

Assimilation of T&S and Altimetry into ocean models with water mass constraints

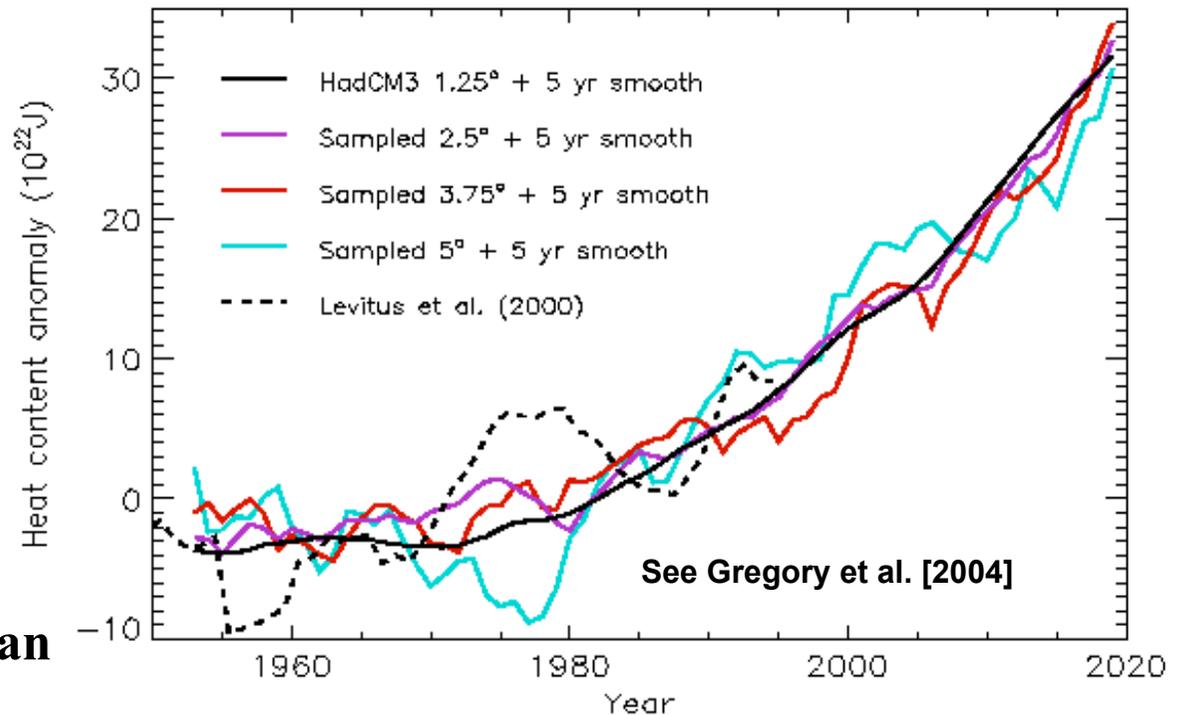
- Applications of ocean data assimilation
 - Reanalysis, Seasonal forecasting, Operational oceanography
- Key ocean data sets
 - Altimeter, In Situ, SST
- Sequential Assimilation methods
- Constraints from oceanography
 - Vertical projection of altimeter sea level
 - Assimilating Temperature with Salinity corrections
 - Assimilating Salinity as $S(T)$ instead of $S(z)$
- Detecting and Accounting for Bias Errors

- Conclusions

Ocean Reanalysis for Climate Studies

- **Global and basin Scale Heat Content**
- **Salinity/Freshwater**
⇒ **Hydrological cycle changes**
- **CO₂ sequestration**
- **North Atlantic Deep Water Volume**
- **Changes in southern ocean T/S properties**
- **Changes in strait transports**
eg. **Arctic overflows (Dixon et al)**

Heat content for Anomaly for the upper 3000m



4D Var approach to state estimation

Main drawback to ocean inverse work is steady state assumption,
Ship section data often measured years apart
In any case what is exact value of “Mean Circulation”

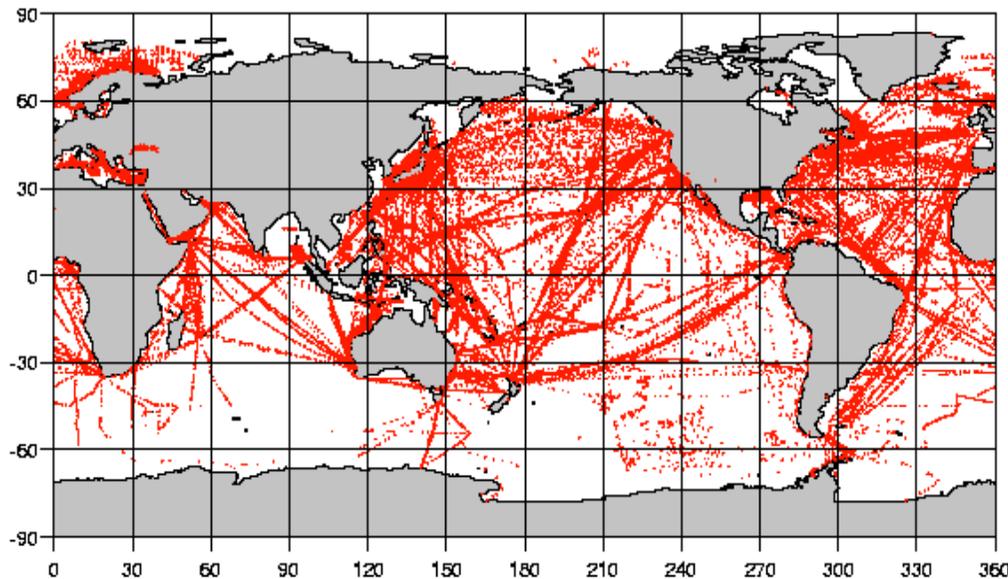
ECCO group (Stammer and Wunsch) are using Least Squares
Cost function approach to model time-evolving circulation over
1992-2002 period, with low resolution model=> 4DVar method

$$\begin{aligned} J = & \frac{1}{2}[(\bar{\zeta} - \bar{\zeta}_{obs})^T \mathbf{W}_{EGM96}(\bar{\zeta} - \bar{\zeta}_{obs}) \\ & + (\zeta' - \zeta'_{TP})^T \mathbf{W}_{TP}(\zeta' - \zeta'_{TP}) + (\zeta' - \zeta'_{ERS})^T \mathbf{W}_{ERS}(\zeta' - \zeta'_{ERS}) \\ & + (\tau_u - \tau_{uobs})^T \mathbf{W}_{NSCAT_z}(\tau_u - \tau_{uobs}) + (\tau_v - \tau_{vobs})^T \mathbf{W}_{NSCAT_y}(\tau_v - \tau_{vobs}) \\ & + (\mathbf{H}_Q - \mathbf{H}_{Qobs})^T \mathbf{W}_{H_Q}(\mathbf{H}_Q - \mathbf{H}_{Qobs}) + (\mathbf{H}_F - \mathbf{H}_{Fobs})^T \mathbf{W}_{H_F}(\mathbf{H}_F - \mathbf{H}_{Fobs}) \\ & + \sum_{i=1}^{12} (\bar{\mathbf{T}}_i - \bar{\mathbf{T}}_{iLev})^T \mathbf{W}_T(\bar{\mathbf{T}}_i - \bar{\mathbf{T}}_{iLev}) + \sum_{i=1}^{12} (\bar{\mathbf{S}}_i - \bar{\mathbf{S}}_{iLev})^T \mathbf{W}_S(\bar{\mathbf{S}}_i - \bar{\mathbf{S}}_{iLev}) \\ & + (\mathbf{T} - \mathbf{SST})^T \mathbf{W}_{SST}(\mathbf{T} - \mathbf{SST}). \end{aligned}$$

**Is this the only way
to assimilate ocean
data for climate
reanalysis studies??**

Historical availability of ocean data

Upper Ocean T(z) 1993



69733 points

Historical T profiles N Atlantic

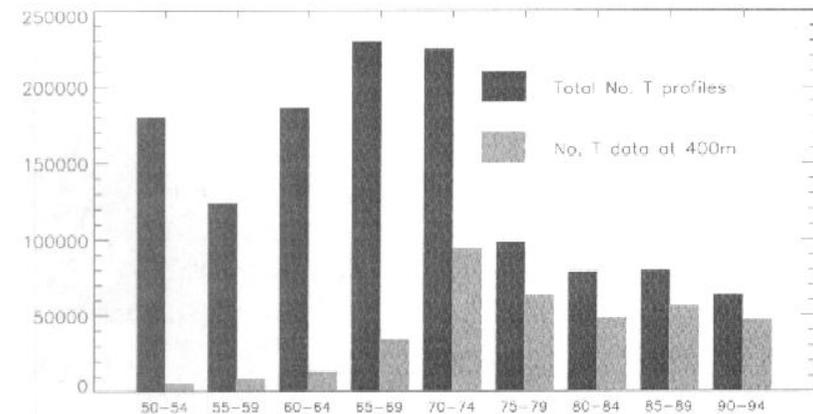
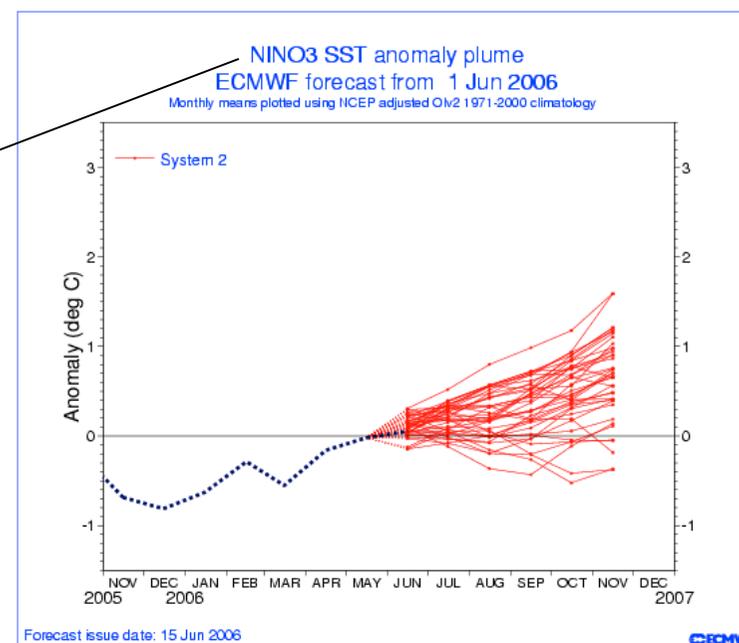
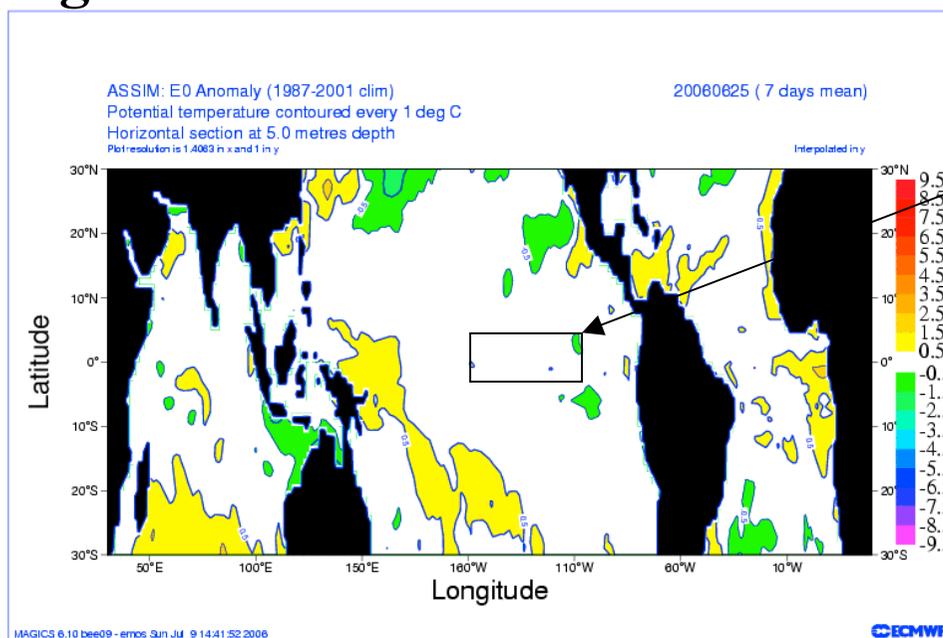
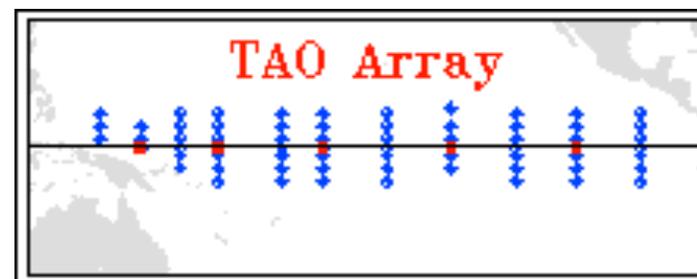


FIG. 1. Numbers of temperature profiles available from the North Atlantic during 5-yr periods from 1950 to 1994. Dark shaded blocks show the total number, and light-shaded blocks show numbers reaching to 400 m or deeper.

**Now XBTs reach 800m
Being superseded by Argo**

Assimilation for Seasonal Weather Forecasting

Based on coupled ocean-atmosphere model with ocean data assimilation run in Ensemble mode => 6 months eg. ECMWF

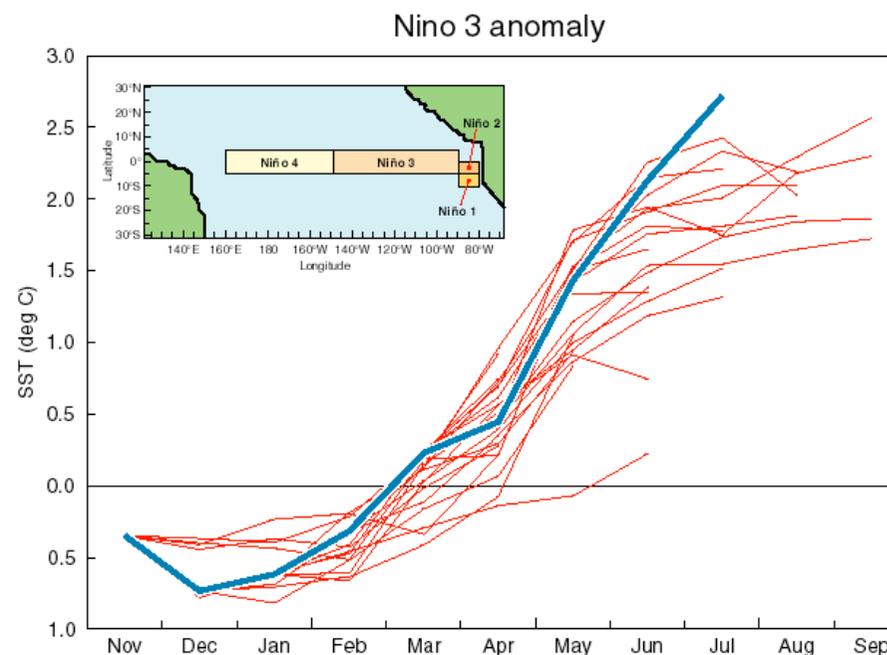


<http://www.ecmwf.int/products/forecasts/d/charts/seasonal/>

Assimilation for Seasonal Weather Forecasting

- Seasonal forecasting operational at ECMWF, NASA etc.
- TAO buoys provide temperatures and currents to 450m
- Assimilate into coupled ocean-atmosphere global models
- Forecast timescale ~6 months
- Forecasting El Nino onset; Niño 3 surf. Temp. anomalies
- Whole set of climate parameters also predicted, eg. rainfall, surface T anomalies

ECMWF Forecasts for the 1997 El Nino

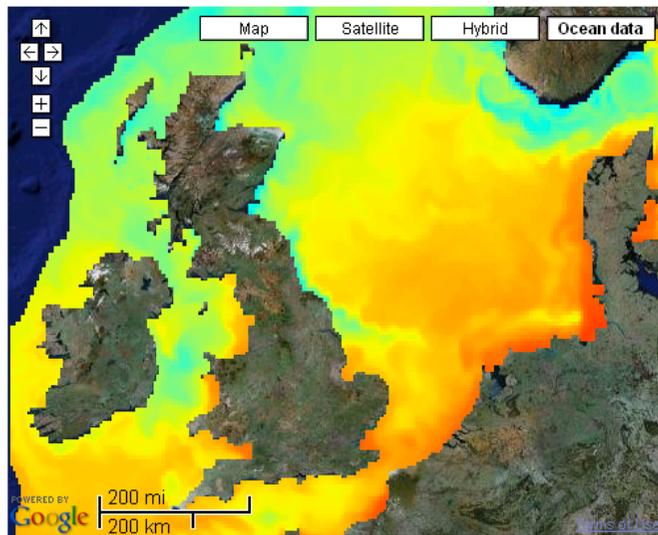


Operational Ocean Forecasting

**Ocean only models forced with winds and fluxes from Met forecasts
Assimilating satellite and in situ ocean data (eg. GOOS and GODAE)
Products from the EU MERSEA Project**

