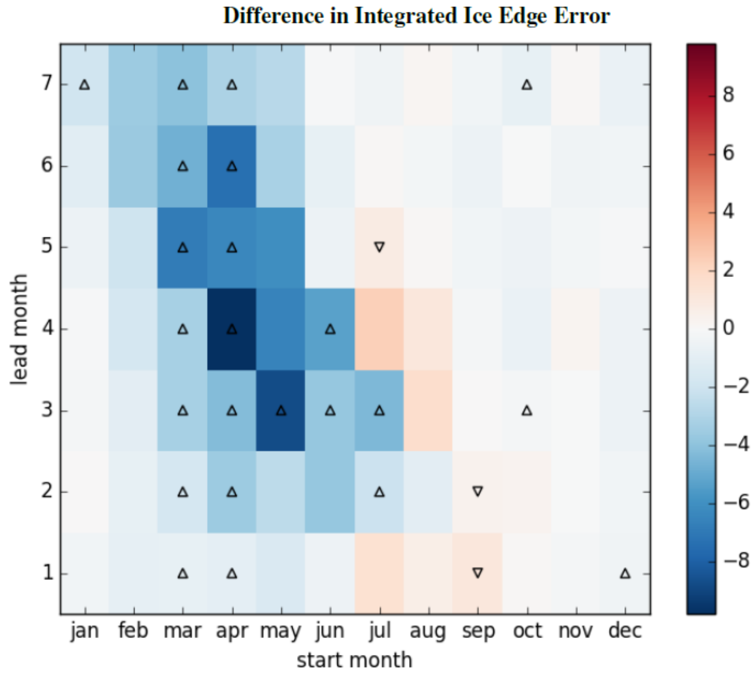
where SIT^n is the nudged thickness, SIT^m is the modelled thickness, SIT^o is the observed thickness, **tau** is the nudging coefficient



Sea-ice forecasts

Difference in forecast Integrated Ice Edge Error
(2011-2016, verified against OSI-401b)

with SIT nudging – No SIT nudging



Balan Sarojini, et al. 2019

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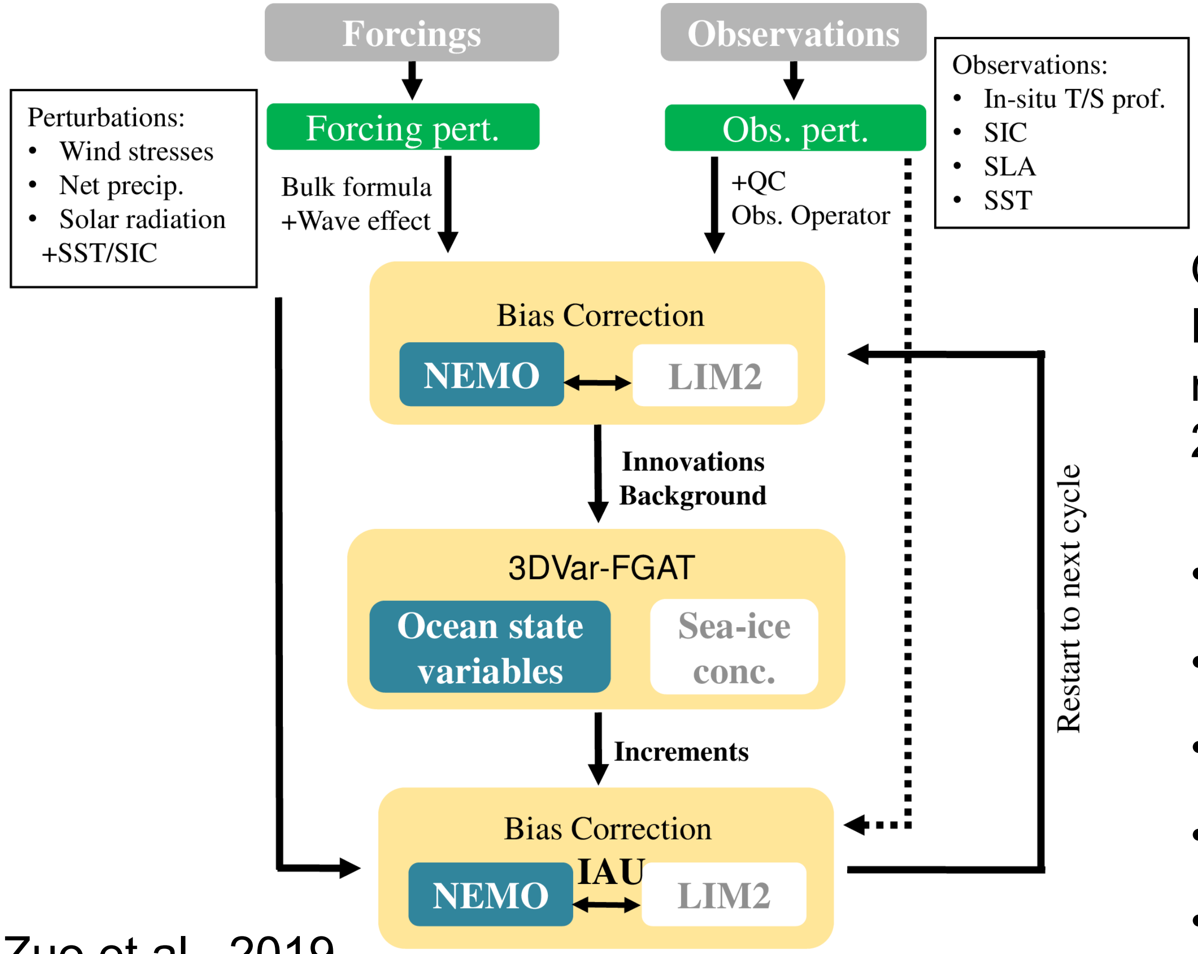
ECMWF Ocean Reanalysis-analysis system



