Lagrangian data analysis: methods and applications

Carthe tutorial

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Overview

- Lagrangian data are data from drifting buoys following the currents with good approximation (Davis, 1991)
- Here we focus on drifters, i.e. Lagrangian instruments sampling the mixed layer (2d view)
- We focus on two main themes:

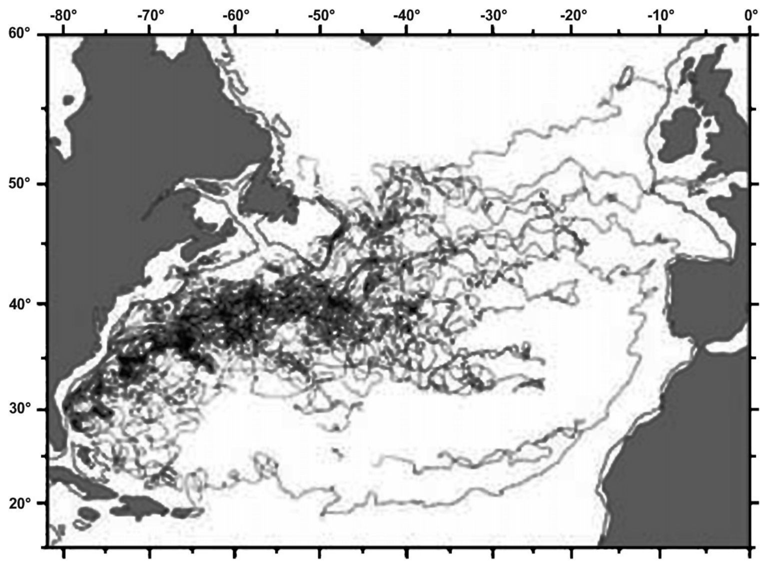
Transport and dispersion studies at various scales: large scale climatic applications and regional scale biological applications

Feature detection from Lagrangian data: looking for eddies and convergence lines

A little history and motivation

• Drifters have been intensively used from decades to sample the ocean remotely, thanks to satellite tracked transmitters that give information on positions (Sybrandy and Niiler, 1992; Niiler et al., 1995)

• During the 80's and 90's drifters have been used to sample the general circulation as "rowing currentmeters", providing direct info on transport and dispersion (Davis 1987, 1991)

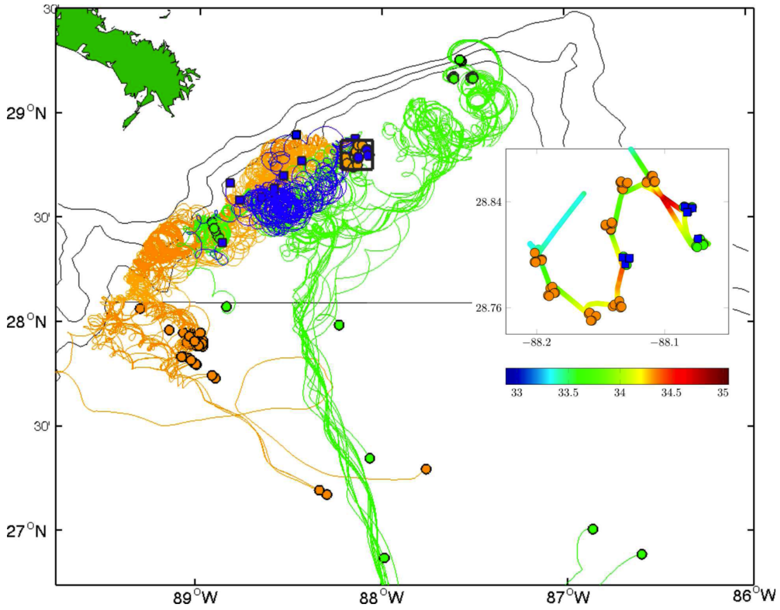


Richardson, 1983

• Sampling strategy was aimed at providing homogeneous coverage of large scale. Single particle statistics has been widely used to compute large scale tracer transport (Colin de Verdiere, 1983; Poulain and Niiler, 1989; Swenson and Niiler, 1996: Bauer et al., 1998: Oh et al, 2000; Lumpkin et al., 2002; Zurbas et al., 2004, 2014)

• Pioneering studies of two-particle statistics started with Richardson and Stommel (1948) annd continued with Kirwan et al. 1978, Davis 1985, Mc Williams et al 1983, La Casce and Bower 2000, La Casce and Ohlmann 2003, often with chance pairs

• Dedicated experiments became more common after 2000, thanks also to gps and increasing position precision (Koszalka et al., 2009, Berti et al 2010, Lumkin end Elipot 2010, Schroeder et al 2011 and 2012)



• Carthe's GLAD is the first experiment dedicated to small scales with massive multi-particle releases, able to provide solid statistical results

Dispersion from single particle and two particle: what is the difference?

• Definitions (in the x- direction for simplicity):

- single particle: absolute dispersion $D_0 = < (x - x_0)^2 >$

- two particle: relative dispersion $D_r = < (x_1 - x_2)^2 >$

where $x(t,x_0)$ is a trajectory position and x_0 is its initial condition; x_1, x_2 are particle pairs; $<>$ is an ensemble average

• To understand the difference between D_0 and D_r, consider the evolution of a cluster of particles, characterized by the displacement of the center of mass, x_c and the spread about x_c , Dx_c.

• It can be shown that *relative dispersion is proportional to cluster spreading*. Two particle statistics is directly related to concentration statistics of a tracer clound.

Absolute dispersion, instead is a measure of particle displacement relative to their initial condition.

• In order to describe tracer dispersion from single particle, it is necessary to introduce additional hypothesis. We will review the “classic” oceanograhical approach to this problem

Transport and dispersion at large scale from single particle statistics: climatic applications

• Goal: to investigate large scale tracer transport due to ocean currents

• Main hypothesis: there is a scale separation between large scale velocity **U=<u>**, that advects the tracer and is treated deterministically, and the eddy field **u'** considered as a random diffusive fluctuation

• Further hypotheses (for simplicity, but not only…): the eddy field statistics are homgeneous and stationary

• Framework: use the advection and diffusion equation (AD)

$$\frac{\partial}{\partial t} C + \mathbf{U} \cdot \nabla C = -\nabla \langle \mathbf{u}' C' \rangle \equiv K \nabla^2 C$$

where C is the tracer concentration, **u**' is the eddy fluctuation, and **K** is the eddy diffusivity, defined as follows

$$K_{ij} = \lim_{t \to \infty} k_{ij}$$

$$k_{ij}(t) = \int_0^t R_{ij}(\tau)\, d\tau$$

$$R_{ij}(\tau) = \left\langle u'_i(t_0)\, u'_j(t_0 + \tau) \right\rangle$$

where **R** is the Lagrangian (along trajectory) eddy velocity autocovariance (Taylor, 1921)

• In homogeneous and stationary flows, **K** is a constant since **R** asymptotically tends to zero, (or equivalently dispersion becomes linear in time)

-----> mean flow **U** and diffusivity **K** are *in principle* observational quantities from Lagrangian data.

------> velocities **u** are computed along trajectories by finite differences of the positions.

From **u**, the mean **U** and fluctuations **u'** are computed, **u = U + u',** and **K** is computed from **u'**

• Once **U** and **K** are computed, the AD eq is used to predict passive tracer evolution, i.e. T and S at large scales.

Estimating mean flow and diffusivity from Lagrangian data: methods and challenges

• In practice, the computation of **U** and **K** is often problematic given that a) the underlying hypothesis of scale separation is not valid; b) data are limited

• How are the "resolved" scales selected? For large scale, climatic applications, scales are typically of the order of degrees in space and months in time, depending also on data availability

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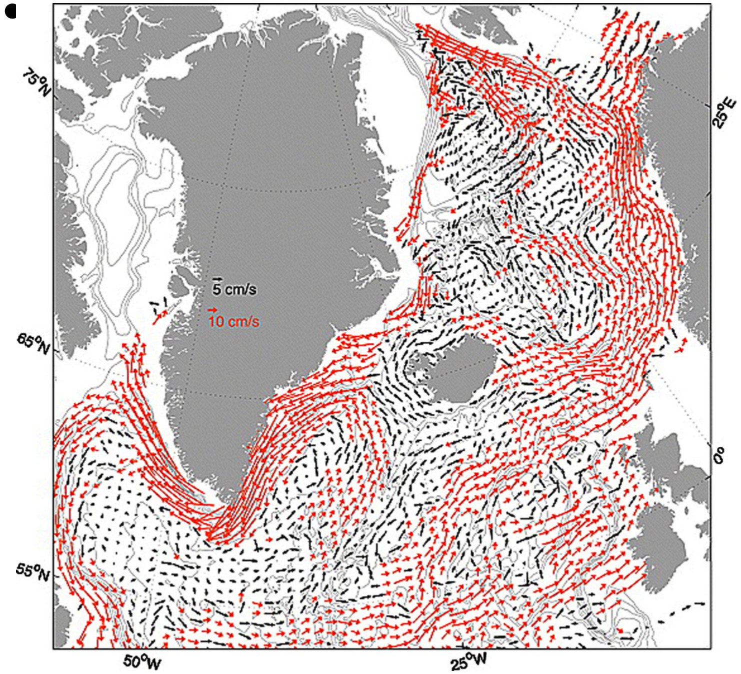
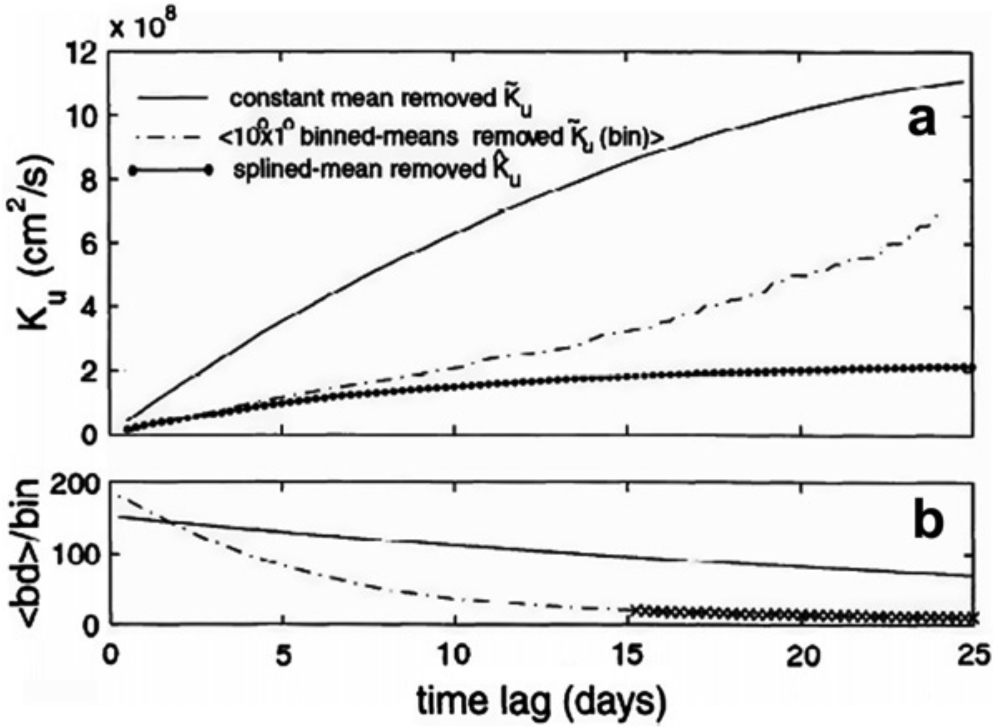


From Jakobsen et al., 2003

• **U** is computed in various ways. The simplest and most used way is "binning" in space and time, i.e. averaging over given intervals. Other methods use spline interpolation or objective analysis (Davis, 1998; Gille (2003; Bauer et al., 1998). All methods can be affected by biases due to data distribution.

