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A Multiscale Approach to High Resolution Observations within a 4DVAR Analysis System

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Overview

1. Problems and Issues with Dense Observations in Modern Ocean Data Assimilation (ODA)

2. Proposed Solution Path (i.e. Multiscale Approaches)

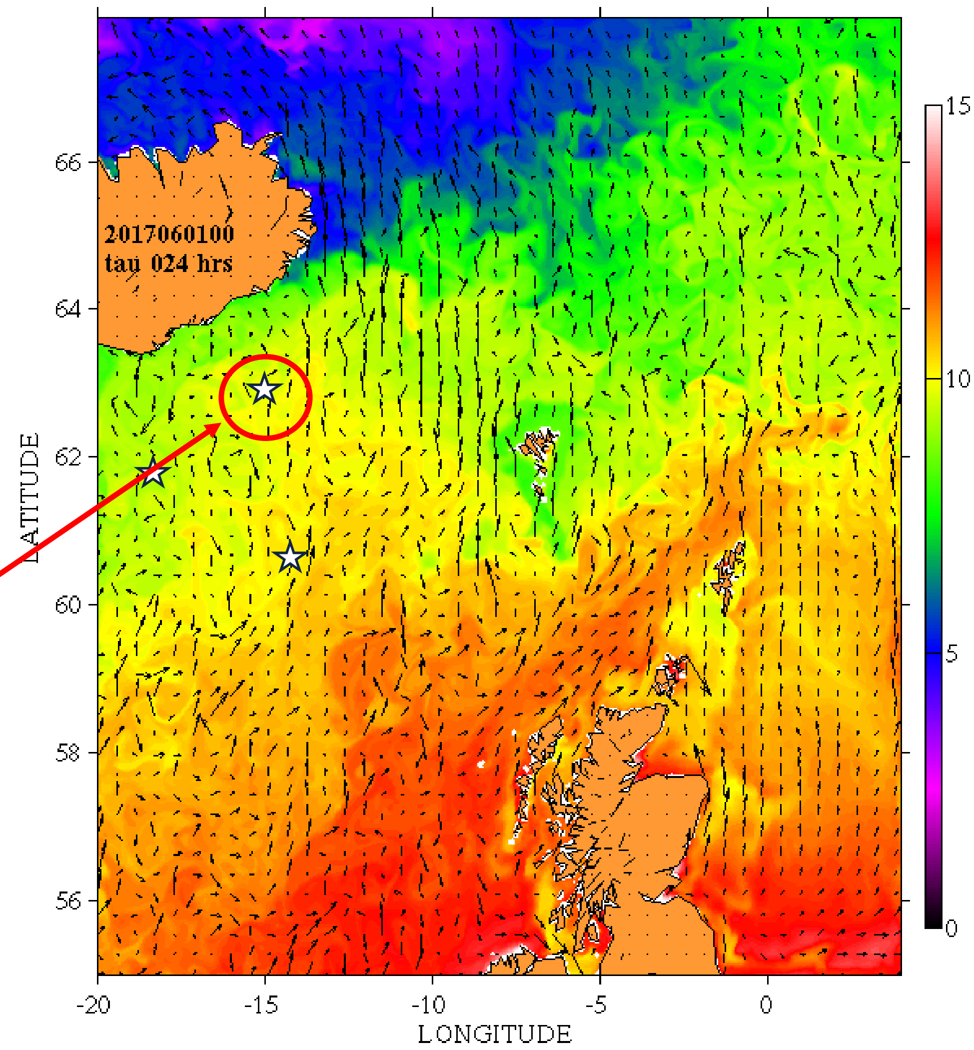
3. First Results from Real Observation Experiment (NREP-17)

Dense Observations in Modern ODA

Most ODA systems are tuned to constrain mesoscale features (eddies and larger)

Dense observations are typically thinned in number or averaged (super observations)

Spatial radius to determine thinning or averaging based on background error correlation scale



Problems with this Approach

- *Scale Aliasing*
  - Observation thinning algorithms do not know what feature scales are most represented by an observation
  - Removing observations based on spatial density alone can lead to small-scale information being aliased to the large-scale
- *Useful Information Can Be Lost*
  - Models are run at higher resolution than days past (≤ 3 km)

This has Given Rise to Multiscale Approaches

Obstacles to Address for Multiscale Approaches

- ❑ *Static Error Covariance with Set Correlation Scale Length*
  - This has led to the use of multi-step analysis solutions
- ❑ *For Multi-Step Solutions (Li et al, 2015): How to Define Scale Lengths for Large and Small Scales*
  - EOF decomposition of time series of background states in order to identify scale lengths
- ❑ *Separate Dynamics at Play*
  - Sub-mesoscale features are not geostrophically balanced

