Multiscale alignment ensemble filtering technique and its application in geoscience

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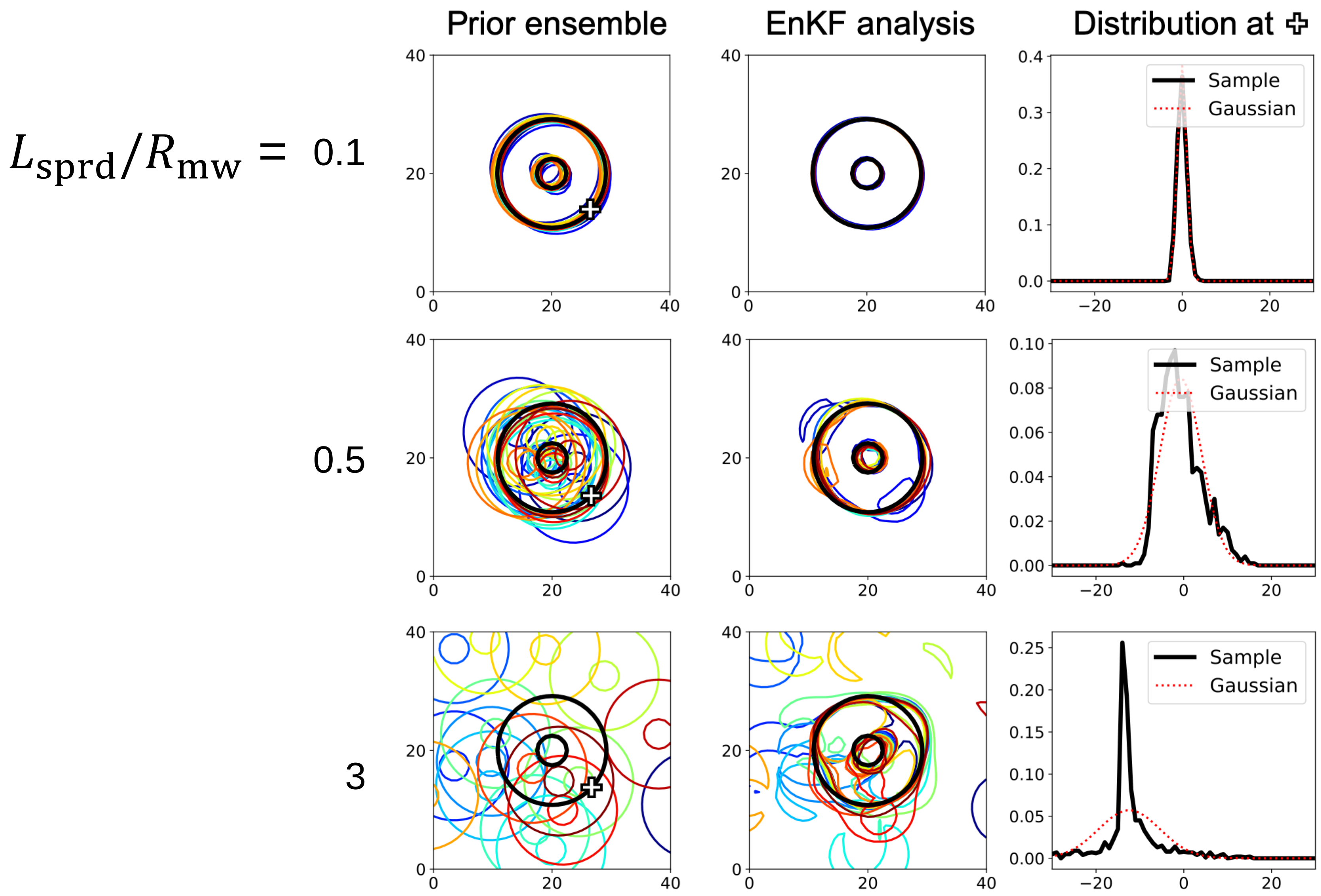
Outline

Motivation and Idea:
- Nonlinearity due to position errors
- The multiscale alignment (MSA) approach for ensemble filtering

Stress testing in a vortex case:
- Optimal number of scales (*Ns*)
- Localization
- Inflation and observation error
- Coherence assumption

Real implementation and path forward:
- Sea ice model (neXtSIM)
- Coupled DA

Nonlinearity due to vortex position errors



Contours of constant wind speed from vortices:
black: truth
colors: ensemble members

As position error L_{sprd} increases,
- error distribution becomes more non-Gaussian,
- EnKF analysis becomes more suboptimal

Data assimilation with position uncertainties

Error model: $\mathbf{X}^b = \mathbf{X}^* + \boldsymbol{\varepsilon}^d + \boldsymbol{\varepsilon}^r$

$\boldsymbol{\varepsilon}^d = \mathbf{X}^b - \mathbf{X}^b(\mathbf{q})$ displacement error

$\boldsymbol{\varepsilon}^r = \mathbf{X}^b(\mathbf{q}) - \mathbf{X}^* \sim \mathcal{N}[0, \mathbf{B}(\mathbf{q})]$ residual (amplitude) error

Bayesian formulation on posterior error distribution:

$$p(\mathbf{X}, \mathbf{q} \,|\, \mathbf{Y}) \propto p(\mathbf{Y} \,|\, \mathbf{X}, \mathbf{q})\, p(\mathbf{X} \,|\, \mathbf{q})\, p(\mathbf{q})$$

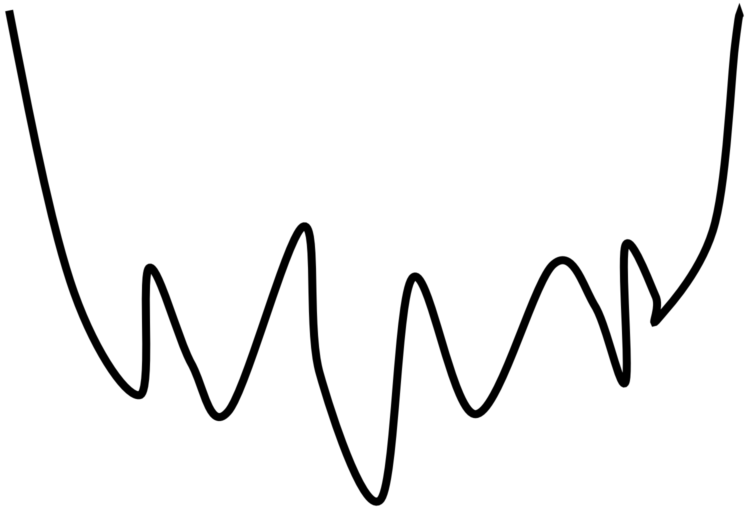
Cost function:

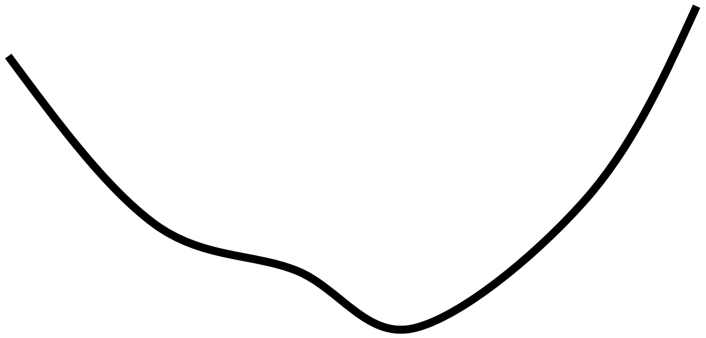
$$J(\mathbf{X}, \mathbf{q}) = \frac{1}{2}\|\mathbf{Y} - H[\mathbf{X}(\mathbf{q})]\|^2_{\mathbf{R}} + \frac{1}{2}\|\mathbf{X}(\mathbf{q}) - \mathbf{X}^b(\mathbf{q})\|^2_{\mathbf{B}(\mathbf{q})} + \frac{1}{2}\ln(|\mathbf{B}(\mathbf{q})|) + L(\mathbf{q})$$

Two-step solver: 1. derive displacement (update $\mathbf{q}$), 2. EnKF update (update $\mathbf{X}$)
(Ravela et al. 2007, Nehrkorn et al. 2015)

Data assimilation with position uncertainties

Topography of $J(\mathbf{x},\mathbf{q})$:
Nonlinearity causes a lot of local minima and difficulty in reaching the global minimum through iterative solver

