Toward improved mapping of Sea Surface Height

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Motivations for going beyond linear objective mapping



SSH sampled with SWOT (from SWOT-L3 simulator)



Today's OI mapping cannot handle nonlinearities :

 \rightarrow Most of the SWOT signal would be filtered out of the maps, unused.

 \rightarrow We need to go beyond linear OI to design new data products



First baroclinic mode PV conservation as a « propagator »

- \rightarrow 1st baroclinic mode known to explain a large part of the eddy variability
- → SSH and a Rossby radius climatology are sufficient to resolve PV conservation in first baroclinic mode framework :



- From given SSH, this system defines a short-term SSH evolution forward and backward in time
- Physical characteristics: Scales >>Lr: wave-like propagation (westward)
 Smaller scales: self-advection

→ We found that at short time scales (until ~10-20 days), the motion of 50km-300km mesoscale eddies is very well explained by this propagator (illustration next slide)

Illustration on a simple case



More details in Ubelmann&Klein&Fu, JTECH, 2015

- The use of the propagator significantly reduces residual errors





 \rightarrow Performing interpolation in the 'propagator space' would 'extend' time decorrelations

Dynamic Optimal Interpoaltion



Idea: keep a centered OI time/space analysis, with above equations M used as a covariance

propagator in time: Dynamic mapping with flow-dependant covariances $\mathbf{x}_{a} = \mathbf{x}_{b} + \mathbf{B}\mathbf{M}_{\mathbf{x}_{g}}^{T}\mathbf{H}^{t}(\mathbf{H}\mathbf{M}_{\mathbf{x}_{g}}\mathbf{B}\mathbf{M}_{\mathbf{x}_{g}}^{T}\mathbf{H}^{T} + \mathbf{R})^{1} |\mathbf{y}_{o} - \mathbf{H}\mathbf{x}_{b} - \mathbf{H}(\mathbf{M}(\mathbf{x}_{g} - \mathbf{x}_{b}) - \mathbf{M}_{\mathbf{x}_{g}}(\mathbf{x}_{g} - \mathbf{x}_{b}))|$

Practically solved in a reduced space (2D Fourier decomposition)~. Iterations on the guess xg.

(e.a. Charney, 1948)

Computing the covariances B' from the linearized propagator



Time evolving guess (integrated forward and backward)

- $\mathbf{G}_k = \mathbf{H} \Gamma_k$
- Γ_k represents the propagated Fourier components (or 'Green functions') by the linear response of the propagator around the guess. G (projected in obs space) is the green function matrix

 $\mathbf{B}^{\mathsf{T}} = \Gamma \mathbf{Q} \Gamma^{\mathsf{T}} \quad \mathbf{Q}$

Q is diagonal, constructed consistently with the spatial covariance (inverse FFT of SSH spectrum)

How do covariances look like



Experimental setup: OSSEs

- Regional study in the Gulf Stream
- Reference SSH field: 'unknown truth' state from a MITgcm global simulation at ~6km resolution.

Constellation of 3 satellites on Jason (2) and AltiKa (1) orbits



Results



Error variance reduction by ~30-35% over 6 month worth of analysis



Conclusions

- A first attempt, will be demonstrated with real obseravtions soon.
- Possible improvements of the propagator:
- \rightarrow Add impact of Ekman current?
- →test SQG framework
- \rightarrow Add cyclo-geostrophy in advection term?
- Altimetry-only so far, but does not exclude multi-sensor approaches for better constraints
- Others possible approaches to "fill" temporal gaps, e.g. optimal transport, ...