Our Approach: Multiscale 4DVAR

The Representer Method for 4DVAR

$$\delta \mathbf{x} = \mathbf{B}\mathbf{H}^{\mathrm{T}}\left(\mathbf{H}\mathbf{B}\mathbf{H}^{\mathrm{T}} + \mathbf{R}\right)^{-1}\left(\mathbf{y} - \mathbf{H}\mathbf{x}^{f}\right)$$

$\mathbf{B}=\mathbf{M}\mathbf{\Sigma}\mathbf{C}\mathbf{\Sigma}^{\mathrm{T}}\mathbf{M}^{\mathrm{T}}$

$\mathbf{M}$ is the TLM
$\mathbf{M}^{\mathrm{T}}$ is the Adjoint
$\mathbf{\Sigma}\mathbf{C}\mathbf{\Sigma}^{\mathrm{T}}$ is the static error covariance

While the TLM and Adjoint provide multiscale, flow-dependent, and dynamically balanced error covariance

…the static error covariance will still filter small-scale information

…and observations that contain small-scale information may still be aliased to the mesoscale or greater

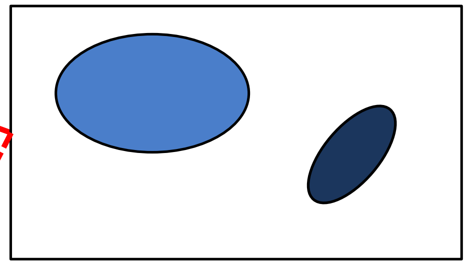
SOLUTION: Separate treatment for the observations and assimilate each set in a two-step assimilation procedure

Our Approach: Multiscale 4DVAR

MS-4DVAR:
Outer Loop #1

Innovations
Call Adjoint
Call Covariance
Call TLM
CG convergence
NO
Inner Loop
Call Adjoint
Call Covariance
Call TLM
Background + increments… on to Loop #2

Innovations (data-model misfits) are averaged to capture mesoscale to large scale features



- *Larger correlation scales to correct meso- to large-scale features*
- *When averaged, innovations of similar magnitude/sign are retained*

Analysis solution from loop #1 becomes background state for loop #2 and new innovations are calculated