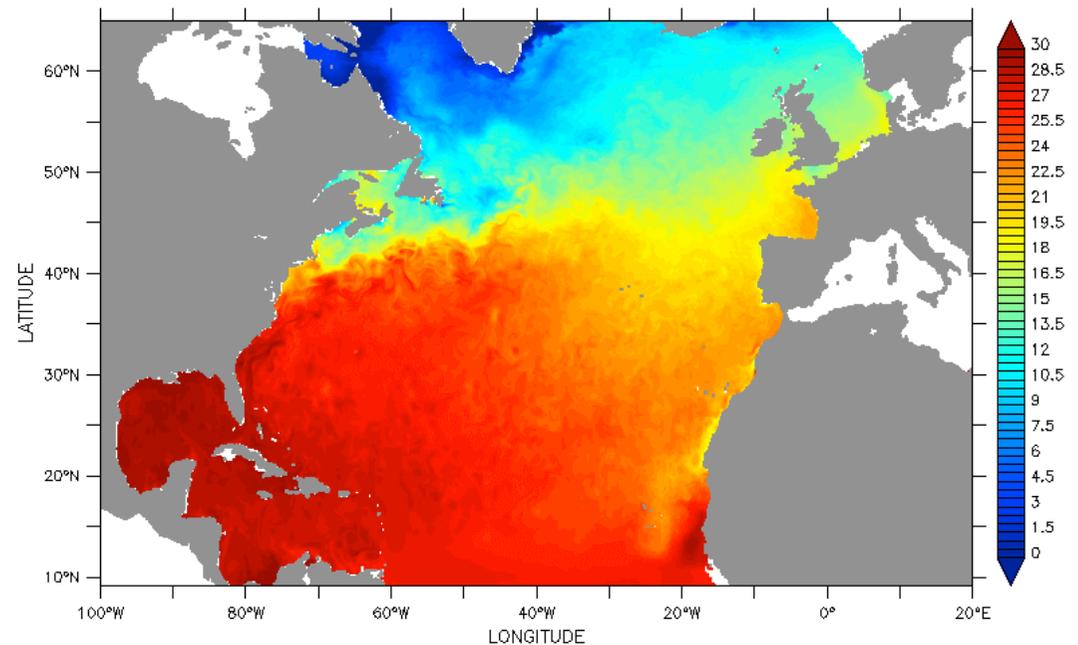
Date/time: 19 Jul 2008 00:00:00

9 10 11 12 13 14 15
16 17 18 19 20 21 22
23 24 25 26 27 28 29
30 31



6km POLCOMS (UK)

North_Atlantic
Mercator Ocean Psy2v2



Depth (m) : 0
Time : 05-jul-2008

Temperature (degC)

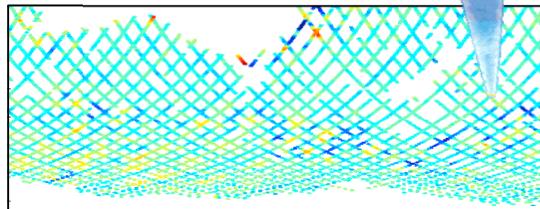
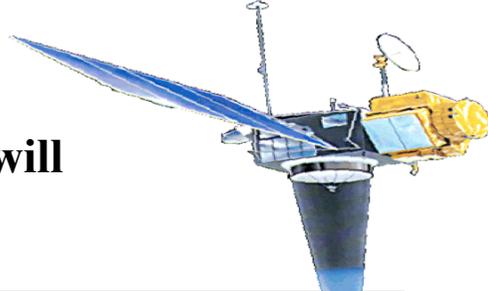
http://bulletin.mersea.eu.org/html/produits/mersea_vs/



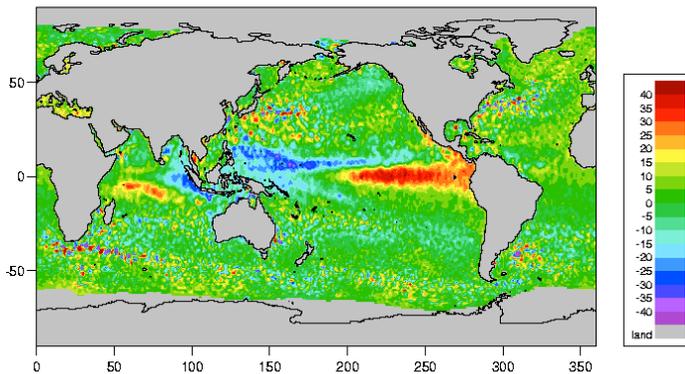
Key Data for Operational Oceanography

Altimetric Sea level anomalies

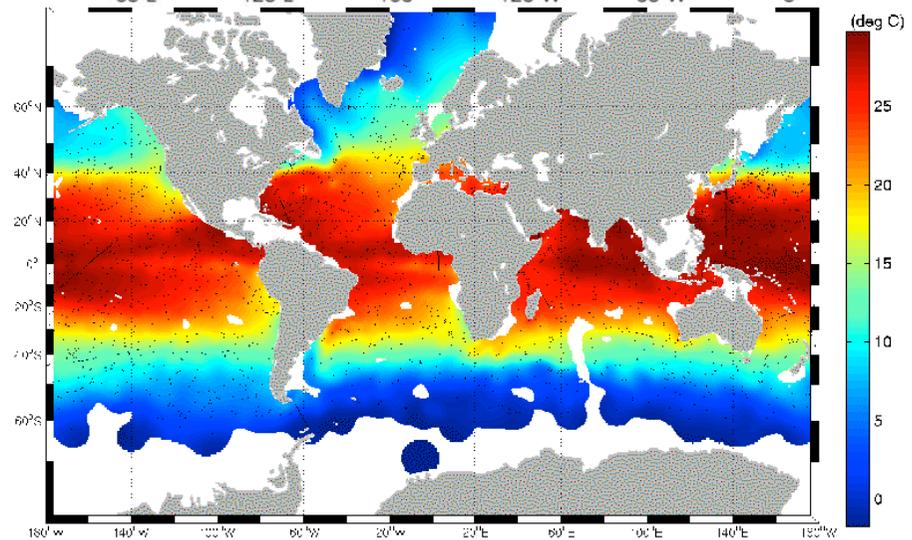
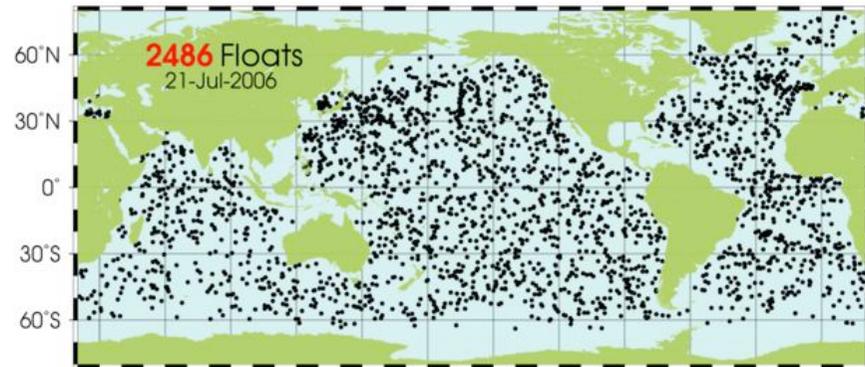
**Note: New
GOCE Geoid will
be vital**



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

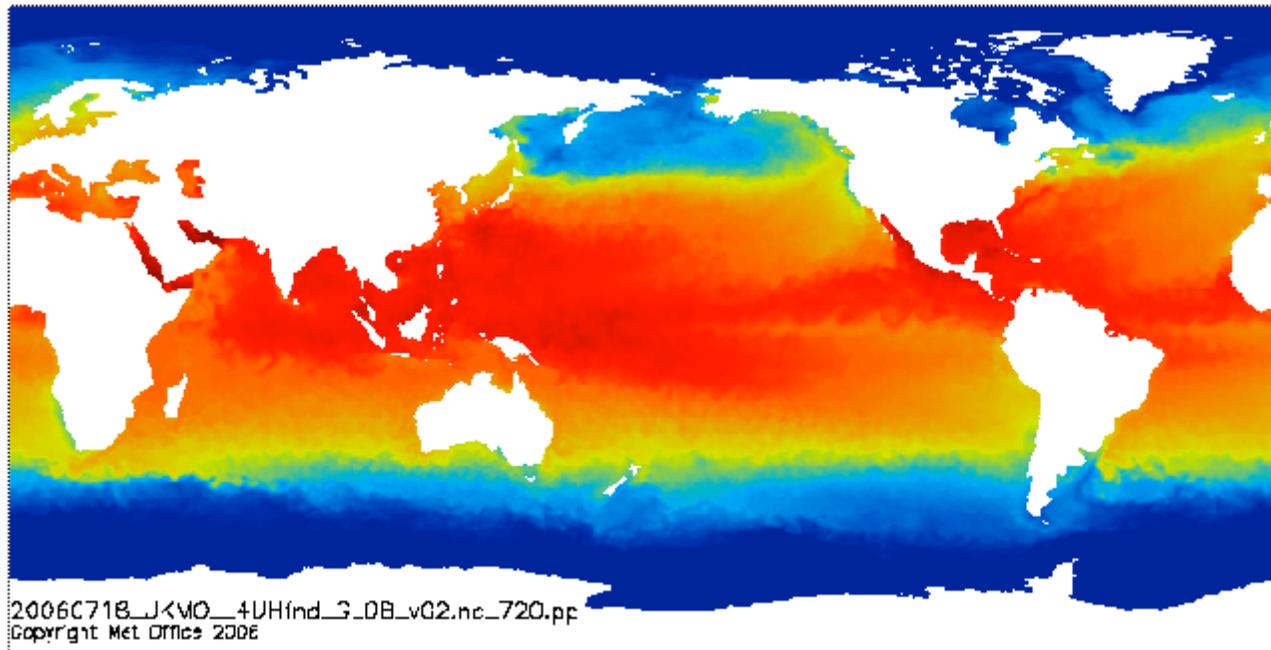


In Situ data from Argo and TAO



Key data sets for operational oceanography

High resolution SST analyses from Microwave and IR satellites



Latest SST Analysis [[Click here for the full resolution png version - 3.5Mb](#)]

NCOF OSTIA product (1km resolution)

http://ghrsst-pp.metoffice.com/pages/latest_analysis/ostia.html

Assimilation for Operational Oceanography

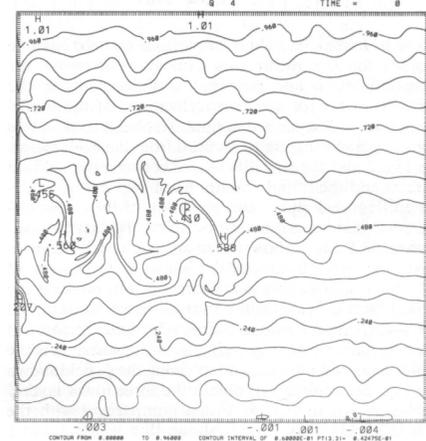
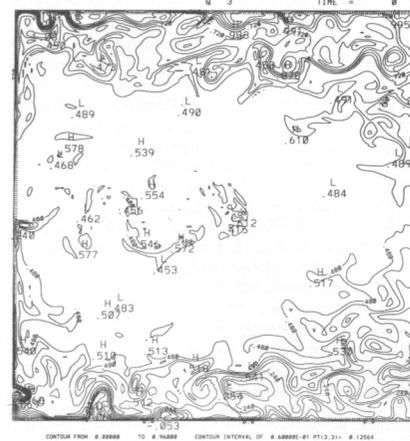
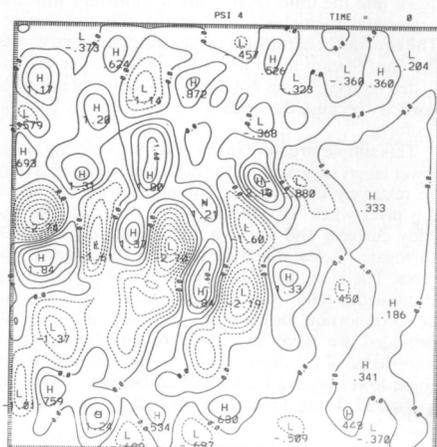
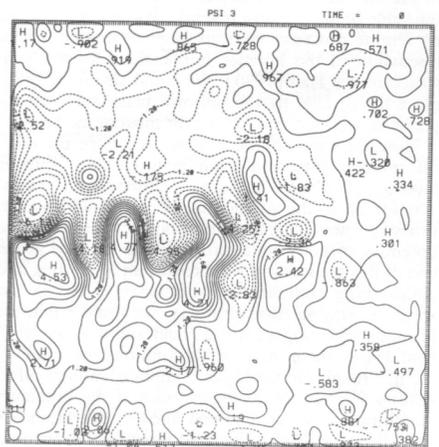
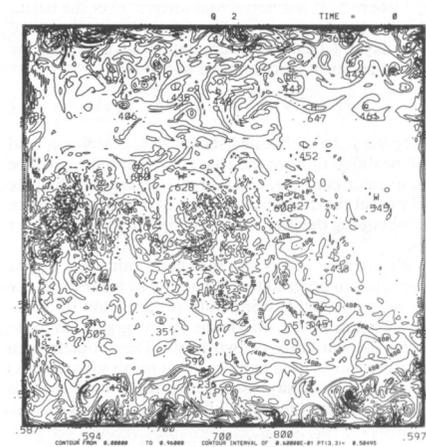
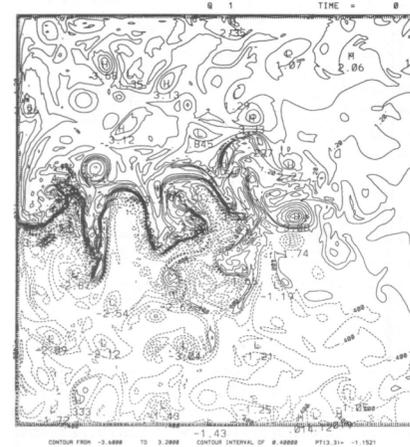
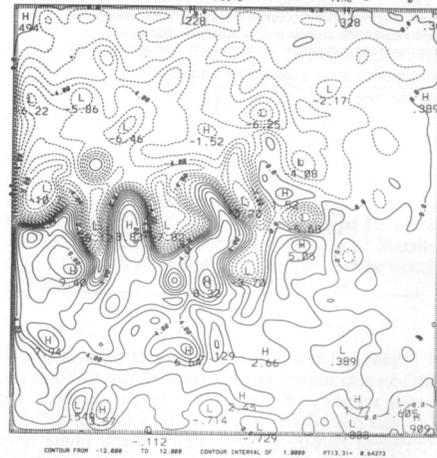
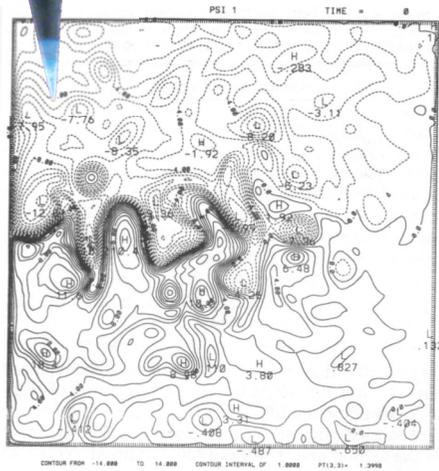
- Sequential Assimilation schemes, Kalman Filter + variants and simplifications are universally used
- Although Operational NWP benefited from 4DVar eg. ECMWF, 4DVar is expensive in oceans, and models too BIASED?
- Key information is the Background Error Covariance
 - Needed to link Observation, SSH or $T(z)$, $S(z)$ profile with changes in whole model state vector
 - Error covariances poorly known from observations
 - Can use physically based covariance information relating
 - Altimetric SSH with T, S profiles in the water column
 - Temperature profiles $T(z)$ with Salinity profiles $S(z)$
 - Horizontal correlations of $S(T)$ compared with $S(z)$
- Consider some **idealised assimilation experiments** in order to understand ocean assimilation constraints (**Altimeter data**)

