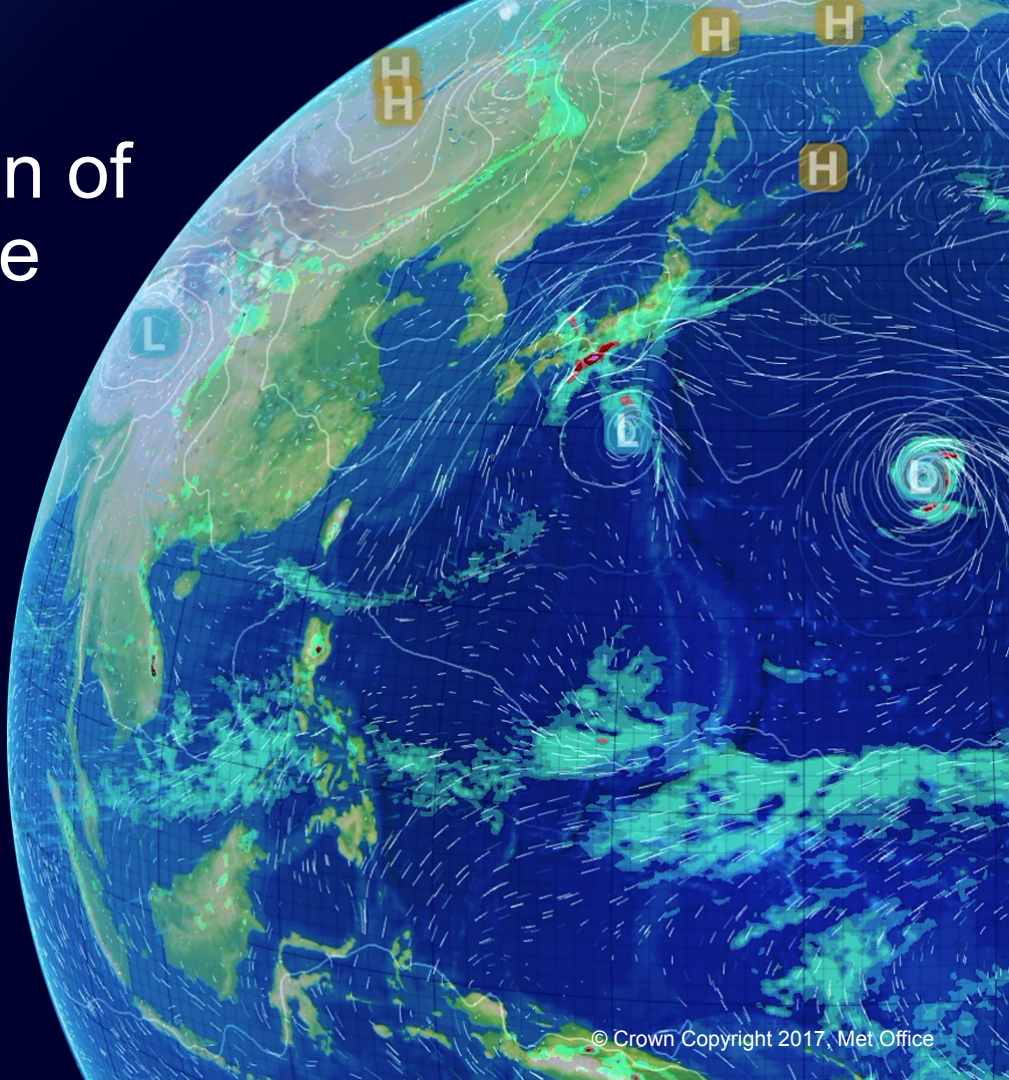


Variational bias correction of Sea Surface Temperature observations

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Introduction

In any coupled system fluxes of heat and moisture between the atmosphere and ocean depend critically on the Sea Surface Temperature (SST). **Biases in SST will lead to biases in these fluxes.**

Assimilation of biased observations will lead to biases in SST. We therefore need to correct for these biases.

Our contribution to ERA-Clim2 is a variational bias correction system for satellite SST observations.

The bias correction scheme combines a variational bias correction method with a correction based upon “observations-of-bias”.

Observations-of-bias are taken as the differences between standard observations and hi-quality reference data.

The bias correction system is designed to give consistent results over long periods of time; including periods where the amount of reference data is much less than it is now.

Our scheme is a variational method where biases are calculated within the assimilation itself.

