

Dynamics of Particle Groups

and the Design of Mobile Sensor Networks



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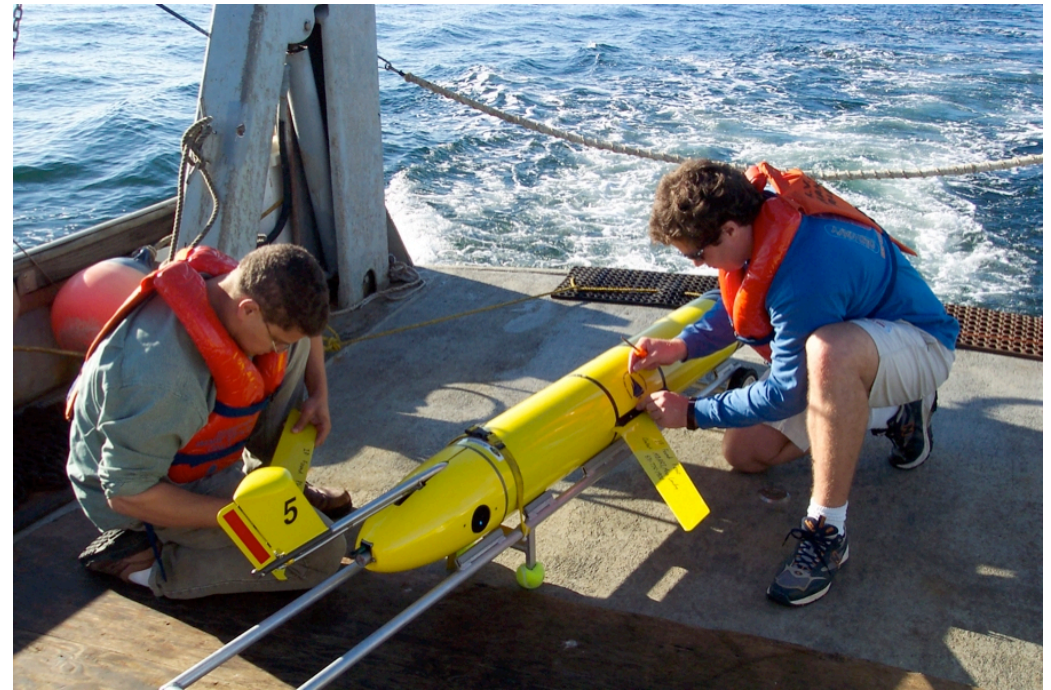


