Assimilation of high-frequency radar currents in the Ligurian Sea

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SANGOMA

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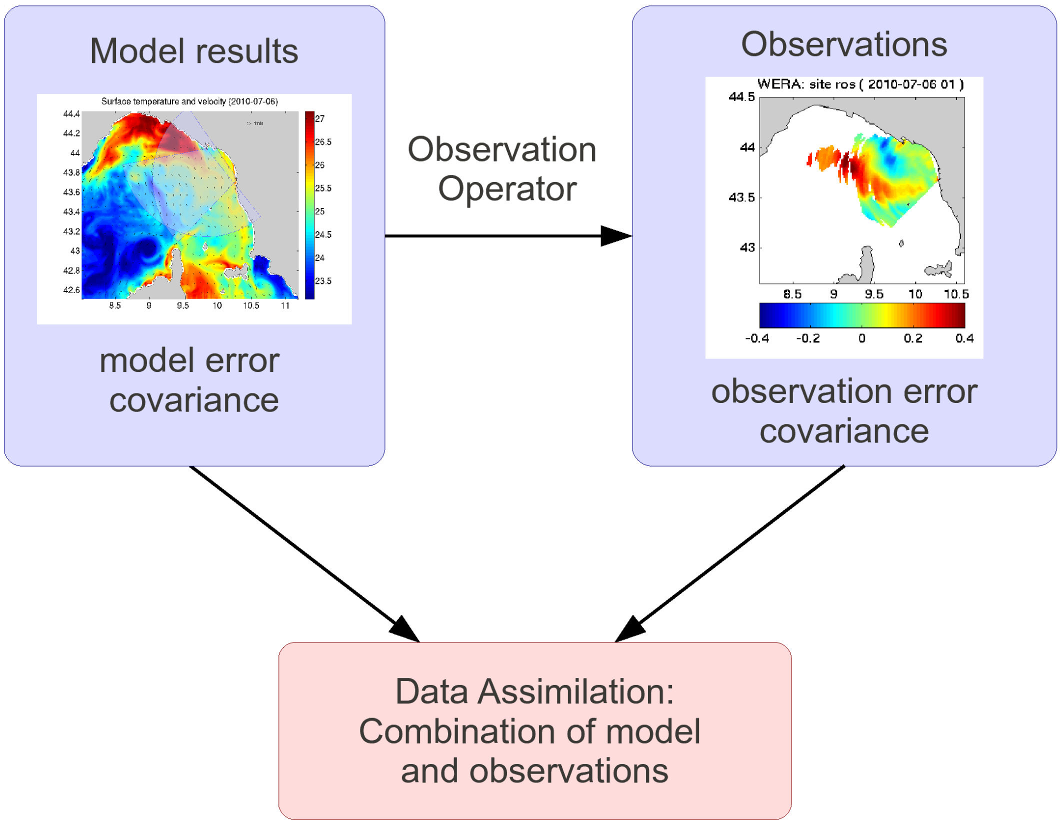
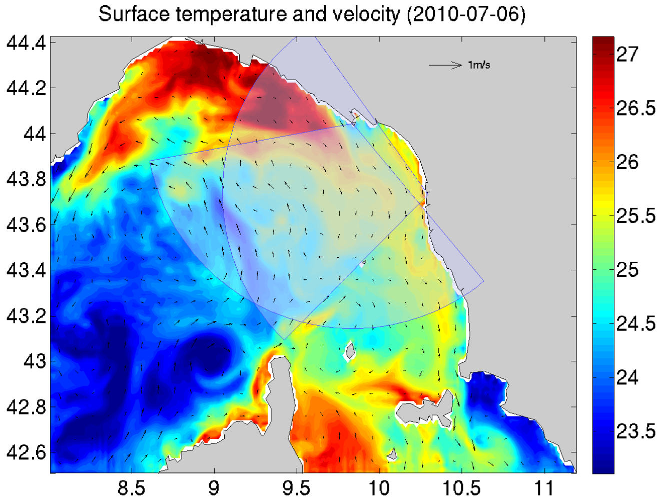

