Model and observation bias correction in altimeter ocean data assimilation in FOAM

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Abstract

We implement a combined online model and observation bias correction system in the UK Met Office FOAM OI ocean data assimilation system. The observation bias scheme is designed to estimate the error in the mean dynamic topography that must be used for altimeter data assimilation. The mean dynamic topography field is added to the altimeter data supplied as sea-level anomalies giving the absolute sea surface height. The bias scheme separately estimates the remaining model bias in the model sea surface height field. The final unbiased estimate of the absolute dynamic topography is assimilated into the FOAM model by adjusting the subsurface density field using the Cooper and Haines scheme. Various diagnostics including the observation minus background statistics show that both model and observation bias correction schemes improve the assimilation results. Combining the schemes provides better results than either alone.

The FOAM system is now transitioning from the Unified Model ocean to a 0.25 degree global NEMO system using the same OI assimilation scheme. Preliminary results are presented using the bias correction scheme with this new system.

INTRODUCTION

Assimilation of altimeter sea-level data is very important to correct the ocean circulation in models. The problem with altimeter assimilation is that there are large biases that exist on small scales due to the insufficiently accurately known geoid. Because of this oceanographers tend to assimilate sea-level anomalies instead of absolute sea-level. However to assimilate SLA we need a mean surface height or mean dynamic topography (MDT) to produce a sea surface height observation. We have estimates of the MDT obtained from gravity observations from ships, from space (e.g. GRACE/GOCE) and from drifter data. These estimates still contain errors which are ~10 cm much larger than the signal error ~3 cm.

To correct this bias we have developed an online altimeter bias correction scheme. The aims of the work are twofold; first to get an improved MDT and second to improve the impact of altimeter assimilation in an ocean data assimilation scheme; the Met Office's FOAM, a sequential assimilation system. The paper is split into parts. First we introduce the FOAM-UM system. Second we describe the bias assimilation method. Third we show some results. Finally, the Met Office are introducing a new ocean analysis system based on the NEMO model and this introduced along with some preliminary results.

FOAM-UM

The FOAM-UM is a daily operational open-ocean forecasting system (see Martin et al. 2007 for a recent description). This system assimilates real time or near real time data including satellite SST, SLA, insitu T+S data from e.g. Argo. The along track altimeter SLA data is obtained from Collecte Localisation Satellites (CLS). The altimeter data is assimilated along with the MDT which is derived from model and observational estimates (see Fig. 1).

All the data types are quality controlled to remove data with gross errors. Next the data assimilated into a previous model 1 day forecast. Then the corrected model is run on for a 5 day forecast forced by Met Office NWP atmospheric forcings. The results are fed into an automatic verification system to monitor the output. The outputs are disseminated to a various customers including the Royal Navy.

The system consists of seven nested models, the 1° global model provides boundaries for the 1/3° North Atlantic/Arctic model and 1/3° Indian ocean model and 1/4° Antarctic model. This in turn provide boundaries for a 1/9° North Atlantic, 1/9° Arabian Sea and 1/9° Mediterranean models. The highest resolution systems provide boundary data for the shelf-seas system.

ALTIMETER ASSIMILATION

The FOAM system uses an OI type assimilation scheme (analysis correction). The altimeter data is assimilated using a modified Cooper & Haines 1996 scheme. This lifts or lowers temperature and salinity levels to fit the required SSH increment using the hydrostatic equation assuming no bottom pressure change.

METHOD

The method is described in detail in Lea et al 2008. The principle is to combine model and observation bias estimation along with the usual model state estimation in a sequential data assimilation system.