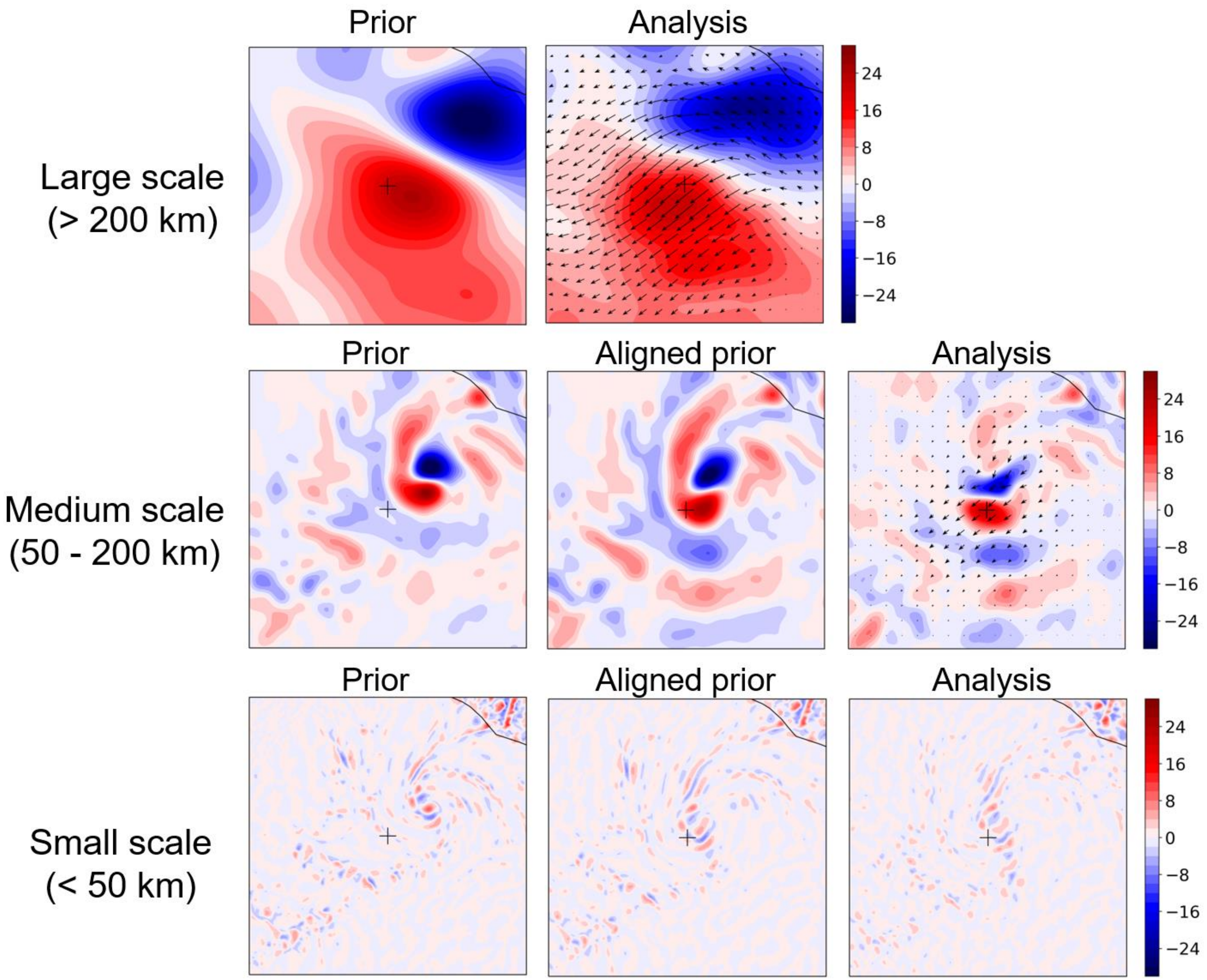




Idea:

Use iterations over scale components (SCs) (outer loops in 4DVar)
The large-scale iteration skips local minima and save a lot of iterations in high-res space
Similar "multiscale idea" used in image processing (optical flow)

The multiscale alignment ensemble filtering idea



Example: Hurricane Patricia (2015)

blue/red shadings: *u*-wind for the *Ns* = 3 scale components.

vectors: the displacement vectors computed from the analysis increments

Iterate over scale components:

1. EnKF assimilate observations,
2. Find displacements (optical flows), which are applied to the smaller scales to align (precondition) the prior,
3. go to next scale …

(MSA; Ying 2019, MWR)

The MSA EnKF algorithm

for s in $1, \ldots, N_s$ **do**

$$\mathbf{x}_{n,s}^{b} = \mathbf{F}_s \mathbf{x}_n$$

$$\mathbf{y}_{n}^{b} = h(\mathbf{x}_n)$$

$$\mathbf{x}_{n,s}^{a} = \mathbf{x}_{n,s}^{b} + \mathbf{L}_s \circ \frac{\mathbf{C}_{x_s,y}}{\mathbf{C}_{y,y} + \sigma_o^2 \mathbf{I}} \left(\mathbf{y}^o - \mathbf{y}_n^b\right)$$ *Filter update step*

if $s < N_s$ **then**

$$\mathbf{q}_{n,s} = \underset{\mathbf{q}}{\operatorname{argmin}} \left\| \mathbf{x}_{n,s}^{b}(\mathbf{q}) - \mathbf{x}_{n,s}^{a} \right\|^2 + w \left\| \nabla \mathbf{q} \right\|^2$$ *Alignment step*

$$\mathbf{x}_n \leftarrow \mathbf{x}_n\left(\mathbf{q}_{n,s}\right) + \mathbf{x}_{n,s}^{a} - \mathbf{x}_{n,s}^{b}\left(\mathbf{q}_{n,s}\right)$$

else

$$\mathbf{x}_n \leftarrow \mathbf{x}_n + \mathbf{x}_{n,s}^{a} - \mathbf{x}_{n,s}^{b}$$