• **K** is also computed in many ways (Davis, 1991). The most common one is based on autocovariance integration. A number of conceptual problems.

• Mean flow removal. If U is not correctly removed, especially in presence of shear, **K** does not asymptote to a constant. Possible solution: increase **U** resolution (depending on data) or methods (Bauer et al., 1998, Mariano et al, 2014); consider minor principal component of diffusivity tensor (Zhurbas et al., 2004).



From Bauer et al., (1998)

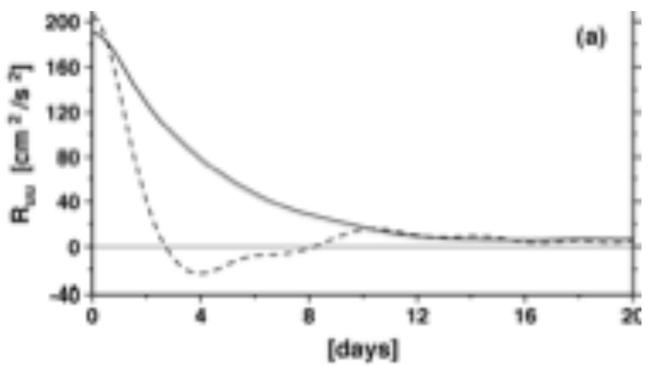
Example of estimates of diffusivity and autocovariance in the Tropical Pacific, varying at varying mean resolution

•Aymptoticity. Computing asymptotic values of **R** is problematic because: a) error increases at long lags: b) drifters sample inhomogeneous regions.

• For this reason, **K** is often computed integrating over finite (short) times. First zero crossing is a common choice

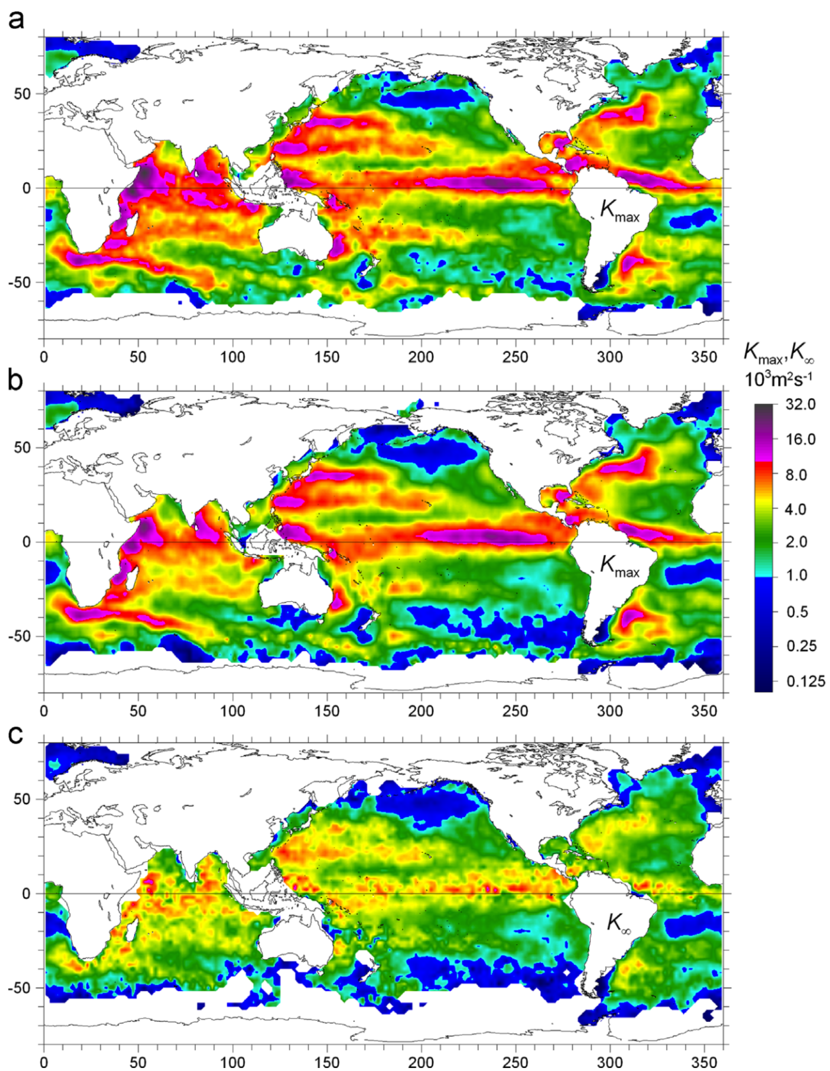
• BUT this can lead to overestimation of **K**, especially in presence of eddies inducing negative lobes in autocovariance (Klocher et al., 2012, Veneziani et al, 2004).

• Possible alternative solution: use parametric approach where the form of **R** is assumed known (Griffa et al., 1995, Mariano et al., 2014)



Example showing two types of autocovariances, exponential and with negative lobe

• Global K values are used to estimate transport of T, S at large scale and as input parameters for climate models



Example of diffusivity computation from Zhurbas et al., 2014.

Top: without seasonal binning

Middle: maximum estimation (first zero crossing)

Bottom: minimum (asymptotic) estimation

Transport and dispersion at regional scales using Lagrangian Stochastic Models (LSM)

• Regional scale transport studies are often applied to spreading of pollutants or biological quantities. Lagrangian Stochastic Models (LSM), that are conceptually similar to AD but more flexible, are often used

• LSMs are a class of models based on stochastic ordinary differential equations that describe the motion of single tracer particles. A hierarchy of LSMs at increasing complexity can be used (Griffa, 1996; Berloff and Mc Williams, 2002)

• The tracer concentration C can be obtained simulating large ensembles of particles and considering their distribution.

• The simplest LSM is the “random walk”, zero order Markov model. For homogeneous and stationary flow, in one dimension:

$$dx = U dt + d\hat{x}$$
$$d\hat{x} = \sqrt{K}\, dw$$
$$K = \sigma^2 T$$

where σ^2 is the variance, T is the integral time and dw is a random increment, <dw>=0, <dwi(t)dw(s)>=δ(t-s)dt, where T=dt/2

• The random walk is exactly equivalent to the AD diffusion. Its pdf equation (Focker Planck) corresponds to AD.

• The first order Markov LSM is the “random flight”, introduced to study developed turbulence and corresponding to the Langevin equation in 1 D, (Risken,1989; Thompson, 1987; Griffa, 1996)

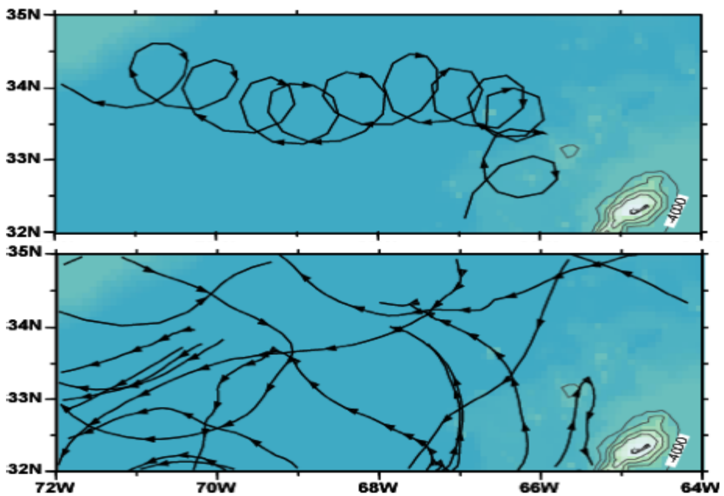
$$dx = (U + u')dt$$
$$du' = -\left(\frac{u'}{T}\right)dt + \sqrt{\frac{2\sigma^2}{T}}\, dw$$

• The first order model can be generalized introducing a coupling between the 2 velocity components trough the spin parameter:

$$\mathbf{du} = -\frac{\mathbf{u}}{\mathrm{T_L}}\mathbf{dt} - \mathbf{\Omega\, v\, dt} + \mathbf{d}\zeta$$

$$\mathbf{dv} = -\frac{\mathbf{v}}{\mathrm{T_L}}\mathbf{dt} + \mathbf{\Omega\, u\, dt} + \mathbf{d}\zeta$$

where T_L is the time scale, and $d\zeta$ is a random increment. The model appropriately describe 2d Lagrangian turbulence and float motion (Reynolds, 2002; Veneziani et al. 2004, 2005b)



Loopers (finite Ω)

Autocovariance: with negative lobe

Nonloopers (Ω =0)

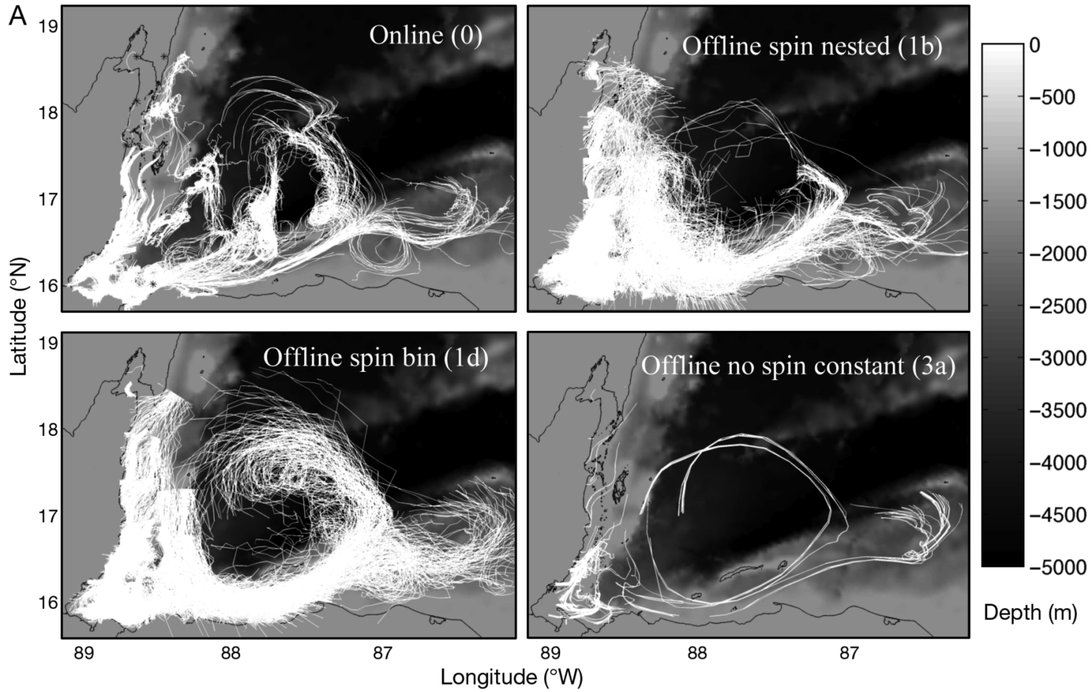
Autocovariance: exponential

• First order (and higher) LSMs have well defined velocity autocovariance, so they can be used to realistically describe initial tracer dispersion (differently from AD)

• LSM's are flexible and can be generalized to introduce inhomogeneous, nonstationary flows, nonlinearity and higher order derivatives like acceleration (Maurizi and Lorenzini, 2001; Pasquero et al., 2001; 2005, Berloff and Mc Williams, 2002). With higher complexity more parameters are needed….