The analysis equations can be derived from a cost function equation:

$$
\begin{aligned}
J =& (\mathbf{y} - \mathbf{H}(\mathbf{x}+\mathbf{b}))^{\mathrm{T}}\mathbf{R}^{-1}(\mathbf{y} - \mathbf{H}(\mathbf{x}+\mathbf{b})) \\
&+(\mathbf{x} - \mathbf{x}^{\mathrm{f}} + \mathbf{c})^{\mathrm{T}}\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}^{\mathrm{f}} + \mathbf{c}) \\
&+(\mathbf{b}^{\mathrm{o}} - \mathbf{b})^{\mathrm{T}}\mathbf{T}^{-1}(\mathbf{b}^{\mathrm{o}} - \mathbf{b}) \\
&+(\mathbf{b} - \mathbf{b}^{\mathrm{f}})^{\mathrm{T}}\mathbf{O}^{-1}(\mathbf{b} - \mathbf{b}^{\mathrm{f}}) \\
&+(\mathbf{c} - \mathbf{c}^{\mathrm{f}})^{\mathrm{T}}\mathbf{P}^{-1}(\mathbf{c} - \mathbf{c}^{\mathrm{f}})
\end{aligned}
\qquad (1)
$$

The variables used are as follows

x – model state vector
y – observation vector
b – observation bias vector
c – model bias vector
T – observation bias error covariance
O – obs bias forecast error covariance
P – model bias forecast error covariance
R – observation error covariance
B – background error covariance
H – observation operator translates from model to observation space

The first term of eqn (1) is the model data misfit which depends on the difference between the model state and the bias corrected observations. The second term is the model background constraint and depends on the difference between the model state estimate and the bias corrected model forecast. The third term is observation bias constraint which depends on the difference between the intial bias $\mathbf{b}^{\mathbf{o}}$ and the observation bias estimate. The fourth term is the bias forecast constraint which depends on the difference between the observation bias forecast (from the previous analysis) and the observation bias estimate. The fifth term is model bias forecast constraint which depends on the difference between the model bias forecast and model bias estimate.

Explicitly finding the minimum of J with respect to **x**, **b** and **c**, that is where $dJ/d\mathbf{x} = 0$, $dJ/d\mathbf{b}=0$, $dJ/d\mathbf{c}=0$ gives the analysis equations we solve

$$\mathbf{x}^a = (\mathbf{x}^f - \mathbf{c}^f) + \mathbf{K}_1\{\mathbf{y} - \mathbf{H}\mathbf{b}^f - \mathbf{H}(\mathbf{x}^f - \mathbf{c}^f)\} \tag{2a}$$

$$\mathbf{K}_1 = (\mathbf{B}+\mathbf{P})\mathbf{H}^T\{\mathbf{H}(\mathbf{B}+\mathbf{P}+\mathbf{LT})\mathbf{H}^T + \mathbf{R}\}^{-1} \tag{2b}$$

$$\mathbf{b}^a = \mathbf{b}^f + \mathbf{F}\{\mathbf{y} - \mathbf{H}\mathbf{b}^f - \mathbf{H}(\mathbf{x}^f - \mathbf{c}^f)\} \tag{3a}$$

$$\mathbf{F} = \mathbf{LTH}^T\{\mathbf{H}(\mathbf{B}+\mathbf{P}+\mathbf{LT})\mathbf{H}^T + \mathbf{R}\}^{-1} \tag{3b}$$

$$\mathbf{c}^a = \mathbf{c}^f - \mathbf{G}\{\mathbf{y} - \mathbf{H}\mathbf{b}^f - \mathbf{H}(\mathbf{x}^f - \mathbf{c}^f)\} \tag{4a}$$

$$\mathbf{G} = \mathbf{PH}^T\{\mathbf{H}(\mathbf{B}+\mathbf{P}+\mathbf{LT})\mathbf{H}^T + \mathbf{R}\}^{-1} \tag{4b}$$

$$\mathbf{b}^f = \mathbf{L}\mathbf{b}^o + (\mathbf{I} - \mathbf{L})\mathbf{b}^f \tag{5}$$

$$\mathbf{L} = \mathbf{O}(\mathbf{T}+\mathbf{O})^{-1} \tag{6}$$

In equations (2b), (3b) and (4b) the part in curly braces is identical which simplifies the computation of these equations significantly. However, there are now five covariance matrices to find values for. We use the same observation and background error covariances as in the standard FOAM-UM system. We assume that the observation bias forecast error covariance is proportional to observation bias error covariance. That is