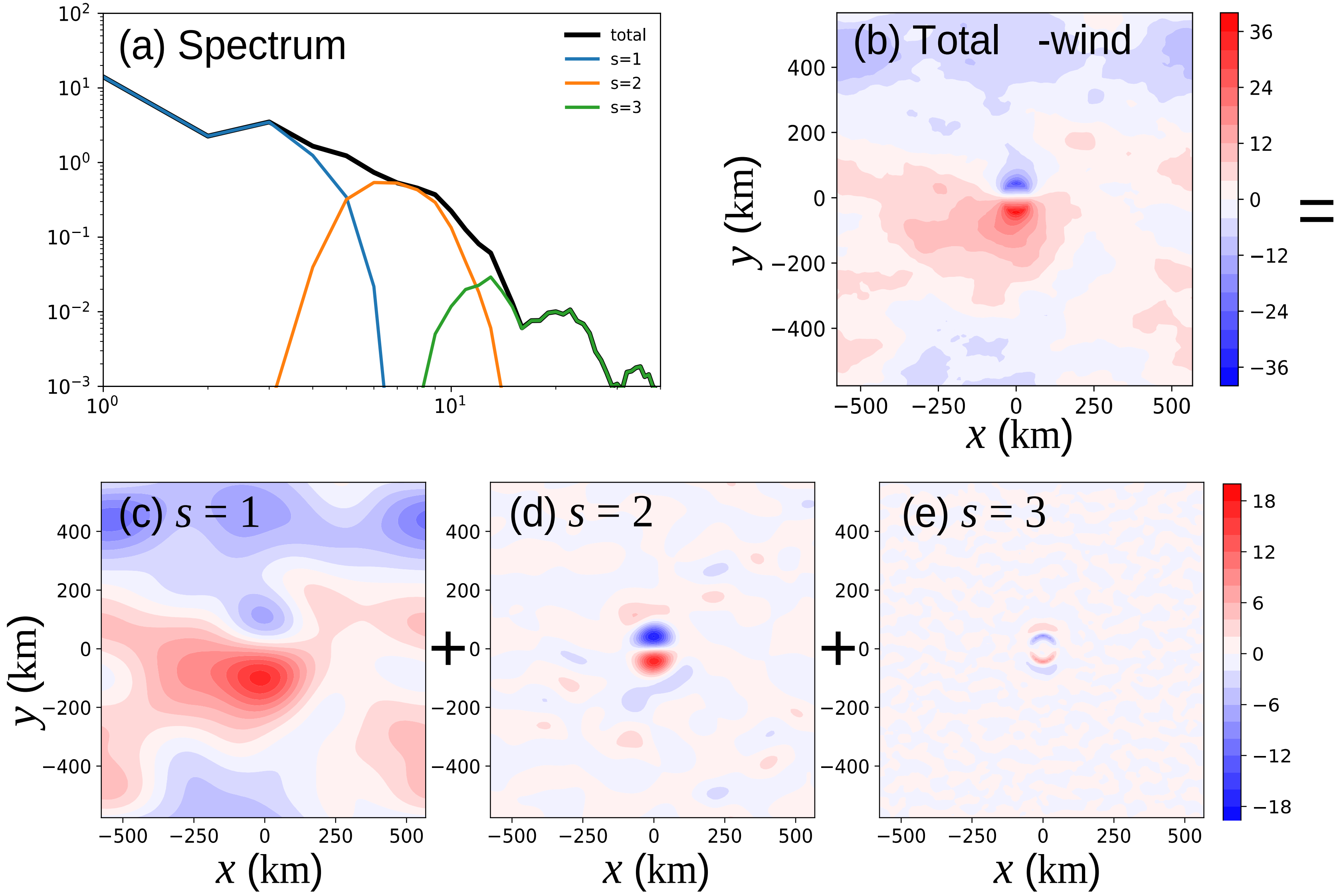
end if

end for

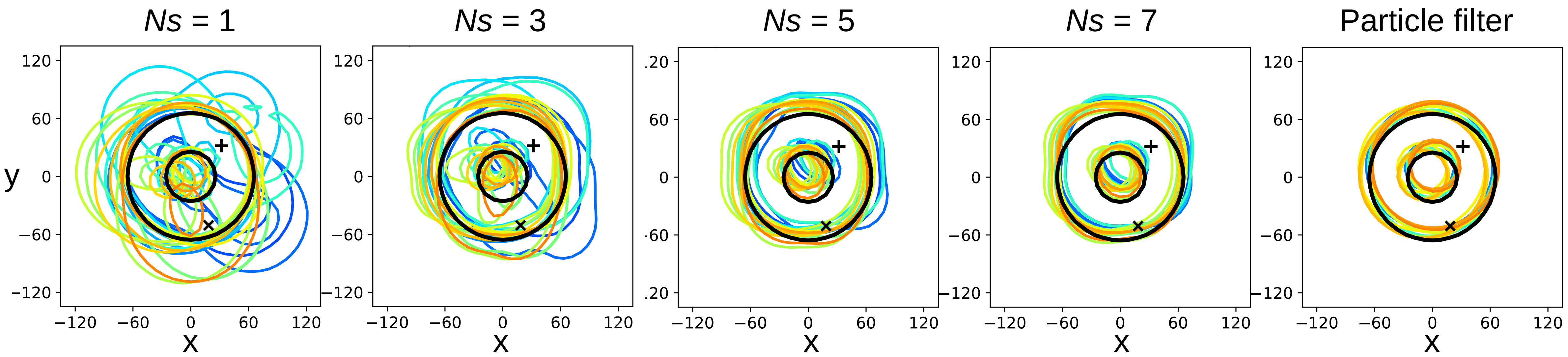
$n = 1, \ldots, N$ indexes ensemble members

$s = 1, \ldots, Ns$ indexes scale components (SC)

Test case: 2D vortex embedded in background flow



Asmptotic behavior as *Ns* increases



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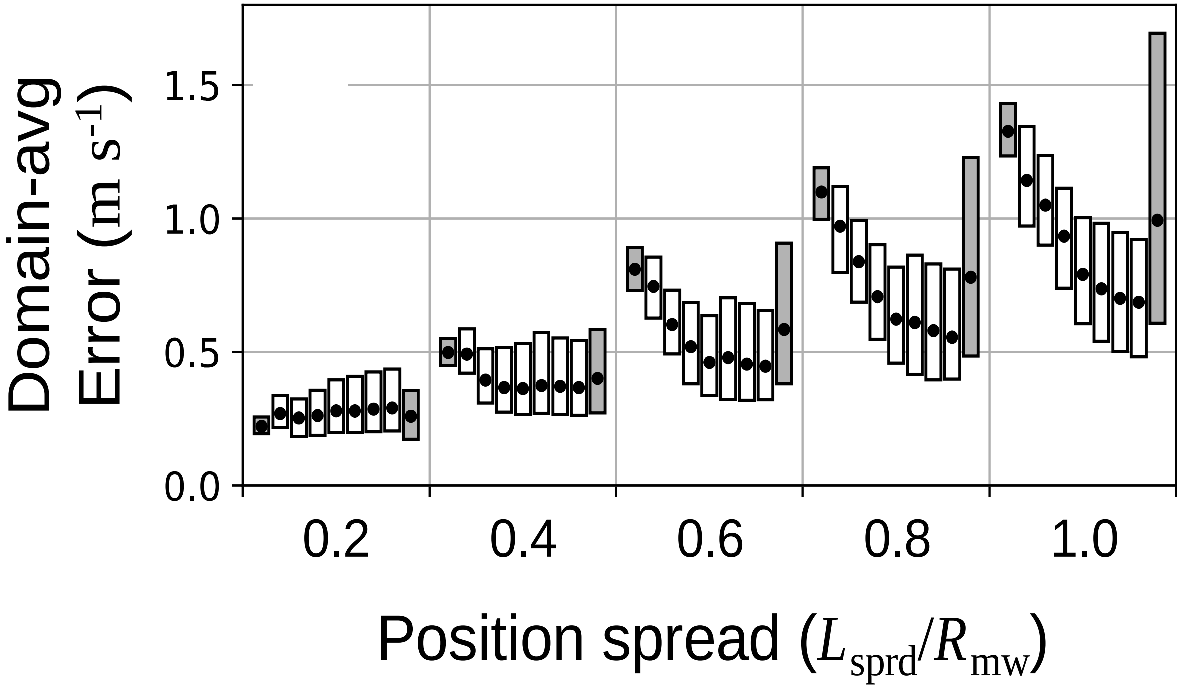
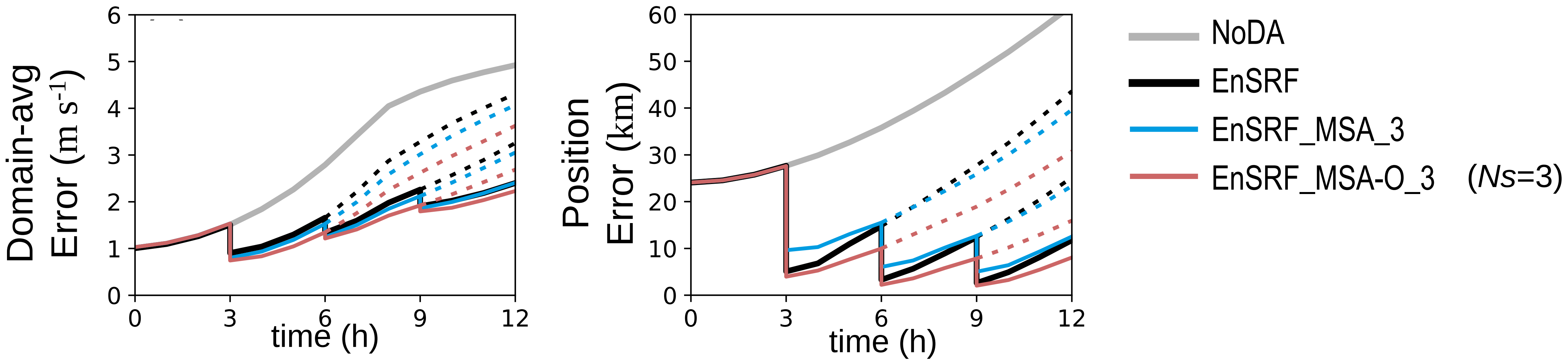


Domain-averaged RMSE from 1000 trials (boxplot)
(left-right: **NoDA**, **EnSRF** *Ns* = 1, 2, …, 7, **PF**)

- Performance improve as *Ns* increases in nonlinear regimes.
- For the quasi-linear regime, some degradation is due to smearing of sharp gradients in alignment.

