

Observation-Model Compatibility in Coastal Data Assimilation

-Filtering & Optimal Spectral Decomposition -

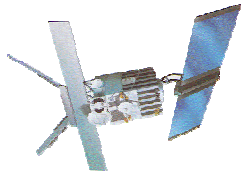
Peter C. Chu

Naval Postgraduate School
and Other Contributors

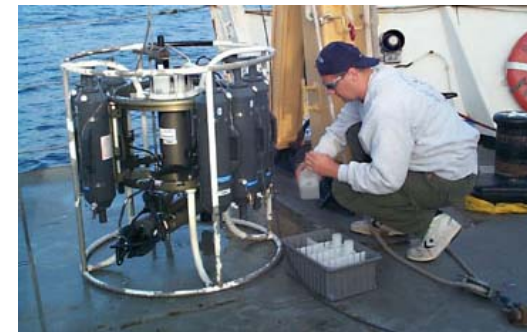
Workshop for Environmental Modeling of California Central Coast
MBARI, Moss Landing, California, 15-16 August 2007

Other Contributors

- Leonid .M. Ivanov, Tatanya Margolina, Chenwu Fan, NPS
- Oleg Melnichenko, University of Hawaii
- N.C. Wells, SOC, UK
- Charles Sun, NOAA/NODC
- George Galanis, George Kallos, University of Athens, Greece



How can we effectively use observational ocean data to represent and to model/predict the ocean state?



Outline

- (1) Model-Data Compatibility
- (2) Filtering Observational Data
- (3) Optimal Spectral Decomposition

(Chu et al., 2003 a, b JTECH)

- ARGO Data: Baroclinic Rossby Waves in Tropical Atlantic (Chu et al. JGR 2007)
- Surface Drifting Buoy Data: Synoptic Current Reversals on the Texas-Louisiana Continental Shelf (Chu et al. 2005 JPO)

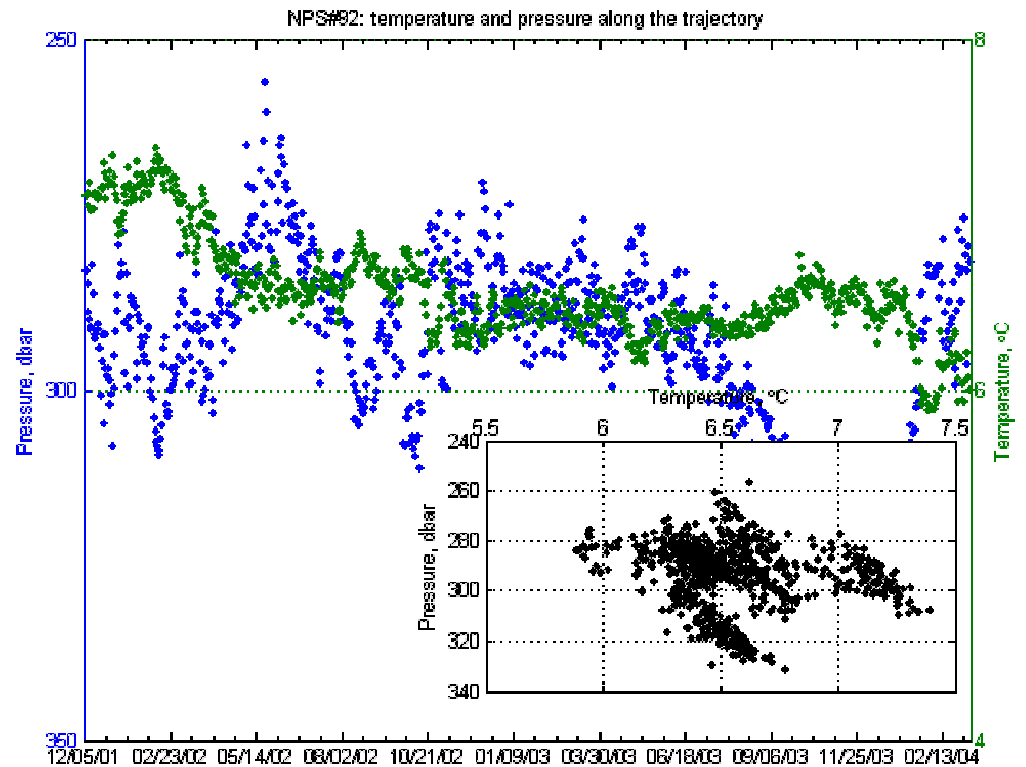
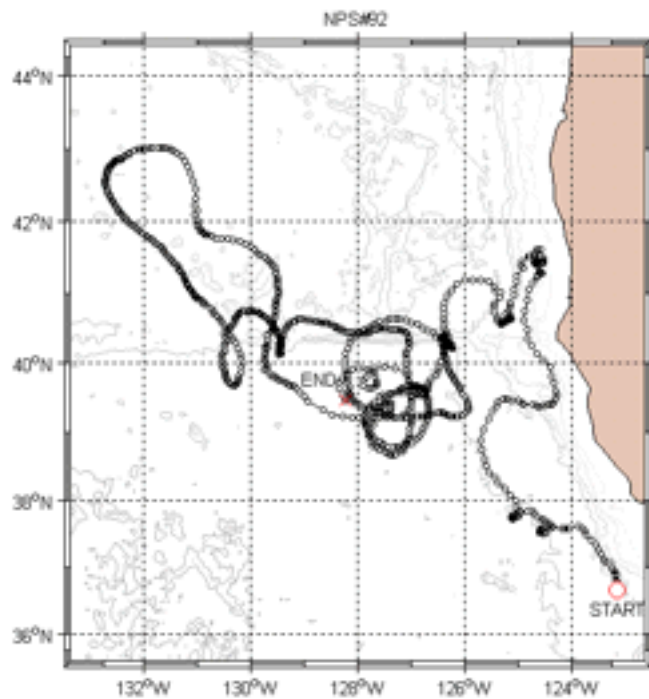
Part-1

Model-Data Compatibility

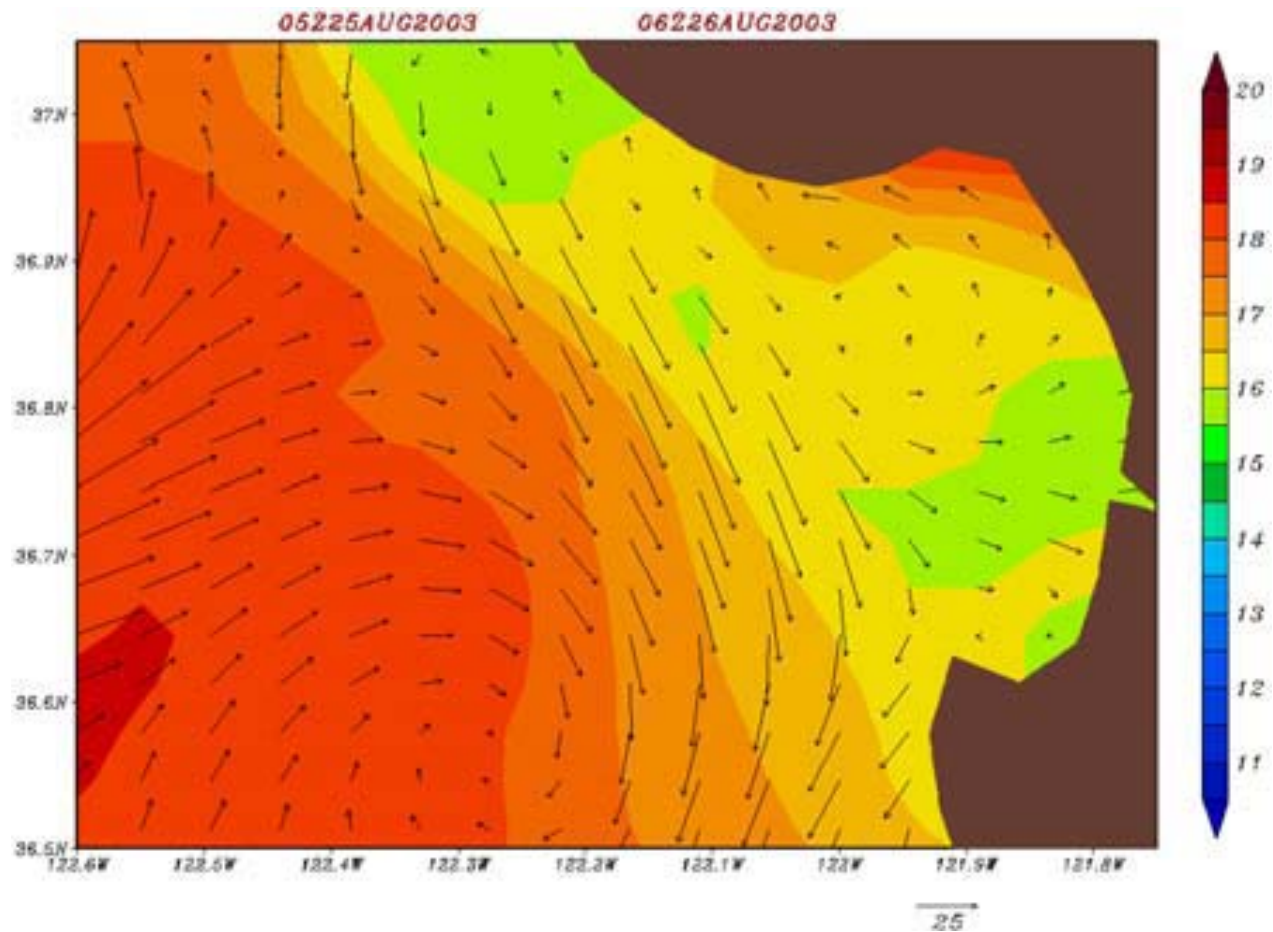
Difference between modeled and observed data

- Model
 - Regular in (t, x, y, z)
 - Representing mean value of a grid cell
- Observation
 - Irregular in (t, x, y, z) usually noisy and sparse
 - Representing value at the observational point

Example: RAFOS Floats (NPS#92) in Monterey Bay (Collins' website)



NCOM Model Data (Hong et al. 2005)