• First order LSMs have been used in many biological applications to study connectivity (Cowen et al., 2000; Paris et al, 2007)

• LSMs are typically used as subgrid scale parametrizations in dynamical mesoscale models. Individual biological behaviour can be easily added.



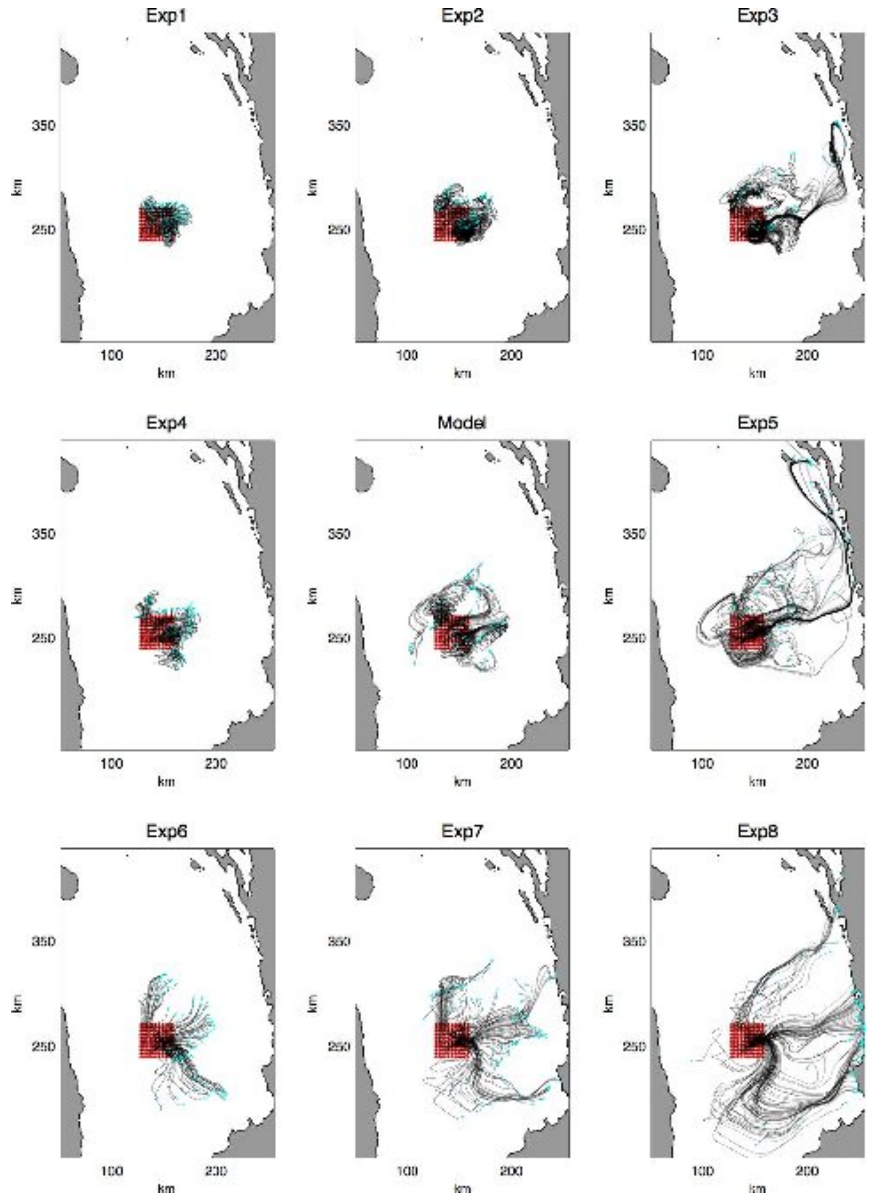
From Paris et al, 2007

• LSMs are very useful but they have strong limitations: they assume scale separation (as AD) and they tend to be overly diffusive, i.e. they do not recognize dynamical boundaries

• A different approach to LSMs has been proposed by Haza et al., (2007, 2012), and applied in Carthe

• Scale separation is relaxed and it is assumed that the dynamical model partially resolvs small scales, even though not correctly.

• The LSM correct the small scale behaviour, modifying the variance and time scale parameters. It does not destroy the dynamical boundaries.



From Haza et al, 2007

Detecting feautures from Lagrangian data: looking for eddies

• Investigating eddies from Lagrangian data has a long history. “Loopers”, i.e. trajectories with multiple loops, have often been considered as eddy indicators (Richardson, 1993)

• Caution: loopers can also be due to waves (inertial, tidal, equatorial, Rossby..) or due to direct wind forcing.---> look for lopers but always check

• Loopers have historically been identified visually (Shoosmith, 2005). Automated methods have been developed recently to investigate large data sets.

• Several methods have been proposed to identify eddies at various scales from drifters (Veneziani et al., 2005; Lankhorst, 2006, Griffa et al., 2008, Lilly et al., 2011)

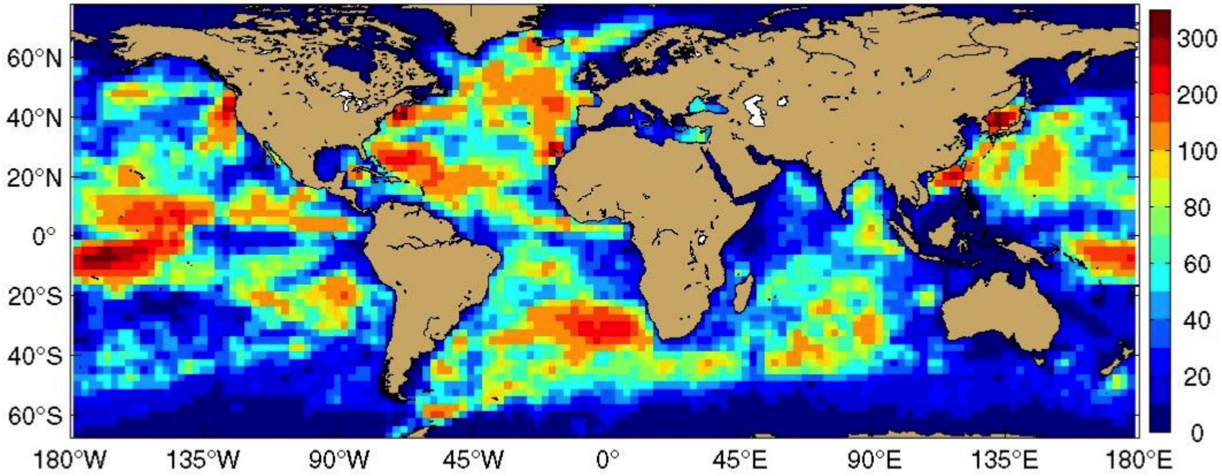
• Here we focus on the spin based method (Veneziani et al., 2005, Griffa et al., 2008)

Data and methodology

We adopt a particle-following methodology and analyze the global data set of satellite-tracked drifters (1992-2006) drougued at 15m (AOML/DAC website)

- **Divide trajectories in 20-days long segments**
- **Estimate inertial period (IP) for each segment**
- **Demean Lagrangian velocities and lowpass filter them at 1.5IP**

Number of T_{seg}=20 days trajectory segments per 5°x5° bins



use a Lagrangian parameter - the **spin Ω** - to characterize particle rotation and polarity

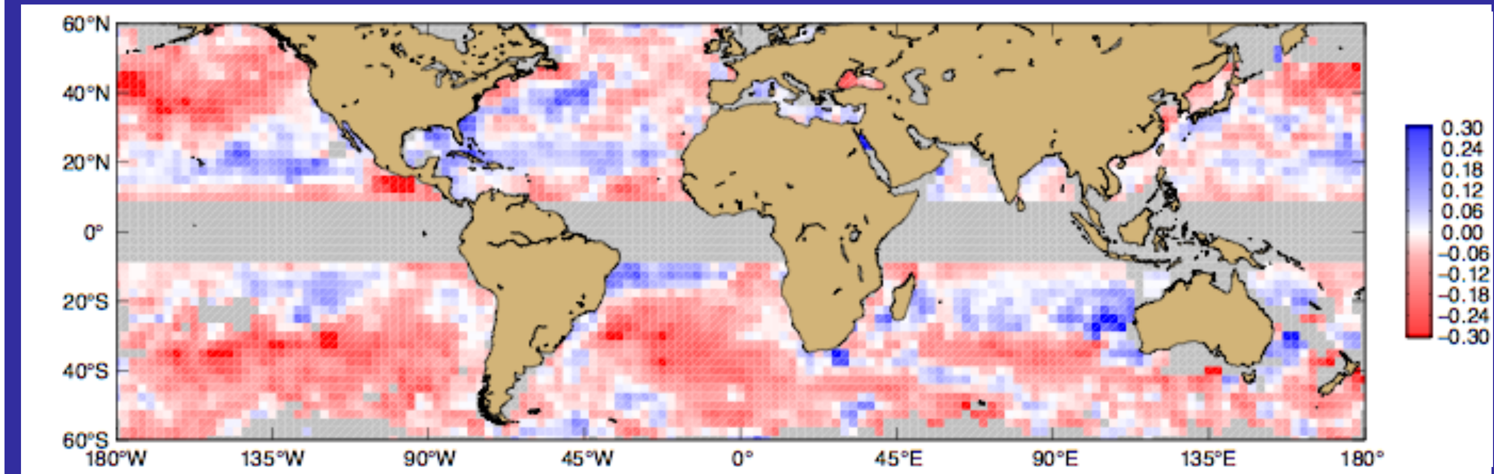
The spin was first introduced in the framework of Lagrangian stochastic models (Borgas et al. 1997):

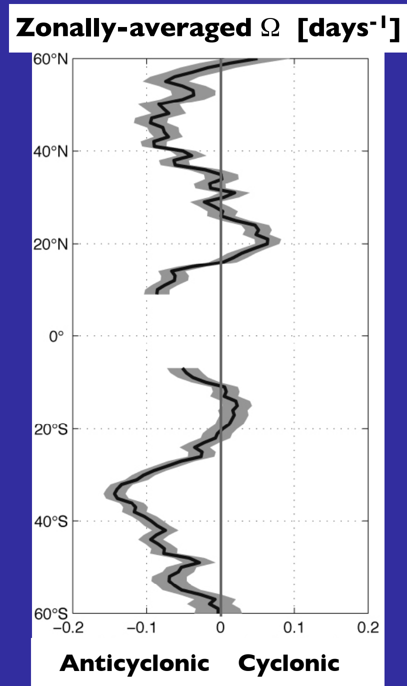
$$\begin{aligned} \mathbf{du} &= -\frac{\mathbf{u}}{\mathrm{T_L}}\mathbf{dt} - \boldsymbol{\Omega}\,\mathbf{v}\,\mathbf{dt} + \mathbf{d}\boldsymbol{\zeta} \\ \mathbf{dv} &= -\frac{\mathbf{v}}{\mathrm{T_L}}\mathbf{dt} + \boldsymbol{\Omega}\,\mathbf{u}\,\mathbf{dt} + \mathbf{d}\boldsymbol{\zeta} \end{aligned}$$

Here, we use Ω **= (udv-vdu)/(2 DT EKE)** to study polarity distribution (Dt is the time sampling, EKE eddy kinetic energy)

positive (**negative**) spin associates to **cyclonic** (**anticyclonic**) motion in the Northern Hemisphere (viceversa in the Southern Hemisphere)

Bin-averaged distribution of polarity Ω *sign(lat) per 5°x5° bins





- eddies associated with the main currents
- two zonal bands:

-**anticyclonic band at 30°-40°, already noticed from rotary spectrum studies (Rio and Hernandez 2003, Elipot 2006)**

-**cyclonic band at 10°-20°, previously unnoticed**

What kind of motion is responsible for the polarity bands?