Specifically we aim to minimise the function:

$$\begin{aligned}
 J = & \quad (\mathbf{x} - (\mathbf{x}^f - \mathbf{x}))^T \mathbf{B}^{-1} (\mathbf{x} - (\mathbf{x}^f - \mathbf{x})) + \cancel{(\mathbf{c} - \mathbf{c}^f)^T \mathbf{S}^{-1} (\mathbf{c} - \mathbf{c}^f)} \\
 & + (\mathbf{b} - \mathbf{b}^f)^T \mathbf{O}^{-1} (\mathbf{b} - \mathbf{b}^f) + (\mathbf{y} - H_y(\mathbf{x} + \mathbf{b}))^T \mathbf{R}^{-1} (\mathbf{y} - H_y(\mathbf{x} + \mathbf{b})) \\
 & + (\mathbf{k} - H_k(\mathbf{b}))^T \mathbf{L}^{-1} (\mathbf{k} - H_k(\mathbf{b}))
 \end{aligned}$$

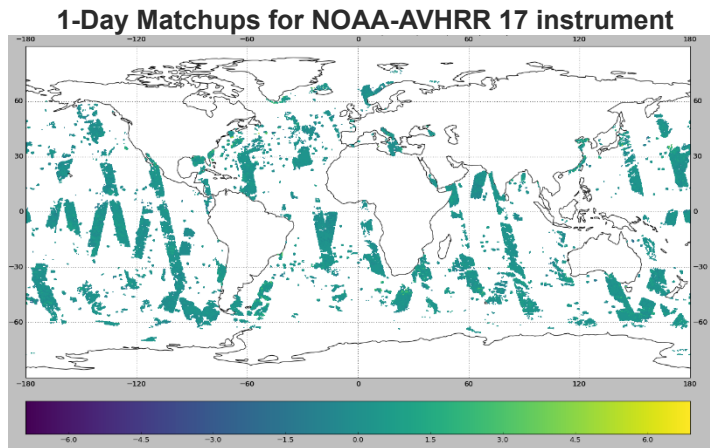
J :-	cost
\mathbf{x} :-	state vector
\mathbf{y} :-	observations
\mathbf{b} :-	observation bias
\mathbf{c} :-	model bias
\mathbf{k} :-	matchups
\mathbf{B} :-	background error covariance
\mathbf{S} :-	model bias error covariance
\mathbf{O} :-	observation bias error covariance
\mathbf{L} :-	matchup error covariance
H_y :-	observation operator for observations
H_k :-	observation operator for matchups

Observations-of-Bias k

We do not have direct observations of the bias.

Instead we use differences between co-located standard observations and assumed 'un-biased' reference data

To prevent cross correlations appearing in the cost function. All observations that are used to calculate the observations-of-bias are **NOT** included in the observation vector y .



The number of co-located observations varies depending on the settings. For our experiments it is **~30% of the biased data and 80% of the reference data**

It is hoped that having these observations in k could be beneficial.

Tests using the Lorenz-63 system

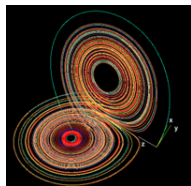
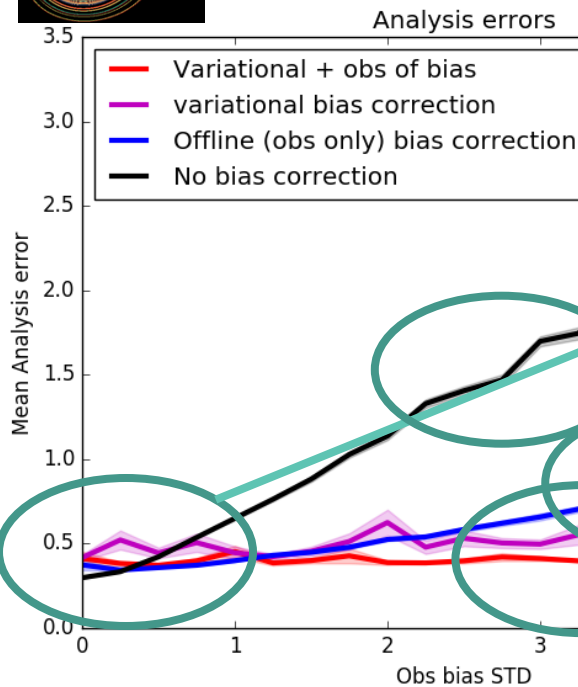
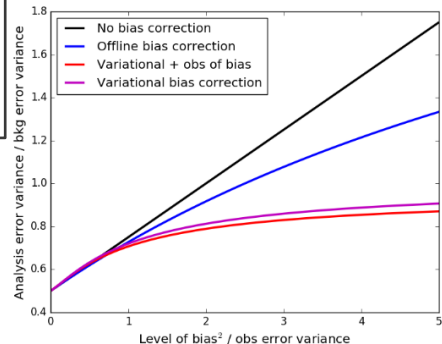