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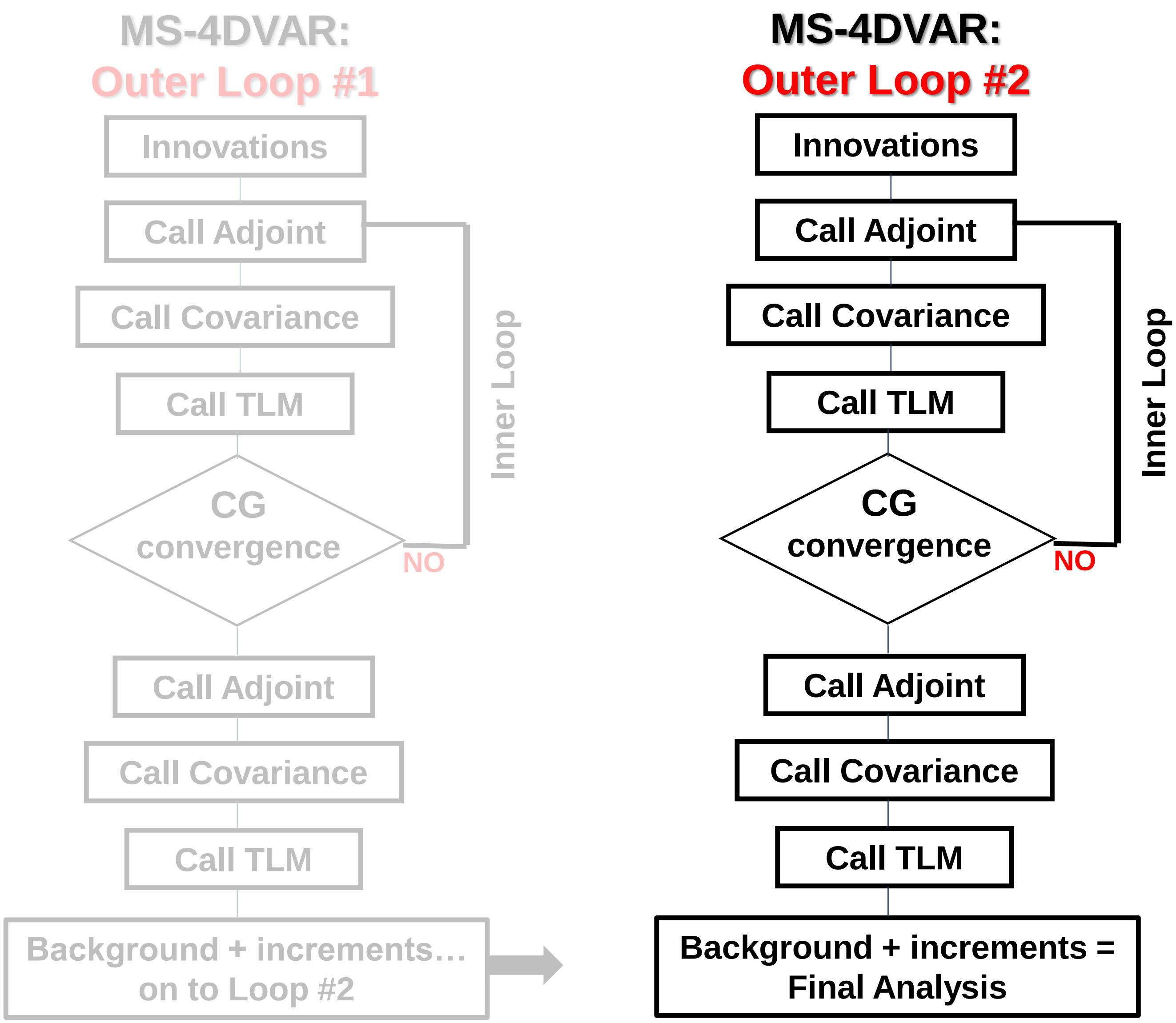
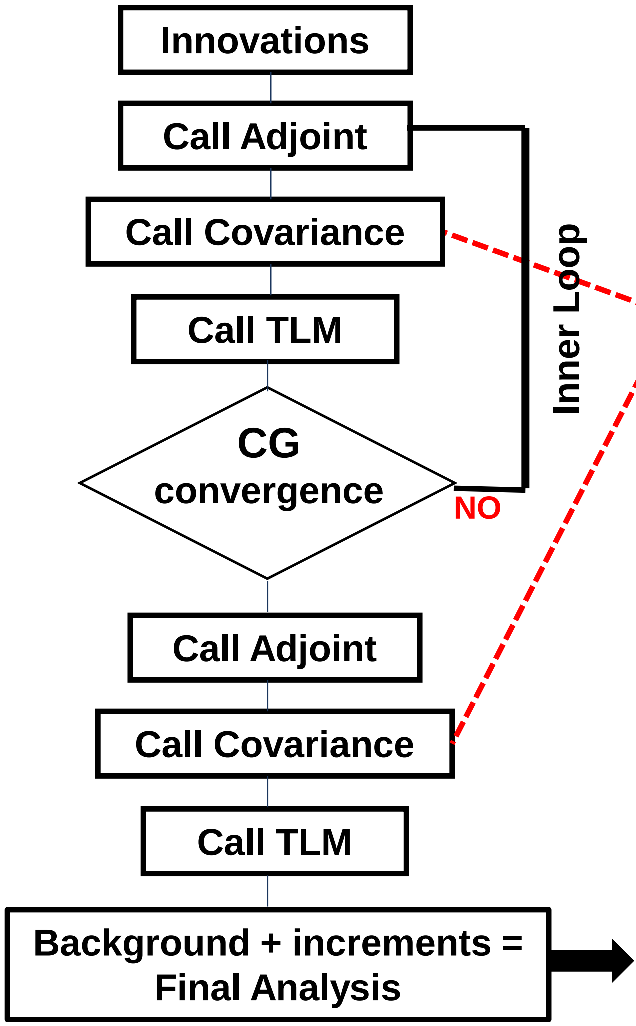
Our Approach: Multiscale 4DVAR