July 15, 2004



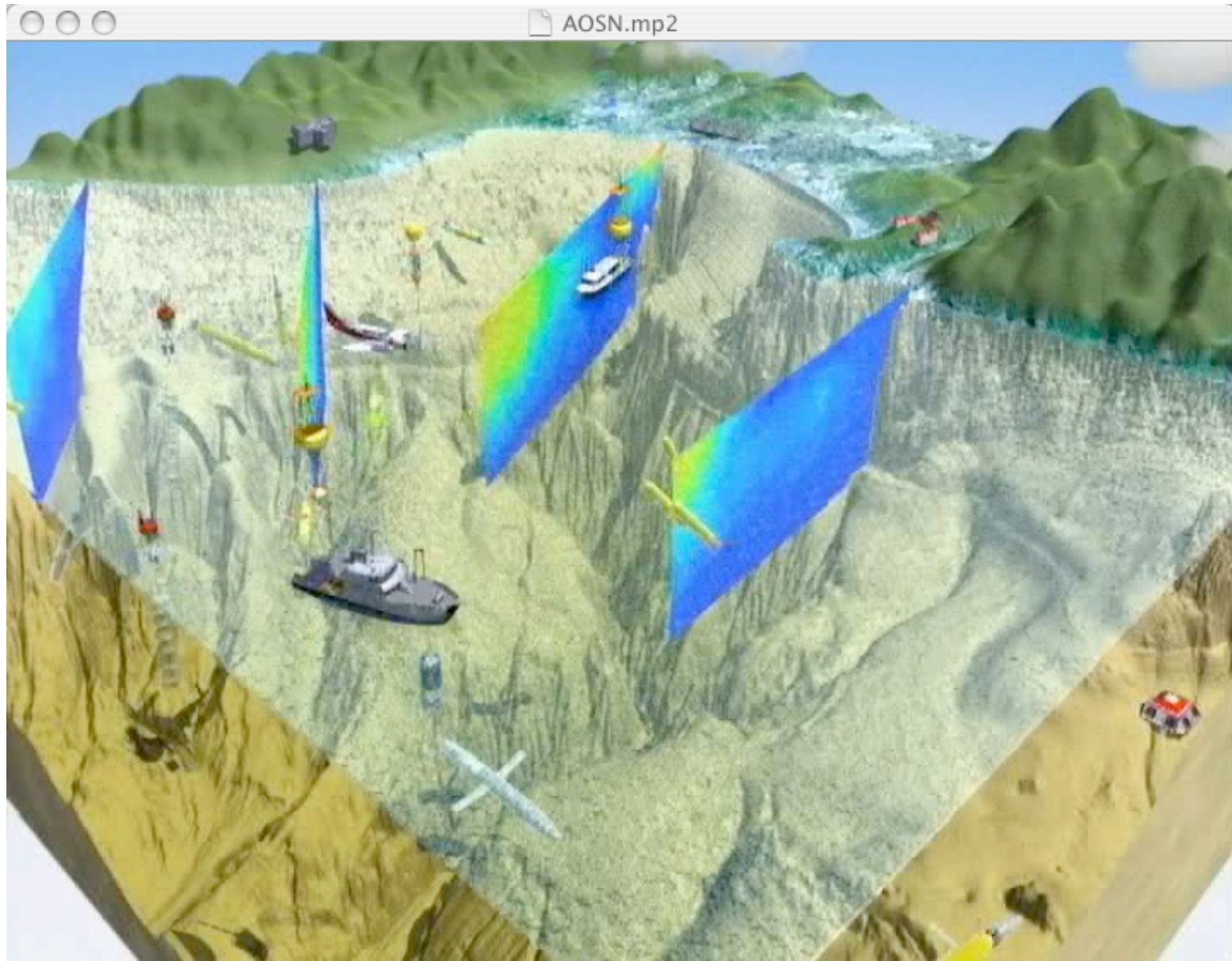
Application: Mobile Sensor Network

- Design **periodic trajectories** for oceanographic broad-area mapping
- Real-time **closed-loop** control for optimal coordination and adaptive sampling

