Recent Developments in the Use of Satellite Observations in Numerical Weather Prediction:

Ocean Data Assimilation

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ECMWF Summer Seminars
September 2007

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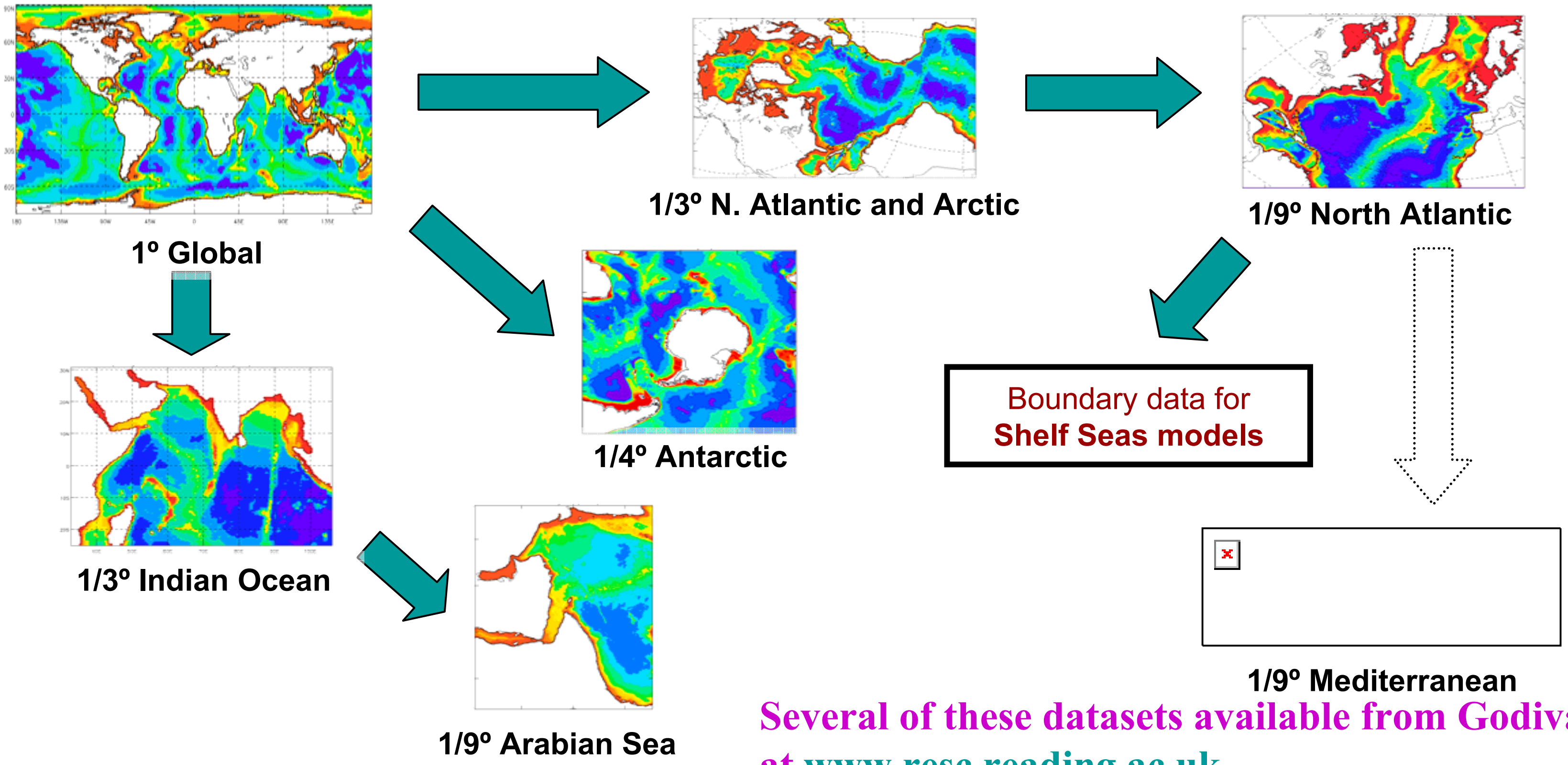
Topics

- **Applications of Ocean DA**
  - Operational Oceanography
  - Ocean Synthesis/Reanalysis
  - Seasonal – Interannual Forecasting (coupled models)
- **Assimilation data sets**
  - Altimeter sea level anomalies
  - The Geoid and the Mean Dynamic Topography
  - In Situ data, (T,S) and Argo
- **Assimilation techniques**
  - Bias treatment
  - State dependent covariances
  - Coupled model assimilation

Operational oceanography at the MetO

- Model resolution is key to capturing the dynamic processes
- All models in transition to NEMO (MetO will run ¼ global version)
- In Situ and **Altimeter** data sets are key for assimilation



Several of these datasets available from Godiva2 at www.resc.reading.ac.uk

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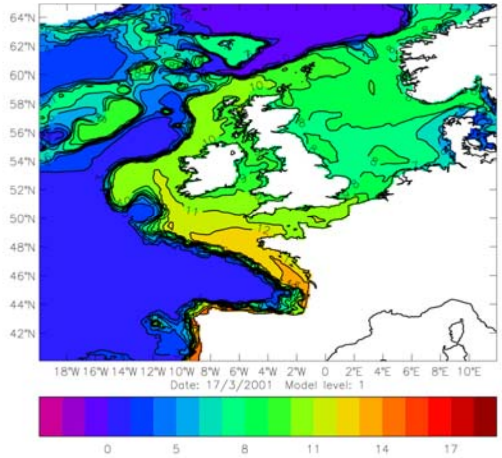
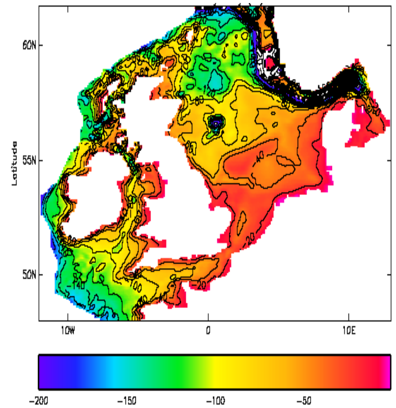
Shelf seas models at MetO

- State of the art model developed with POL
- Driven with Met Office Numerical Weather Prediction
- Can produce a range of output
  - tidal, met & density driven currents
  - temperature, salinity, seasonal stratification
- Forecasts of tidal currents and sea level elevation available years ahead, through NCOF
- Currently assimilation under research

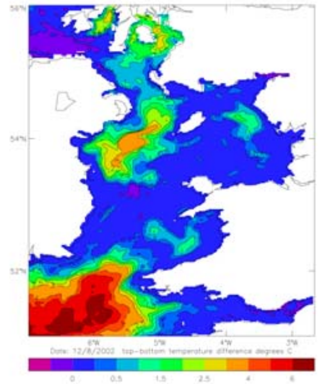
Atlantic Margin Model (AMM) – 12km Resolution



Medium Resolution Continental Shelf (MRCS) – 6km Resolution



Irish Sea – 1.8km Resolution



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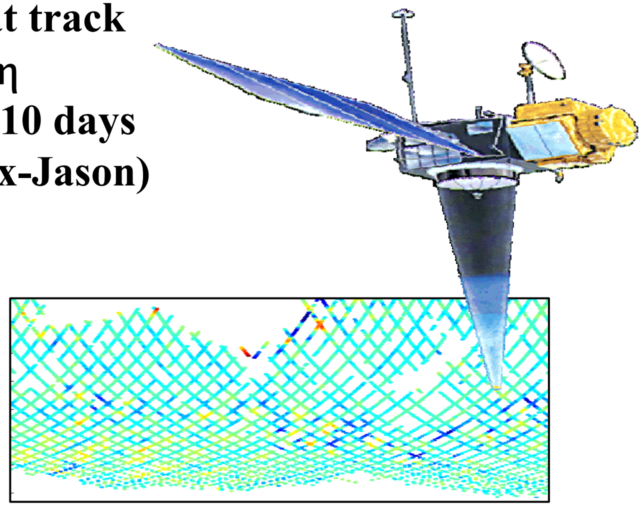
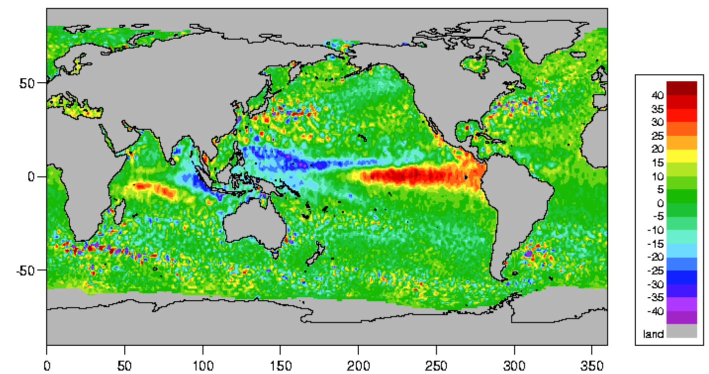
Key Data for Operational Oceanography

Altimetric Sea level **anomalies**

Repeat track
SSH=η
every 10 days
(Topex-Jason)

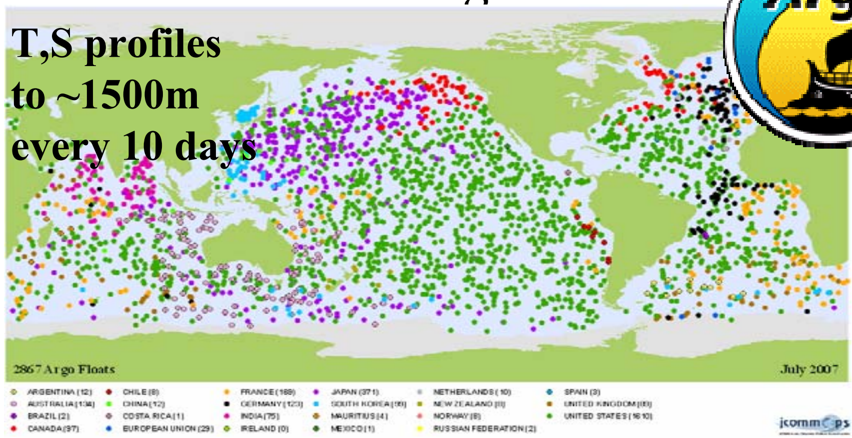


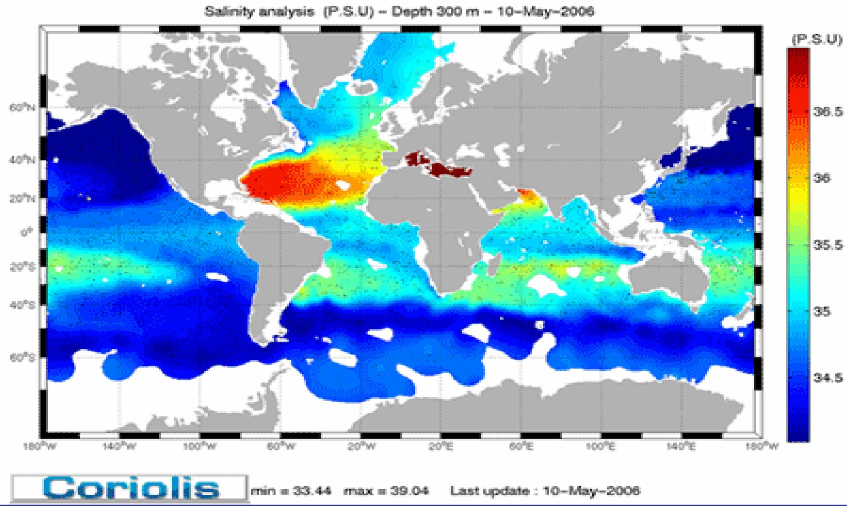
TOPEX + ERS2 sea surface height anomaly (cm). 25 November 1997.



In Situ data from Argo and TAO

T,S profiles
to ~1500m
every 10 days





Complementary

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Two Key problems of Altimeter Assimilation

- Projecting the sea surface height signal below the surface
  - Covariance functions
  - Physically based methods
- How to treat the mean sea surface height or Mean Dynamic Topography?
  - MDT from elsewhere eg. Ocean model
  - Error characteristics very different from Altimeter anomalies
  - Problem in Observation bias

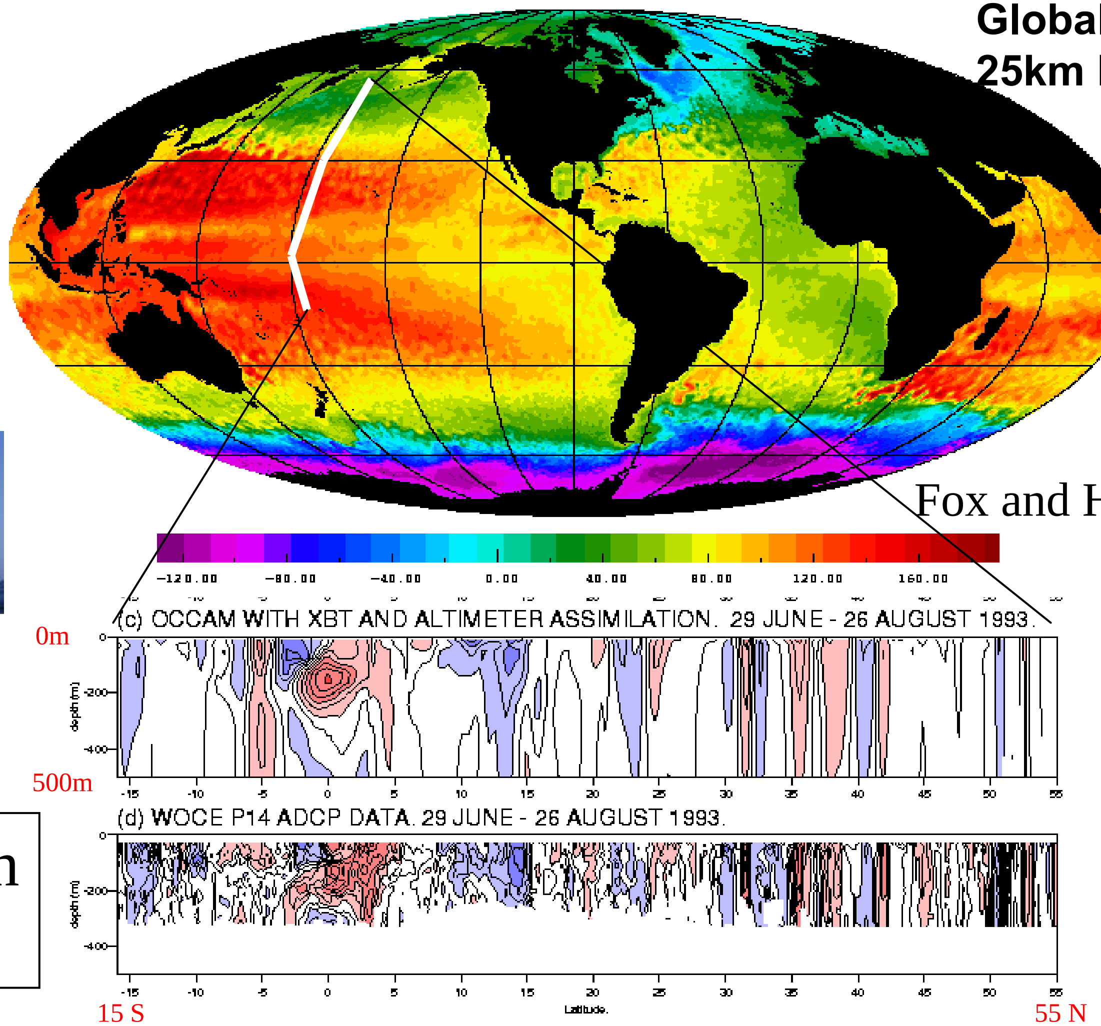
Assimilation of Satellite Altimeter

Altimeter
SSH_anomaly
η_a

In Situ
T(z)

