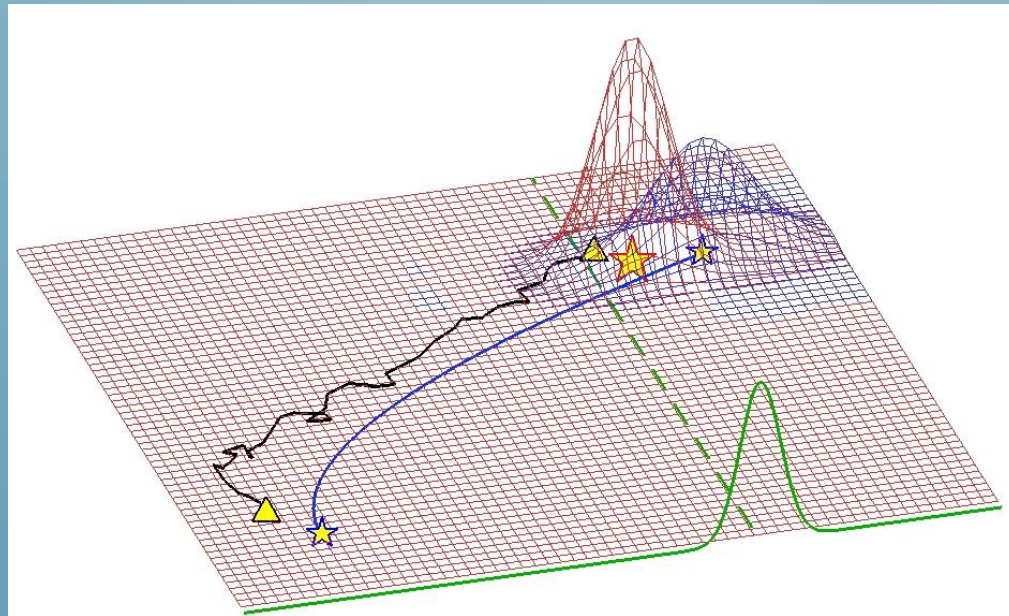


A TUTORIAL ON ASSIMILATING LAGRANGIAN DATA INTO OCEAN MODELS



DATA ASSIMILATION

Objectives of DA:

- Combine ocean *data* and *models*
- obtain best *state estimate*
- reflect *uncertainty* in estimates
 - typically as *pdf*, probability density function

Primary Tool: *Bayes Theorem*

x = state

y = obs

$$P^{\text{posterior}}(x|y) = P^{\text{obs}}(y|x) P^{\text{prior}}(x)$$

MODELS AND DATA

Ocean model:

$\mathbf{x} \in \mathbf{R}^N$ – state vector comprising all relevant dynamical variables

(e.g. flow velocity, temperature, salinity, etc. at each grid point)

$$d\mathbf{x}^f = M(\mathbf{x}^f, t)dt$$

prognostic model

$$d\mathbf{x}^t = M(\mathbf{x}^t, t)dt + \boldsymbol{\eta}(t)dt$$

actual evolution

$$E[\boldsymbol{\eta}(t)\boldsymbol{\eta}^T(t')] = \delta(t-t')\mathbf{Q}(t)$$

covariance of the model residual

Observations:

$$y_i^o = H_i[\mathbf{x}_i^t] + \boldsymbol{\varepsilon}_i$$

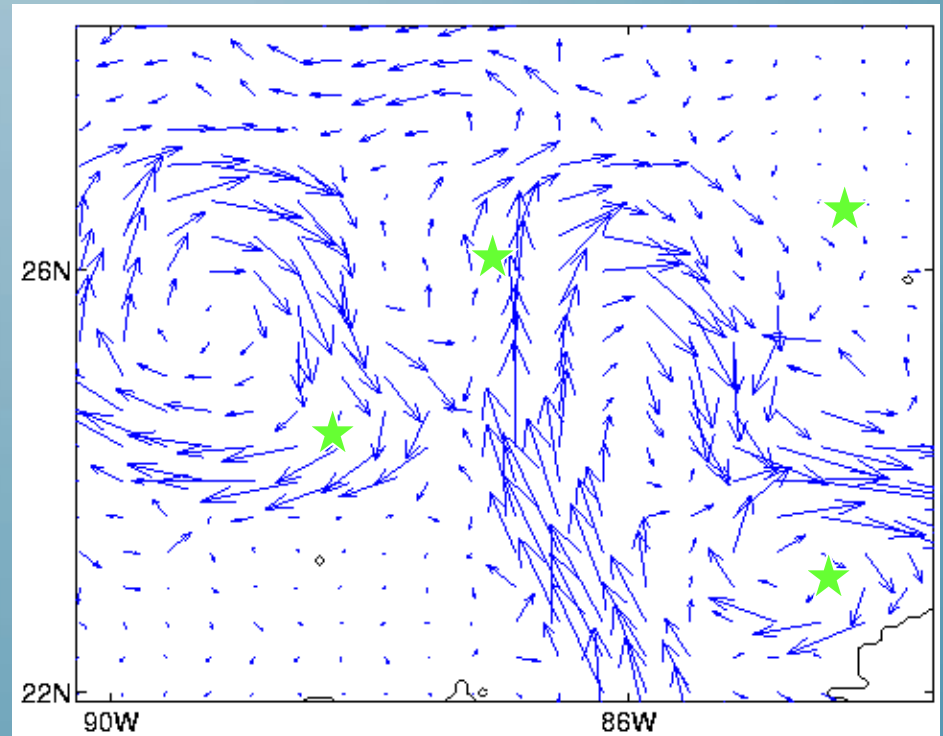
H_i – observation operator

$\boldsymbol{\varepsilon}_i$ – observation error

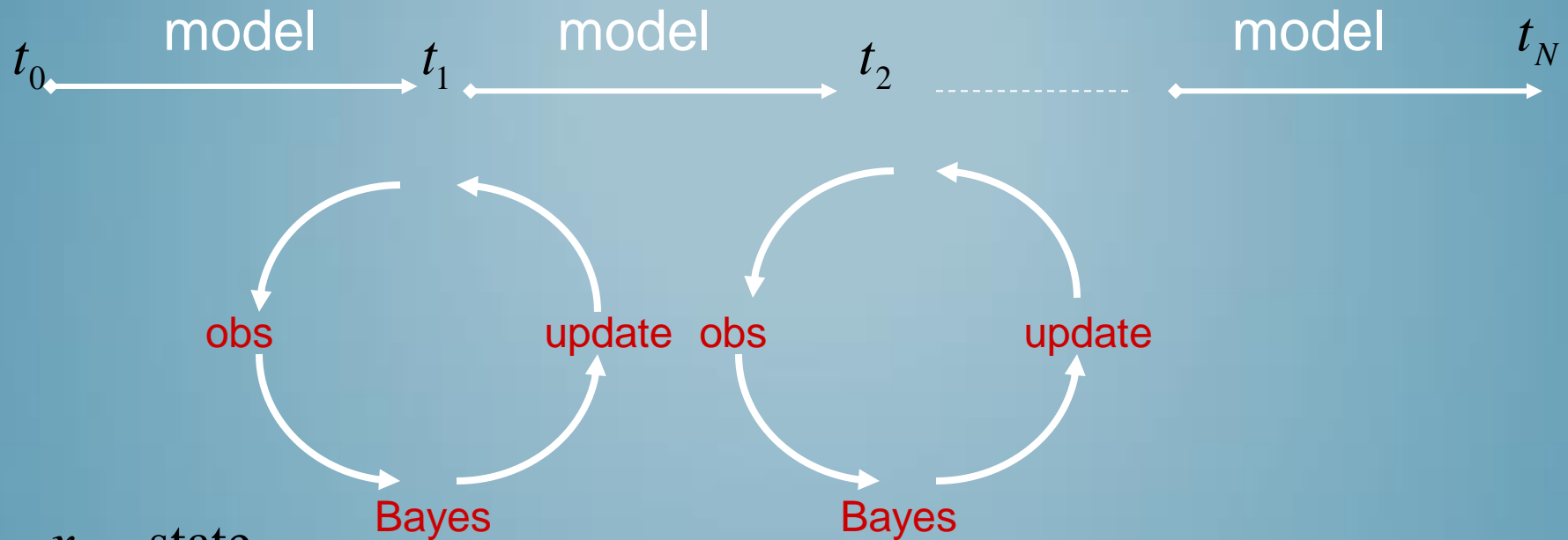
$y_i^o \in \mathbf{R}^L$, typically $L \ll N$