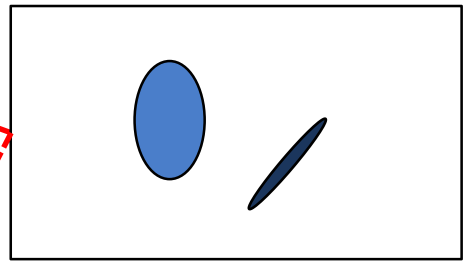


Our Approach: Multiscale 4DVAR

MS-4DVAR:
Outer Loop #2



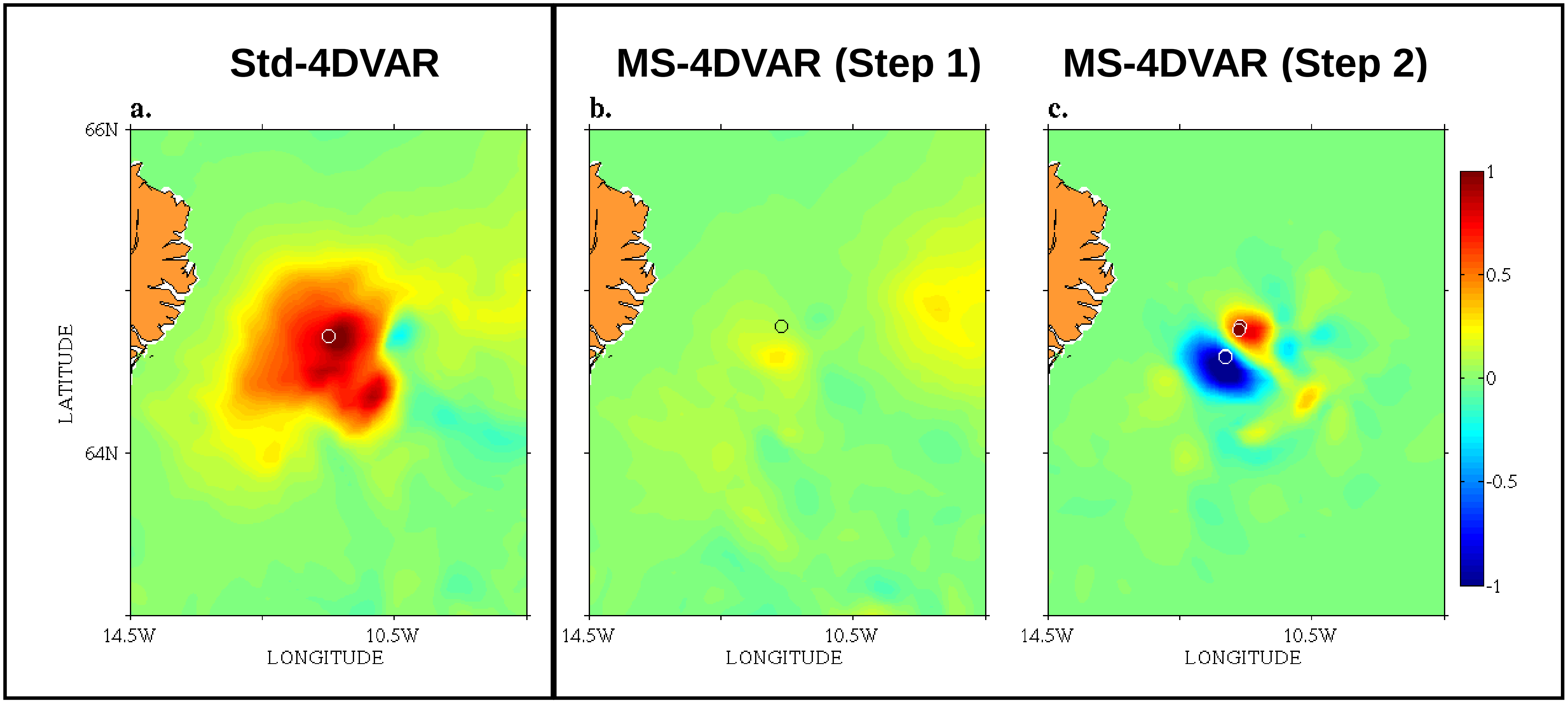
All observations are included
(no averaging of innovations)



- *Small correlation scales to resolve fine details*
- *Innovations of large-scale features are small (well-constrained by 1st outer loop)*

Forecast background + increments from both outer loops are combined to give final analysis