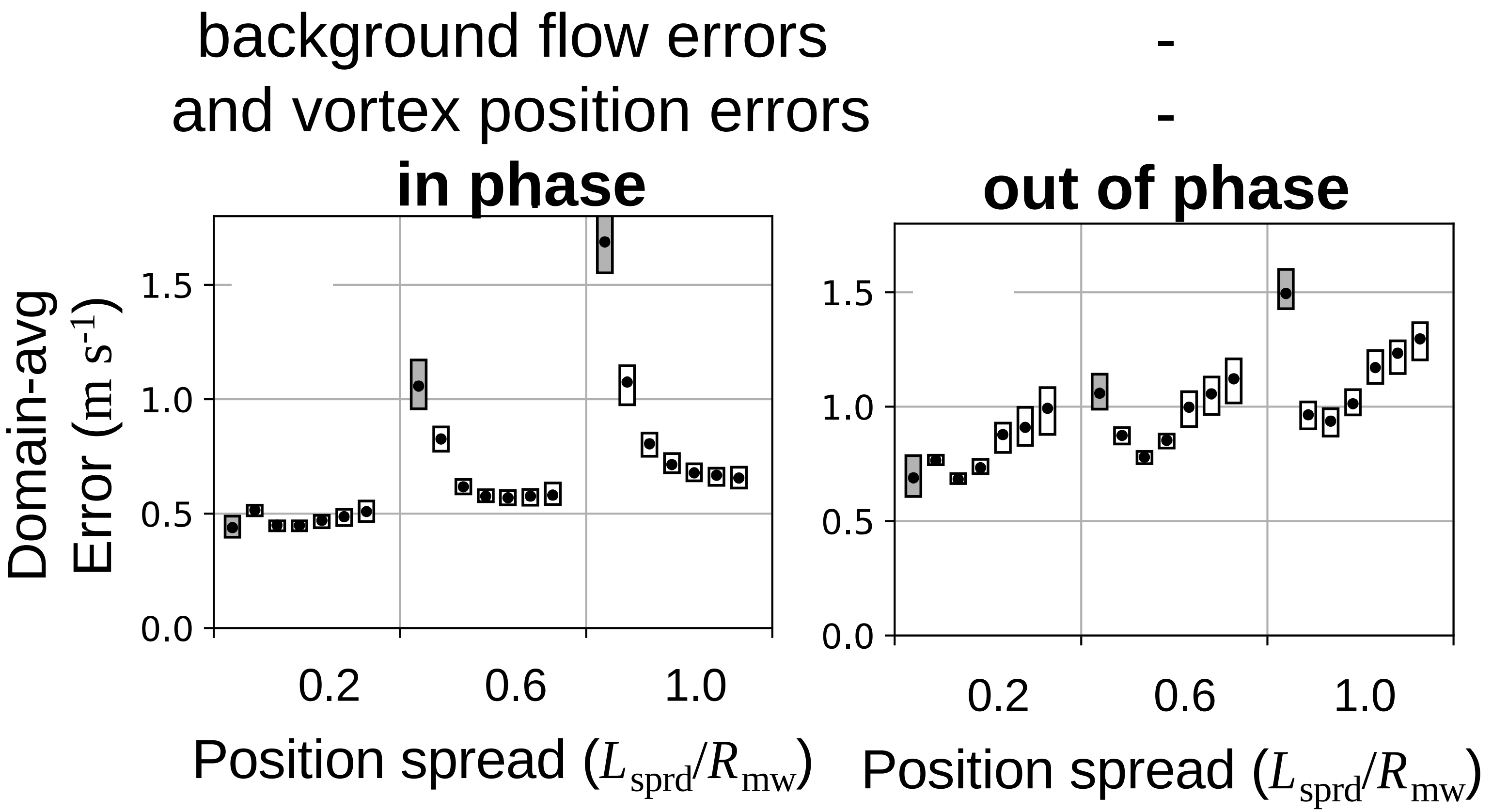
Performance in a cycling DA experiment



Assimilating filtered observation at corresponding scales (MSA-O) improves filter update and the overall performance.

MSA-O outperforms EnSRF in both analyses and forecasts
at equal cost! (MSA ensemble size is reduced to compensate for increased *Ns*)

Issue when deviating from coherence assumption



MSA makes **a coherence assumption** (large-scale pattern analysis increment → displacements → align the small-scale features)

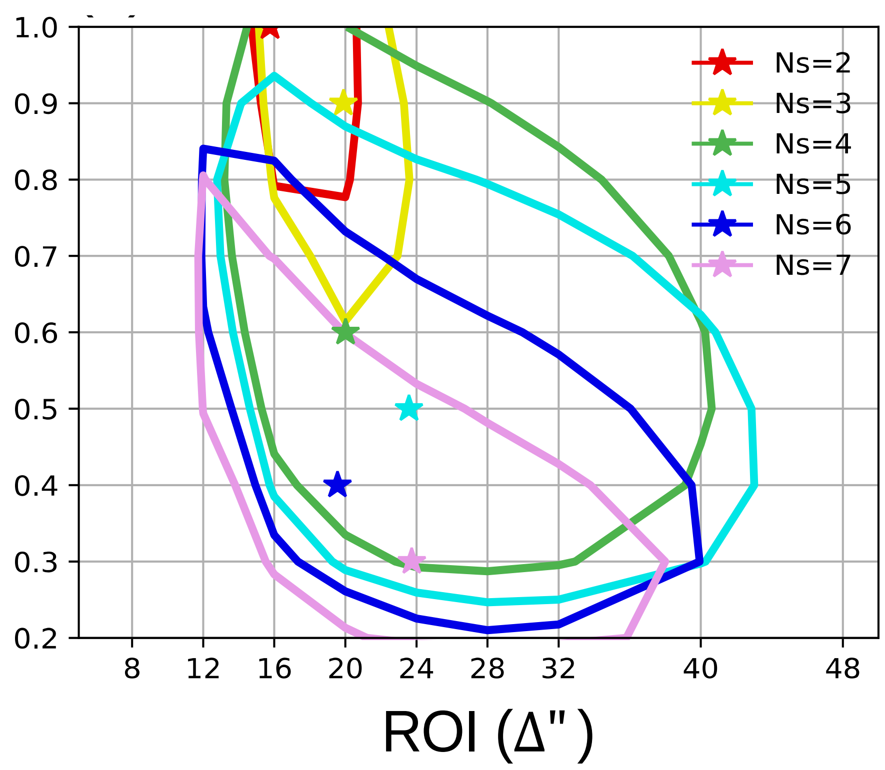
If background flow errors are incoherent with the vortex position error (out-of-phase), the MSA performance degrades.

How often does this happen in real applications?

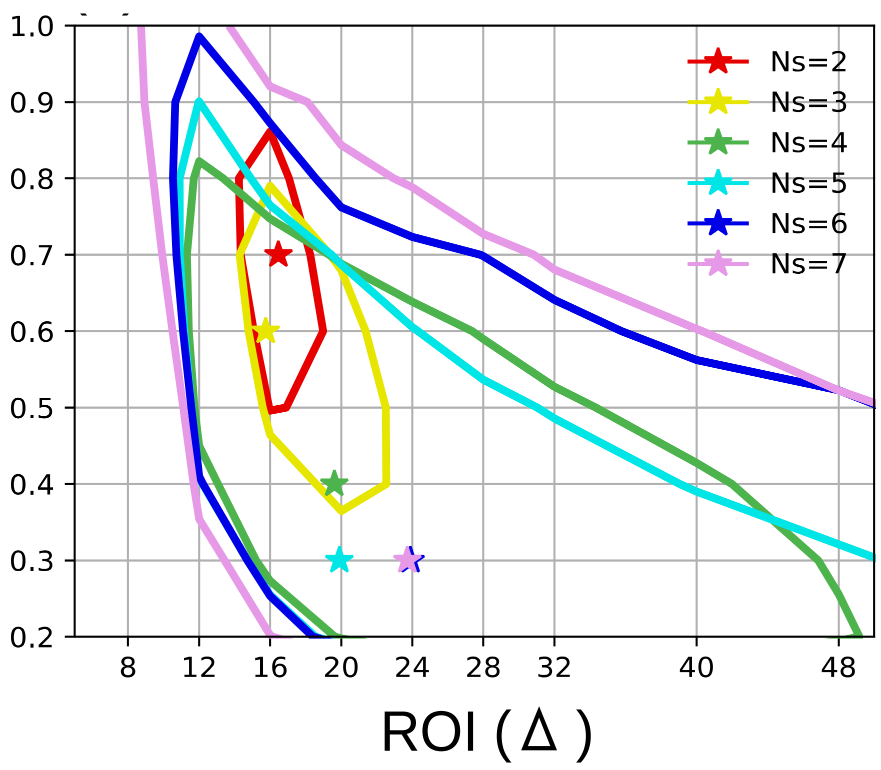
Tuning for the best localization parameters

Localization function (Gaspari-Cohn): $L_{i,j} = \alpha \times \mathrm{GC}(|\mathbf{r}_i - \mathbf{r}_j|, \mathrm{ROI})$