Model results
Surface temperature and velocity (2010-07-06)
model error
covariance
Observation
Operator
Observations
WERA: site ros (2010-07-06 01)
observation error
covariance
Data Assimilation:
Combination of model
and observations

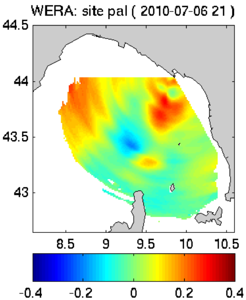
Model

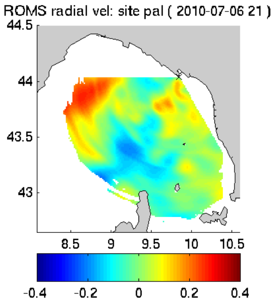
- ROMS nested (off-line) in Mediterranean Ocean Forecasting System
- 1/60 degree resolution and 32 vertical levels
- Currents: Western & Eastern Corsican Current, Northern Current, inertial oscillation, mesoscale currents
- Two WERA HF radar systems (Palmaria, San Rossore) by NATO Undersea Research Centre (NURC) from 2009 to 2010.



Observations

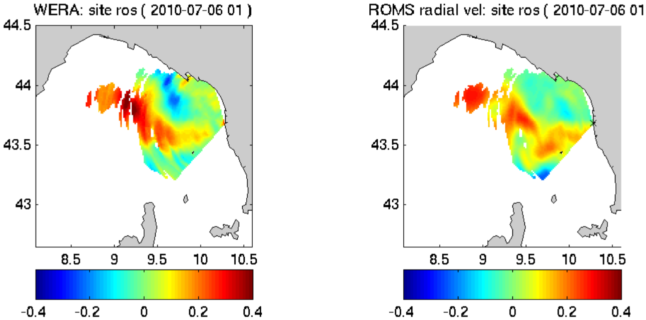
- Frequency of $\nu = 12.359$ MHz and coupled to a wave length of $\lambda_b = 12.13$ m,
- Radial currents are measured and used for the assimilation
- Angular resolution of 6 degrees, radial resolution of 2.4 km
- Currents are averaged over 1 h



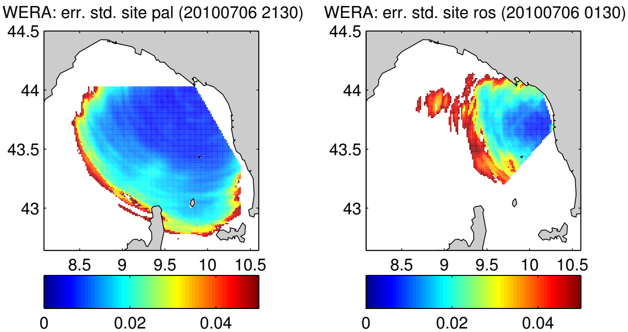


Radial currents on 2010-07-06 21:30 relative to the Palmaria site: left panel shows WERA measurements and right panel shows ROMS results without assimilation.

Observations



Radial currents on 2010-07-06 01:30 relative to the San Rossore site: left panel shows WERA measurements and right panel shows ROMS results without assimilation.



Observation error standard deviation.

Observation operator

- Radial currents are extracted from model currents $\mathbf{u}$:

$$u_{\mathrm{HF}} = \frac{k_b}{1 - \exp(-k_b h)} \int_{-h}^{0} \mathbf{u} \cdot \mathbf{e}_r \exp(k_b z) dz \tag{1}$$

  - $k_b = \frac{2\pi}{\lambda_b}$
  - $\mathbf{e}_r$ is the unit vector pointing in the direction opposite to the location of the HF radar site
  - Positive values: current away from the system
  - Essentially represent an weighted average over the upper meters.
- Smoothed in the azimuthal direction by a diffusion operator to filter scales smaller than 6 degrees