$\mathbf{O} = \gamma_b \mathbf{T}$ where γ_b =0.01. The correlation width is 40 km which is the scale of the largest MDT errors. The variance is obtained from the Rio (2005) MDT error estimate (Fig 2b). This is multiplied by 5 in order to better represent the variability between MDT products.
The model bias forecast error covariance **P** is given a uniform variance of 9×10^{-3} and a correlation scale of 400 km.

The bias models for **b** is persistence and **c** is a decay on a 90 day timescale.

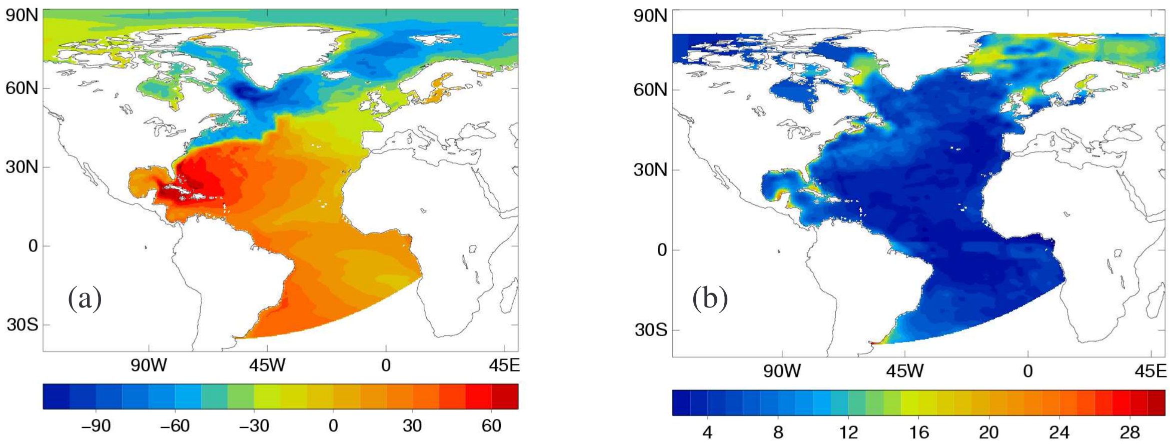

Fig 1. (a) MDT in cm from model mean field and observation based estimates. (b) MDT error in cm from Rio (2005) multiplied by 5.

RESULTS

We run four 5-year hindcast assimilation experiments assimilating altimeter and other data types to study the effects of the observation and model altimeter bias correction schemes separately and combined running along with a full assimilation system. The experiments performed are as follows:

STD with no bias correction
OBS with observation bias correction only
MOD with model bias correction only
OAM with observation and model bias correction

These experiments are all performed with the 1/3° North Atlantic/Arctic model with boundary data coming from the 1° global model (which does not assimilate altimeter data). See Fig 2 for the domain for the model used.

Results are assessed using innovations with are the bias corrected observations minus the bias corrected model forecast

$$\mathbf{y} - \mathbf{Hb}^{f} - \mathbf{H}(\mathbf{x}^{f} - \mathbf{c}^{f}) \qquad (7)$$

These give information about the remaining bias in the results.

	Mean innovations /cm	Standard deviation /cm
STD	0.317	9.56
OBS	0.150	8.71
MOD	0.032	9.10
OAM*	**0.005**	**8.56**

Table 1: Mean and standard deviation of innovations for the last 4 years of the 5 year hindcasts.

In Table 1 we examine the average innovations over the whole domain and time period excluding a 1 year spin-up. The mean innovations and standard deviation are both the lowest when combining observation and model bias correction in expt OAM. Where we correct only one bias type OBS is most effective in reducing the standard deviation. The mean innovations would be reduced more if there was no observation bias constraint applied, see the third term in eqn (1).