Our Approach: Multiscale 4DVAR

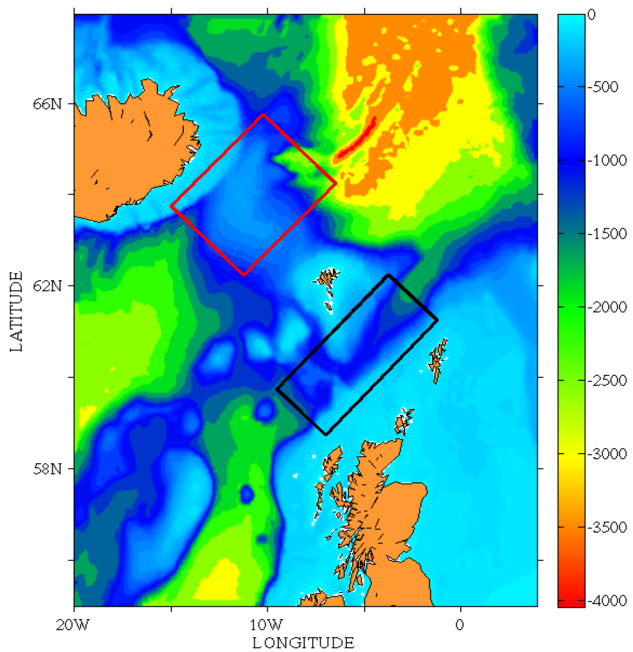


(a) Standard 4DVAR (Std-4DVAR) increment (shaded region) from selected innovation (colored dot)

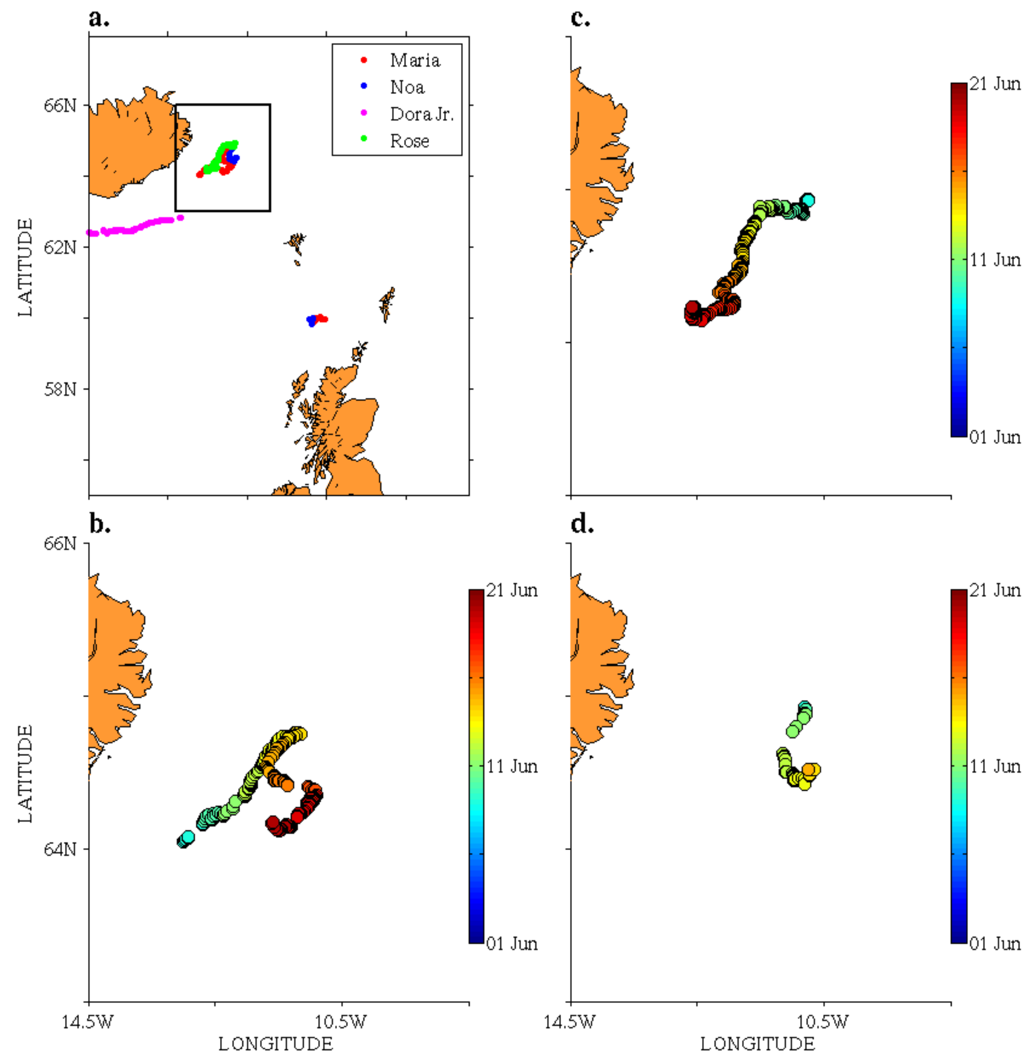
(b) Large-scale increment from averaged observations