Identify single loopers using the spin parameter and look at their characteristics and distribution

Need a spin threshold Ω_0 such that:

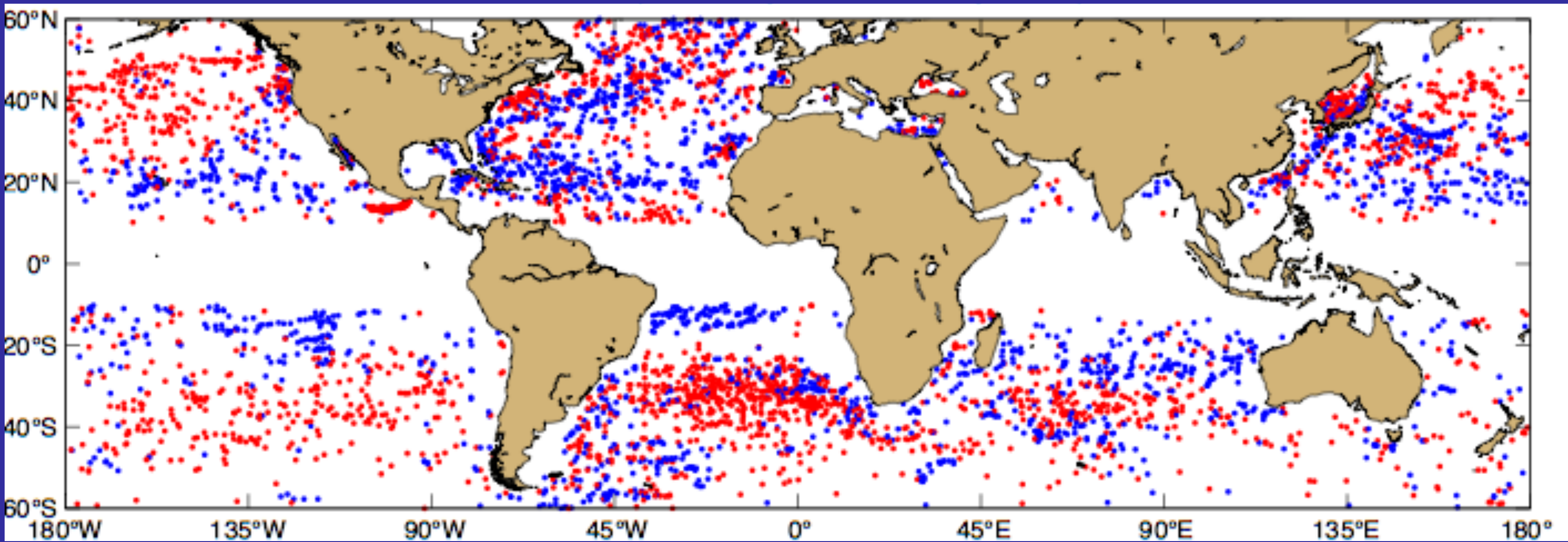
$\Omega > \Omega_0 \longrightarrow$ looper

$\Omega < \Omega_0 \longrightarrow$ nonlooper

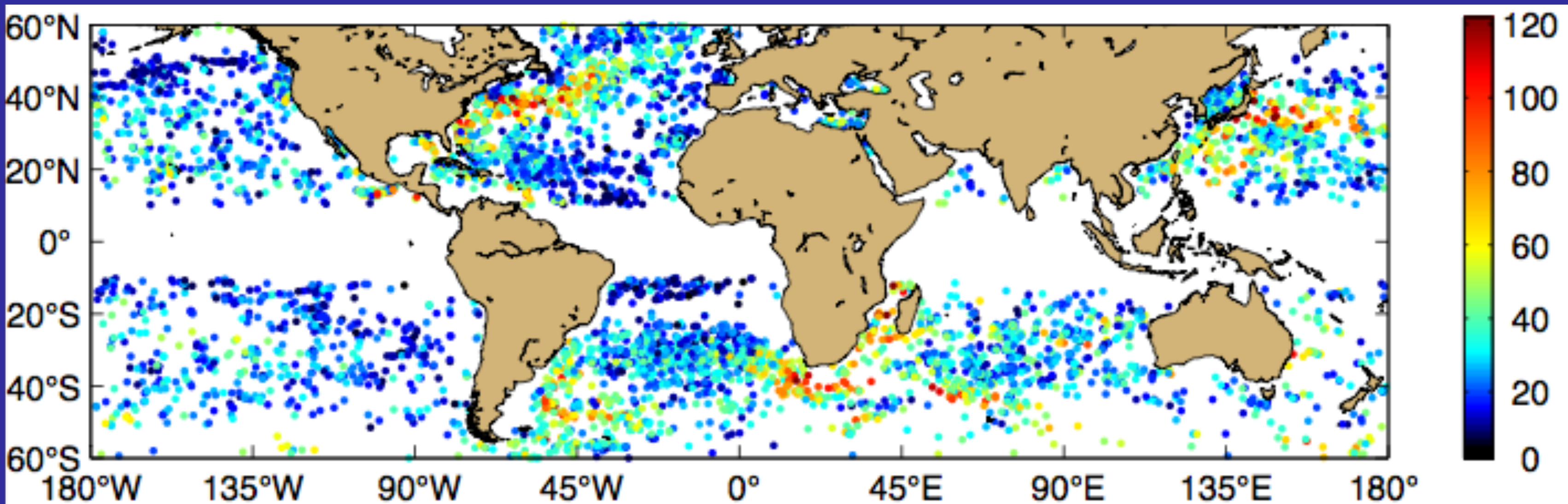
Extensive preliminary analysis to define Ω_0

We found $\Omega_0 \sim 0.4$ days^{-1}

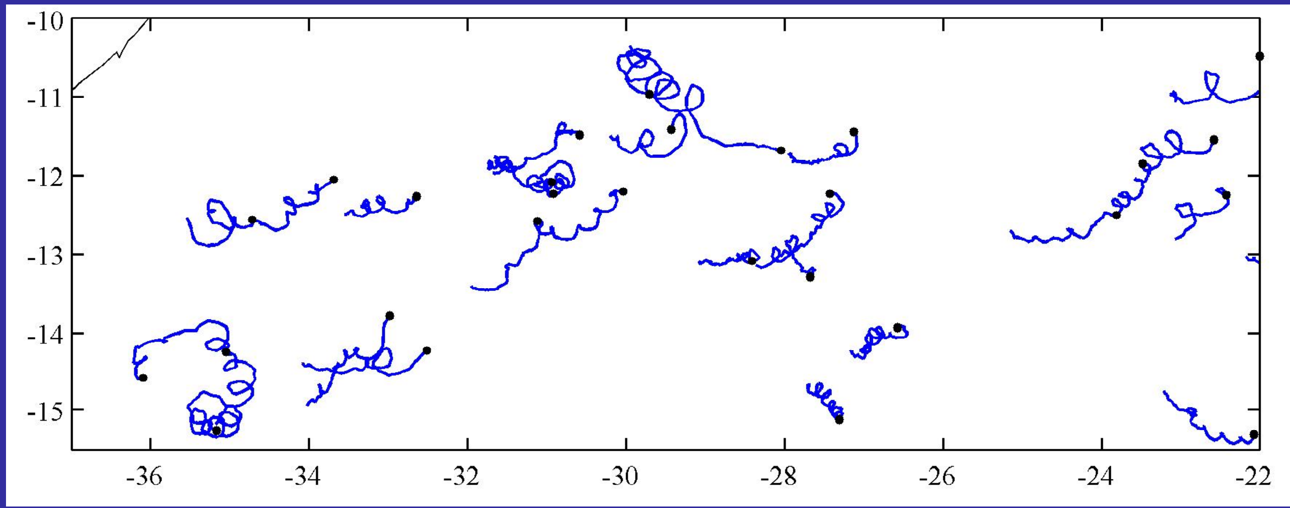
| Ω |>0.5 days^{-1} (blue=cyclones red=anticyclones)



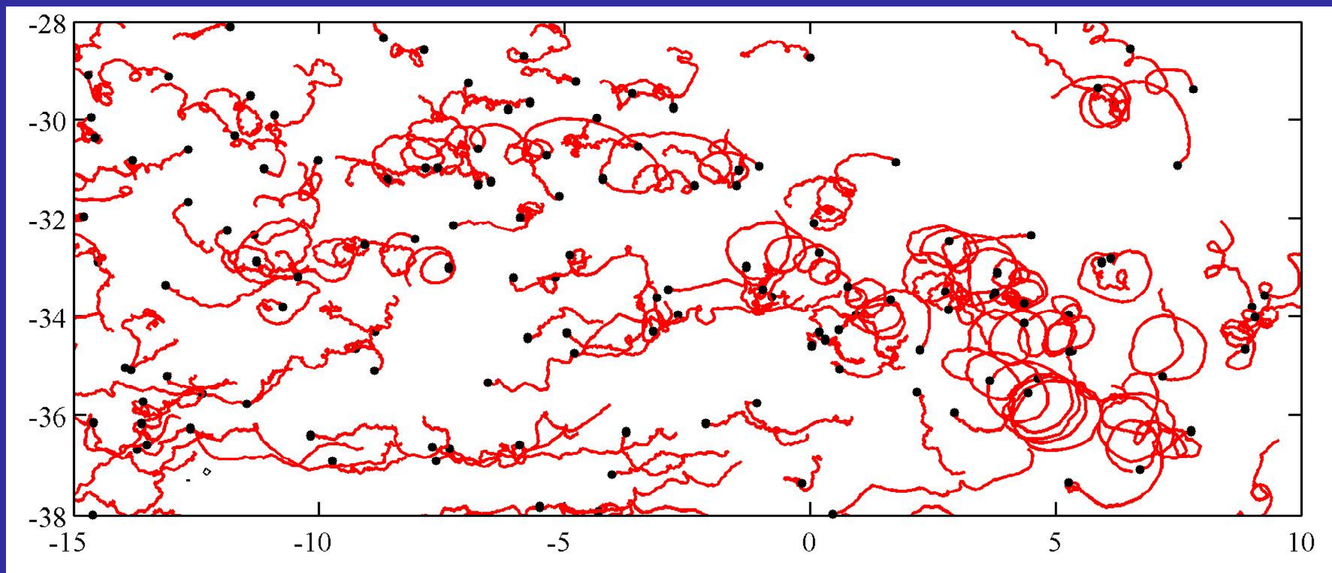
Looper radius (km) R=sqrt(2σ)/ Ω



Example of loopers in the zonal bands



cyclones



anticyclones

What are the generation mechanisms of the small scale structures in the polarity bands?