Assimilation

Ship Validation
WOCE Cruise



Covariance vertical projection of sea level

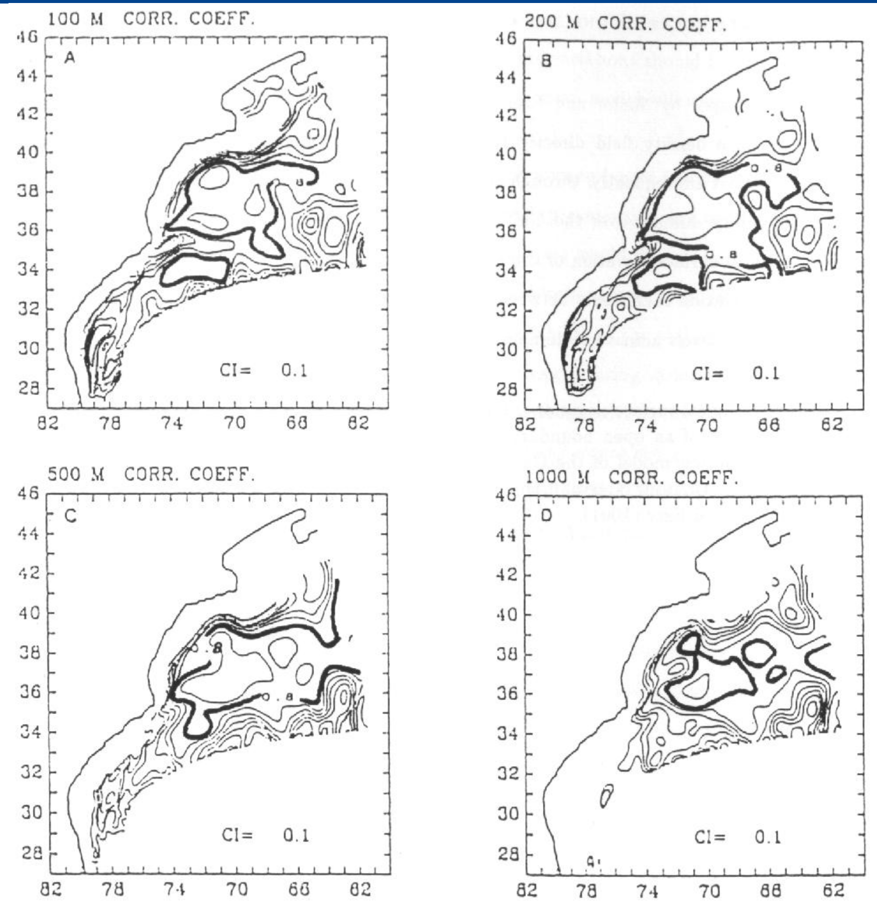
US East Coast model

Mellor and Ezer (1991)

- Sea level correlated with subsurface density
- Correlations based on model variability

Potential problems

- Must perform long model runs to generate correlations
- Must store and retrieve correlations for assimilation (which may vary in x,y,t)
- State dependent covariance may be needed, eg. ENSO v. non-ENSO years, (could forecast covariances)



Solid contour = correlation coeff. of $\rho(z)$ with η of 0.8

Altimeter assimilation by thermocline displacement Δh

Sea surface height correlated with thermocline displacements

Displacements $\propto$ Stratification

PV and water mass conserving

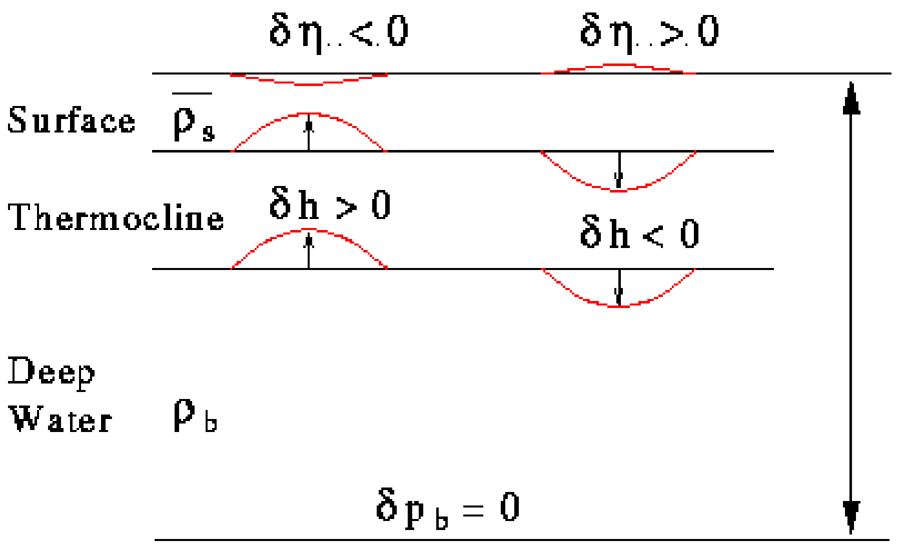
$$\mathbf{q} = \frac{\mathbf{f}}{\rho_0} \frac{\partial \rho}{\partial \mathbf{z}}.$$

Model **q(ρ)** is preserved by Assimilation provided;

$$\Delta \rho = \frac{\partial \rho}{\partial \mathbf{z}} \Delta \mathbf{h},$$

Solve for **Δh** by assuming deep pressure unchanged

$$-\rho_0 g \delta\eta = \mathbf{g} \int_{-\mathbf{H}}^{0} \Delta \rho \, d\mathbf{z},$$



Cooper and Haines (1996)

- **Simple to implement**
- **Gives flow dependent covariances**
- **Allows other *in situ* data to alter water masses**
- **Can build physical covariances as balancing operators eg.Var assimilation schemes eg. Weaver et al 2005, QJ**

$$\Delta \rho = \frac{\partial \rho}{\partial \mathbf{z}} \Delta \mathbf{h},$$

- **But won't work for deep barotropic circulations eg. at high latitudes**

A linearized balance operator for global ocean assimilation (Weaver *et al*., 2005, QJRMS)

- Balance Operator based on Observed Ocean Temperature

Temperature	$\delta T^k = \delta T^k = \delta T^k$
Salinity	$\delta S^k = \mathbf{K}_{ST}^{k-1}\delta T^k + \delta S_U^k = \delta S_B^k + \delta S_U^k$
SSH	$\delta\eta^k = \mathbf{K}_{\eta\rho}^{k-1}\delta\rho^k + \delta\eta_U^k = \delta\eta_B^k + \delta\eta_U^k$
u-velocity	$\delta u^k = \mathbf{K}_{up}^{k-1}\delta p^k + \delta u_U^k = \delta u_B^k + \delta u_U^k$
v-velocity	$\delta v^k = \mathbf{K}_{vp}^{k-1}\delta p^k + \delta v_U^k = \delta v_B^k + \delta v_U^k$

Treat as approximately mutually independent (Derber & Wu, 1998, MWR).

Density	$\delta\rho^k = \mathbf{K}_{\rho T}^{k-1}\delta T^k + \mathbf{K}_{\rho S}^{k-1}\delta S^k$
Pressure	$\delta p^k = \mathbf{K}_{p\rho}\delta\rho^k + \mathbf{K}_{p\eta}\delta\eta^k$

Components of the balance operator

Salinity balance
(approx. T-S conservation)

$$\delta S_B^k = \gamma^{k-1} \left(\partial S \big/ \partial z \right)_{S=S^{k-1}} \left(\partial z \big/ \partial T \right)_{T=T^{k-1}} \delta T^k$$

SSH balance
(baroclinic)

$$(\nabla \cdot H \nabla) \delta \eta_B^k = -\nabla \cdot \int_{z=-H}^{0} \int_{z'=z}^{0} \left(\nabla \delta \rho^k (z') / \rho_0 \right) dz' dz$$

u-velocity balance
(geostrophy with
β-plane approx. near eq.)

$$\delta u_B^k = -\frac{1}{\rho_0} \left(\frac{W_f}{f} + \frac{W_\beta}{\beta} \frac{1}{a} \frac{\partial}{\partial \varphi} \right) \frac{1}{a} \frac{\partial \delta \tilde{p}^k}{\partial \varphi}$$

v-velocity
(geostrophy, zero at eq.)

$$\delta v_B^k = \frac{1}{\rho_0} \frac{W_f}{f} \frac{1}{a \cos \varphi} \frac{\partial \delta \tilde{p}^k}{\partial \lambda}$$

Density
(linearized eq. of state)

$$\delta \rho^k = \rho_0 \left(-\alpha^{k-1} \delta T^k + \beta^{k-1} \left(\delta S_B^k + \delta S_U^k \right) \right)$$

Pressure
(hydrostatic approx.)

$$\delta \tilde{p}^k(z) = \int_{z'=z}^{0} \delta \rho^k (z') \, g \, dz' + \rho_0 g \left(\delta \eta_B^k + \delta \eta_U^k \right)$$

$+ \beta$–plane correction

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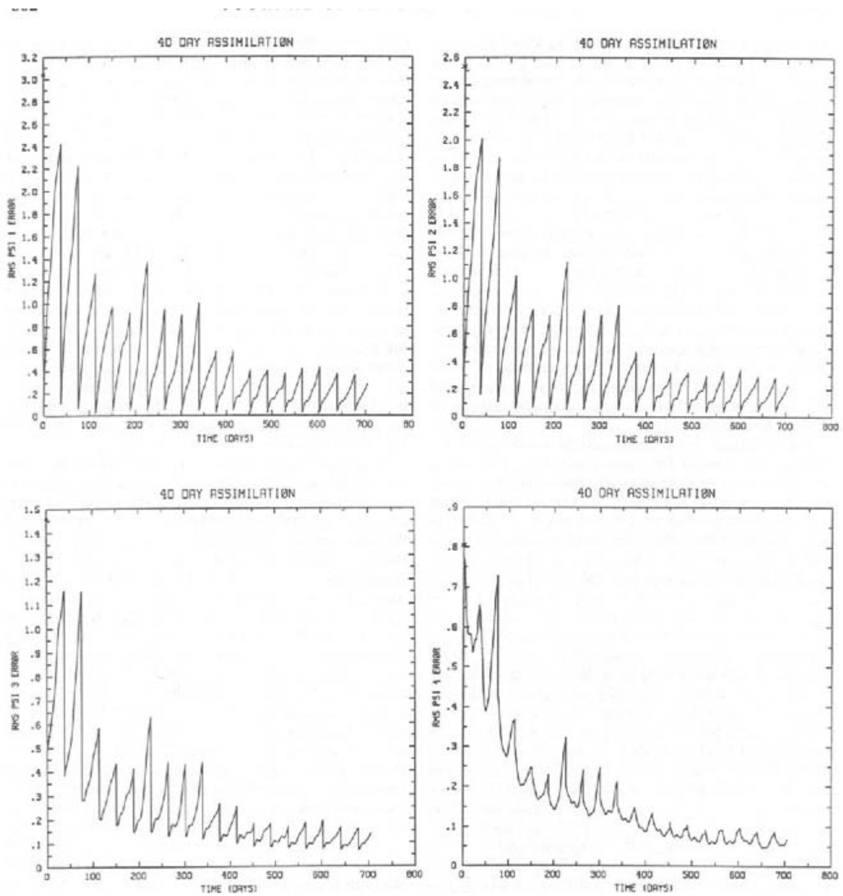
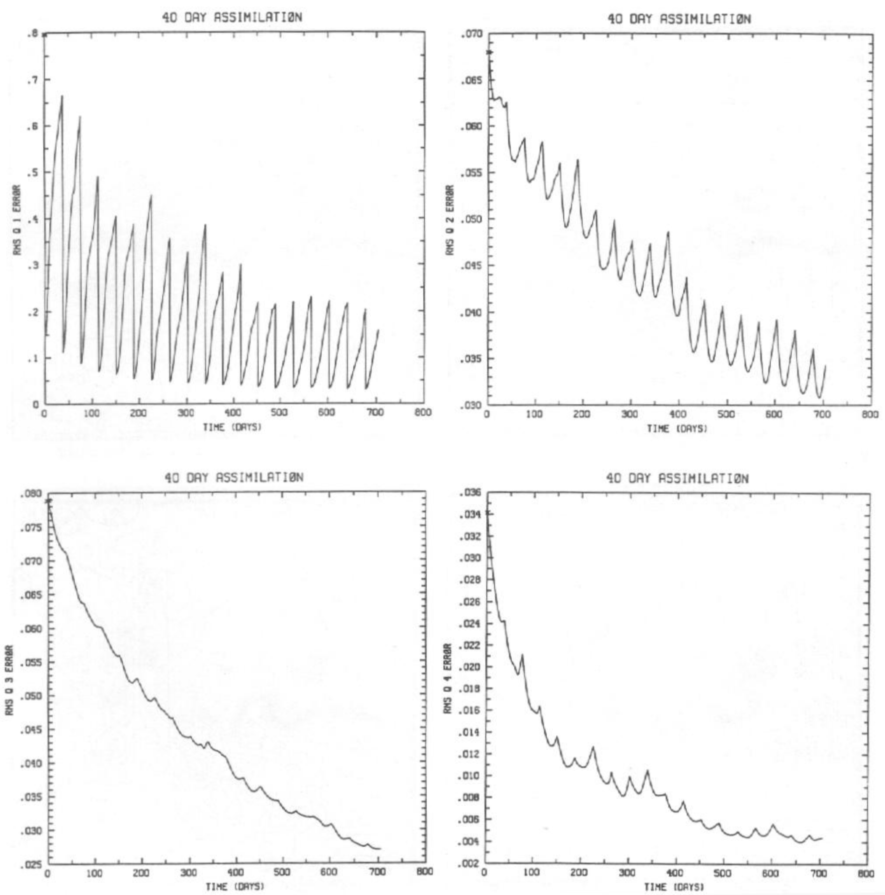
Twin experiment assimilation of ψ_1 every 40 days
4-layer QG box ocean model