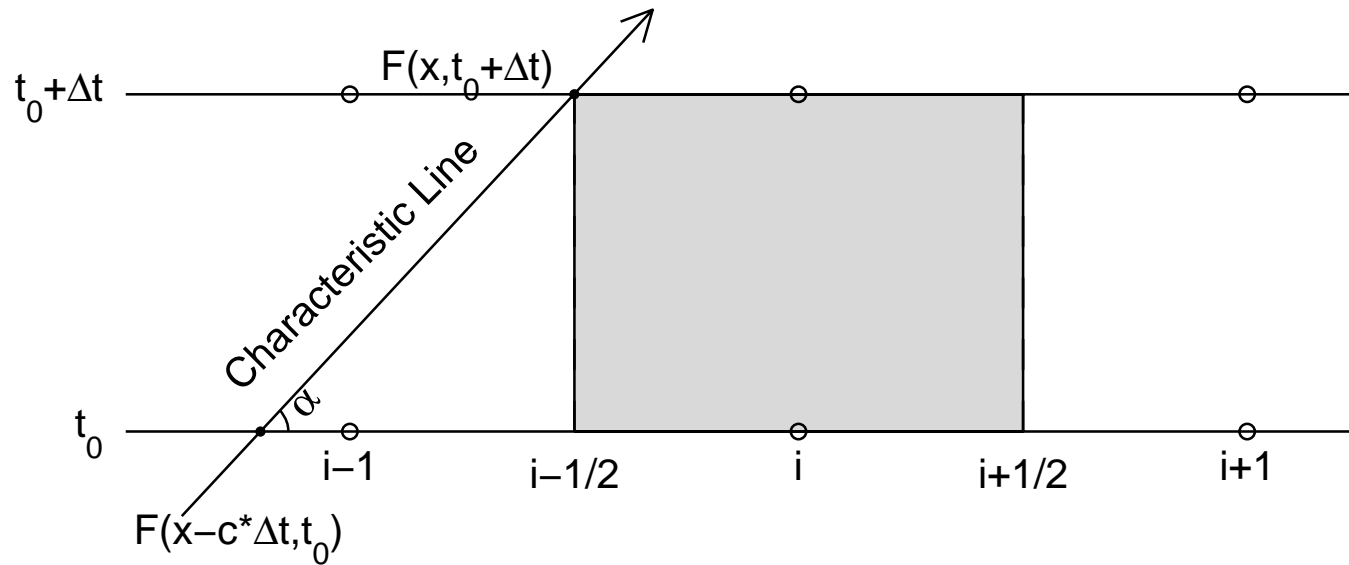


Advection-Diffusion Equation

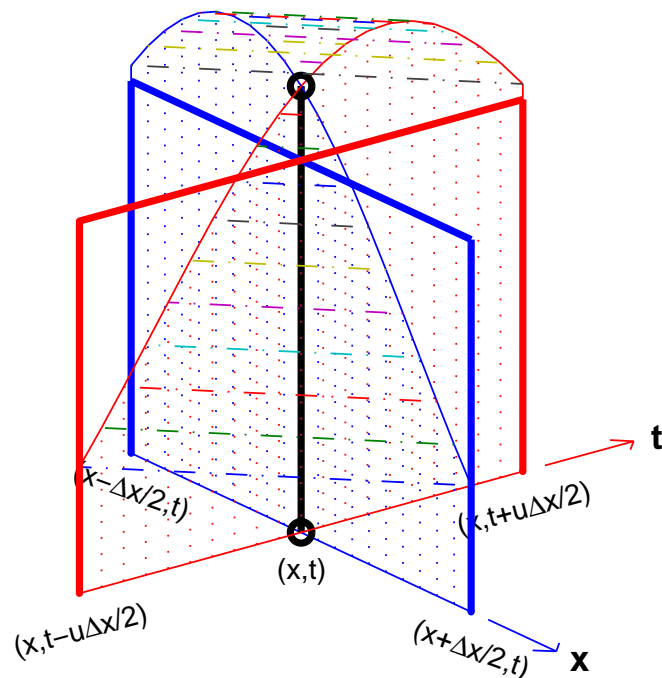
$$\frac{\partial \Phi}{\partial t} + \nabla \cdot (\mathbf{V}\Phi) = \nabla \cdot (\kappa \nabla \Phi) + S.$$

$$\frac{\tilde{\Phi}_{i,j,k}^{n+1} - \tilde{\Phi}_{i,j,k}^n}{\Delta t} = \frac{\langle \overline{F} \rangle_{i+\frac{1}{2},j,k} - \langle \overline{F} \rangle_{i-\frac{1}{2},j,k}}{\Delta x} + \frac{\langle \overline{G} \rangle_{i,j+\frac{1}{2},k} - \langle \overline{G} \rangle_{i,j-\frac{1}{2},k}}{\Delta y} + \frac{\langle \overline{H} \rangle_{i,j,k+\frac{1}{2}} - \langle \overline{H} \rangle_{i,j,k-\frac{1}{2}}}{\Delta z} + \hat{S}_{i,j,k},$$

Characteristic Line



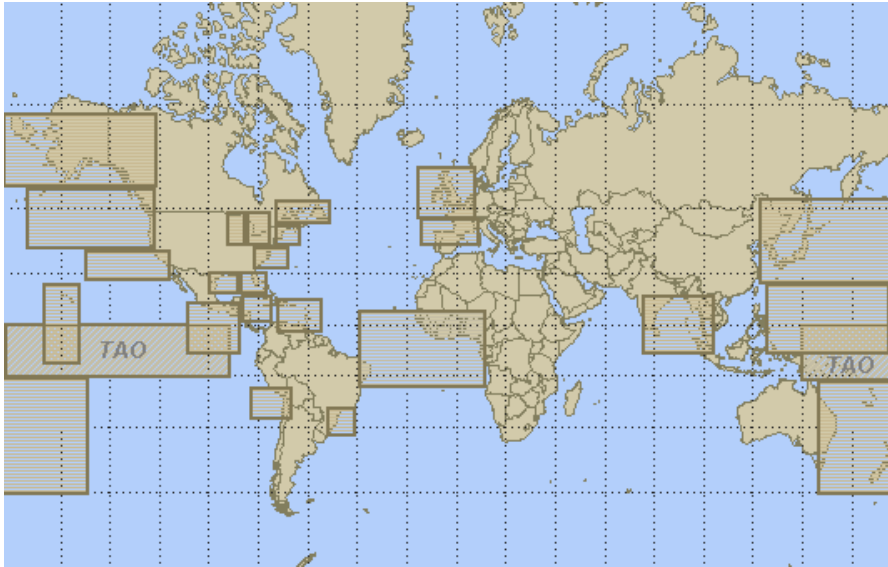
Modeled-Observational Data Difference at the same location



- (1) Observation \rightarrow along the red curve
- (2) Model \rightarrow spatial mean (upper blue line)
- (3) Temporal mean of observation \leftrightarrow Model

NOAA Buoy Data Center \leftrightarrow WAM

significant wave height



WAM-4 model
(Galanis et al., 2006)

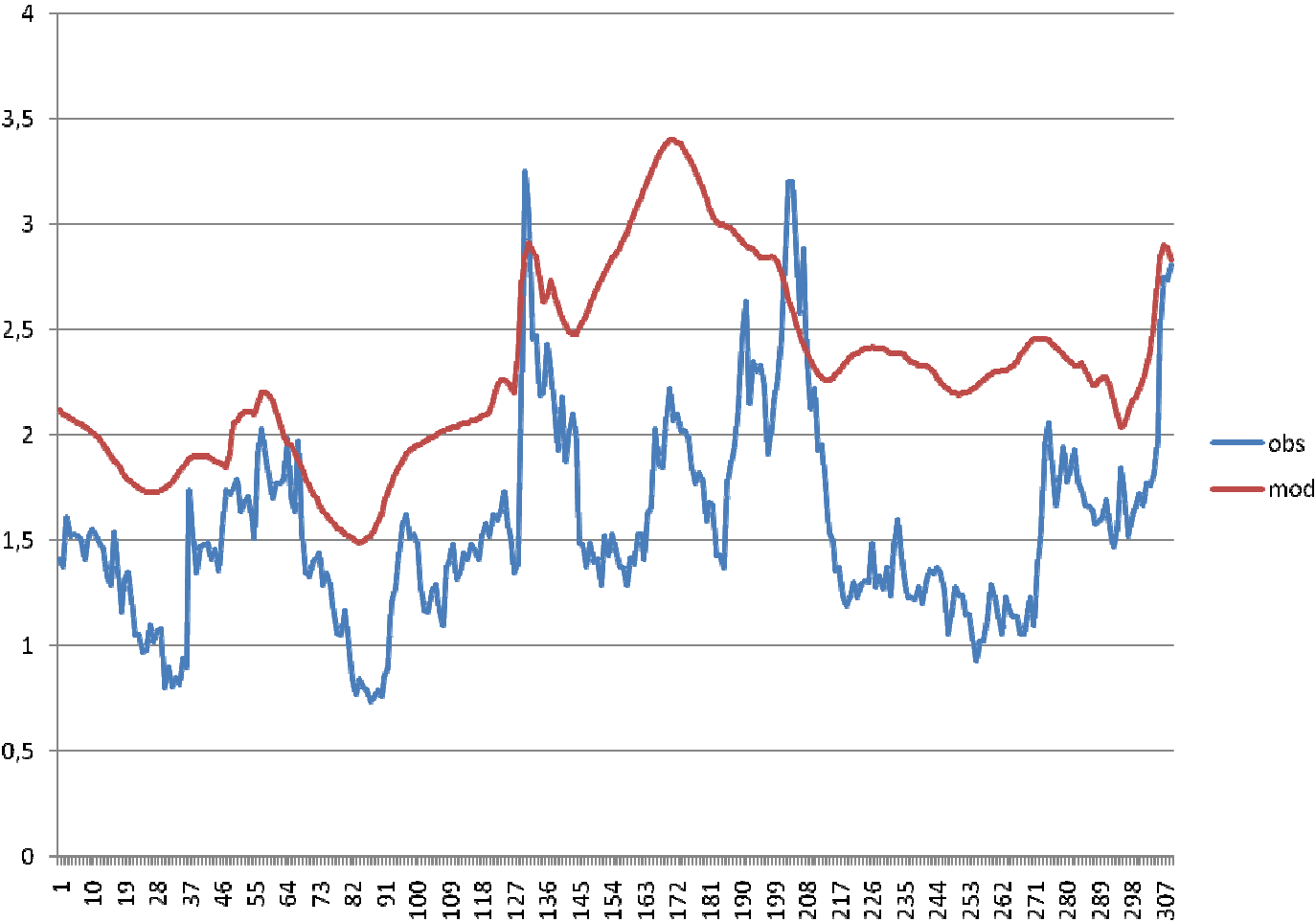
Near California Coast



WAM -4

- (1) Integrating on 30 frequencies and 24 directions.
- (2) First integration frequency \rightarrow 0.0417 Hz
- (3) Time step \rightarrow 300 seconds
- (4) Spatial grid \rightarrow $0.5^\circ \times 0.5^\circ$
- (5) Wind input (10 m) \rightarrow NCEP/GFS $0.5^\circ \times 0.5^\circ$

Observational and WAM Modeled Data



Part-2 Data Filtering

Kolmogorov-Zurbenko (KZ) Filter

KZ Filter

- Original Data

$$x_i^0$$

- First Iteration

$$x_i^1 = \frac{1}{2q+1} \sum_{j=-q}^q x_{i+j}^0$$

- Second Iteration

$$x_i^2 = \frac{1}{2q+1} \sum_{j=-q}^q x_{i+j}^1,$$

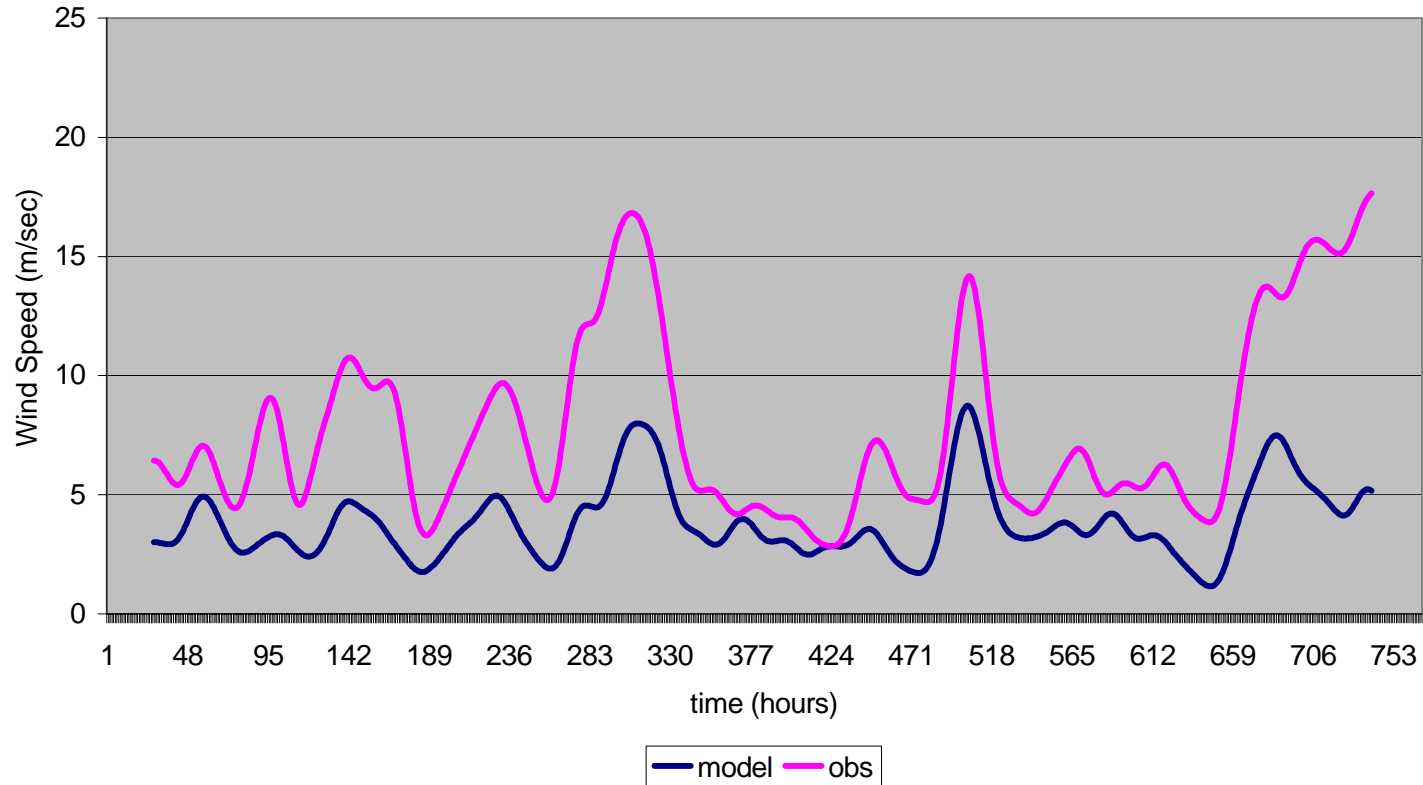
- Number of Iteration (N) $(2q+1) \cdot \sqrt{N} \leq P$