Image from Wikipedia
(<https://commons.wikimedia.org/w/index.php?curid=2074483>)

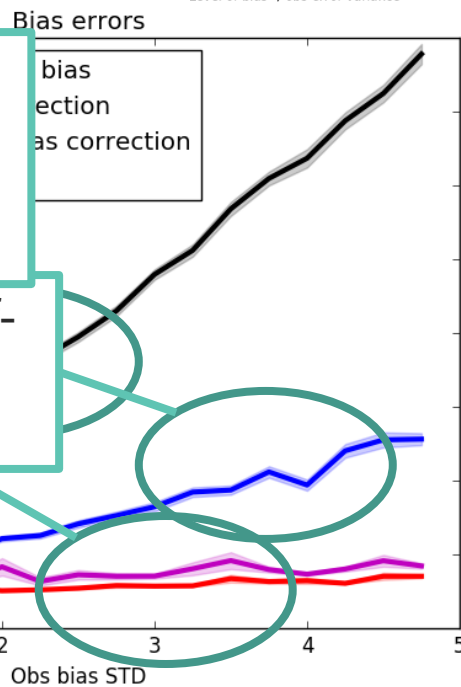
Results are similar to what is expected for an ideal linear system



But errors increase

The variational schemes are stable with respect to the bias. Best results are when using the observations-of-bias

When using obs-of-bias errors also grow, but slower



Results from a 3 year reanalysis

To test the bias correction scheme we ran four 3 year experiments (2008-2010):

NoBias:- No bias correction, all observations assimilated directly

VarOnlyBias:- Variational bias correction, no observations-of-bias

ObsOnlyBias:- Offline bias correction using just the observations-of-bias (similar to old Met Office system)

VarObsBias:- Variational bias correction including observations-of-bias

In all 4 cases, the same observations were used, but their distribution between the observation vector (\mathbf{y}) and observations-of-bias vector (\mathbf{k}) differs.

To simulate the loss and introduction of a reference data source, **AATSR data is assimilated in 2008 and 2010, but is withheld during 2009.**

Mean bias fields for AMSR

In 2008 (and 2010), bias fields are very similar for all 3 methods.

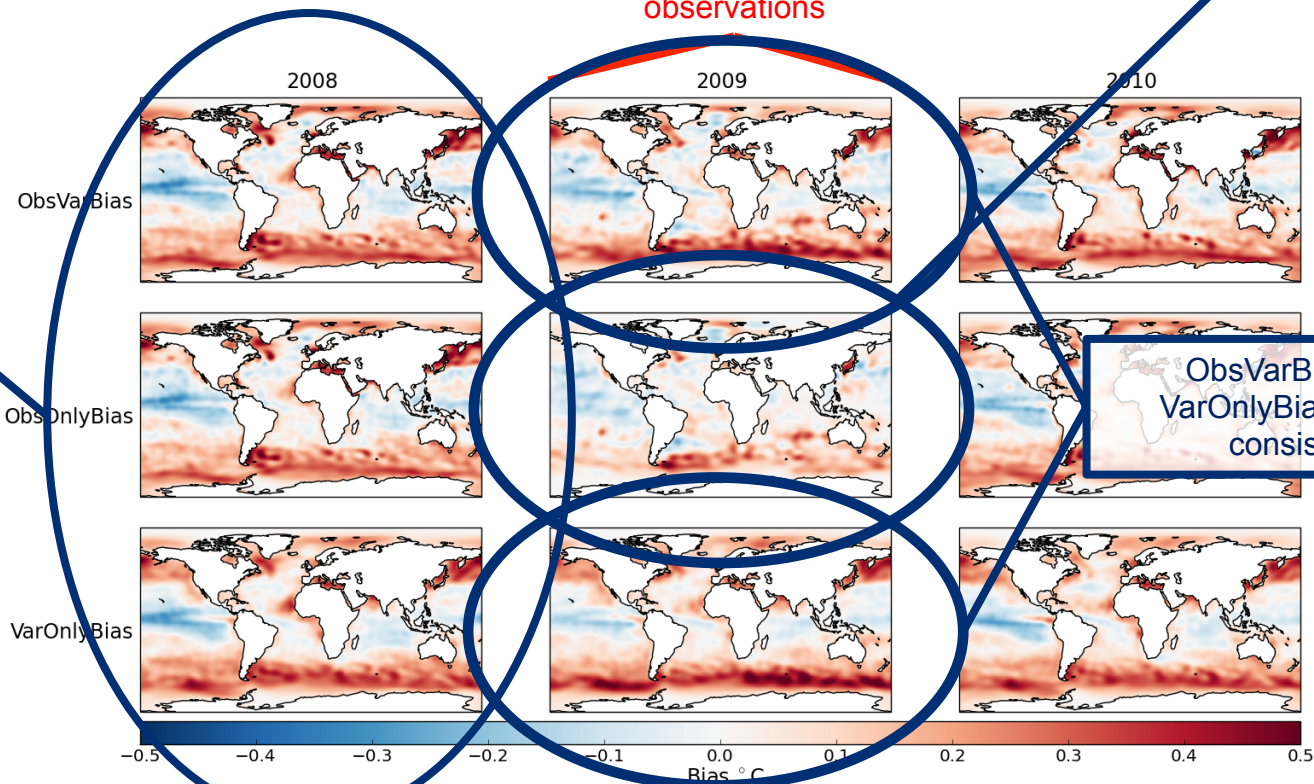
ObsVarBias and **ObsOnlyBias** are almost identical.