Assimilating raw obs
to update the 1st SC

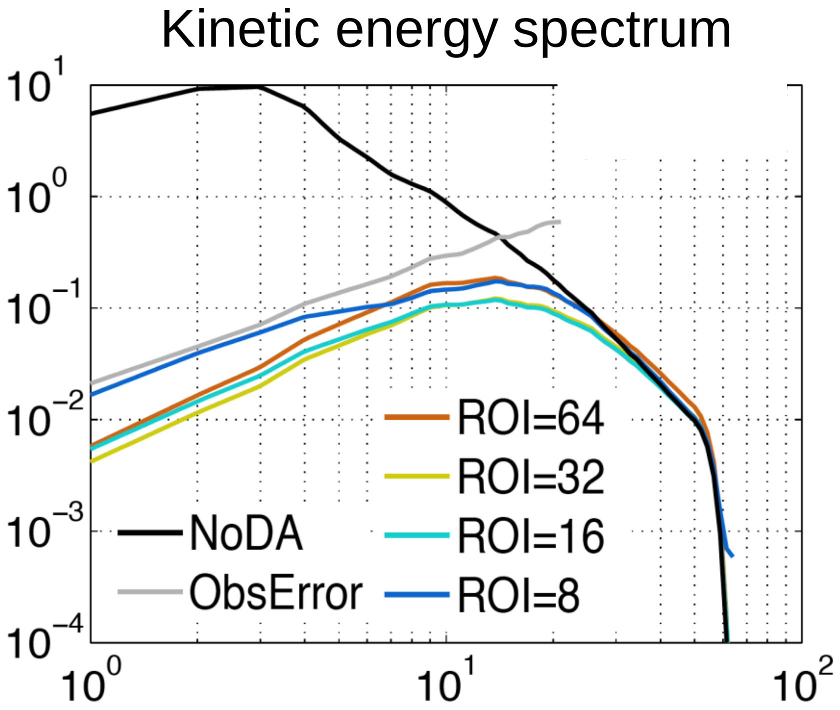


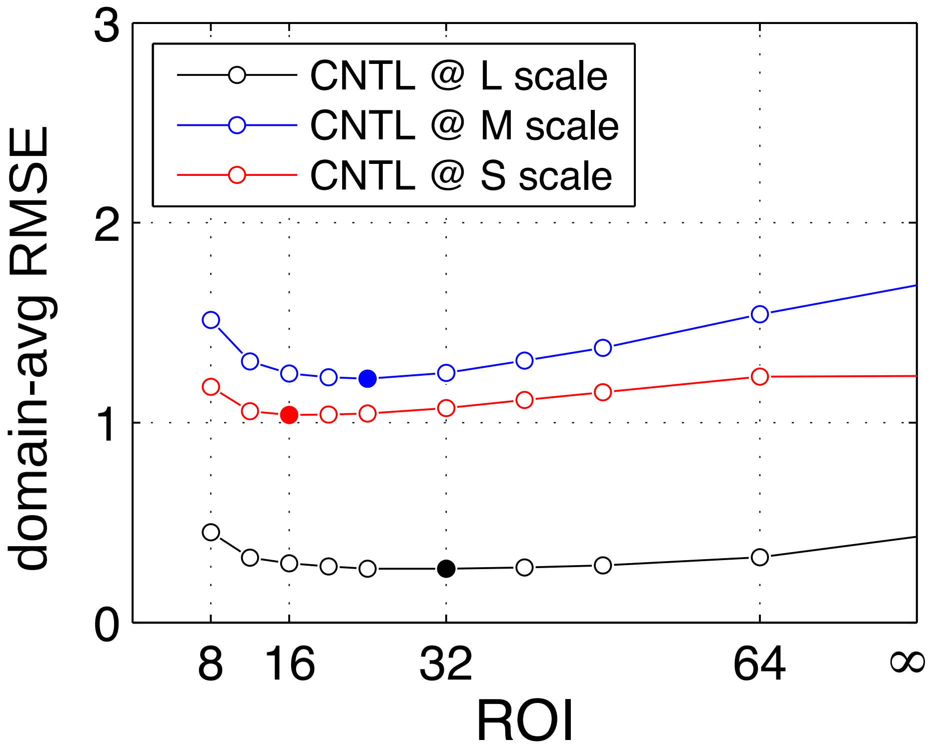
Assimilating filtered obs at corrsp. scale
to update the 1st SC



Tuning for the best localization parameters

Test in a QG model case: using different ROI and compare analysis error at different scales
Best ROI depends on: 1. physical corr scale, 2. ensemble size, and 3. obs network



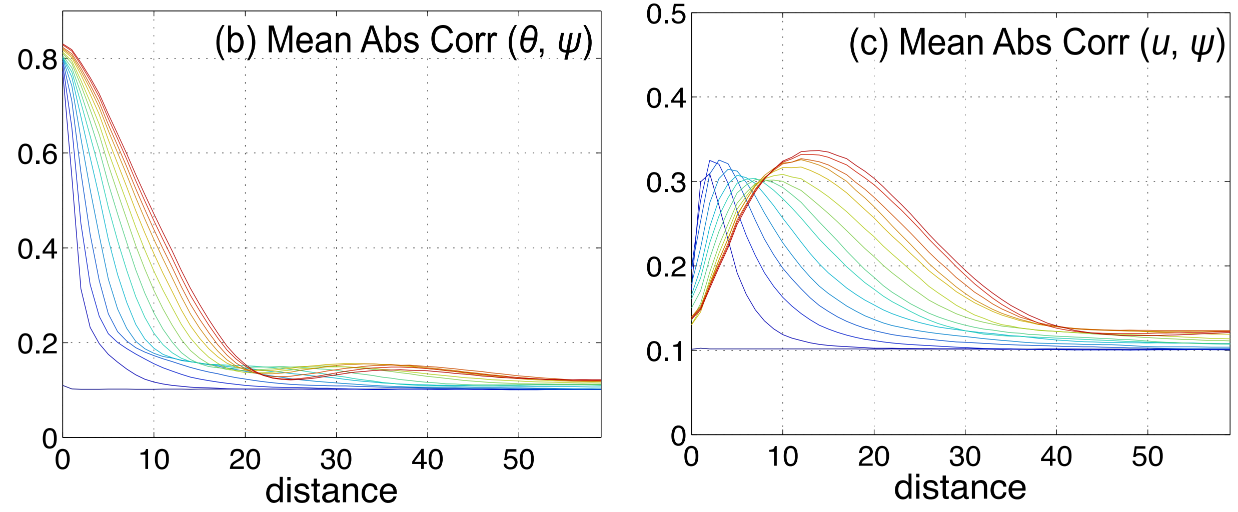


(Ying, Zhang, & Anderson, 2018)

Tuning for the best localization parameters

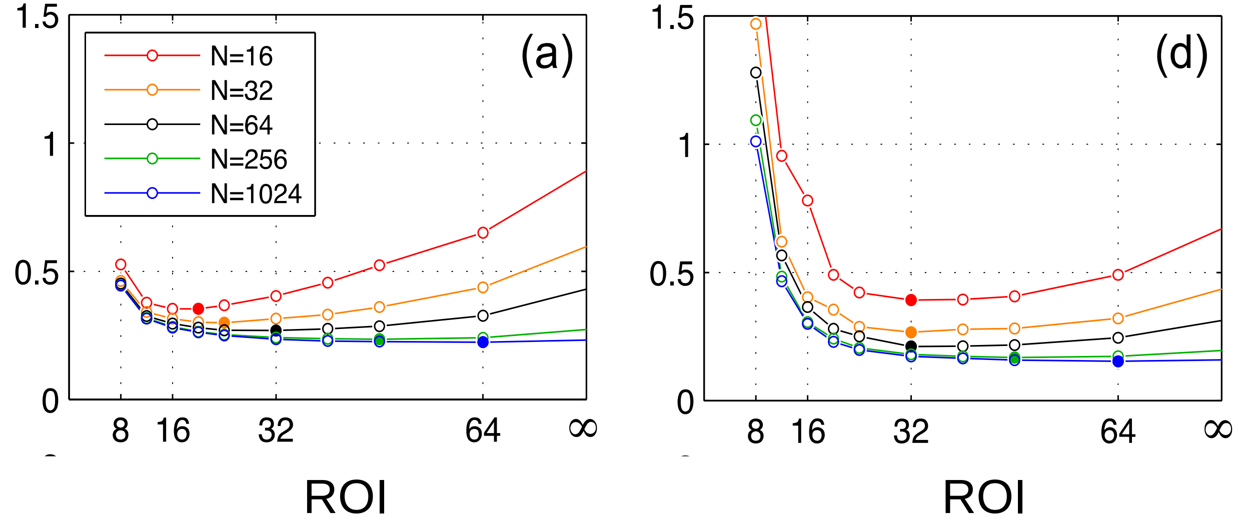
Impact of nonlocal observations:

time evolution of mean absolute correlation functions as errors grow upscale



assimilate θ assimilate u,v

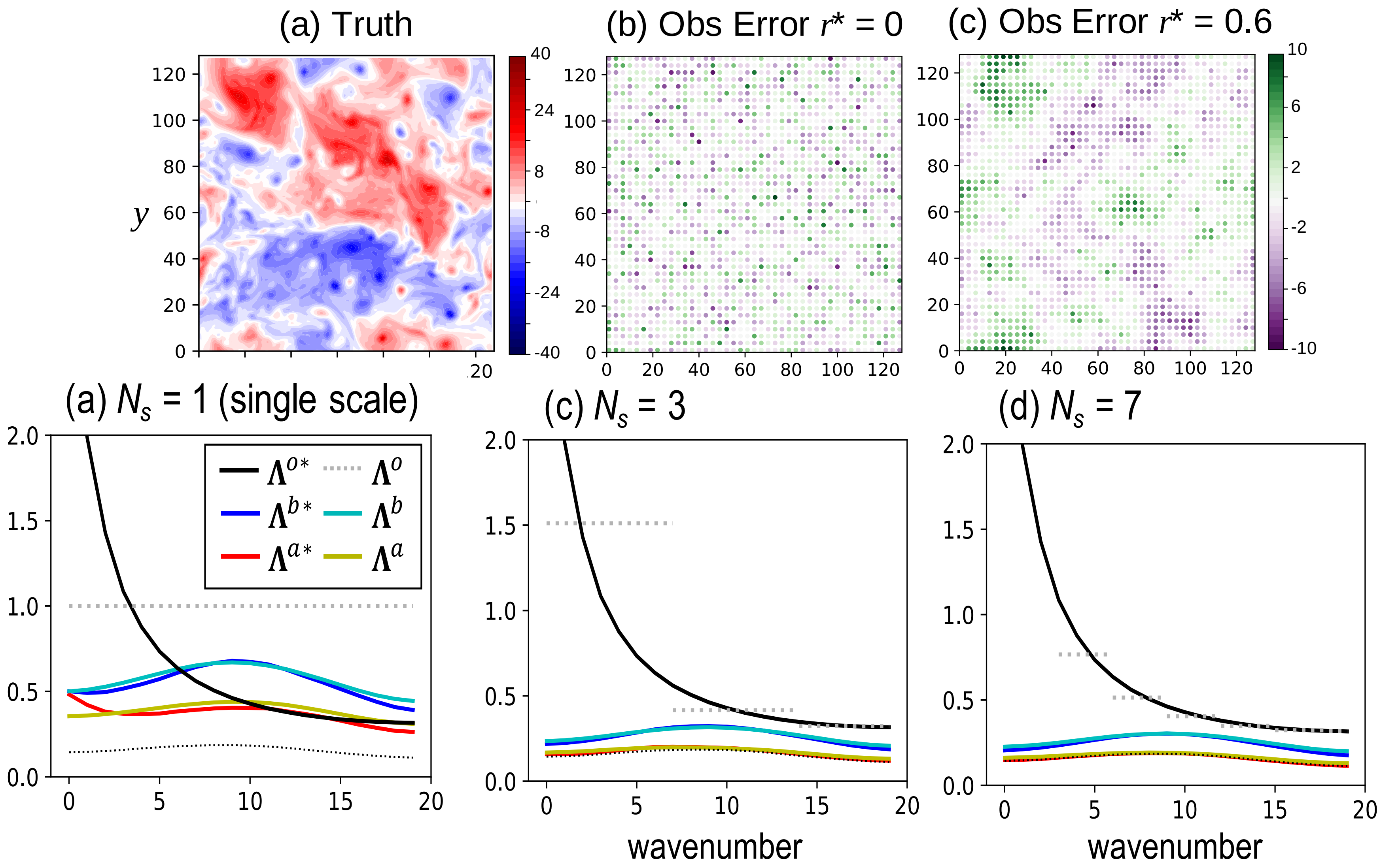
L-scale analysis RMSE with respect to ROI



Purely distance-based localizations are not ideal for nonlocal observations. (across-variable & across-scale)

Tuning for the best localization parameters

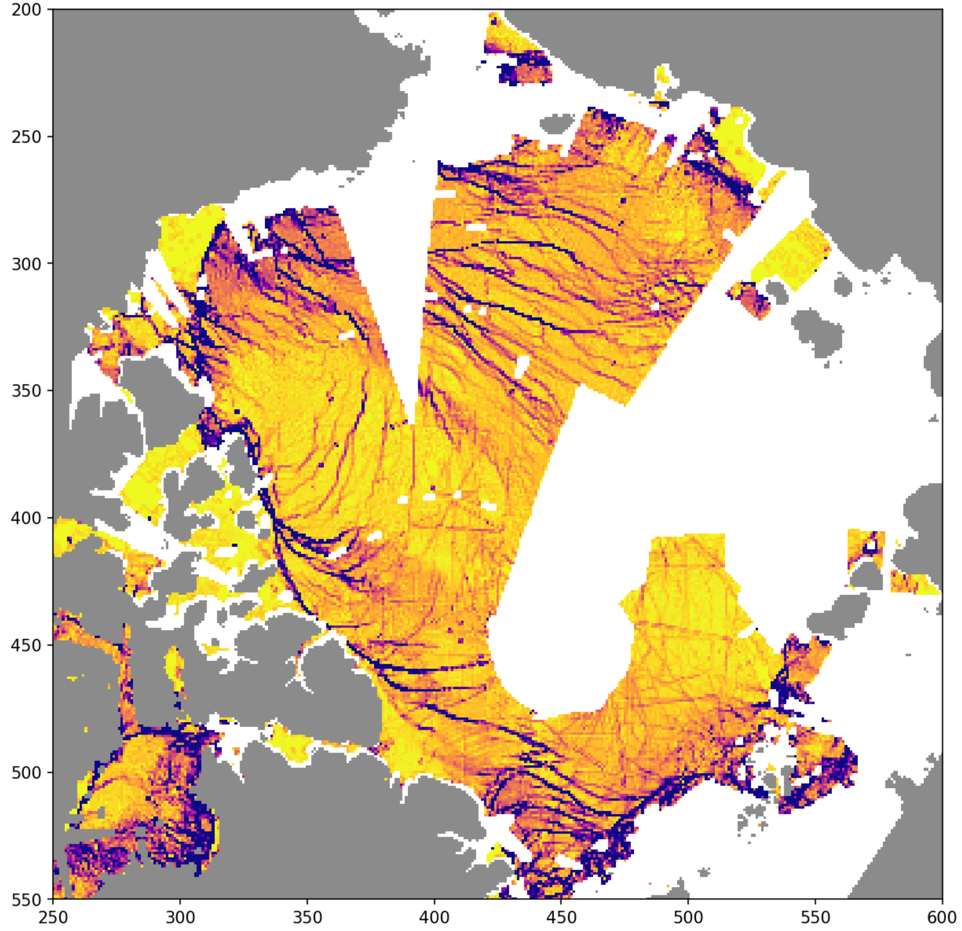
Effect of α: observation error inflation; cross-scale update has large representation errors

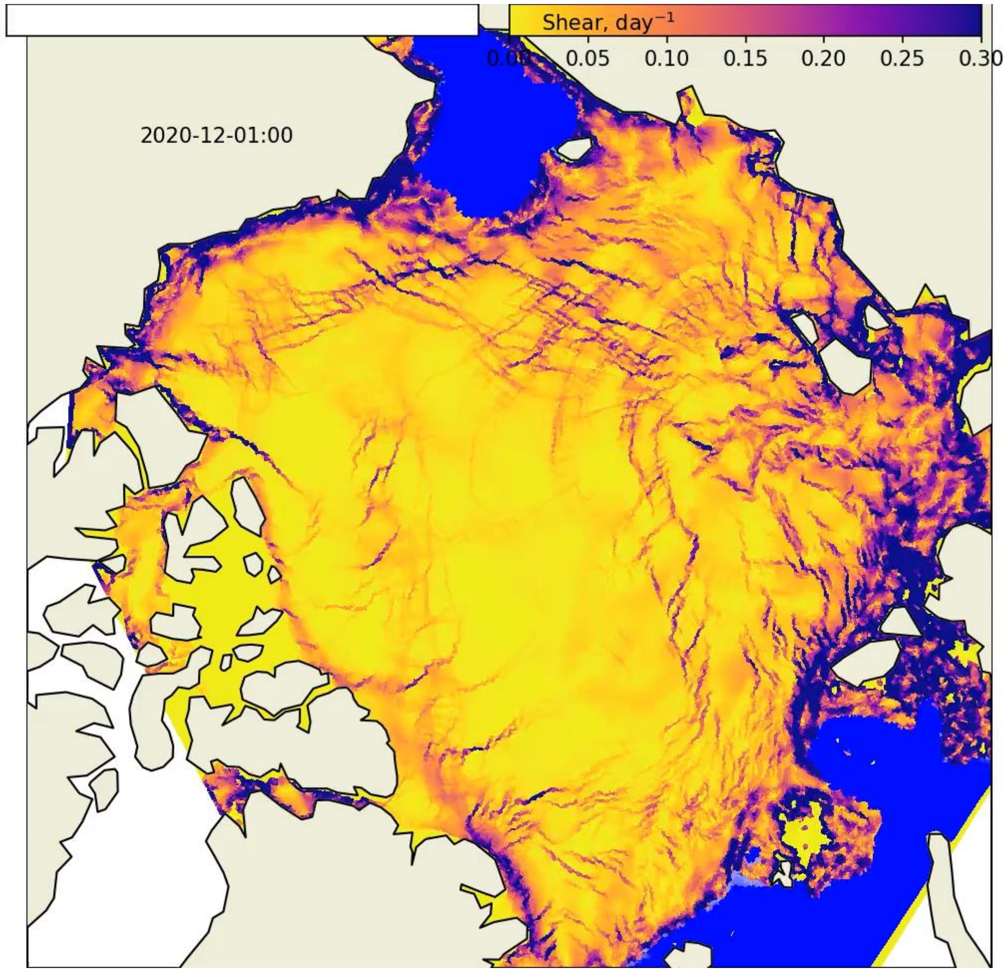


(Ying 2020)