- $P \rightarrow$ Time Steps

- Appropriate selection of the parameters (N, P, q) leads to smoothed time series of observational and modeled data

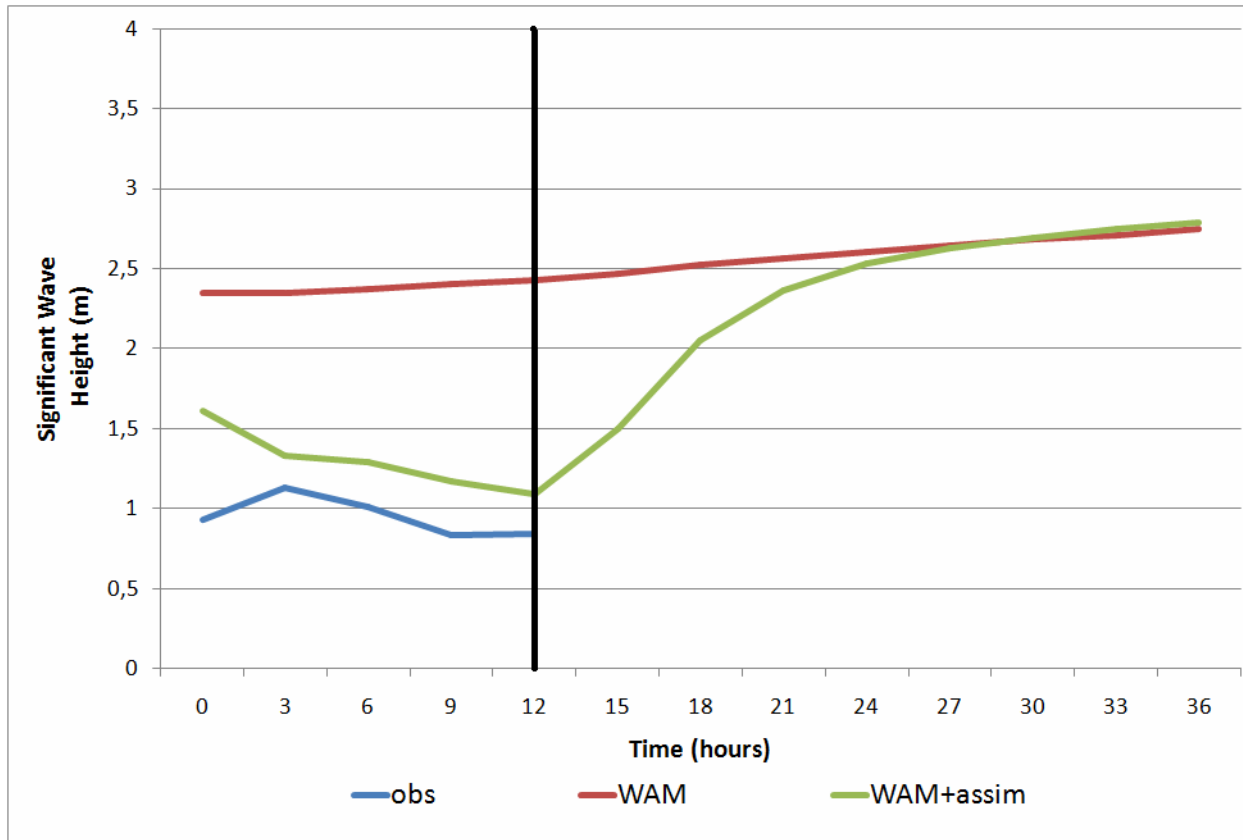
Observations vs Forecasts

Filtered data (> 1 day)



Daily variability has been removed.
The systematic error has not been affected.

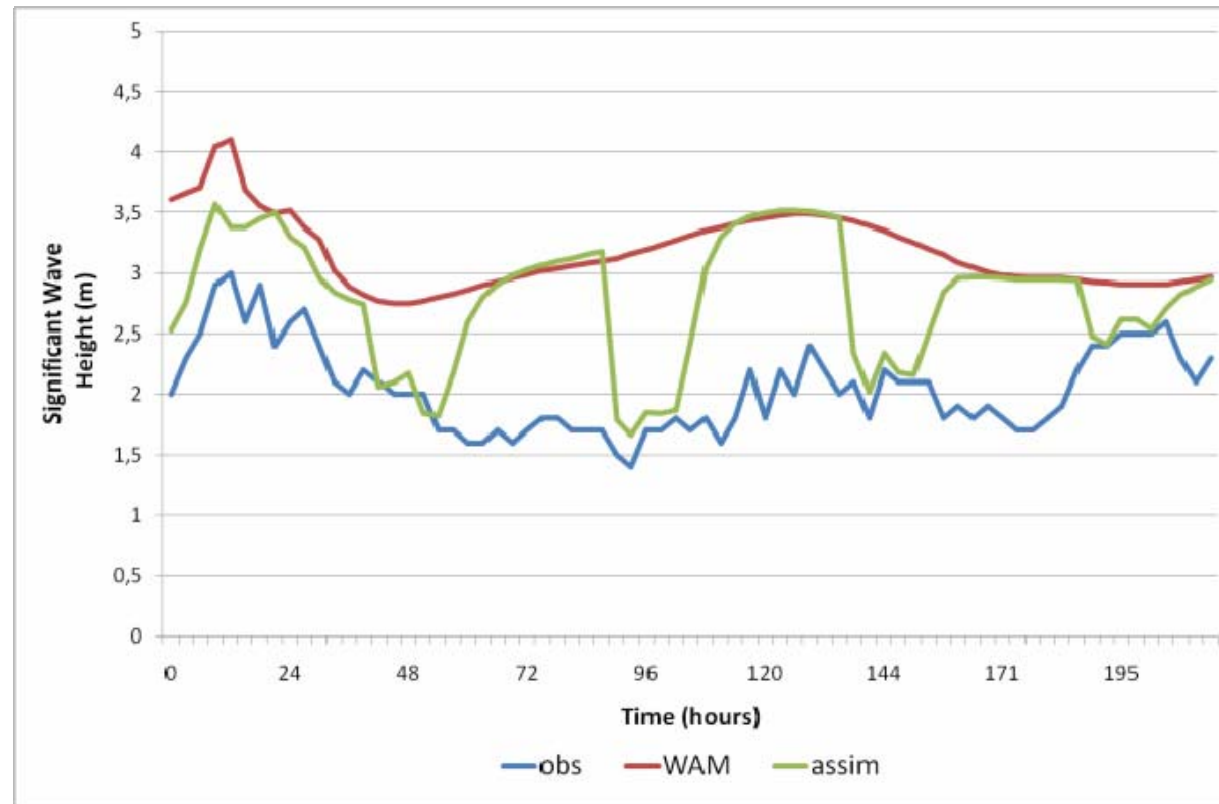
Data Assimilation Window (12 hrs)



Assimilating SWH for 12 hrs and running the model for 24 hrs

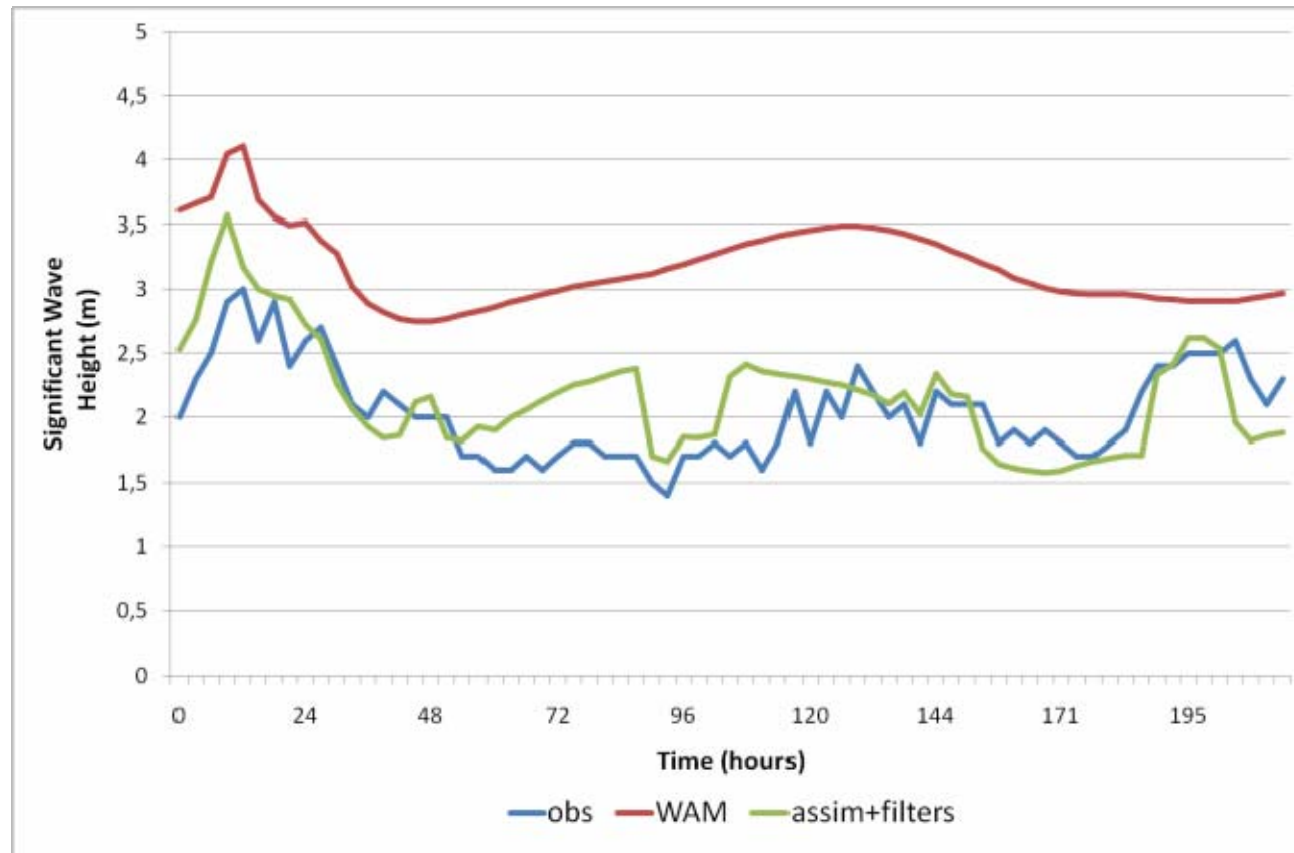
Assimilation → Kalman Filter

Model with data assimilation (Kalman Filter) and no KZ (Buoy- D)



Data (Significant Wave Height) input → Every hours

Model with data assimilation (Kalman Filter) and KZ (Buoy- D)