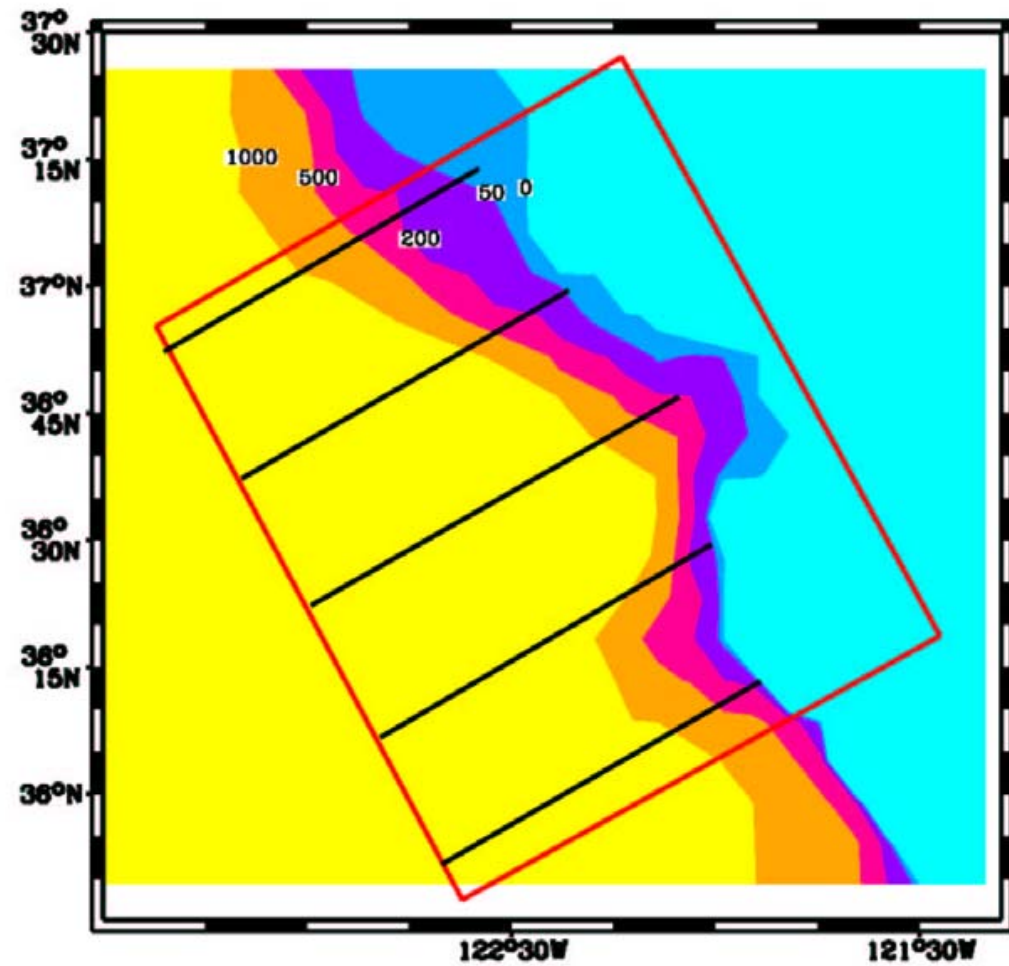


AOSN-II, Monterey Bay, CA USA 2003

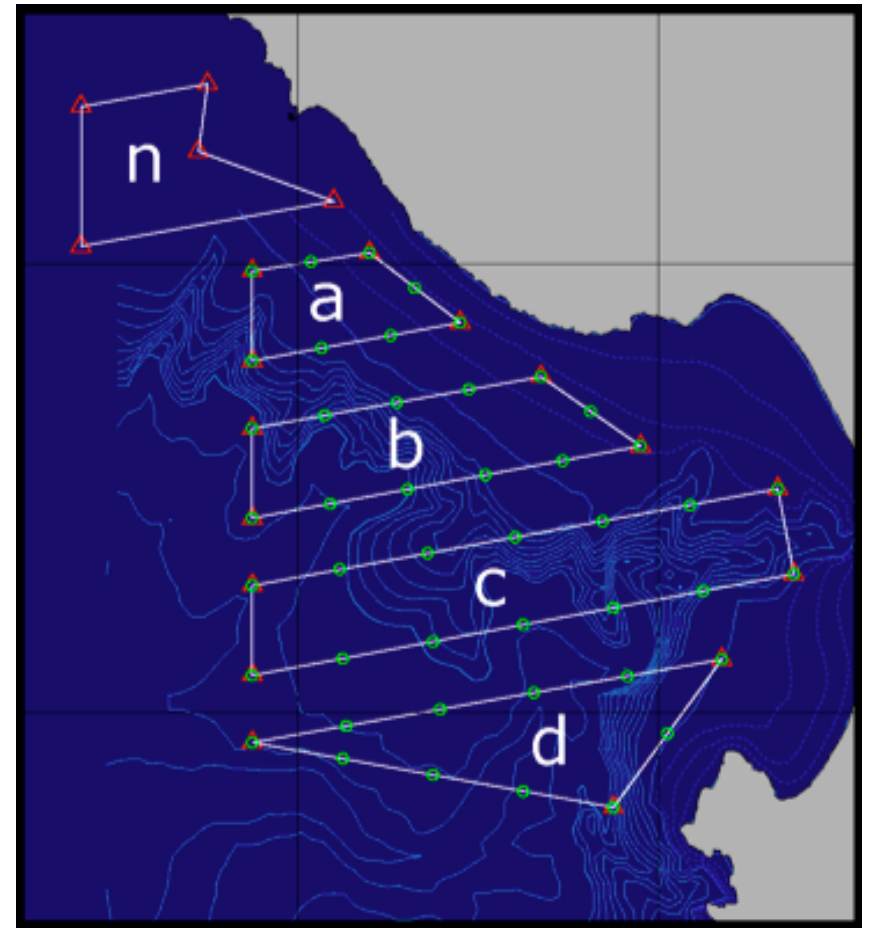
AOSN-II Monterey, CA August 2003



AOSN-II Glider Plan

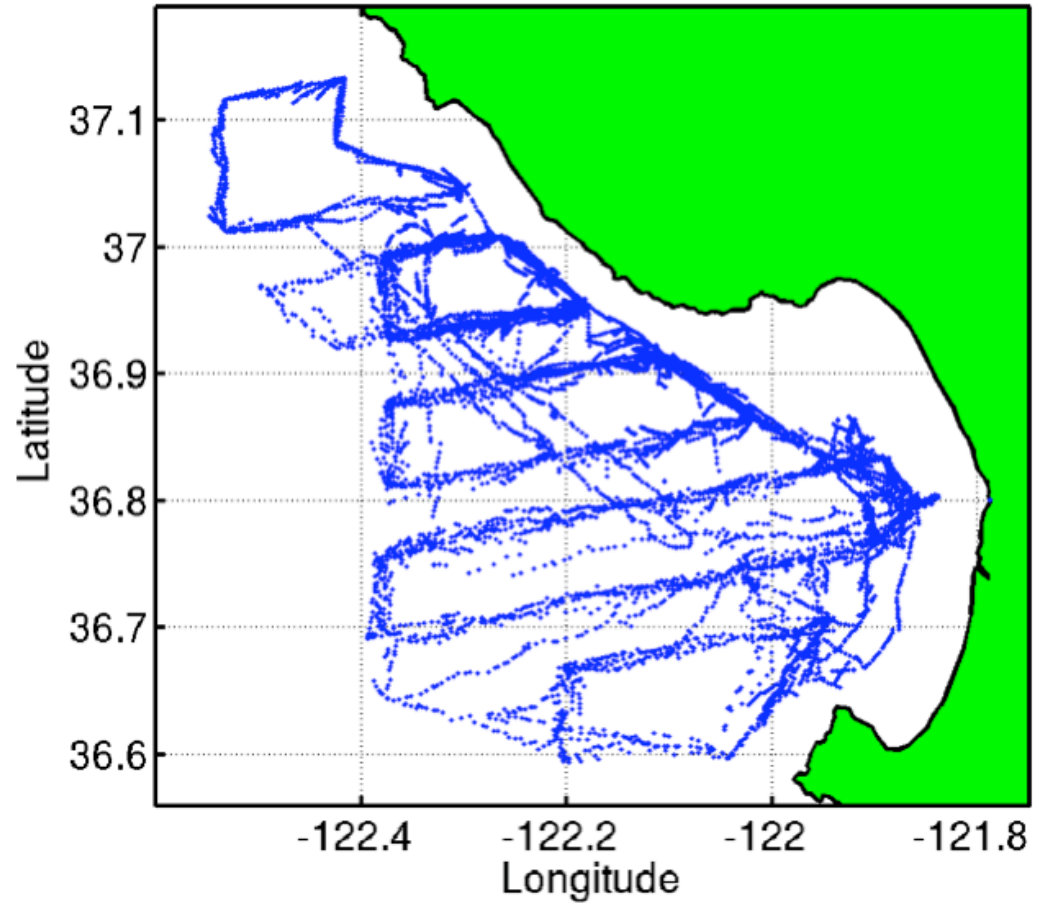
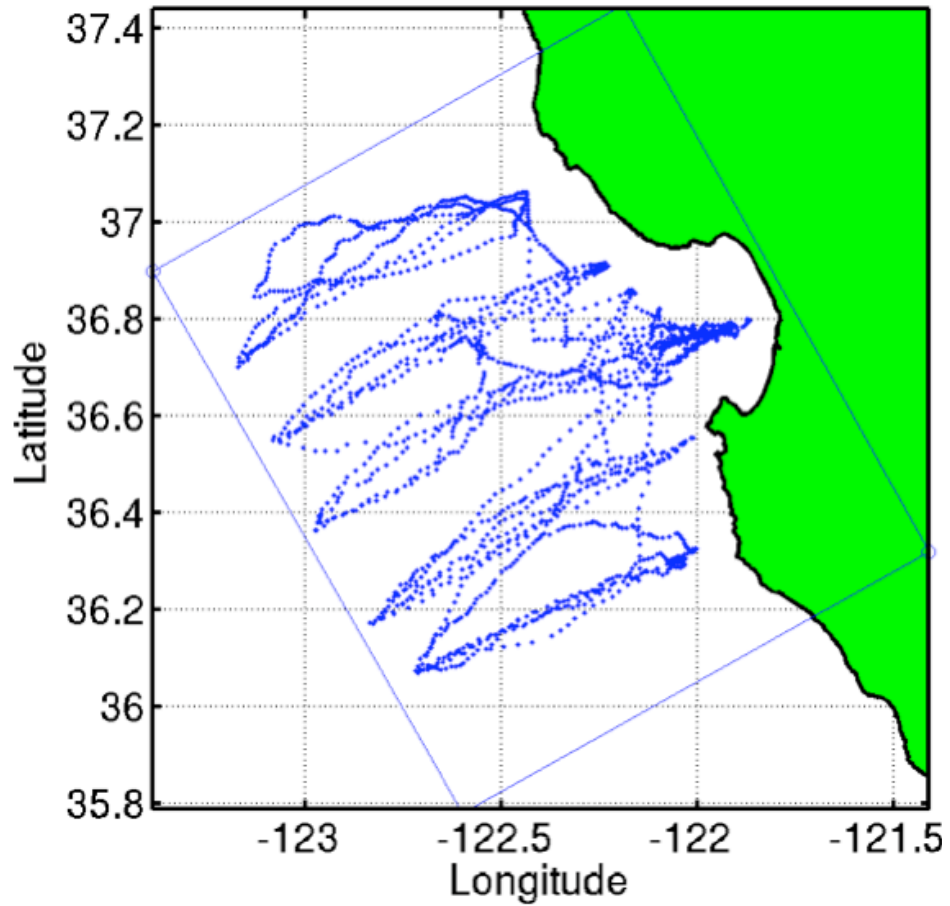