$\psi_1 - \psi_4$



$q_1 - q_4$



Note $q_2 - q_4$ unchanging at assimilation times

Altimeter Twin in OCCAM 36 level PE model assimilating SSH

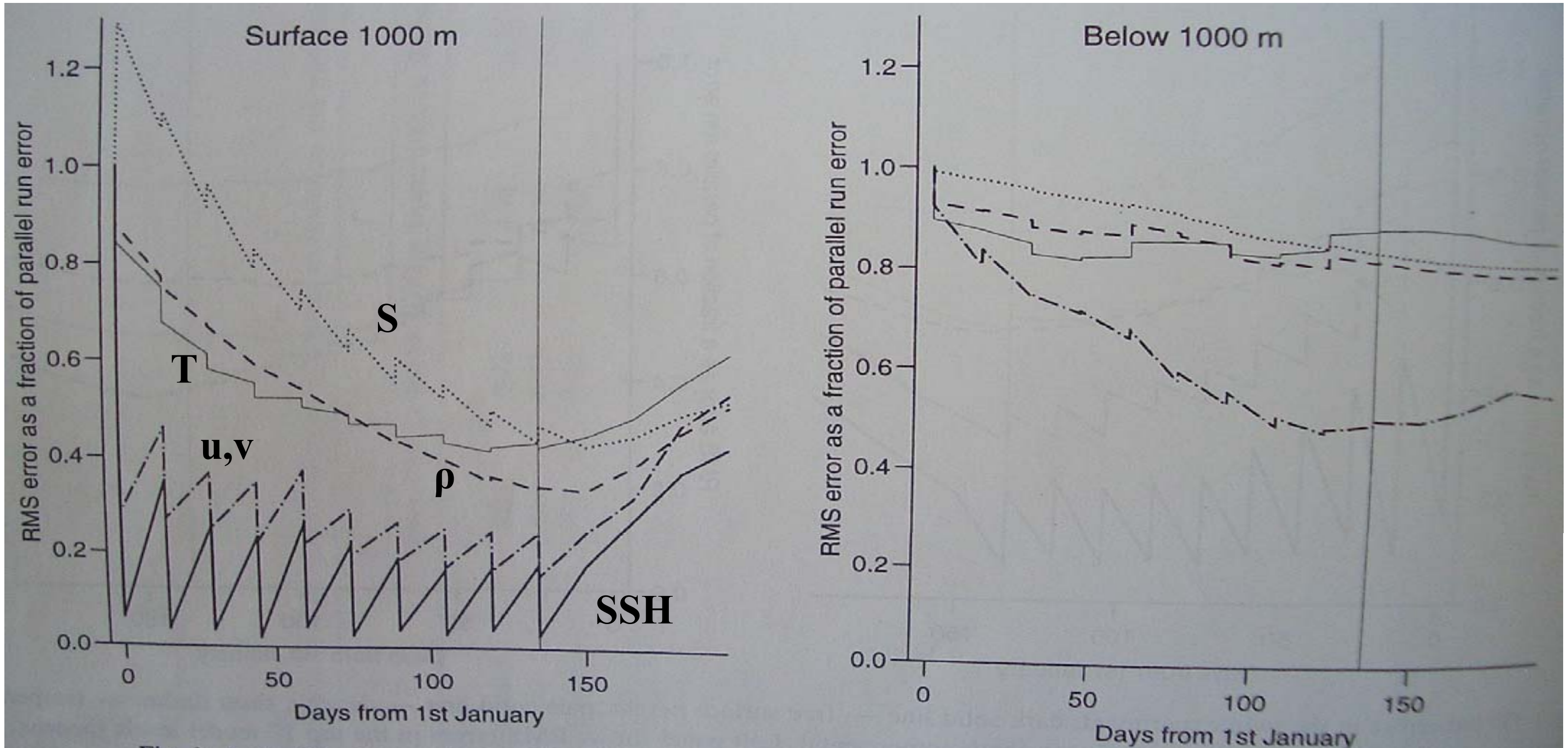


Fig. 3. As for Fig. 1 but calculated for the Gulf Stream/North Atlantic Current region. 30–80°W, 30–45°N.

Fox et al 2001a

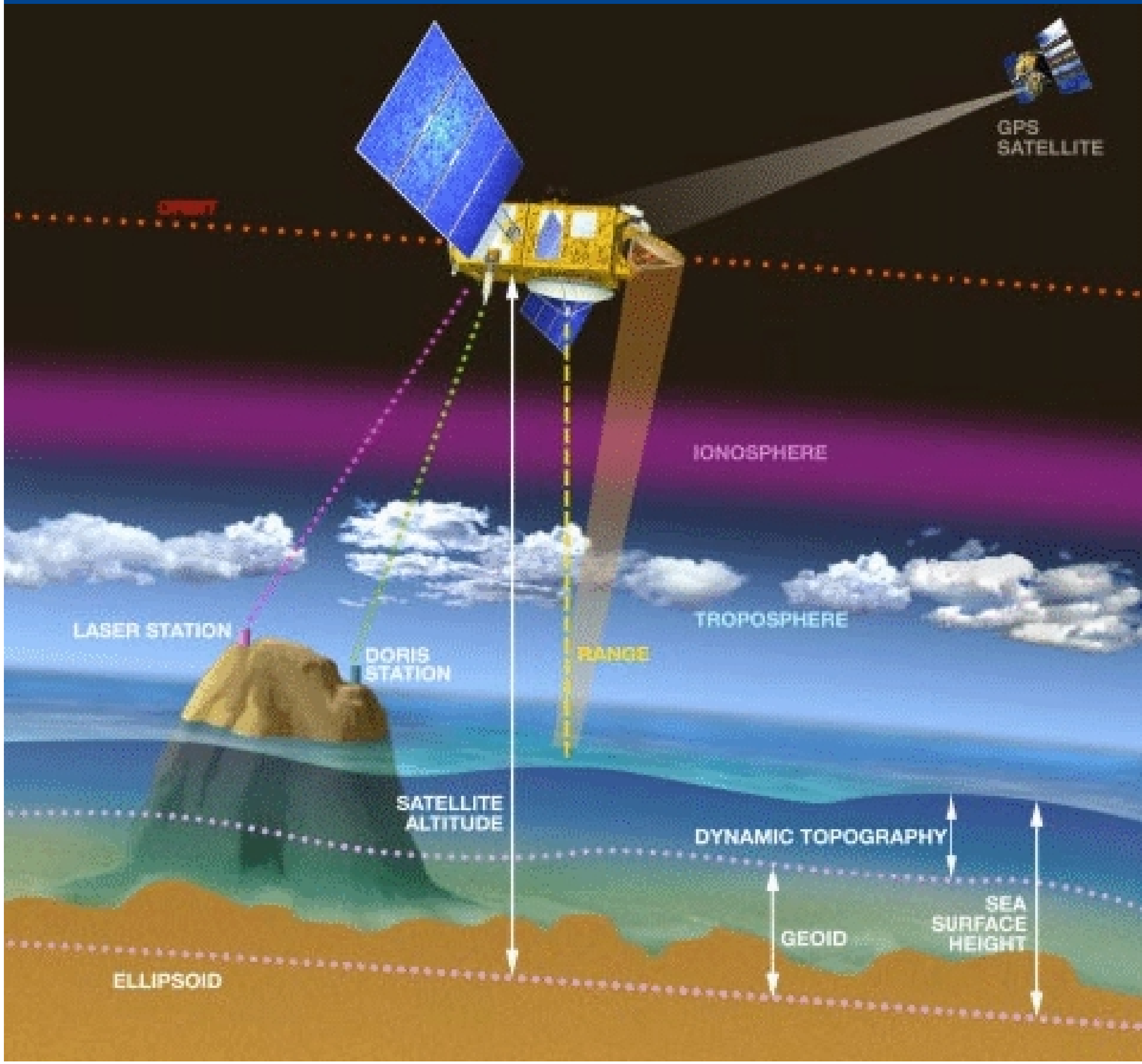
Note that subsurface T,S converge

Perhaps now could use Argo to demonstrate in real ocean?

Two Key problems of Altimeter Assimilation

- Projecting the dynamic topography signal below the surface
  - Covariance functions
  - Physically based methods
- How to treat the Mean Dynamic Topography?
  - MDT from elsewhere eg. Ocean model
  - Error characteristics very different from Altimeter anomalies
  - Problem in Observation bias

The Geoid, Altimetry and Ocean Dynamic Topography



- Geoid = surface of constant gravitational potential energy
- Sea level relative to Geoid = Dynamic Topography (DT) => Geostrophic currents
- Altimeters measure sea level relative to Earth ellipsoid not Geoid
- Can only use time-varying altimetry for oceanography because Geoid is not well known

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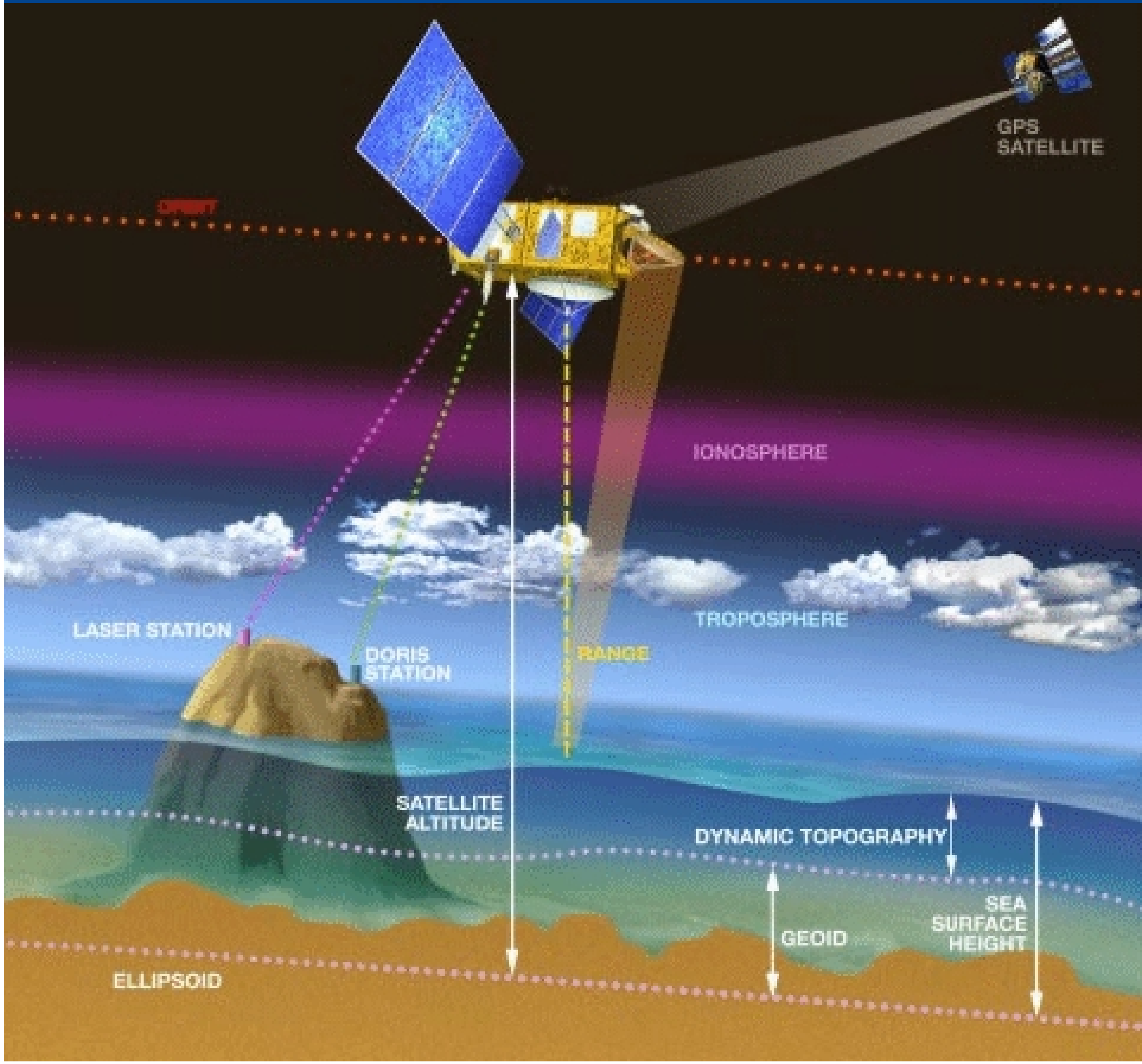
The Geoid, Altimetry and Ocean Dynamic Topography



Assimilation assumes <u>full DT</u>

DT= MDT + SSH_anomaly
where
MDT = Time mean DT

Like to use
MDT = Mean_SSH – Geoid

In practice
MDT model product

Error characteristics of
SSH_anomaly and MDT
Completely different

DT= MDT + SSH_anomaly
MDT error represents
constant observation bias

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Bias in Data Assimilation

- Dee (2006) Review in QJRMS
- 3D Variational formulation easiest to understand (derivable from Bayesian analysis; Drecourt et al; 2006)

$$2J(x,b,c) = (y-b-x)^T R^{-1}(y-b-x) + (x-x^f+c)^T B^{-1}(x-x^f+c) + (b-b^f)^T O^{-1}(b-b^f) + (b^T T^{-1} b +) (c-c^f)^T P^{-1}(c-c^f)$$

Minimise J wrt x,b,c

y =observation

x =model state

b =**observation bias**

c =**model forecast bias**

Superscript f are forecast values

Observation operators have been omitted

R =observation error covariance

B =model background error covariance

O =observation bias forecast error covariance

T= observation bias error covariance

P =model forecast bias error covariance

Drecourt et al 2006
Lea et al 2007 (draft)

Bias in Data Assimilation

- Solution (Analysed variables ^{a})

$$x^a = (x^f - c^f) + K\{(y - b^f) - (x^f - c^f)\} \qquad K = (B+P)[B+P+O+R]^{-1}$$

$$b^a = b^f + F\{(y - b^f) - (x^f - c^f)\} \qquad F = O[B+P+O+R]^{-1}$$

$$c^a = c^f + G\{(y - b^f) - (x^f - c^f)\} \qquad G = P[B+P+O+R]^{-1}$$

or $$x^a = (x^f - c^a) + K_1\{(y - b^a) - (x^f - c^a)\} \qquad K_1 = B[B+R]^{-1}$$

y =observation
x =model state
b =observation bias
c =model forecast bias

R =observation error covariance
B =model background error covariance
O =observation bias forecast error covariance
P =model forecast bias error covariance

- Usual problems are: (i) Knowing the Covariance errors: $\mathbf{O = \gamma_b T;\ P = \gamma_c B}$

(ii) Sequential 3DVar requires bias models:

Can use Persistence $\mathbf{b^f(t+1) = b^a(t);\quad c^f(t+1) = \beta c^a(t)}$ (β = 3 month decay)

Drecourt et al 2006
Lea et al 2007 (draft)

3D-Var cost function with model and obs. bias

$$J = (\mathbf{y} - \mathbf{H}(\mathbf{x}+\mathbf{b}))^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{H}(\mathbf{x}+\mathbf{b}))$$ Model data misfit

$$+ (\mathbf{x} - \mathbf{x}^f + \mathbf{c})^T \mathbf{B}^{-1} (\mathbf{x} - \mathbf{x}^f + \mathbf{c})$$ Background constraint

$$+ (\mathbf{b}^o - \mathbf{b})^T \mathbf{T}^{-1} (\mathbf{b}^o - \mathbf{b})^T$$ Obs bias constraint

$$+ (\mathbf{b} - \mathbf{b}^f)^T \mathbf{O}^{-1} (\mathbf{b} - \mathbf{b}^f)$$ Obs bias forecast constraint

$$+ (\mathbf{c} - \mathbf{c}^f)^T \mathbf{P}^{-1} (\mathbf{c} - \mathbf{c}^f)$$ Model bias forecast constraint

x – model state
y – observation
R – observation error covariance
B – background error covariance
H – observation operator

b – observation bias
c – model bias
T – observation bias error covariance
O – obs bias forecast error covariance
P – model bias forecast error covariance

Drecourt et al 2006
Lea et al 2007 (draft)

