On the Development of an Efficient Ensemble Data Assimilation and Forecasting System for the Red Sea

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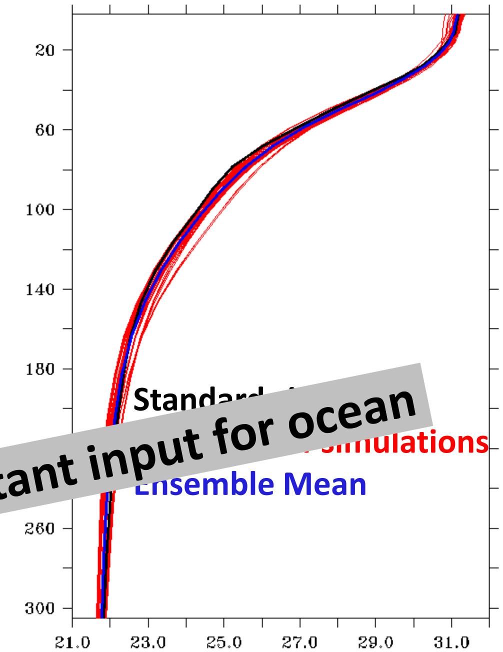
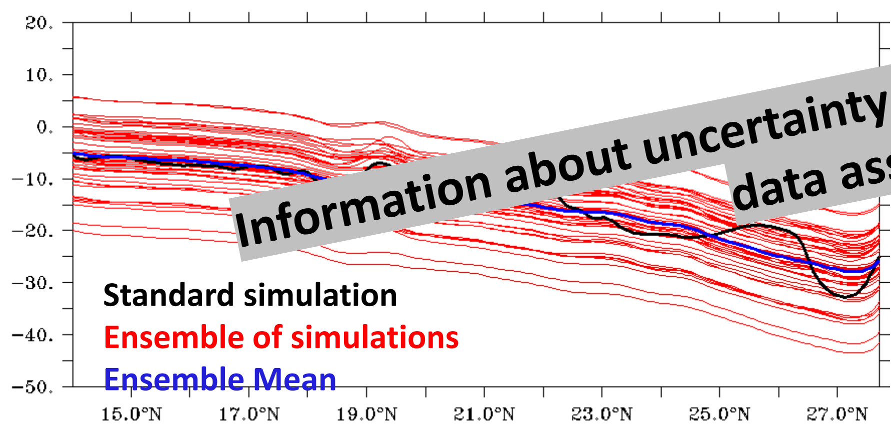
Sources of **Forecast Errors**

- Uncertainties in
  - Initial conditions
  - Atmospheric forcing
  - Model physics
  - Boundary conditions (relevant for regional models)
  - Bathymetry (more relevant near coast)

Temperature profile at an arbitrary location in the RS



Sea Surface Height (cm) at an arbitrary location in the RS



Information about uncertainty is an important input for ocean data assimilation

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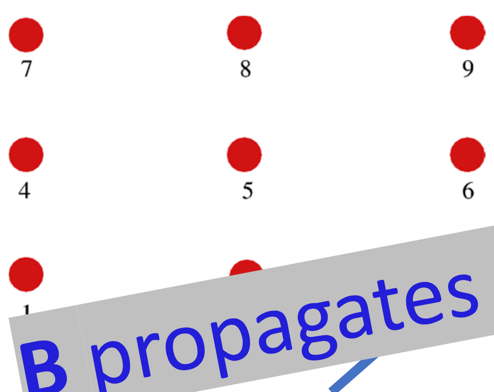
Forecast Error Covariance (**B**): It's role

$$X^a = X^b + BH^T[HBH^T + R]^{-1}[Y - HX^b]$$

Model Grid



Observation location

$$X^b = \begin{bmatrix} x_1^b \\ x_2^b \\ x_3^b \\ \vdots \\ x_9^b \end{bmatrix}$$

$$Y = [y_o]$$

$$H = [0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]$$

B=

$$\begin{bmatrix} B_{11} & B_{12} & . & . & B_{19} \\ B_{21} & B_{22} & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & B_{99} \end{bmatrix}$$

$$R = [\sigma_o^2]$$

$$\begin{bmatrix} x_1^a \\ x_2^a \\ x_3^a \\ \vdots \\ . \\ x_9^a \end{bmatrix} = \begin{bmatrix} x_1^b \\ x_2^b \\ x_3^b \\ \vdots \\ . \\ x_9^b \end{bmatrix} + \begin{bmatrix} B_{13} \\ B_{23} \\ B_{33} \\ \vdots \\ . \\ B_{93} \end{bmatrix} \frac{(y_o - x_3^b)}{(B_{33} + \sigma_o^2)}$$

B propagates observations to non-observed variables

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How to account for these uncertainties in ensemble methods?

- Pre-selecting an appropriate ensemble(s) from an available dataset - EnOIs
  - **Advantages:** Computationally very efficient
  - **Limitations:** Does not well-represent the error-of-the-day, especially when dealing with rapidly varying dynamics
- Dynamically evolve the ensemble using the model - EnKFs
  - **Advantages**: Represents the error-of-the-day
  - **Limitations**: collapses in the ensemble spread, computationally demanding.
- Combine the two methods - Hybrid

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Objective

Build an efficient, in terms of cost and performance, high-resolution ocean data assimilation system for the Red Sea (RS), for forecasting and reanalysis.

Configuration of Data assimilation system

❖ **Ocean Model: MITgcm**

- ✓ 30E-50E & 10N-30N covering Red sea and Gulf of Aden, connecting the Arabian sea in the east
- ✓ 4km resolution and 50 levels
- ✓ Vertical resolution: 50 levels with 5m resolution in the upper 200 m and 300m resolution in the deeper layers
- ✓ Forcing: 0.5 x 0.5 ECMWF ensemble
- ✓ Boundary Conditions: Daily 25km-resolution GLORYS ocean reanalysis
- ✓ GEBCO Bathymetry and KPP vertical mixing scheme

❖ **Assimilation package: DART (Data Assimilation Research Package)**

- ✓ Ensemble Adjustment Kalman Filter (EAKF)
- ✓ Localization: 300 km in the horizontal (no-vertical localization)
- ✓ Assimilate:
  - Satellite Level-4 Reynolds SST. **0.1 - 0.6 degC** observations error
  - Satellite Level-3 altimeter SLA (merged). **4cm** observations error
  - In situ T & S profiles from EN4 dataset (fully QC'd). **0.5 degC and 0.2 psu** observations error