5 SIO Spray Gliders



10 WHOI Slocum Gliders

AOSN-II Glider Measurements



Overview of Talk

- Feedback control laws for stabilization of **collective motion**
- Quantitative **metrics** for evaluation/planning of measurement distributions
- Sensor network **design** for adaptive oceanographic sampling

Self-Propelled Particle Model

[Justh and Krishnaprasad, 2002]

All-to-all coupling of **constant speed** particles subject to steering controls:

$$\dot{\mathbf{r}}_k = e^{i\theta_k}$$

$$\dot{\theta}_k = u_k$$

$$\mathbf{r}_k \in \mathbb{R}^2 \text{ and } \theta_k \in S^1$$

$$k = 1, \dots, N$$

Singularly Perturbed System

[Sepulchre, Paley and Leonard, 2003]

Time scale separation **decouples** alignment and spacing controls:

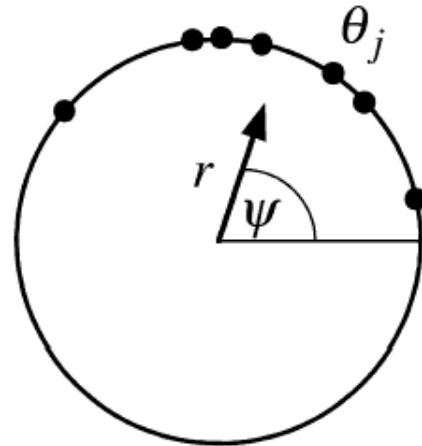
$$\begin{aligned}\dot{\mathbf{r}}_k &= e^{i\theta_k} \\ \epsilon \dot{\theta}_k &= \underbrace{\epsilon u_k^{spac}}_{\text{slow}} + \underbrace{u_k^{align}}_{\text{fast}}\end{aligned}$$

$$|\epsilon| = \frac{1}{|K|} \ll 1$$

Complex Order Parameter

[Kuramoto, 1975]

Centroid of particles phases on unit circle:



$$p_{m\theta} = \frac{1}{N} \sum_{j=1}^N e^{im\theta_j} = r_m e^{i\psi_m}$$

$Np_\theta \equiv$ group linear momentum

Alignment Control

Define control in terms of **gradient** of scalar potential:

$$V_m = \frac{N}{2} |p_m \theta|^2$$

$$\nabla_k V_m = \frac{1}{N} \sum_{j=1}^N \sin(m(\theta_j - \theta_k))$$

Example: **first harmonic** only

$$K u_k^{align} = \frac{K_1}{N} \sum_{j=1}^N \sin(\theta_j - \theta_k)$$

Parallel Motion

Positive coupling of the first harmonic synchronizes the particle phases in the fast dynamics:

$$K_1 = 1 \Rightarrow p_\theta = 1$$

Formation Control

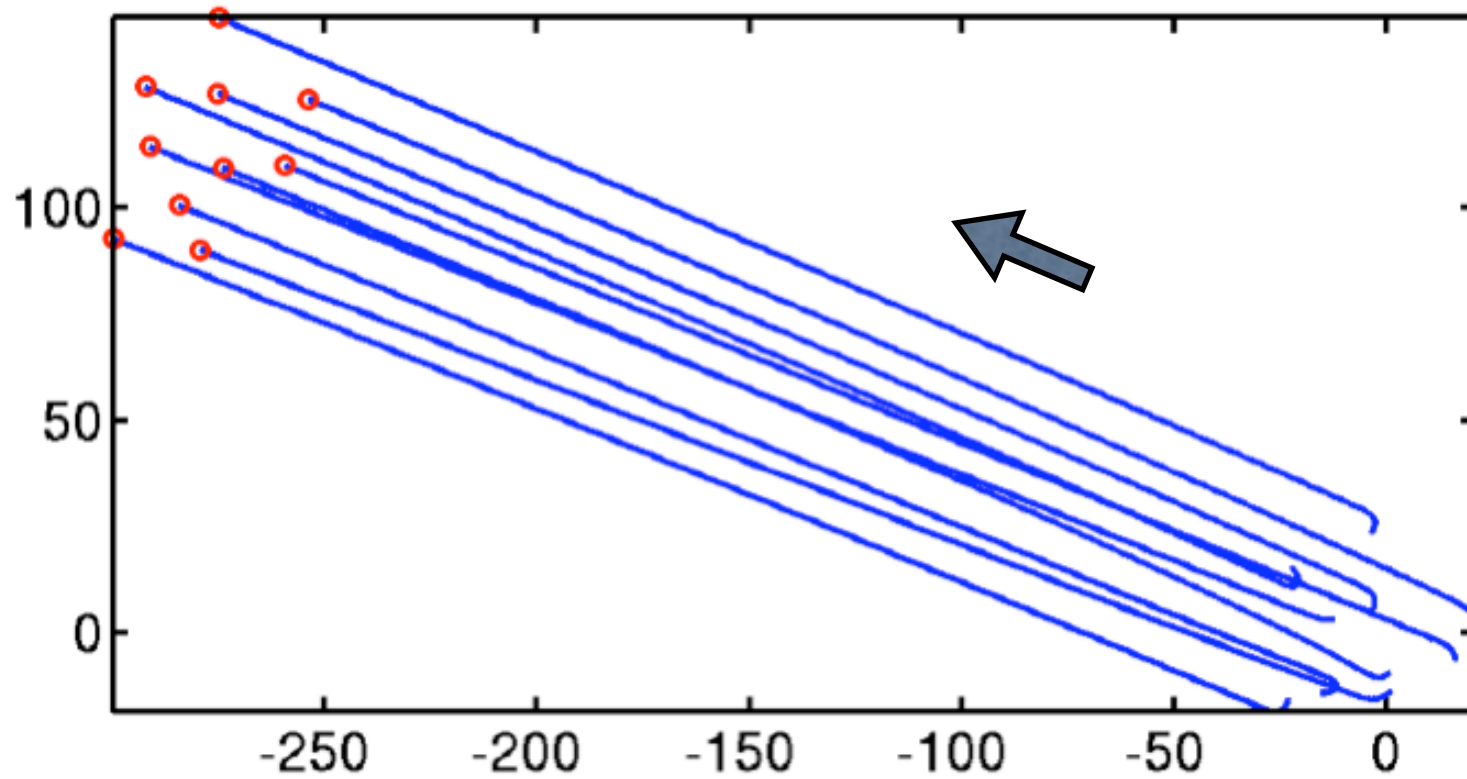
Choose spacing control that inserts **nonlinear springs** between all pairs of particles:

[Bachmayer and Leonard, 2002]

$$U_I(\mathbf{r}_{kj}) = \log \|\mathbf{r}_{kj}\| + \frac{\rho_0}{\|\mathbf{r}_{kj}\|}$$
$$u_k^{spac} = - \sum_{j \neq k}^N \langle \nabla U_I(\mathbf{r}_{kj}), i e^{i\theta_k} \rangle$$
$$U = \sum_{j=1}^N \sum_{k>j}^N U_I(r_{jk})$$

Parallel Motion

$$N = 10, \rho_o = 10$$



Circular Motion

Negative coupling of the alignment **anti-synchronizes** the phases in the fast dynamics

$$K_1 = -1 \Rightarrow p_\theta = 0$$

For compatibility, the slow dynamics must remain on the **balanced manifold**

$$\dot{p}_\theta = \frac{1}{N} \sum_{j=1}^N e^{i\theta_j} \dot{\theta}_j = P_\theta^T u^{spac} = 0$$

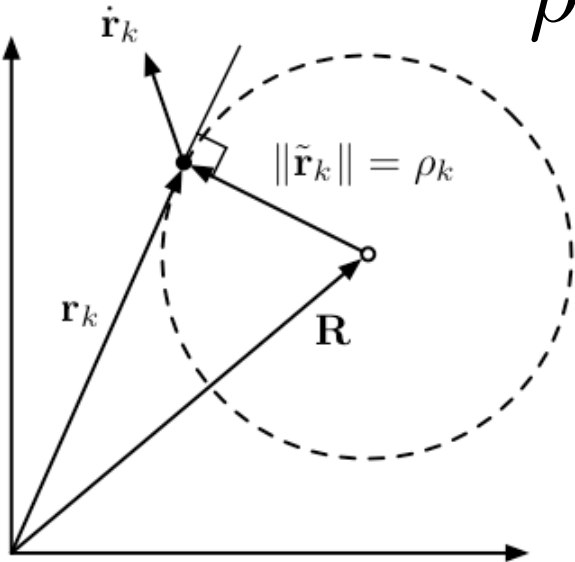
$$u^{spac} = \Pi u^{bal}, \quad \Pi = (I - P_\theta (P_\theta^T P_\theta)^{-1} P_\theta^T)$$