Zuo et al., 2019

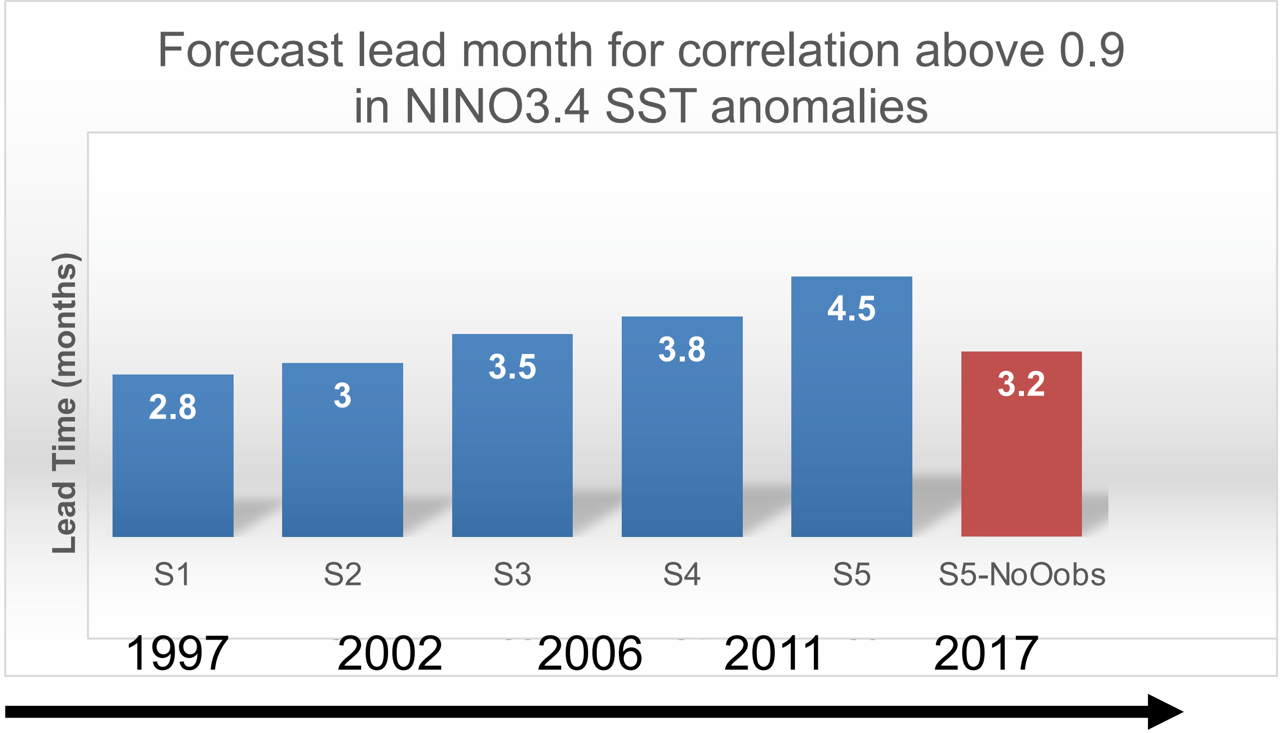
Overview of the OCEAN5 setup

OCEAN5 is the 5th generation of ECMWF ocean and sea-ice ensemble reanalysis-analysis system (Zuo et al., 2018, 2019).

