A – MISSION:
Autonomous Marine Intelligent Swarming Systems for Interdisciplinary Observing Networks

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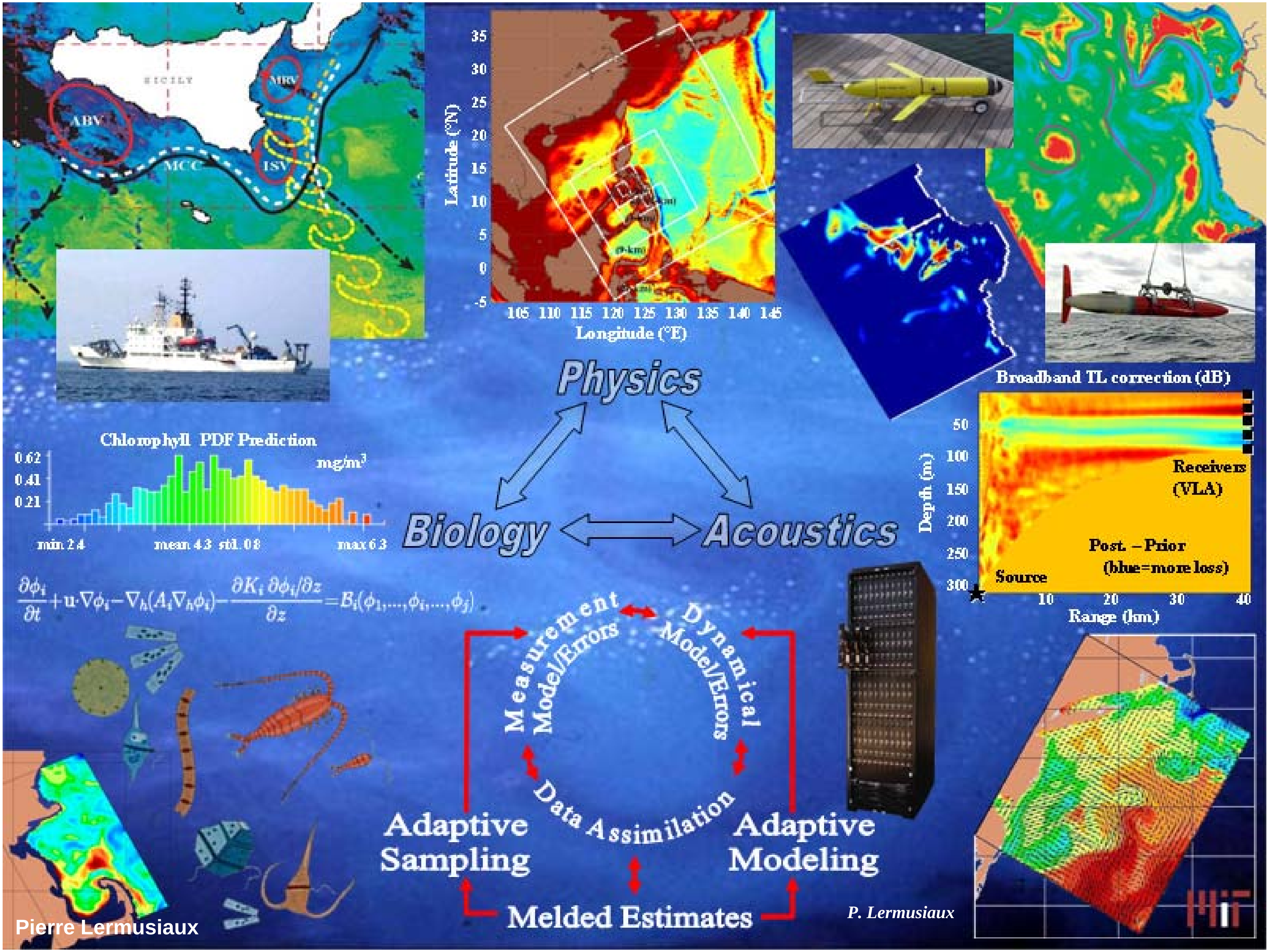
Multidisciplinary Simulation, Estimation and Assimilation Systems (MSEAS)
http://mseas.mit.edu/

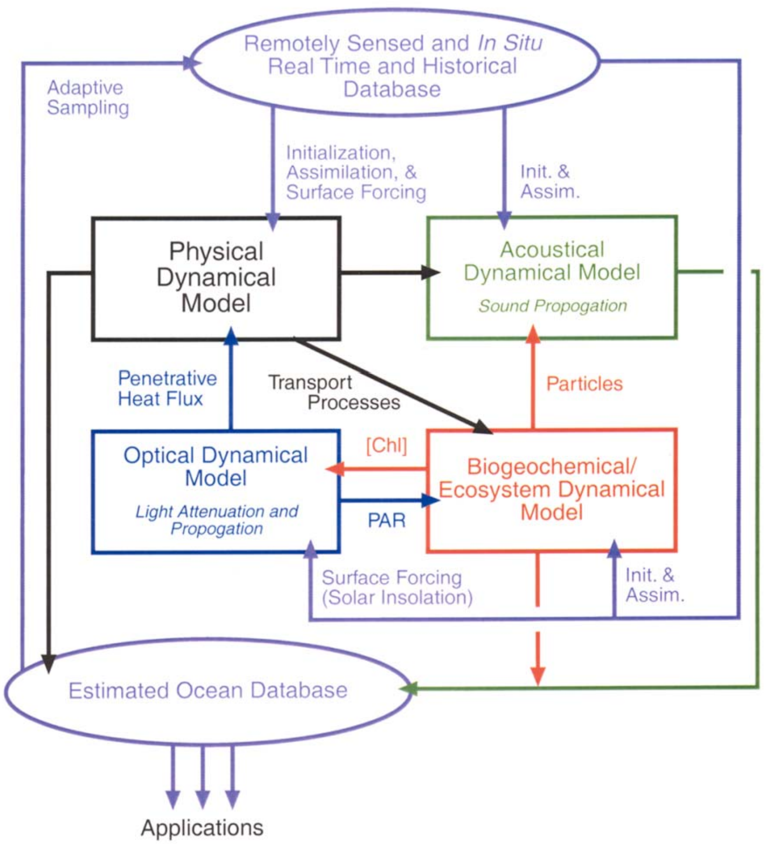
- **Introduction**
- **Research Goals and Problem Statement**
- **Our background in Ocean Autonomy and Adaptive Sampling**
- **Novel Science and Methodologies for Autonomous Marine Intelligent Swarming**
- **Some Items for Discussions**

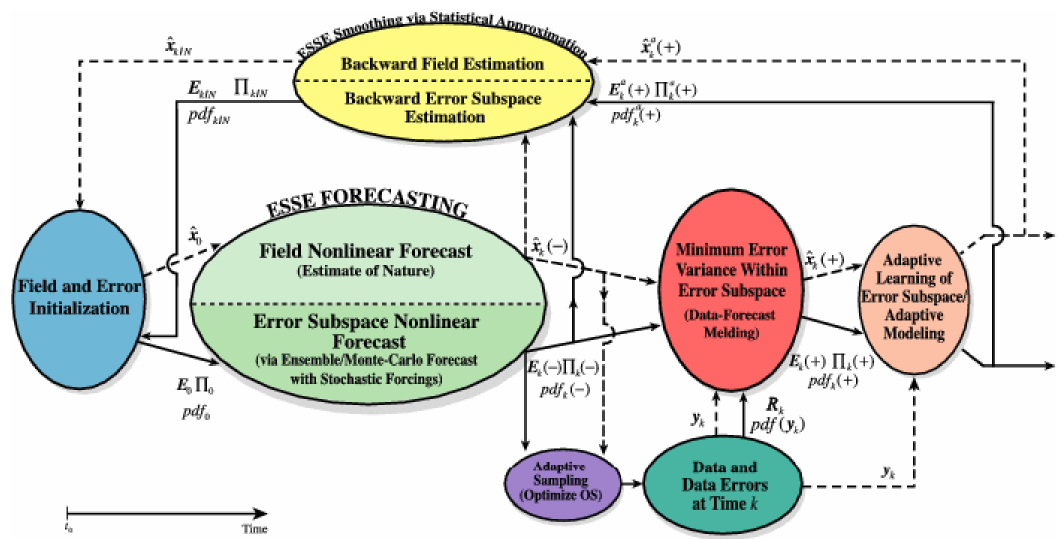
Thanks to ONR



SICILY
ABV
MRV
ISV
MCC
Latitude (°N)
Longitude (°E)
Physics
Biology
Acoustics
Chlorophyll PDF Prediction
mg/m^3
min 2.4
mean 4.3 std 0.8
max 6.3
$$\frac{\partial \phi_i}{\partial t} + u\cdot\nabla\phi_i - \nabla_h(A_i\nabla_h\phi_i) - \frac{\partial K_i\, \partial\phi_i/\partial z}{\partial z} = B_i(\phi_1,\ldots,\phi_i,\ldots,\phi_j)$$
Broadband TL correction (dB)
Depth (m)
Range (km)
Receivers (VLA)
Post. – Prior (blue=more loss)
Source
Measurement Model/Errors
Dynamical Model/Errors
Data Assimilation
Adaptive Sampling
Adaptive Modeling
Melded Estimates
P. Lermusiaux
Pierre Lermusiaux

MIT Multidisciplinary Simulation Estimation and Assimilation System (MSEAS)





Stochastic Ocean Modeling Systems

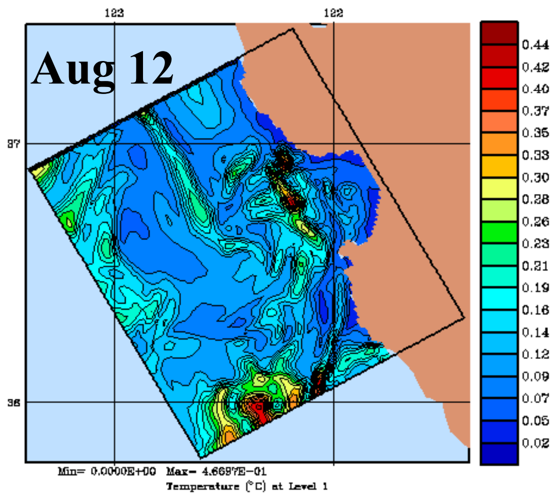
Free-surface PE, Generalized Biological models, Coupled to acoustic models, XML schemes to check configuration, unstructured grid models