$E[\boldsymbol{\varepsilon}_i \boldsymbol{\varepsilon}_m^T] = \delta_{im} \mathbf{R}_i$ – observation

error covariance



SEQUENTIAL DATA ASSIMILATION (METHODS: KALMAN FILTERS, PARTICLE FILTERS)



$x =$ state

$y =$ obs

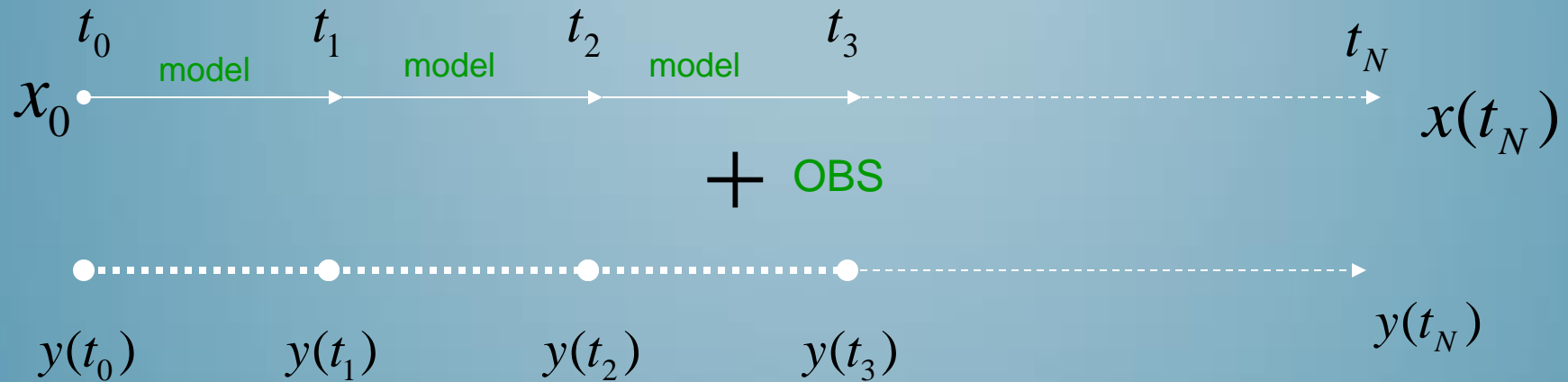
$$P^{\text{posterior}}(x|y) = P^{\text{obs}}(y|x) P^{\text{prior}}(x)$$

Key: difference in methods is how we obtain the distributions on RHS

- Kalman: approximate pdfs with Gaussians
- Particle: approximate posterior with discrete samples

SMOOTHING – COMBINING ALL DATA AT ONCE (METHODS: 4DVAR, MCMC SAMPLING)

Model runs + observations \longrightarrow state estimate



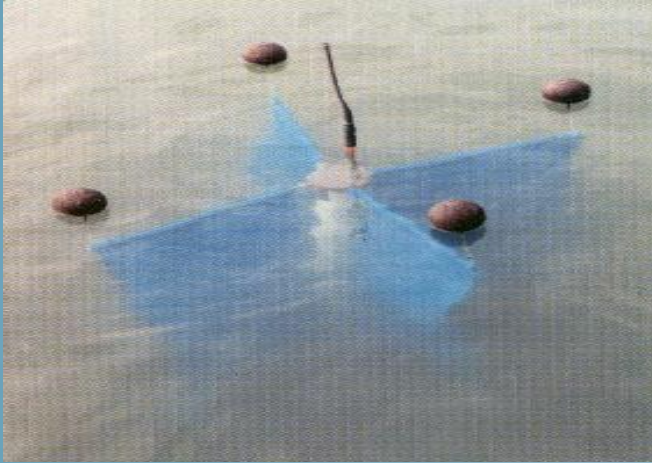
Bayes:
$$P^{\text{posterior}}(x|y) = P^{\text{obs}}(y|x) P^{\text{prior}}(x)$$