Impact of Data Assimilation and Filtering

WAM-no assimilation and KZ filtering
 WAM2 –assimilation and no KZ filtering
 WAM3 – Assimilation and KZ-filtering

	Buoy A			Buoy B			Buoy C		
	WAM	WAM2	WAM3	WAM	WAM2	WAM3	WAM	WAM2	WAM3
Bias	0.51	0.21	0.02	0.39	0.08	-0.19	0.99	0.72	0.33
RMSE	0.70	0.55	0.46	0.64	0.49	0.47	1.10	0.89	0.55
Nbias	0.42	0.28	0.21	0.33	0.22	0.17	1.05	0.73	0.40
	Buoy D			Buoy E			Buoy F		
	WAM	WAM2	WAM3	WAM	WAM2	WAM3	WAM	WAM2	WAM3
Bias	0.68	0.39	0.10	0.62	0.27	-0.02	0.88	0.44	0.02
RMSE	0.80	0.60	0.38	0.79	0.56	0.42	0.96	0.65	0.27
Nbias	0.44	0.27	0.16	0.43	0.24	0.15	0.74	0.38	0.15

Part-3

Optimal Spectral Decomposition

Spectral Decomposition

$$u_{KM} = \sum_{k=1}^K a_k(z, t^\circ) \frac{\partial \Psi_k(x, y, z, \kappa^\circ)}{\partial y} + \sum_{m=1}^M b_m(z, t^\circ) \frac{\partial \Phi_m(x, y, z)}{\partial x},$$
$$v_{KM} = - \sum_{k=1}^K a_k(z, t^\circ) \frac{\partial \Psi_k(x, y, z, \kappa^\circ)}{\partial x} + \sum_{m=1}^M b_m(z, t^\circ) \frac{\partial \Phi_m(x, y, z)}{\partial y}$$

Basis Functions (Open Boundaries)

(Chu et al., 2003 a,b JTECH)

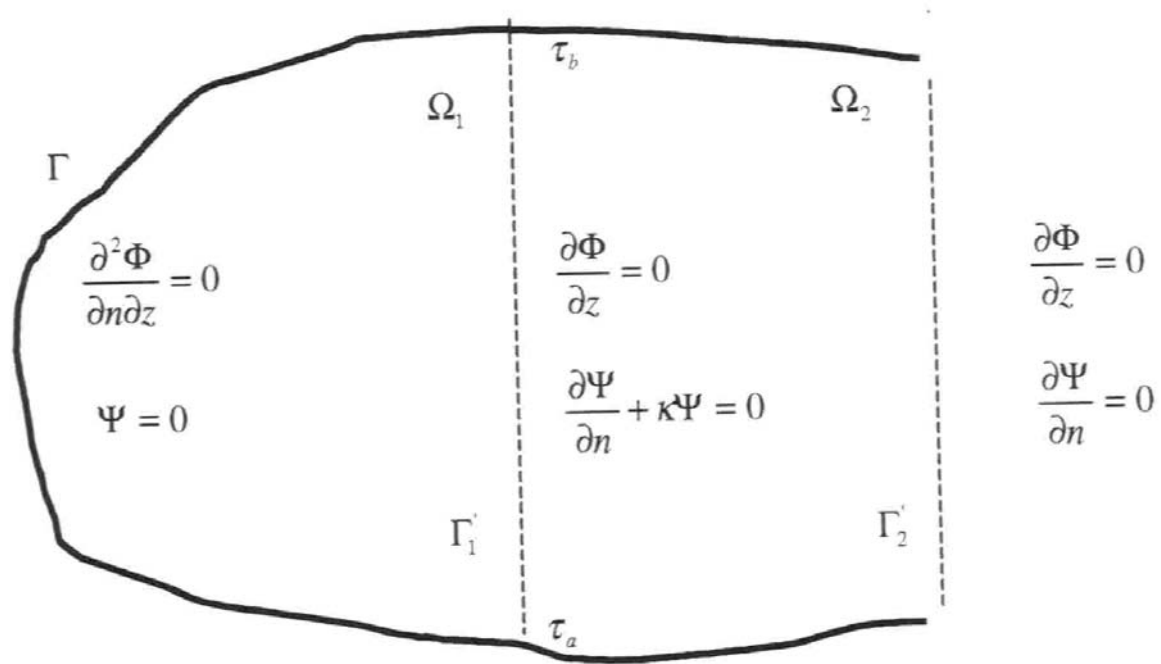
$$\Delta \Psi_k = -\lambda_k \Psi_k,$$

$$\Delta \Phi_m = -\mu_m \Phi_m,$$

$$\Psi_k|_{\Gamma} = 0, \quad \frac{\partial \Phi_m}{\partial n}|_{\Gamma} = 0,$$

$$\left[\frac{\partial \Psi_k}{\partial n} + \kappa(\tau) \Psi_k \right] |_{\Gamma'_1} = 0, \quad \Phi_m|_{\Gamma'_1} = 0,$$

Boundary Conditions



Benefit of Using OSD

- Ocean Topographic Configuration →
Basis Functions (Pre-Determined)

Vapnik (1983) Cost Function → Optimal Mode Truncation

$$J(a_1, \dots, a_K, b_1, \dots, b_M, \kappa, P) = \frac{1}{2} \left(\|u_p^{obs} - u_{KM}\|_P^2 + \|v_p^{obs} - v_{KM}\|_P^2 \right) \rightarrow \min,$$

$$J_{emp} = J(a_1, \dots, a_K, b_1, \dots, b_M, \kappa, P).$$

$$\text{Prob} \left\{ \sup_{K, M, S} |\langle J(K, M, S) \rangle - J_{emp}(K, M, S)| \geq \mu \right\} \leq g(P, \mu)$$

$$\lim_{P \rightarrow \infty} g(P, \mu) = 0$$

Optimal Truncation

- Gulf of Mexico, Monterey Bay, Louisiana-Texas Shelf, Tropical Atlantic
- $K_{\text{opt}} = 40$, $M_{\text{opt}} = 30$

Determination of Spectral Coefficients (Ill-Posed Algebraic Equation)

$$\mathbf{A} \hat{\mathbf{a}} = \mathbf{QY},$$

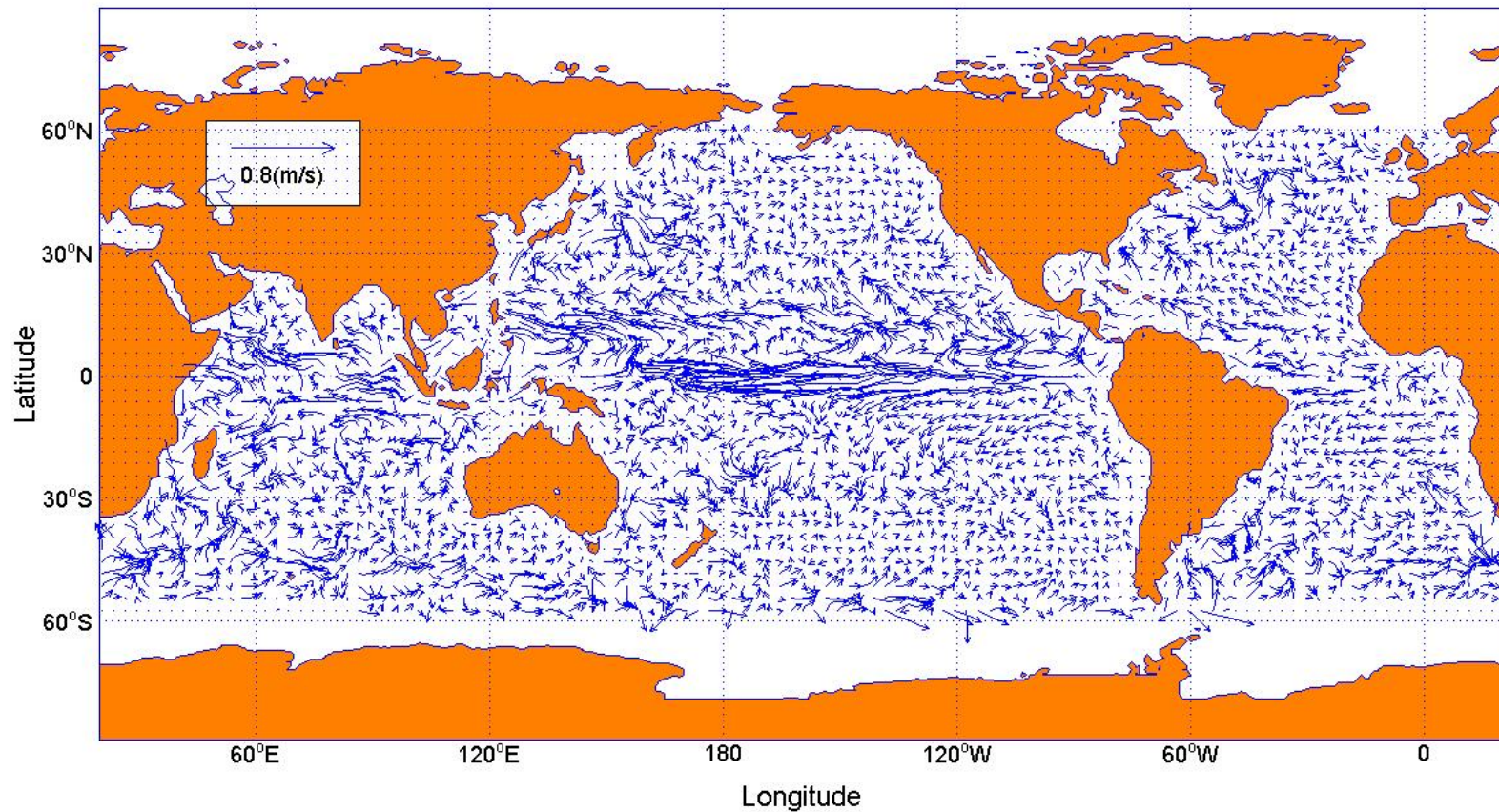
Rotation Method (Chu et al., 2004)

$$\mathbf{SA}\hat{\mathbf{a}} = \mathbf{SQY},$$

$$J_1 = \|\mathbf{A}\|^2 - \frac{\|\mathbf{SQY}\|^2}{\|\mathbf{a}\|^2} \rightarrow \max,$$