Quasi-Geostrophic Box model of the Subtropical and Subpolar ocean gyres



$\psi_1 - \psi_4$

Potential Vorticity $q_1 - q_4$



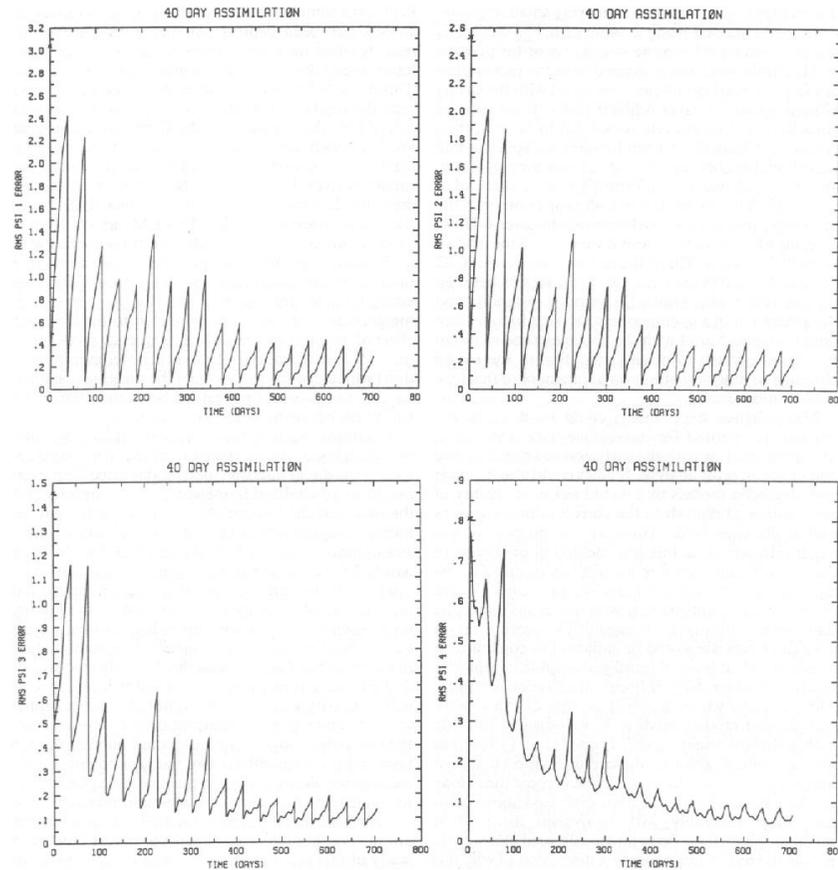
Vertical correlations of ψ , q completely different \Rightarrow useful

$$Dq_{2,3}/Dt = 0$$

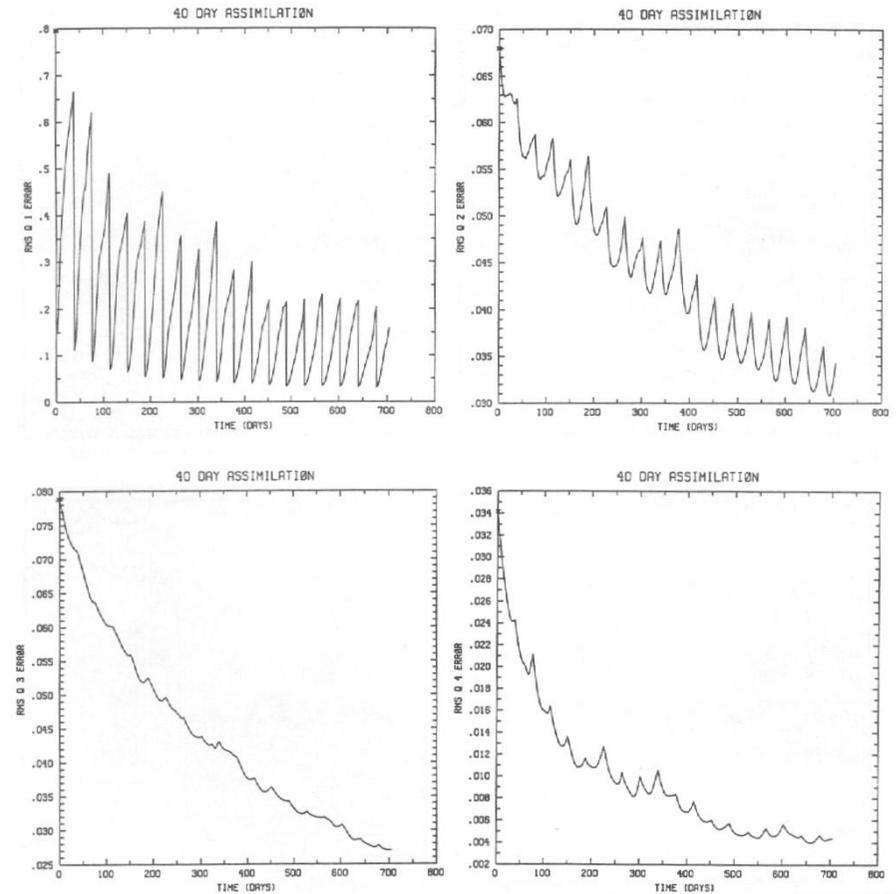
Haines (1991)

Twin experiment assimilation of ψ_1 every 40 days

$\psi_1 - \psi_4$

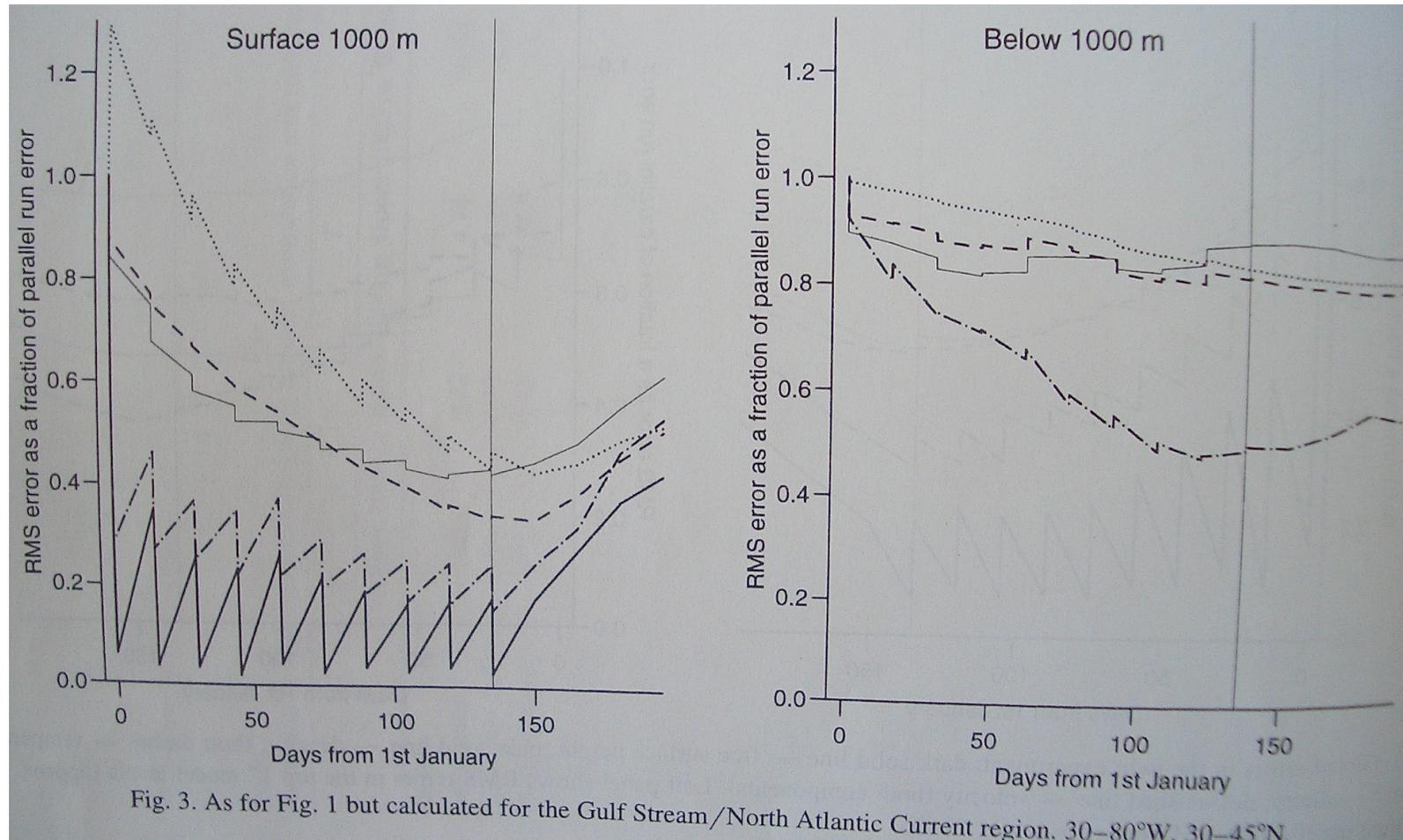


$q_1 - q_4$



Note that $q_2 - q_4$ still converge

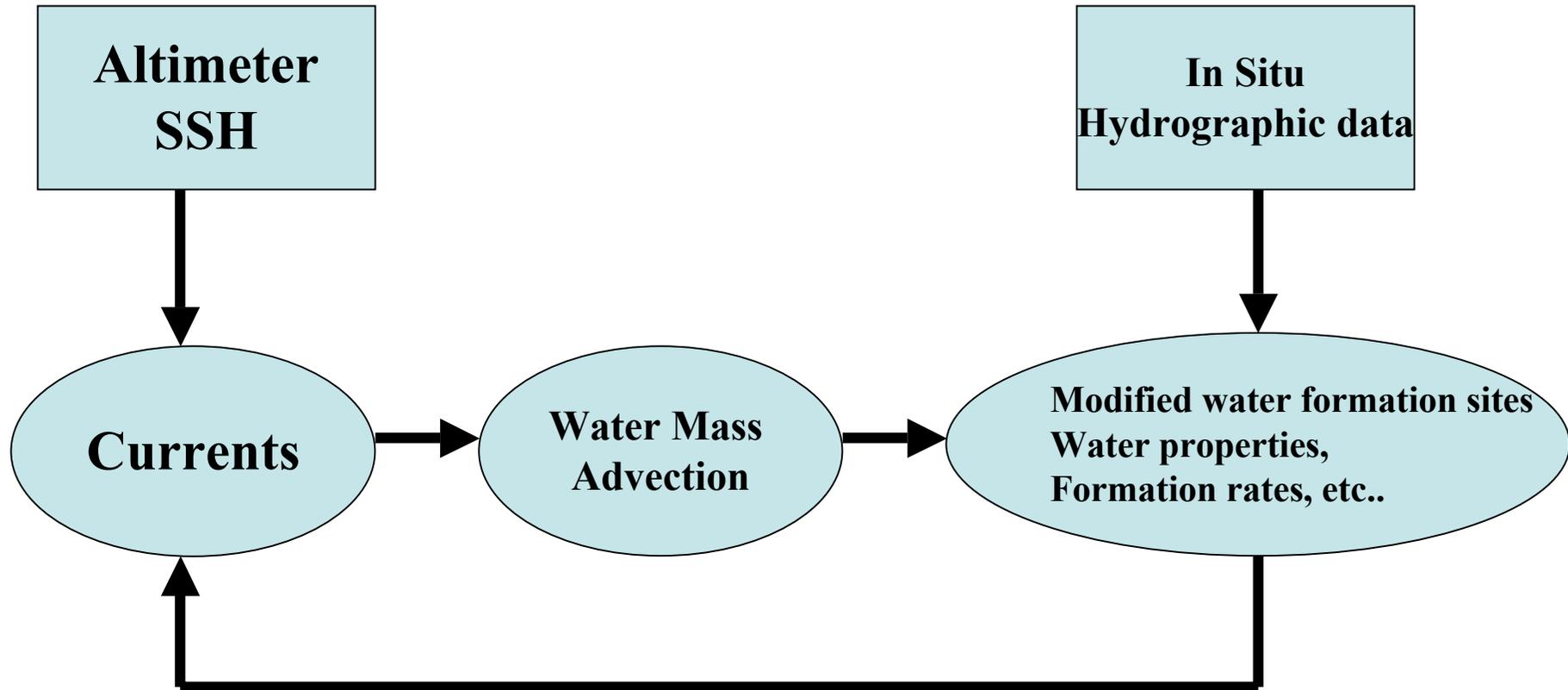
Twin experiment in OCCAM 36 level model assimilating Sea surface height



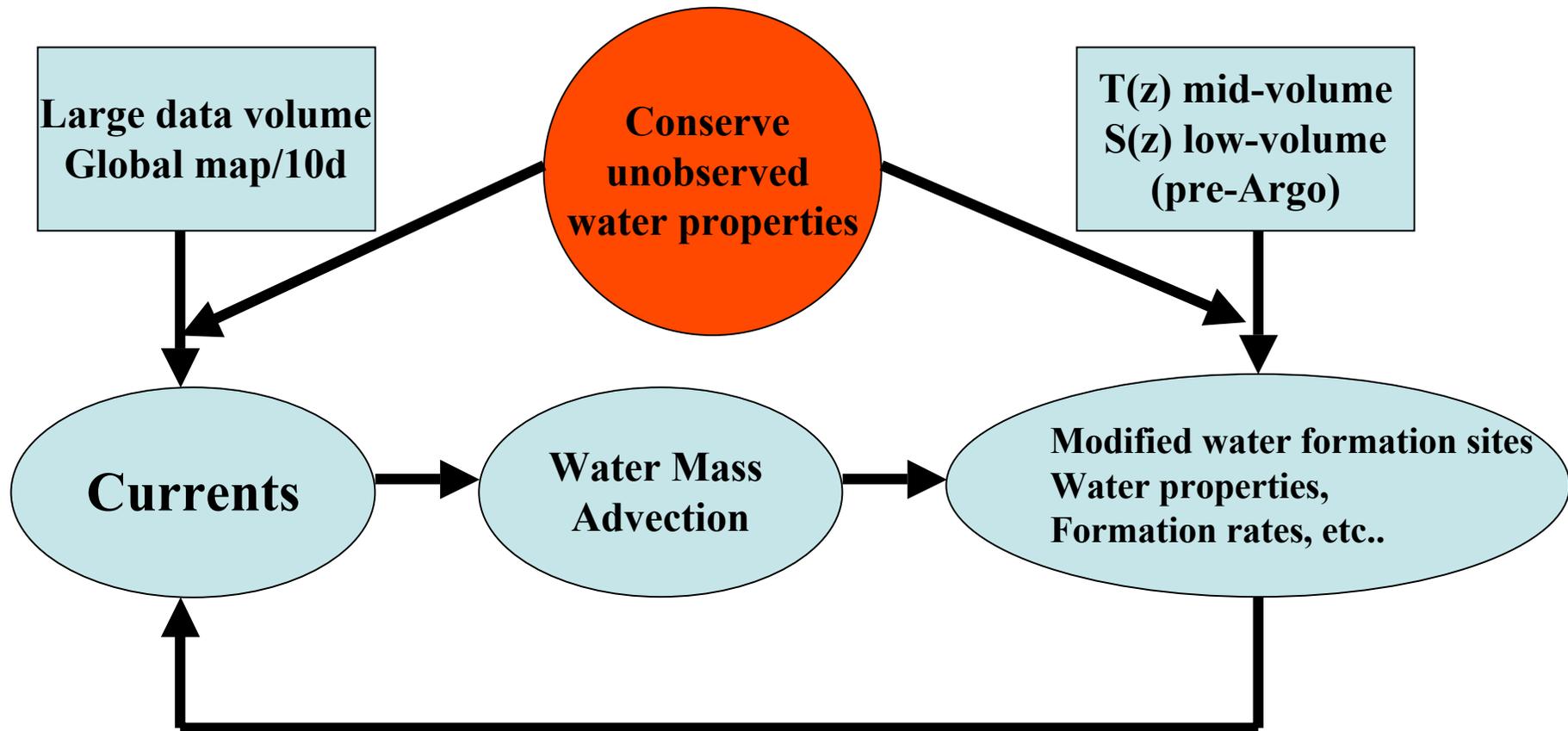
Note that subsurface T,S still converge

Fox et al 2001a

Relationship between Altimeter and In Situ Assimilation



Relationship between Altimeter and In Situ Assimilation



Altimeter assimilation by thermocline displacement Δh

Cooper and Haines (1996) extended idea to Primitive Equation models

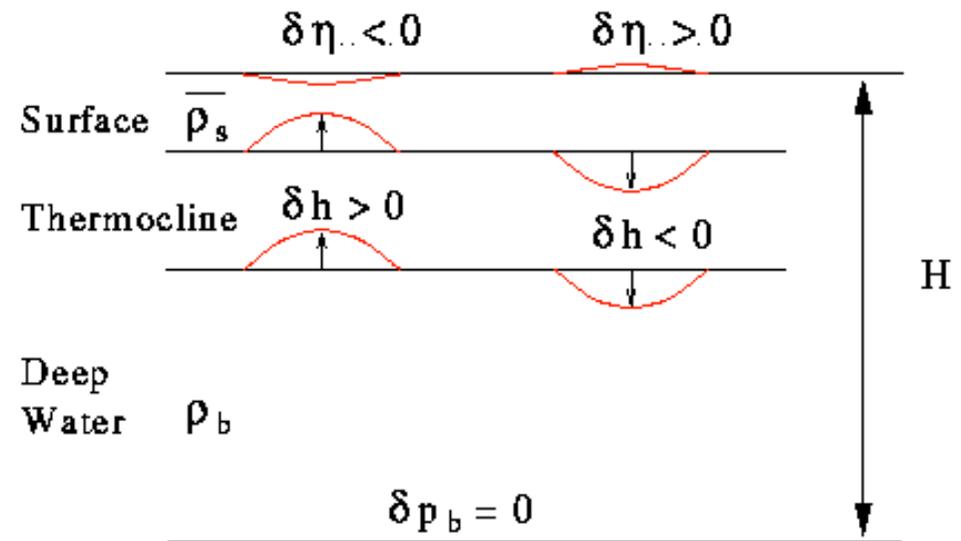
$$\mathbf{Dq}(\rho)/Dt = 0 \quad \mathbf{q} = \frac{\mathbf{f}}{\rho_0} \frac{\partial \rho}{\partial \mathbf{z}}$$