Beacon Control Law

In the slow dynamics, the particle **center of mass** is fixed

[Justh and Krishnaprasad, 2002]

$$u_k^{bal} = -f(\rho_k) \left\langle \frac{\tilde{\mathbf{r}}_k}{\rho_k}, ie^{i\theta_k} \right\rangle - \left\langle \frac{\tilde{\mathbf{r}}_k}{\rho_k}, e^{i\theta_k} \right\rangle$$

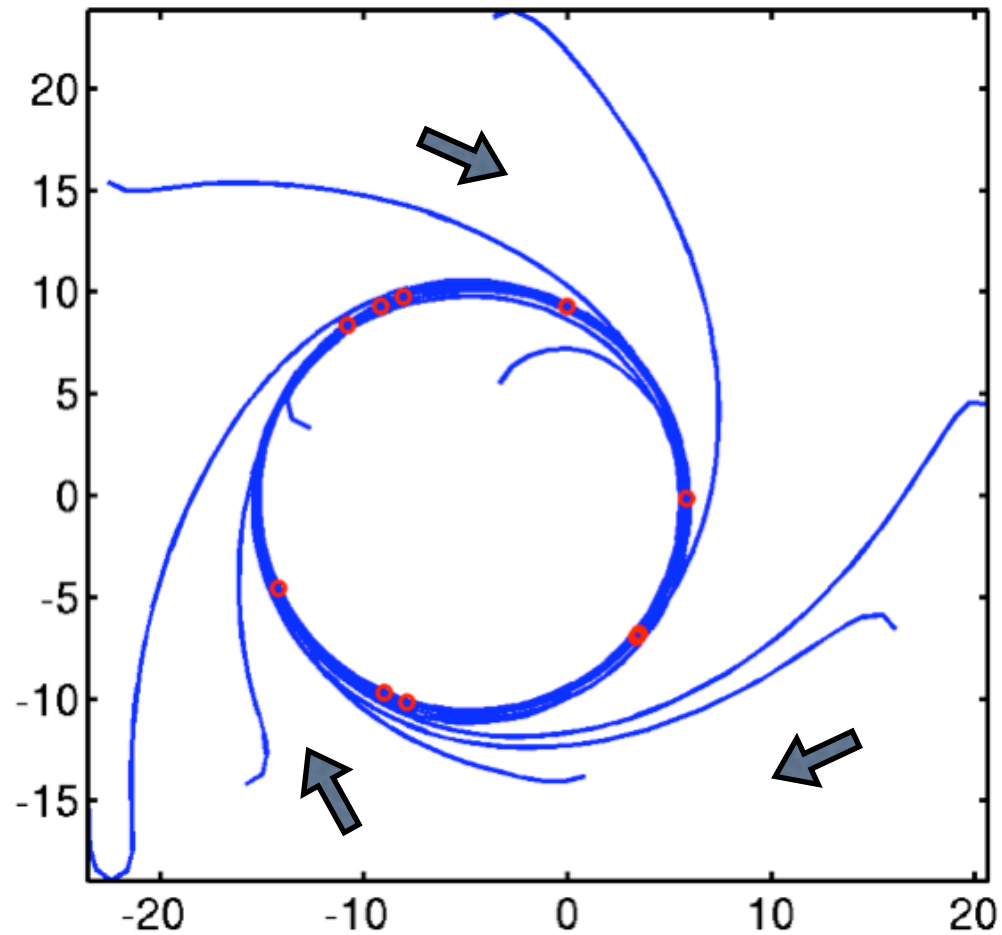


$$f(\rho_k) = 1 - \left(\frac{\rho_o}{\rho_k} \right)^2$$

$$U_k = -\log \left| \left\langle \frac{\mathbf{r}_k}{\rho_k}, ie^{i\theta_k} \right\rangle \right| + \int_{\bar{\rho}}^{\rho_k} \left(f(s) - \frac{1}{s} \right) ds$$