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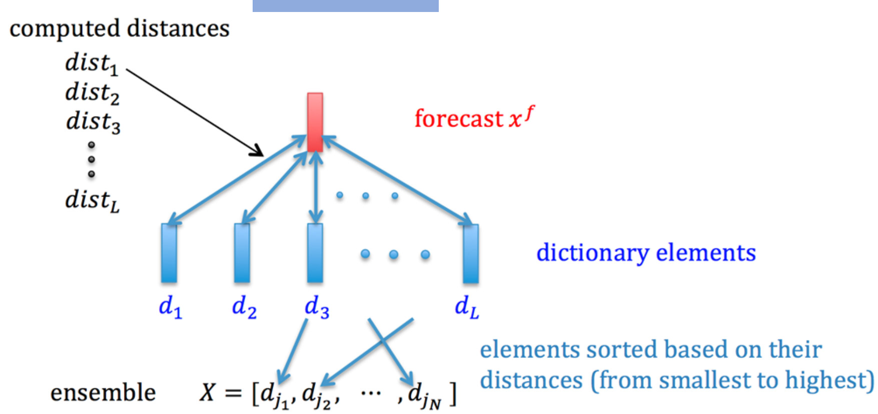
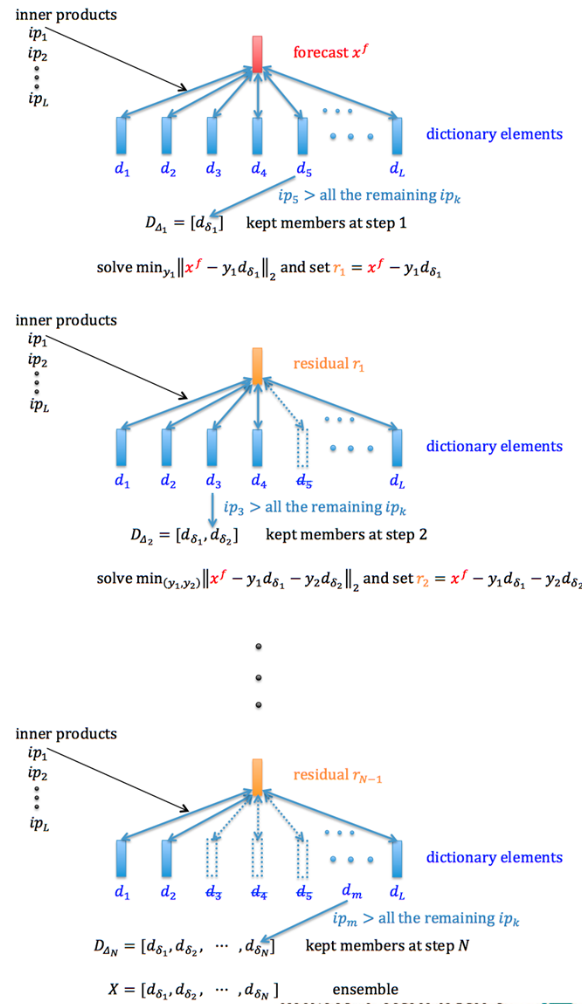
EnOIs: pre-selection of ensembles

- EnOI- Uses a climatological ensembles
- Adaptive EnOI – Selects a new ensemble at every assimilation cycle
  - ✓AEnOI-L2 –based on the distance from the present forecast
  - ✓AEnOI-OMP –find a smallest possible subset of elements that best represents the forecasted state.

AEnOI-L2



AEnOI-OMP



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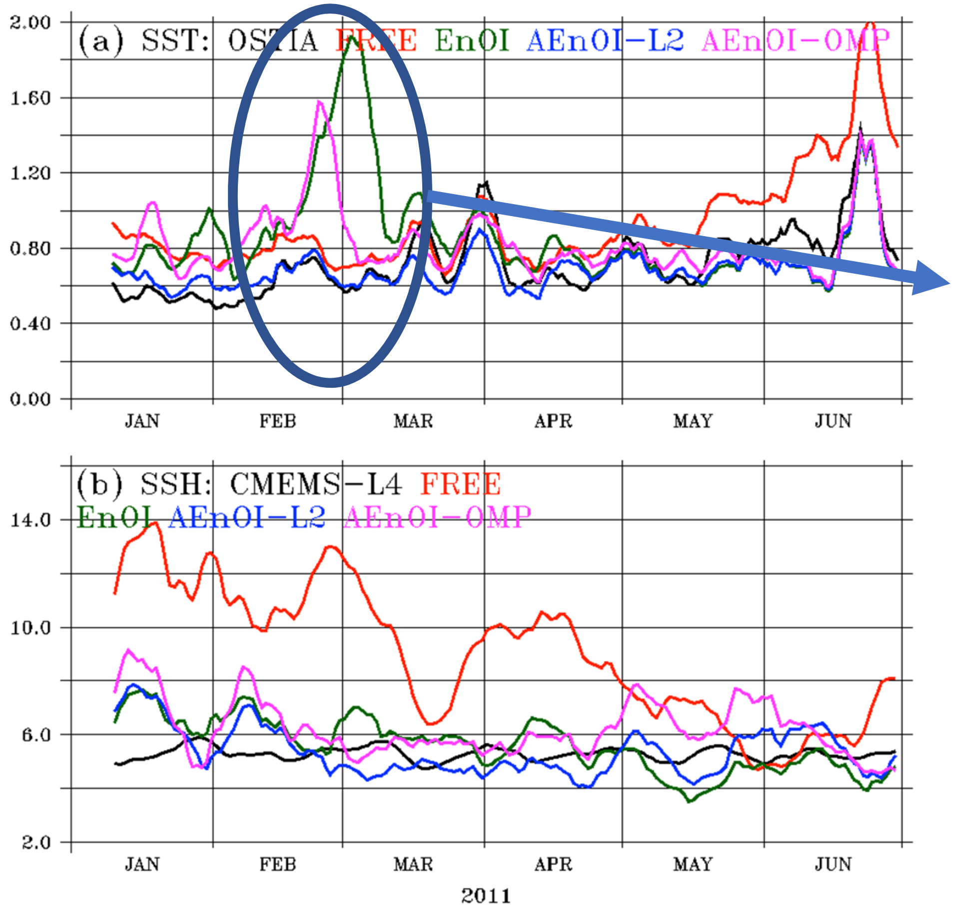
Time-evolution of (daily averaged forecast) SST and SSH RMSDs



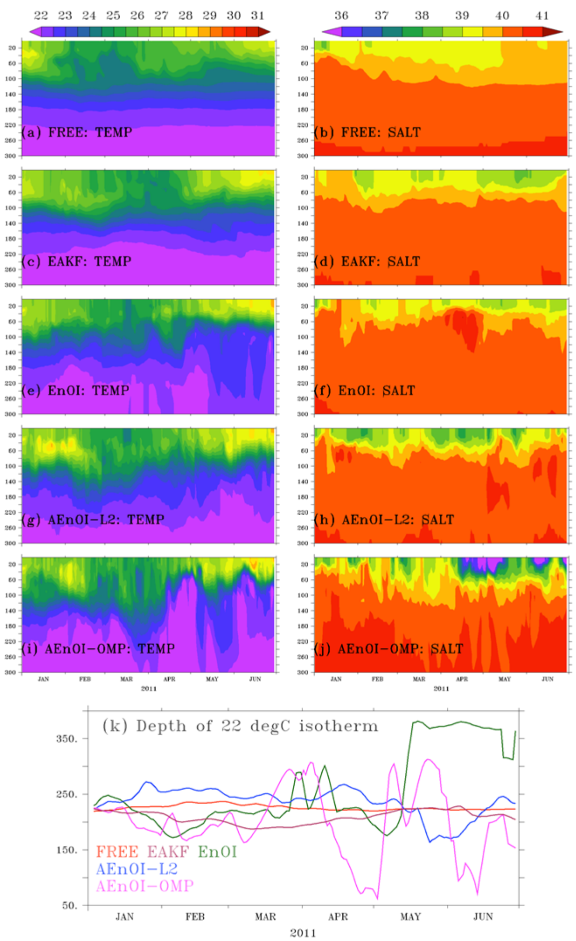
Major factors for degradations:

- ✓ Repercussions from dynamical imbalances in the subsurface
- ✓ Spurious error correlations at the surface ???
- ✓ Data over-fitting

Degradations in the subsurface

Central Red Sea (38E, 22N)

Temperature Salinity



Majorly factors for degradations:

- ✓ Spurious-correlations in the background error covariance matrix ???
- ✓ Dynamical imbalances

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EAKF methods: Flow-dependent ensembles

Experiment	Initial condition	Atm. Forcing	Physics	Assimilation
Fexp	Model state at 1st Jan, 2011	Ensemble mean	STANDARD	No
Iexp	50-member ensemble based on hindcasts recentered on 1st Jan, 2011.	Ensemble mean	STANDARD	Yes
IAexp	50-member ensemble based on hindcasts recentered fon1st Jan, 2011.	50-member ensemble	STANDARD	Yes
IAPexp	50-member ensemble based on hindcasts recentered on 1st Jan, 2011.	50-member ensemble	RANDOM across members	Yes

Iexp → Accounts uncertainties in the initial conditons
IAexp → Accounts uncertainties in the initial conditions and atmospheric forcing
IAPexp → Accounts uncertainties in the initial conditions, atmospheric forcing, and model physics

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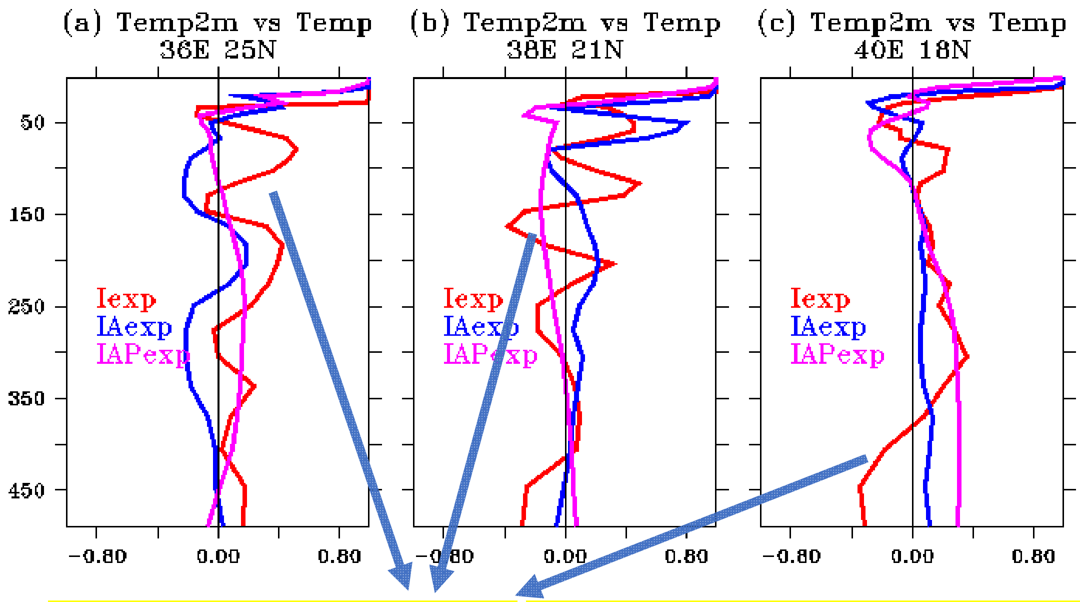
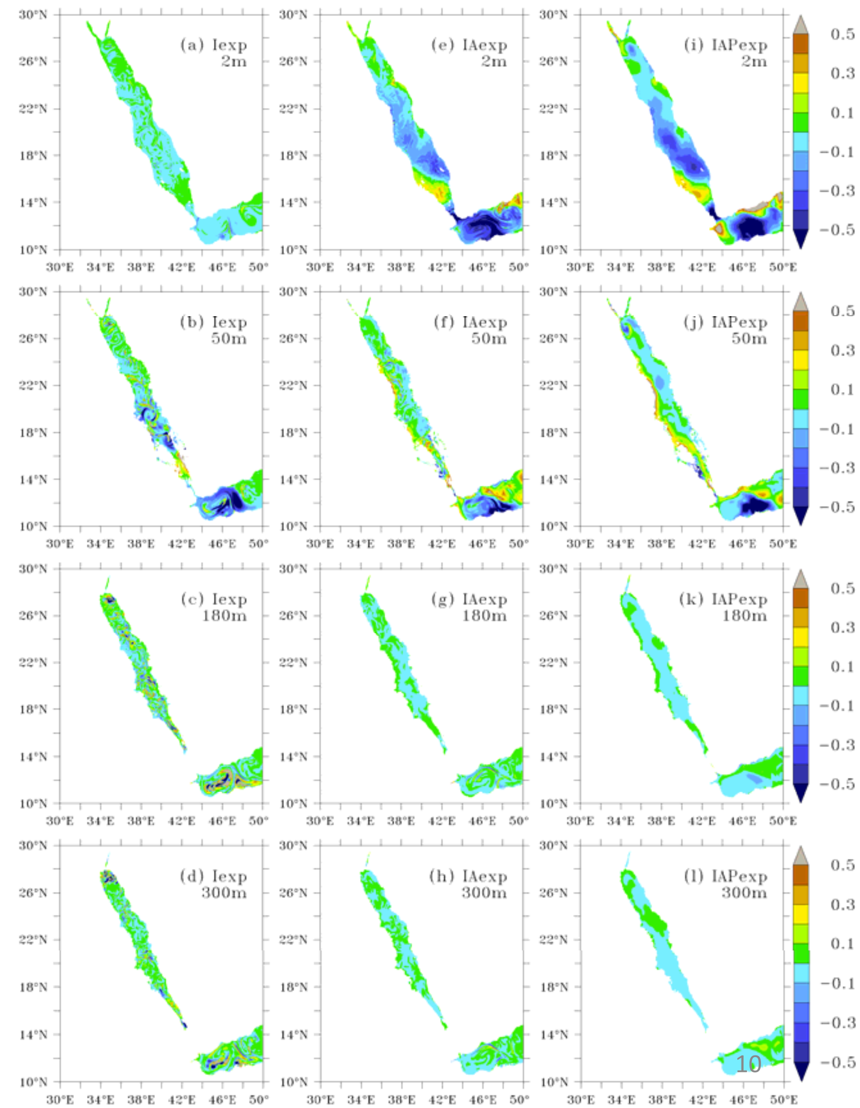
Background Error correlations (vertical) on 1st October, 2011

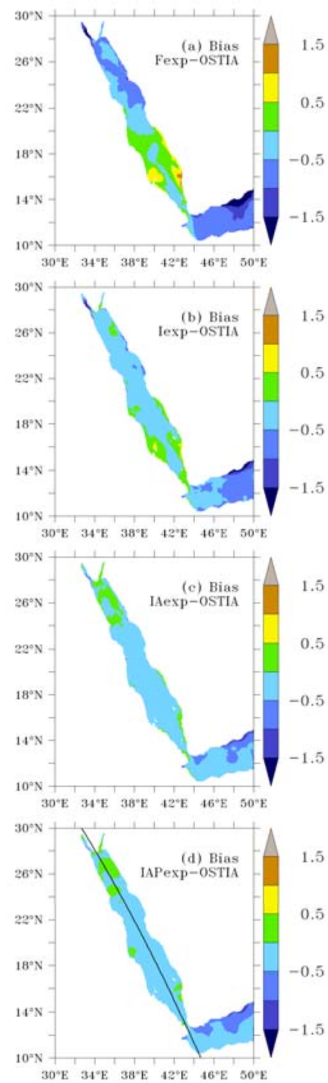


Too Noisy correlations in *Iexp* become more organized in *IAPexp*.