VarOnlyBias has slightly weaker biases in some areas, and slightly stronger biases in others, but has a similar pattern

In 2009 we used many fewer reference observations

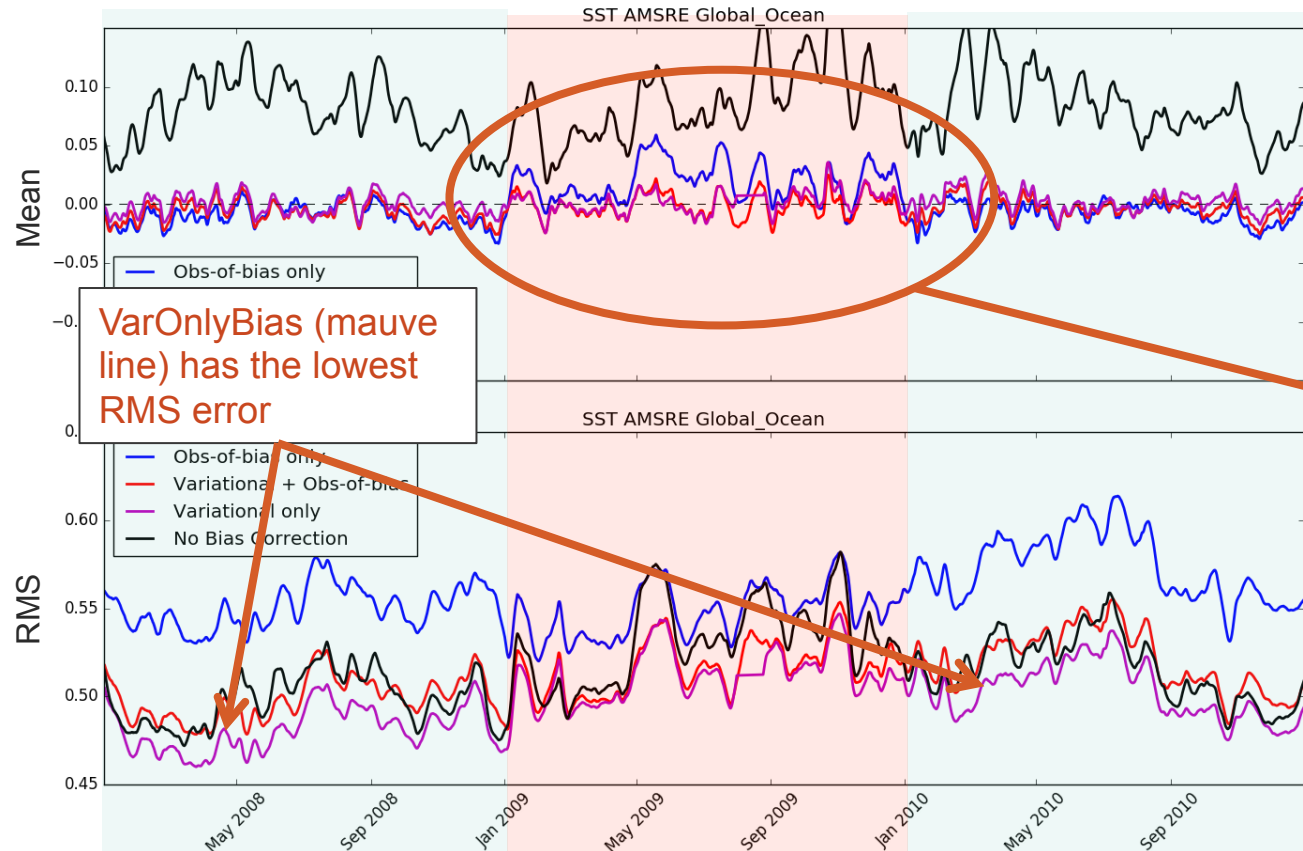
In 2009, **ObsOnlyBias** is very patchy and inconsistent with the other years