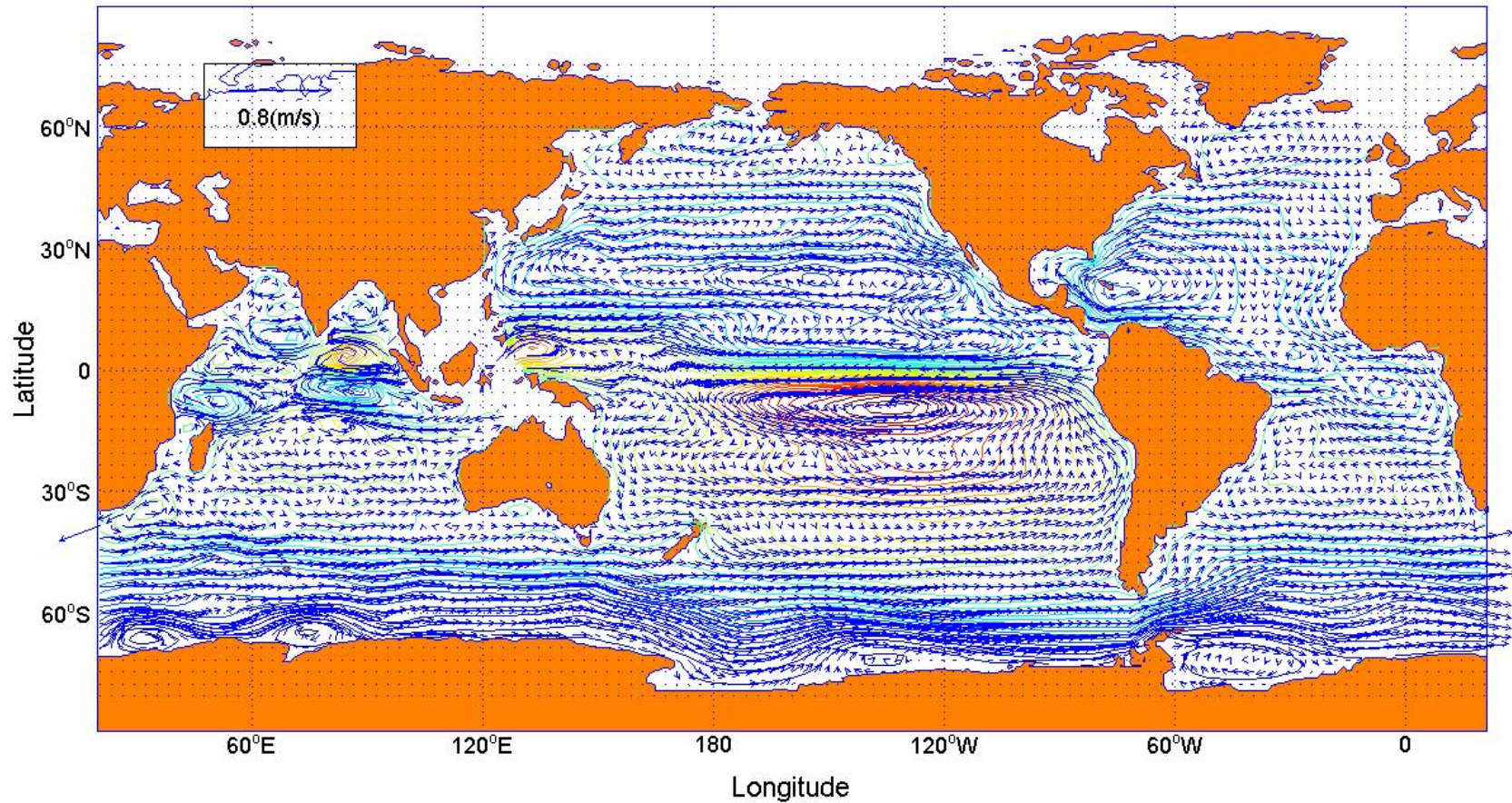
Near-realtime ocean surface currents derived from satellite altimeter and scatterometer data
NOAA OSCAR Data: <http://www.oscar.noaa.gov/>

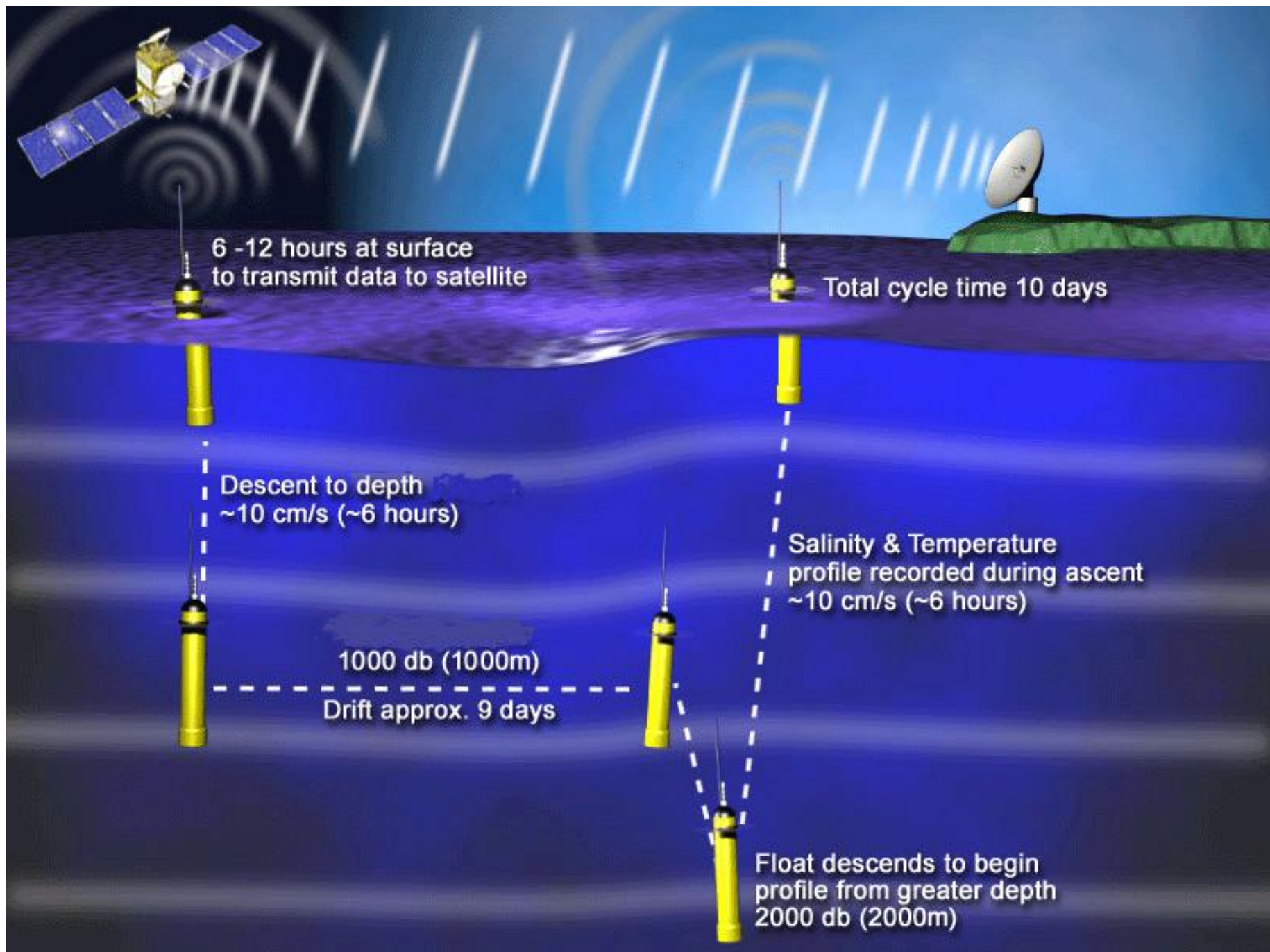
Original Data 2007 Jan 14



OSD on OSCAR Data

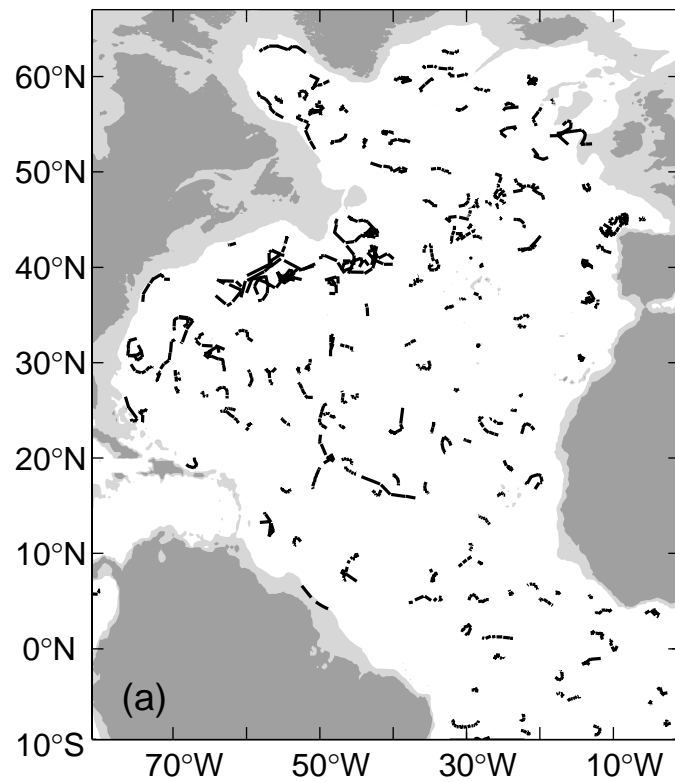
OSD smooth data 2007 Jan 24



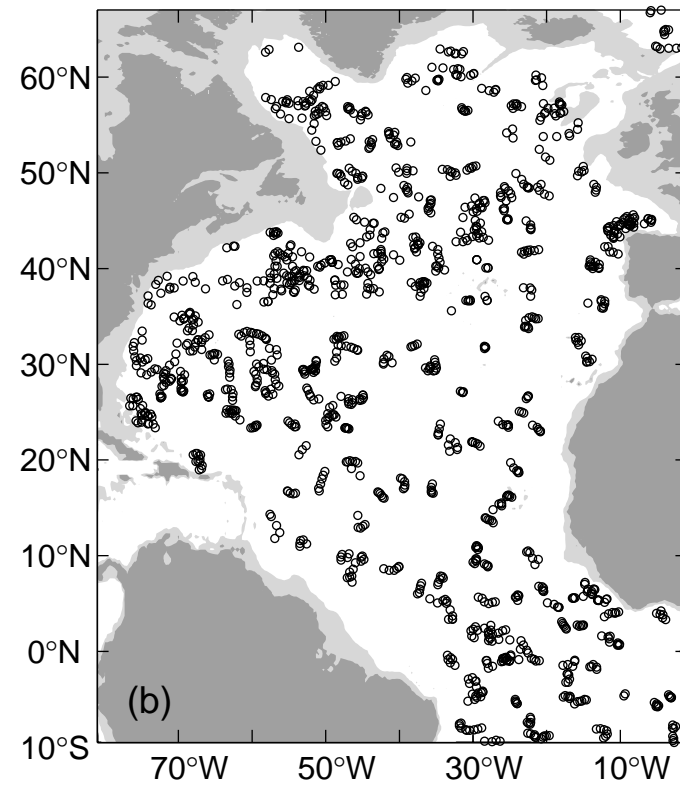


ARGO Observations (Oct-Nov 2004)