Model $\mathbf{q}(\rho)$ is preserved by Assimilation provided;

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

Solve for $\Delta \mathbf{h}$ by assuming deep pressure unchanged

$$\Delta p(0) = g \int_{-H}^0 \Delta \rho dz,$$

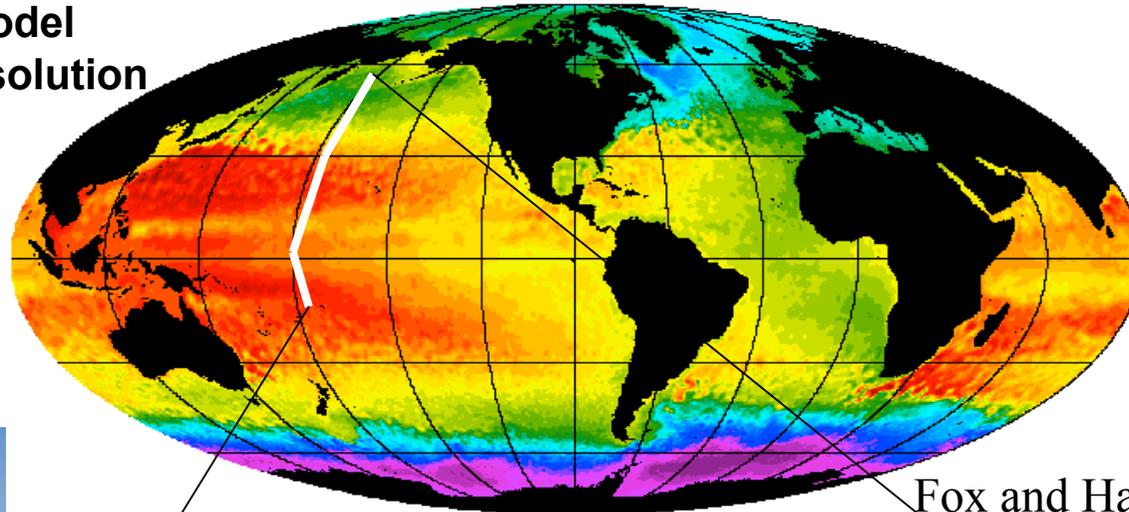


(Different closure to Haines 1991;
 ψ_1 observed, $\mathbf{q}_2, \mathbf{q}_3$ and ψ_4 from model)

Assimilation of Satellite Altimeter



Global Model
25km Resolution

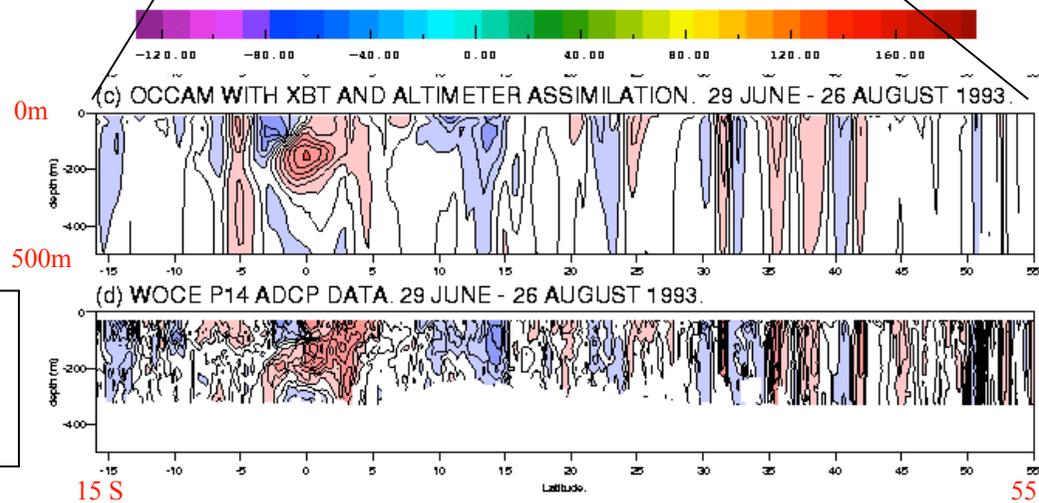


Fox and Haines 2003



Assimilation

Ship Validation
WOCE Cruise



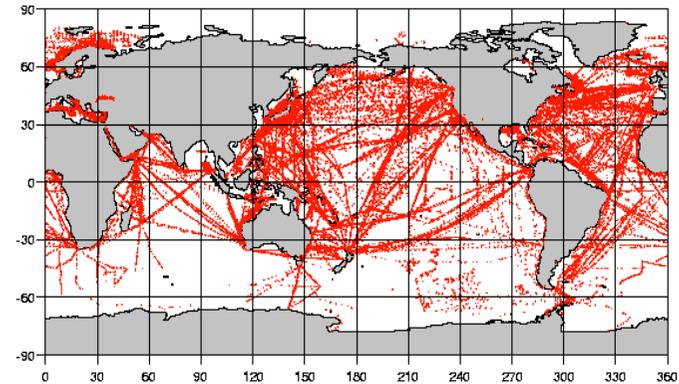
Nice features of altimeter assimilation with conserved water masses

- Simple to apply (don't need pre-calculated covariances)
- Can derive implied vertical covariances analytically so can incorporate into standard assimilation methods
- Vertical covariances are automatically time and flow dependent
- Conservation of water properties allows other assimilation data to determine water mass properties and volumes. **Particularly important for Reanalysis and Climate work => gives method similar properties to 4DVar**
- Has been used at;
 - UK Met Office, ECMWF, Mercator (in SEEK filter), HYCOM
- Other Assimilation methods sharing water conservation property
 - Oschlies and Willebrand 96: Velocity covariances
 - Gavart and De Mey 97: Potential density depth covariances
 - Greatbatch et al 2001:- Semi-prognostic method

Assimilation of T profile data

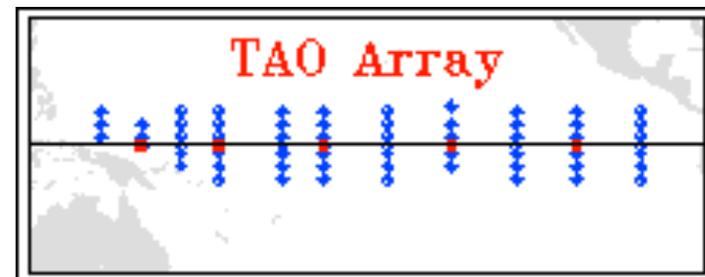
- Historically T(z) profiles make up vast bulk of in situ ocean measurements
- MBTs down to 400m before 1970's
- XBTs down to 800m after 1970's
- Voluntary Observing Ship program
- Highly non-isotropic coverage
- Basis of Levitus estimates of climatic warming of oceans
- El Nino TAO array also mainly T(z) to 400m

- Being superseded by Argo profiling floats
 - T and S down to 2000m with near isotropic coverage



Assimilation of T profile data at ECMWF (pre 2000)

- Assimilation of TAO T profiles from tropical Pacific has been main focus of all seasonal forecasting projects
- ECMWF use OI assimilation, Smith et al (1991)
- 10 days of data assimilated together
- T(z) profiles vertically interpolated to model levels
- Separate horizontal OI on each model level
 - 1500km zonal, 200km meridional scales at Equator
- Observations and model T data given equal weight
- TAO T profiles only reach 450m
- Salinity not updated