● anticyclonic band (30°-40°)

• Rio and Hernandez (2003) and Elipot (2006) show that the wind also has anticyclonic polarity at these latitudes, and that there is significant coherence between wind and drifters velocity

➡ suggests that the anticyclonic band could be partly wind induced

• Located in the region of the Subtropical Front (Tomczak et al. 2004)

What are the generation mechanisms of the small scale structures in the polarity bands?

- **cyclonic band (10°-20°)**

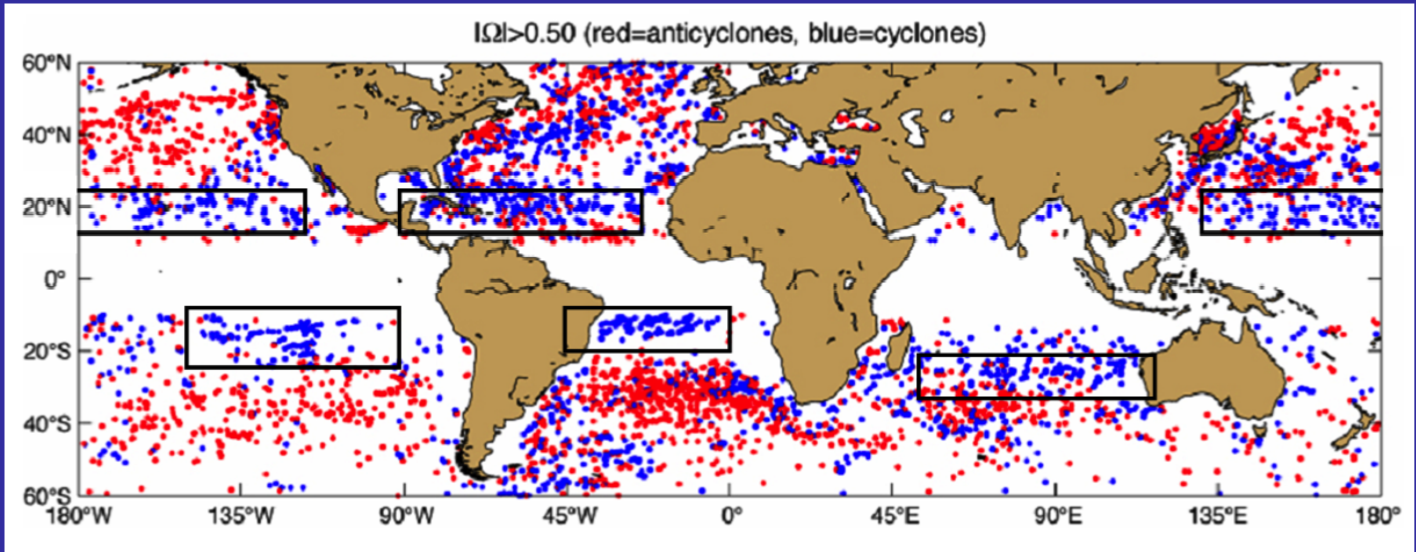
• Coherence with the wind is significantly reduced and no definite wind polarity is detected (Rio and Hernandez 2003)

• Scales and structures of loopers are consistent with submesoscale vortices (SMVs)

• SMVs are often related to mixed layer front instabilities

The cyclonic regions are characterized by surface Salinity Subtropical Fronts and coincide with regions of formation of subtropical Barrier Layers (Sato et al. 2006)

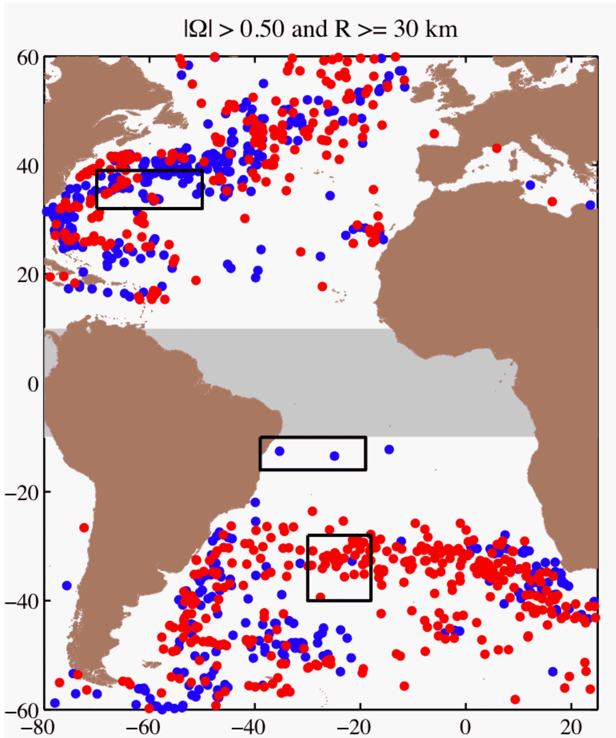
Barrier Layers distribution



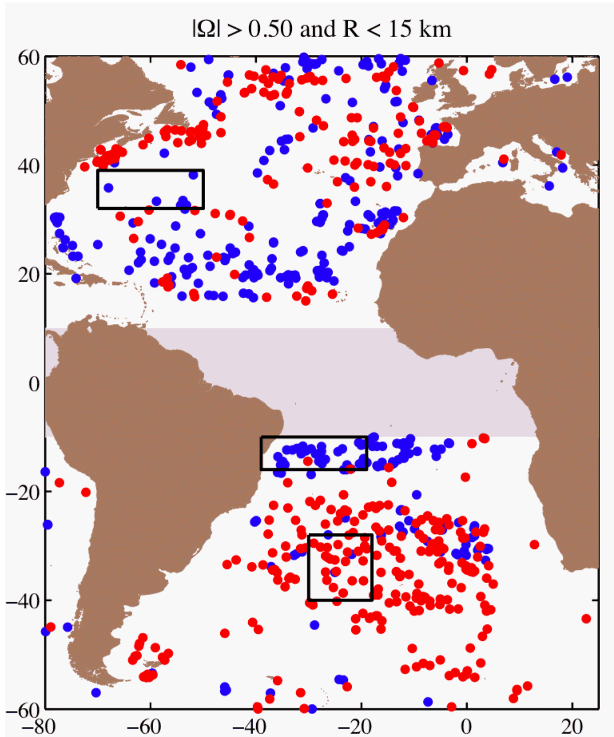
Suggestion: the cyclonic structures are SMVs due to baroclinic instabilities of the surface mixed layer. May play a role in subtropical BLs formation

Separate distribution of loopers at different scales

Mesoscale structures



Smaller structures



Small scale loopers are prominent in the two bands and in mesoscale active regions, and they are absent in the regions of formation of rings

• Motivated by these findings, a further investigation was performed using high resolution models in two selected regions: the Gulf Stream recirculation (Mensa et al., 2013), and the South Atlantic BL region (Veneziani et al., 2014).

• Both areas are submesoscale rich, especially in winter, but with very different properties.

• In the Gulf Stream recirculation, the submesoscale is primarily due to frontal instabilities of mesoscale eddies, and is strain dominated

• In the South Atlantic BL region, where mesoscale is very weak, submesoscale is mainly due to instability of surface salinity fronts, and is mostly elliptic and cyclonic. It contributes to Barrier Layer formation

---> Results confirm that the spin method helps diagnosing the elliptic part of the flow

Detecting feautures from Lagrangian data: looking for convergence lines

- During the Carthe's experiments we often observed drifters converging along lines and moving coherently
- Convergence lines can be due to different processes at different scales: mesoscale fronts; small scale salinity fronts; Langmuir cells; internal wave signaturea
- They are characterized by different scales in space and time and by different density properties and velocity with respect to alignment lines
- We are presently investigating methods to quantitatively identify them from drifter data and investigate their nature
- Preliminary results from S. Marini and M. Berta (CNR, ISMAR) (from yesterday…)
- Identify convergence lines ("streaks" for lack of a better term) using parameters suggested by relative dispersion analysis (Poje et al., 2014)

Streaks definition

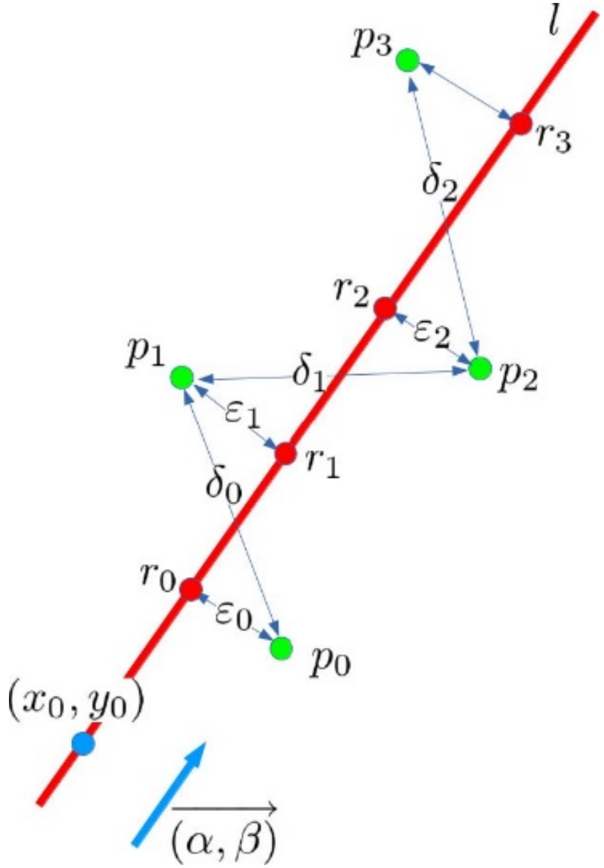
A **STREAK** is a line l through the point (x_0,y_0) and parallel to the vector (α,β) such that a set of ***N*** particles (drifters):

1.lies not further than ***ε*** from the line l ;