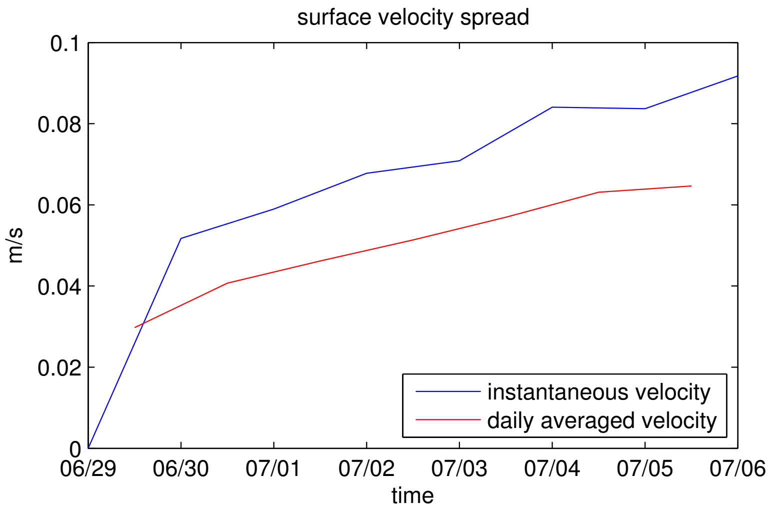
Model errors covariance

- Estimated by ensemble simulation (with 100 members) where uncertain aspect of the model are perturbed
- Perturbed zonal and meridional wind forcing
- Perturbed boundary conditions (elevation, velocity, temperature and salinity)
- Perturbed momentum equation (ε)

$$\frac{d\mathbf{u}}{dt} + \boldsymbol{\Omega} \wedge \mathbf{u} \;=\; -\frac{1}{\rho_0}\nabla_h p + \frac{1}{\rho_0}\nabla \cdot \mathbf{F}^{\mathbf{u}} + \nabla_h \wedge \; \varepsilon \, \mathbf{e}_z \qquad (2)$$

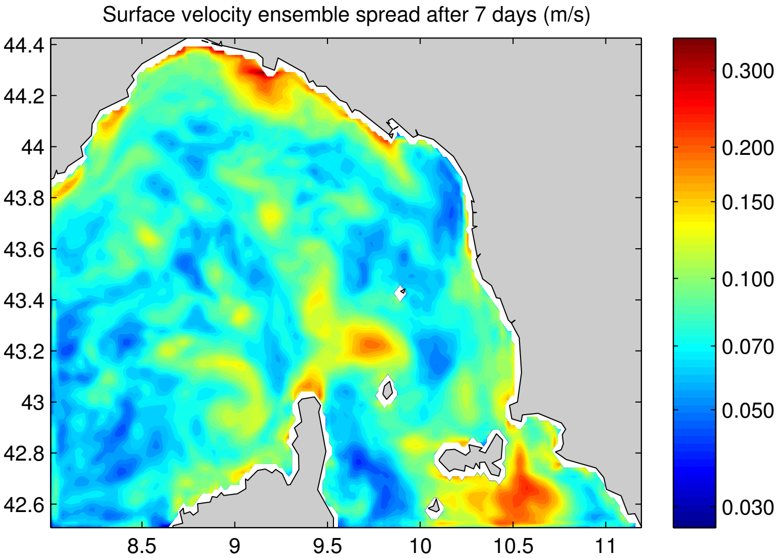
  - where $\nabla_h = \mathbf{e}_x \frac{\partial}{\partial x} + \mathbf{e}_y \frac{\partial}{\partial y}$
  - does not create horizontal convergence or divergence (linked to barotropic waves)
  - can create mesoscale flow structures (absent or misplaced)