Method:
Analysis equations

$$\mathbf{x}^a = (\mathbf{x}^f - \mathbf{c}^f) + \mathbf{K}_1\{\mathbf{y} - \mathbf{H}(\mathbf{L}\mathbf{b}^o + (\mathbf{I} - \mathbf{L})\mathbf{b}^f) - \mathbf{H}(\mathbf{x}^f - \mathbf{c}^f)\} \quad ..$$

$$\mathbf{K}_1 = (\mathbf{B} + \mathbf{P})\mathbf{H}^T\{\mathbf{H}(\mathbf{B} + \mathbf{P} + \mathbf{L}\mathbf{T})\mathbf{H}^T + \mathbf{R}\}^{-1} \quad ....$$

State analysis

$$\mathbf{b}^a = \mathbf{H}(\mathbf{L}\mathbf{b}^o + (\mathbf{I} - \mathbf{L})\mathbf{b}^f + \mathbf{F}\{..\}$$

$$\mathbf{F} = \mathbf{L}\mathbf{T}\mathbf{H}^T\{....\}$$

Observation bias analysis

$$\mathbf{c}^a = \mathbf{c}^f - \mathbf{G}\{..\}$$

$$\mathbf{G} = \mathbf{P}\mathbf{H}^T\{....\}$$

Model bias analysis

Method applied to Altimeter assimilation in N Atlantic model at Met Office

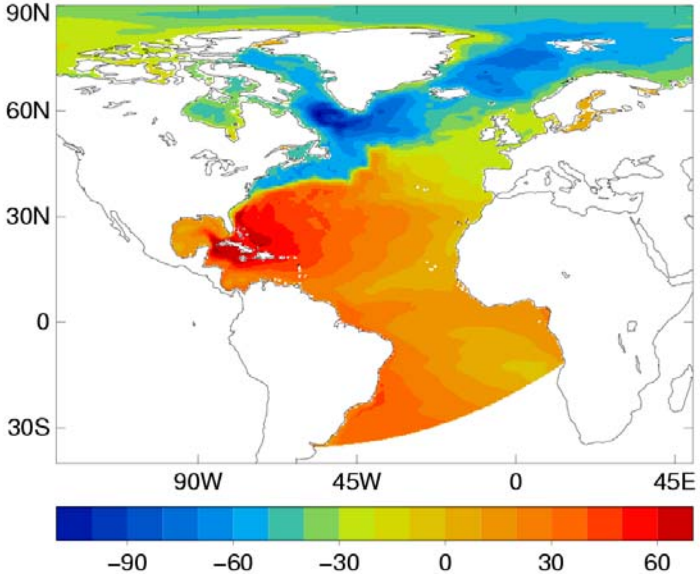
R – observation error covariance
B – background error covariance
T – observation bias error covariance
O – obs bias forecast error covariance
P – model bias forecast error covariance

Simplify by assuming

$\mathbf{O} = \gamma_b \mathbf{T}$ $\gamma_b = 0.01$ (**b** units cm MDT bias)
$\mathbf{P} = \gamma_c \mathbf{B}$ $\gamma_c = 10^{-3}$ (**c** units cm/day Model drift)

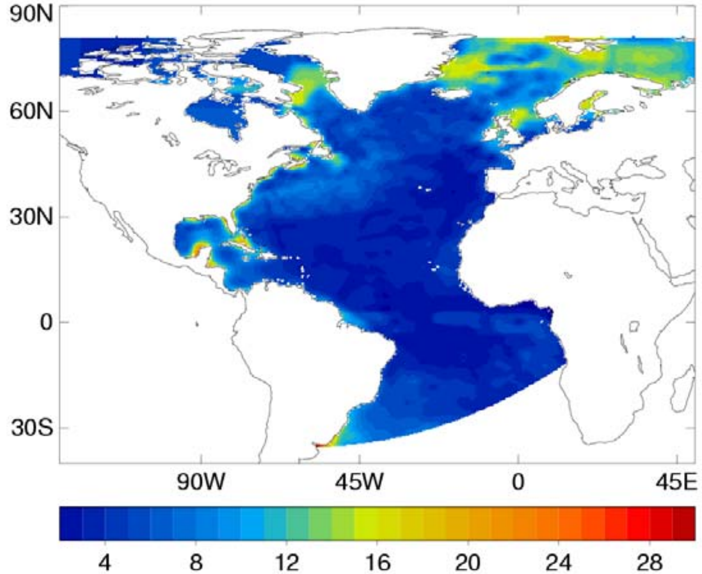
MDT Bias applied to Altimeter assimilation in N Atlantic model at Met Office

Original MDT /cm



Combined model mean, Singh and Kelly and GOCINA

Original MDT error /cm

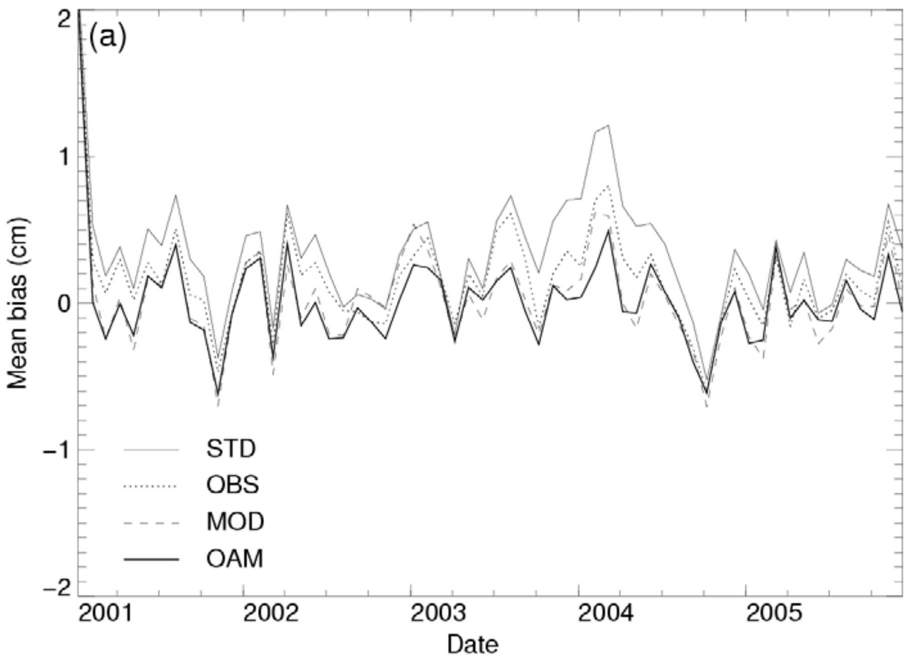


Rio (2005) MDT error (times 5) – use for **T**

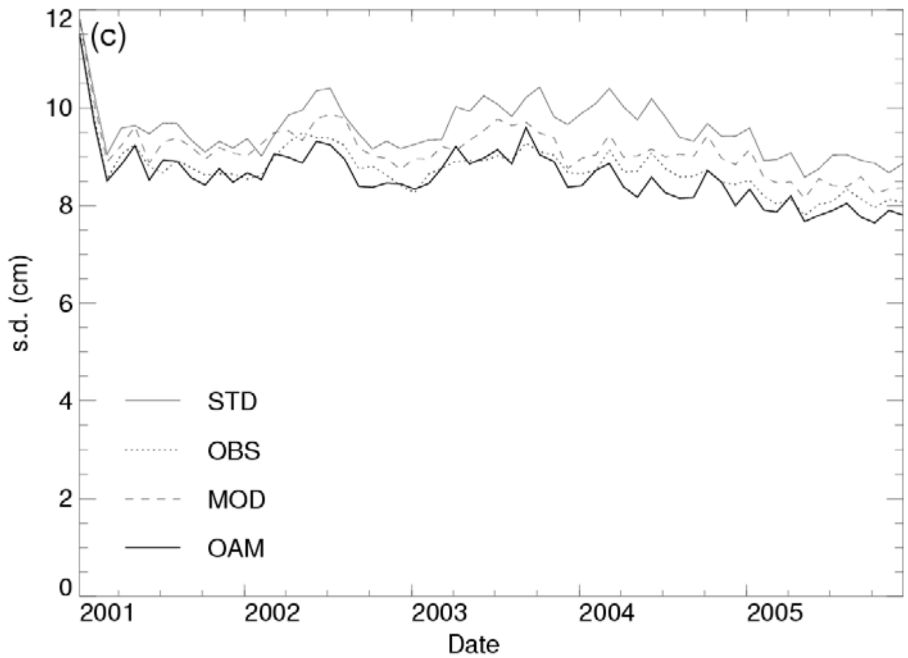
MDT and errors will come from GOCE mission data

Time series of innovations

Mean innovations

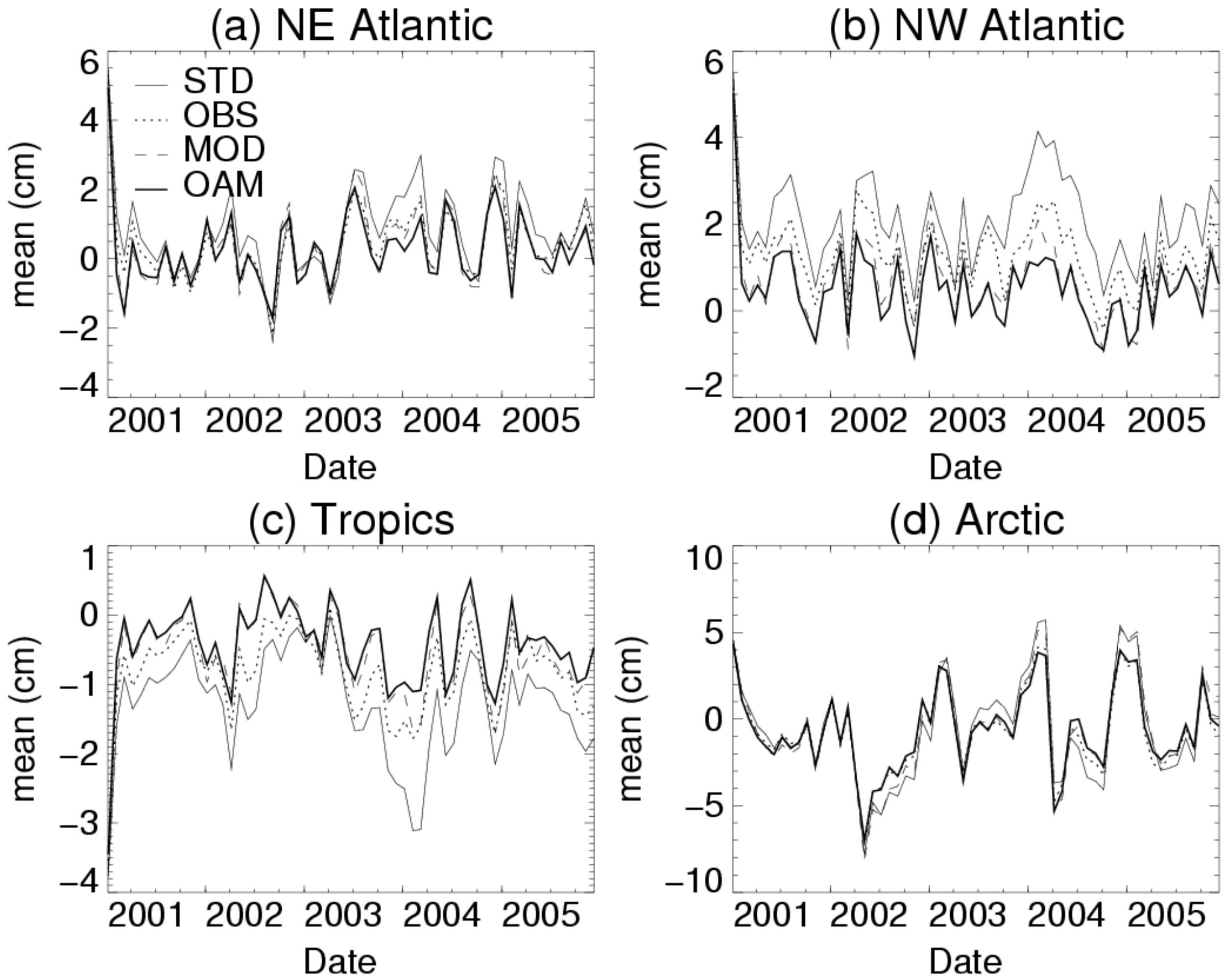


s.d. innovations

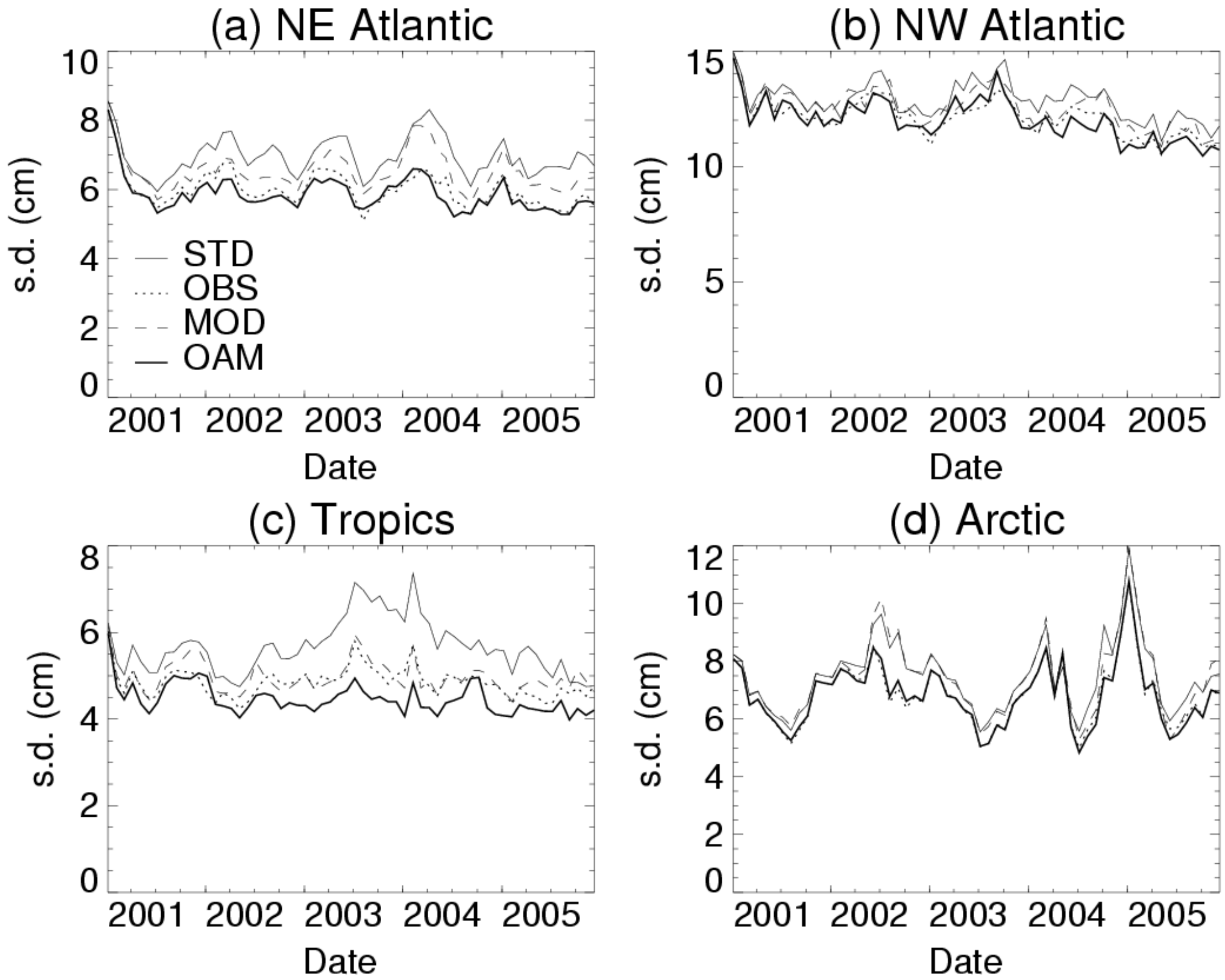


- Time variability and RMS reduced by bias correction
- Obs bias correction most effective in reducing RMS