The sea ice deformation assimilation problem

Deformation of ice drift (shear/div)





Important features (ice leads, ridge) for near-term ice forecast (relevant for navigation)
New neXtSIM with advanced brittle rheology (BBM, Olason et al. 2021)

Current simple assimilation approach

x: sea ice concentration

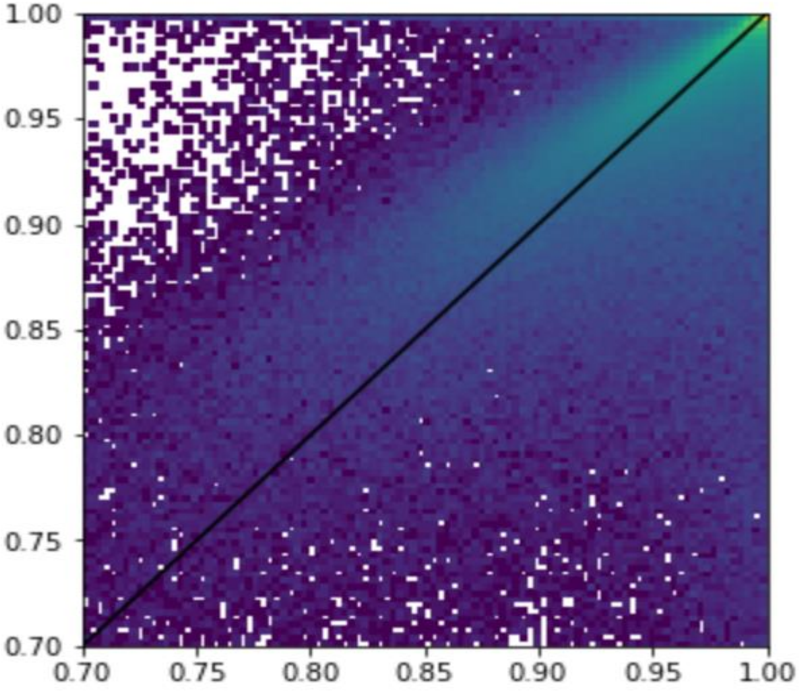
y: total deformation

$x = 1 - c_1 y$

$\mathbf{x}^o = H^{-1}(\mathbf{y}^o)$

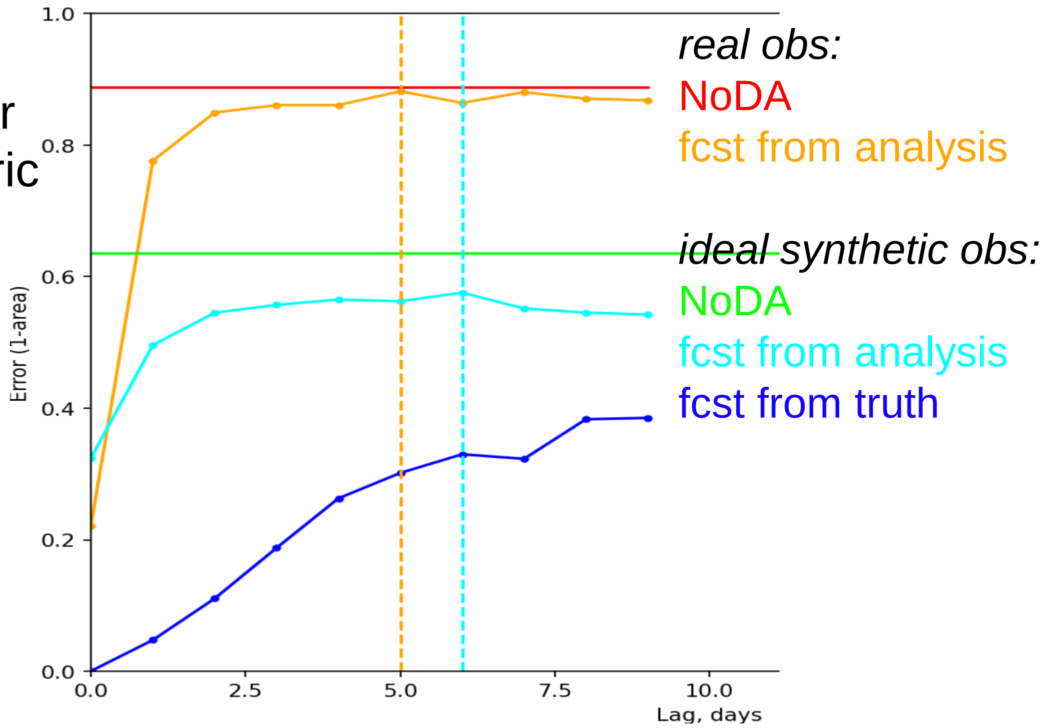
$\mathbf{x}^a = \mathbf{x}^b + \mathbf{W}(\mathbf{x}^o - \mathbf{x}^b)$