- Ocean: NEMOv3.4
- Sea-ice: LIM2
- Resolution: ¼ degree with 75 levels
- Assimilation: 3DVAR-FGAT
- 5 ensemble member
- Forcing: ERA-int

Application of Ocean analysis: coupled forecasts

OCEAN5 provides ocean and sea-ice initial conditions for all ECMWF coupled forecasting system: (ENS, HRES, Seasonal). OCEAN5 also provides SST and SIC conditions for the ECMWF atmospheric analysis system (Browne et al., 2018)

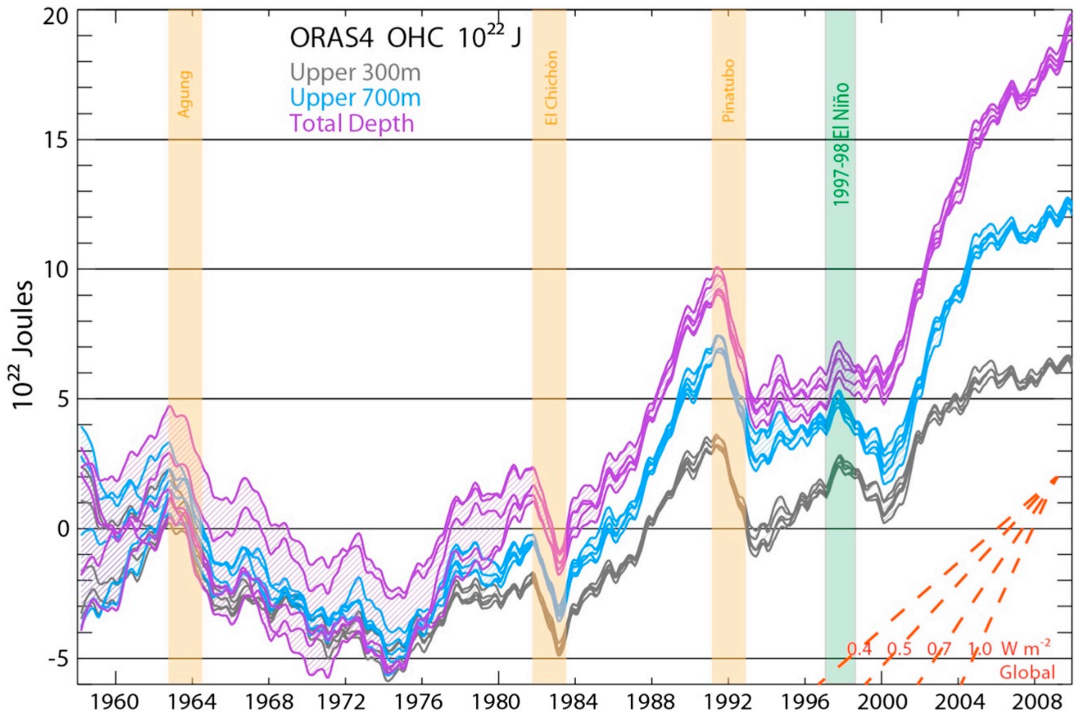


- Gain about 2 months in ENSO prediction
- Without Ocean observation and DA, we would lose about 15 years of progress.

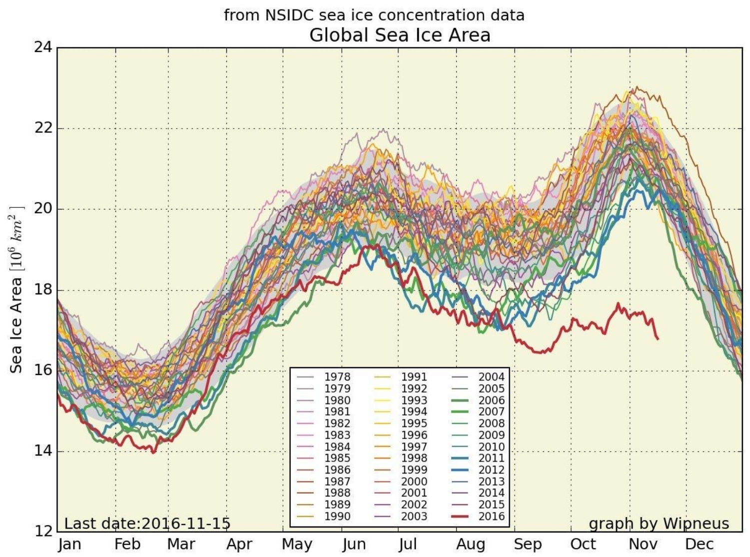
Application of Ocean ReAnalysis: climate monitoring