ObsVarBias and **VarOnlyBias** remain consistent



Global Obs minus Bkg for AMSRE

The plots show the difference between AMSRE data and a 1 day forecast of the model.



↕ The overall bias is much reduced

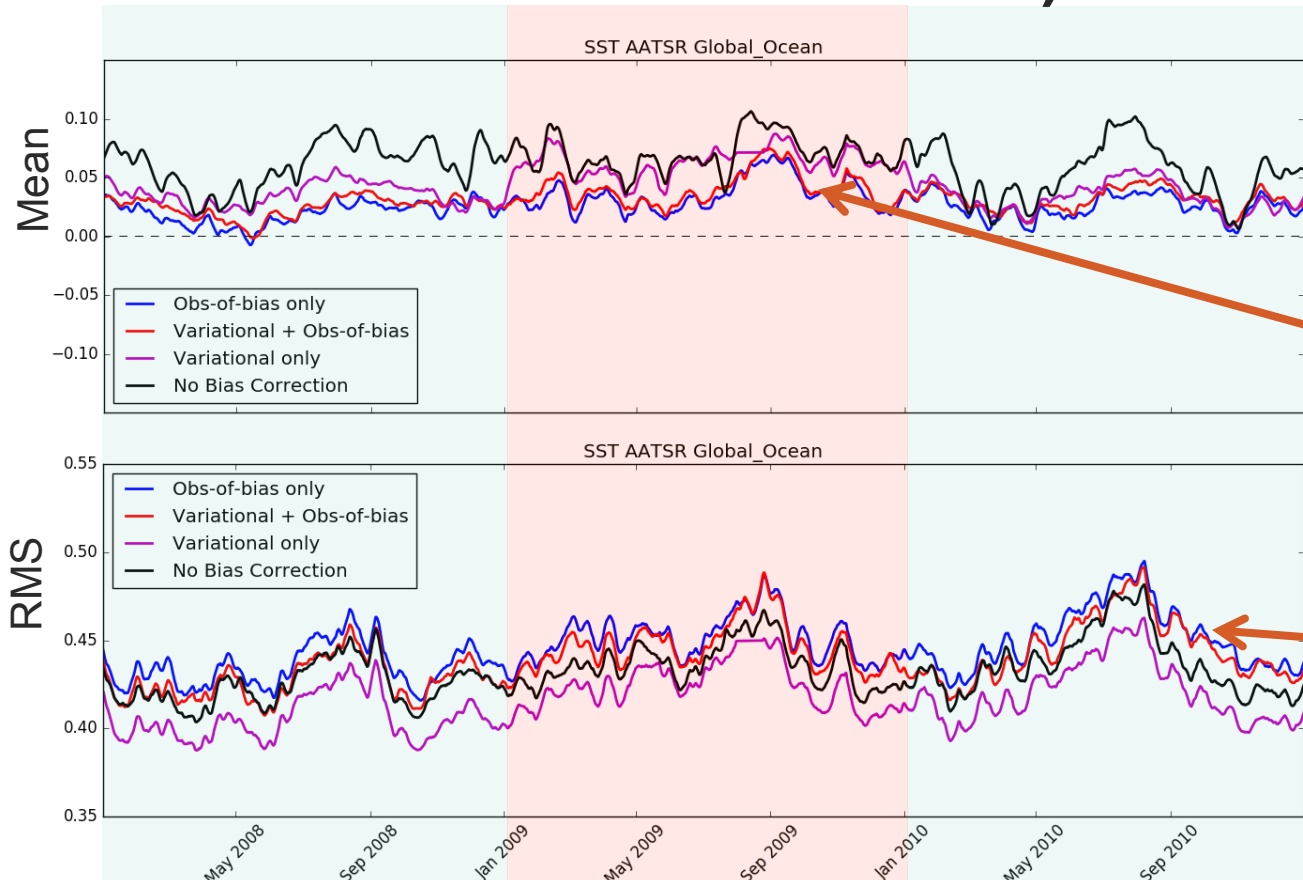
In the period with fewer reference observations, ObsOnlyBias (blue line) does not do as well