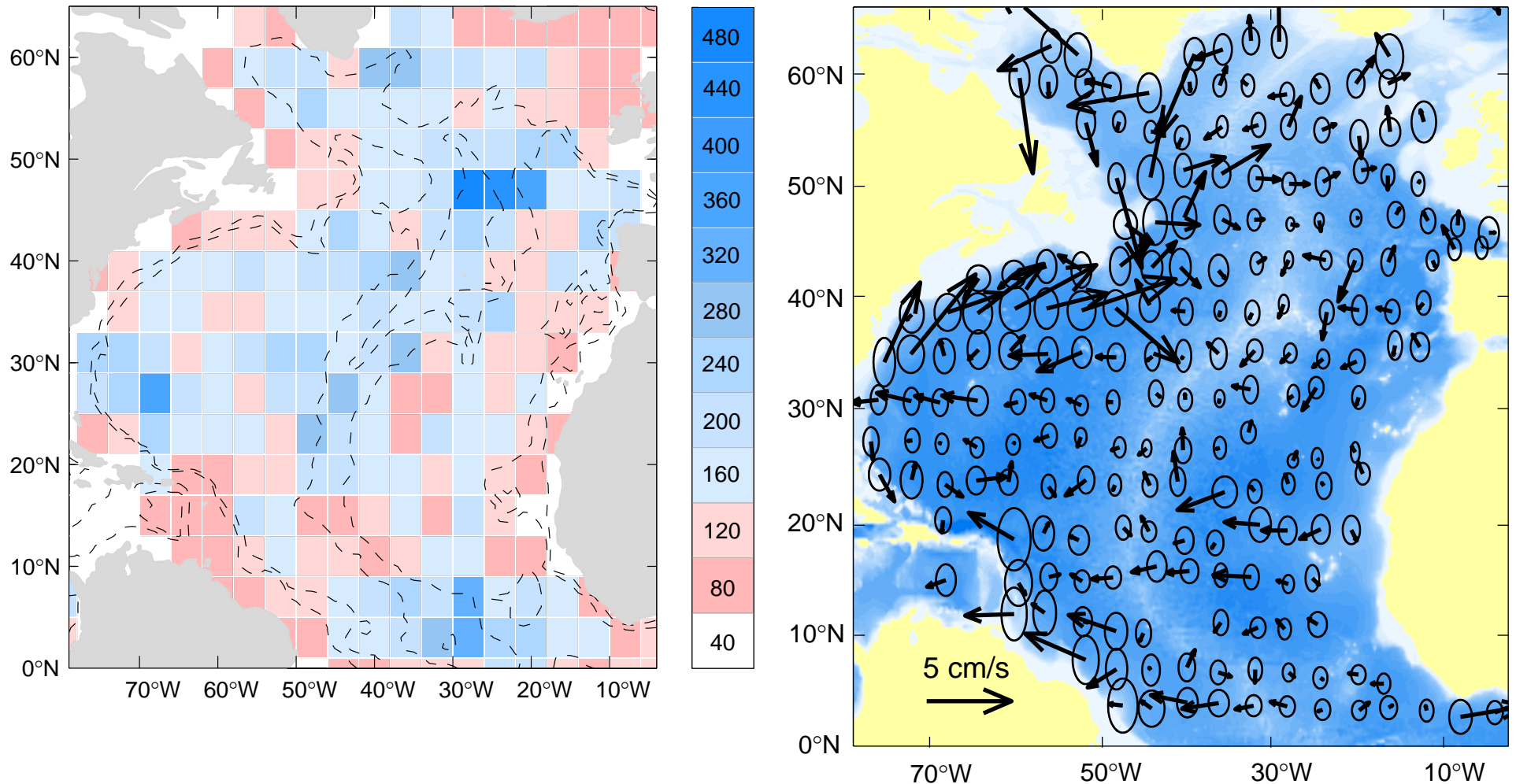
(a) Subsurface tracks



(b) Float positions where (T,S) were measured

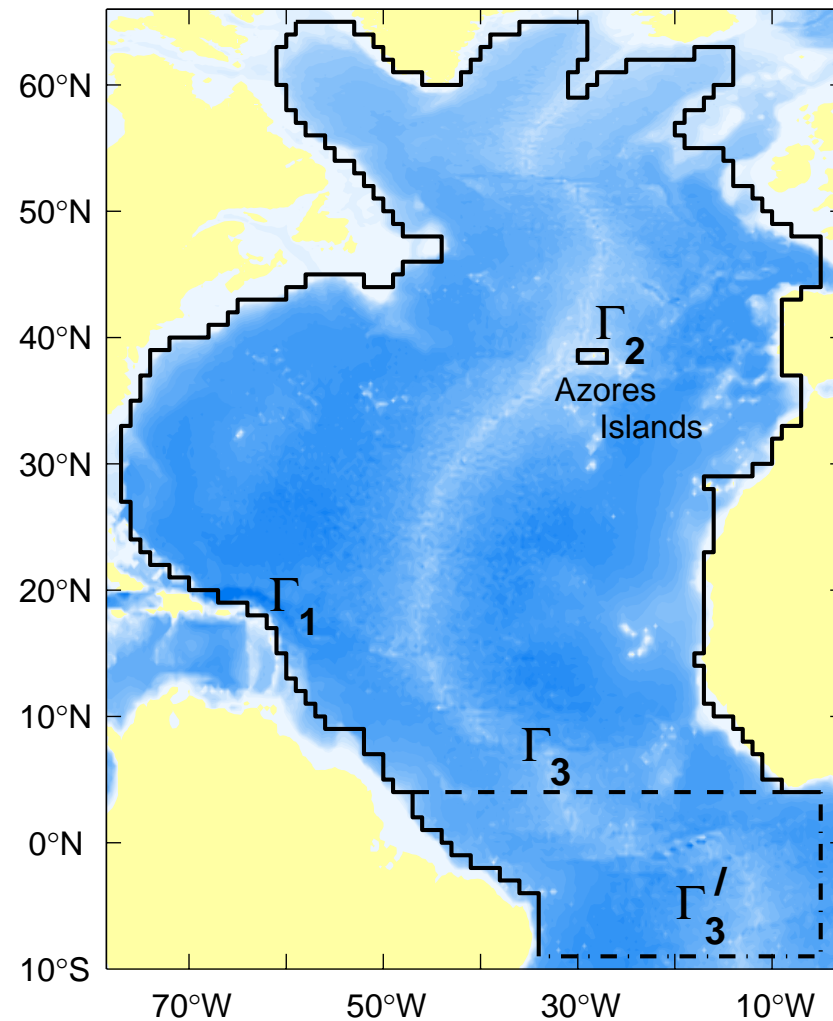


Circulations at 1000 m estimated from the original ARGO float tracks (bin method) April 2004 – April 2005

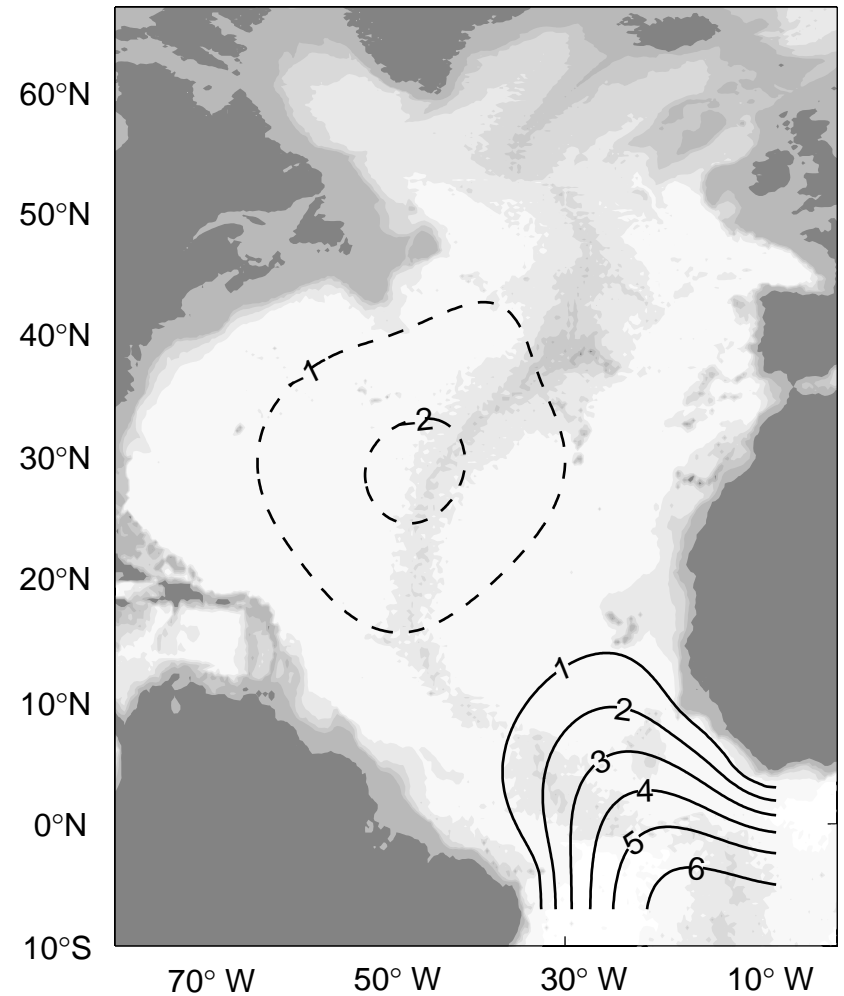
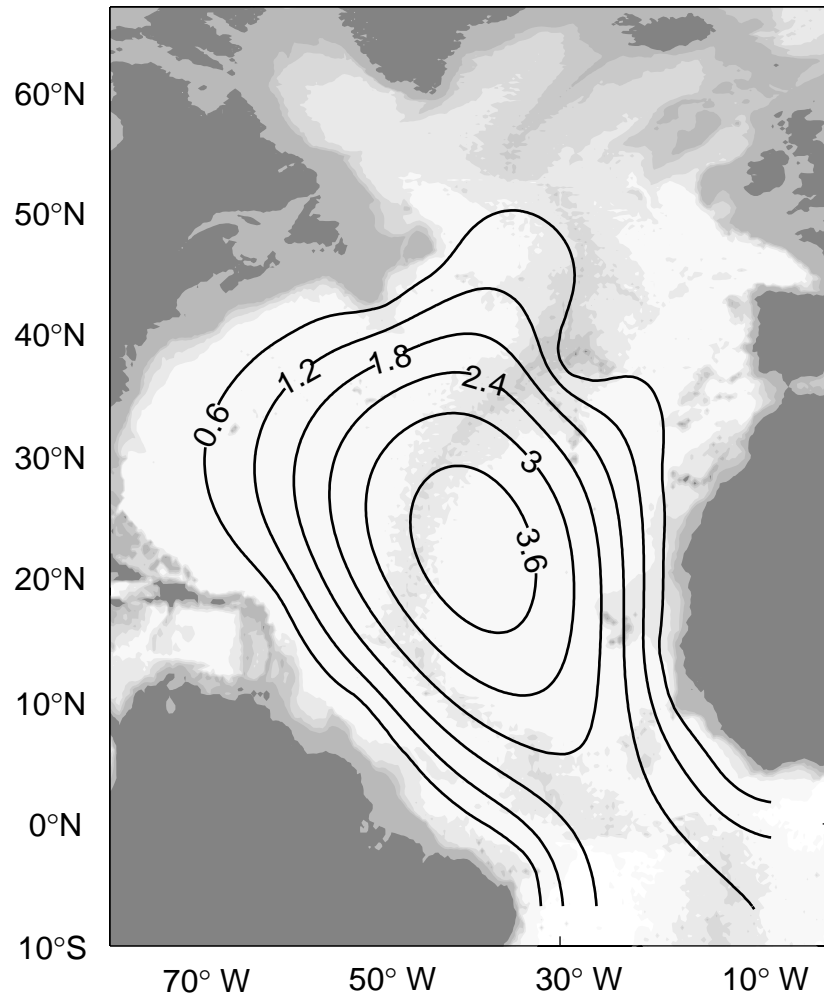


It is difficult to use such noisy data into ocean numerical models.