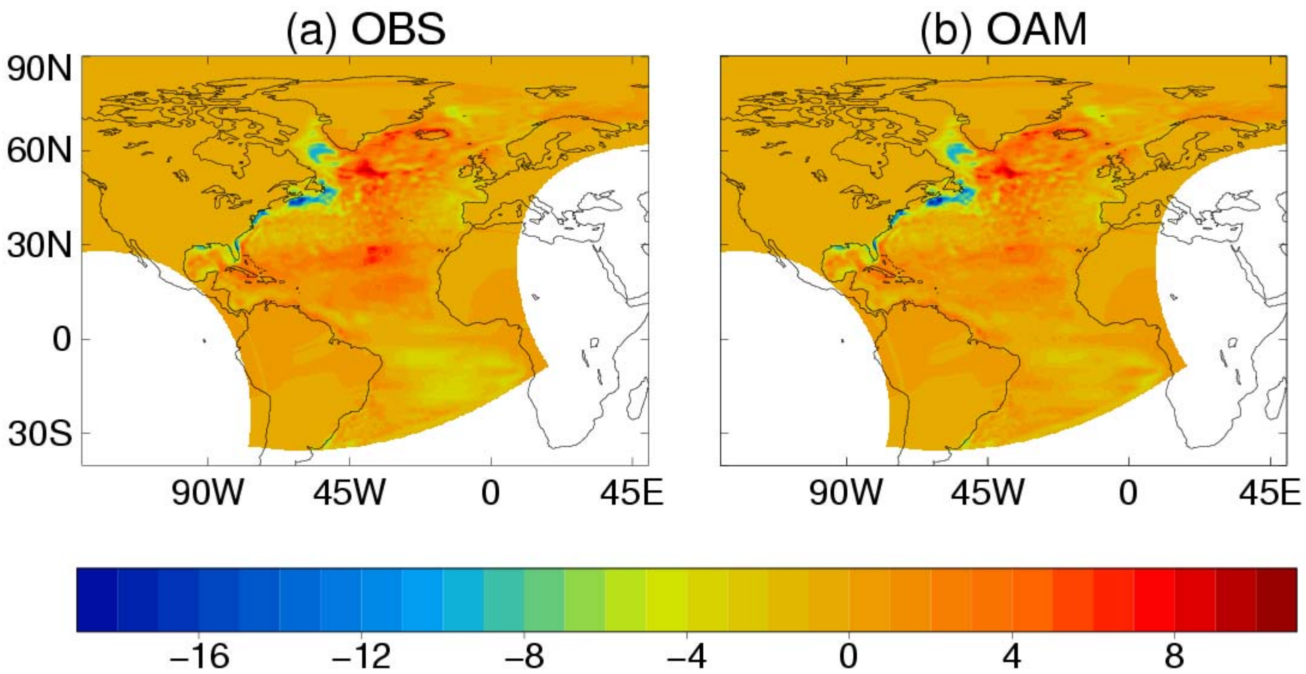
Mean Innovations in areas



Std dev of innovations in areas

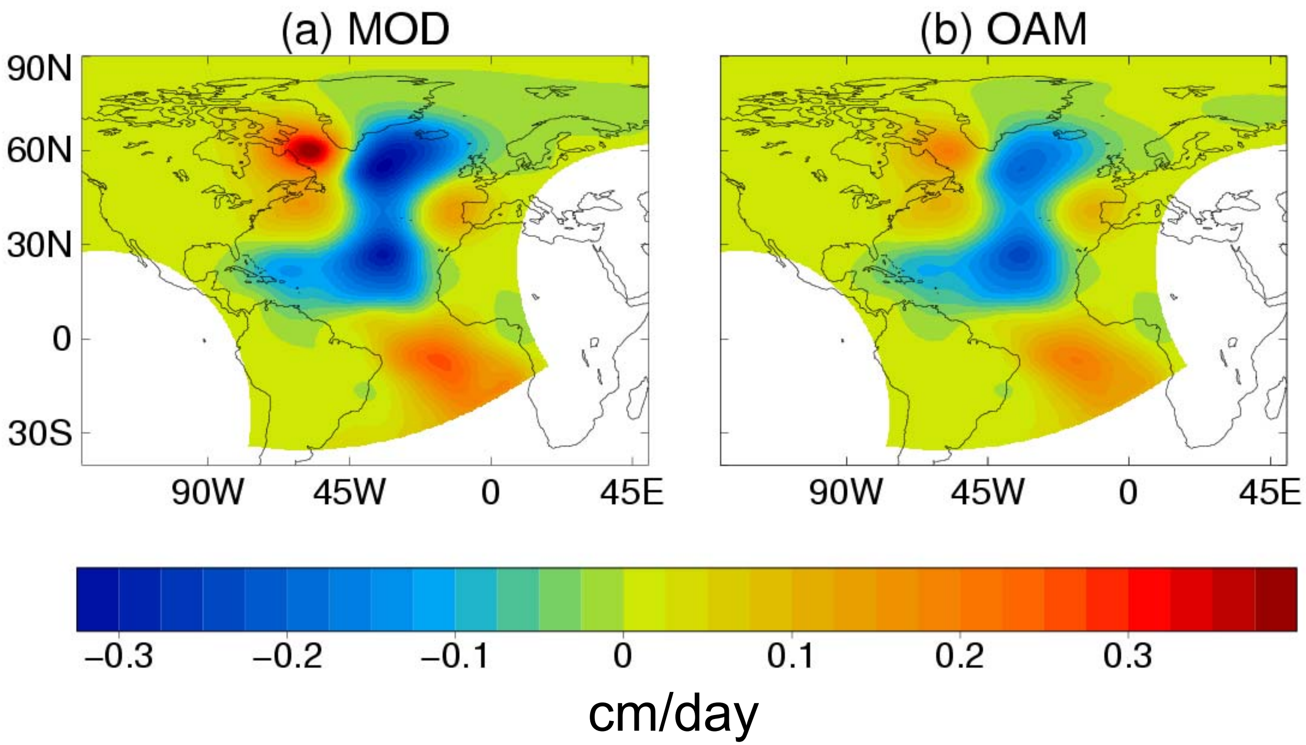


Mean obs bias field (**b** field)



- MDT lowered north of Gulf Stream, increased in sub-tropical gyre
- Pattern similar for both OBS and OAM. The model bias not significantly affecting the MDT estimate.

Mean model bias field (**c** field)



- Small mean model bias (units cm/day). Model is positively biased north of Gulf Stream and negatively biased in the sub-tropical gyre.
- Same pattern (with reversed sign) as **b** field (using the same info).

Data Assimilation for Ocean Synthesis/Reanalysis

Aims:

Recover ocean signals relevant to climate change (1950-present)

Changes in water masses

Changes in Ocean circulation (geostrophic) based on ρ measurements (eg. thermohaline circulation)

Changes in ocean heat content

Changes in ocean salinity=> hydrological cycle

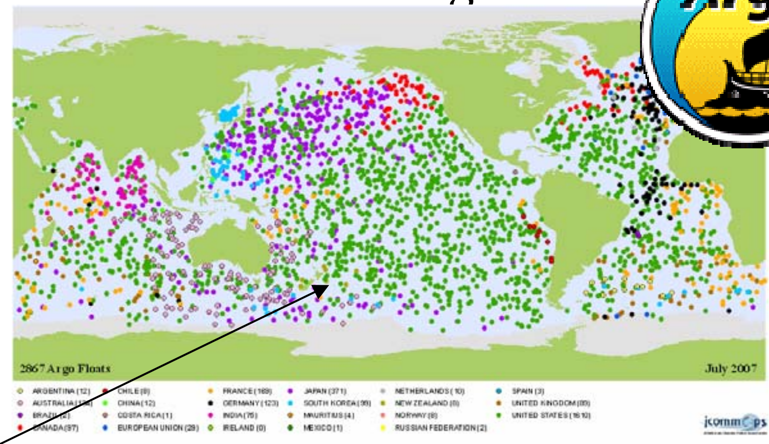
Infer errors/changes in air-sea fluxes from budgets

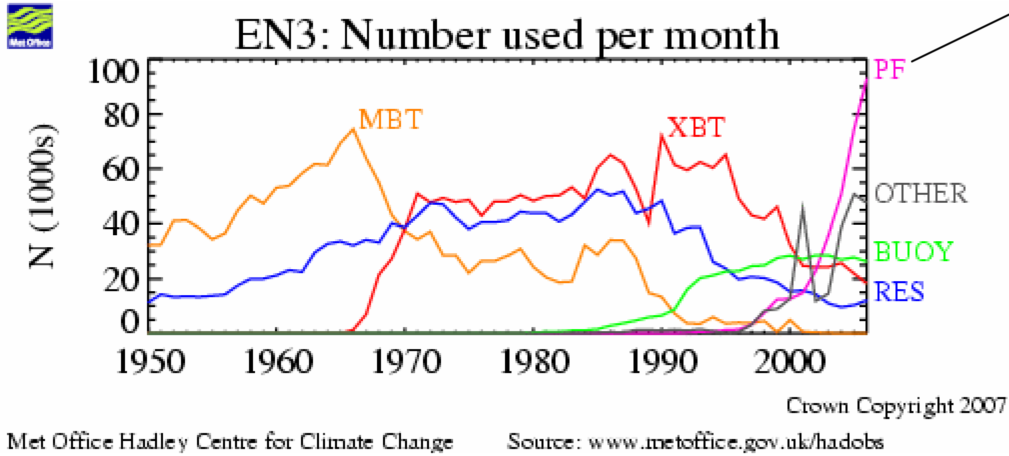
Key Data for Ocean Synthesis/Reanalysis

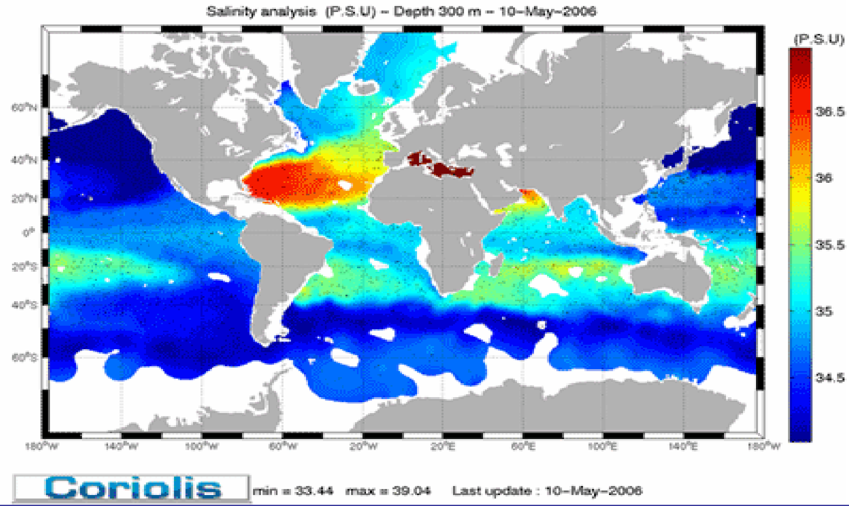
In situ data
T(z) profiles or
T(z) and S(z) profiles => ρ(z)

Instruments, spatial distribution and depth ranges vary through time

In Situ data from Argo PF



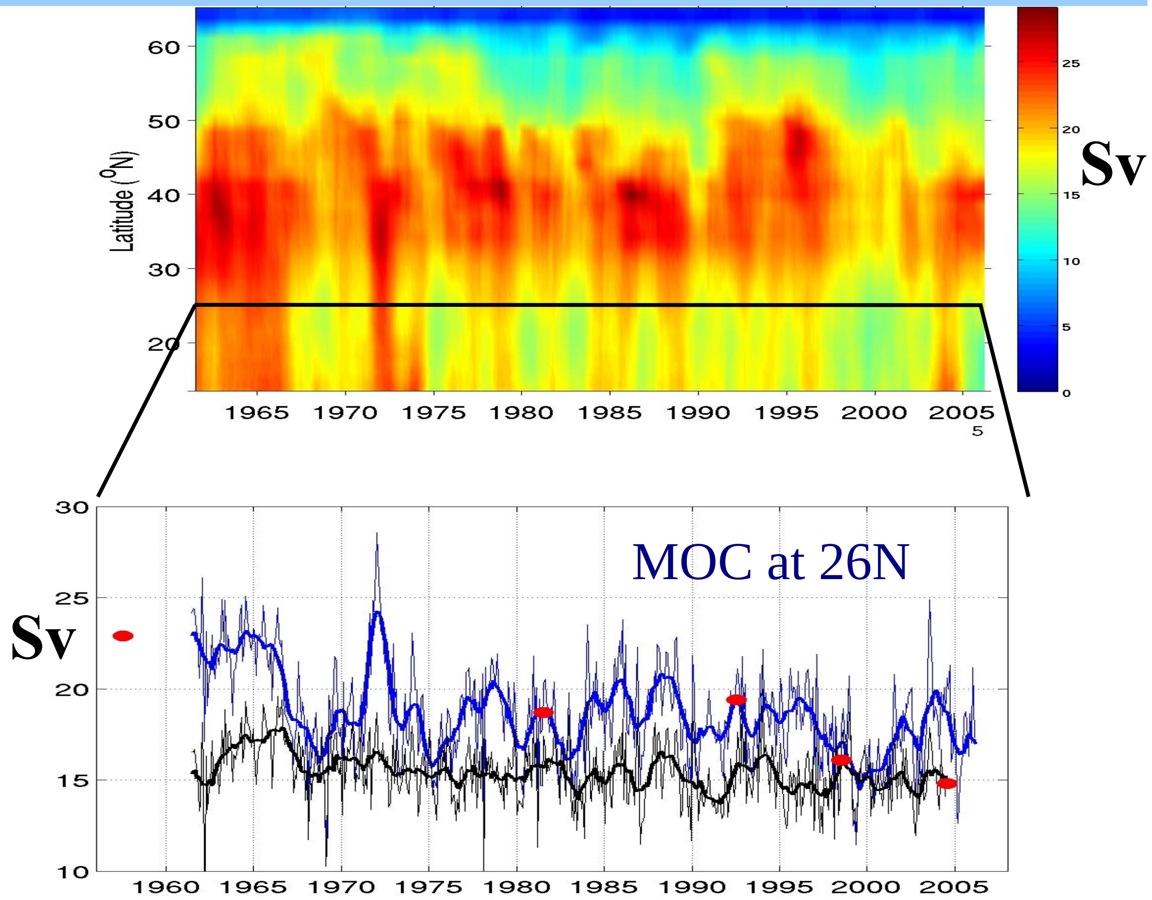




ECMWF Ocean Reanalysis 3 (ORA3)

- 47 year ocean reanalysis from ECMWF Seasonal Forecasting System 3
- 1° resolution ocean model with tropical enhancement
- Assimilates T(z) and salinity on isotherms S(T)

Atlantic Meridional Overturning Circulation



Balmaseda et al 2007 sub.