(c) Small-scale increment from full observation set

NREP17 Glider Deployment Near Iceland-Faroe Front (IFF)

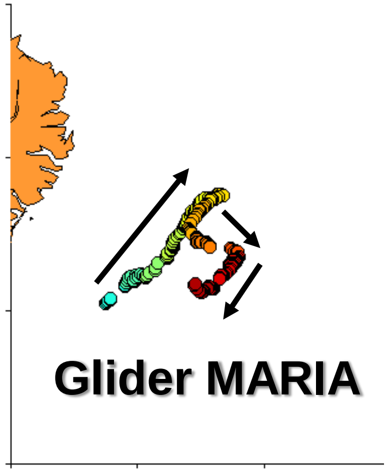


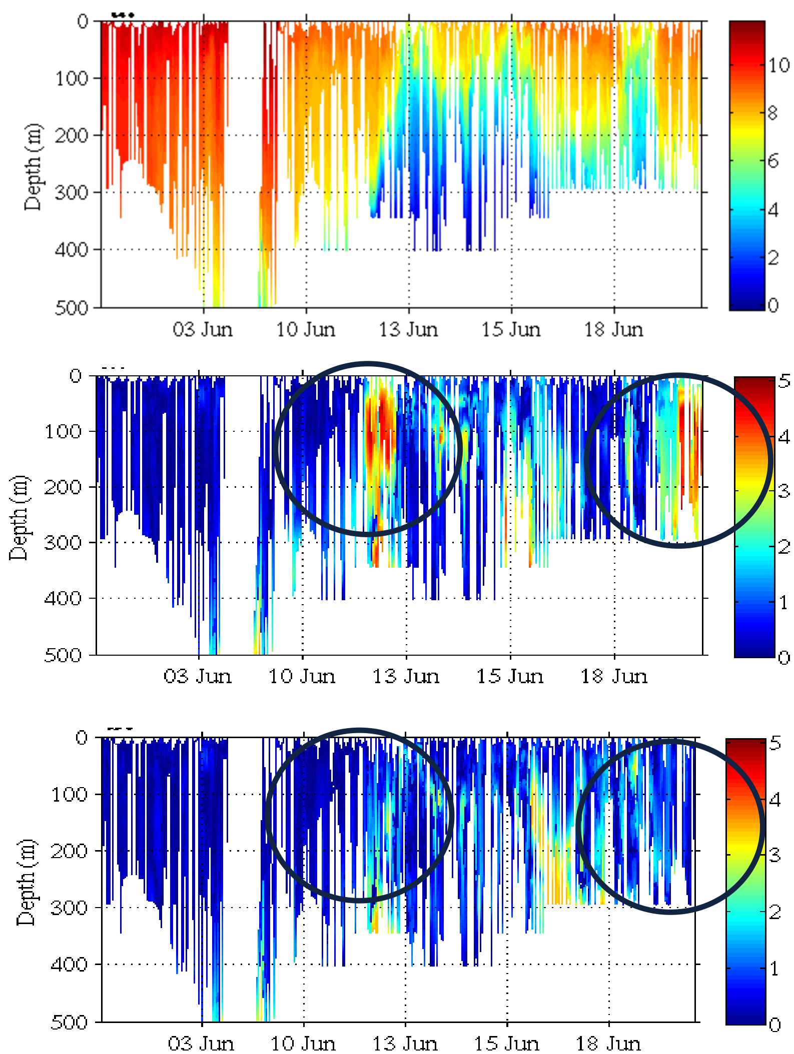
IFF region where cold Nordic and warm Atlantic waters meet (red box)