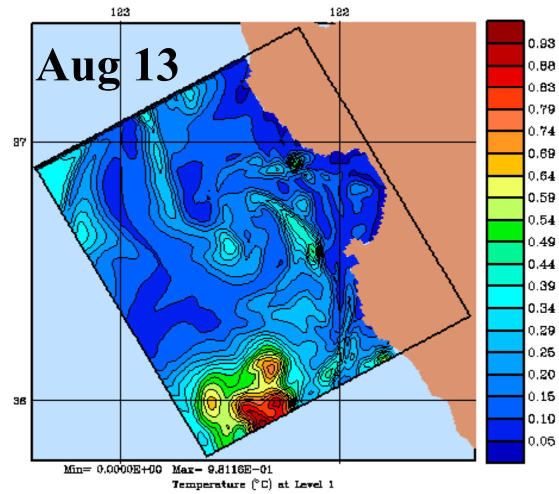
Error Subspace Statistical Estimation

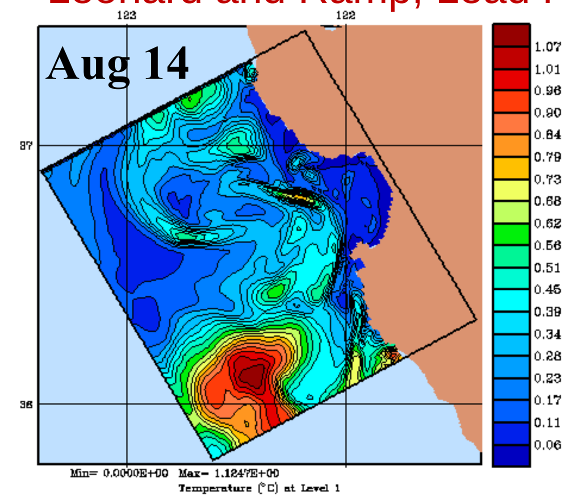
Uncertainty forecasts, Ensemble-based, Multivariate DA, Adaptive sampling, Adaptive modeling, Towards multi-model estimates

ESSE Surf. Temp. Error Standard Deviation Forecasts for AOSN-II

Leonard and Ramp, Lead PIs

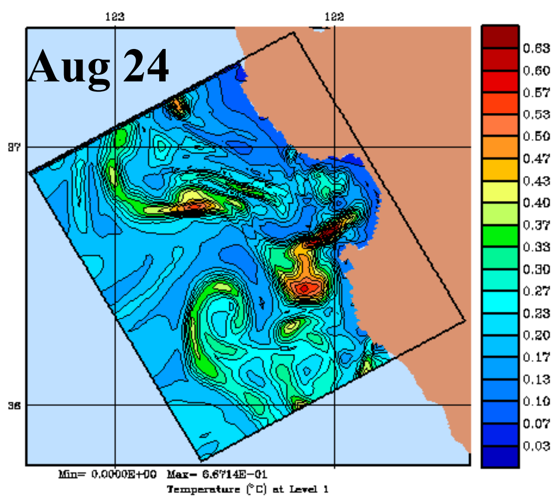


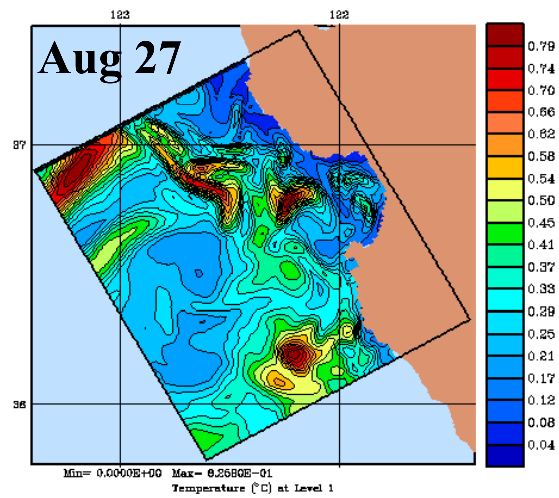


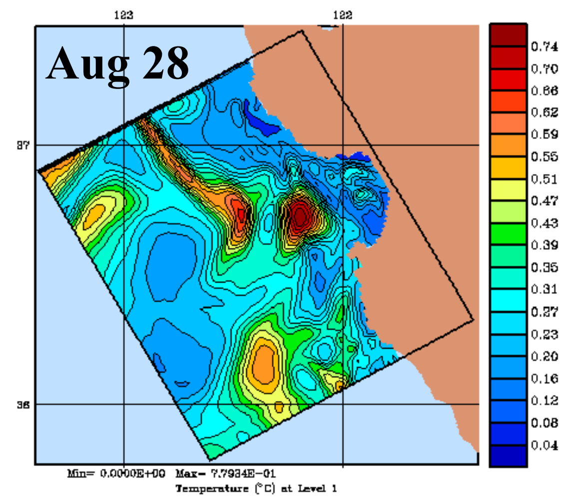


Start of Upwelling

First Upwelling period







End of Relaxation

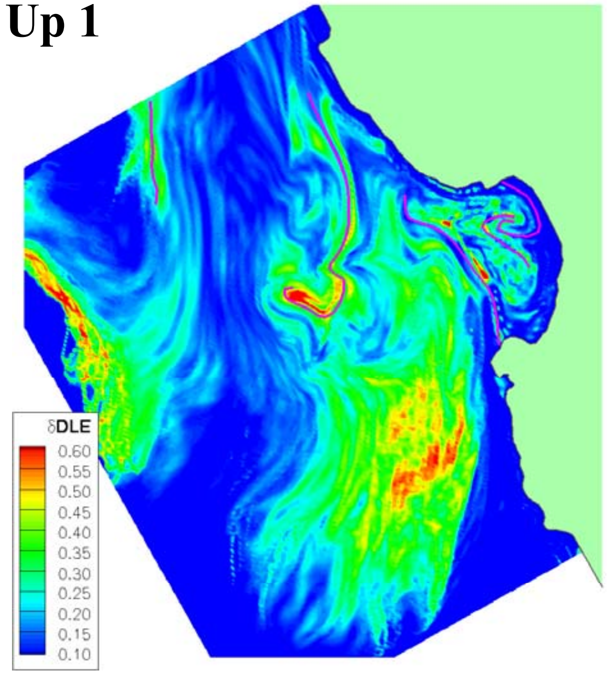
Second Upwelling period

- **Real-time consistent error forecasting, data assimilation and adaptive sampling (1 month)**
- **ESSE results described in details and posted on the Web daily**

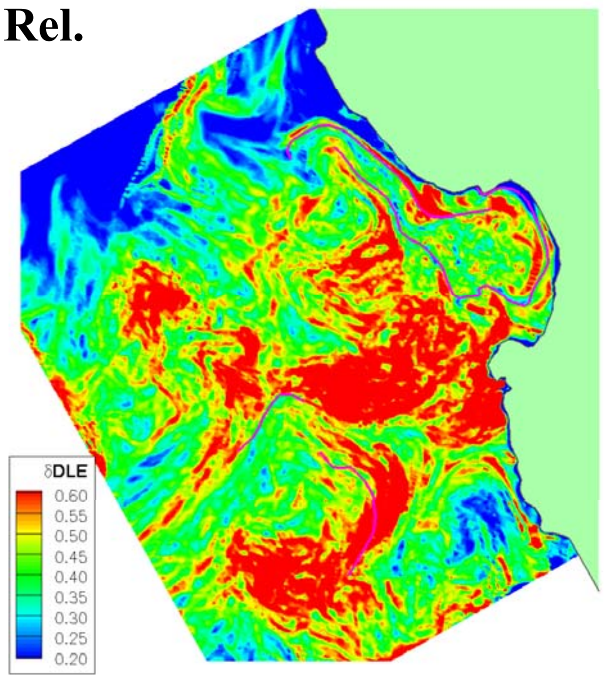
Mean Lagrangian Coherent Structures overlaid on DLE error std estimate for 3 dynamical events

- Two upwellings and one relaxation (**about 1 week apart each**)
- Uncertainty estimates allow to identify most robust LCS (more intense DLE ridges are usually relatively more certain)
- Different oceanic regimes have different LCS uncertainty fields and properties

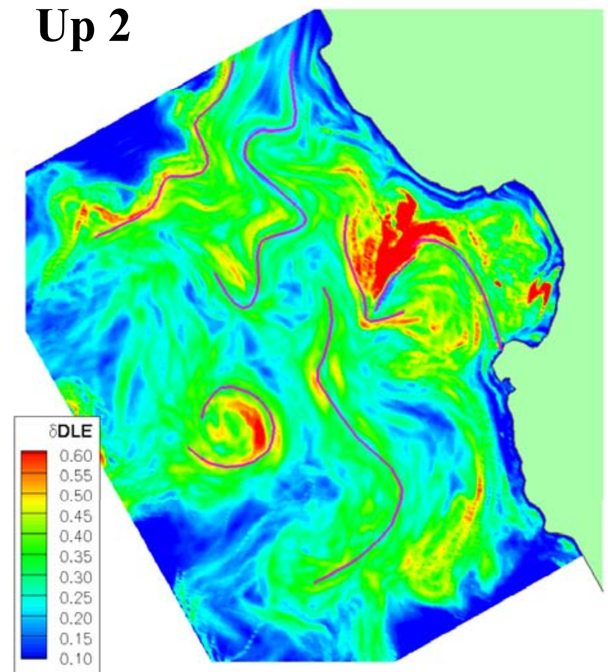
Up 1



Rel.



Up 2



[Lermusiaux and Lekien, 2005. and In Prep, 2009

Lermusiaux, JCP-2006

Lermusiaux, Ocean.-2006]

Research Goal and Objectives

Goal:

Research and develop new formalisms and methodologies for <u>optimal marine sensing</u> using <u>collaborative swarms</u> of autonomous platforms (AUVs, gliders, ships, moorings, remote sensing) <u>that are smart</u>, i.e. <u>knowledgeable about the predicted environment, acoustic performance and uncertainties</u>, and about the <u>predicted effects of their sensing</u>

Specific objectives:

- Research <u>autonomous sensing swarms and formations</u> that <u>exploit</u> the <u>multi-scale, multivariate, 4D environmental-acoustic marine dynamics and predictabilities</u>
- <u>Utilize swarming schemes</u> based on control theory, dynamical system theory, artificial intelligence and bio-inspired behaviors, and <u>update them so that</u> in the high-level global optimization, <u>data to be collected affect predictions</u> and <u>thus feedback</u> to the optimal autonomy
- <u>Combine the swarming schemes with our nonlinear adaptive schemes</u> which forecast the impact of future data to define the optimal autonomy
- <u>Develop new schemes and compare</u> them in idealized and realistic simulations
- <u>Motivate</u> our fundamental research based efficiency and robustness for optimal <u>naval operations, undersea surveillance, homeland security and coastal protection</u>

Our General Autonomy Problem Statement

Consider the spatially-discretized dynamical stochastic prediction (SPDEs) of the ocean state ***x*** and the data $\mathbf{y}_k$ collected by a spatially-discretized sampling ***H*** of a swarm of underwater vehicles:

$$d\mathbf{x} = \mathbf{M}(\mathbf{x}, t) + d\boldsymbol{\eta} \qquad (1)$$

$$\mathbf{y}_k = \mathbf{H}(\mathbf{x}_k, t_k) + \varepsilon_k \qquad (2)$$

Consider optimum estimate of **x** knowing $\mathbf{y}_k$ that is a function of the conditional probability p(**x**, t | $\mathbf{y}_k$) which is itself governed between observations by a Fokker–Planck equation (Lermusiaux, JCP-2006).

General problem statement: Predict and evolve ***H*** such that an objective function *J*, that is a function of the optimal estimate of **x** and of the evolving sensing plan **H(t),** is maximum.