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* Obs from Bryden et al. (2005)

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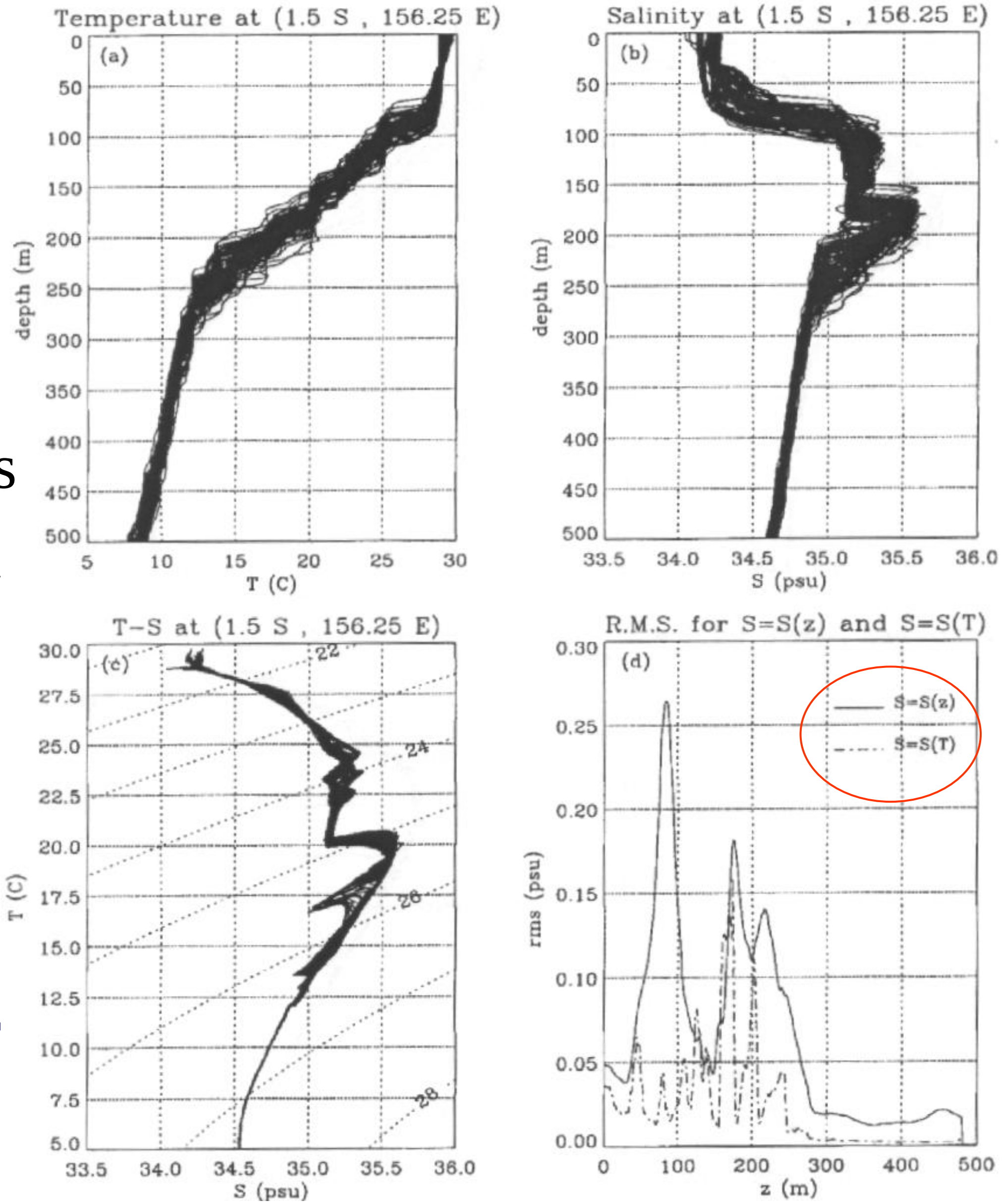
Dynamic v. thermodynamic variability

104 CTD profiles
over 10 days in
W. Equatorial Pacific

Reduced variance in
S(T) => water properties
not altered by High-freq
waves

Model Representivity
of S(T) better than for
S(z) or T(z)



Troccoli et al
(1999)

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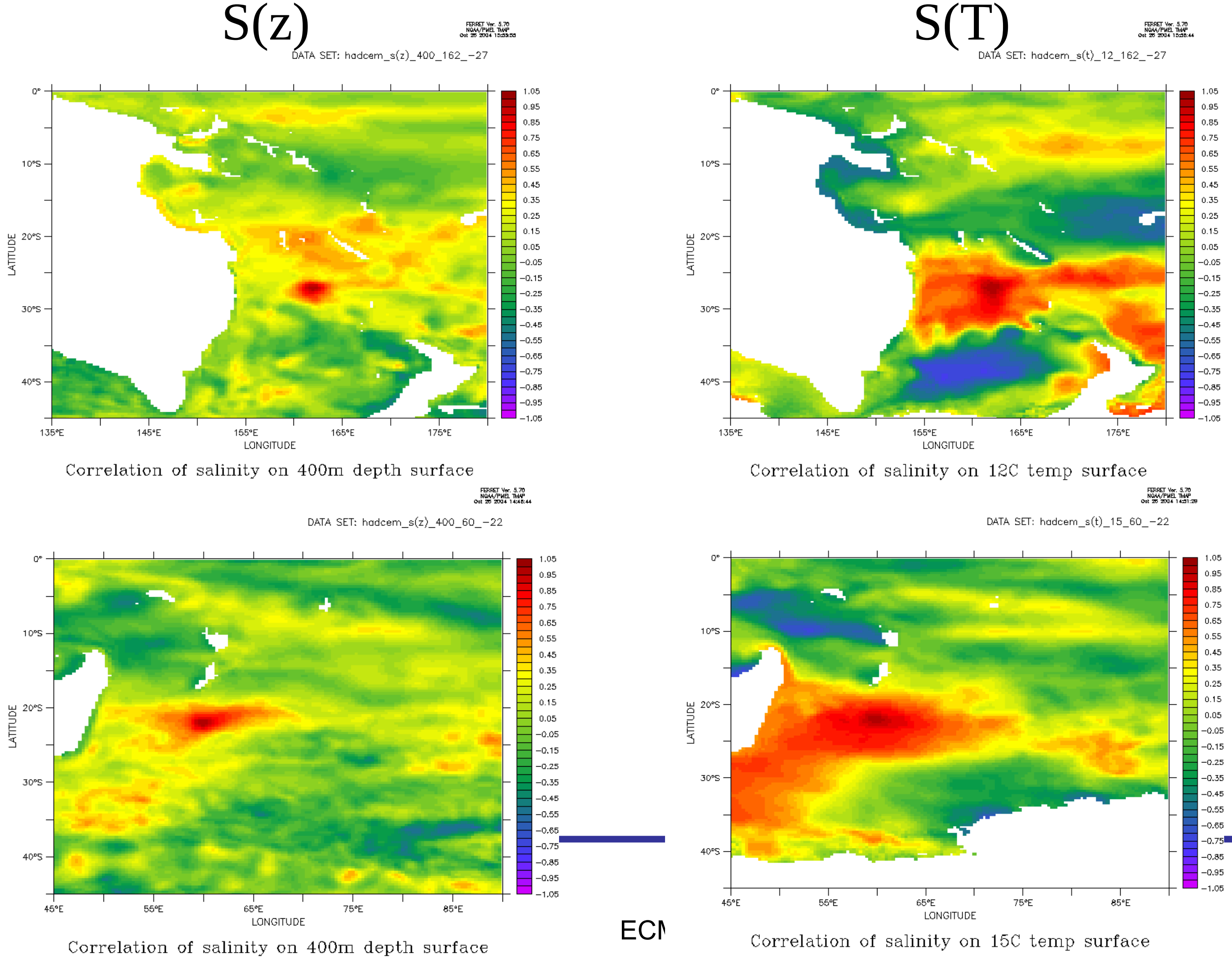
One point Salinity correlation maps HadCEM 1/3 model

S(z) S(T)



Expect error Covariances of S(T) to be larger Scale than S(z) => Useful in assimilation of Salinity data, especially for Reanalysis

Haines et al (2006)

Generalized observation operator

- Collocate observations on depth, isotherm and isopycnal levels
- By evaluating model-data difference on isotherm or isopycnal levels can better assess errors in water mass properties.
- For isotherms:
  - Given T,S -> Calculate T(z), S(T) for model and observations

    $T'(z) = T_b(z) + \Delta T(z)$

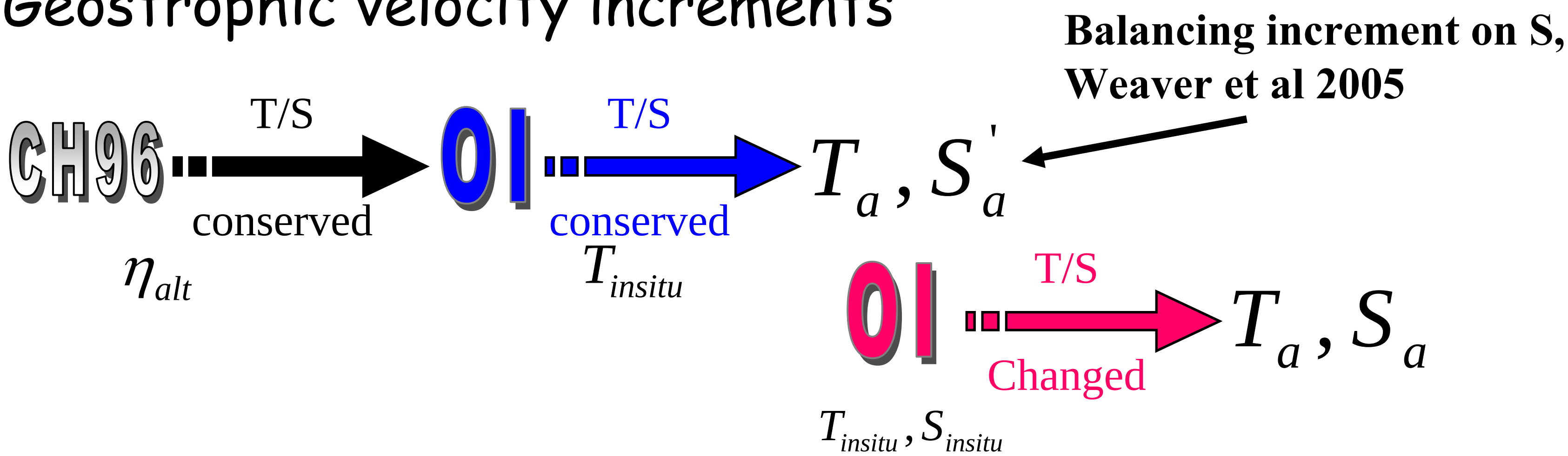
    $S'(T) = S_b(T) + \Delta S(T)$ implemented in ECMWF ORA3
- For isopycnals:
  - Given T, S -> Calculate Z(ρ), π(ρ) for model and observations

    $Z'(\rho) = Z_b(\rho) + \Delta Z(\rho)$

    $\pi'(\rho) = \pi_b(\rho) + \Delta\pi(\rho)$ where π(T,S,p) is "spice" orthogonal fn. to ρ(T,S,p)

ECMWF System 3 ocean analysis

- Sequential assimilation (every 10 days)
- In situ and altimeter assimilation
- Geostrophic velocity increments



Second OI using Salinity data to correct the T/S relationship

Assimilation of S(T) not S(z)

$$S_a(T_a) = S'_a(T_a) + K'(S_o(T_o) - HS_b(T_o))$$

Note conservation of water masses => Complementary data contributions

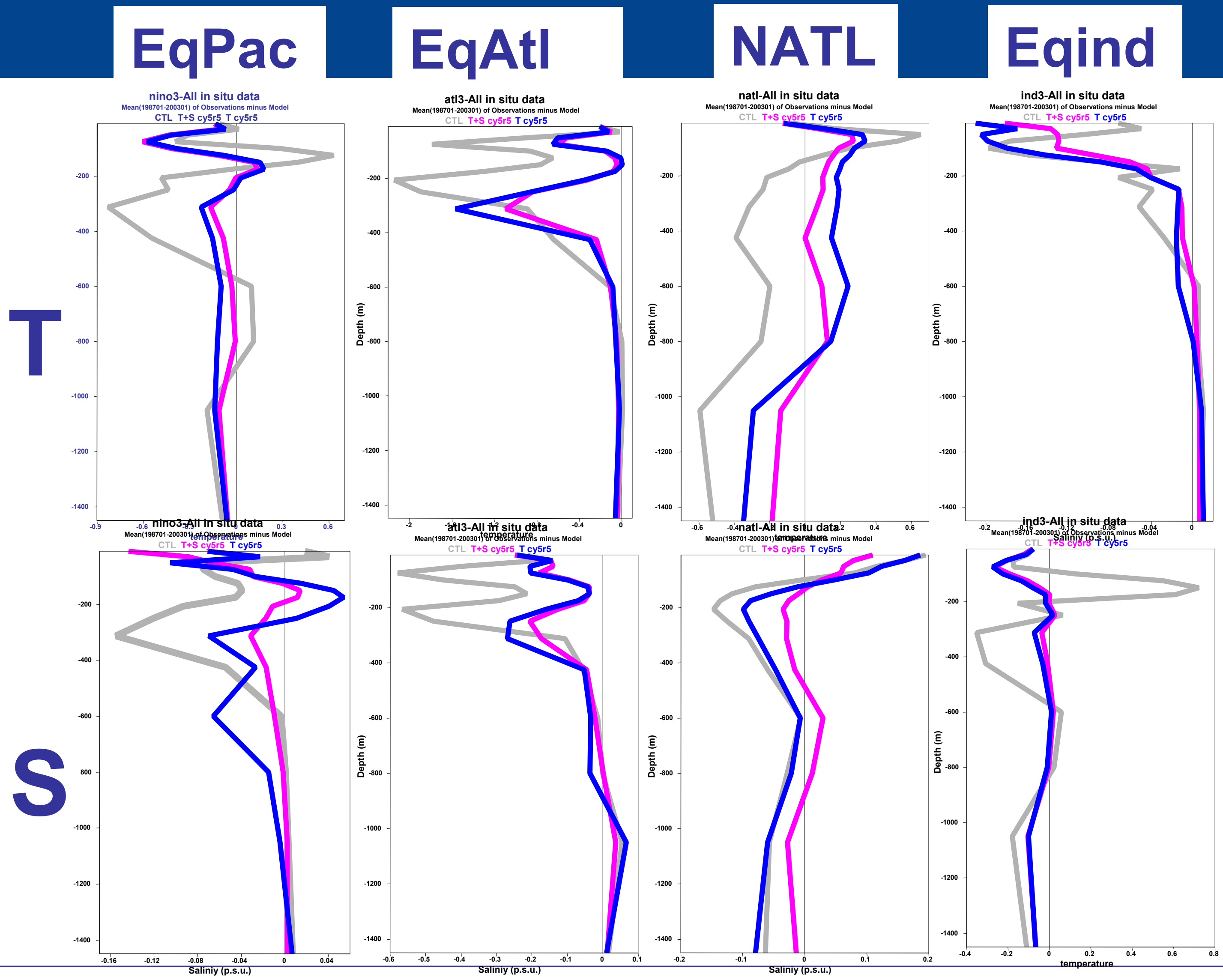
Salinity assimilation improves temperature