Key: difference in methods is how we obtain the distributions on RHS

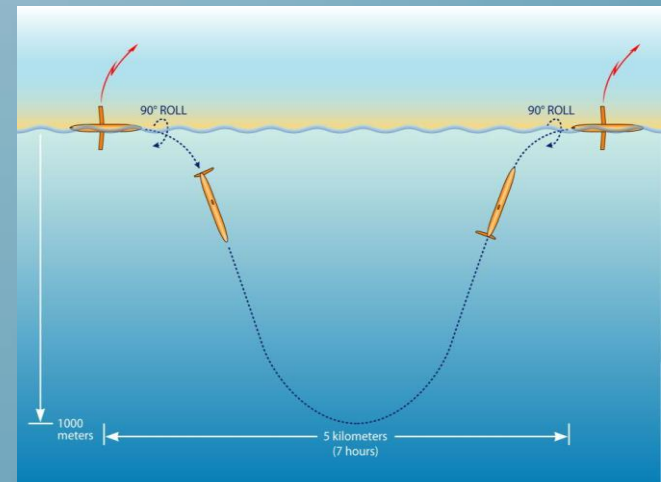
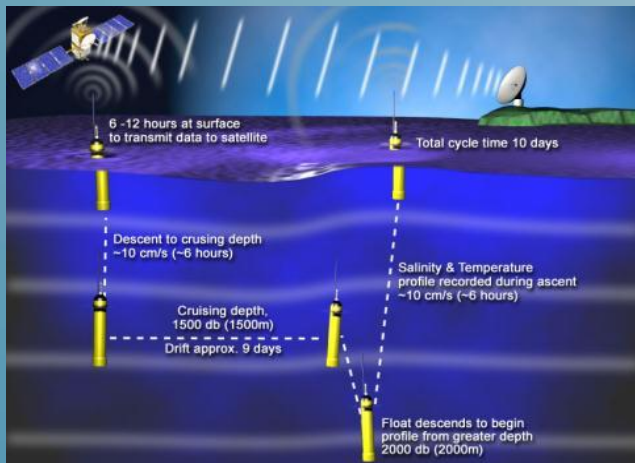
- MCMC SAMPLING: sample exact posterior distribution
- 4DVAR: obtains mode of posterior

LAGRANGIAN OCEAN DATA

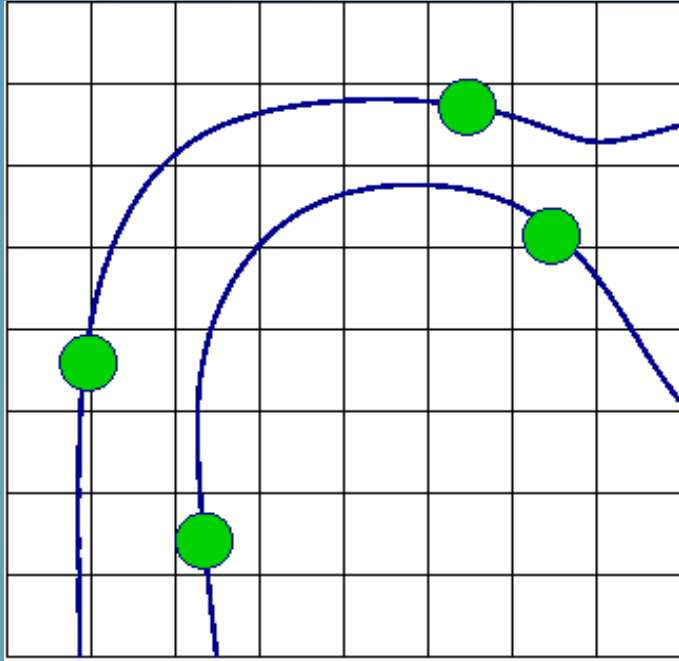
Argo floats (Lagrangian at depth)



Ocean Gliders (semi-Lagrangian)



LAGRANGIAN DATA ASSIMILATION



Lagrangian observations from drifters, gliders, and floats do not give the data in terms of model variables.

Solution: Include drifter coordinates into the model

$$\mathbf{x} = \begin{pmatrix} \mathbf{x}_F \\ \mathbf{x}_D \end{pmatrix} \quad - \text{ augmented state vector}$$