ORAS4 suggests that there is more heat absorbed by the deeper ocean after 2004.

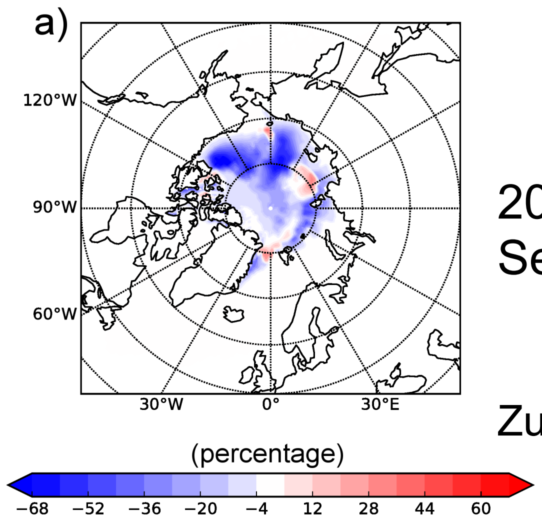
ocean heat content changes



Balmaseda et al., 2013



Sea-ice extent anomalies

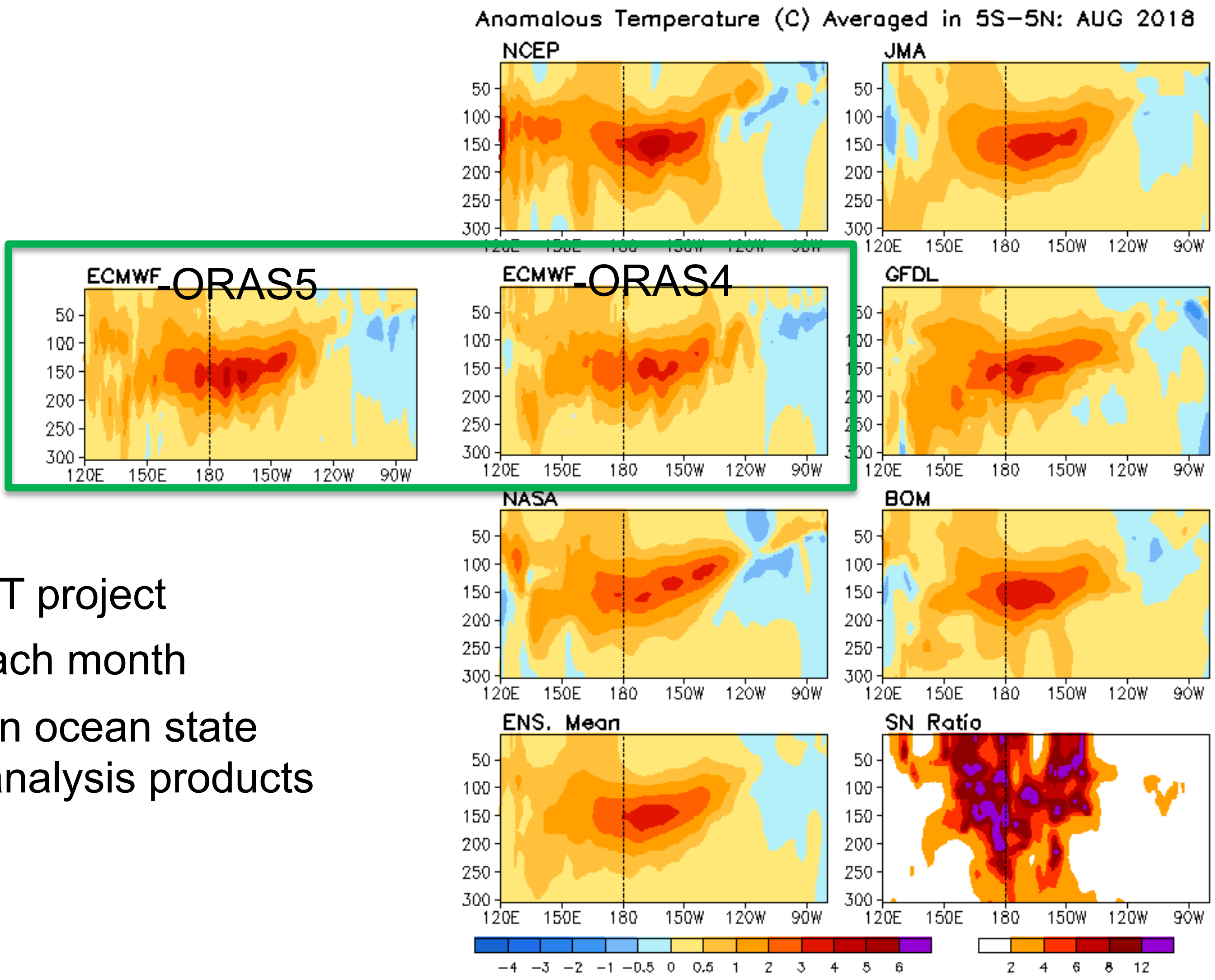


2016
September

Zuo & Lien, 2018

Application of ocean analysis: RT monitoring

Real-Time monitoring of ENSO state Ref: 1981-2010



Contribution to the ORIP-RT project

- Update on the 1st day each month
- Compare the latest mean ocean state with 8 other RT Ocean analysis products

ECMWF

Summary

- **Data assimilation in the ocean serves a variety of purposes**, from climate monitoring to initialization of coupled model forecasts and ocean mesoscale prediction.
- This lecture dealt mainly with ocean DA for **initialization of coupled forecasts and reanalyses**, with a global ocean model in climate resolution and use **NEMOVAR** as an example.
- Compared to the atmosphere, **ocean observations are sparse**. The main source of information are temperature and salinity profiles, sea level and ocean wave from altimeter, SST/SIC/SIT from satellite and in-situ.
- ECMWF NEMOVAR uses a incremental **3DVar-FGAT** configuration and linearized cost function. The BGE covariance is modelled use **balance** operator and **diffusion** operator.
- Data assimilation changes **the ocean mean state**. consistent ocean reanalysis requires an explicit treatment of model biases.
- Assimilation of ocean observations reduces the **large uncertainty** due to model and forcing errors. It improves the initialization of coupled forecasts in NWP, and provides **calibration and initialization** for reforecast for seasonal forecasts and decadal forecasts.