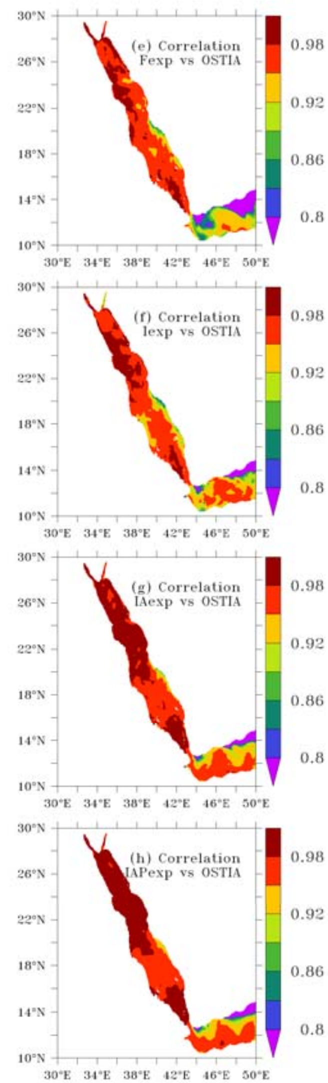
Analysis corrections on 1st October, 2011



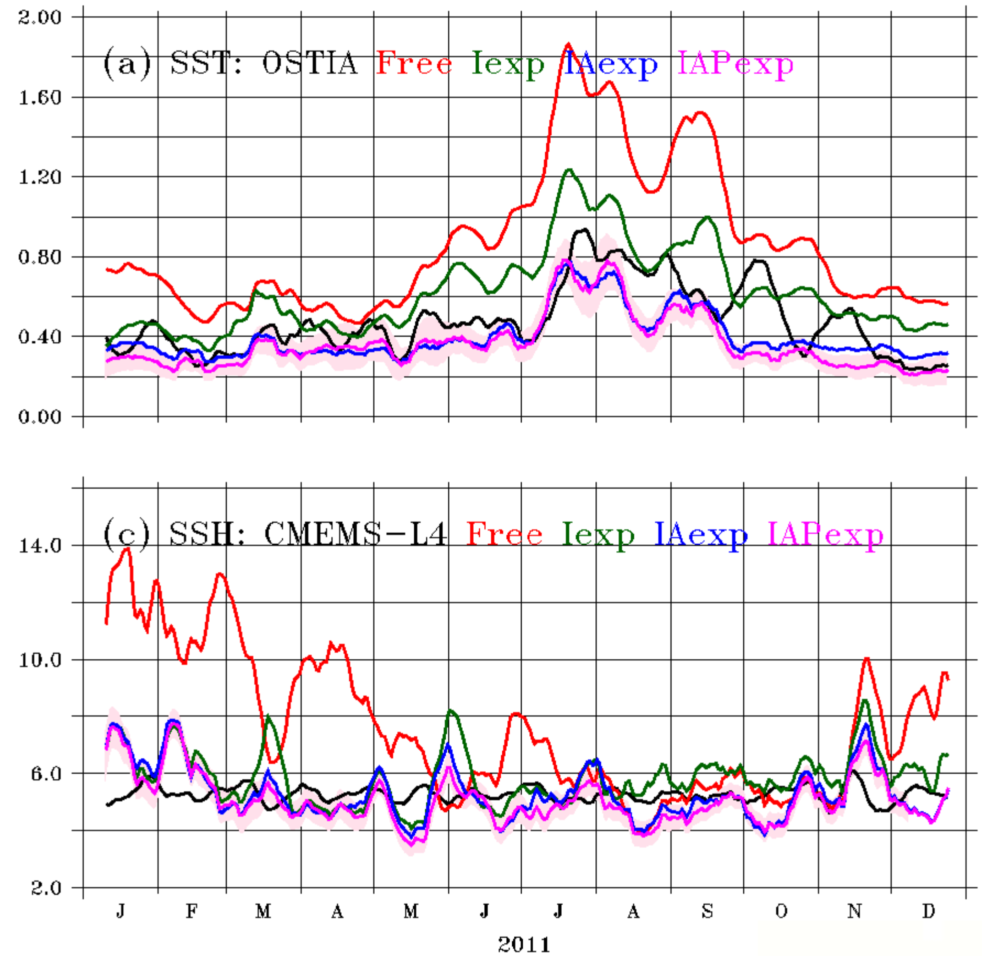
SST bias



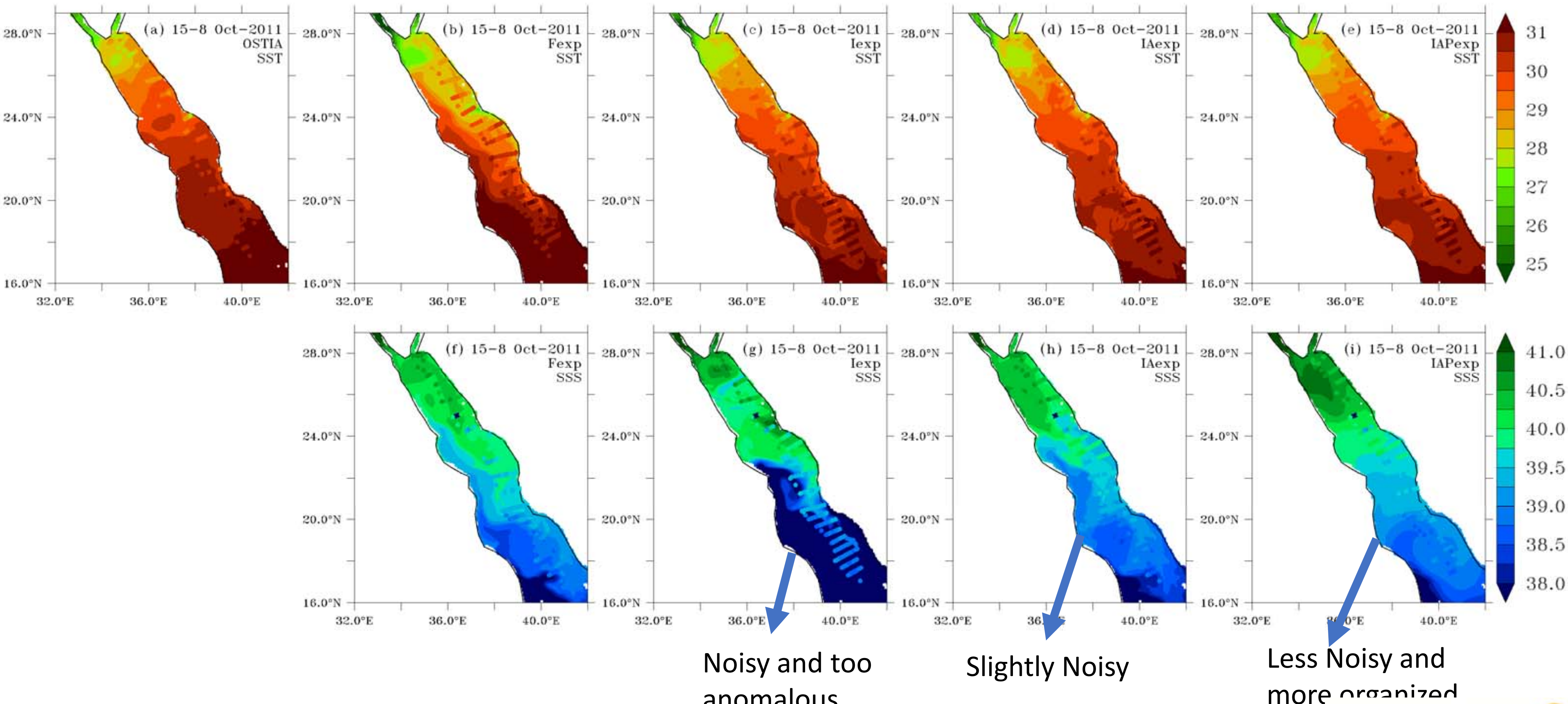
SST Correlation



Root Mean Square Differences



Comparisons with in-situ SST and SSS observations from WHOI/KAUST cruise



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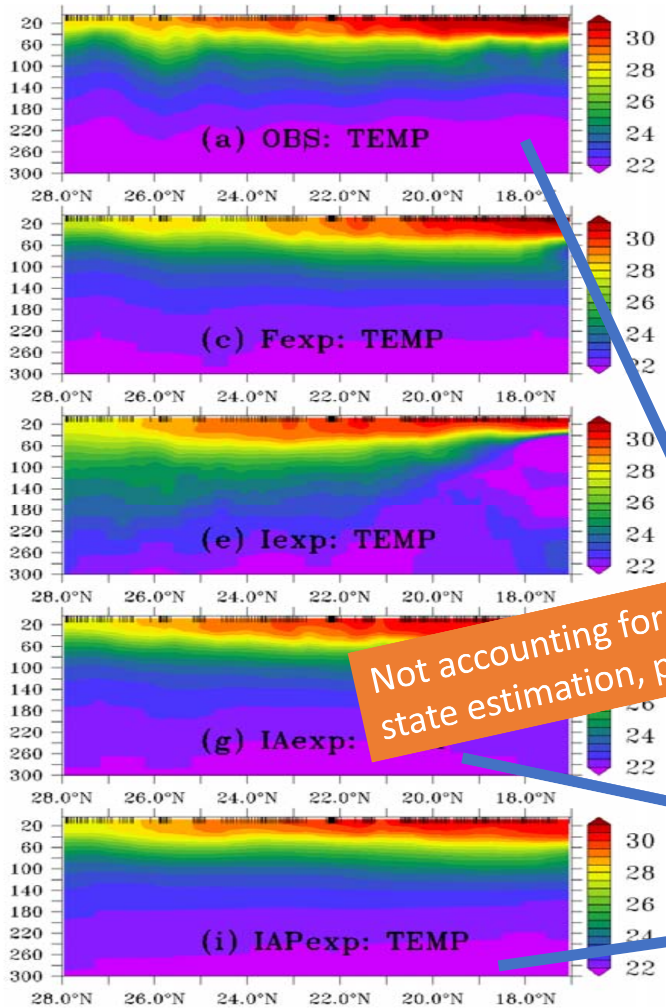
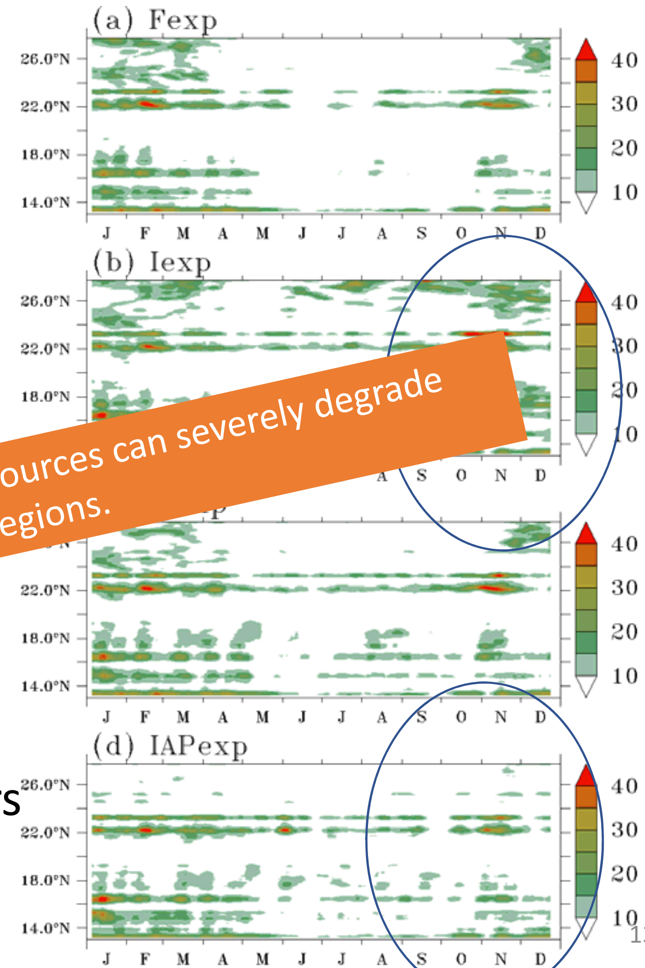
Subsurface Temperature comparisons from WHOI/KAUST cruise



Maximum Vertical Velocity in the ocean column along RS axis



Not accounting for uncertainties from sufficient sources can severely degrade state estimation, particularly in the data sparse regions.

Improved biases in the deep layers with *IAPexp*

Hybrid-EAKF: Complimenting flow-dependent ensembles with pre-selected ensembles

Traditional Hybrid methods (e.g. Wang et al., 2007)

$$\mathbf{\Sigma}^{p,H} = (1-\alpha)\mathbf{\Sigma}^{p} + \alpha\mathbf{B}, \qquad \text{with} \quad 0 \le \alpha \le 1$$

We implemented the Hybrid method in the context of the 2-steps, which act update of EAKF with DART, directly on the ensembles

$$\mathbf{X}^{H} = \left[K_d\,\mathbf{X}'^{p}, \qquad K_s\,\mathbf{X}'^{s}\right] + \bar{\mathbf{x}}^{p}$$

Where $K_d = \sqrt{\frac{(1-\alpha)(N_d+N_s-1)}{N_d-1}}$ and $K_s = \sqrt{\frac{\alpha(N_d+N_s-1)}{N_s-1}}$

The analysis-ensemble is prepared by re-centering the dynamic analysis-ensemble onto the Hybrid analysis-ensemble -mean

$$\mathbf{x}_i^{u,H} = \bar{\mathbf{x}}^{u,H} + (\mathbf{x}_i^{u} - \bar{\mathbf{x}}^{u}), \qquad i = 1, \dots, N_d$$