Ensemble spin-up



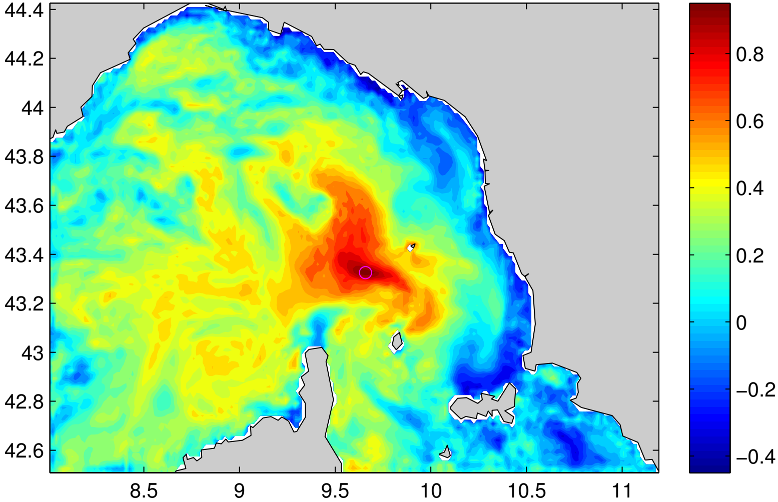
- Ensemble of IC is created by a 7 day ensemble integration starting from the same IC but with perturbed forcing (ensemble spin-up)
- Spin-up should create mesoscale circulation features

Velocity spread



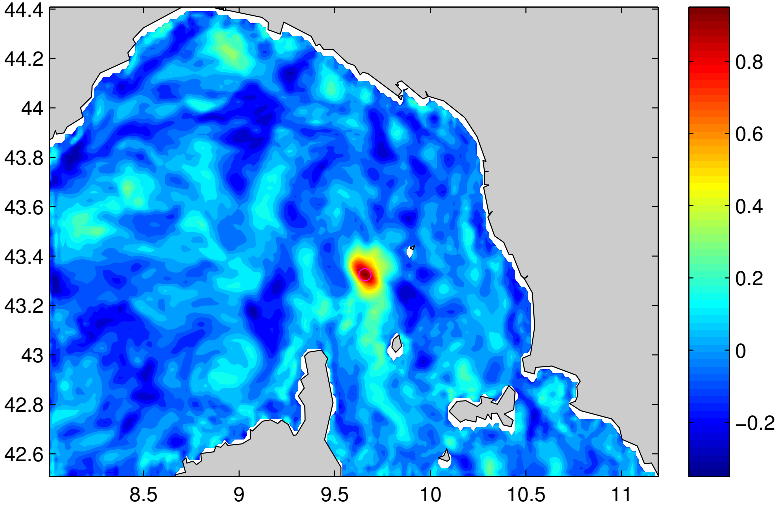
- Velocity spread after 7 days
- Largest uncertainties near eddies

Spatial correlation



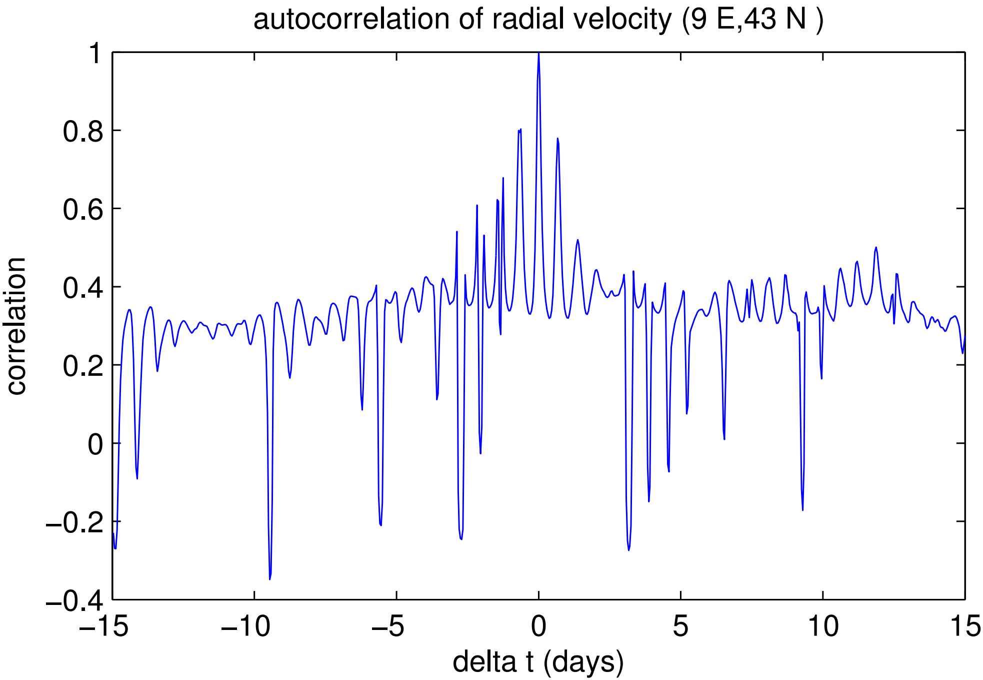
- Correlation of temperature at a specific point (magenta circle) and other surface grid points
- Resulting length-scale is about 50 km