model simulated sea ice concentration



reconstructed sea ice concentration from simulated deformation

Error metric

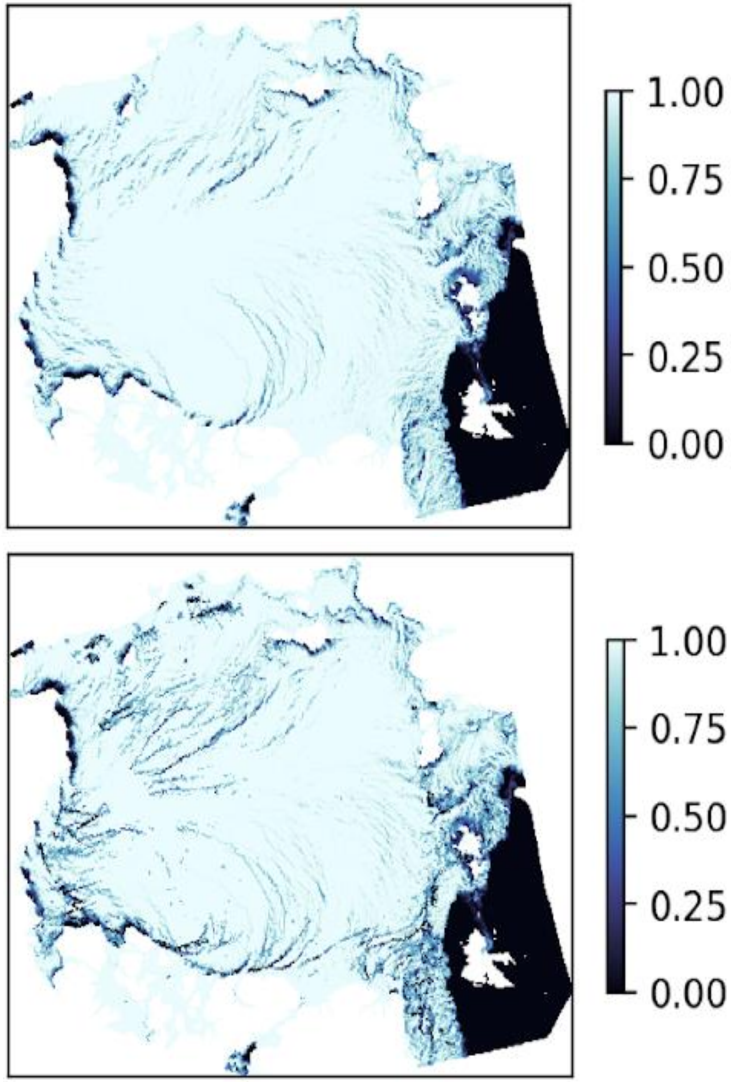


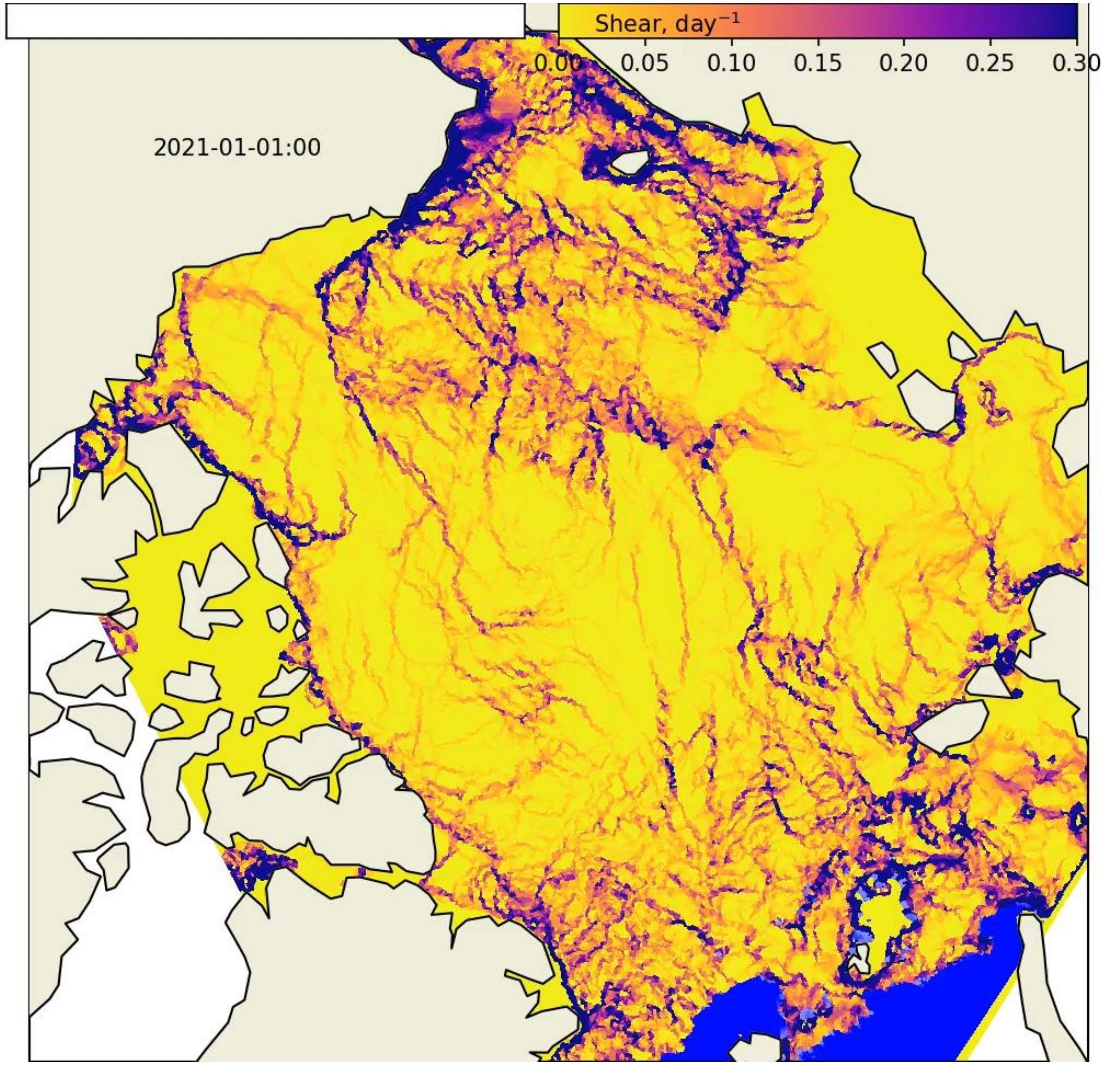
forecast lead time (days)

Current simple assimilation approach

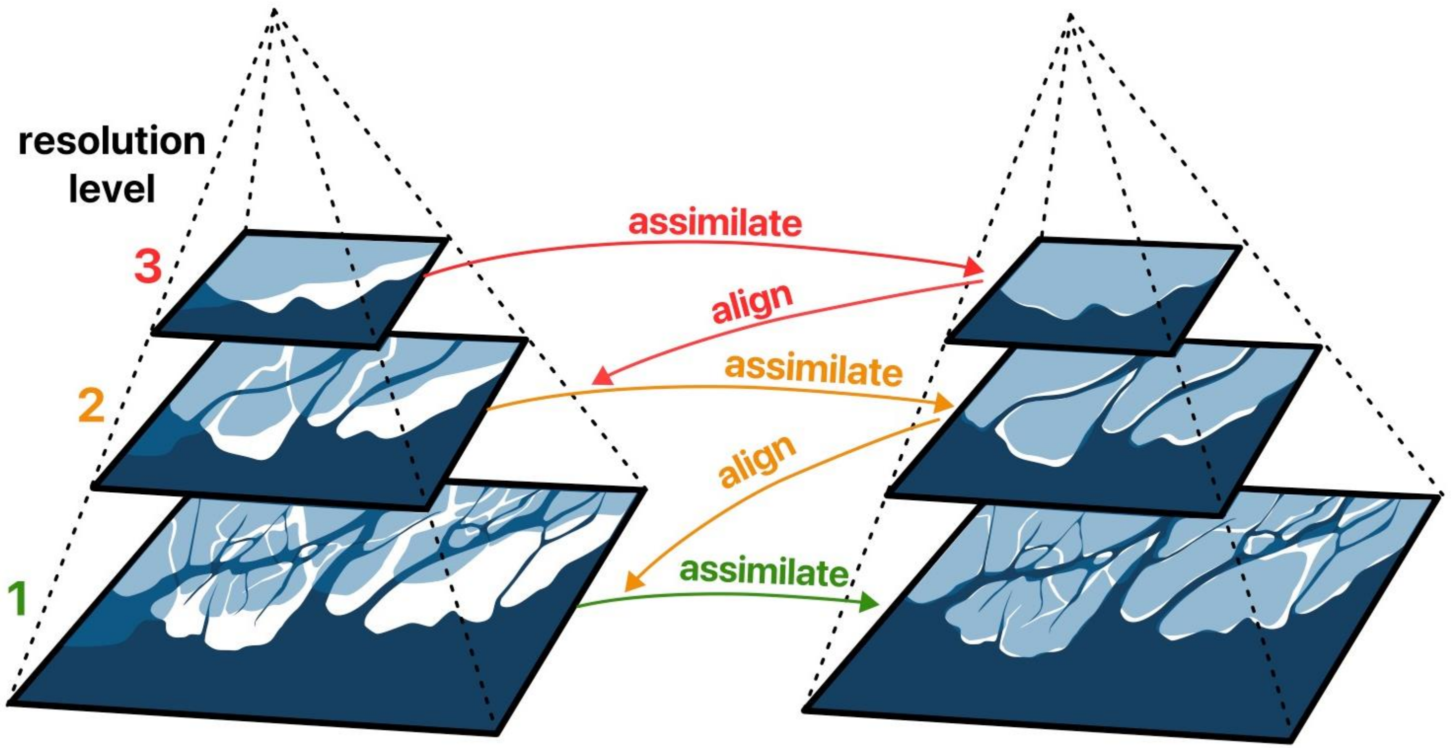
prior

posterior





Next step: implement MSA approach for ice-atmosphere-ocean system



At NERSC:
- sea ice model: neXtSIM
- ocean model: HYCOM (TOPAZ)
- atmospheric model: WRF

Coupled DA:
- assimilate deformation and correct both ice condition and boundary forcing will improve forecast performance

Software challenge:
- Many versions of EnKF codes exist
- Make modulerized design and build the scale iteration for MSA (reusing old software or making new ones?)

Take home message

Motivation and Idea: Position errors in multiscale systems cause a lot of nonlinearity, the multiscale alignment (MSA) approach for ensemble filtering attempts to improve performance.

Stress testing the MSA in a vortex case:
- Improved forecasts as number of scales (*Ns*) increase
- Tuning of best localization and inflation parameters for each scale.
- Coherence assumption raises some issue in real applications.

Real implementation and path forward: sea ice (coupled?) DA in neXtSIM+HYCOM+WRF

References

- Ying, Anderson & Bertino, Performance of the multiscale alignment ensemble filter in reducing vortex position errors, *MWR, in review*
- Korosov, Rampal, Ying, et al. Towards improving short-term sea ice predictability using deformation observations, *The Cryosphere, in review*

For more information/discussion: yue.ying@nersc.no