J represents properties to be optimized by evolving swarming plans **H**: (uncertainties, hot-spots, coverage)

New aspects: swarms, multi-scale, nonlinear, knowledgeable of ocean

Remarks on General Problem Statement

- Our autonomy problem is more than learning from data only (based on eqn. (2) only), which is often referred to as onboard routing with or without communications among vehicles
- Also more than classic robotics problems such as obstacle avoidance by swarms of vehicles or path planning that minimize energy utilization using the flow field. In these cases, the optimum estimation of the ocean state (based on fluid SDEs) is not used
- Also more than using dynamical system theory to steer groups of agents (also not coupled with ocean estimation itself)
- <u>Our Plan: combine schemes so that ocean prediction, learning and swarming are all part of single problem, with all feedbacks</u>
- Theoretical work generic and applicable to varied domains where the fields to be sensed are dynamic and of large-dimensions. However, applications focus on marine operations

Ocean Autonomy and Adaptive Sampling: Multiple Facets

Foci	- Optimal science & applications (Physics, Acoustics and Biology) - Demonstration of adaptive sampling value, etc.
Objective Functions	i. Maintain synoptic accuracy (e.g. regional coverage) ii. Minimize uncertainties (e.g. uncertain ocean estimates), or iii. Maximize sampling of expected events (meander, eddy, filament) Multidisciplinary or not - Local, regional or global, etc.
Time and Space Scales	i. Tactical scales (e.g. minutes-to-hours adaptation by each vehicle) ii. Strategic scales (e.g. hours-to-days adaptation for cluster/swarm) iii. Experiment scales
Assumptions	- Fixed or variable environment (w.r.t. asset speeds) - Objective function depends on the predicted data values or not - With/without constraints (operational, time and cost).
Methods	Control, Bayesian-based, Nonlinear programming, (Mixed)-integer programming, Simulated Annealing, Genetic algorithms, Neural networks, Fuzzy logics, Artificial intelligence, etc

Choices set the type of Autonomy research

a) Adaptive sampling via ESSE

[Lermusiaux, DAO-1999; Lermusiaux, Physica D-2007; Lermusiaux and Majumdar, In prep.]

- Objective: Minimize predicted trace of error covariance (T,S,U,V error std Dev).
- Scales: Strategic/Experiment. Day to week.
- Assumptions: Small number of pre-selected tracks/regions (based on quick look on error forecast and constrained by operation)
- Example of Problem solved: e.g. Compute today, the tracks/regions to sample tomorrow, that will most reduce uncertainties the day after tomorrow.

- Objective field changes during computation and is affected by data to-be-collected
- Model errors ***Q*** can account for coverage term

Dynamics:	$dx = M(x)dt + d\eta$	$\eta \sim N(0, Q)$
Measurement:	$y = H(x) + \varepsilon$	$\varepsilon \sim N(0, R)$

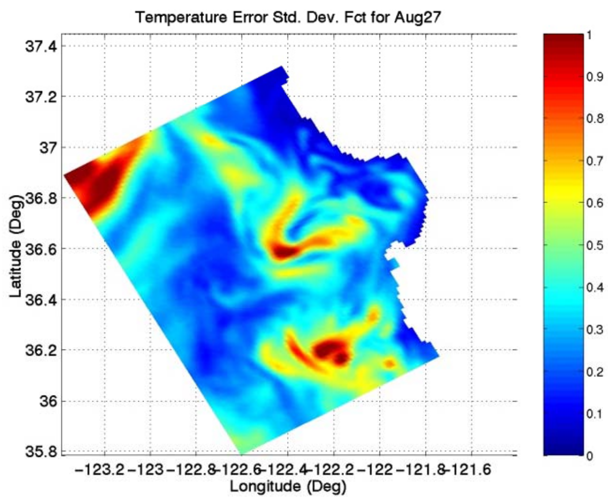
Non-lin. Err. Cov.:

$$dP/dt = \langle (x-\hat{x})(M(x)-M(\hat{x}))^T \rangle + \langle (M(x)-M(\hat{x}))(x-\hat{x})^T \rangle + Q$$

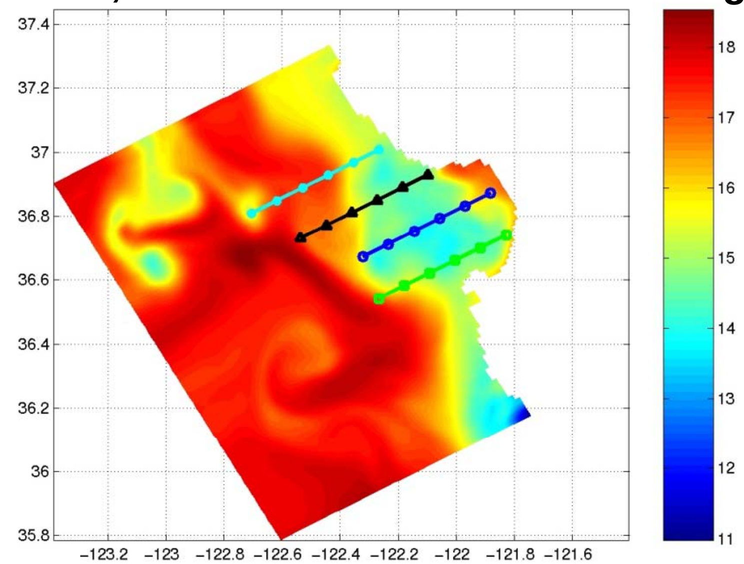
Metric or Cost function: e.g. Find future H_i and R_i such that

$$\underset{H_i,R_i}{Min} \quad tr(P(t_f)) \qquad or \qquad \underset{H_i,R_i}{Min} \int_{t_0}^{t_f} tr(P(t))\ dt$$

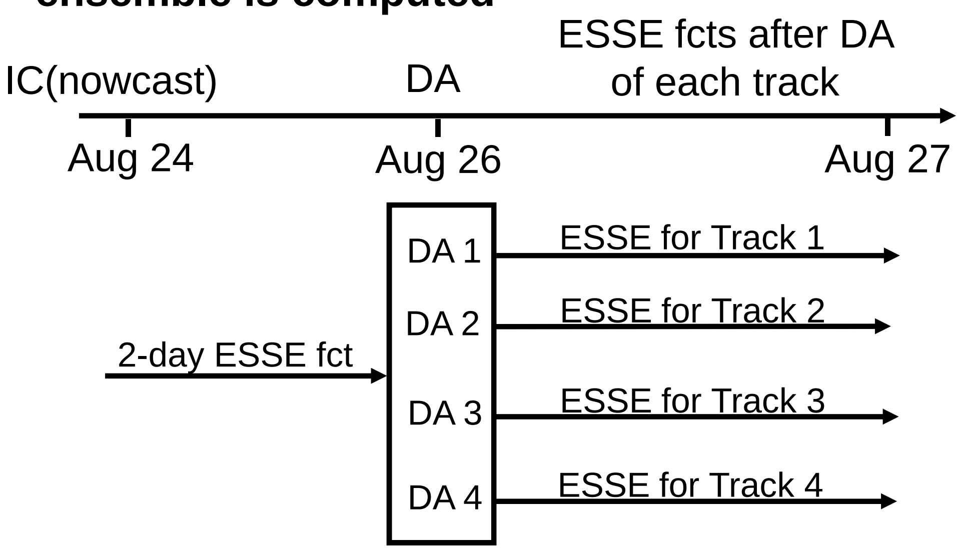
Which sampling on Aug 26 optimally reduces uncertainties on Aug 27?



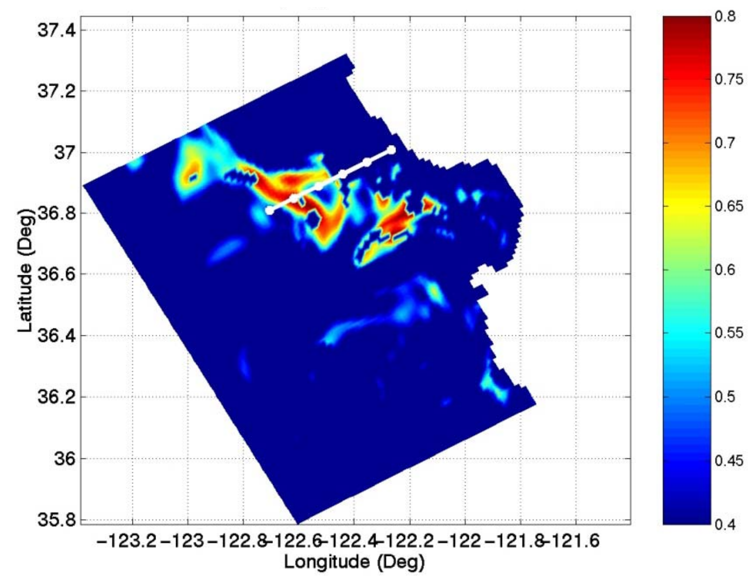
4 candidate tracks, overlaid on surface T fct for Aug 26



- **Based on nonlinear error covariance evolution**
- **For every choice of adaptive strategy, an ensemble is computed**



Best predicted relative error reduction: track 1



Challenges for Stochastic Ocean Flows

Computational Challenges for the deterministic problem

- Large dimensionality of the problem, un-stationary statistics
- Wide range of temporal and spatial scales (turbulent to climate)
- Very limited observations

Need for stochastic modeling …

- Approximations inherent in the deterministic models
- Parametric uncertainties
- Boundary conditions uncertainties
- Measurement models
- Uncertainties on initial conditions

Need to combine computational model with …

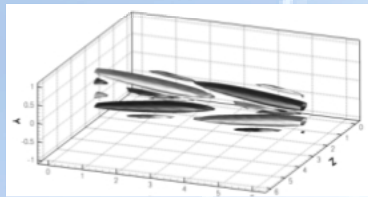
- Available data
- Measurement models

Overview of Uncertainty Predictions Schemes

$$\boxed{\boldsymbol{u}(\boldsymbol{x},t;\omega)} = \hat{\boldsymbol{u}}(\boldsymbol{x},t) + \sum_{i=1}^{s} \boxed{Y_i(t;\omega)}\boxed{\boldsymbol{u}_i(\boldsymbol{x},t)}$$

Uncertainty propagation via POD method

[C. Rowley, Oberwolfach, 2008]



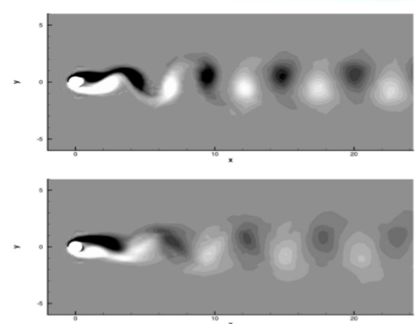
According to Lumley (Stochastic tools in Turbulence, 1971) it was introduced independently by numerous people at different times, including Kosambi (1943), Loeve (1945), Karhunen (1946), Pougachev (1953), Obukhov (1954).

Uncertainty propagation via generalized Polynomial-Chaos Method

Xiu & Karniadakis, J. Comp. Physics, 2002

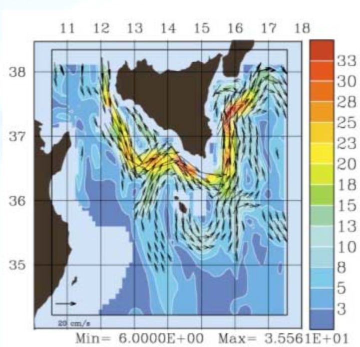
Knio & Le Maitre, Fluid Dyn. Research, 2006

Meecham & Siegel, Phys. Fluids, 1964



[Xiu & Karniadakis, J. Comp. Physics, 2002]

[Lermusiaux & Robinson, Deep Sea Research, 2001]



Uncertainty propagation via Monte Carlo method restricted to an "evolving uncertainty subspace"

(Error Subspace Statistical Estimation - ESSE)

Lermusiaux & Robinson, MWR-1999, Deep Sea Research-2001

Lermusiaux, J. Comp. Phys., 2006

B. Ganapathysubramanian & N. Zabaras, J. Comp. Phys., (under review)

Evolving the full representation

Major Challenge : Redundancy

$$\boldsymbol{u}(\boldsymbol{x},t;\omega)=\bar{\boldsymbol{u}}(\boldsymbol{x},t)+\sum_{i=1}^{s}Y_i(t;\omega)\boldsymbol{u}_i(\boldsymbol{x},t)$$

First Step (easy): Separate deterministic from stochastic subspace

Commonly used approach: Assume that $\overline{Y_i(t;\omega)}=0$

Second step (tricky): Evolving the finite dimensional subspace $\mathcal{V}_S$

A separation of roles: What can $\dfrac{dY_i(t;\omega)}{dt}$ tell us ?