Spatial correlation



- Correlation of zonal velocity at a specific point (magenta circle) and other surface grid points
- Resulting length-scale is about 10 km
- Adequately observing surface velocity would require measurements with higher spatial resolution than the resolution of temperature measurements

Temporal correlation



Periodicity of 16 h (period of inertial oscillations is 17.6 h)

Data assimilation scheme

- Time dimension embedded in estimation vector $\mathbf{x}$
- Different definitions of estimation vector are possible:
  - $\mathbf{x} = (\text{model trajectory})$, *i.e.* model state at all time instances
  - $\mathbf{x} = (\text{uncertain forcing fields})$, here IC, BC, wind and stochastic error term at all time instances
  - $\mathbf{x} = (\text{model trajectory}, \text{uncertain forcing fields})$
- The optimal $\mathbf{x}$ is given by the Kalman analysis (using non-linear observation operators as in Chen and Snyder (2007)):

$$\mathbf{x}^a = \mathbf{x}^b + \mathbf{A}\left(\mathbf{B} + \mathbf{R}\right)^{-1}\left(\mathbf{y}^o - h(\mathbf{x}^b)\right) \tag{3}$$

- where the matrices $\mathbf{A}$ and $\mathbf{B}$ are covariances estimated from the ensemble.

$$\mathbf{A} = \mathrm{cov}(\mathbf{x}^b, h(\mathbf{x}^b)) = \left\langle (\mathbf{x} - \langle\mathbf{x}\rangle)\left(h(\mathbf{x}) - \langle h(\mathbf{x})\rangle\right)^T \right\rangle \tag{4}$$

$$\mathbf{B} = \mathrm{cov}(h(\mathbf{x}^b), h(\mathbf{x}^b)) = \left\langle (h(\mathbf{x}) - \langle h(\mathbf{x})\rangle)\left(h(\mathbf{x}) - \langle h(\mathbf{x})\rangle\right)^T \right\rangle \tag{5}$$

where $\langle\cdot\rangle$ is the ensemble average.