↕ The RMS error for the ObsOnlyBias system is also worse



Met Office

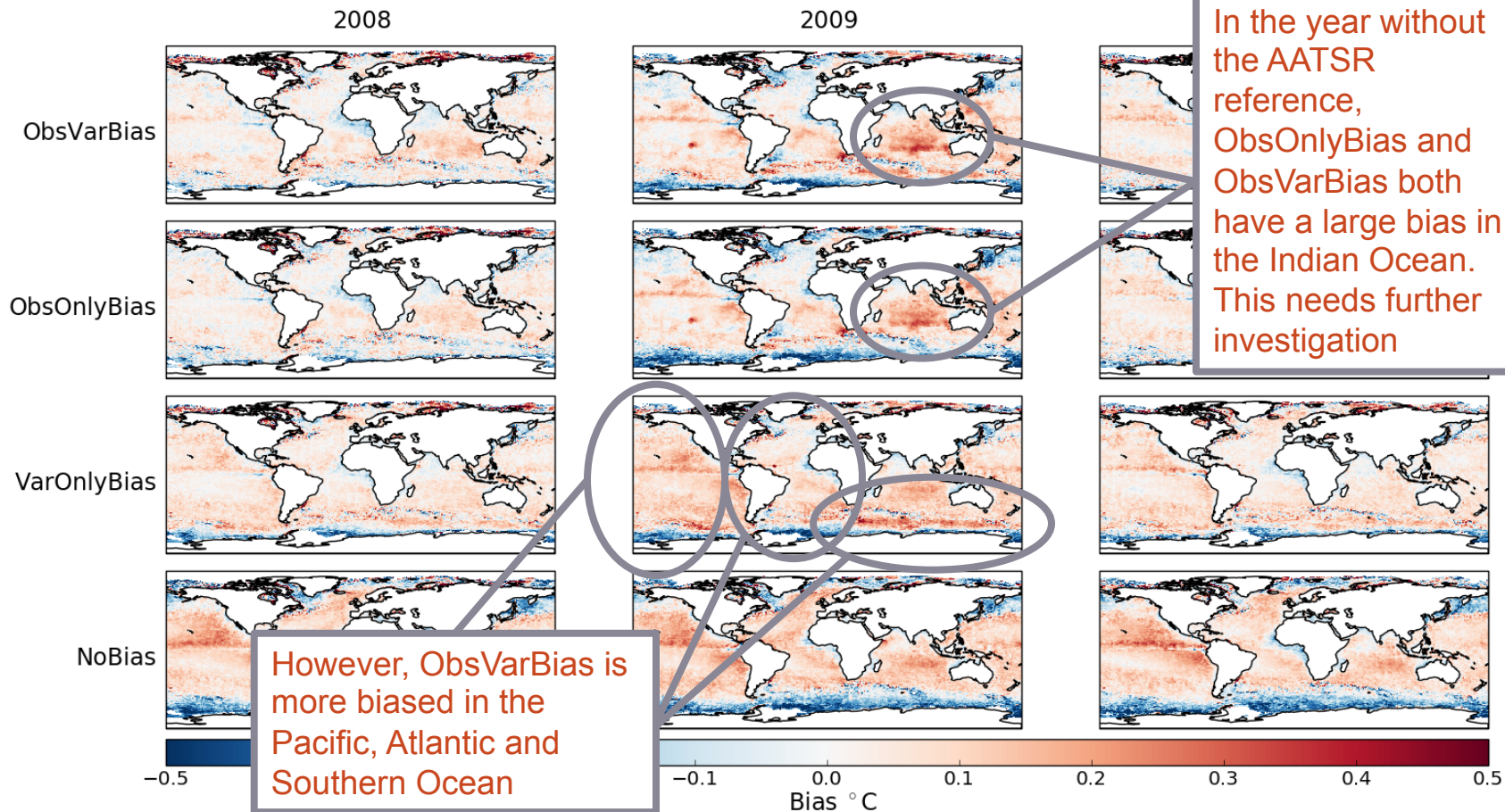
Global Obs minus Bkg for AATSR (a reference dataset)



The Obs based bias corrections ObsOnlyBias and ObsVarBias are less biased than VarOnlyBias.

But have increased RMS values, often exceeding NoBias. Too many obs-of-bias rather than direct observations?

Met Office Mean Obs minus Bkg for AATSR (1°Bins)



Continue validating results from experiments

Write up as paper, currently in prep.