***Only** how the stochasticity evolves $\boxed{\text{inside}}$ $\mathcal{V}_S$*

A separation of roles: What can $\dfrac{\partial \boldsymbol{u}_i(\boldsymbol{x},t)}{\partial t}$ tell us ?

*How the stochasticity evolves **both** $\boxed{\text{inside}}$ and normal to $\mathcal{V}_S$*

source of redundancy

Natural constraint to overcome redundancy

Restrict evolution of $\mathcal{V}_S$ to be normal to $\mathcal{V}_S$ i.e.

$$\int \frac{\partial \boldsymbol{u}_i(\boldsymbol{x},t)}{\partial t}\boldsymbol{u}_j(\boldsymbol{x},t)\,d\boldsymbol{x}=0 \qquad \text{for all} \quad i=1,\dots,s \quad \text{and} \quad j=1,\dots,s$$

Dynamically Orthogonal Evolution Equations

Theorem: For a stochastic field described by the evolution equation

$$d\boldsymbol{u}(\boldsymbol{x},t;\omega)=\mathcal{L}\left[\boldsymbol{u}(\boldsymbol{x},t;\omega)\right]dt+\sum_{r=1}^{R}\Phi_r(\boldsymbol{x},t)\,dW_r(t;\omega) \qquad \boldsymbol{x}\in\boldsymbol{D}$$

$$\boldsymbol{u}(\boldsymbol{x},t_0;\omega)=\boldsymbol{u}_0(\boldsymbol{x},t_0;\omega) \quad \boldsymbol{x}\in\boldsymbol{D} \qquad\qquad \mathcal{B}\left[\boldsymbol{u}\,|_{\partial\boldsymbol{D}}\right]=h\left[\partial\boldsymbol{D}\right]$$

assuming a response of the form $\boldsymbol{u}(\boldsymbol{x},t;\omega)=\hat{\boldsymbol{u}}(\boldsymbol{x},t)+\sum_{i=1}^{N}Y_i(t;\omega)\,\boldsymbol{u}_i(\boldsymbol{x},t)$

we obtain the following reduced-order evolution equations

Ito SDE describing evolution of stochasticity inside $\mathcal{V}_S$

$$dY_j(t;\omega)=\left[\int_{\boldsymbol{D}}\left\{\mathcal{L}\left[\boldsymbol{u}(\boldsymbol{y},t;\omega)\right]-E^{\omega}\left[\mathcal{L}\left[\boldsymbol{u}(\boldsymbol{y},t;\omega)\right]\right]\right\}\boldsymbol{u}_j(\boldsymbol{y},t)\,d\boldsymbol{y}\right]dt+\sum_{r=1}^{R}dW_r(t;\omega)\int_{\boldsymbol{D}}\Phi_r(\boldsymbol{y},t)\,\boldsymbol{u}_j(\boldsymbol{y},t)\,d\boldsymbol{y}$$

Family of PDEs describing evolution of stochastic subspace $\mathcal{V}_S$

$$\frac{\partial\boldsymbol{u}_j(\boldsymbol{x},t)}{\partial t}=E^{\omega}\left[Y_i(t;\omega)\,\mathcal{L}\left[\boldsymbol{u}(\boldsymbol{x},t;\omega)\right]\right]\boldsymbol{C}^{-1}_{Y_iY_j}-E^{\omega}\left[\int_{\boldsymbol{D}}\boldsymbol{u}_k(\boldsymbol{y},t)\,Y_i(t;\omega)\,\mathcal{L}\left[\boldsymbol{u}(\boldsymbol{y},t;\omega)\right]d\boldsymbol{y}\right]\boldsymbol{C}^{-1}_{Y_iY_j}\boldsymbol{u}_k(\boldsymbol{x},t)$$

$$\mathcal{B}\left[\boldsymbol{u}_j\,|_{\partial\boldsymbol{D}}\right]=E^{\omega}\left[Y_i(t;\omega)\,h\left[\partial\boldsymbol{D}\right]\right]\boldsymbol{C}^{-1}_{Y_iY_j}$$

PDE describing evolution of mean field

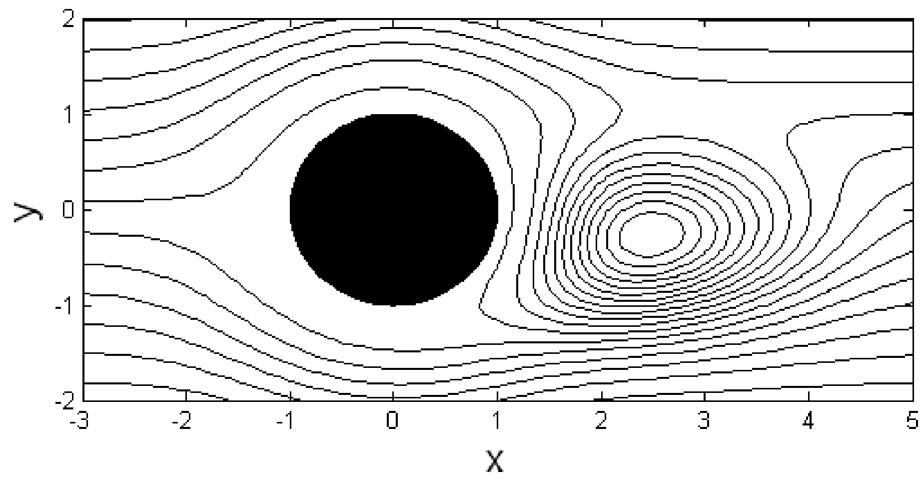
$$\frac{\partial\bar{\boldsymbol{u}}(\boldsymbol{x},t)}{\partial t}=E^{\omega}\left[\mathcal{L}\left[\boldsymbol{u}(\boldsymbol{x},t;\omega)\right]\right] \qquad \mathcal{B}\left[\bar{\boldsymbol{u}}\,|_{\partial\boldsymbol{D}}\right]=E^{\omega}\left[h\left[\partial\boldsymbol{D}\right]\right]$$

Sapsis and Lermusiaux, Physica D, Submitted

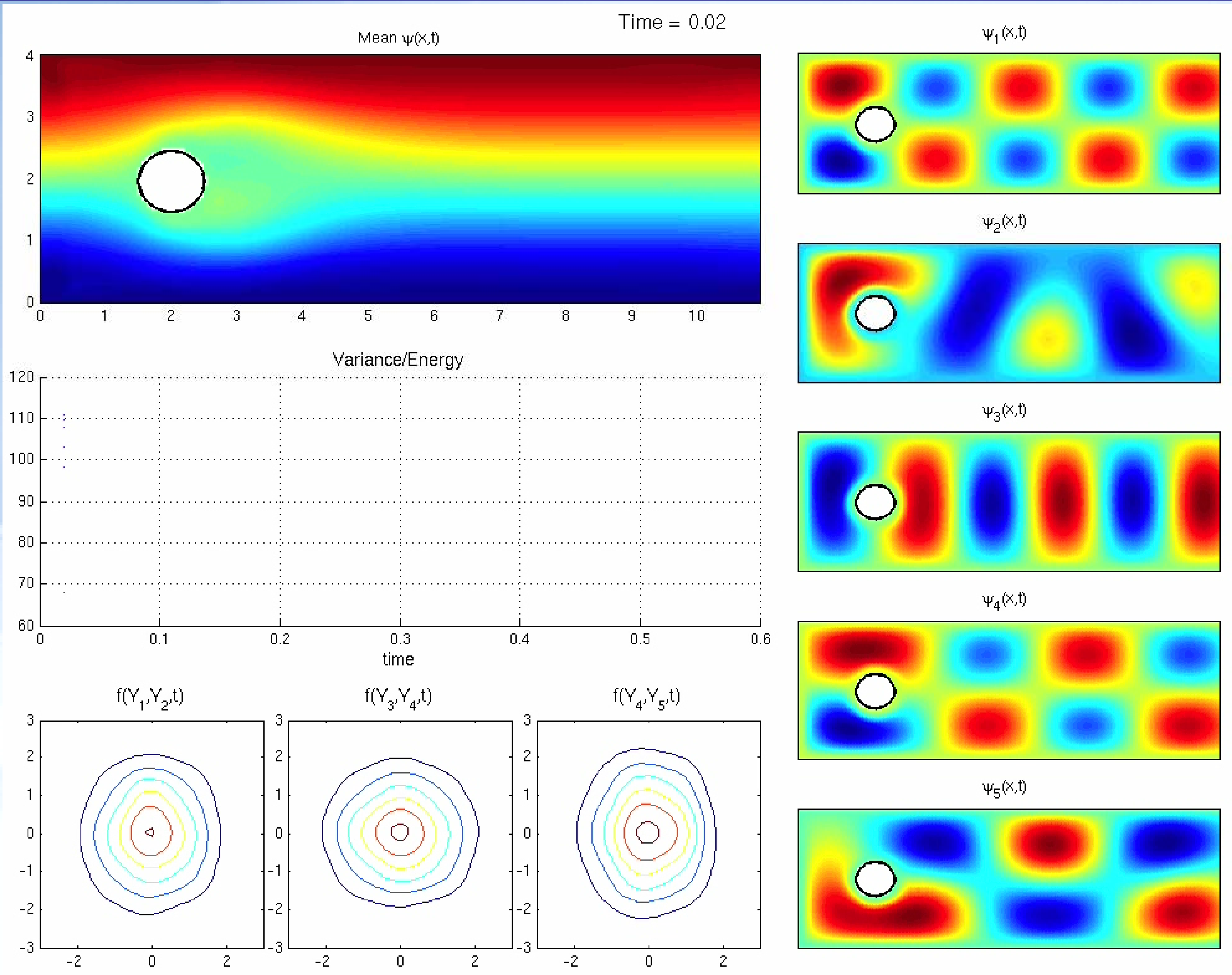
Application II: Navier-Stokes behind a cylinder

von – Kármán vortex street behind a cylinder

Re = 100



Application II: Navier-Stokes behind a cylinder



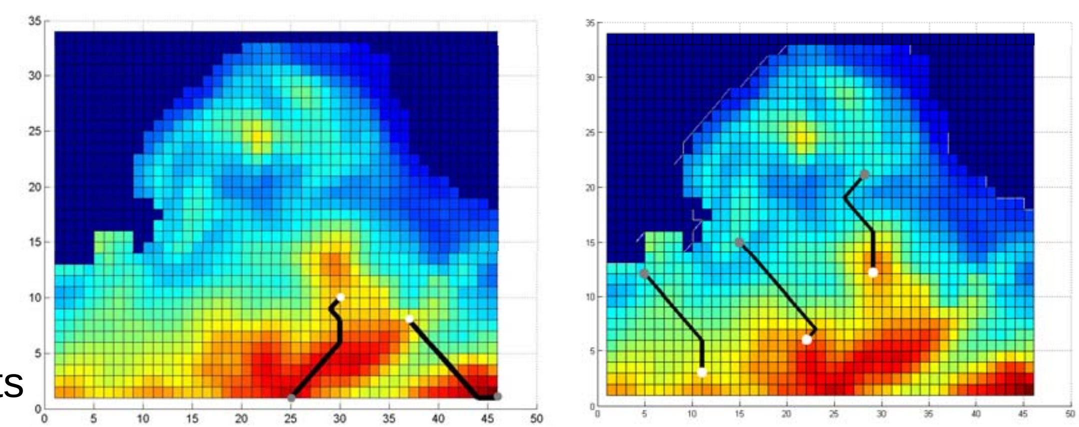
b) Optimal Paths Generation for a “fixed” objective field