We can also examine the innovations in more detail by binning the results into 1°×1° bins in Fig 2. There is a distinctive pattern in the uncorrected bias in Fig 3a with positive innovations in the subtropical gyre and negative innovations North of the Gulf Stream and in the South Atlantic. The bias correction schemes substantially reduce this bias pattern.

Finally we can look at the bias fields that the system estimate to see if the scheme produces sensible values. In Fig 3 the four-year mean observation bias is shown for the OBS and OAM experiments where the observation bias is estimated. It is clear that the model bias does not significantly impact the observation bias which suggests that we have a robust estimate of observation bias. The pattern implies that the MDT should be raised north of the gulf scheme and lowered to the south.

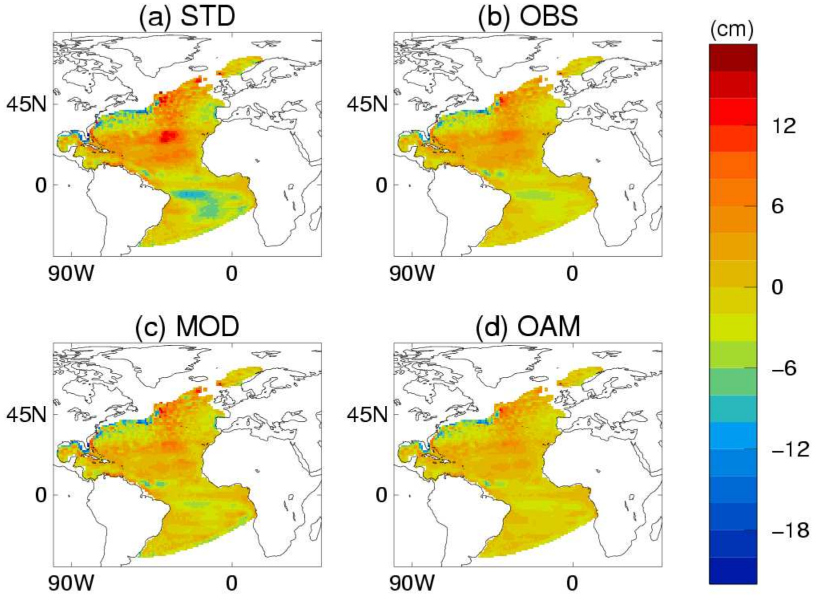

Fig 2. Mean innovations in cm for the last 4 years of the 5 year hindcasts.