Circular Motion

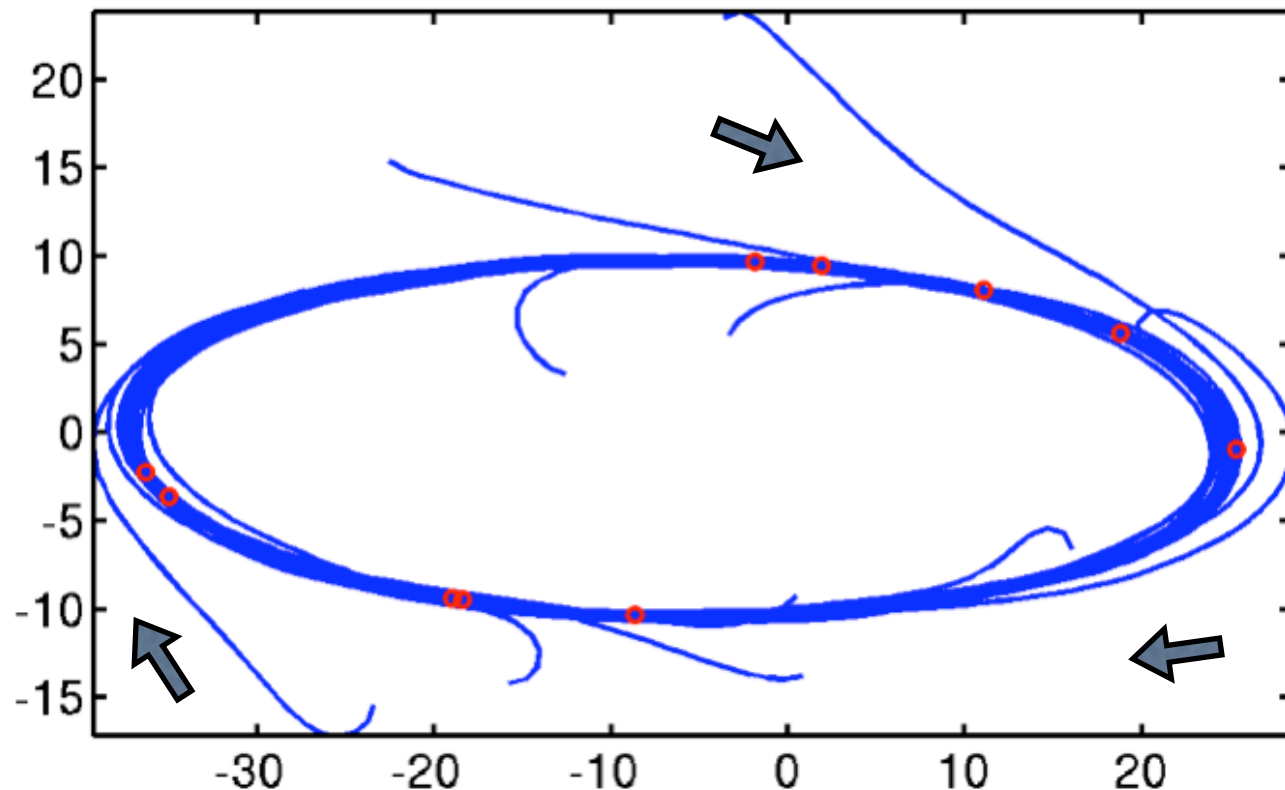
$$N = 10, \rho_o = 10$$



Extension: Shape Changes

Modify **beacon control law** to track elliptical trajectory:

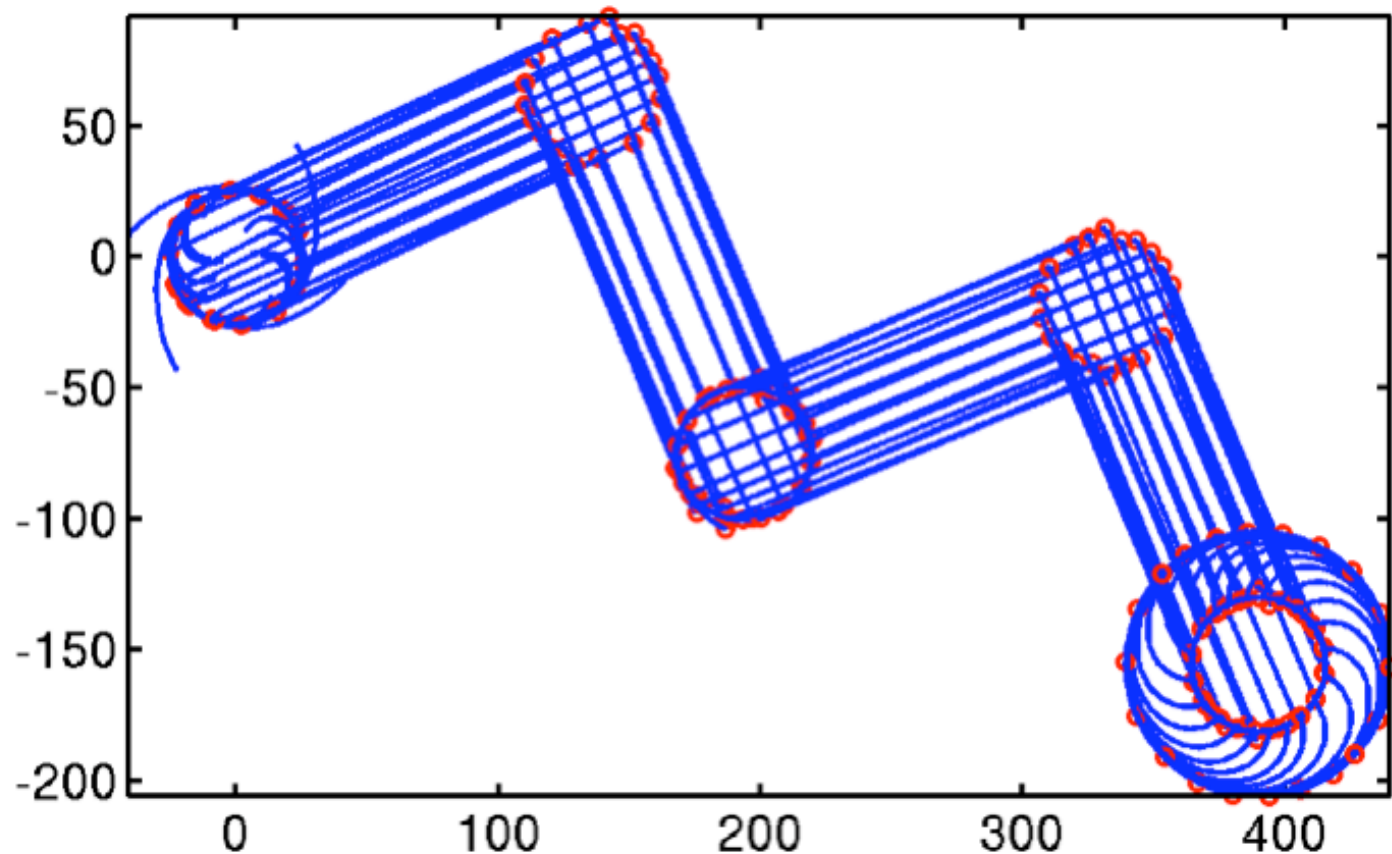
$$N = 10, a = 30, b = 10, e = \sqrt{1 - \frac{b^2}{a^2}} = 0.94$$