[Yilmaz et al., IEEE-Oceans-2006; Yilmaz et al, IEEE Trans.-JOE-2008]

- Objective: Compute exact optimal path that maximizes function (e.g. error standard deviation of temperature field)
- Scales: Strategic/Tactical
- Main Assumption: Speed of platforms >> time-rate of change of environment. The objective field is fixed during the computation of the path and is not affected by new data
- Problem solved: assuming the objective is like that now and will remain so for the next few hours, where do I send my gliders/AUVs?
- Method: *Combinatorial optimization (Mixed-Integer Programming, using Xpress-MP)*
  - Objective field (error stand. dev.) represented as a piecewise-linear: solved *exactly* by MILP
  - Possible paths defined on discrete grid: set of possible path is thus finite (but large)
  - Constraints imposed on vehicle displacements dx, dy, dz for meaningful path

Example:
Two and Three Vehicles, 2D objective field (3D examples also done)

Grey dots: starting points
White dots: MIP optimal end points



b) Optimal Path Generation for a “Variable” Objective Field

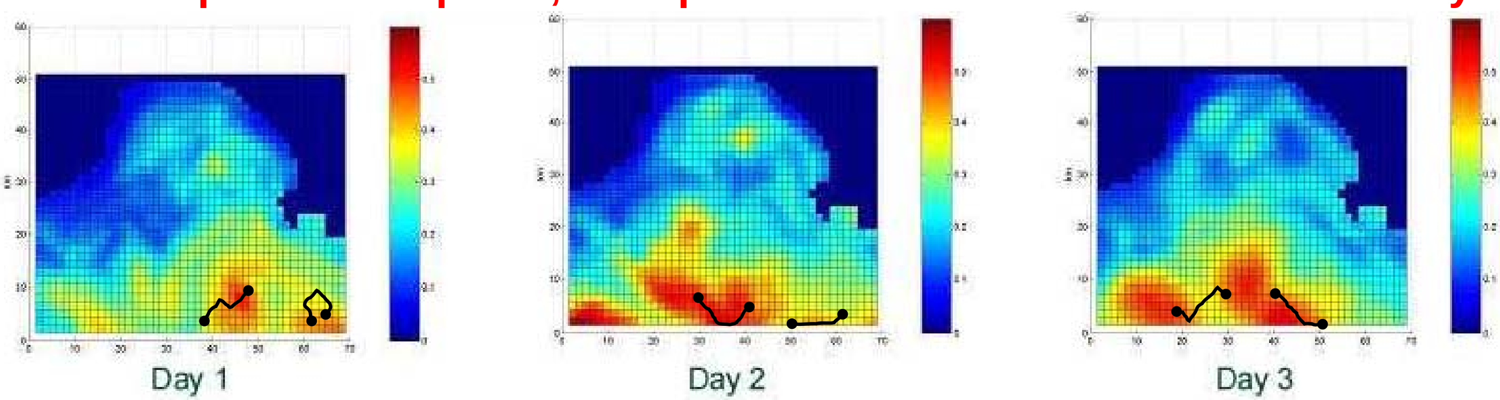
[Yilmaz and Lermusiaux, Ocean Modeling, To be submitted]

Combines MILP optimization with ESSE assimilation in forecast mode:

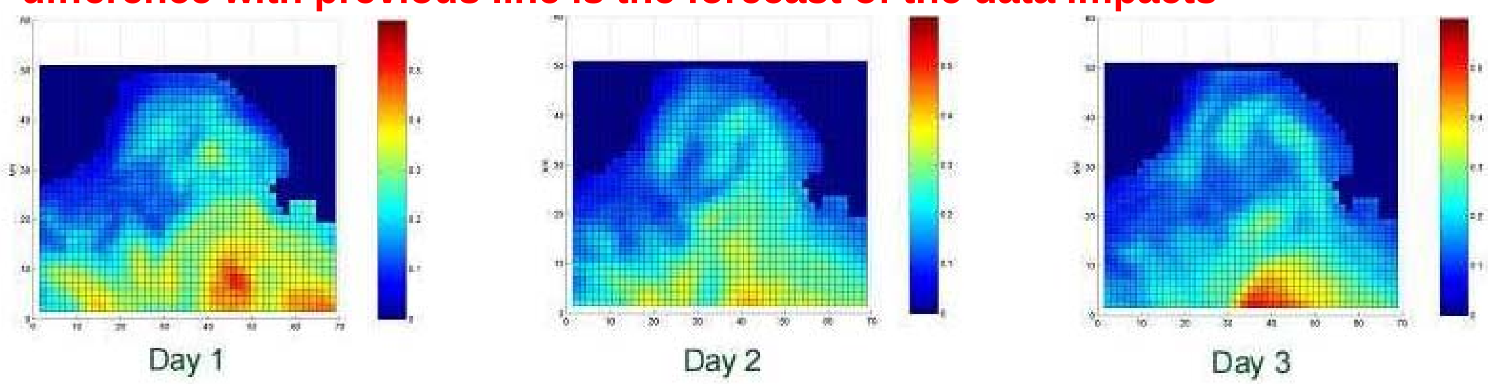
- **MILP computes optimal paths for *n* days using ESSE forecast uncertainties**
- **ESSE assimilates forecast data for day 1, updates forecast errors for days 2 to n**
- **MILP re-computes paths for days 2 to n based on updated ESSE forecast**
- **ESSE assimilates forecast data for day 2, updates errors for days 3 to n, …, etc**

- **MILP computes paths that samples largest ESSE forecast errors for the next 3 days**
- **ESSE assimilates the unknown forecast data for day 1, new ESSE errors are predicted for days 2 and 3, and a new MILP search is done for the last 2 days**
- **ESSE assimilates the forecast data for day 2, predicts a new error for day 3 and a final MILP search is done for this final day 3**
- **Result: predicted optimal paths for 3 days**

Result: Optimal AUV paths, on top of Prior ESSE error forecast for 3 days



Posterior ESSE error forecast for 3 days (after DA of forecast optimal AUVs): difference with previous line is the forecast of the data impacts

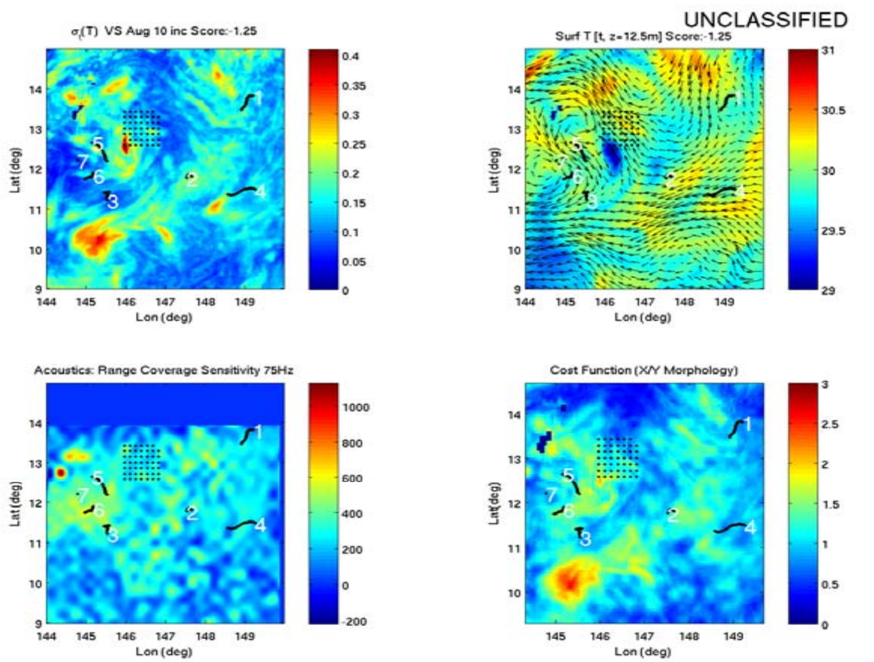


c) Nonlinear Path Optimization using Genetic Algorithms:

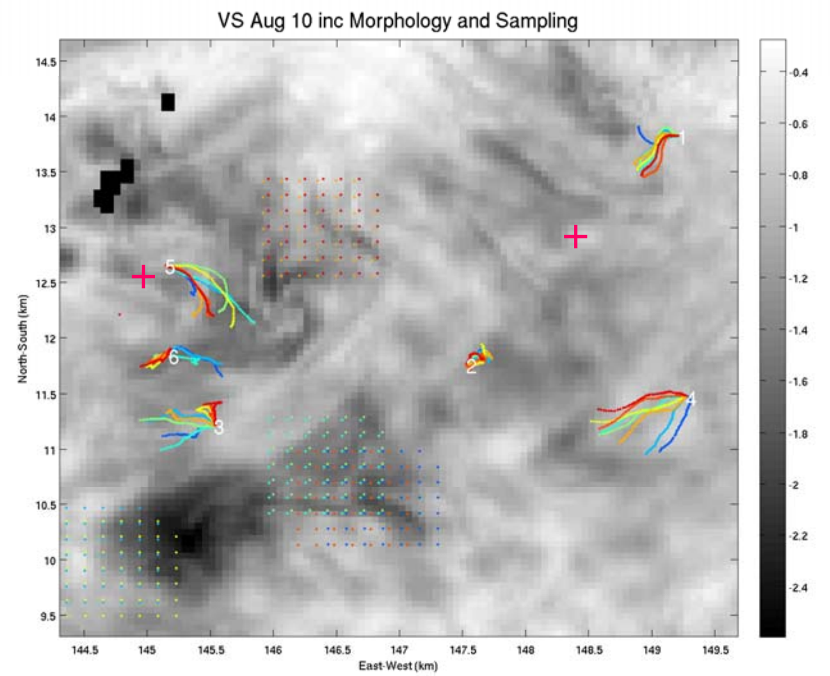
VS07 (Pacific) and AWACS (NE shelfbreak)

[Heaney, Lermusiaux and Duda, JFR-2007 and OM-2009]

Main advantages: Easy to combine multiple cost functions, Nonlinear ”Optimization”