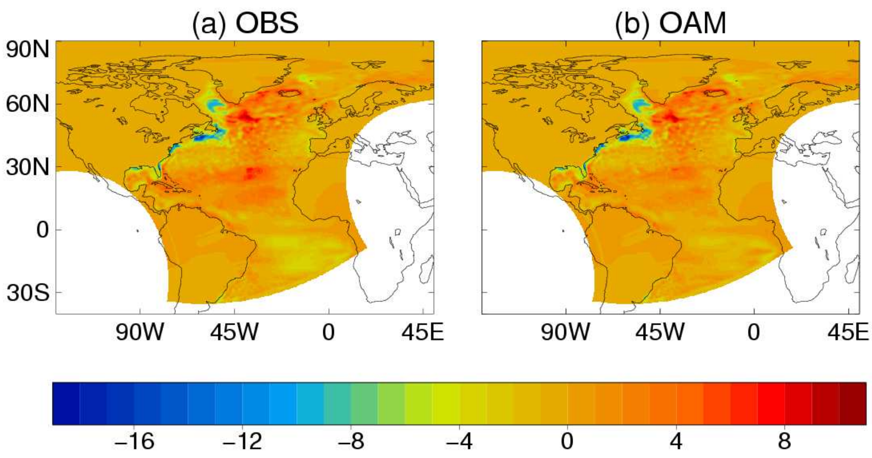

Fig 3. Four-year mean observation bias in cm for the appropriate experiments

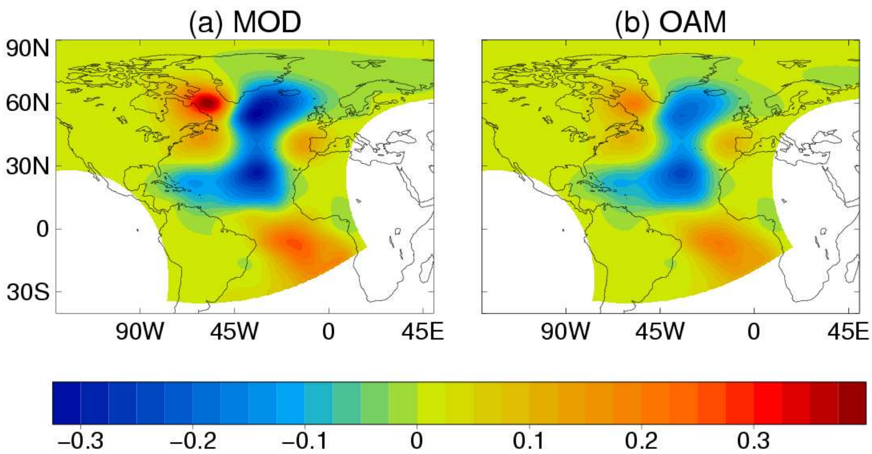

Fig 4. Four-year mean model bias in cm/day for the appropriate experiments

The model bias four-year mean field for experiments MOD and OAM is relatively small in a range +/-0.4 cm /day (Fig 4). The relatively small value is encouraging since we expect the time mean signal to be preferentially picked up by the observation bias. The overall pattern is similar to the observation bias but with the reversed sign. This could indicate a problem with separating fully the bias types.

SUMMARY OF FOAM-UM RESULTS

It is difficult to separate observation and model bias because we are using one piece of information the innovations. We can use extra knowledge to try to separate bias types for example, covariance scales and different models for the bias evolution. We have been successful in reducing the mean innovations. Also (not shown) are some small reduction in the in-situ temperature and salinity errors when assimilating with altimeter observation and model bias correction. But there is some correlation between obs and model bias suggesting some misidentification of the bias.

FOAM-NEMO RESULTS

The Met Office are moving the FOAM system from the UM ocean to a system based on NEMO ORCA025 which is 1/4 degree resolution. This uses the Cooper and Haines 1996 method, to assimilate the altimeter data as in the old system. However with the new system we use the Rio (2005) MDT and an Mediterranean MDT from the same group. This MDT does however still require bias correction. In the results below we will be using only the observation altimeter bias correction.

The FOAM-NEMO system is based on the Global ¼˚ (ORCA025) model where grid, bathymetry and river outflow climatology are provided by Mercator through My Ocean project. In ORCA025 are nested N Atlantic, Mediterranean and Indian Ocean models at 1/12˚ (Fig 5). All configurations have 50 levels with 1m resolution near surface.