Three primary gliders cross IFF: (b) Maria, (c) Rose, and (d) Noa

Observations Compared to Analysis





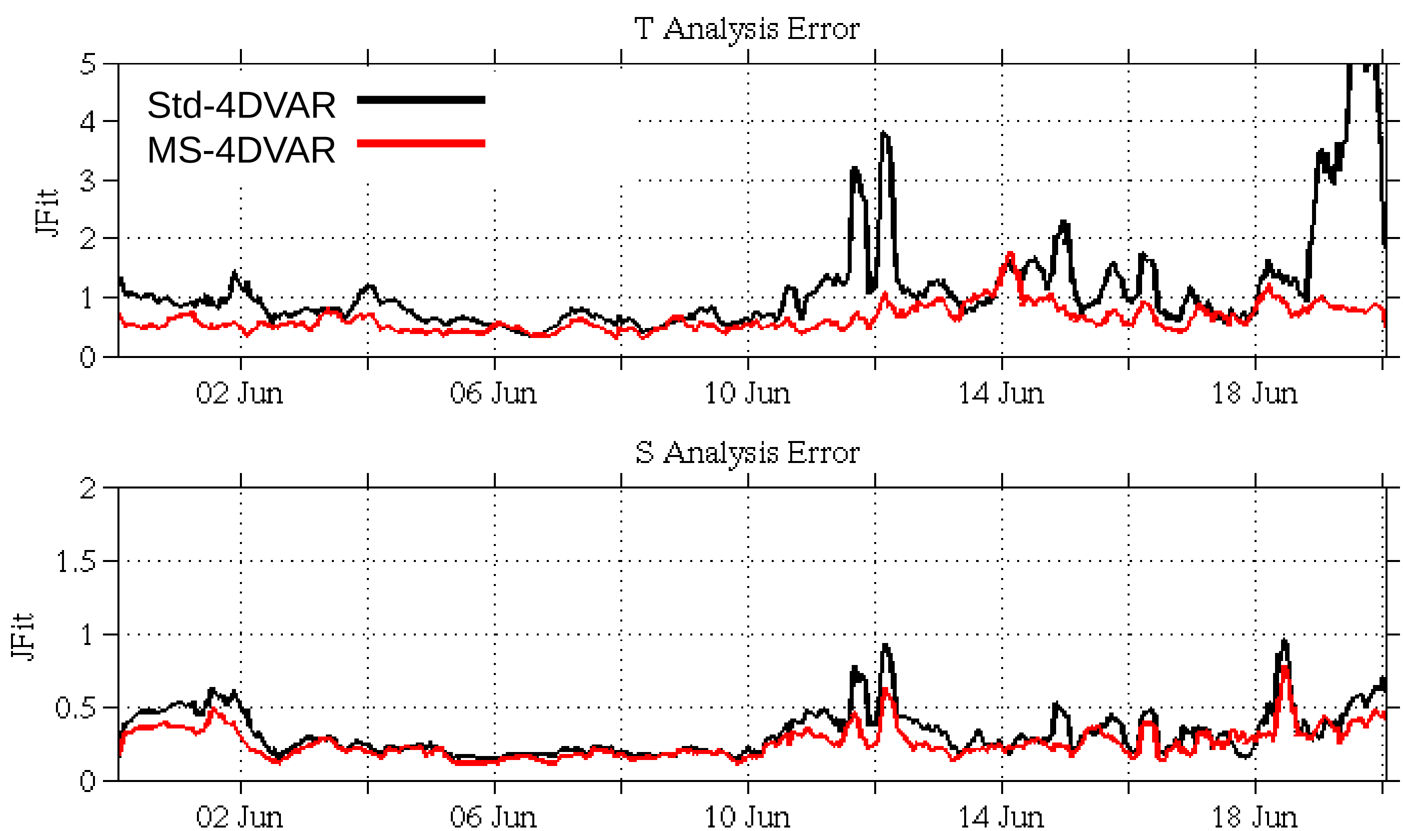
Temperature profiles along Glider Maria track

Obs minus analysis for Std-4DVAR approach

MS-4DVAR does a better job of positioning the temperature front (seen in the Maria data) than Std-4DVAR

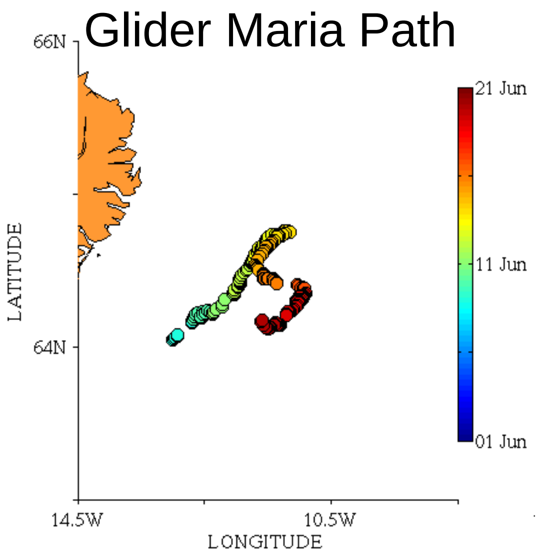
Obs minus analysis for MS-4DVAR approach