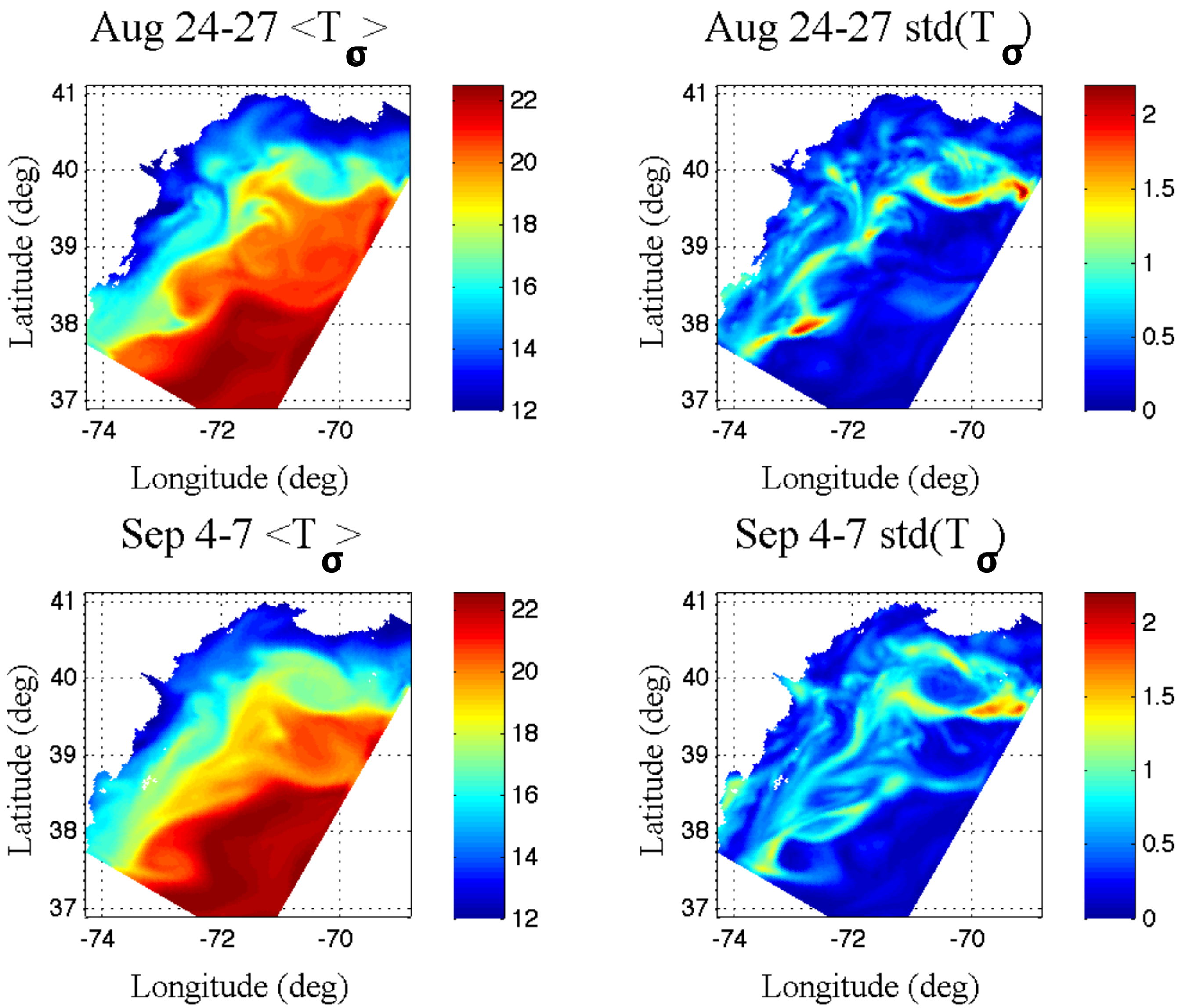
Cost functions for [UL] forecast temporal standard deviation of T in upper layer (looking for ocean variability), [UR] spatial mean of T (looking for fronts and eddies) with mean currents, [LL] acoustic coverage variability (RED most variable), and [LR] weighted average of all 3. Best tracks (lowest cost functions-RED in LL) are laid on top . Glider tracks consider vertical mean of upper 1000m ocean currents (UR) as they vary over forecast period.



5 possible 48-hour tracks for gliders and AXBT sampling array. Tracks to optimize environmental observations and improve model (RED ranked best). These are overlaid on the overall morphology from LR panel to left.

Cost function includes convergence for eventual pick up near the two magenta crosses (+).

c) GA Scheme Evaluation: Comparing Strategies using Data-Assimilation Ocean Dynamics Set-up



Before Tropical Storm Ernesto

After Tropical Storm Ernesto

Time-Averaged Temperature
(T_σ = T along the 24.7 g/cm^3 isopycnal)

Temperature Uncertainty
(Ensemble standard deviation)

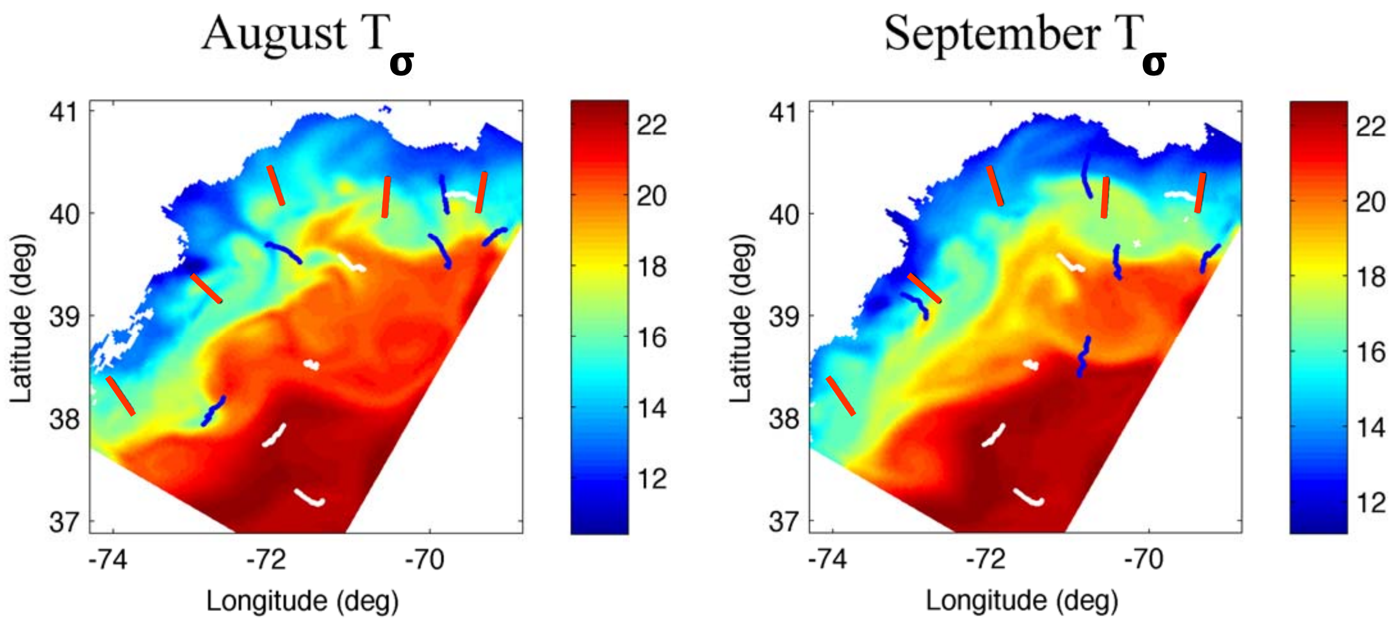
PFJL- MIT

c) GA Scheme Evaluation: Comparing Strategies using Data-Assimilation

Three Types of Strategies

[Heaney, Lermusiaux, Haley and Duda, 2009]