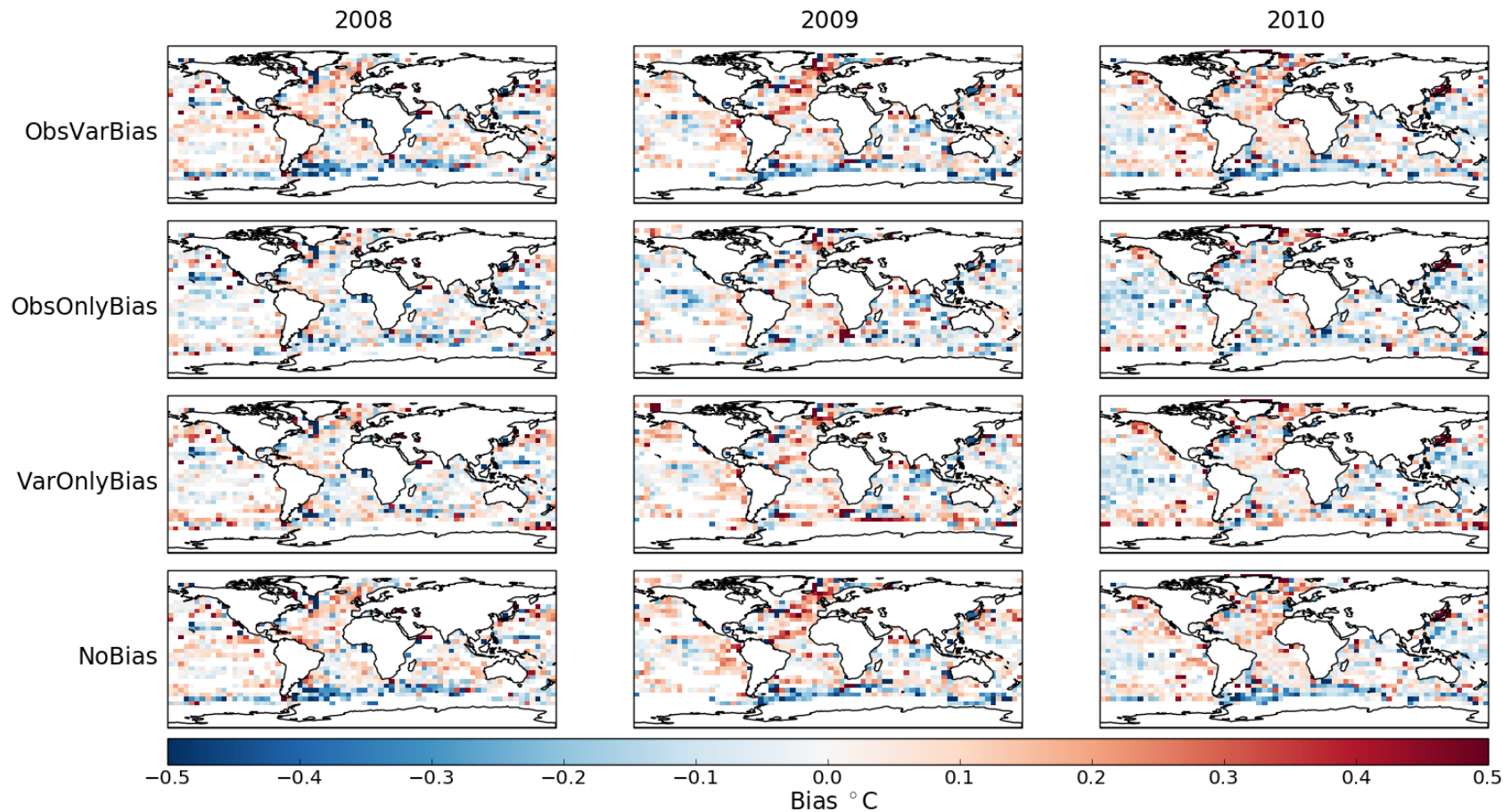
Work on estimating better values for the covariances **O** and **L**.

Try to get a better ratio between the number of observations and the number of observations-of-bias. Possibly assimilate the mean of the observations, rather than the observations directly (this would be less correlated with the observations-of-bias than the raw observations)

Work towards a methodology for dealing with model error as well as observation error.