$\mathbf{\Sigma}^{p}$ flow-dependent covariance
$\mathbf{B}$ Static covariance
$\mathbf{\Sigma}^{p,H}$ Hybrid covariance
α weighting factor

$\mathbf{X}^{H}$ Hybrid ensemble
$\mathbf{X}'^{p}$ EAKF prior ensemble anomalies
$\mathbf{X}'^{s}$ pre-selected static ensemble anomalies
$\bar{\mathbf{x}}^{p}$ mean of the prior ensemble
$\bar{\mathbf{x}}^{u}$ mean of the EAKF updated ensemble
$\bar{\mathbf{x}}^{u,H}$ mean of Hybrid updated ensemble
$\mathrm{x}_i^{u,H}$ Hybrid i^{th} updated ensemble member
N_d size of the dynamic ensemble
N_s size of the pre-selected static ensemble

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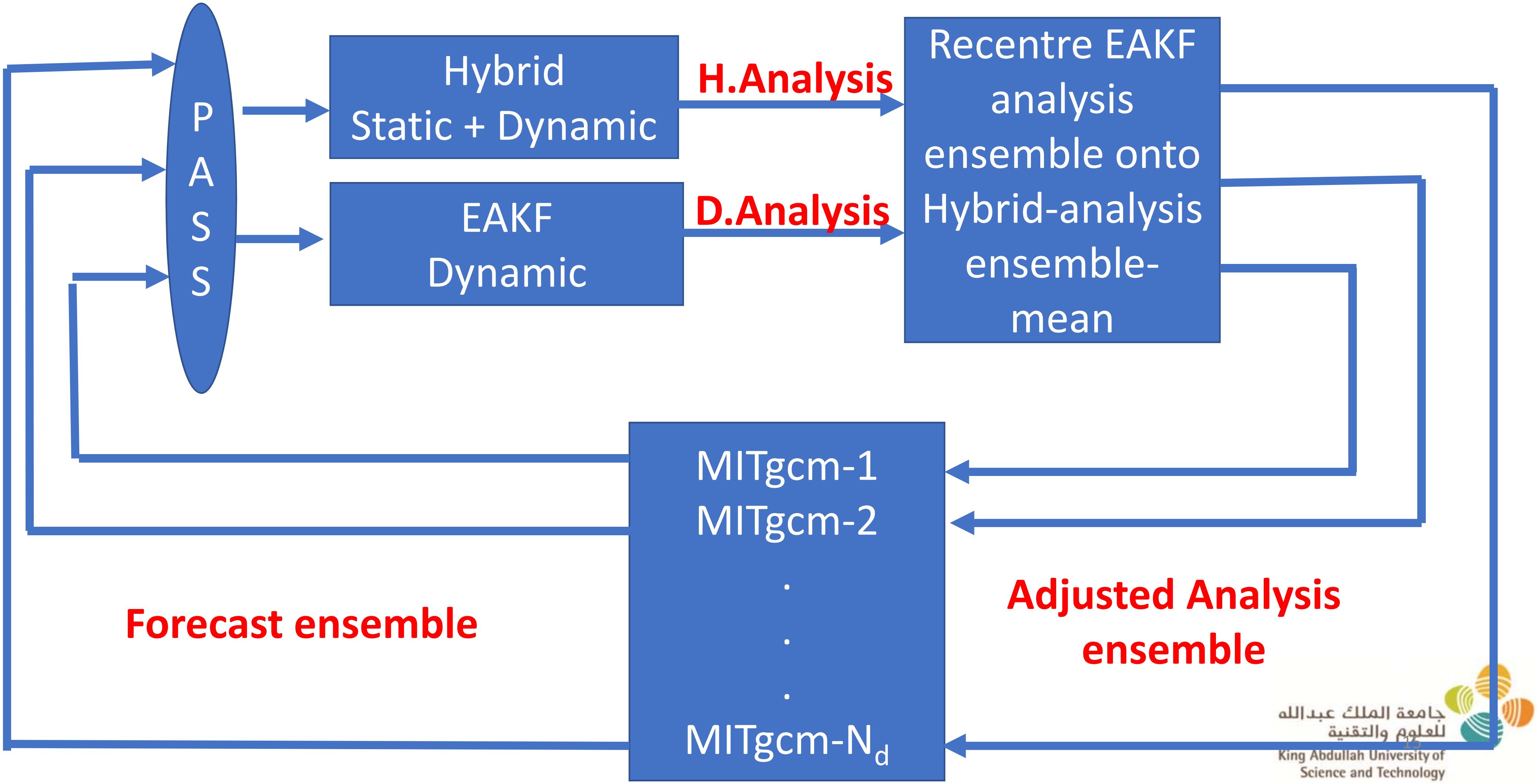
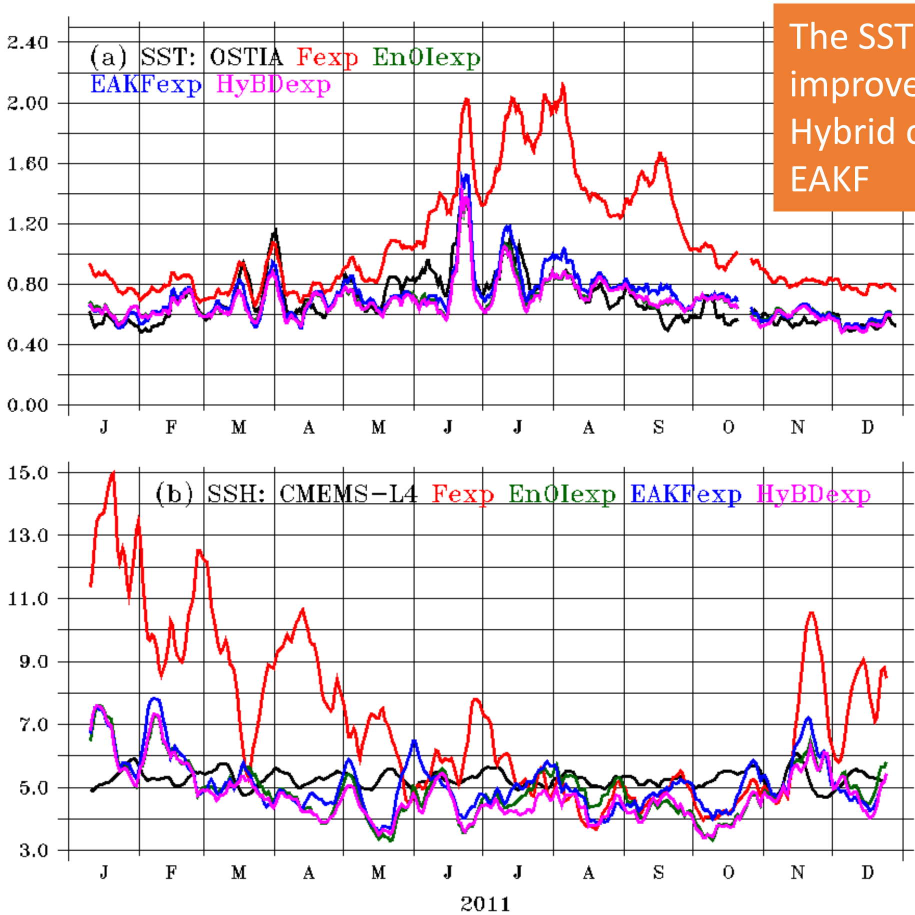
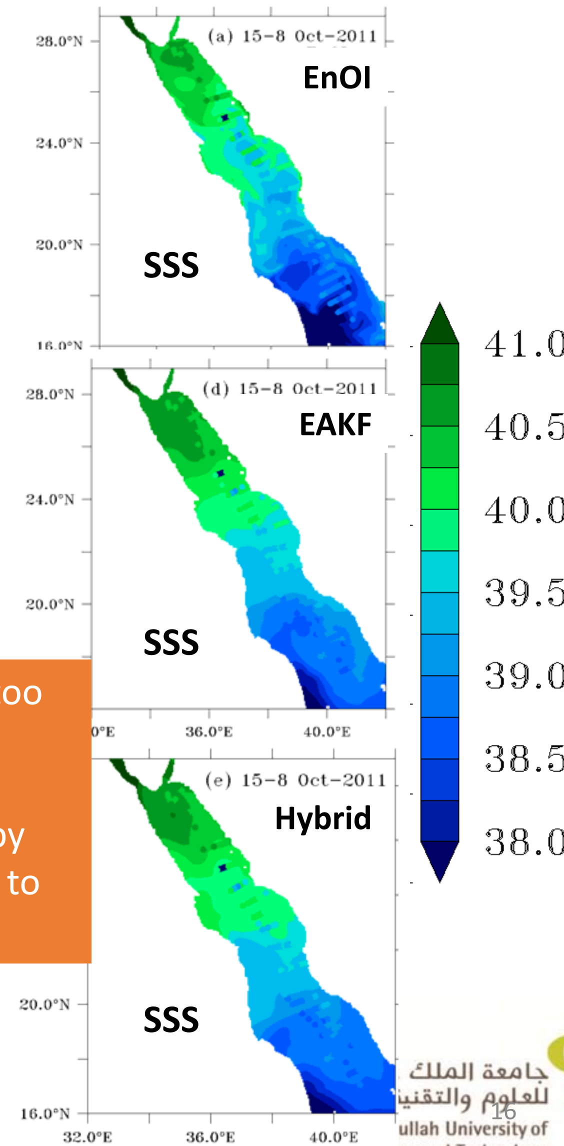
Hybrid-EAKF Flowchart