Two dynamic situations: before (Aug) and after (Sep) Ernesto

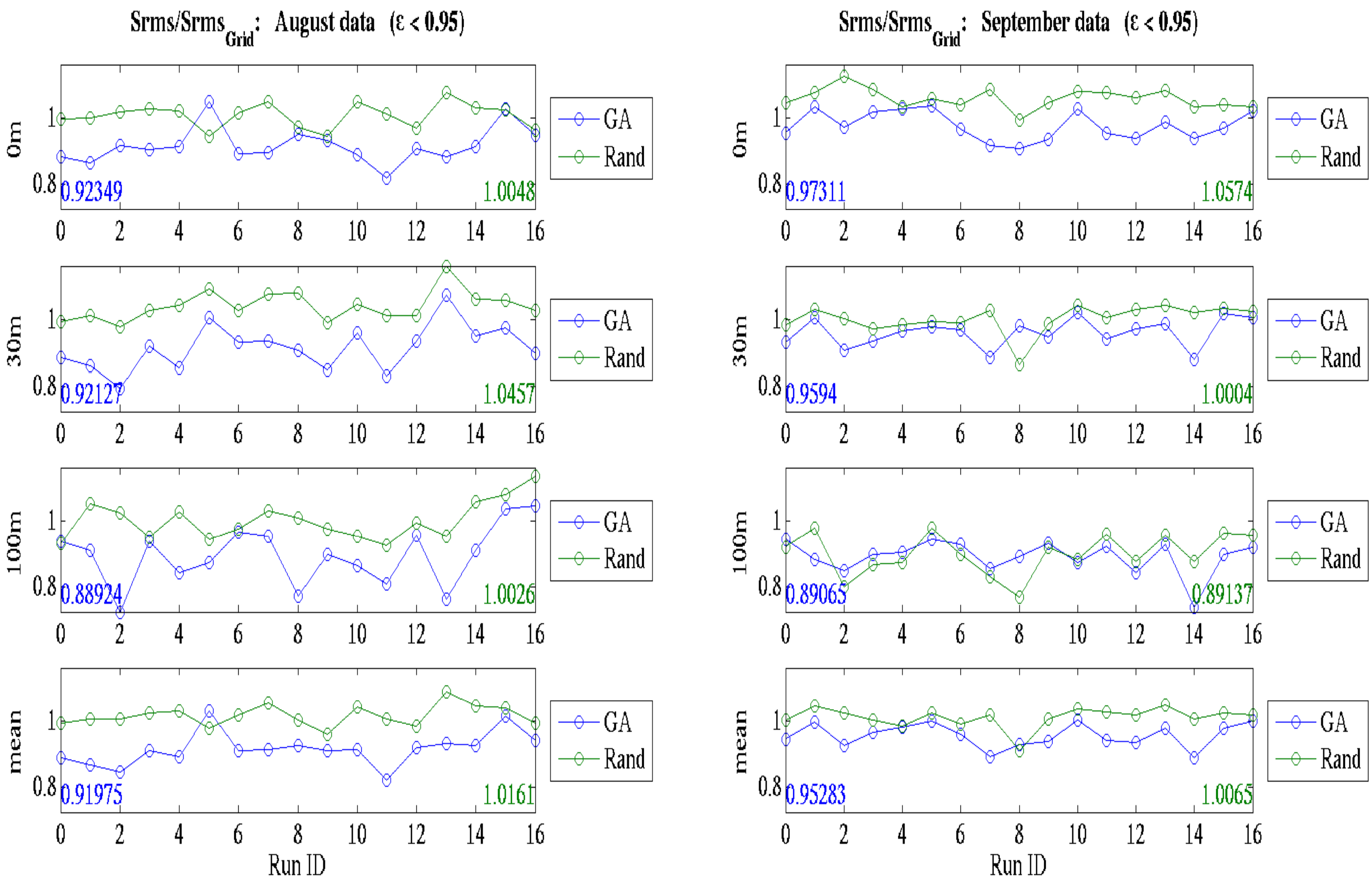


Five gliders to be optimized over 48 hours of sampling within large domain

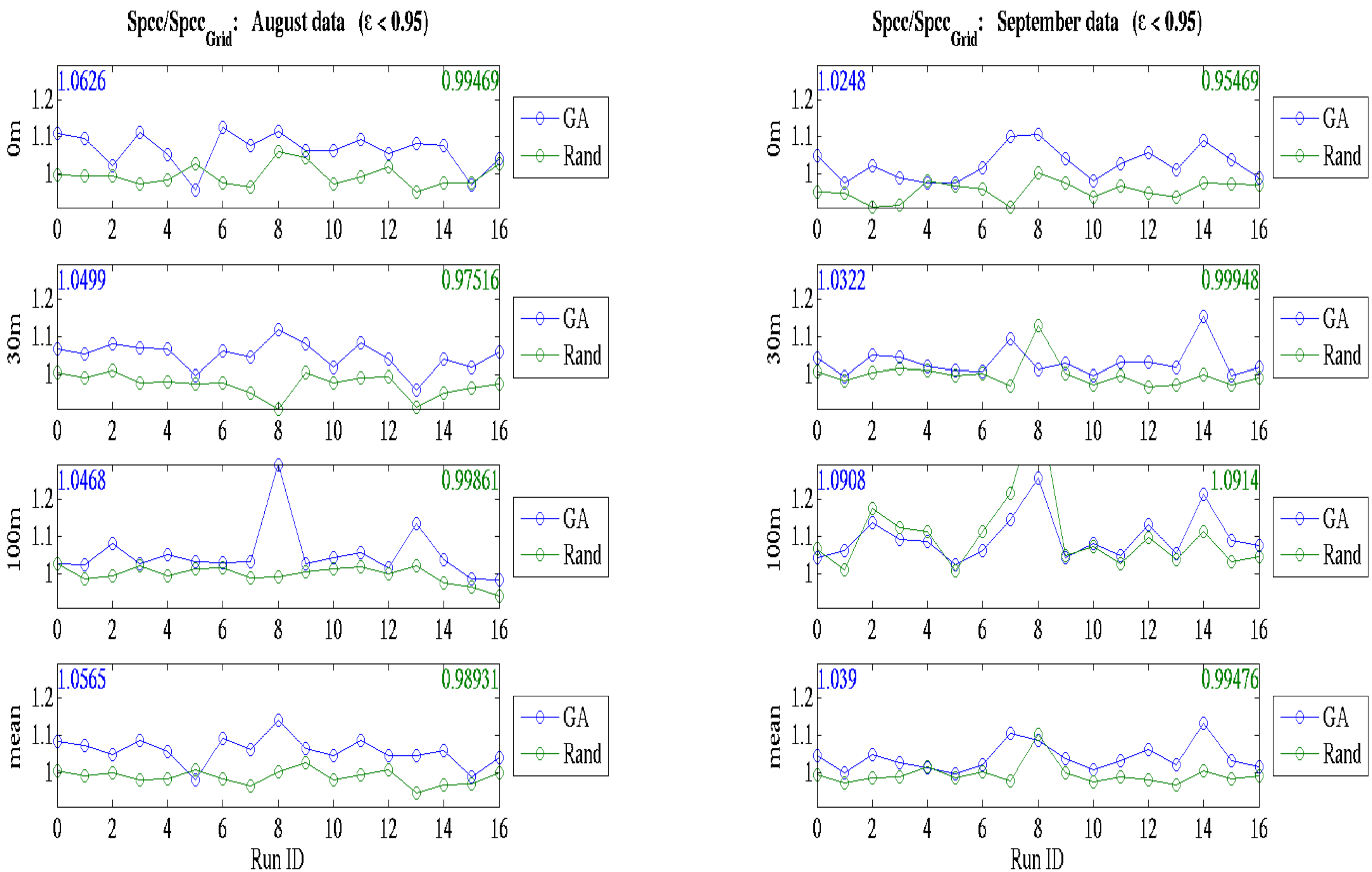
Three Types of Sampling Paths

- *Grid* (red): the "smart" oceanographer
- *Random* (white)
- *Genetic Algorithm* (blue): GA paths computed to minimize chosen cost function

Paths overlaid on T_σ surface for August 24-27 (left) and September 4-7 (right)



[Heaney, Lermusiaux, Haley and Duda, To be submitted-2009]



[Heaney, Lermusiaux, Haley and Duda, To be submitted-2009]

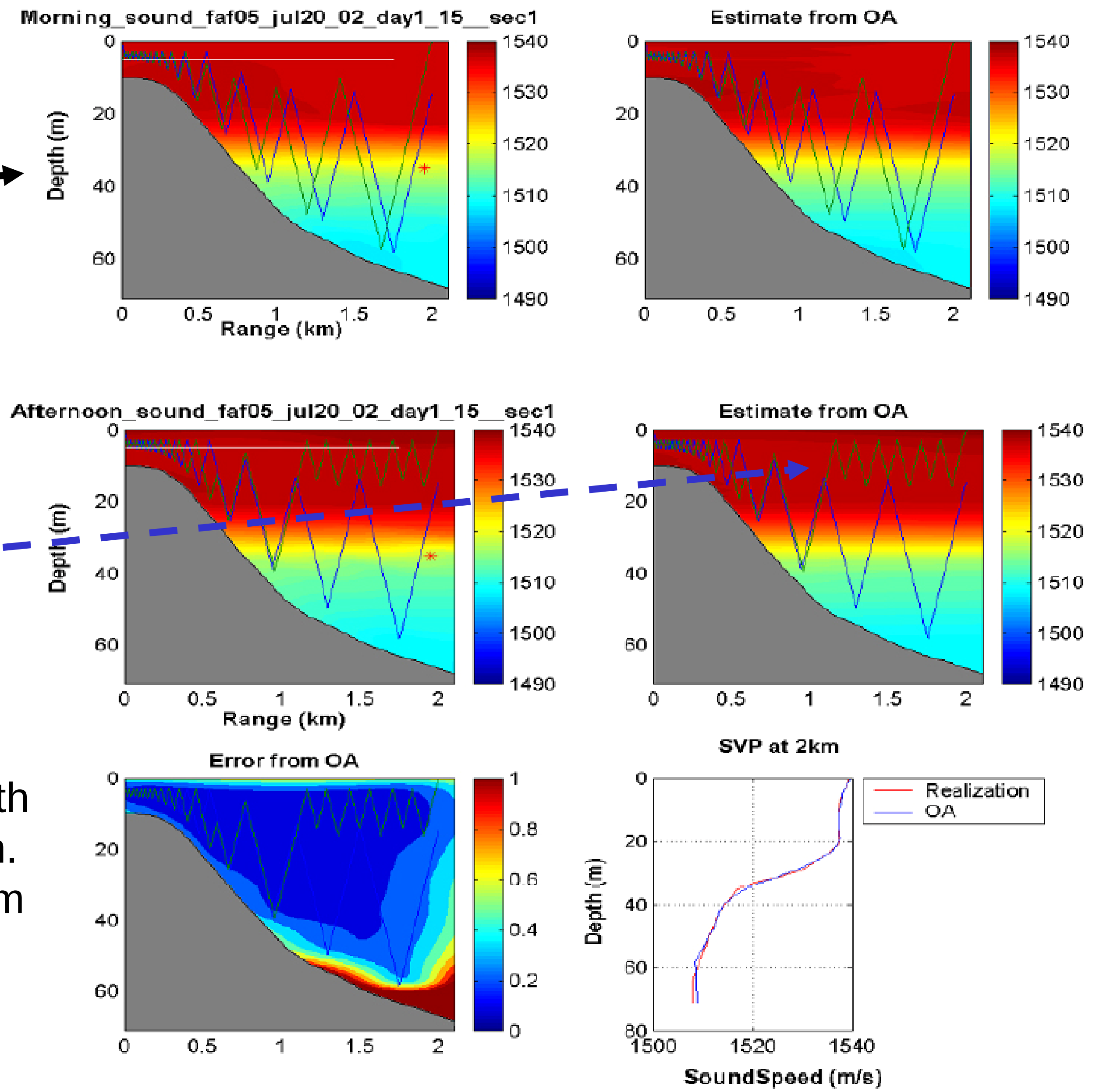
f) Acoustically Focused Adaptive Sampling

[Wang, Lermusiaux, Schmidt et al, IEEE-Oceans-2006; J.Mar.Sys.-2009]

Uses simple Dynamic-Programming with ESSE assimilation to guide subsequent Onboard Routing

Morning

Afternoon



Forecast of onboard adaptive Yoyo control of AUV to capture ``afternoon effects”

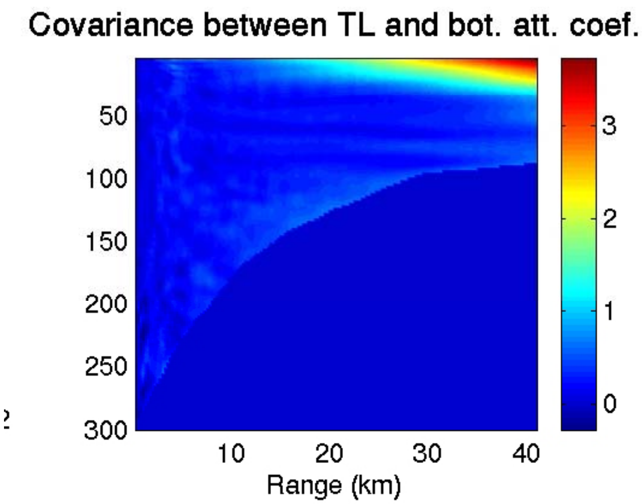
Legend:

- Blue line: forward AUV path
- Green line: backward path.
- AUV avoids surface/bottom by turning 5 m before surface/bottom

Our Interdisciplinary Applications with Potential for Autonomous Marine Intelligent Swarming Systems

❖ Adaptive Ocean-Acoustic sampling of water column to invert for the seabed

- Covariance fields computed using ESSE and ocean-acoustic models
- For a 400Hz source at 300m depth, they show where to measure TL and to take an ocean profile to best estimate the mean bottom attenuation coefficient



❖ Web-based command and control of asset directly from models

- e.g. Kayaks during PN07, see our paper [Xu et al,

❖ Adaptive Sampling for optimum "Underwater Acoustic Sparse Aperture System Performance": see our paper [Burton et al, IEEE-Oceans-2009]

❖ Other acoustic efforts in our ONR projects: Optimize sensor depths, ranges and frequencies for the "Acoustic Climate"

❖ Biological Adaptive Sampling and Swarming

Novel Science and Methodologies for Autonomous Marine Intelligent Swarming

- Research formalisms and principled methods for optimal marine sensing using collaborative swarms of platforms that are smart

- Intelligence: ability to adapt swarm sensing based on
  i. Predicted ocean and acoustic performance and their uncertainties
  ii. Predicted effects of environmental and acoustic sensing

- Develop new global dynamic swarm and high-level optimization schemes
  i. Optimal control and dynamical systems
  ii. Artificial intelligence and Game Theoretic schemes
  iii. Bio-inspired and agile sensing with predictive adaptive sampling