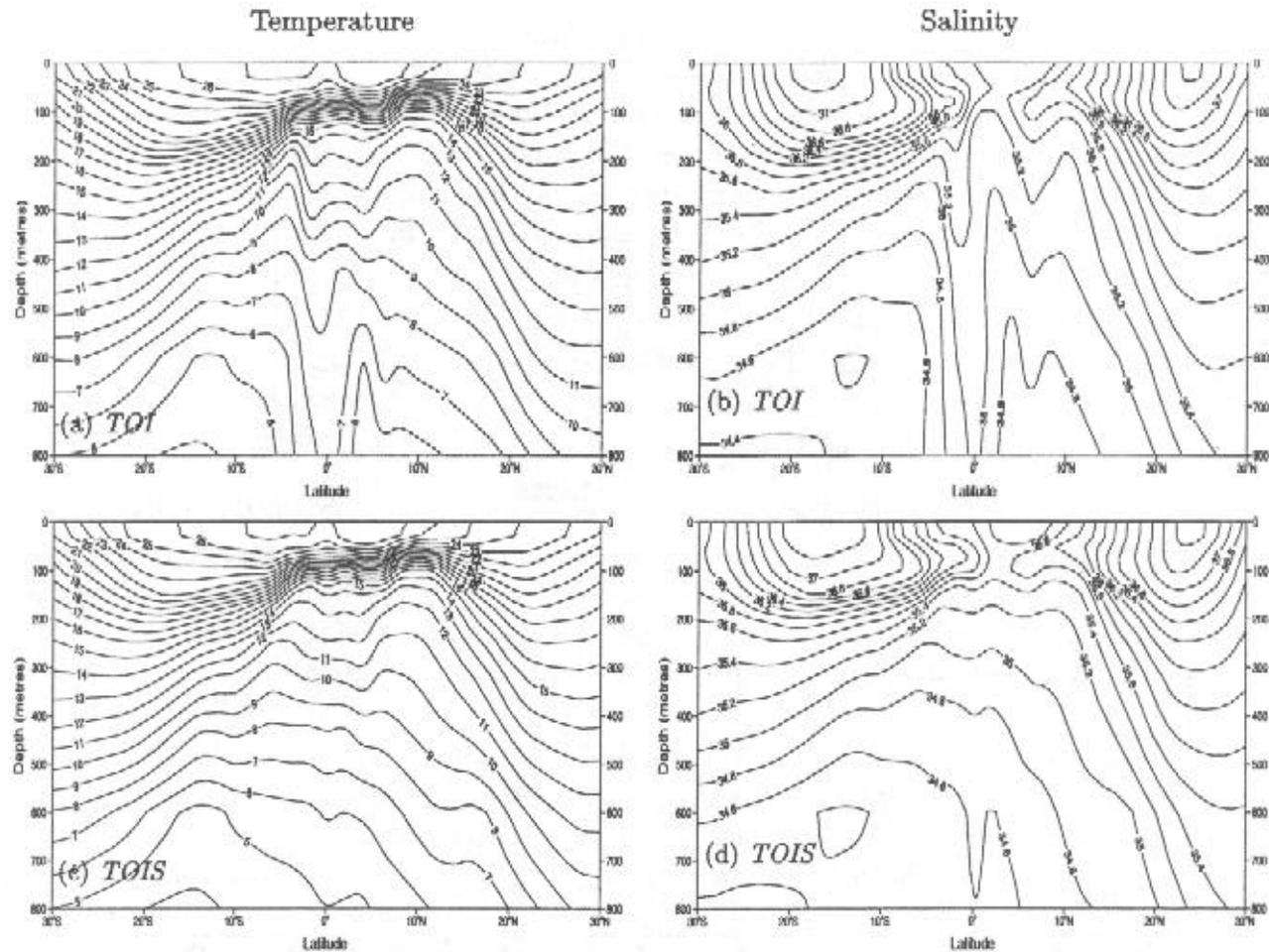


Mean meridional sections 30W from 1990-98

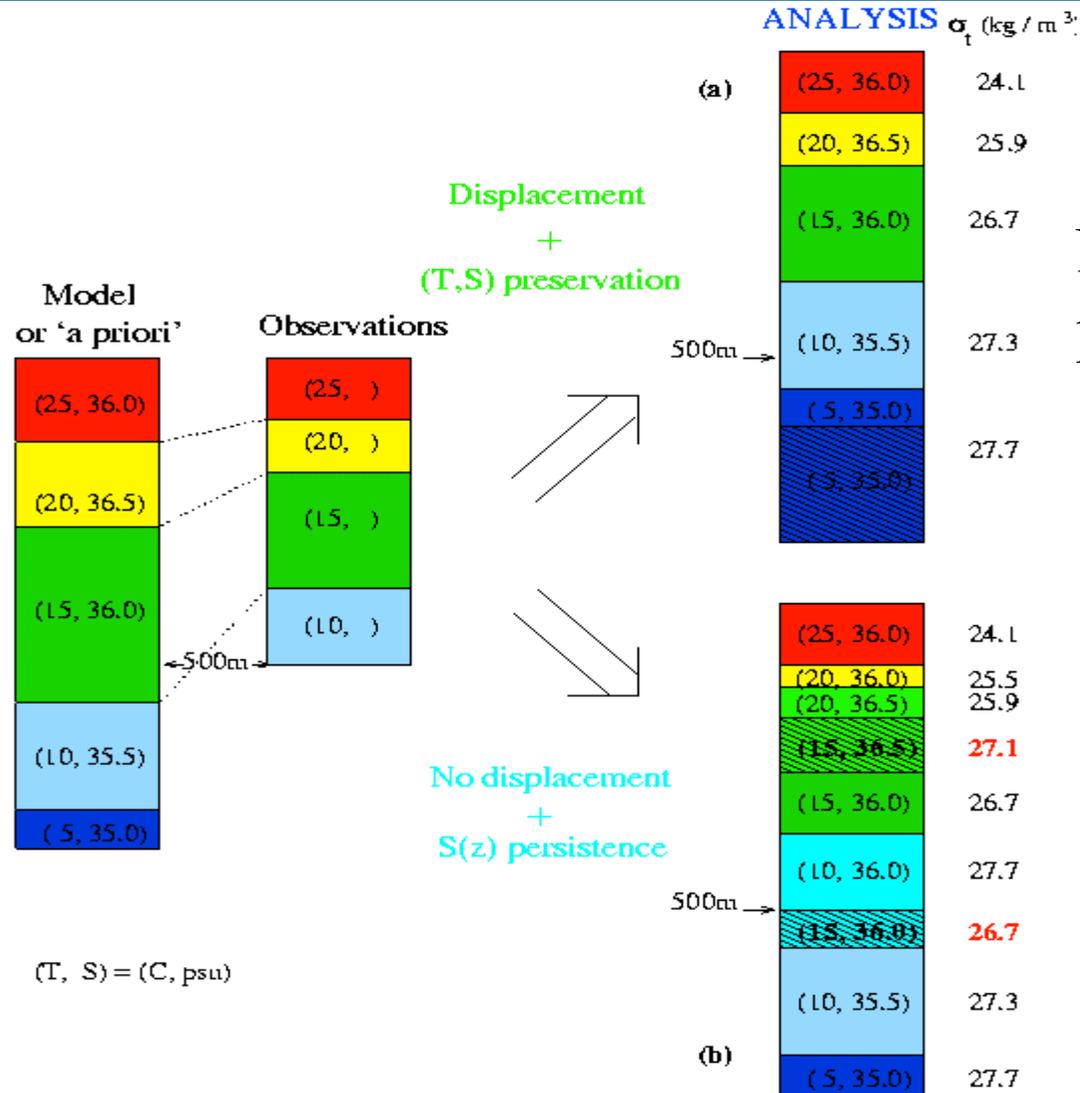
ECMWF assimilation experiments

Old assimilation
 $T(y,z)$ $S(y,z)$
sections

T/S preserving
assimilation
sections



T-profile assimilation with T/S conservation



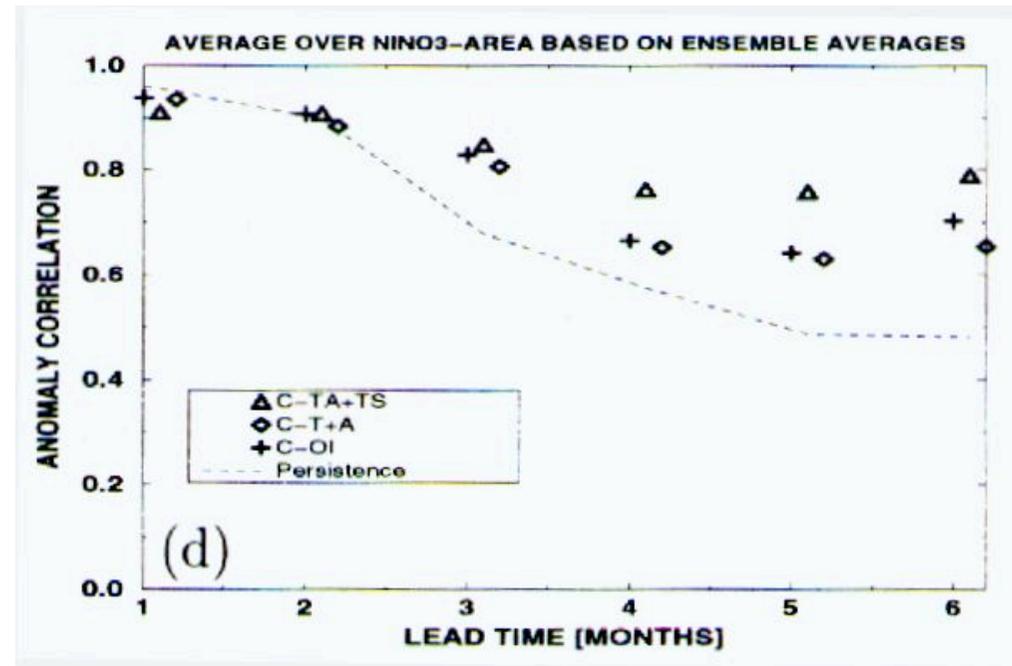
New Analysis profile

Old Analysis profile

Troccoli and Haines (1999)

ECMWF Forecasts of Nino3 temperatures

5 member ensemble forecasts started every 3 months from 1993-1997 = 100 forecasts



C-OI = Original T assimilation

C-T+A = + Altimeter data

C-TA+TS = + T/S conservation scheme

Segsneider et al 2001

Complementarity between Altimeter and T profile assimilation

- Altimeter = Vertical thermocline displacement
- T-profile = S(T) preserved + displacement
- Both preserve S(T) which neither observe
- Both preserve volume(ρ) or volume(T) *except*
- T-profile => changes in volume(ρ) in upper water column where observations made

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

Assimilation of S profile data

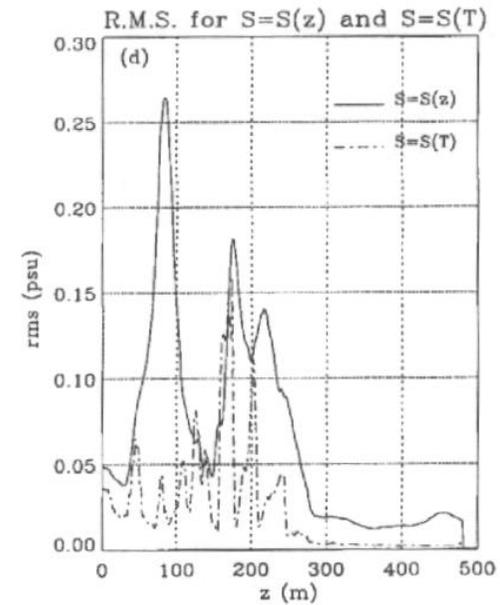
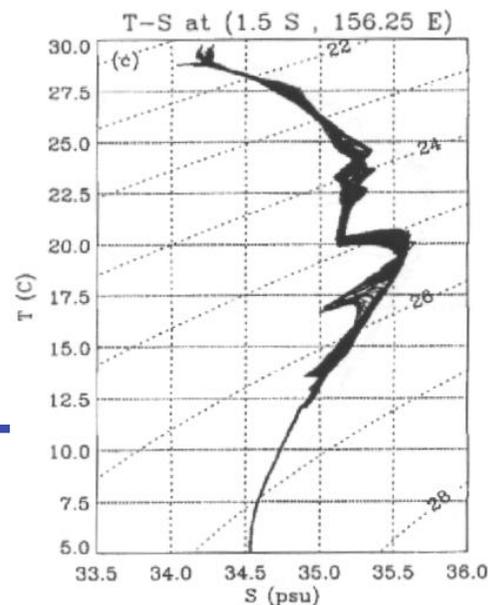
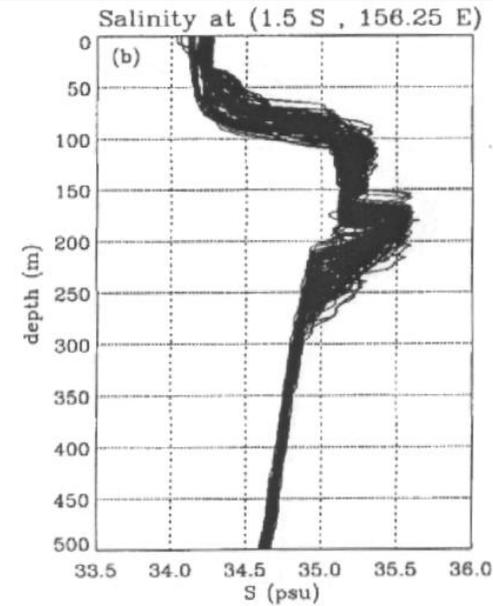
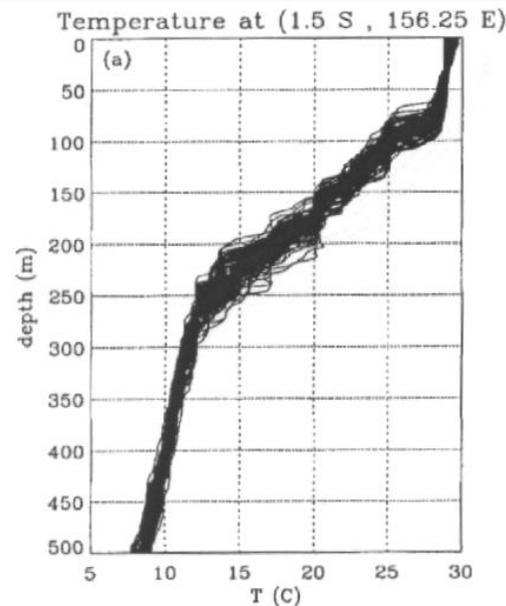
- Ocean salinity difficult to measure (Conductivity corrected for T)
- CTD measured from research ships: eg. Section data such as WOCE or specific local research programs
- Very little historical data
- Important climatic signals in Salinity variability
 - Great Salinity Anomaly; Dixon et al. (1996)
 - Changes in polar-equator salinity gradient => changes in hydrological cycle (evaporation-transport-precipitation) Curry et al (2003)
 - Controls density structure in polar oceans
- Much Salinity variability is highly correlated with T variability
 - How to take advantage of this during assimilation of S data?
 - Otherwise $S(z)$ gives very little additional information over $T(z)$

Salinity variance in z and T space

104 CTD profiles
over 10 days in
W. Equatorial Pacific

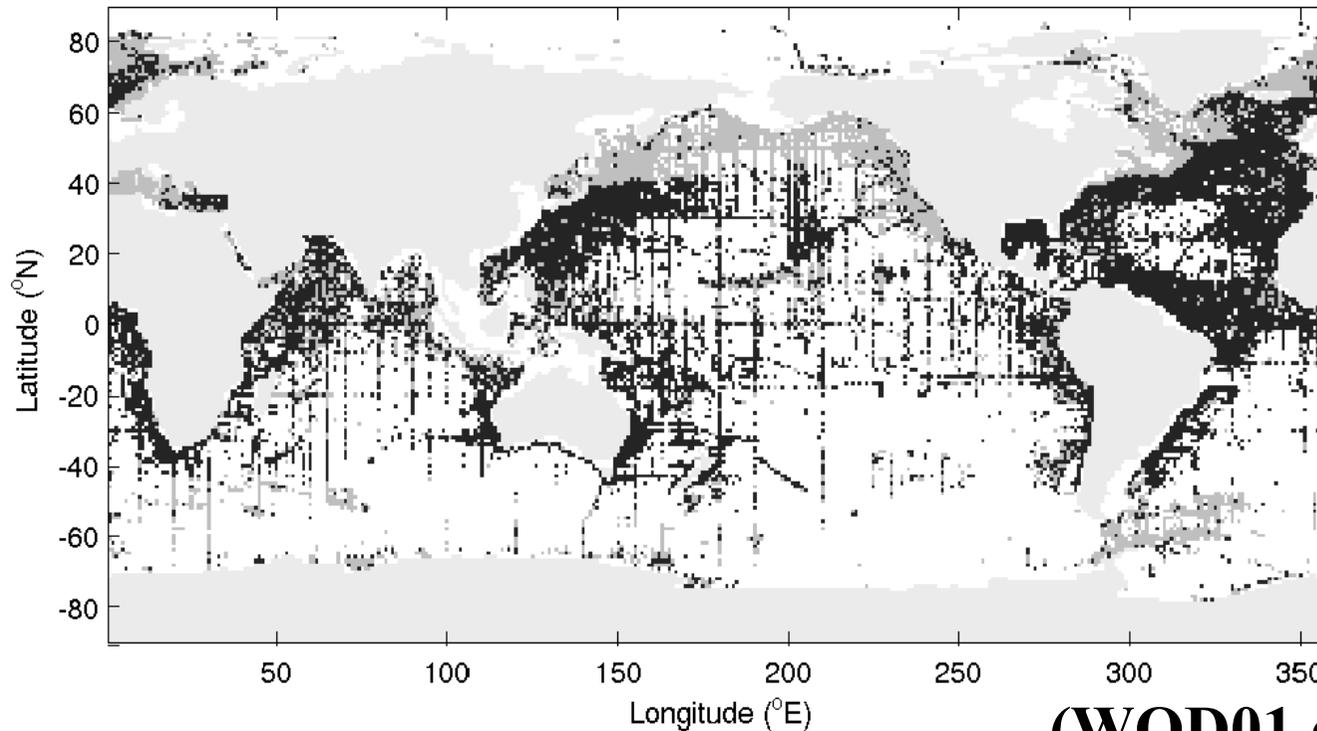
Reduced variance in
 $S(T)$ suggests value of
 T/S preservation during
assimilation

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



Troccoli and
Haines (1999)

Ratio of S variance on depth surface and Isotherms



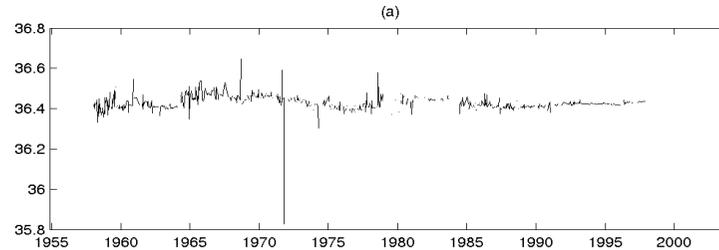
(WOD01 data)

*Ratio ($S(z)$ variance / $S(T)$ variance) in $1 \times 1^\circ$ bins for 40 years of data.
The 300m depth and the mean isotherm at that depth define salinities.
Bins with ratio > 1 black; ratio < 1 dark grey.*

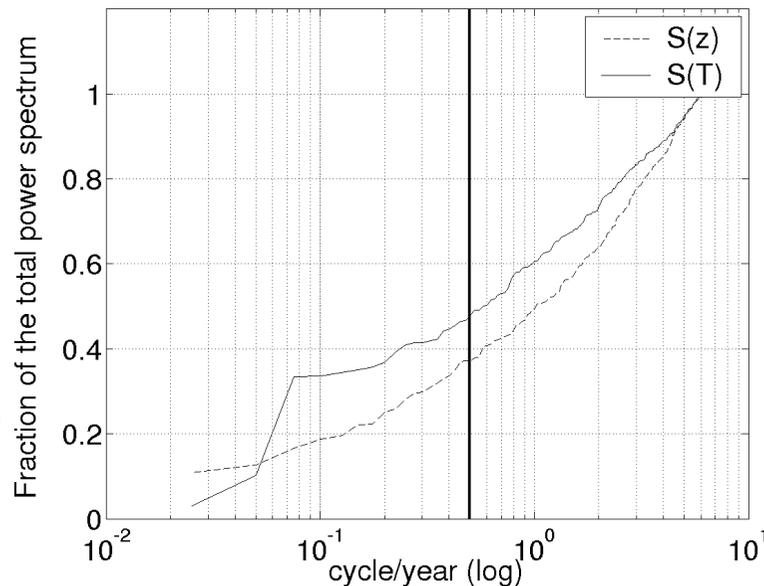
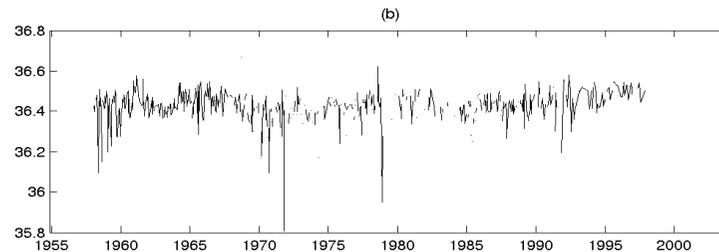
Haines et al (2006)

Bermuda Salinity timeseries

S(17.4C)



S(400m)



S(z) has more
Variability at
High Frequencies
Dynamical Origin

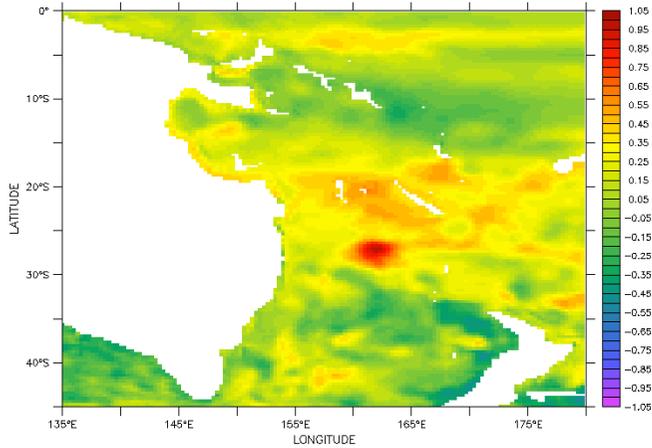
Remaining variability
in S(T)
Lower Frequency
Thermodynamic Origin

Lower Representivity
error

Different Spatial
Scales too

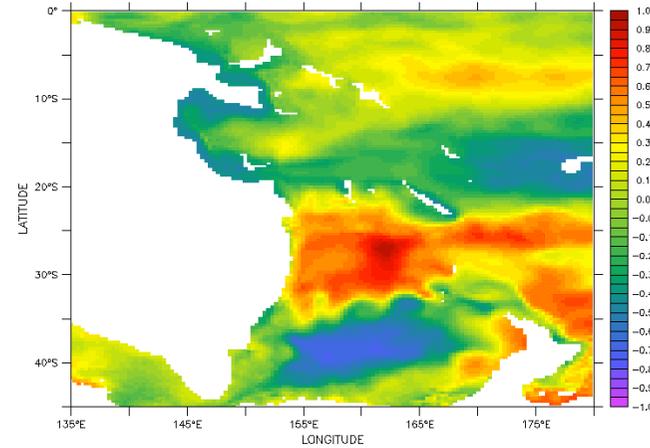
One point S correlation maps HadCEM 1/3 model