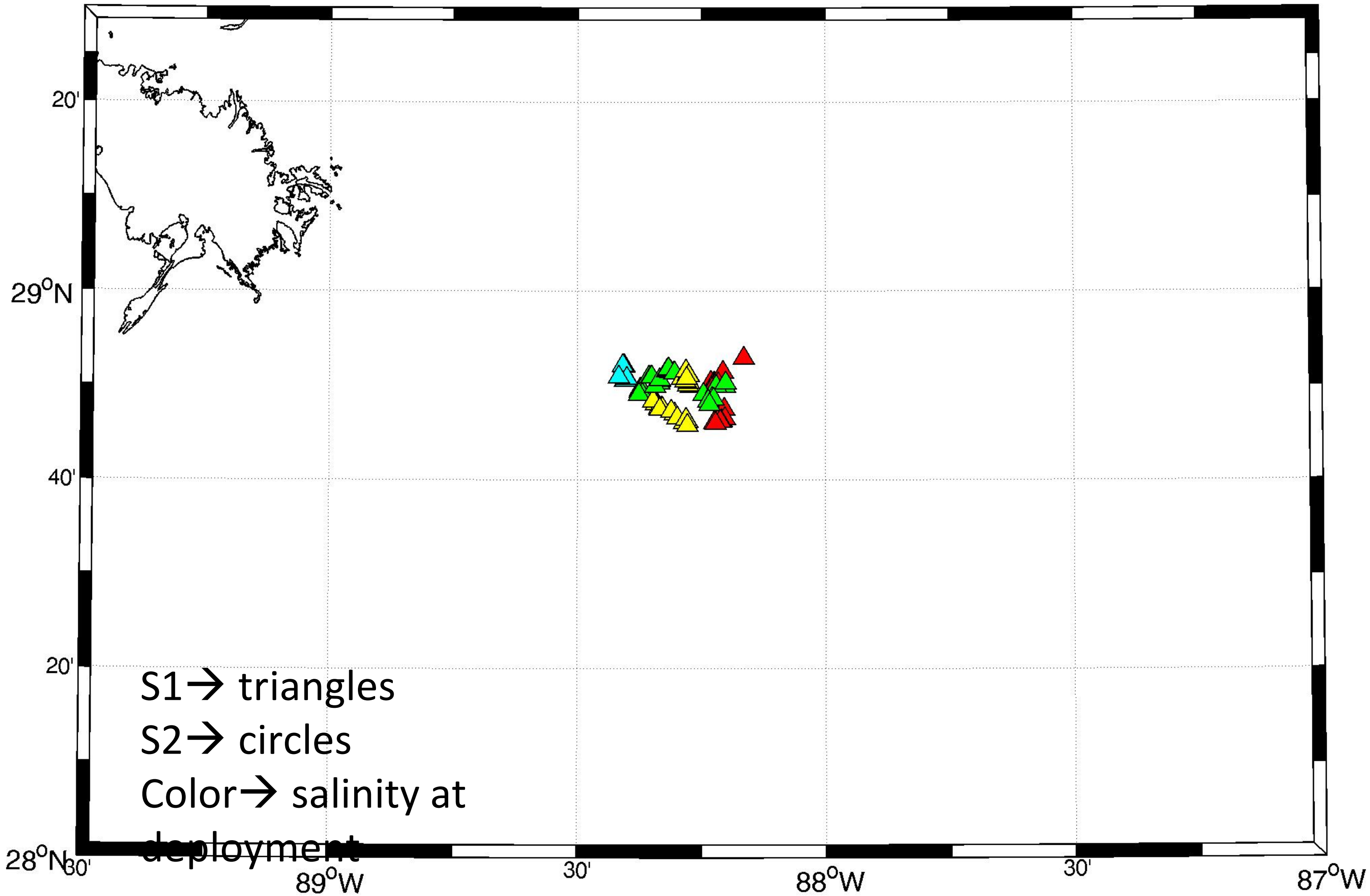
2.the distance between two adjacent particles is not larger than ***δ*** ;

3. ***N*** is at least 3 ;

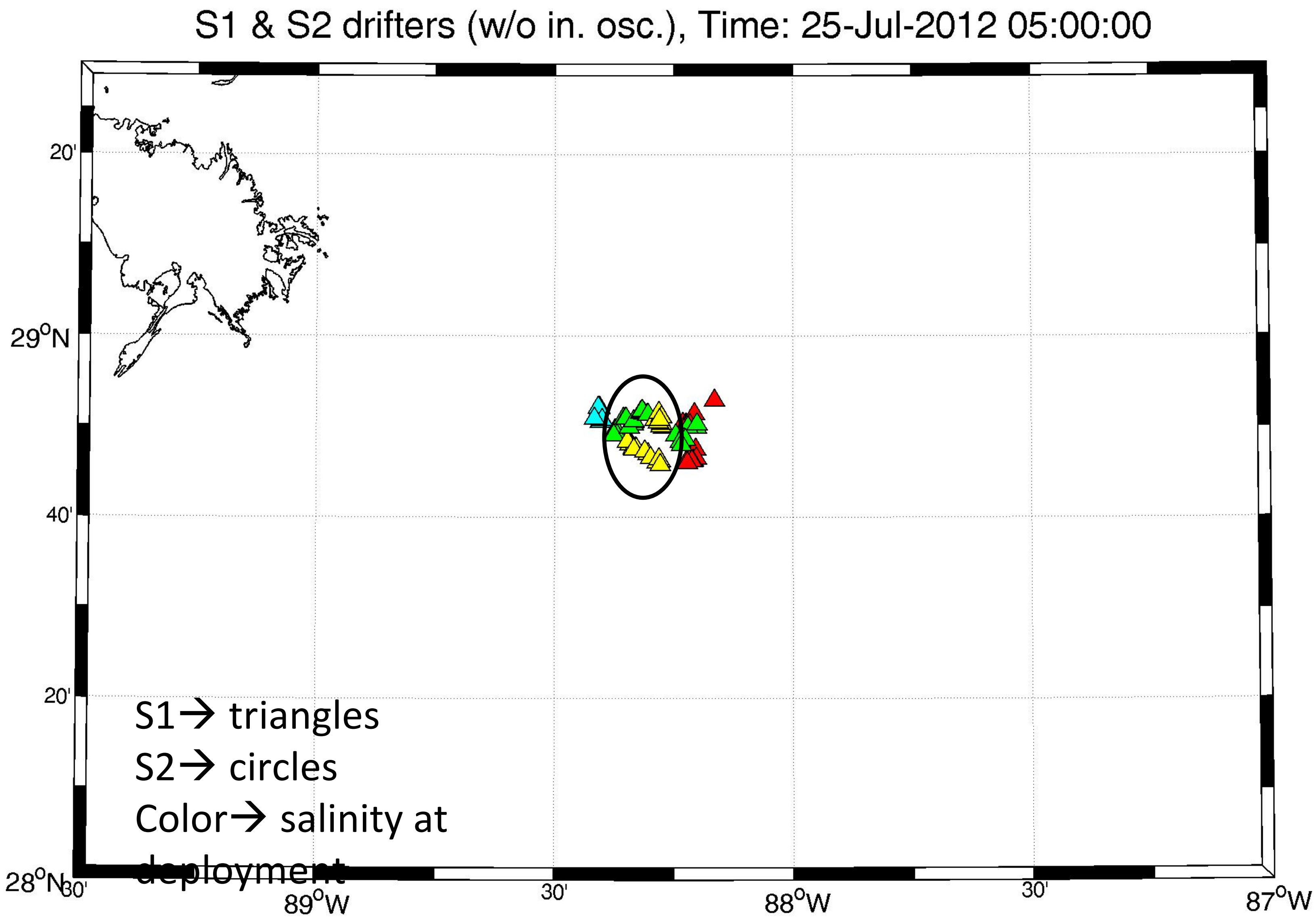
4.a subset ***s*** of ***N*** belongs to the same streak, i.e. it respects conditions 1 and 2, at least for a time period ***τ*** .