Boundary Configuration → Basis Functions for OSD



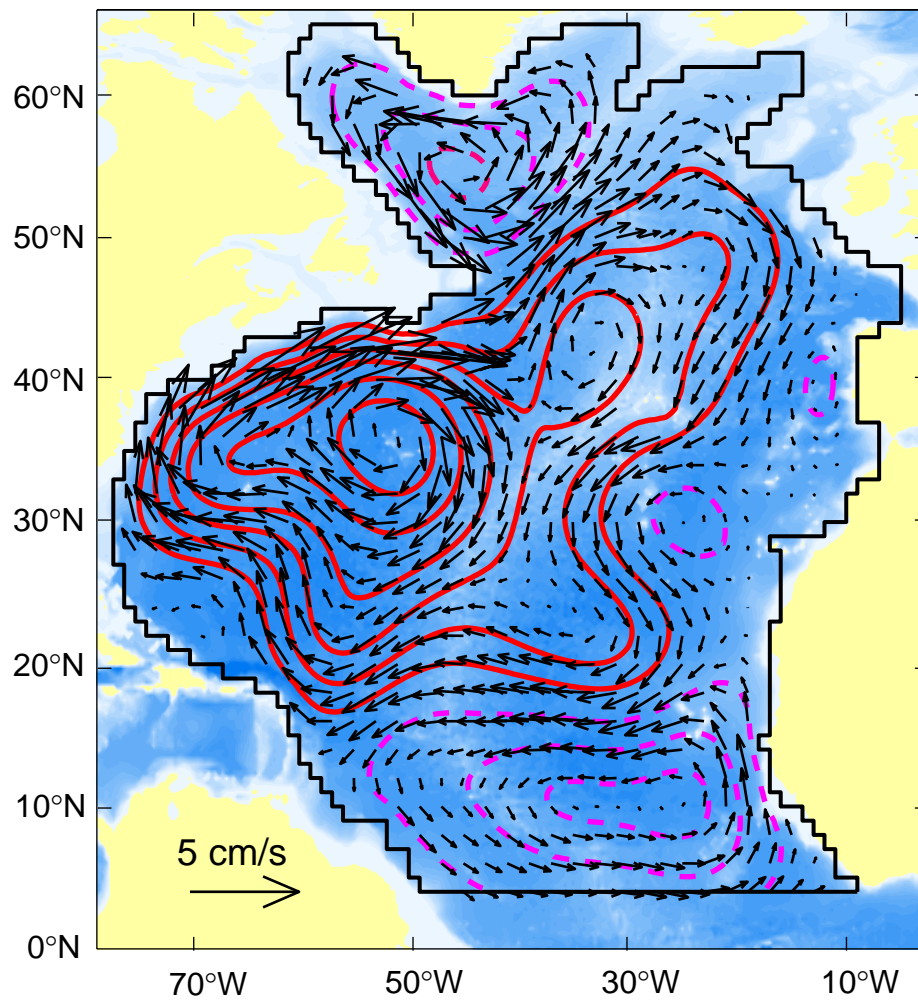
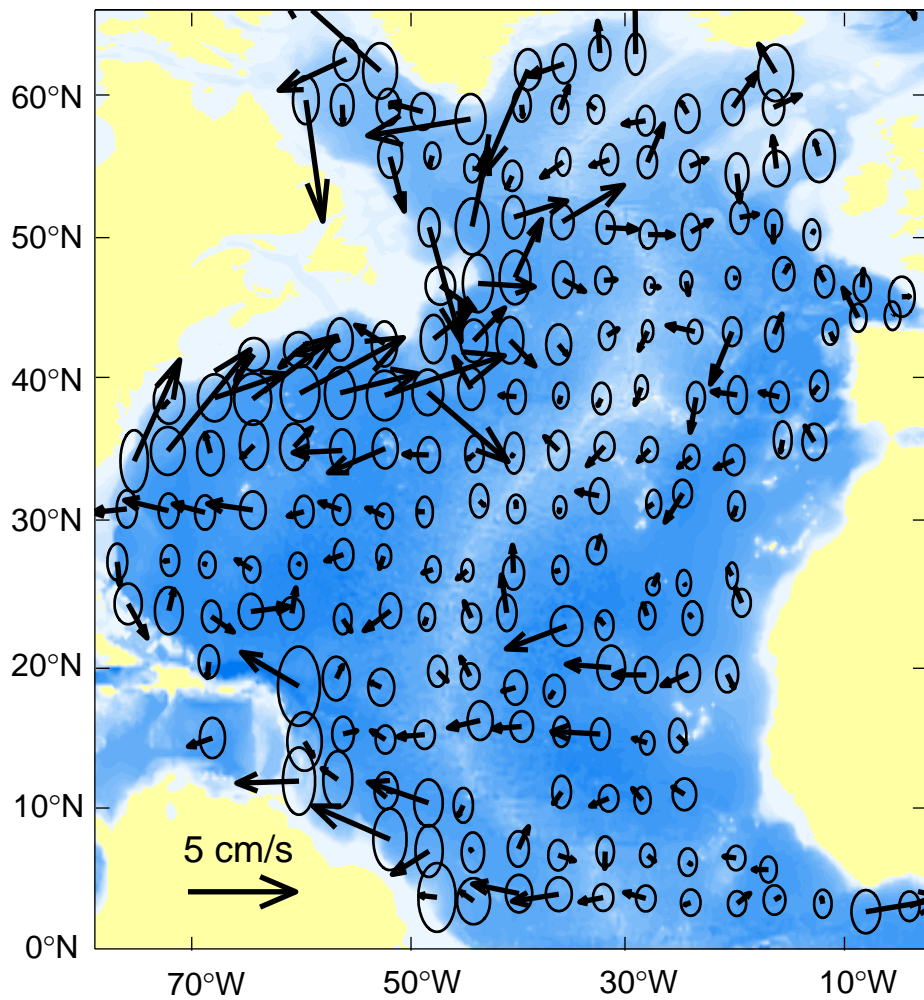
Basis Functions for Streamfunction Mode-1 and Mode-2



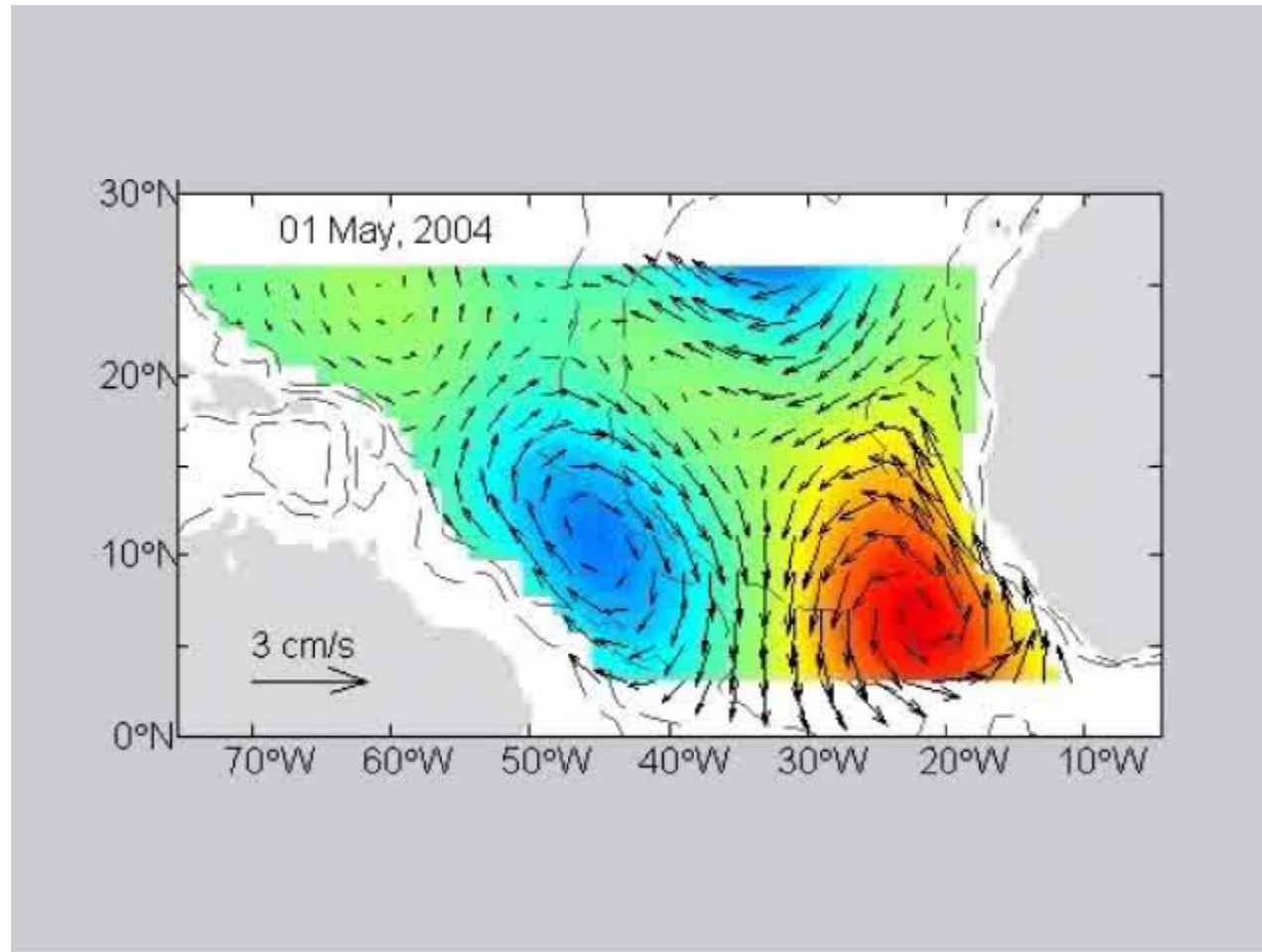
Circulations at 1000 m (March 04 to May 05)