$S(z)$



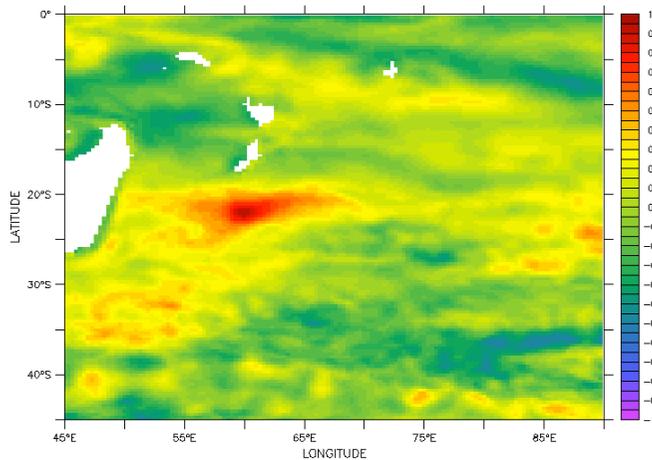
Correlation of salinity on 400m depth surface

$S(T)$



Correlation of salinity on 12C temp surface

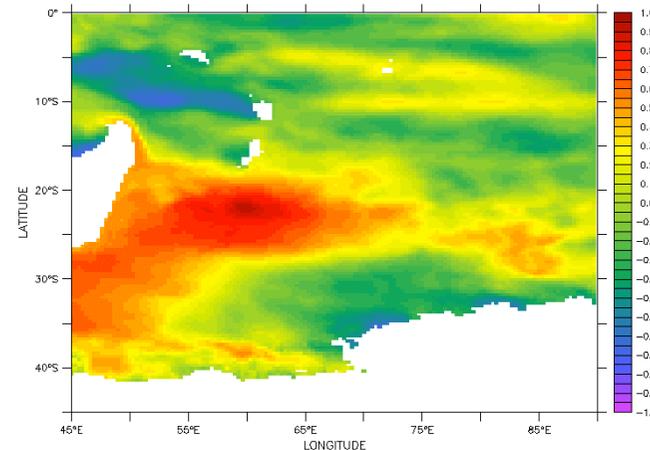
DATA SET: hadcem_s(z)_400_60_-22



Correlation of salinity on 400m depth surface

ENVIRONMENTAL SYSTEMS SCIENCE CENTRE

DATA SET: hadcem_s(t)_15_60_-22



Correlation of salinity on 15C temp surface

13 August 2000

**Expect error
Covariances of
 $S(T)$ to be larger
Scale than $S(z)$
 \Rightarrow Useful in
assimilation of
Salinity data,
especially for
Reanalysis**

Assimilation of Salinity at ECMWF

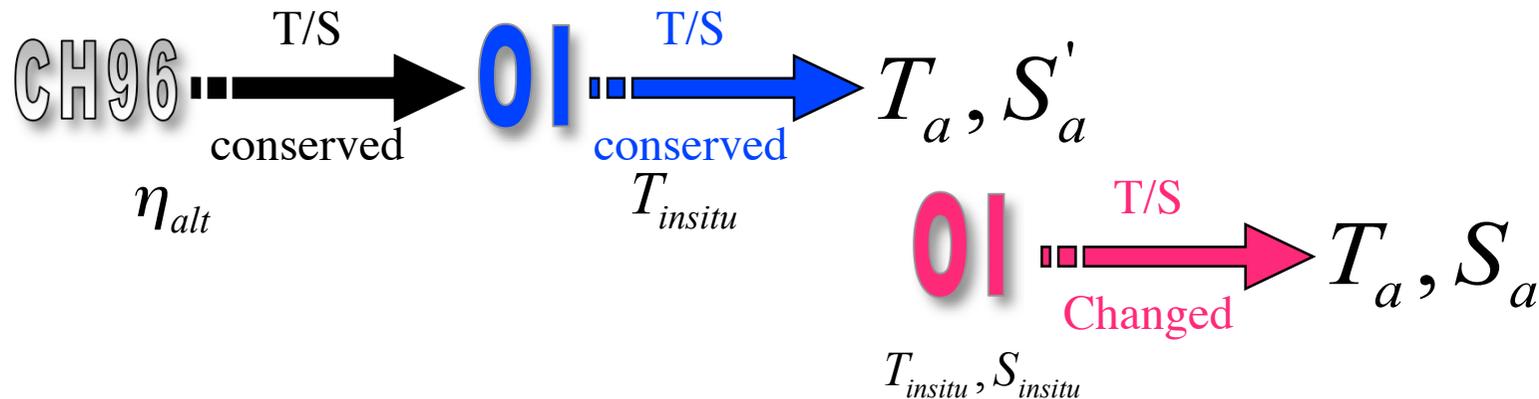
Two stage salinity assimilation process (Implemented by Arthur Vidard)

1) TH99: $S(T)$ unaltered by T assimilation.

$$\Delta S(T) = 0 ; \Delta S_T(z) \neq 0$$

2) Salinity assimilation: $\Delta S(T) \neq 0 ; \Delta S_S(z) \neq 0$

Idea: perform a second OI using T+S data to correct the T/S relationship (Haines et al 2006: Mon. Weath. Rev.)



$$S_a(\mathcal{E}_a) = S'_a(\mathcal{E}_a) + K'((S_{bo}(\mathcal{E}_a) - H_{bb}(\mathcal{E}_a)))$$

➔ Allow an increase in correlation radius in K'

In Situ Assimilation method

Standard method:

$$T_a(z) = T_b(z) + K_T [T_o(z) - H T_b(z)]$$

$$S_a(z) = S_b(z) + K_{S_z} [S_o(z) - H S_b(z)]$$

S(T) algorithm:

$$T_a(z) = T_b(z) + K_T [T_o(z) - H T_b(z)]$$

$$S'_a(z) = S_b(z) + \Delta S_T, \text{ such that}$$

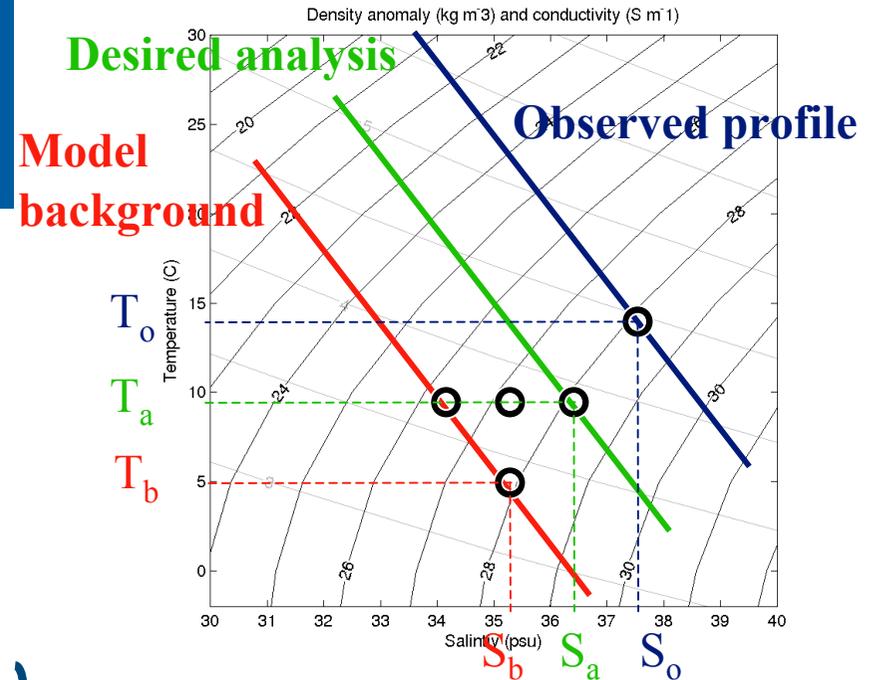
$$\Delta S_T \text{ ensures } S'_a(T_a) = S_b(T_a)$$

$$S_a(T_a) = S'_a(T_a) + K_{S_T} [S_o(T_a) - H S_b(T_a)]$$

} from a T obs

} from an S obs

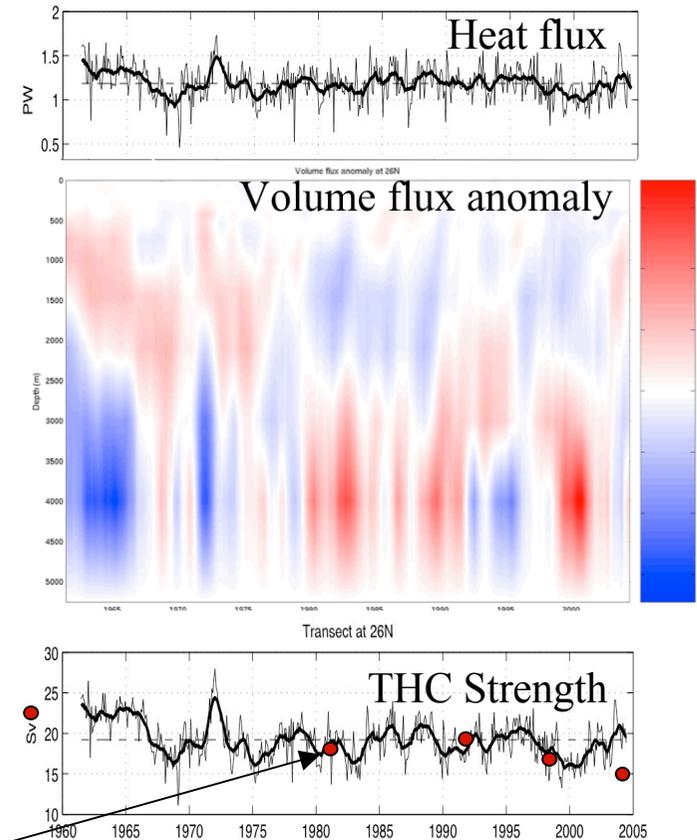
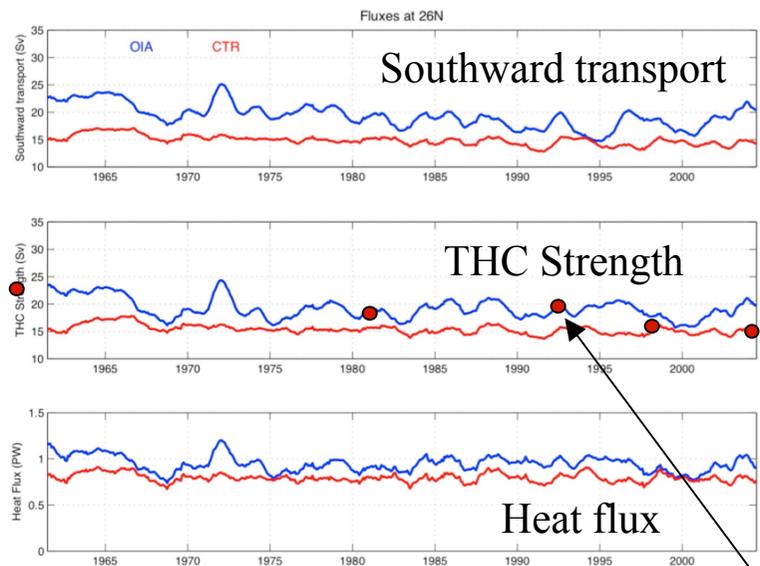
---> K_{S_T} allows spreading over much greater distances than K_{S_z} due to increased covariance length scales.
Also, second salinity increment is independent of the 1st!



Recovering THC strength from an ECMWF Ocean Reanalysis

Thermohaline overturning circulation in the North Atlantic

Assimilation vs Control: fluxes at 26N



Section analyses from Bryden et al 2005

Conservation properties in sequential assimilation

Altimeter Assimilation

Displacement $\Delta h \Rightarrow$ Gross Isopycnal geometry
+ Currents (geostrophy)

- Volume and T/S properties preserved on isopycnals
- Adiabatic (Thermodynamically Reversible)

T Profile Assimilation

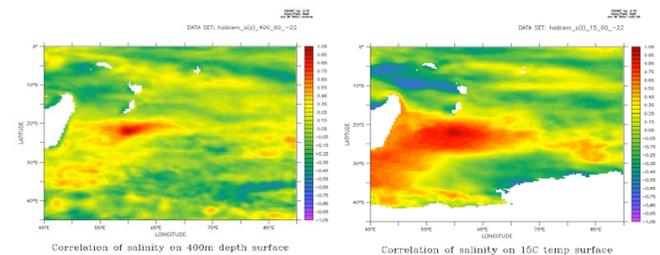
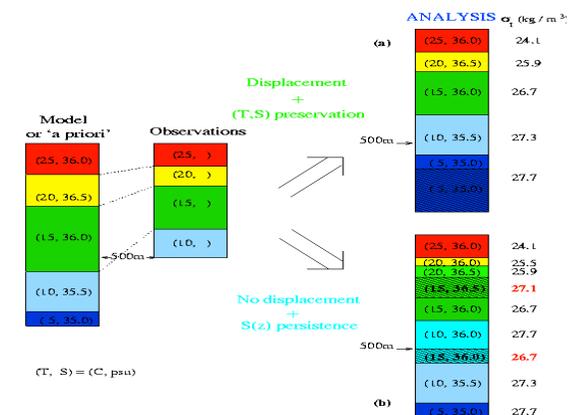
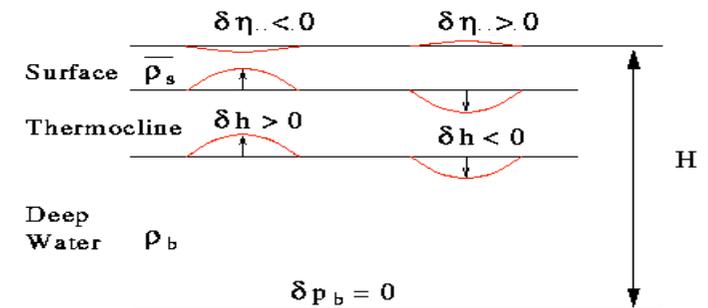
$T(z) \Rightarrow$ Isothermal Water Volumes

- S(T) properties preserved (since salinity is not observed)
- Volumes and T/S preserved below deepest observation

S(T) Assimilation

$S(T) \Rightarrow$ Isopycnal Water Properties

- Large scale, slow variations associated with ventilation and climatic change



WOCE Atlantic Section A16

Water property distributions
give qualitative information
on circulation pathways

Note:

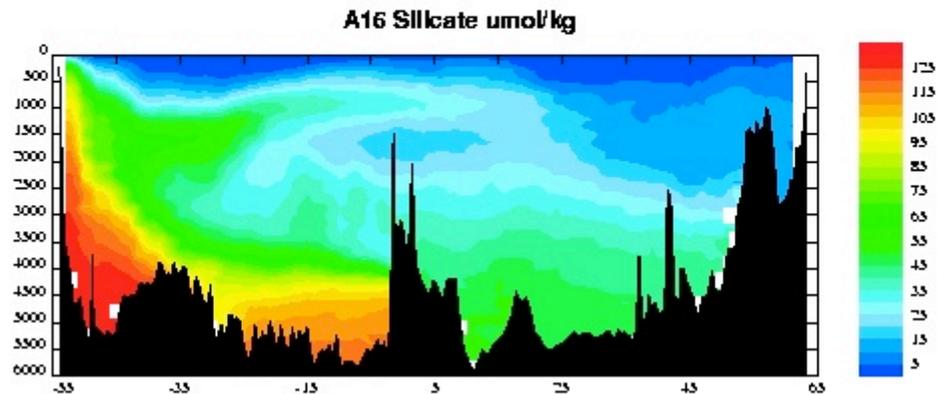
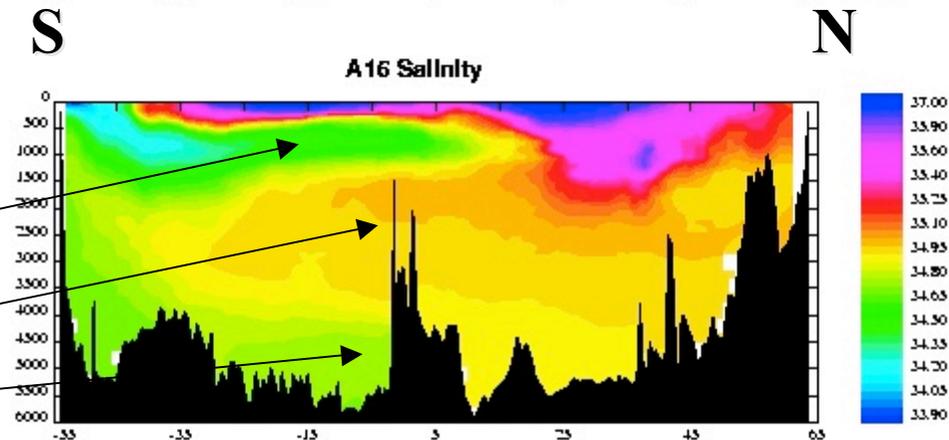
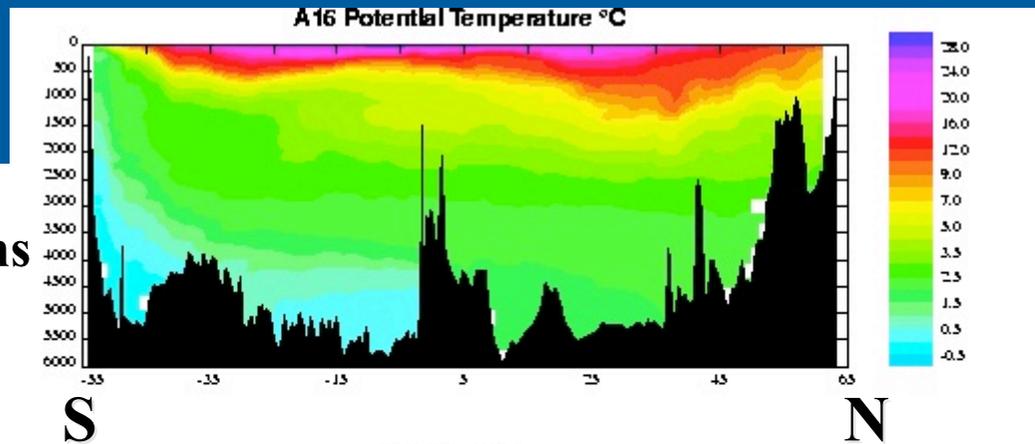
Water mass origins