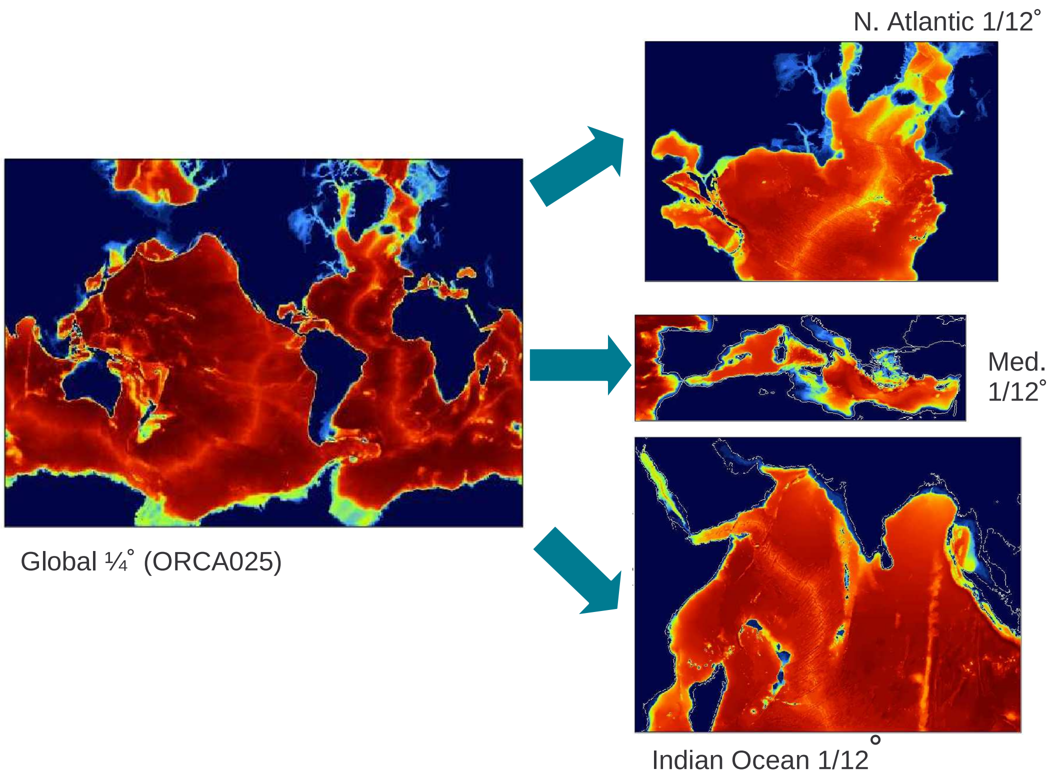

Fig 5. FOAM-NEMO configurations which replace all the configurations describe in the "FOAM-UM" section.

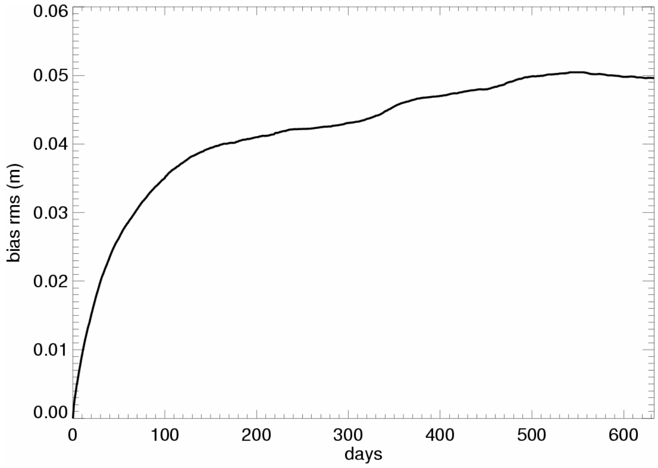

Fig 6. Observation bias spin up shown with the bias spatial rms as a function of time.

The spin up of the observation bias in ORCA025, starting from zero bias, is shown in Fig 6 and indicates an approximately 6 month timescale. The spin-up could be sped up by increasing the observation bias forecast error covariance, but at the risk of increasing the noise due to day to day variations in the altimeter data.