No assim

T assim with balancing increment ΔS_T only

T and S(T) assimilation

Vidard et al

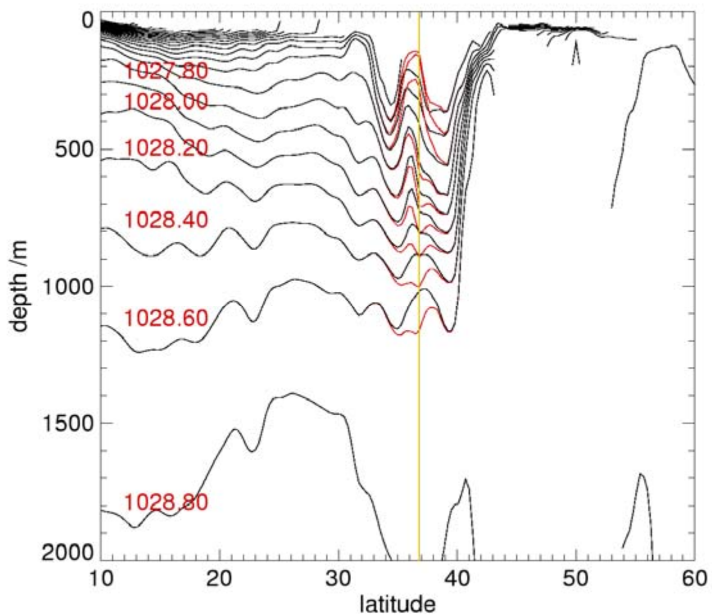


Mean Observation Minus Background in selected regions for temperature and salinity

Isopycnal assimilation:
Assimilation of 1 observation profile

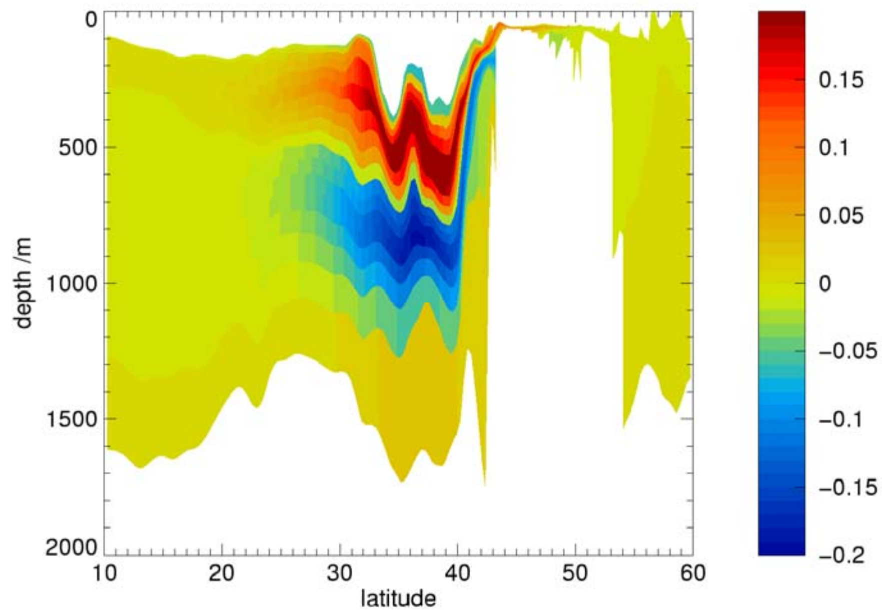
T(z), S(z) → z(ρ) , π (ρ) → Assimilate → T(z), S(z)

Density level depth z(ρ)
before and after assimilation



Correlation width 60 km

Spiciness increment π (ρ)



Correlation width 400 km

Long window 4dVar

Data Assimilation for Coupled-Model Prediction

Aims:

Seasonal Forecasting eg. El Nino

Interannual-decadal forecasting

Based on Coupled Atmosphere-Ocean models

Ocean initial conditions crucial=> ocean assimilation

Prediction based on Ensembles (average Atm. noise)

Coupled assimilation really required to have initial atmosphere-ocean boundary layers consistent

Perhaps other properties should also be assimilated eg. Sea Ice, Snow cover, Soil Moisture?

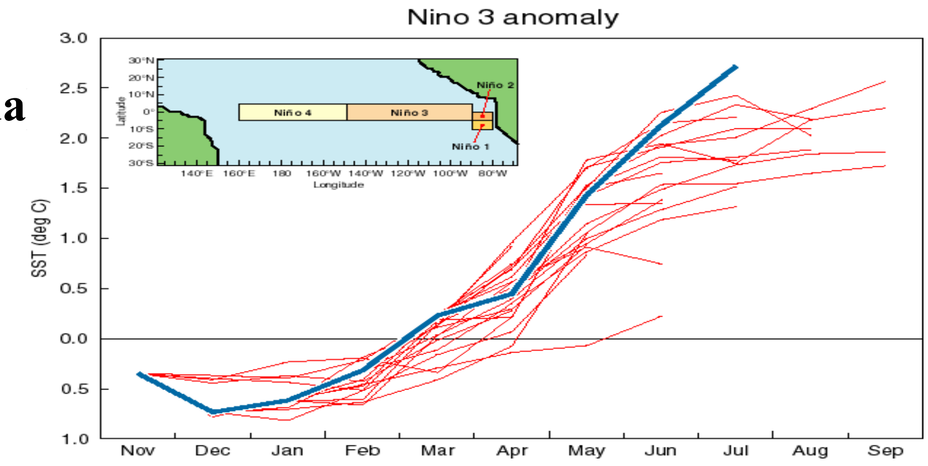
Seasonal Forecasting

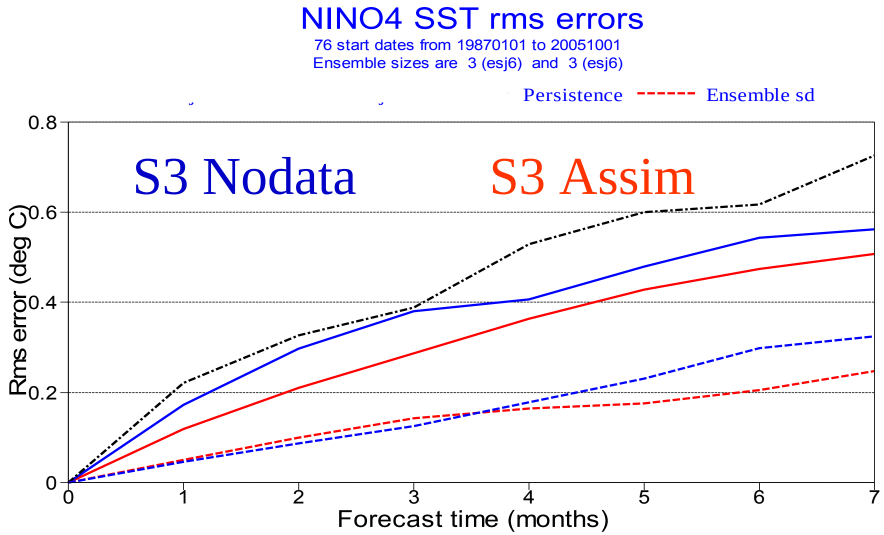
At ECMWF ocean assimilation scheme as for Reanalysis ORA3 (Balmaseda

- Ocean only model run forced with atmospheric ERA-ops and ocean assimilation
- Then coupled to IFS atmosphere for coupled ensemble forecasts

SST shocks common eg. Stockdale 1997

Direct assimilation into coupled system?
- Latif et al. 2004, nudge SST of coupled model: relies on atmos+ocean adjusting
- Coupled 4dVar? => problem with atmospheric noise





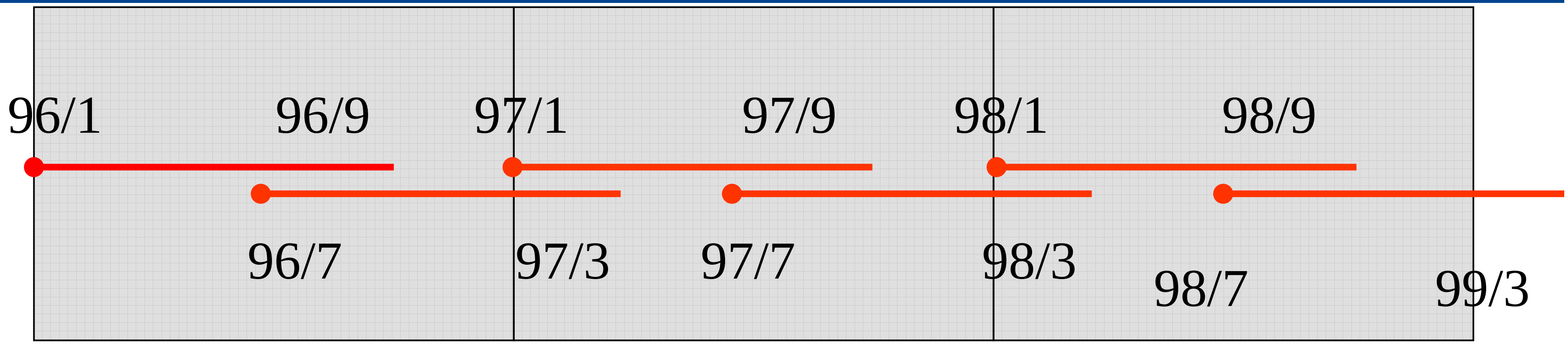
Coupled Data Assimilation at JAMSTEC

thanks to Dr Sugiura and Prof. Awaji

- Assimilation into a fully coupled GCM
- By means of 4D-VAR
  - Long assimilation window (9 month)
  - Correction of model climatology by parameter estimation
  - Correction of seasonal to interannual trajectory by initialization
  - Atmospheric data are also assimilated
  - Weather mode is treated as noise

➔To be suitable for Seasonal to Interannual state estimation and prediction

CDA Assimilation windows



Control Variables

1. Ocean initial condition
2. Bulk parameters controlling Air-sea fluxes of ;

* 97/1 = January of 1997

Momentum $$\tau = \alpha_D C_D |v| v,$$

Sensible heat $$H = c_p \alpha_H C_H |v| (\theta_{sfc} - \theta),$$

Latent heat $$E = \rho \alpha_E C_E |v| (q_{sat} - q),$$

adjustment factors (x,y,10daily)

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Experimental Settings of Coupled DA

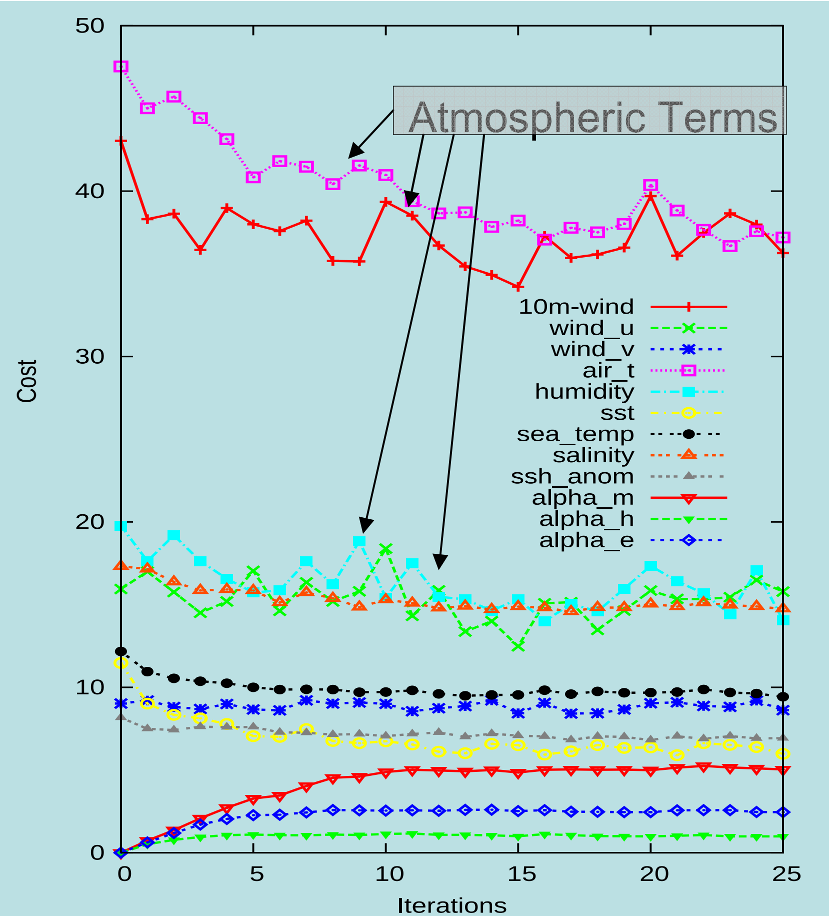
- Coupled Model (CFES):
  - T42L24 AFES for AGCM
  - 1x1deg L45 MOM3 for OGCM
  - IARC SeaIce model
  - MATSIRO Model for Land
- Observational Data
  - Atmosphere:
    - NCEP's BUFR data U,V,T,Q (10daily)
    - SSM/I sea wind scalar x ERA40 wind direction (10daily)
  - Ocean:
    - T/P altimeter data(10daily)
    - Reynolds SST (10daily)
    - WOA data T,S (monthly)
    - Ocean Data Assimilation Product T,S(monthly)
- Adjoint Code
  - Adjoint OGCM and adjoint AGCM are coupled [Line by line transformation by TAMC,TAF]
  - Temporal averaging of forward field for the adjoint integration is applied to smooth the basic field
  - Adjoint AGCM contains damping terms to suppress the strong adjoint sensitivity from weather fluctuations.

$$-\frac{\partial \boldsymbol{\lambda}}{\partial t} = \left(\frac{\partial \mathrm{M}}{\partial \mathbf{x}} \right)^T_{\mathbf{x}=\bar{\mathbf{x}}} \boldsymbol{\lambda} - \boldsymbol{\Gamma}\boldsymbol{\lambda} + \mathbf{H}^T \mathbf{R}^{-1} \left(\mathbf{H}\bar{\mathbf{x}} - \mathbf{y} \right)$$

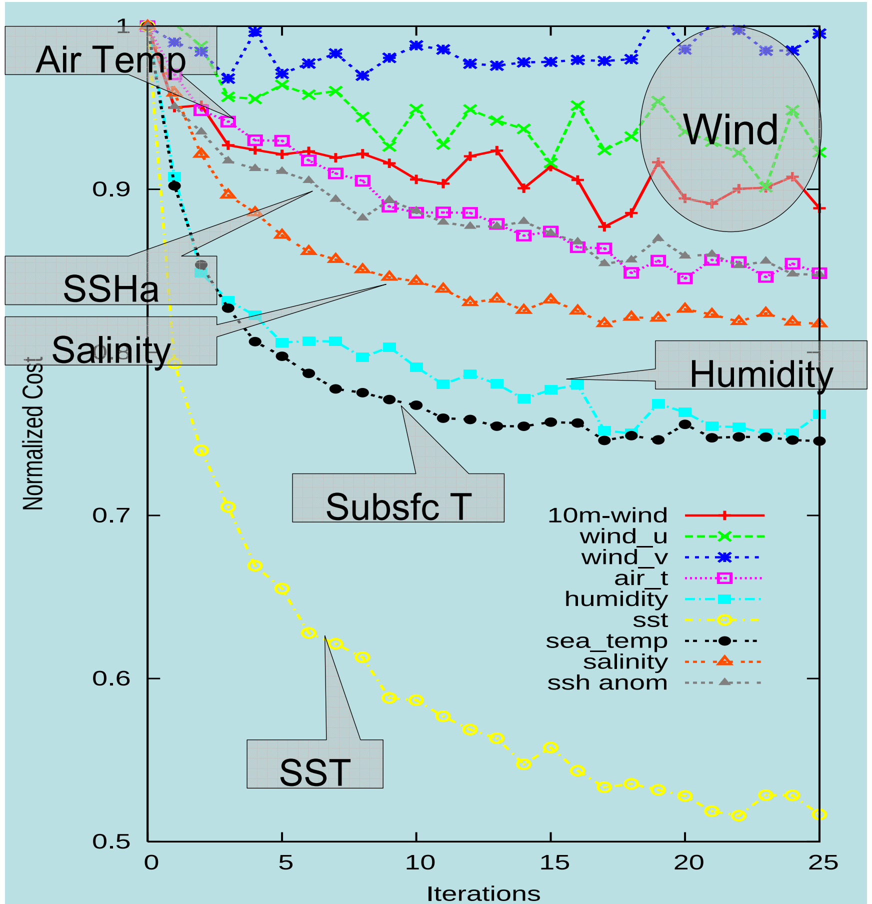
$\boldsymbol{\lambda}$: adjoint variables, $\bar{\mathbf{x}}$: temporal average, $-\boldsymbol{\Gamma}\boldsymbol{\lambda}$: damping.