AIW,

NADW,

ABW

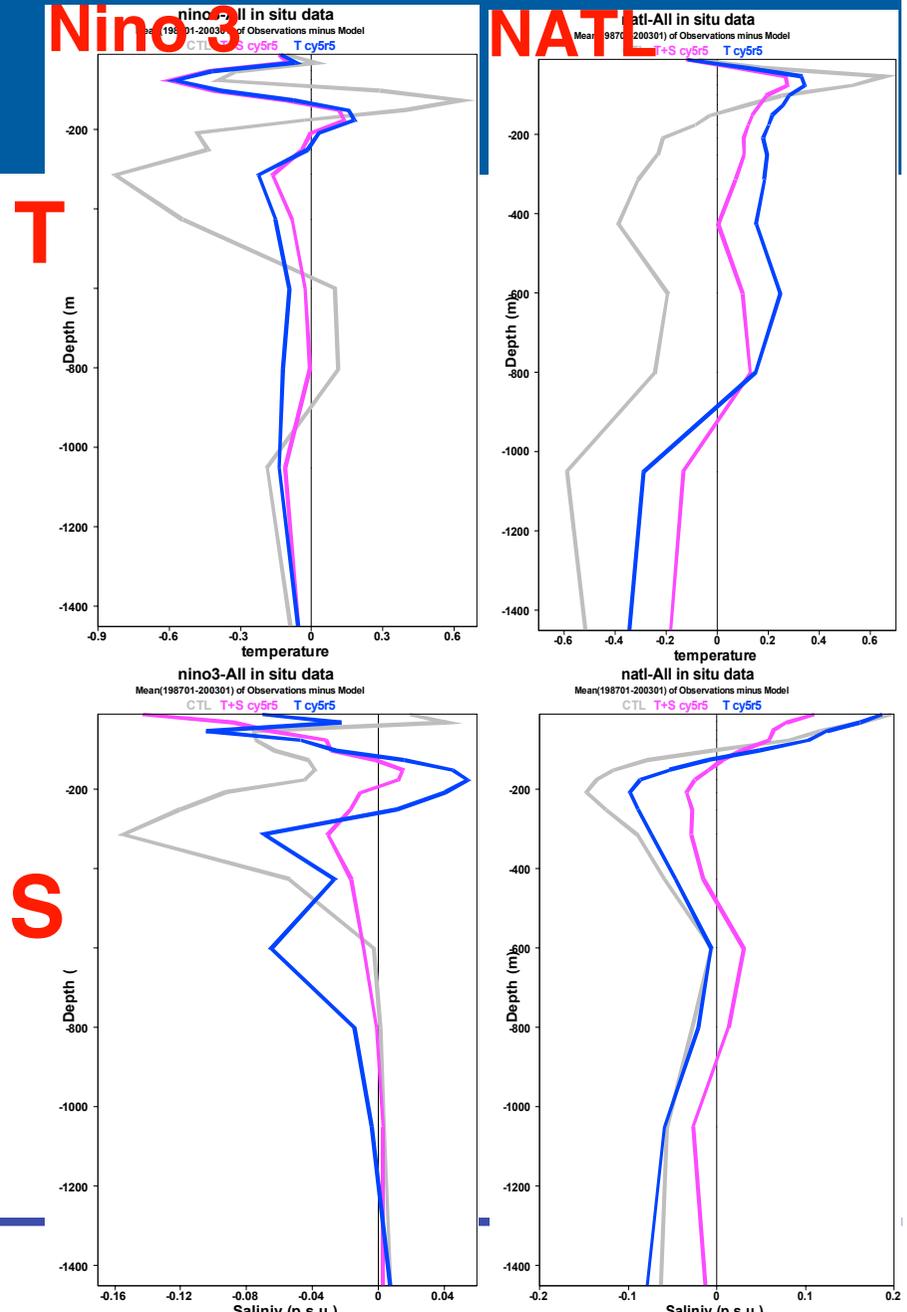
Lagrangian conservation
of water properties
important in assimilation



Frascati August 2006

Improving T through S assimilation

- Temperature assimilation can improve salinity directly since S(T) conserved
- Salinity assimilation can also improve Temperature, but only indirectly through improved advection
- Obs - Background errors Preliminary results from ENACT project reanalysis 1993-2001



CTL; OI(T); OI(T+S)

ty ag

Error reductions through assimilation

EqPac

EqAtl

NATL

EqInd

Vidard et al

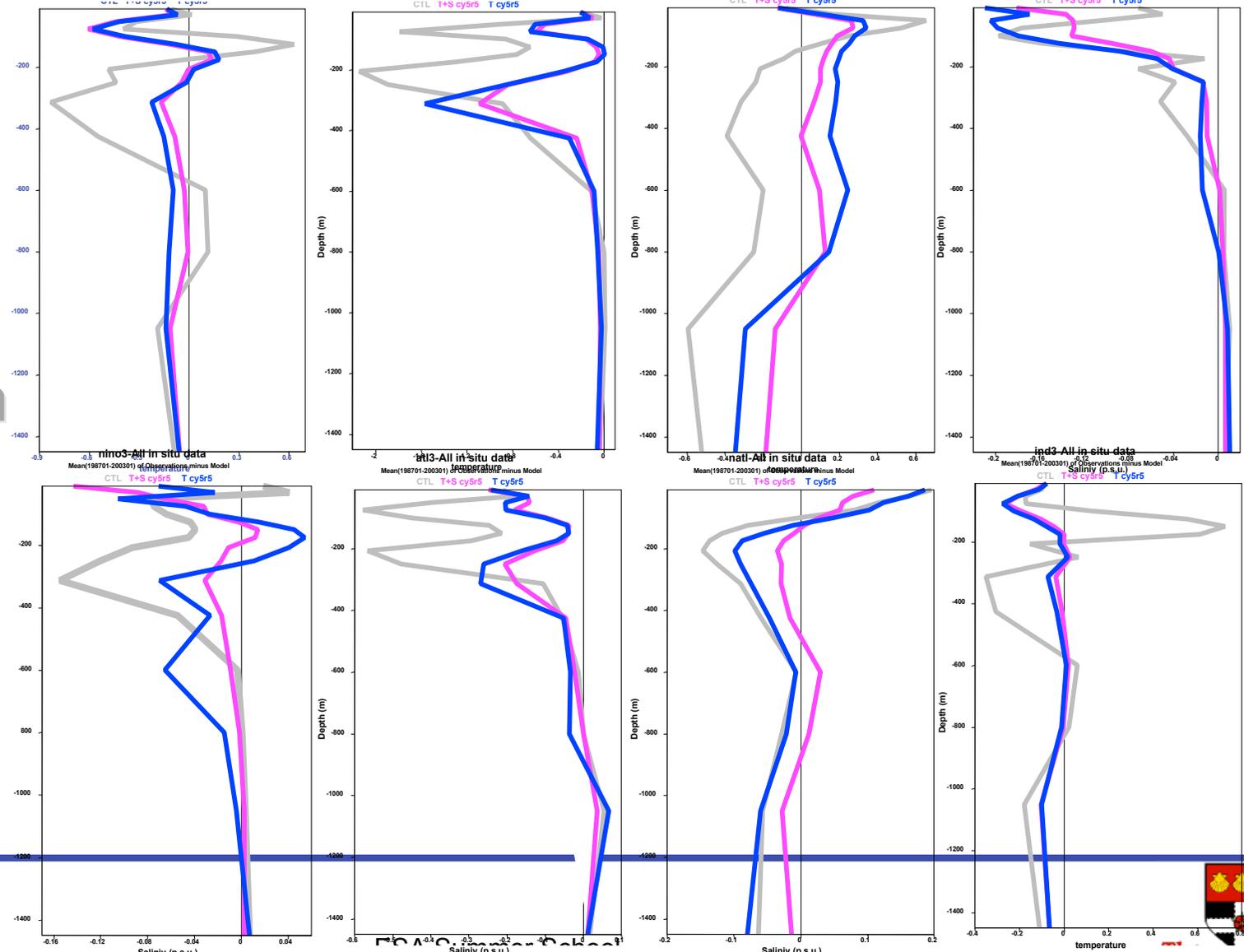
T

No assim

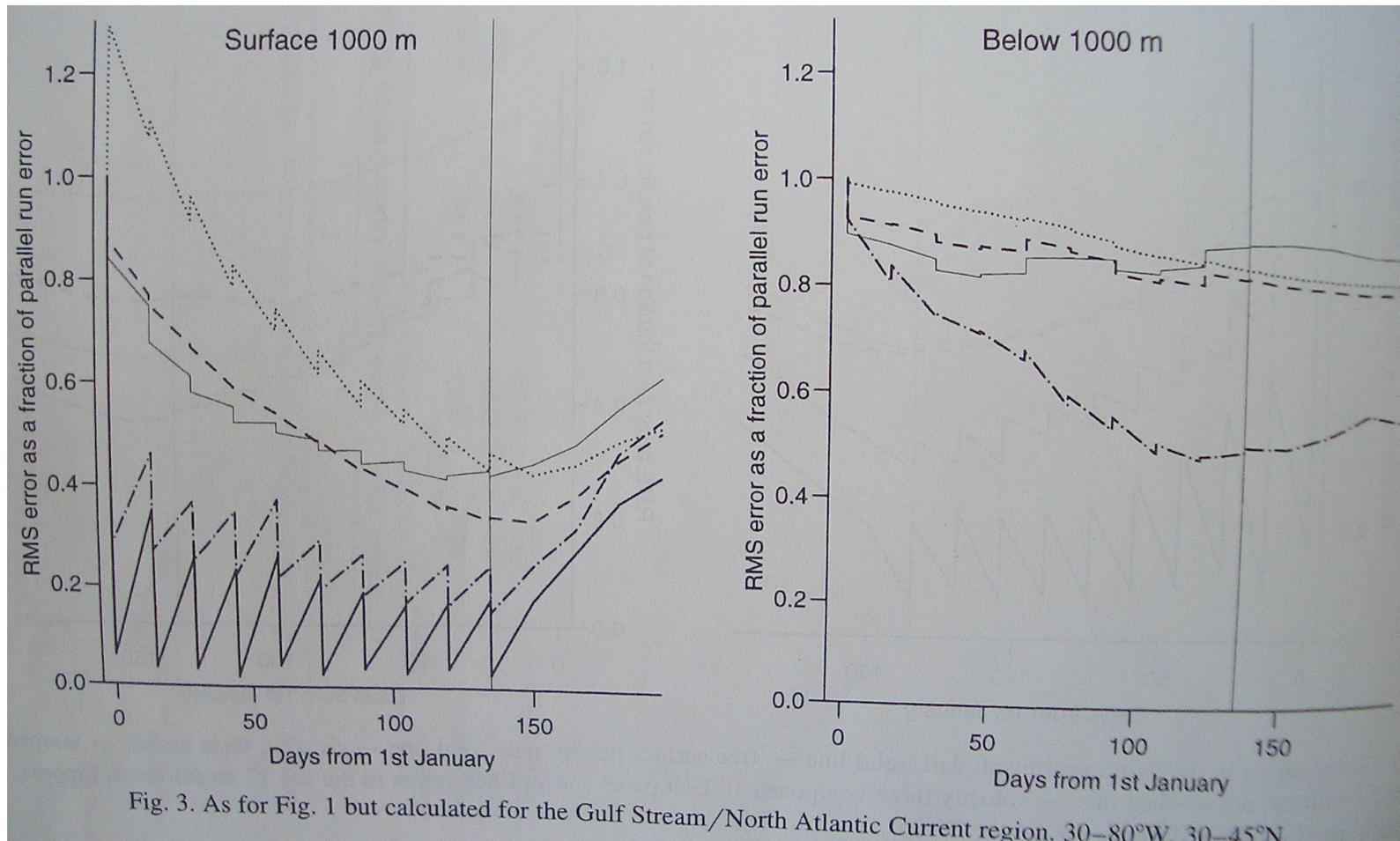
T assim

T+S ass.

S



Twin experiment in OCCAM 36 level model assimilating Sea surface height



Note that subsurface T,S still converge

Fox et al 2001a

Bias and diagnostics of bias in ocean models

- Much of optimal assimilation theory assumes that the models and observations are unbiased. This is definitely not the case for ocean models
- Detection of bias is easy: if the innovations do not average to zero then the model (or data) is biased
- In this case one of the main effects of data assimilation is to counteract the bias eg. model drift
- Methods used to correct for bias in ocean models
 - ‘Pressure Correction’ Bell et al (2000)
 - Semi-prognostic method Greatbatch....
- Having detected bias it should be accounted for in assimilation error analysis or else the weighting of new observations will be poorly handled
- **Need to have a bias model**

Accounting for Bias in Data Assimilation

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

$$2J(\mathbf{x}, \mathbf{b}, \mathbf{c}) = (\mathbf{y} - \mathbf{b} - \mathbf{x})^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{b} - \mathbf{x}) + \quad \text{Minimise } J \text{ wrt } \mathbf{x}, \mathbf{b}, \mathbf{c}$$
$$(\mathbf{x} - \mathbf{x}^f + \mathbf{c})^T \mathbf{B}^{-1} (\mathbf{x} - \mathbf{x}^f + \mathbf{c}) +$$
$$(\mathbf{b} - \mathbf{b}^f)^T \mathbf{O}^{-1} (\mathbf{b} - \mathbf{b}^f) +$$
$$(\mathbf{c} - \mathbf{c}^f)^T \mathbf{P}^{-1} (\mathbf{c} - \mathbf{c}^f)$$