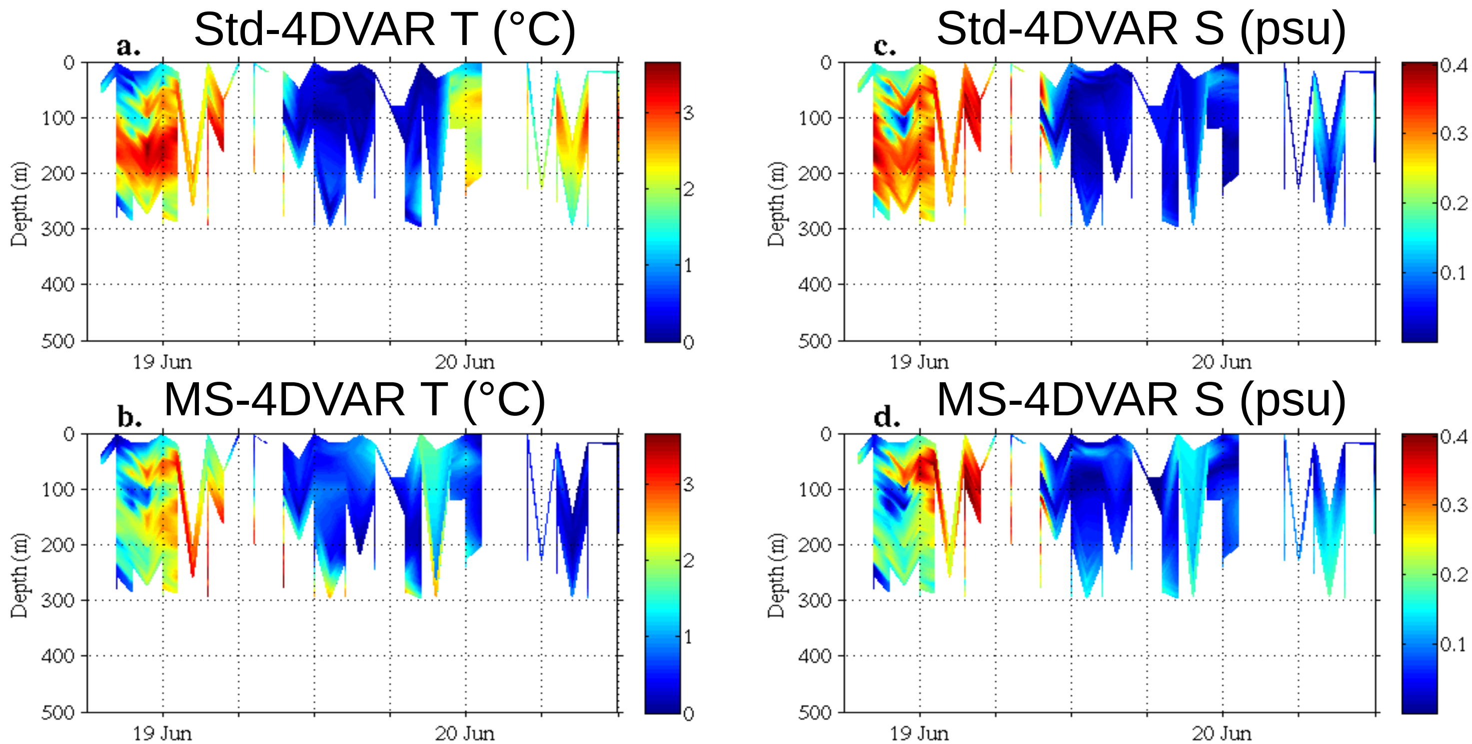
Statistical Fit to Observations



Overall, MS-4DVAR fits temperature and salinity data better than Std-4DVAR in the region of the IFF

Improvement to Forecast





Glider Maria crosses the Iceland-Faroe front once more during the experiment

On the second pass through, the forecast fields from the MS-4DVAR run match the glider Maria temperature and salinity better than Std-4DVAR

This suggests that the forecast from MS-4DVAR may be superior to Std-4DVAR in the vicinity of the IFF

Summary

- The Multiscale 4DVAR shown here is able to:
  - Assimilate high-density profile observations accurately (in a MAE sense)
  - Maintain stability in the TLM
  - Produce a forecast that is as good (if not slightly better than) Standard 4DVAR
  - Reduces scale aliasing
- The Multiscale 4DVAR scheme here can be used for other high-spatial density observations (i.e. SWOT altimeter obs)
- Future work needed on defining the scale lengths in the static error covariances
- Future work needed on dynamic balance operators for static error covariances

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