S1 & S2 drifters (w/o in. osc.), Time: 25-Jul-2012 05:00:00



S1→ triangles
S2→ circles
Color→ salinity at deployment


S1 & S2 drifters (w/o in. osc.), Time: 25-Jul-2012 05:00:00
20'
29°N
40'
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30'
89°W
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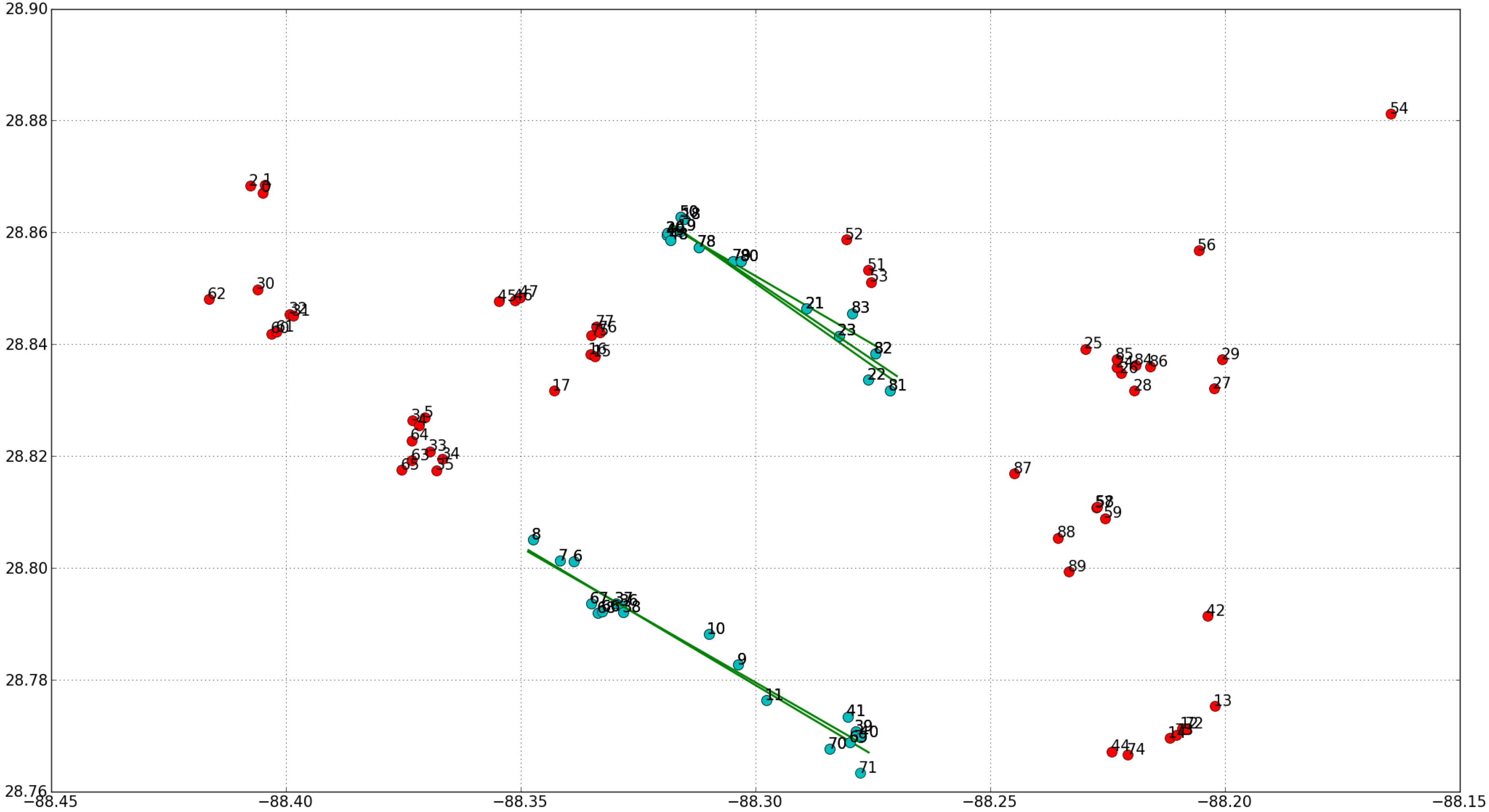
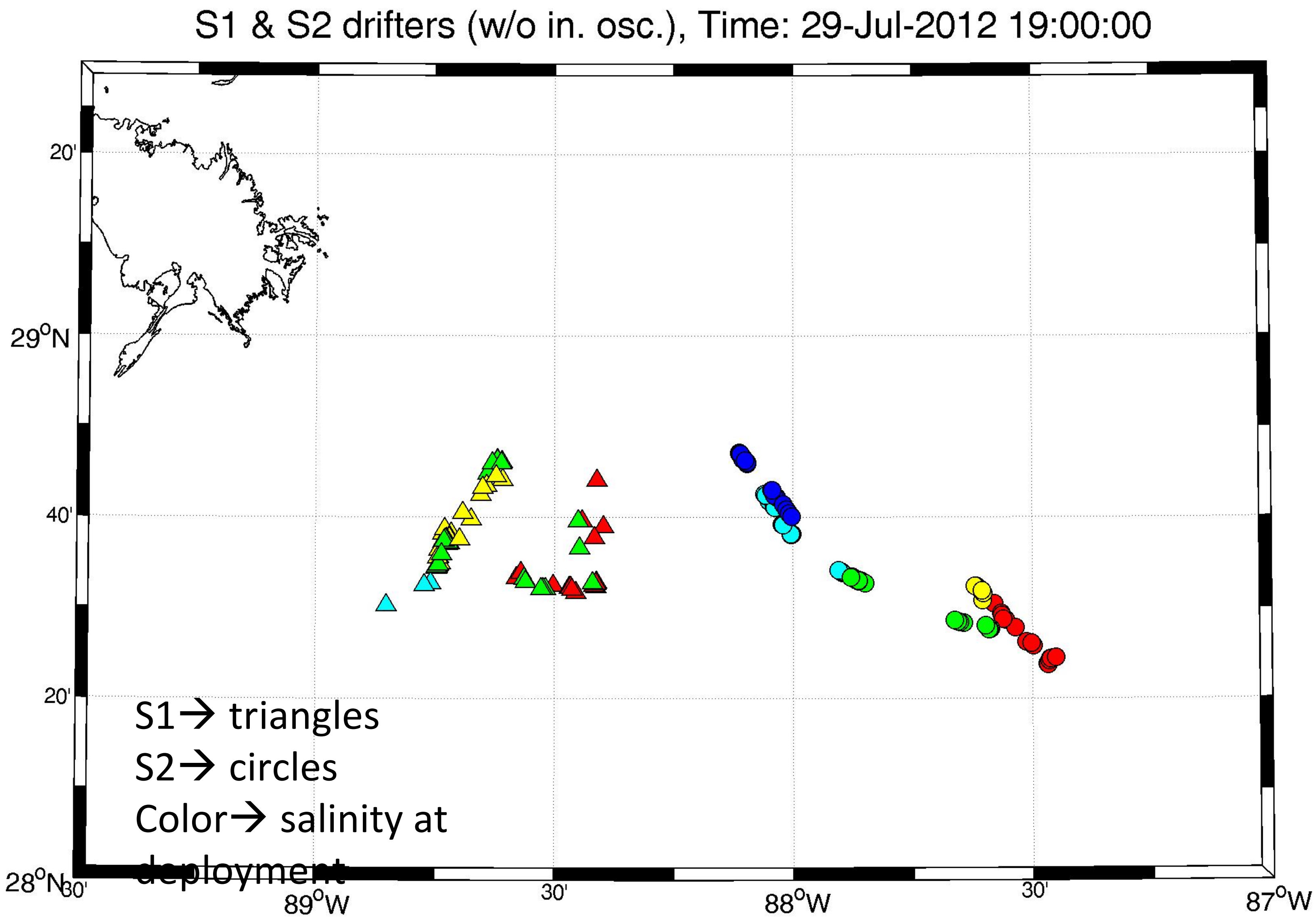
88°W
30'
87°W
S1→ triangles
S2→ circles
Color→ salinity at deployment

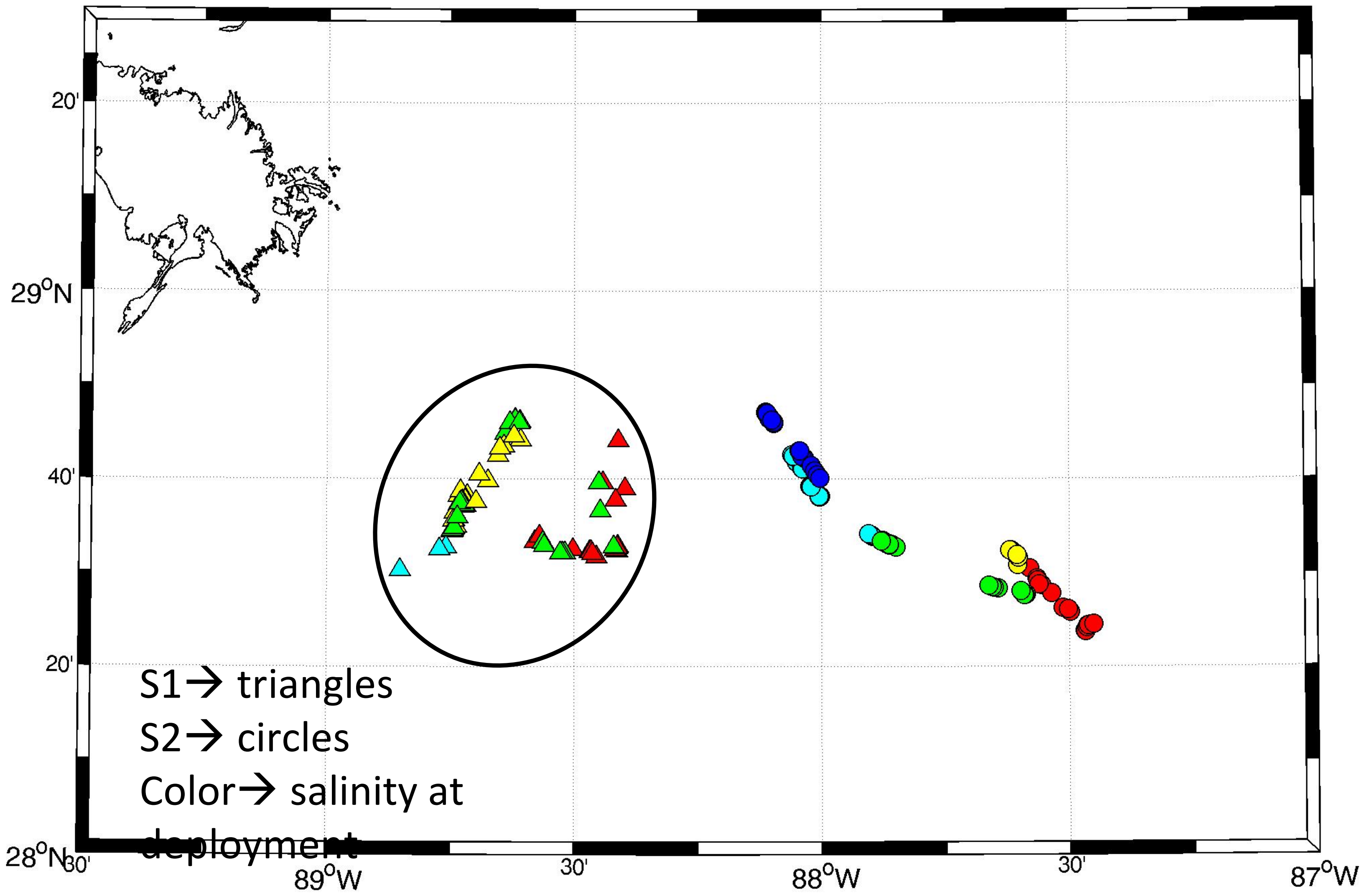
S1 streaks for 25-Jul-2012 05:00



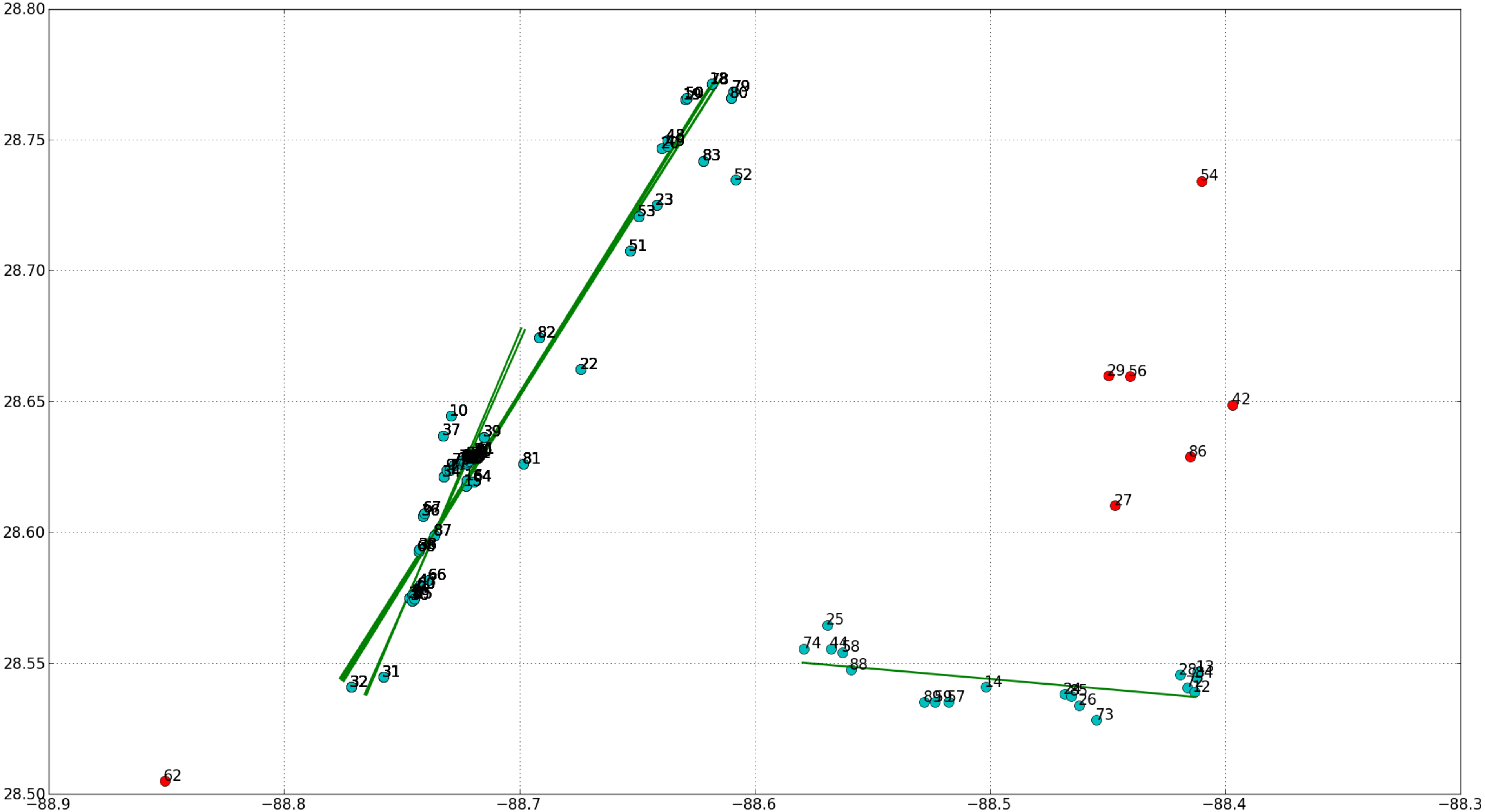
N= 4 part.; δ= 2km; ε= 0.5km; s= 1 part.; τ= 12 h