The CDA cost function minimisation

Cost variation for the period from Jul1996



Normalized cost variation in the 1990s



Atmospheric cost terms show some fluctuations with iteration. SST cost significantly reduced.

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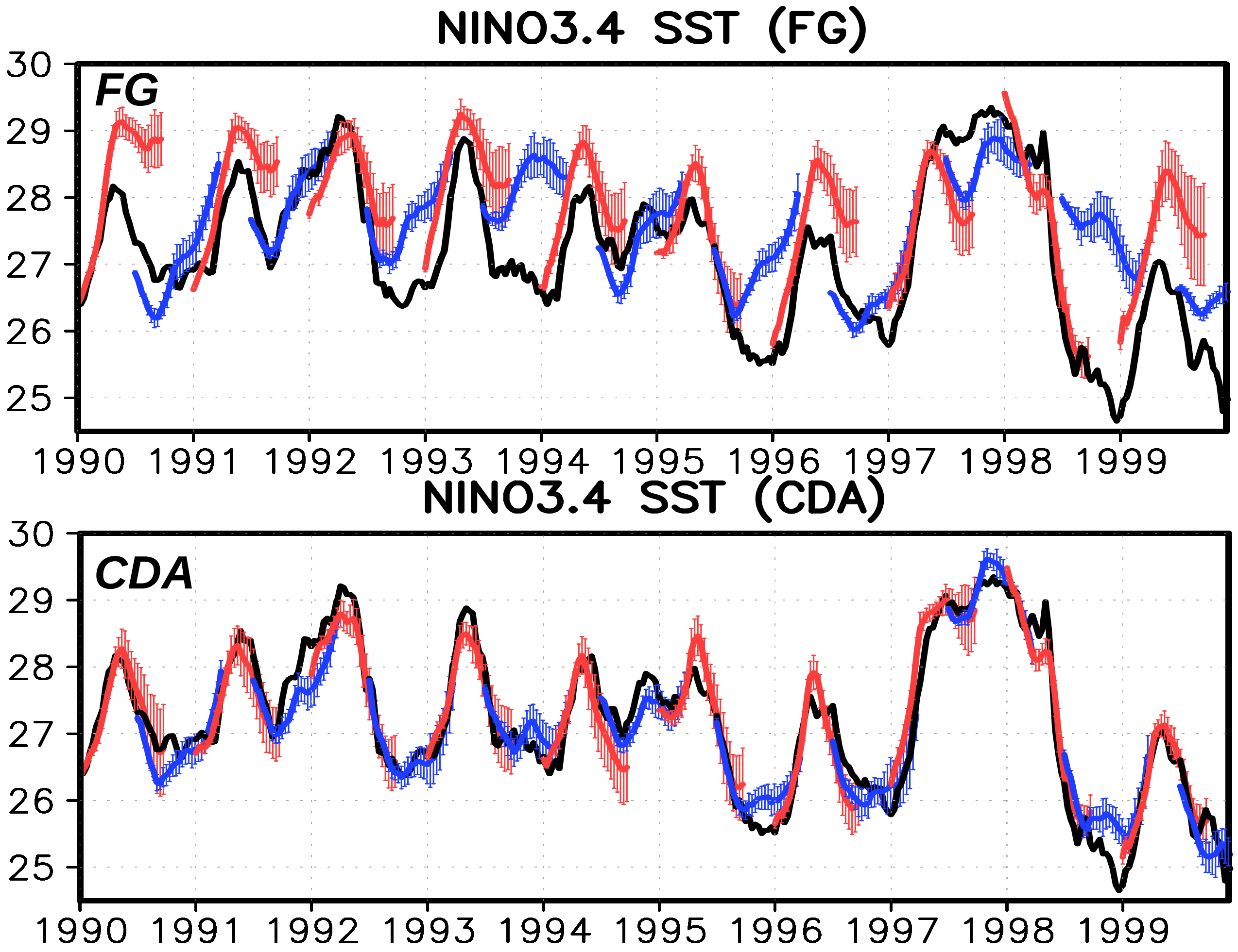
Coupled DA Seasonal prediction



Top: Firstguess

Bottom: CDA

Red: from Jan.

Blue: from Jul.

Black: Obs.

Error bars are for the spread of ensemble runs with 11-different atmospheric initial conditions. Nino3.4 SST is much more realistic in the CDA analysis field.

Coupled DA Summary

- The optimizations of ocean initial condition and of bulk parameters enable us to reproduce coupled field realistically.
  - Extraction of coupled/climate mode works to some extent by temporal averaging of forward fields and simple damping terms in adjoint code which is shown by the reduction of the cost values for coupled field.
  - Regarding El Nino, the departures from observation do not grow in the 9-month assimilation windows which verifies that our CDA works properly as a smoother.
- This system is also useful for prediction.
  - Bulk parameter adjustment will be useful to represent properly the climatological mean state by the Coupled GCM.
  - Optimal ocean initial condition fit to the coupled model useful for Seasonal-Interannual prediction because it contains proper tendency information thanks to the 4d-Var and hence Reduces Shocks.

Hadley Centre Decadal Prediction (DePreSys)

HadCM3 coupled model

Assimilation: ANOMALY
- **Atm. nudged to ERA15/40**
- **Ocean nudged to filtered ocean T, S gridded anal. from HadCM3 Covariances**

all the time running in coupled mode

Hindcast ensembles (4-9) generated every 3-6 months through 1979-2005

Skill in SST, OHC and global SAT assessed out to 9 years ahead

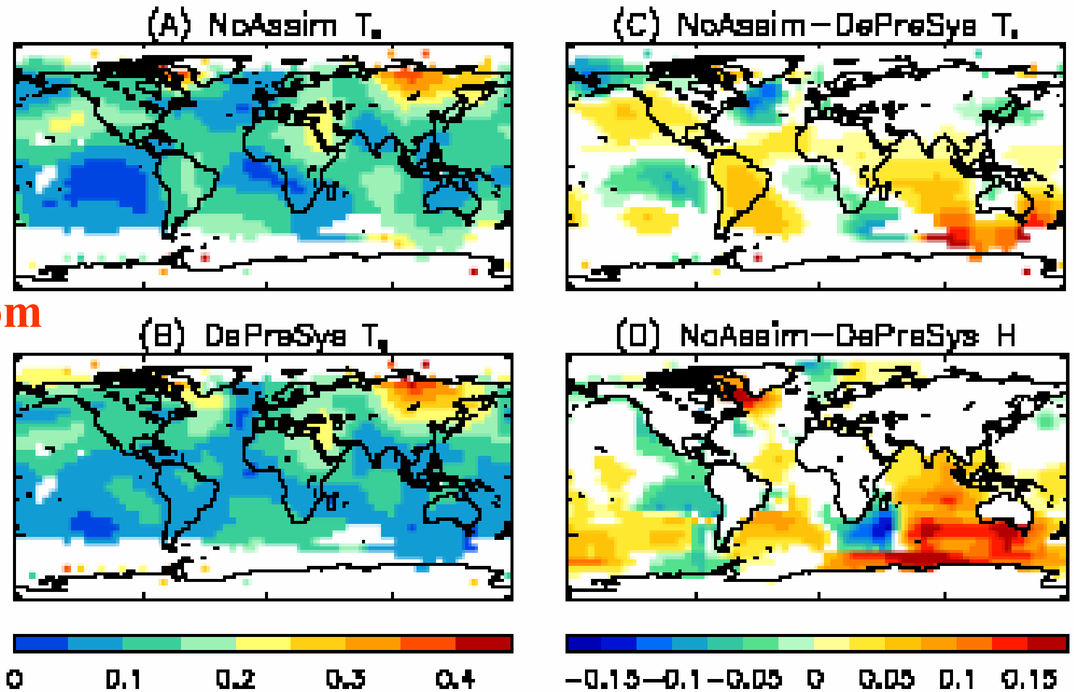


Figure 3: Impact of initial conditions on regional hindcast skill. (A) RMSE of 9-year mean T_s anomalies (relative to 1979-2001) for the ensemble-mean NoAssim hindcasts, verified against observations from HadCRUT2v (*36–38*). (B) As A but for DePreSys. (C) NoAssim minus DePreSys RMSE of 9-year mean T_s. Differences are only shown where they are significant at the 5% level (*18*). (D) As C but for 9-year mean H anomalies (relative to 1941-1996). In all panels, each 5° latitude by 5° longitude pixel represents the RMSE for predictions of T_s spatially averaged over the 35° latitude by 35° longitude box centred on that pixel.

9yr Mean Hind. Skill

Smith et al 2007 Science

Sensitivity of DePreSys system to Ocean Assimilation

- DePreSys system implemented on set of NERC compute Clusters (GCEP project)

- Figures show Global surface air temperature and Nino3.4 hindcasts from Jan 1997 during the great 1997 ENSO
- Changing ocean initial conditions can give big increases in skill predicting both strength and timing of 1997 ENSO
- Will this carry over to skill statistics for interannual timescales?

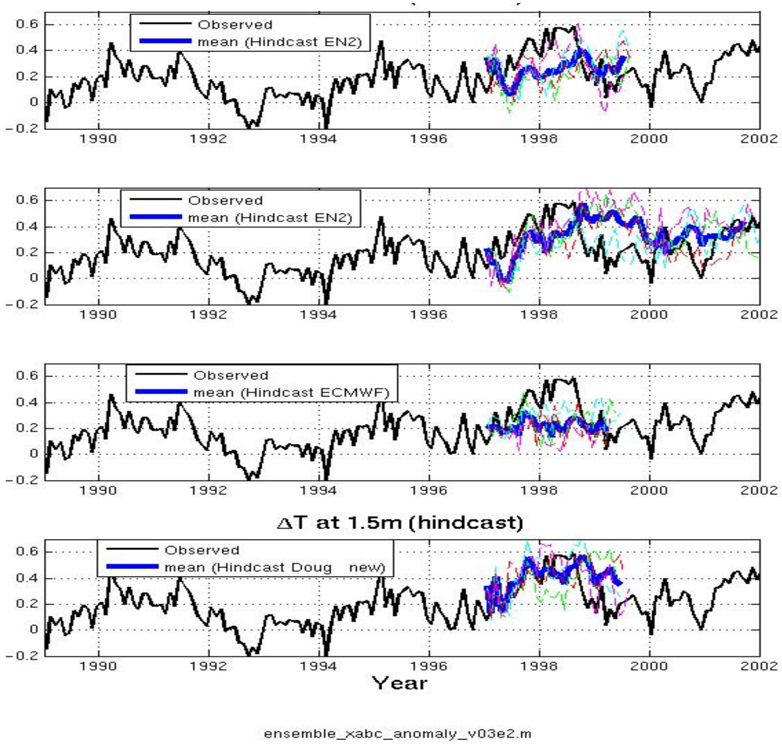
Global Surface Air Temperature (STA) anomaly

DePreSys Original

EN2 ocean

ECMWF ORA3 ocean

New ocean anomalies

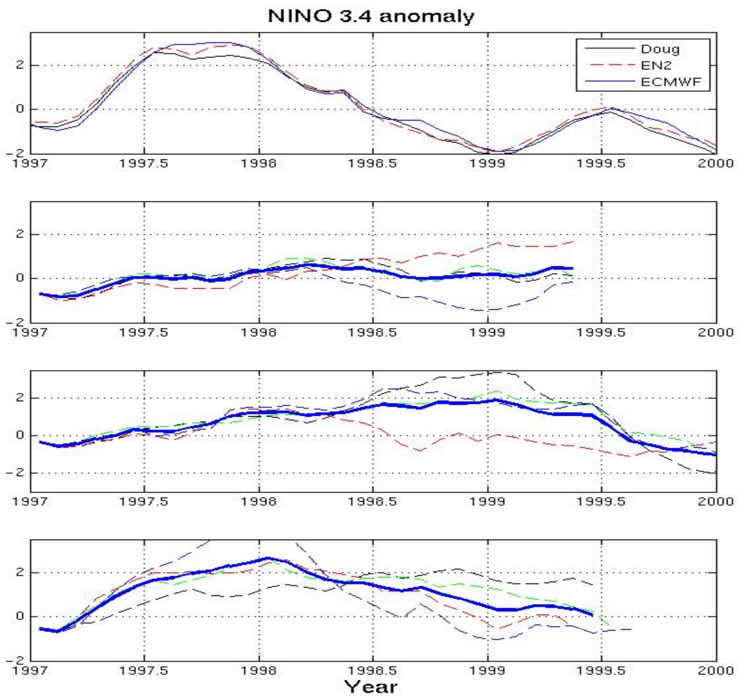


Truth

DePreSys Original

EN2 ocean

New ocean anomalies



Ensemble runs started from Jan 1997

Ocean DA Challenges

- To make most effective use of altimeter data in combination with new geoid data; ESA-GOCE mission
- Demonstrate effective combination of Argo and Altimeter data through DA and make critical OSE assessments
- Ocean reanalysis for climate? Can this be done more effectively than atmospheric reanalyses, eg. using slow thermodynamic timescales in the ocean? => CLIVAR-GSOP (Global Synthesis and Observations Panel)
- Initialising coupled atm.-ocean models for seasonal-decadal ensemble prediction
  - Huge implications if coupled predictions other than for ENSO can be demonstrated
- Many other ocean DA challenges not covered eg. coastal / biological / medium range NWP