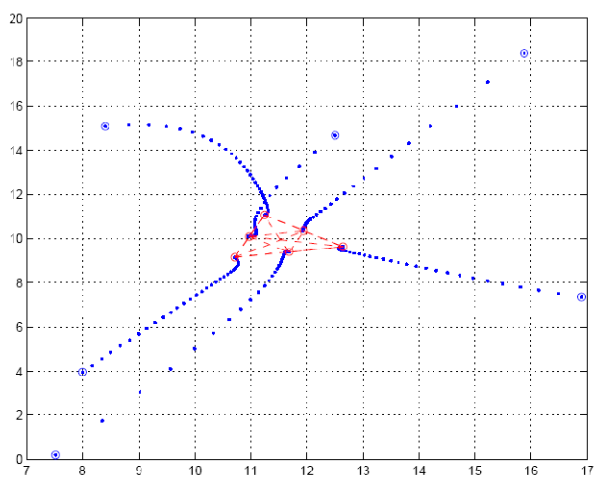
- Combine swarming schemes with our MSEAS adaptive schemes

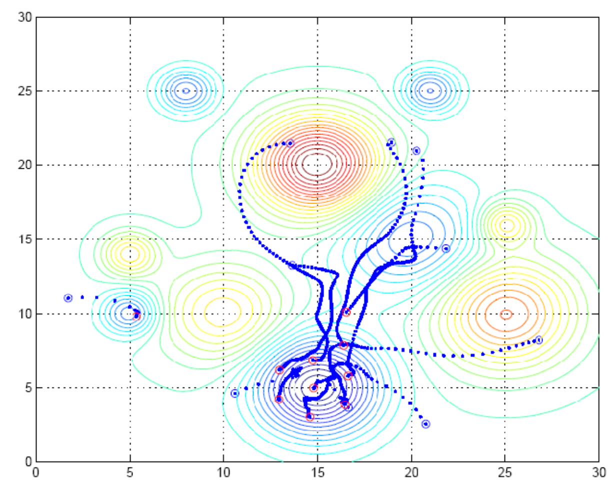
- Research motivated by naval applications

i) Optimal control and dynamical systems for Autonomous Marine Intelligent Swarming

- Review: Optimal control and dynamical systems methods:
  - Artificial potential functions *[Gazi and Passino, IEEE-2004], [Kim et al, JIRS-2006]* combined with sliding- mode control *[Gazi, IEEE-2005]*
  - Hybrid of genetic algorithm and particle swarm optimization (HGAPSO) *[Juang, IEEE-2004]*: Introduces the concept of “maturing phenomenon” in nature into the evolution of individuals originally modeled by GA
  - Decentralized algorithm for adaptive flocking of robot swarms *[Lee and Chong, IEEE-2008]*.
  - Contraction theory *[Lohmiller and Slotine, IJC-2005]*: Dynamic analysis and non-linear control system design tool based on exact differential analysis of convergence.
- Our specific objective: Augment the above methods with Bayesian estimates for the optimal future sampling plans and the impacts of the sampling on these plans.

Example: Swarm aggregations using artificial potentials and sliding-mode control *[Gazi, IEEE-2005]:*





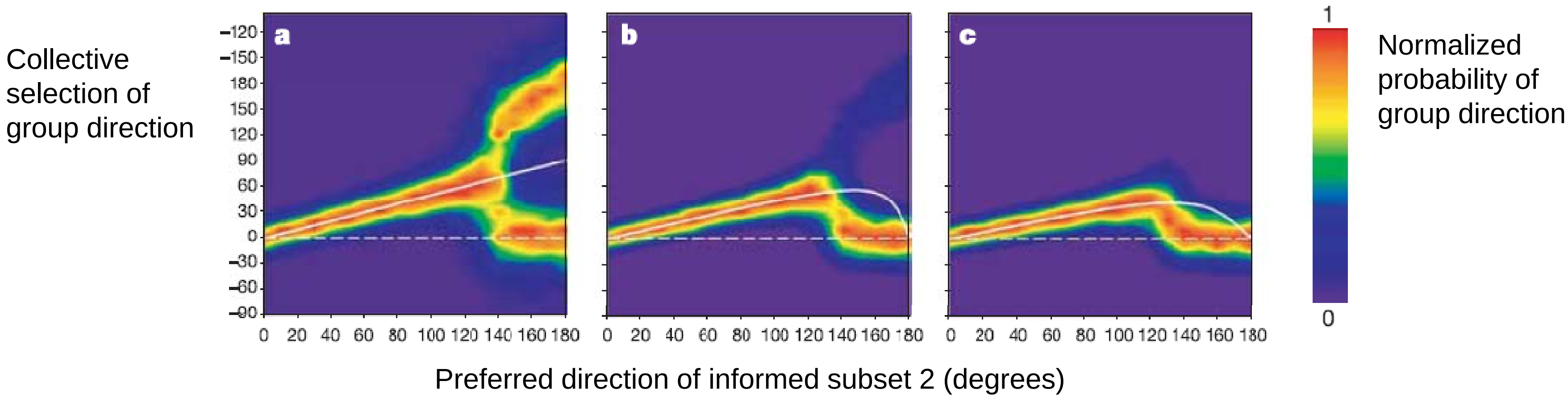
ii) Artificial Intelligence for our A-MISSION

- Review: Artificial intelligence *[Russell and Norvig, Prentice Hall-2003] and agents [Kohn and Nerode, IEEE-1992, Symp.- 1993]* :
  - Optimizing asset management handled using evolutionary algorithms *[Ashlock, Springer-2006]*, examples of which are:
    - Genetic algorithm *[Mitchell, MIT Press-1996]*: New candidates generated by combinations of pairs of existing candidates.
    - Harmony search algorithm *[Mahdavi, AMC-2007]*: New candidates generated from a random selection of elements of existing solutions combined with random values.
  - Hybrid algorithms combining evolutionary algorithms with gradient based algorithms *[Engelbrech, Wiley-2006]*: Improves convergence to local solutions.
  - Reinforcement learning algorithms *[Sutton and Barto, MIT Press-1998]*, such as dynamic programming *[Bertsekas, Athena-2000]*, temporal difference learning *[Tesouro, ML-1992].*
  - Lorenz-2003 weather forecast model combined with backward selection algorithm *[Roy et al. LNCS-2007]*
- Our specific objectives:
  - Apply/modify these methods to full nonlinear ocean SPDEs
  - Utilize our recent theoretical results on Dynamically Orthogonal equations for efficient uncertainty predictions *[Sapsis and Lermusiaux, Physica D-2009 (submitted)]*.
  - Utilize Adaptive Modeling *[Lermusiaux, Phys.D-2007]* to improve the forecast model.

iii) Bio-Inspired and Agile Sensing for our A-MISSION

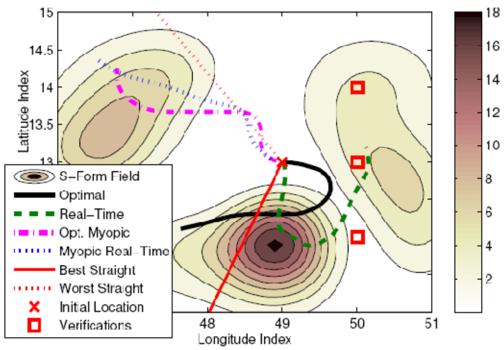
- Review: Existing control algorithms based on bio-inspired behavior.
  - Effective leadership and decision making in biological systems *[Couzin et al., Nature-2005].*
  - Control algorithms that stably coordinate sensors on structured tracks optimized over a minimal set of parameters *[Leonard et al., IEEE-2007]*
  - Multi-agent system motivated by decision making in animal groups *[Nabet et al., Proc. ISMTNS-2006].*
- Our research objectives:
  - Combine bio-inspired schemes with Bayesian estimation of optimal future sampling
  - Augment bio-inspired sensing with smart prediction capability:
    - Account for impacts of swarm sensing of future field estimates

Ex: Leadership and decision-making in animal groups on the move *[Couzin et al., Nature-2005]*

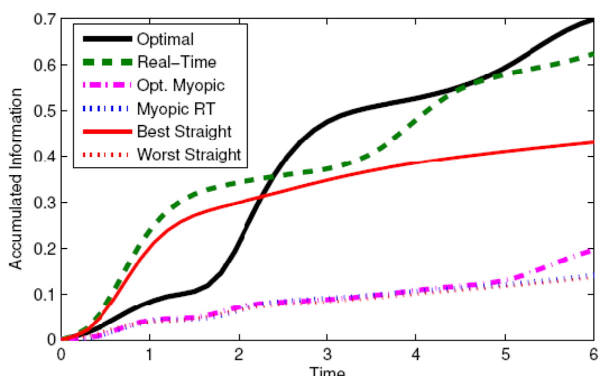


Example: Continuous Motion Planning for Information Forecast *[Choi and How, IEEE-2008]*

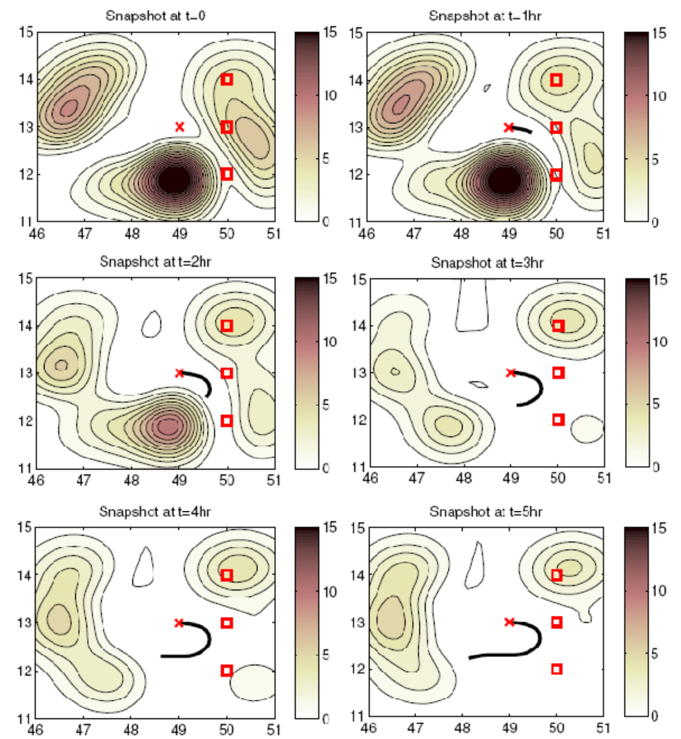
- Planning of continuous paths for mobile-sensors to improve long-term forecast performance.
  - ➢Quantify information gain for linear-time varying system in: a. filter form, b. smoother form.
  - ➢Path planning techniques used to provide optimal solutions
- Numerical Example: 2-D weather forecast problem (Lorenz-2003 model).



Sensor trajectories for different strategies



Accumulated information for different strategies



Optimal trajectory snapshots every hour overlaid on the information potential field.

- <u>Our research objectives</u>: extend to full nonlinear SPDEs and utilize our recent DO stochastic decompositions *[Sapsis and Lermusiaux, Physica D-2009 (submitted)]*.

A – MISSION:
Autonomous Marine Intelligent Swarming Systems for Interdisciplinary Observing Networks

Some Items for Discussions

- **Posing the problem: finding simpler problems that can be solved and lead to the complex problem solution likely key**
- **Combine “Noisy Game Theoretic” and “Bio-inspired” schemes with our ocean SPDEs estimation and swarming?**
- **Is hierarchical approach required for multiscale schemes? Wavelets?**
- **Proof convergence in nonlinear multiscale systems (use our DO expansion?)**
- **Transfer our intelligent swarming with real/robust Navy Systems?**

Thanks to ONR

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