Forecast-Data comparisons at the surface



The SST and SSH are improved by 20% in Hybrid compared to EAKF

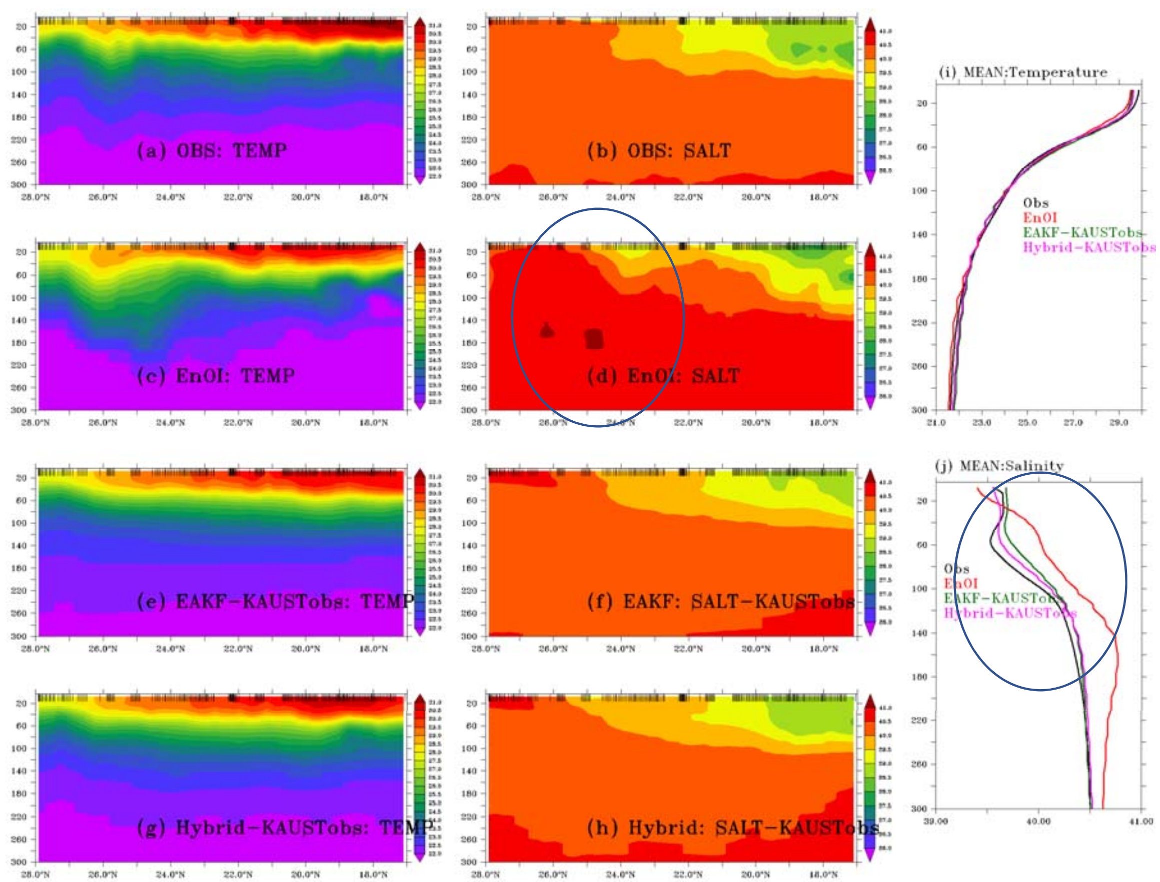


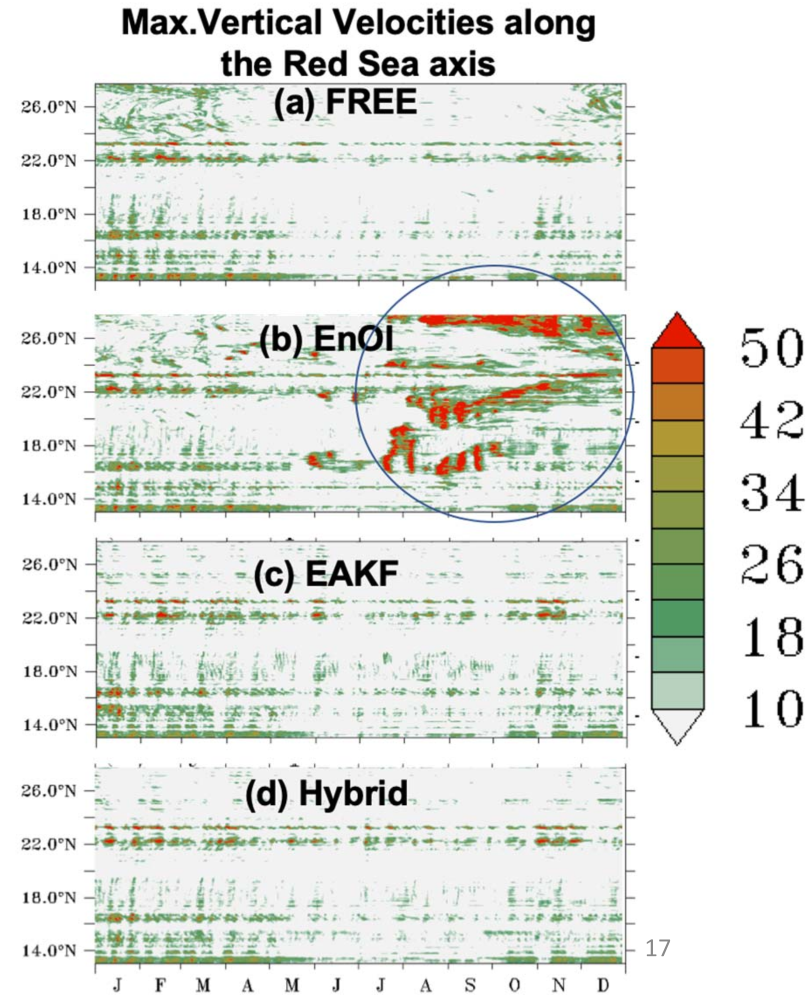
Non-assimilated SSS is too noisy in EnOI