S1 & S2 drifters (w/o in. osc.), Time: 29-Jul-2012 19:00:00
20'
29°N
40'
20'
28°N
30'
89°W
30'
88°W
30'
87°W
S1→ triangles
S2→ circles
Color→ salinity at
deployment

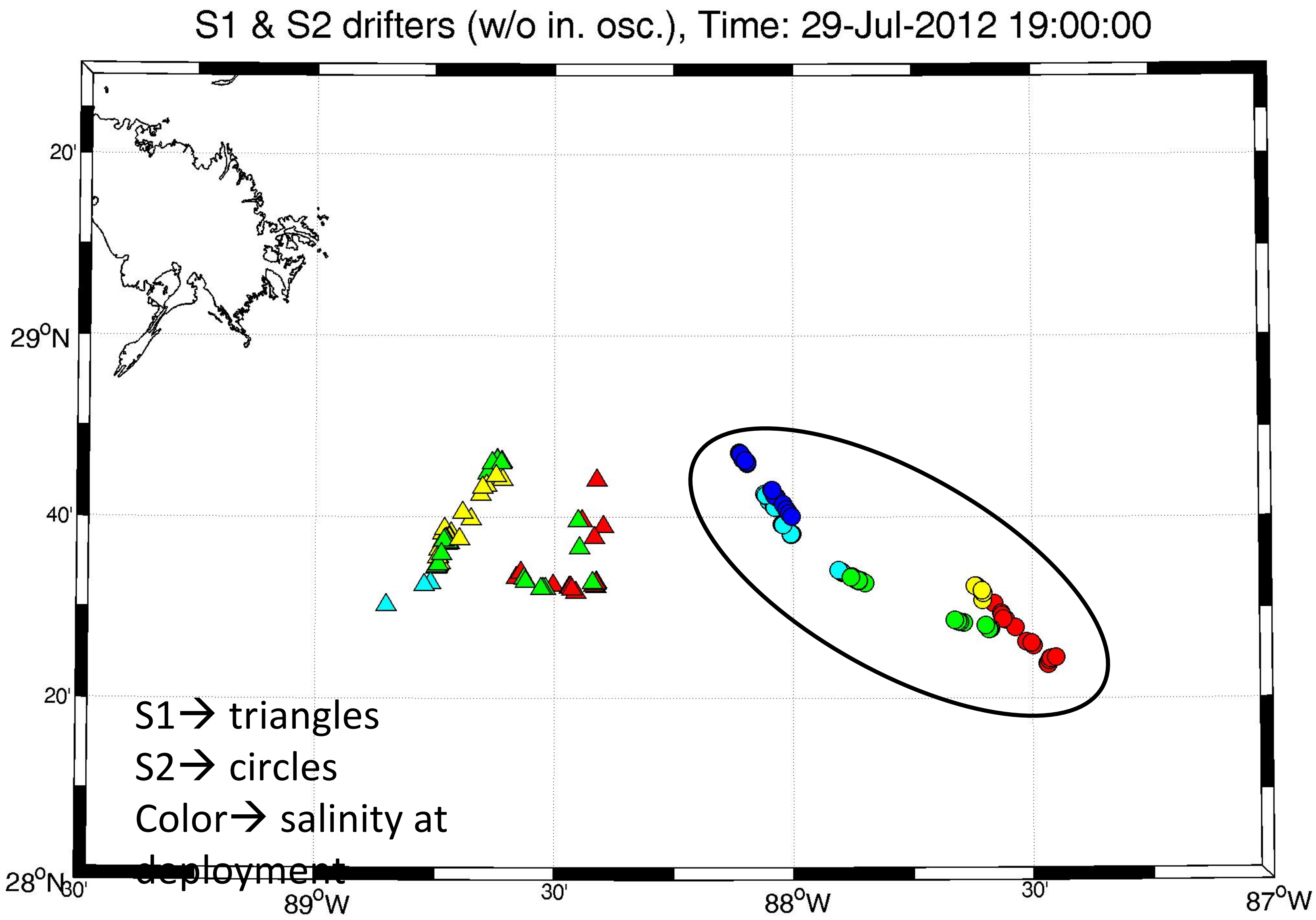
S1 & S2 drifters (w/o in. osc.), Time: 29-Jul-2012 19:00:00



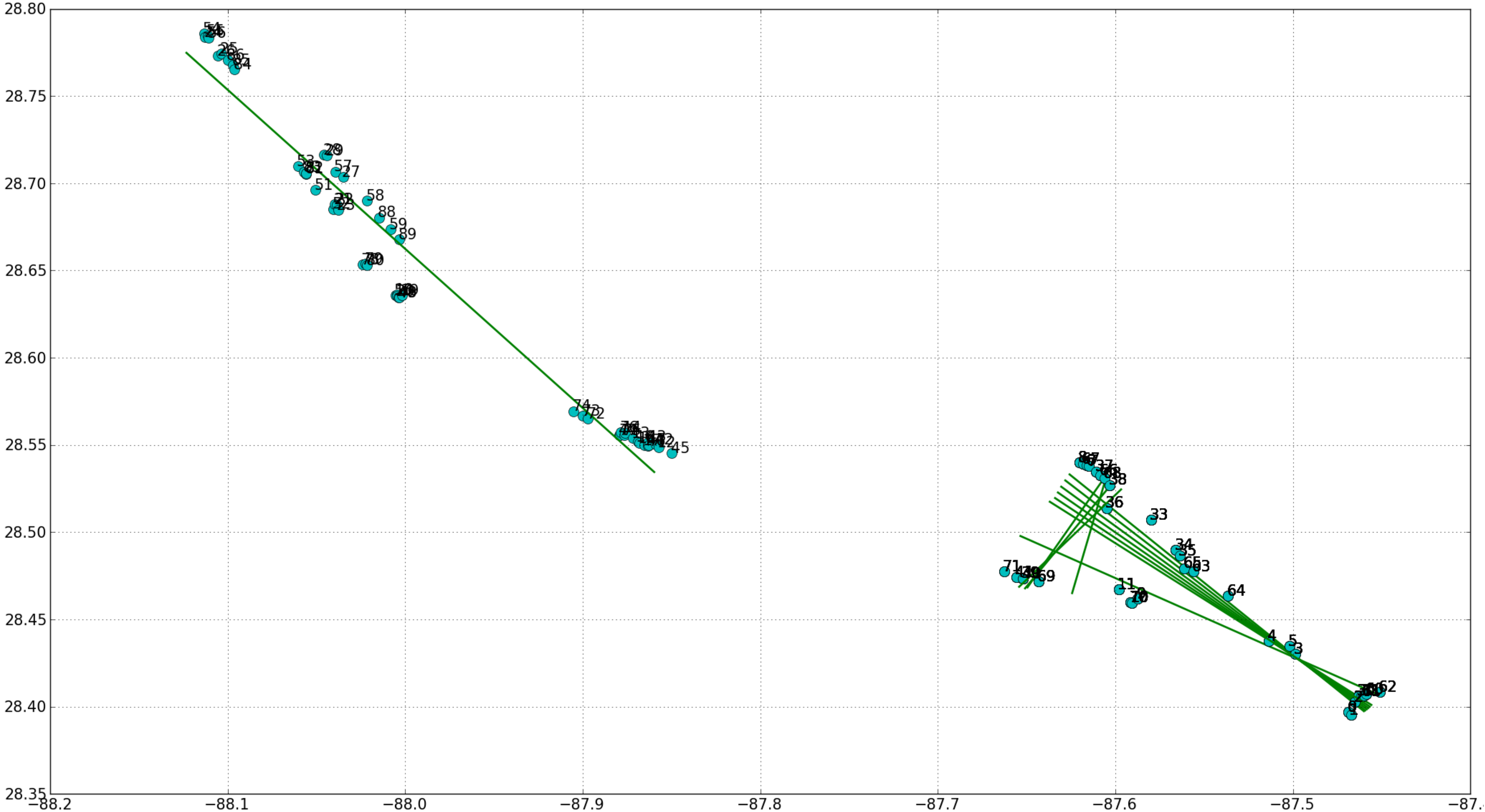
S1 streaks for 29-Jul-2012 19:00



N= 4 part.; δ= 8km; ε= 2km; s= 1 part.; τ= 12 h


S1 & S2 drifters (w/o in. osc.), Time: 29-Jul-2012 19:00:00
20'
29°N
40'
20'
28°N
30'
89°W
30'
88°W
30'
87°W
S1→ triangles
S2→ circles
Color→ salinity at deployment

S2 streaks for 29-Jul-2012 19:00



N= 4 part.; δ= 15km; ε= 5km; s= 1 part.;
τ= 12 h

• The method shows good potential

• It is sensitive to parameter choice

• Next steps:

• Analyze the identified streaks to get insights on dynamics. Some of them appear characterized by velocity along the line (fronts), others across the line (instabilities, waves?)

• Identify best strategy to choose the parameters. Several possibilities.

- parameters can be chosen a-priori according to some criteria (time after deployment, targeted dynamics, size of observed cluster)

- training by expert identification

- UQ methods

•The stochastic term $\boldsymbol{\mu}$ represents the “missing component”, i.e. the component of the eddy field that is not correctly described by the model. It can be considered as a Lagrangian subgrid scale (LSGS) model.

• In many papers in the literature $\boldsymbol{\mu}$ is (arbitrarily) assumed to be a Markov 1 model. The parameters σ^2 and T are often chosen ad hoc in order to obtain statistics close to the historical Lagrangian data in the area (Dutkiewicz et al., 1993; Paris et al., 2004).

▪ In a recent paper (Haza et al., 2006), the question of how to objectively determine $\boldsymbol{\mu}$, in order to obtain a corrected statistics of $\mathbf{x}_c$ that match historical data has been considered.

• Under some simplifying assumptions it is shown theoretically

that **μ** obeys to (for a single component) :

$$d\mu/dt = a\, du_m/dt + b\, u_m + c\mu,$$

where a, b, c depend on the statistics of the model, $\sigma^2{}_m, T_m$, and of the real in-situ data, $\sigma^2{}_r, T_r$,

$$a=(\sigma_r \sqrt{T_m})/(\sigma_m \sqrt{T_r}) - 1,$$

$$b = \sigma_r/(\sigma_m \sqrt{T_m T_r}) - 1/T_r$$

$$c= -1/T_r .$$

μ