Further Readings

Ocean Data assimilation

- Balmaseda, M. A., Dee, D., Vidard, A., & Anderson, D. L. T. (2007). A multivariate treatment of bias for sequential data assimilation: Application to the tropical oceans. *Quarterly Journal of the Royal Meteorological Society*, *133*(622), 167–179.
- Mogensen, K., Alonso Balmaseda, M., & Weaver, A. (2012). The NEMOVAR ocean data assimilation system as implemented in the ECMWF ocean analysis for System 4. Technical Memorandum (Vol. 668).
- Weaver, A. T., Deltel, C., Machu, É., Ricci, S., & Daget, N. (2005). A multivariate balance operator for variational ocean data assimilation. Quarterly Journal of the Royal Meteorological Society, 131(613), 3605–3625.
- Zuo, H., Balmaseda, M. A., Boisseson, E. De, Hirahara, S., Chrust, M., & Rosnay, P. De. (2017). A generic ensemble generation scheme for data assimilation and ocean analysis. *ECMWF Tech Memo*, *795*.

Ocean DA and Reanalysis

- Balmaseda, M. A., Mogensen, K., & Weaver, A. T. (2013). Evaluation of the ECMWF ocean reanalysis system ORAS4. Quarterly Journal of the Royal Meteorological Society, 139(674), 1132–1161.
- Zuo, H., Balmaseda, M. A., & Mogensen, K. (2015). The new eddy-permitting ORAP5 ocean reanalysis: description, evaluation and uncertainties in climate signals. Climate Dynamics.
- Zuo, H., Balmaseda, M. A., Tietsche, S., Mogensen, K., & Mayer, M. (2019). The ECMWF operational ensemble reanalysis-analysis system for ocean and sea-ice : a description of the system and assessment. *Ocean Science*, (January), 1–44.