Bin Method

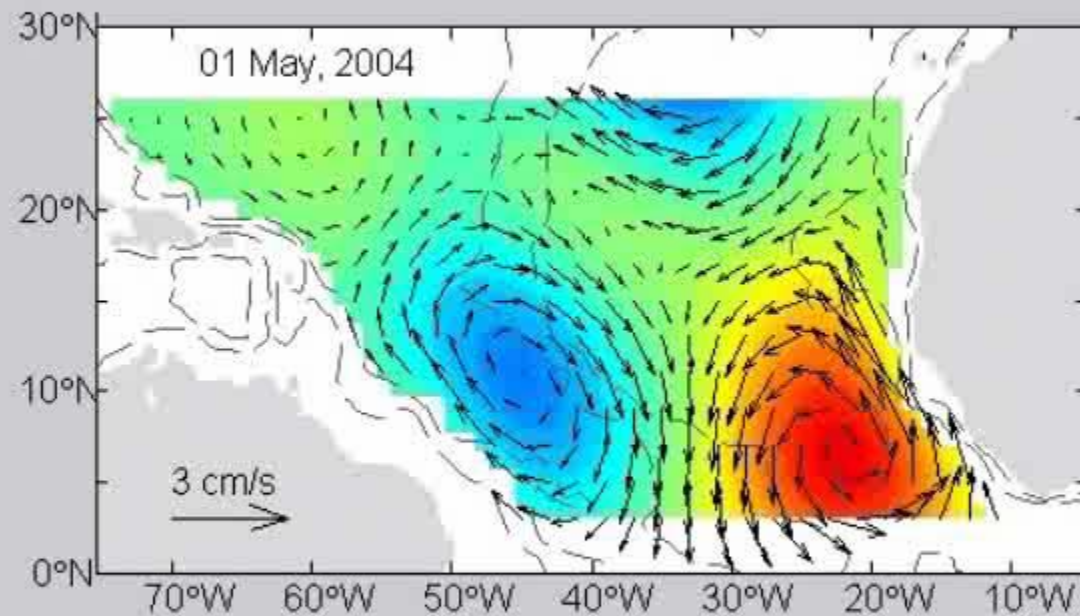
OSD



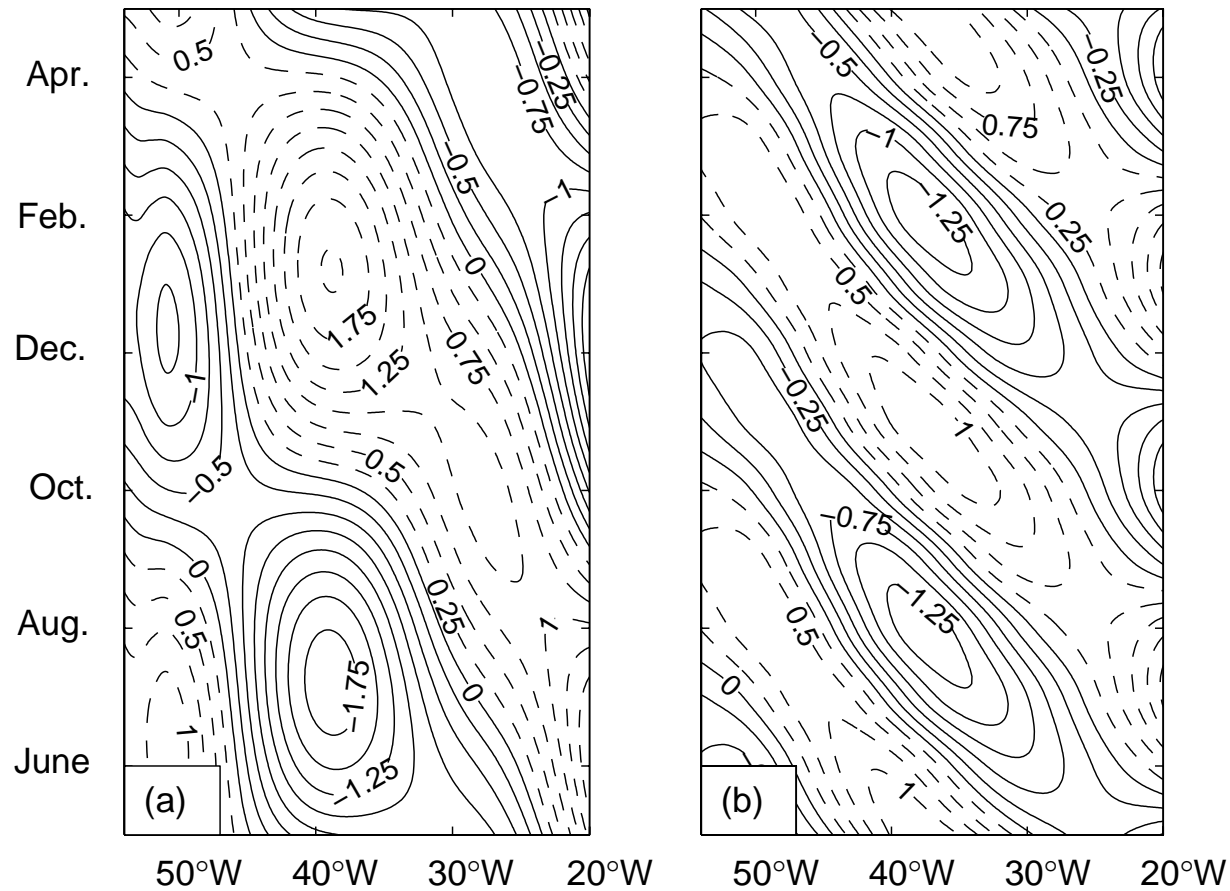
Annual Component



Semi-annual Component



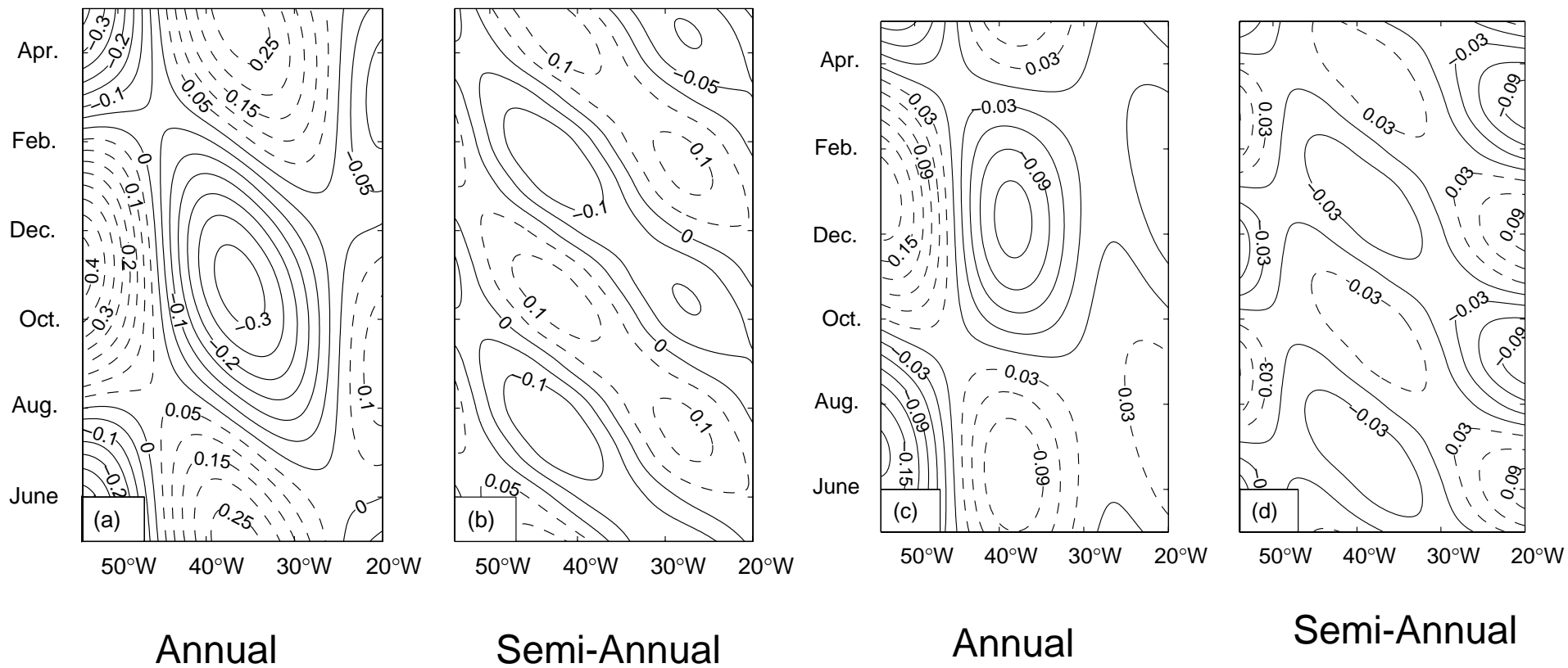
Time –Longitude Diagrams of Meridional Velocity Along 11°N



Annual

Semi-Annual

Time –Longitude Diagrams of temperature Along 11°N

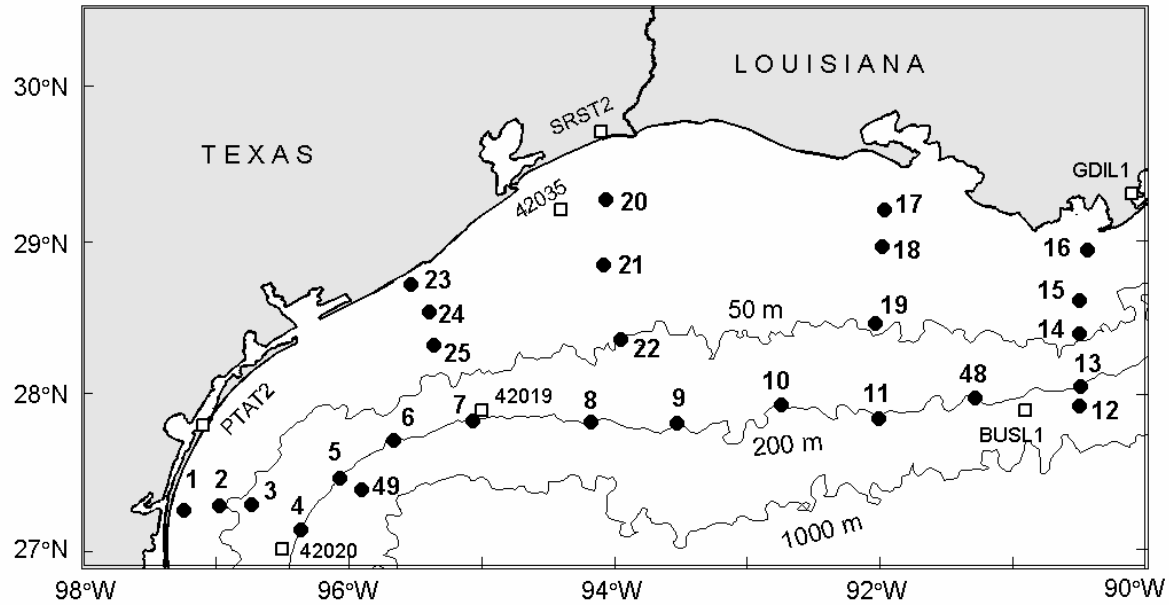


OSD for Analyzing Combined Current Meter and Surface Drifting Buoy Data

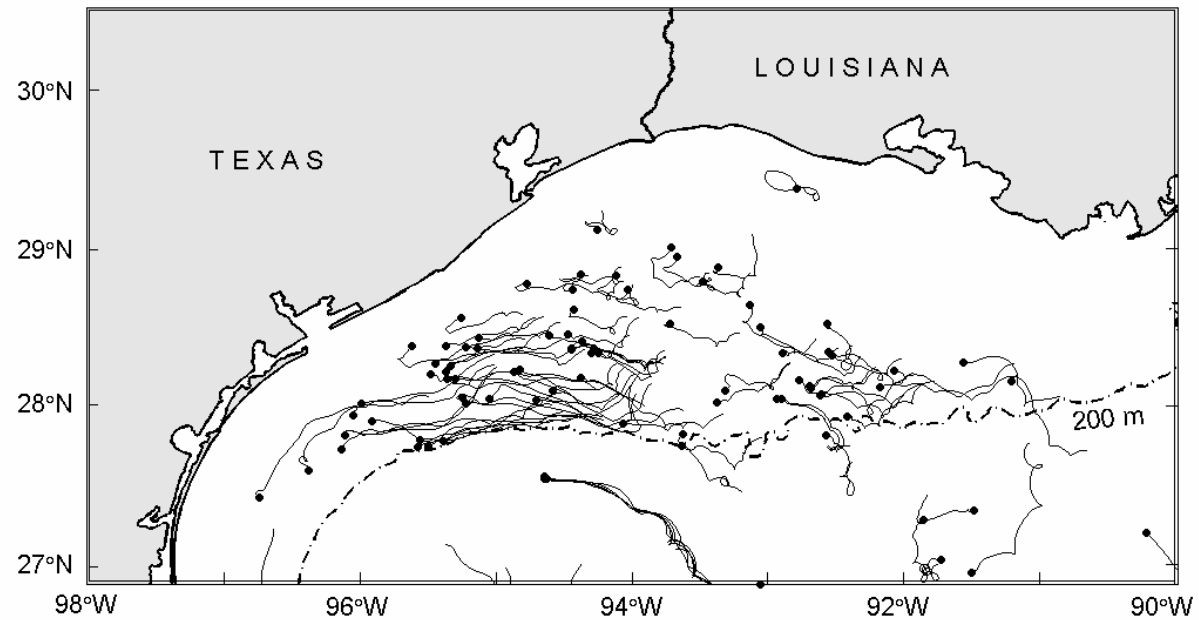
Ocean Velocity Observation

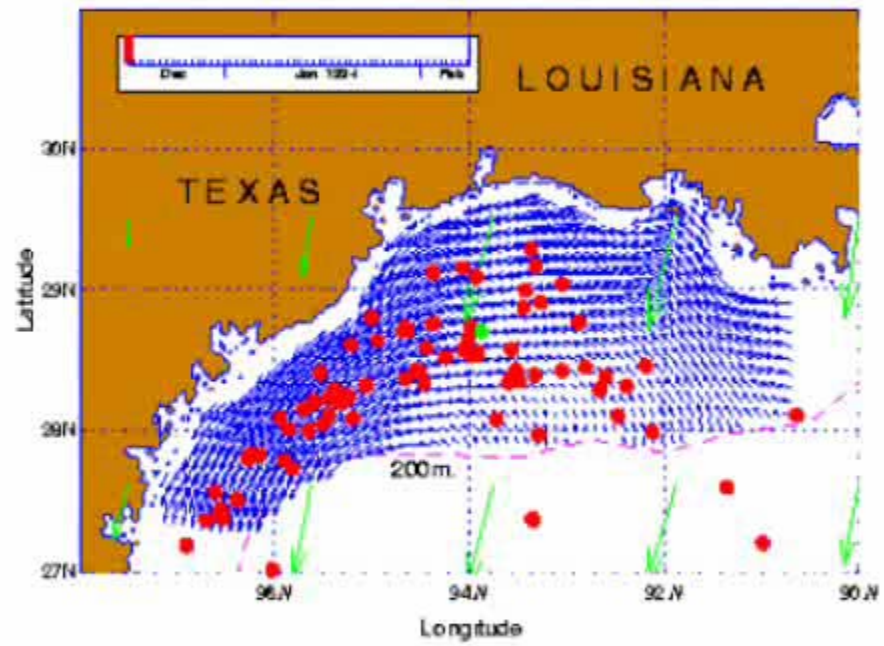
- 31 near-surface (10-14 m) current meter moorings during LATEX from April 1992 to November 1994
- Drifting buoys deployed at the first segment of the Surface Current and Lagrangian-drift Program (SCULP-I) from October 1993 to July 1994.

Moorings and Buoys



LTCS current reversal detected from SCULP-I drift trajectories.





Conclusions

- (1) Data analysis is important for coastal modeling and prediction.
- (2) KZ filter reduces model-data incompatibility.
- (3) OSD is an effective method for establishing gridded data from sparse and noisy ocean observations.