\mathbf{y} = observation

\mathbf{x} = model state

\mathbf{b} = **observation bias**

\mathbf{c} = **model forecast bias**

Superscript f are forecast values

Observation operators have been omitted

\mathbf{R} = observation error covariance

\mathbf{B} = model background error covariance

\mathbf{O} = observation bias error covariance

\mathbf{P} = model forecast bias error covariance

Accounting for Bias in Data Assimilation

- Solution (Analysed variables ^a)

$$\mathbf{x}^a = (\mathbf{x}^f - \mathbf{c}^f) + \mathbf{K} \{(\mathbf{y} - \mathbf{b}^f) - (\mathbf{x}^f - \mathbf{c}^f)\}$$

$$\mathbf{b}^a = \mathbf{b}^f + \mathbf{F} \{(\mathbf{y} - \mathbf{b}^f) - (\mathbf{x}^f - \mathbf{c}^f)\}$$

$$\mathbf{c}^a = \mathbf{c}^f + \mathbf{G} \{(\mathbf{y} - \mathbf{b}^f) - (\mathbf{x}^f - \mathbf{c}^f)\}$$

$$\mathbf{K} = (\mathbf{B} + \mathbf{P}) [\mathbf{B} + \mathbf{P} + \mathbf{O} + \mathbf{R}]^{-1}$$

$$\mathbf{F} = \mathbf{O} [\mathbf{B} + \mathbf{P} + \mathbf{O} + \mathbf{R}]^{-1}$$

$$\mathbf{G} = \mathbf{P} [\mathbf{B} + \mathbf{P} + \mathbf{O} + \mathbf{R}]^{-1}$$

or
$$\mathbf{x}^a = (\mathbf{x}^f - \mathbf{c}^a) + \mathbf{K}_1 \{(\mathbf{y} - \mathbf{b}^a) - (\mathbf{x}^f - \mathbf{c}^a)\} \quad \mathbf{K}_1 = \mathbf{B} [\mathbf{B} + \mathbf{R}]^{-1}$$

y = observation

x = model state

b = observation bias

c = model forecast bias

R = observation error covariance

B = model background error covariance

O = observation bias error covariance

P = model forecast bias error covariance

Usual problems are: (i) Knowing the Covariance errors

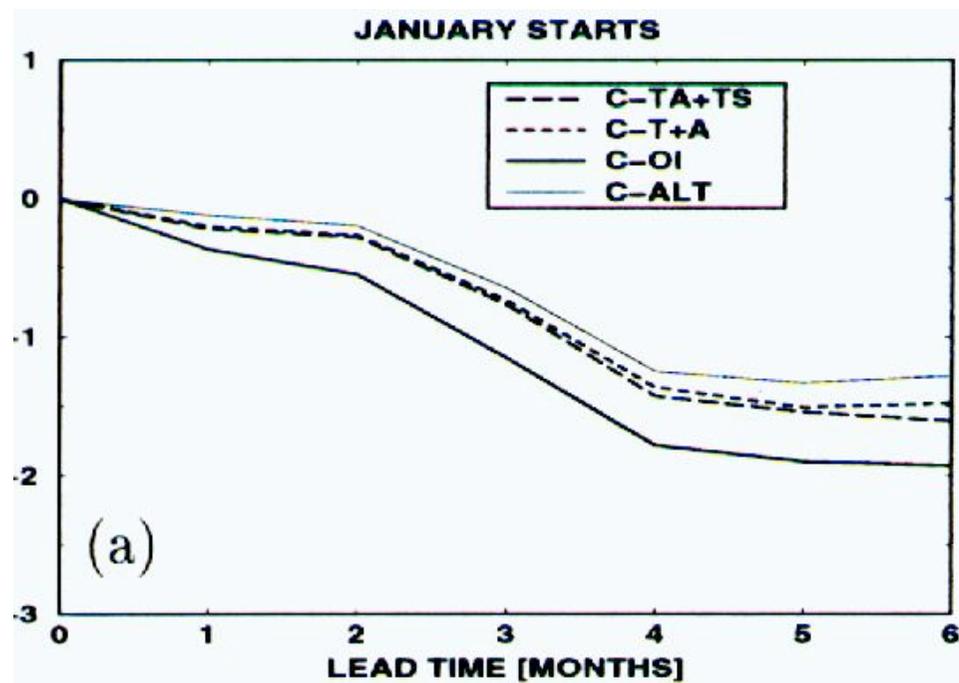
(ii) Sequential 3DVar requires bias models for

$$\mathbf{b}^f(t+1) = \mathbf{M}_b[\mathbf{b}^a(t)]; \quad \mathbf{c}^f(t+1) = \mathbf{M}_c[\mathbf{c}^a(t)];$$

Comments on Bias Modelling

- **Known Biases** $\{b^f(t); c^f(t)$ known a priori eg. previous runs}
 - $x^a = (x^f - c^f) + K \{(y - b^f) - (x^f - c^f)\}$ $K = (B+P)[B+P+O+R]^{-1}$
 - $b^f(t) = 0; c^f(t) = 0$ is particular case
 - $(B+P)$ total model err cov.; $(O+R)$ total obs. err.
- **Persistent Biases** $\{b^f(t+1)=b^a(t); c^f(t+1)=c^a(t)\}$
 - $x^a = (x^f - c^f) + K \{(y - b^f) - (x^f - c^f)\}$ $K = (B+P)[B+P+O+R]^{-1}$
 - $b^a = b^f + F \{(y - b^f) - (x^f - c^f)\}$ $F = O[B+P+O+R]^{-1}$
 - $c^a = c^f + G \{(y - b^f) - (x^f - c^f)\}$ $G = P[B+P+O+R]^{-1}$
 - If O, P i.e. F, G are small \Rightarrow may hope to converge to \sim constant b, c
 - Simplifications also arise if $P = \alpha B; O = \beta R \Rightarrow$ all Innovations proportional
- **Attribution of Bias:** When are O, P sufficiently different to allow identification of misfits $\{(y - b^f) - (x^f - c^f)\}$?
- Should always check total misfits are consistent with $B+P+O+R$

Drift in ocean temperatures in tropical Pacific during 6 month free runs of ECMWF coupled model



Drift must be removed to interpret ENSO forecasts
Stockdale 1997

Accounting for bias during data assimilation

$\mathbf{x}_{k+1} = \mathbf{M}(\mathbf{x}_k, \mathbf{u}_k)$ deterministic model

\mathbf{x}_k variables, \mathbf{u}_k parameters, at time k

For a general biased model

$\mathbf{x}_{k+1} = \mathbf{M}^t(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{T}(\mathbf{b}_k)$

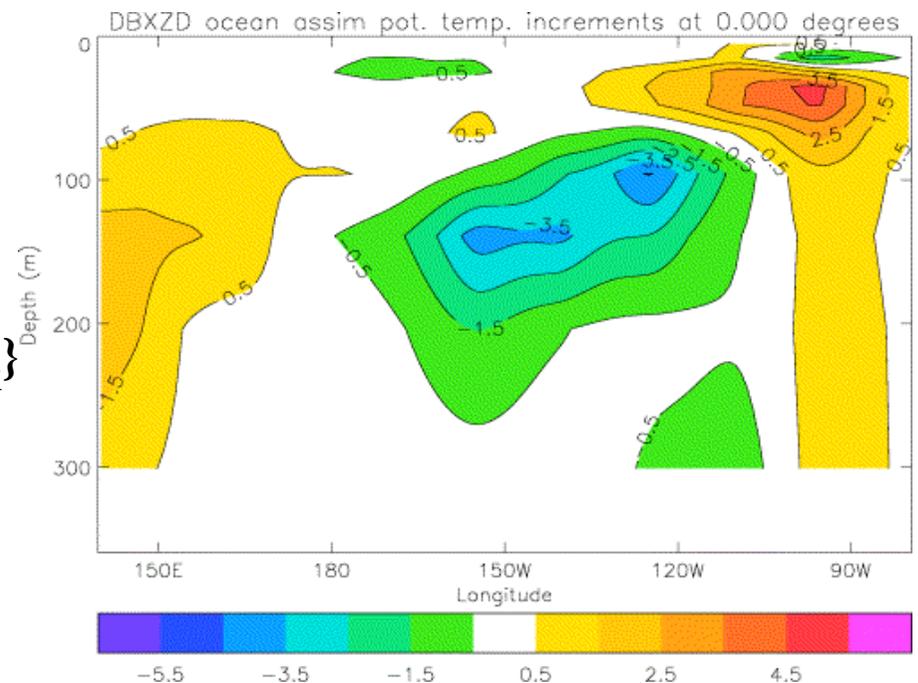
\mathbf{M}^t true model, \mathbf{b}_k bias variables

**Now define new State vector $\{\mathbf{x}_k, \mathbf{b}_k\}$
with model for bias evolution**

$\mathbf{b}_{k+1} = \mathbf{W}(\mathbf{b}_k, \mathbf{x}_k) + \boldsymbol{\zeta}_k$,

$\boldsymbol{\zeta}_k$ white noise

Mean assimilation T increments in
Met Office assimilation in
Equatorial Pacific, Bell et al 2002



In sequential assimilation \mathbf{x}_k will converge to \mathbf{x}_k^t
provided bias model \mathbf{W} is correct

Bell et al 2002 assumed Equatorial T bias due to wrong wind stress $\tau(x,y,t)$

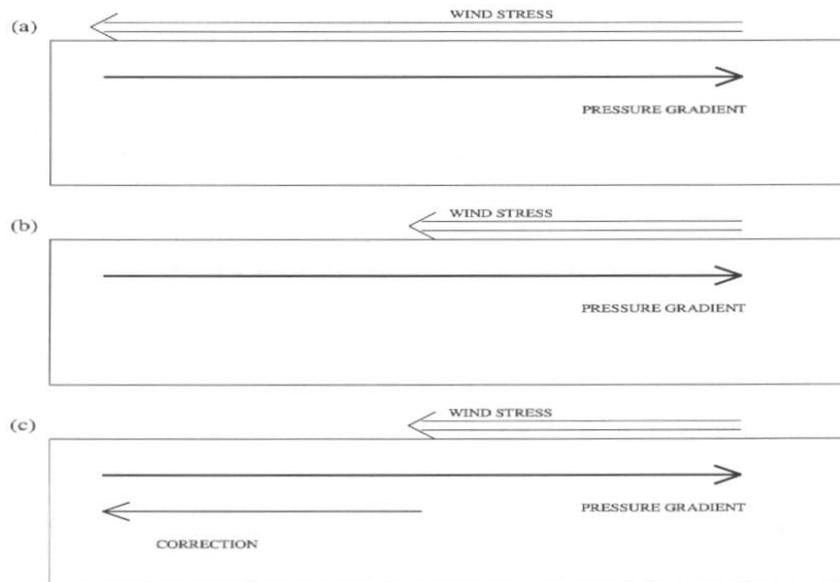
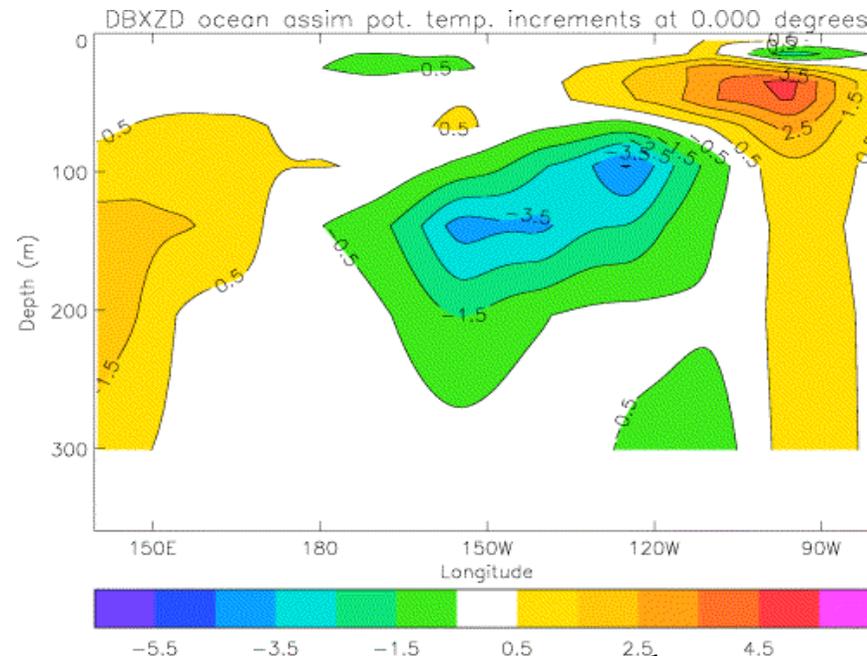


Figure 10. Schematic of the main dynamical balance along the equator between the surface wind stress and pressure gradient: (a) reality, (b) data assimilation and (c) pressure correction.



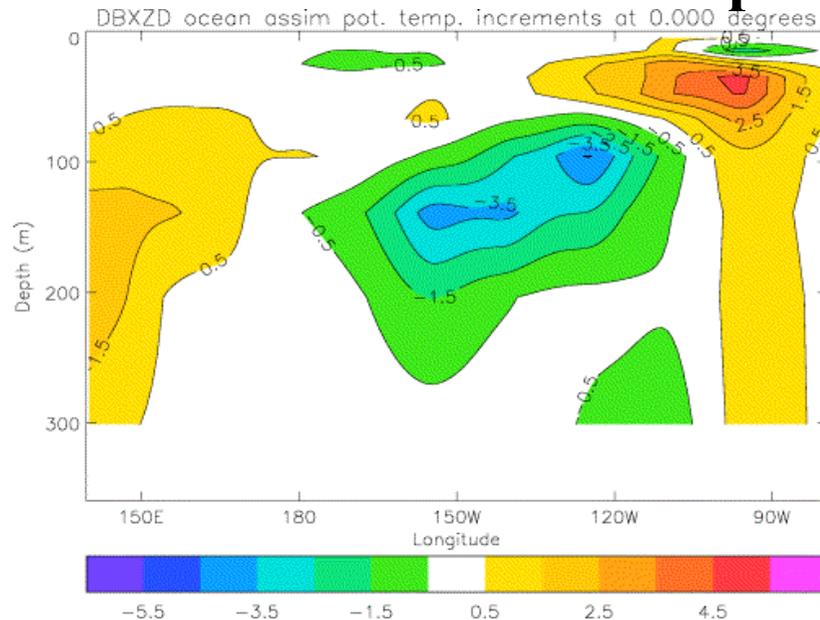
But they modelled the bias with pressure field $p^b(x,y,z,t)$

$$\frac{\partial u^m}{\partial t} + \Gamma(u^m) - fv^m = -\frac{\partial(p^m + p^b)}{\partial x} + \frac{\partial \tau_{xz}}{\partial z},$$

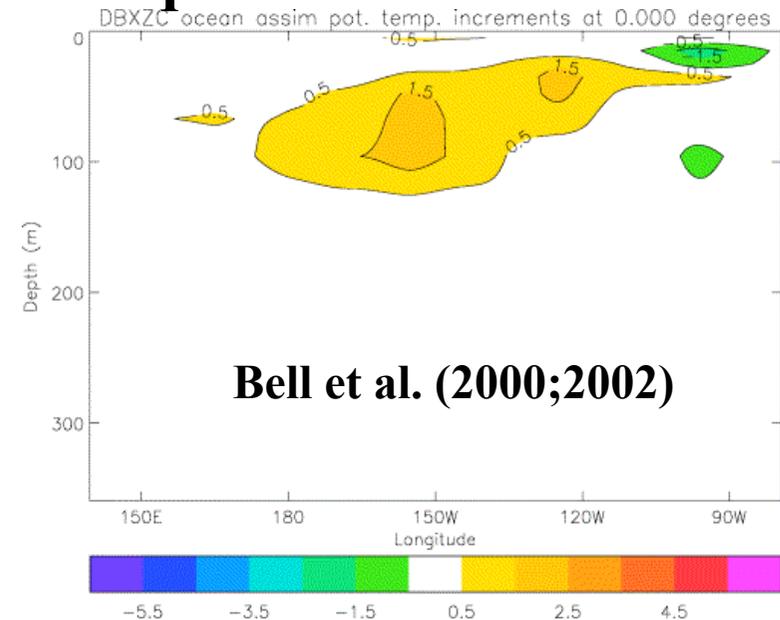
$$\frac{\partial v^m}{\partial t} + \Gamma(v^m) + fu^m = -\frac{\partial(p^m + p^b)}{\partial y} + \frac{\partial \tau_{yz}}{\partial z},$$

Example of Bias Modelling in Seasonal Forecasting

Zonal Temp. errors in Equatorial Pacific



**Mean T (Obs-Backgd) misfits
assuming Unbiased model**



Mean T misfits using a Bias model

- Method reduces undesirable transients while allowing T to approach T^{true}
- Could one recover the cause of the bias (probably wind stress error)?
- Similar method reduces misfits in Ocean Reanalysis; Chepurin et al (2005)

Bias diagnostics in a high-resolution global ocean model

- No alteration of data assimilation (DA) procedure
- Aim is to diagnose mean misfits/innovations directly as biases in physical processes
 - 1 Assimilation impacts on *Local* Heat budget (or other tracers)
 - 2 Assimilation impacts on water volumes in each temperature class within an *Extended Region*, eg. N. Atlantic (c.f. ocean inverse theory)
- Consider a model 'held' close to observational trajectory by DA against a drift tendency
 - (a) How do we quantify role of DA in preventing drift?
 - (b) How do we identify drift with inadequacies of physics?

Conclusions

- **Lagrangian conservation of water properties provides useful constraints for both steady state ocean inverse problems and time evolving ocean data assimilation**
- **Generates state-dependent multivariate covariances in a natural way**
- **Provides a framework for obtaining climate quality ocean reanalyses using sequential data assimilation**
- **Useful in operational oceanography and seasonal forecasting when error covariances poorly defined empirically**
- **Allows improved assimilation of salinity (and potentially other tracer) data by reducing “Representivity” errors and increasing Kalman gain**
- **Model bias should also be accounted for correctly in order to correctly weight assimilated data.**

End of second Lecture