Smoother scheme

- For a linear model and an infinite large ensemble, equation (3) minimizes,

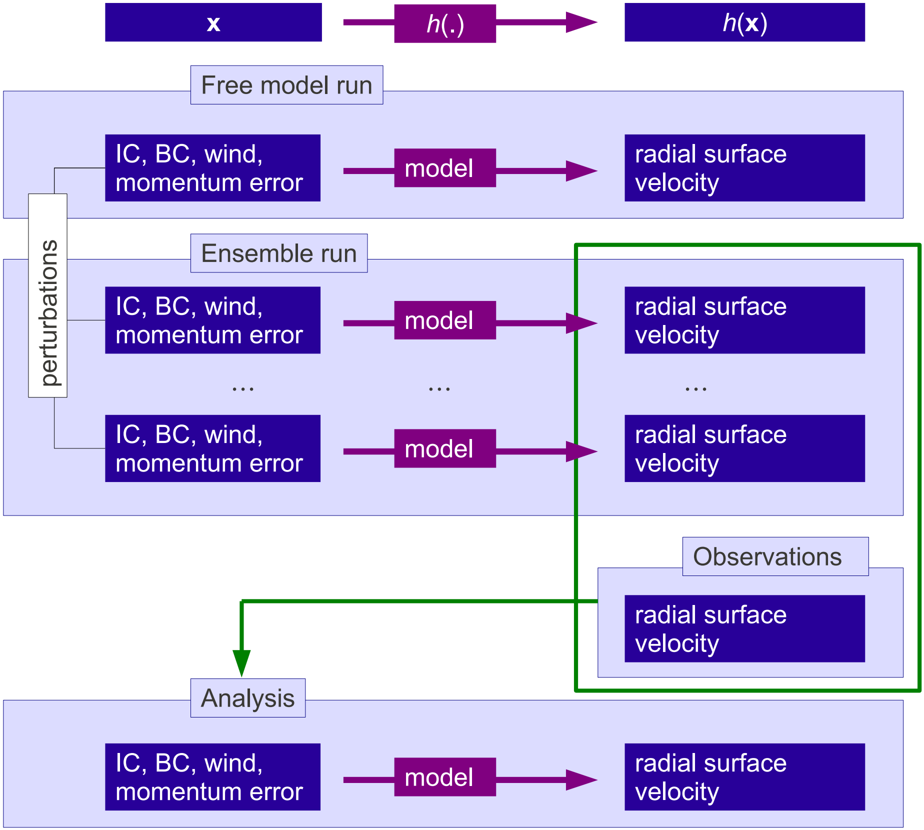
$$J(\mathbf{x}) = (\mathbf{x} - \mathbf{x}^b)^T \mathbf{P}^{b^{-1}} (\mathbf{x} - \mathbf{x}^b) + (\mathbf{y}^o - h(\mathbf{x}))^T \mathbf{R}^{-1} (\mathbf{y}^o - h(\mathbf{x})) \quad (6)$$

  or

$$J(\mathbf{x}) = (\mathbf{x} - \mathbf{x}^b)^T \mathbf{P}^{b^{-1}} (\mathbf{x} - \mathbf{x}^b) + \sum_n (\mathbf{y}_n^o - (h(\mathbf{x})_n))^T \mathbf{R}_n{}^{-1} (\mathbf{y}_n^o - (h(\mathbf{x})_n)) \quad (7)$$

  where n refers to the indexed quantifies at time n. This is the cost function from which 4D-Var and Kalman Smoother can be derived.

- Approach is closely related to Ensemble Smoother (van Leeuwen, 2001), 4D-EnKF (Hunt *et al.*, 2007) and AEnKF (Sakov *et al.*, 2010) where model trajectories instead of model states are optimized and to the Green's method with stochastic "search directions"


x
h(.)
h(x)
Free model run
IC, BC, wind, momentum error
model
radial surface velocity
perturbations
Ensemble run
IC, BC, wind, momentum error
model
radial surface velocity
...
...
...
IC, BC, wind, momentum error
model
radial surface velocity
Observations
radial surface velocity
Analysis
IC, BC, wind, momentum error
model
radial surface velocity

Twin experiment

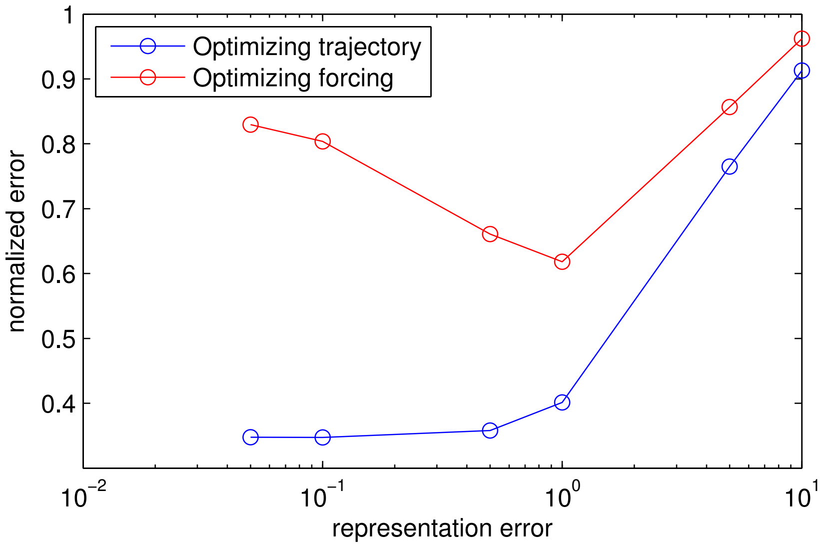
Scheme of a twin experiment:

- Model is run with initial conditions (IC), boundary conditions (BC), forcing fields (e.g. here winds fields) that are assume to be the "true" solution.
- Pseudo-observations are extracted from this simulation.
- Perturbation are applied to IC, BC and forcing fields.
- Based on those perturbed fields and the extracted pseudo-observation we determine if the "true" solution can be recovered.

Variable	RMS$(\mathbf{x}^f, \mathbf{x}^t)$	RMS$(\mathbf{x}^a, \mathbf{x}^t)$
Temperature	0.080	0.067
Salinity	0.0063	0.0057
u-wind	0.61	0.40
v-wind	0.60	0.54

- RMS for temperature, salinity and currents is a volume average.
- Assimilation window is 48 hours here.

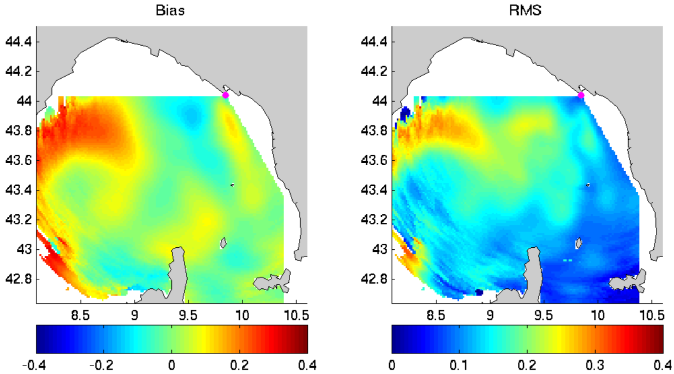
Estimation of trajectory versus estimation of forcing fields



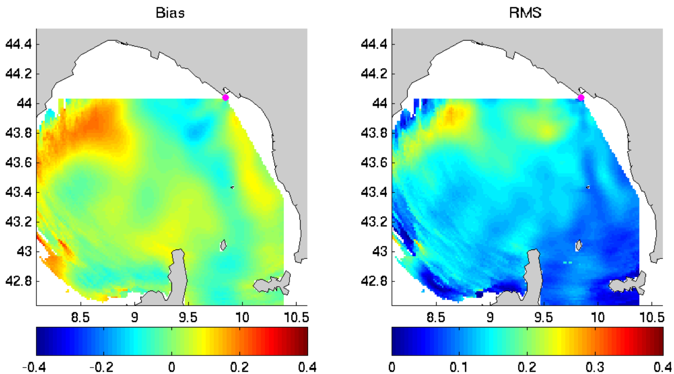
- Assimilation of real data now
- Both approaches equivalent for linear system (and additive noise)
- Unrealistic “ensemble extrapolation” when too small observation errors are used
  $\rightarrow$ model trajectory and forcing fields are inconsistent