Significantly improved by Hybrid, even compared to EAKF

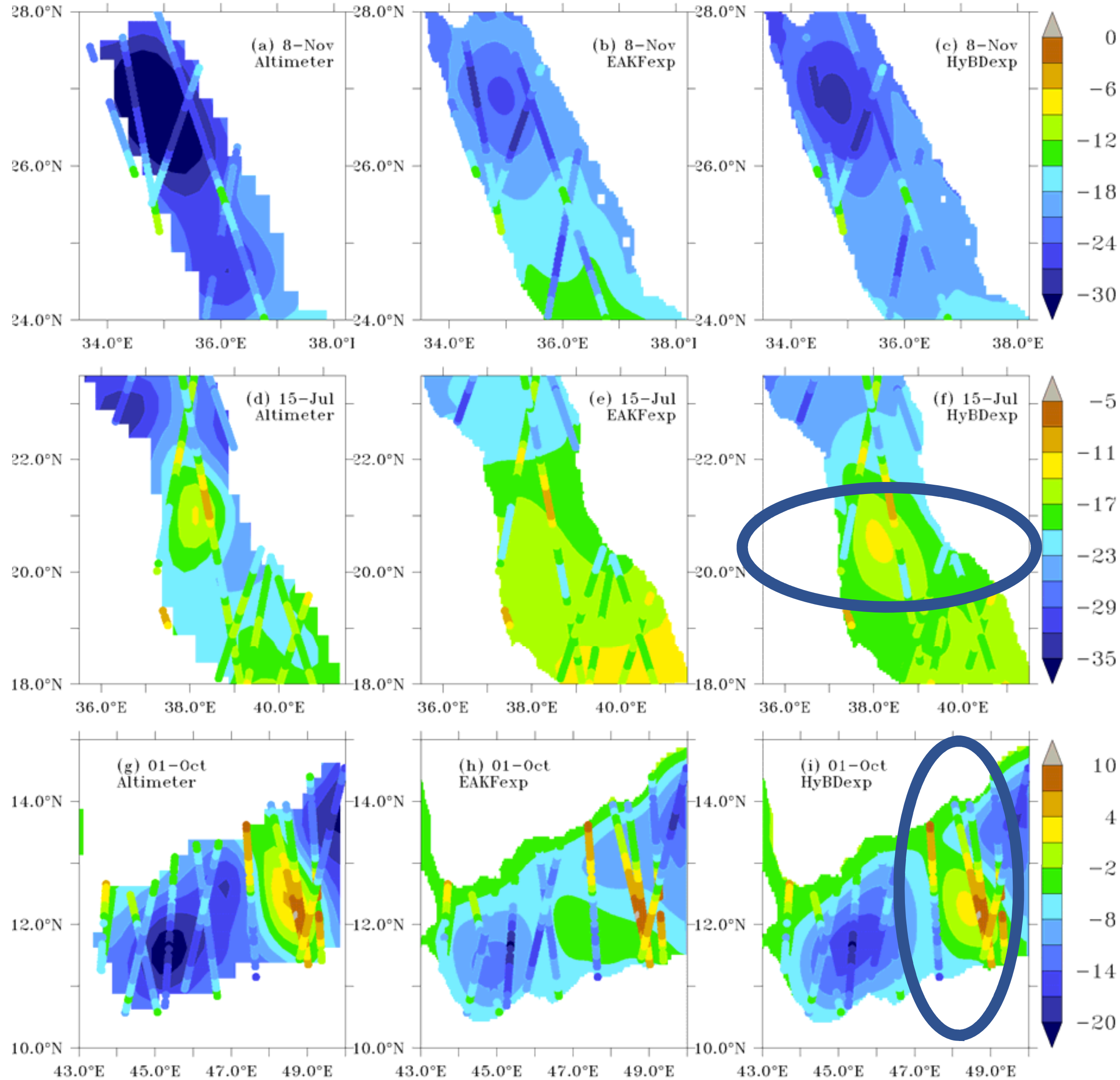
Forecast-Data comparisons in the sub-surface

Comparisons with independent WHOI/KAUST cruise observations





Comparison for Eddy features



Hybrid is best, even better than the interpolated product

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Summary

- EnOI-alone methods, which rely on pre-selected ensembles, are prone to spurious corrections.
- Dynamically evolving the ensemble to account for uncertainties in initial conditions, atmospheric forcing and internal physics is greatly beneficial.
- Combining the dynamical ensemble with a pre-selected (climatological) ensemble with the Hybrid method enforces smoothness in the background covariance and greatly reduce computational cost.
- Hybrid method enhances the impact of assimilated observations and provides improved and dynamically balanced state

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List of Publications

Toye, H., P. Zhan, G. Gopalakrishnan, A.R. Kartadikaria, H. Huang, O. Knio, and I. Hoteit, (2017). Ensemble data assimilation in the Red Sea: sensitivity to ensemble selection and atmospheric forcing. *Ocean Dynamics.* 67, 915–933, http://dx.doi.org/10.1007/s10236-017-1064-1.

Raboudi N.F., B. Ait-El-Fquih, C. Dawson, and I. Hoteit (2019). Combining Hybrid and One-step-Ahead smoothing for efficient short-Storm Surface Forecasting with an Ensemble Kalman Filter. *Quarterly Journal of Royal Meteorological Society,* 147, 3283-3300, doi: 10.1175/MWR-D-18-0410.1.

Sanikommu S., H. Toye, P. Zhan, S. Langodan, G. Krokos, O. Knio, and I. Hoteit, (2020). Impact of Atmospheric and model physics perturbations on a high-resolution ensemble data assimilation system of the Red Sea. *J. Geophy. Res.,* Under Review.

Toye H., S. Sanikommu, N. F. Raboudi, and I. Hotiet (2020). A Hybrid Ensemble Adjustment Kalman Filter based High-resolution data Assimilation Systerm in the Red Sea: Implementation and Evaluaiton. *Quarterly Journal of Royal Meteorological Society*, Submitted

Toye H., P. Zhan, F. Sana, S. Sanikommu, N. Raboudi, and I. Hoteit (2020). Adaptive Ensemble optimal interpolation for efficient data assimilation in the Red Sea. *Journal of Computational Science*, submitted

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