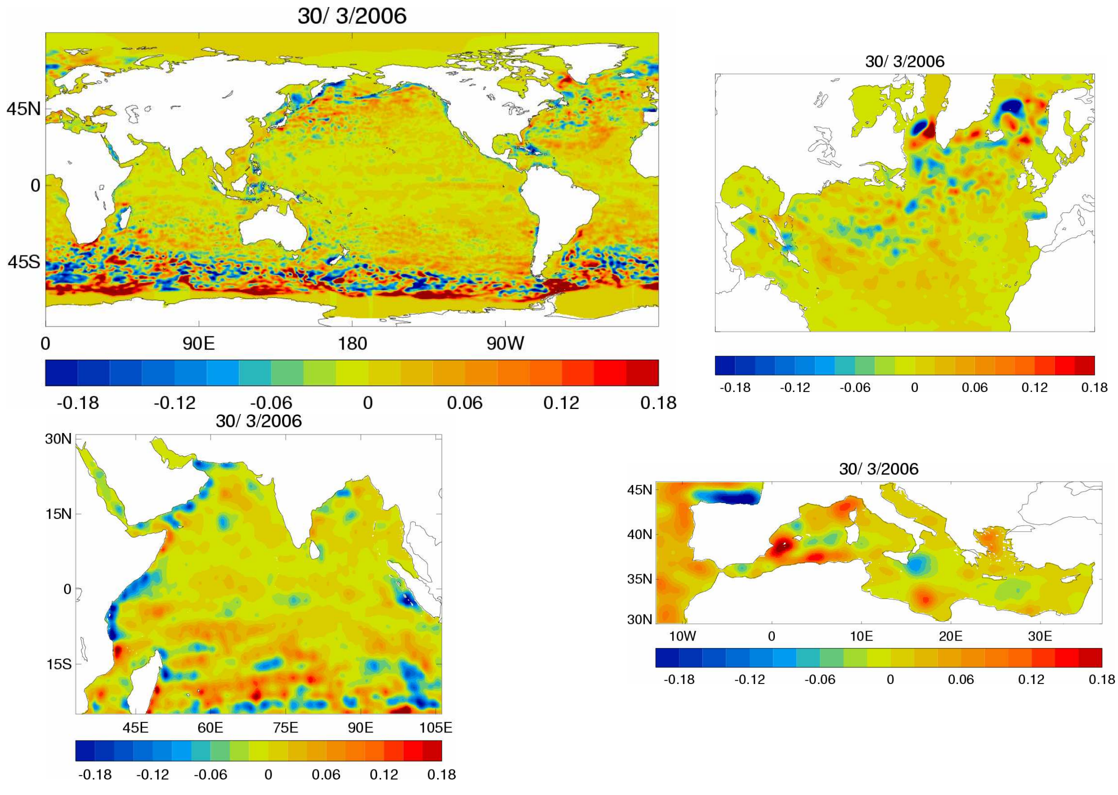

Fig 7. Observation bias fields for the different regional configurations on 30 March 2006. All the hindcasts shown started 2 Jan 2005.

In Fig 7 the observation bias fields found by the assimilation system for the different regional models are shown. In all cases a hindcast was started 2 Jan 2005 and run for 15 months until 30 Apr 2006 to give the instantaneous observation bias shown here. The interesting result is that bias estimates for the regional models match well in pattern the equivalent bias field in the global model. Examples are a negative bias north of Spain in the global, North Atlantic and Mediterranean models. Also a quadrupole pattern in the Western Atlantic is seen in the global and North Atlantic models. These matching bias values with models with different resolutions give an additional indication that we are capturing an observation bias signal and not just attributing model bias to the observation bias.

DISCUSSION

We have developed a working scheme which combines online observation and model bias schemes in altimeter data assimilation. This scheme reduces mean and time variability of innovations compared to no bias correction. We have achieved some sensible division between the model and observation bias is achieved with the time variations preferentially in the model bias. The division is set by the bias covariances, models and also the feedback from changes in the model bias. Altering the weights suggests this is near optimal. Verification with temperature and salinity data shows the bias schemes are perhaps slightly improved compared to the standard altimeter assimilation.

We have implemented the scheme in NEMO ¼ degree global model. Initial results encouraging global SSH RMS reduced from 12 cm to 9 cm. Different resolution models have bias fields which match in many respects. We may, therefore, be identifying a robust observation bias signal. As with the UM the temperature and salinity statistics also show small reductions in RMS errors. Due to the encouraging results of this work the observation bias correction is implemented in the operational system. We plan to test the model bias correction in FOAM-NEMO and compare the results in detail to runs with no bias correction.

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