Error statistics for Palmaria Site

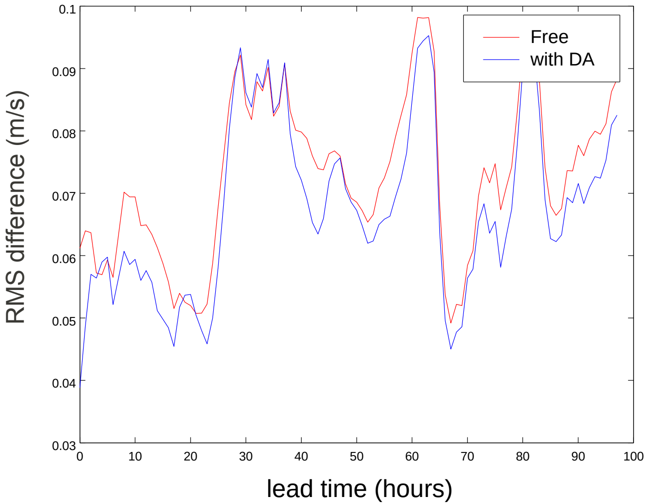
Without assimilation (positive values: current away from the magenta dot)



With assimilation



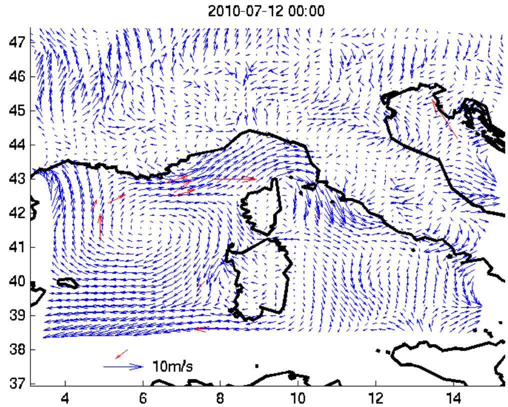
Forecasts



- Impact of data assimilation on velocity forecast
- Comparison with surface currents from Palmaria
- HF radar assimilation improves the strength of the Northern Current and this improvement persists for some time.

Simulation with atmospheric model (WRF)

- Blue arrows: WRF 10m wind vectors, red arrows: in situ wind measurements from ICOADS (International Comprehensive Ocean-Atmosphere Data Set).
- 3 WRF domains at 30, 10, 3.33 km resolution (two-way nesting).
- 30-km grid model nested (one-way) into the Global Forecast System
- 28 vertical layers



Model results with different wind forcings

- Total RMS differences (m/s):

	Pal.	Ros.
COSMO	0.14	0.11
WRF	0.13	0.14

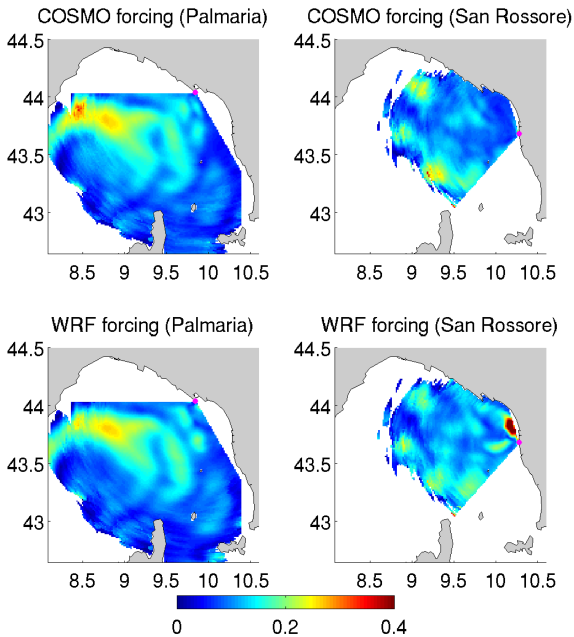


Figure 1: Radial surface current RMS difference

Conclusions

- Embedding the time dimension into the state vector leads to a smoother scheme (which is very simple to implement)
- Smoother schemes can be used to estimate the optimal model trajectory or forcing field
- Both approaches are not equivalent for non-linear systems or multiplicative noise
- The challenge is to make consistent analyzes
- Derive "optimal" perturbation first → rerun the model with corrected forcing
- The source code of smoother schemes is available at `http://modb.oce.ulg.ac.be/alex` or by email (a.barth@ulg.ac.be).

Acknowledgments

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