Additional Slides

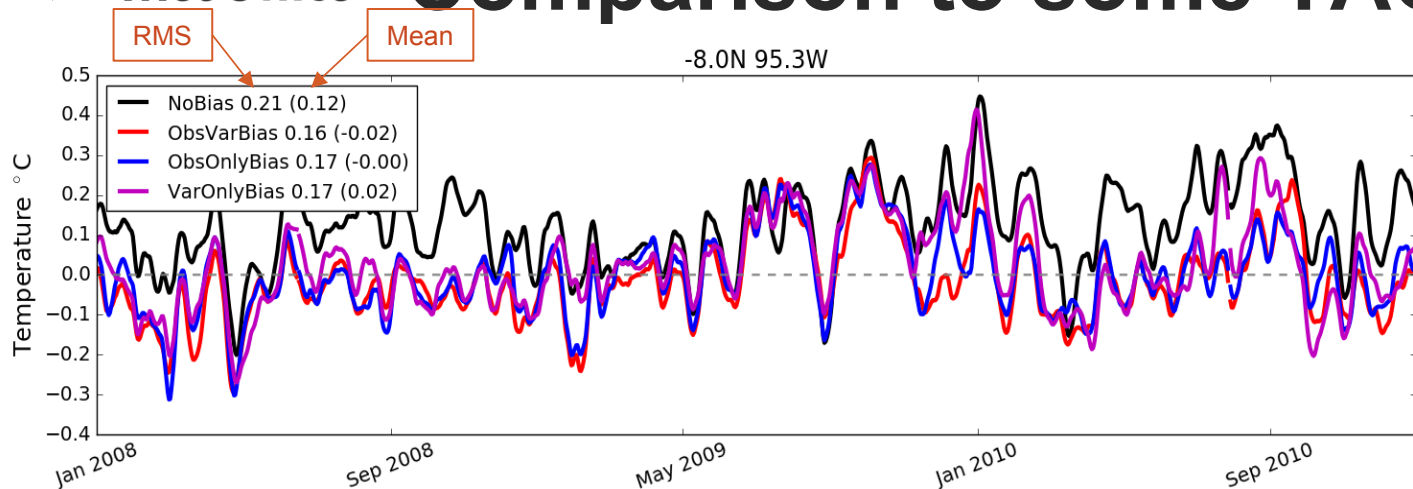
Met Office Mean Obs minus Bkg for validation obs (5° Bins)





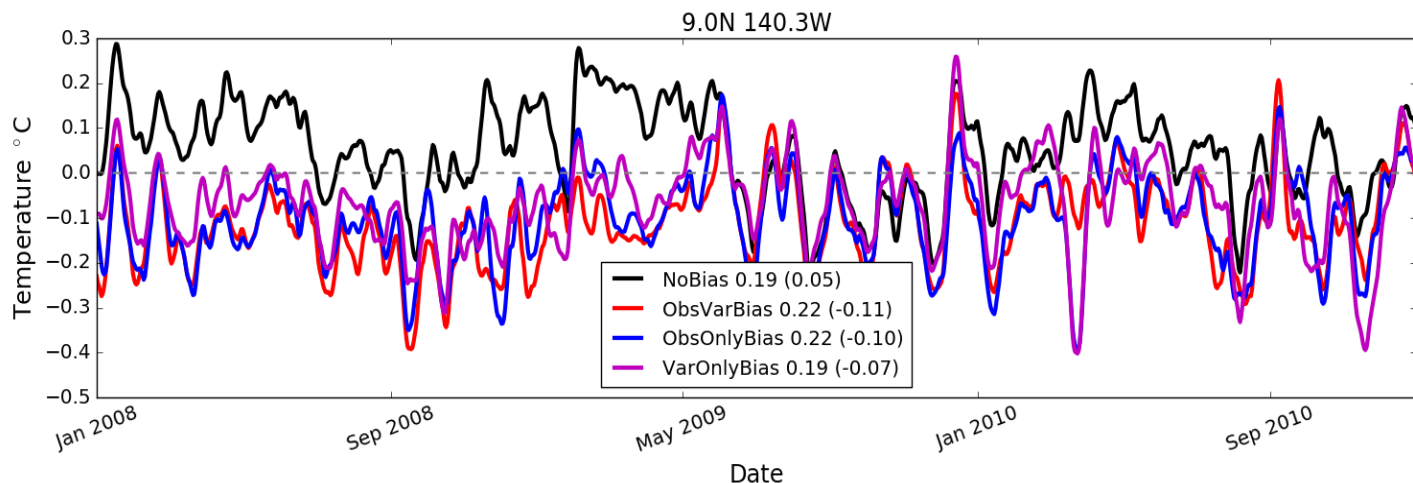
Met Office

Comparison to some TAO moorings



Results shown are the TAO observations minus the nearest model value.

Results have been smoothed using a 30 day Butterworth filter



Disclaimer: these are the more extreme results, other TAO moorings show smaller differences between NoBias and the other experiments