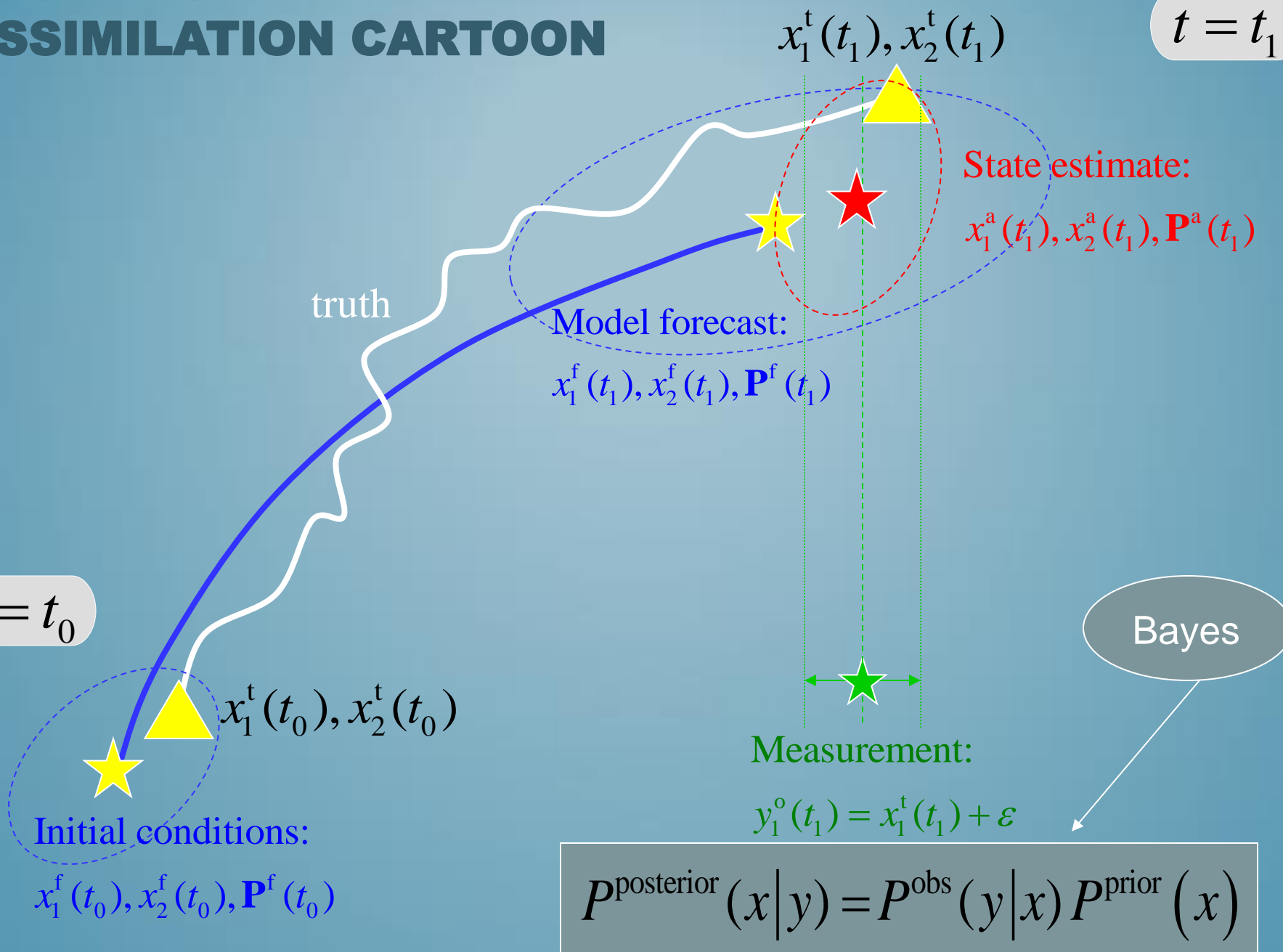
$$\frac{d\mathbf{x}_F^f}{dt} = M_F(\mathbf{x}_F^f, t) \quad - \text{ flow equations}$$

$$\frac{d\mathbf{x}_D^f}{dt} = M_D(\mathbf{x}_D^f, \mathbf{x}_F^f, t) \quad - \text{ tracer advection equations}$$

LAGRANGIAN DATA ASSIMILATION CARTOON

$t = t_1$

$t = t_0$



$$P^{\text{posterior}}(x|y) = P^{\text{obs}}(y|x) P^{\text{prior}}(x)$$

LAGRANGIAN DATA ASSIMILATION EXAMPLE

- Model initialized with no eddy present
- Eddy is “discovered” and tracked with incorporation of Lagrangian data
- Below: analysis snapshots of eddy shedding
(*Vernieres, Jones, Ide Phys. D, 240, 2011*)