Extension: Trajectory Tracking

[Paley, Leonard and Sepulchre, 2004]

$$N = 20, \rho_o = 25$$



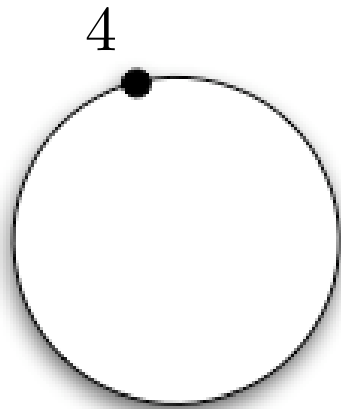
Higher Harmonics

Stabilize higher harmonics of **complex order parameter**:

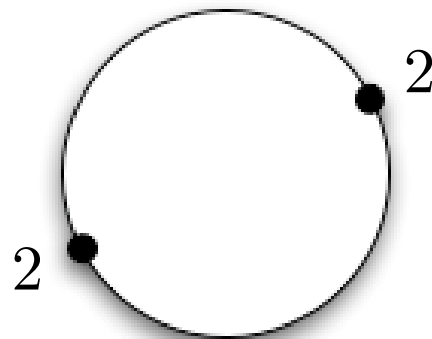
$$K_m > 0 \Rightarrow p_{m\theta} \rightarrow 1$$

$$K_m < 0 \Rightarrow p_{m\theta} \rightarrow 0$$

Example: $N = 4$

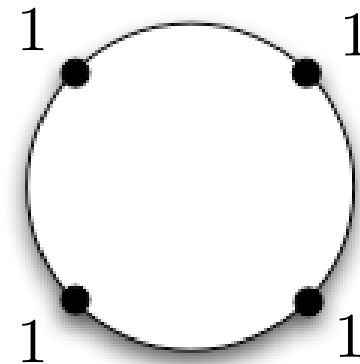


$$p_\theta = 1$$



$$p_\theta = 0,$$

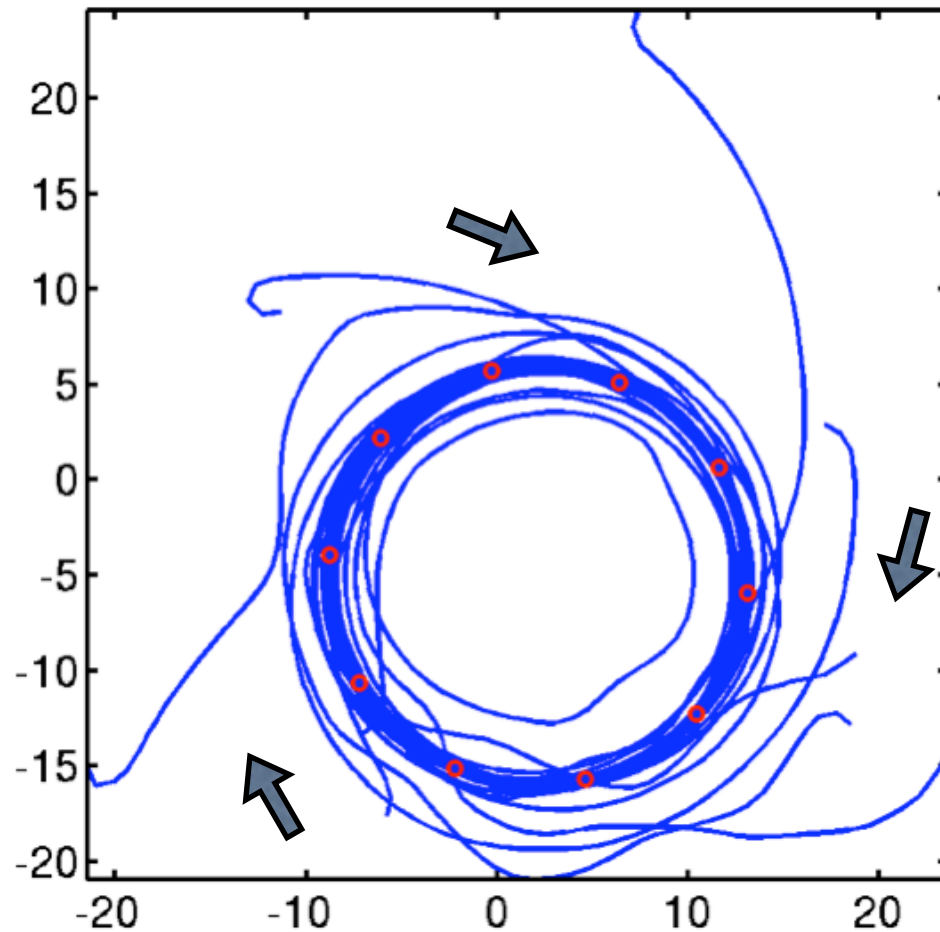
$$p_{2\theta} = 1$$



$$p_\theta = p_{2\theta} = 0$$

Stabilization of the Splay State

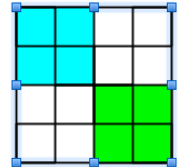
$$p_\theta = p_{2\theta} = \dots = p_{\frac{N}{2}\theta} = 0$$

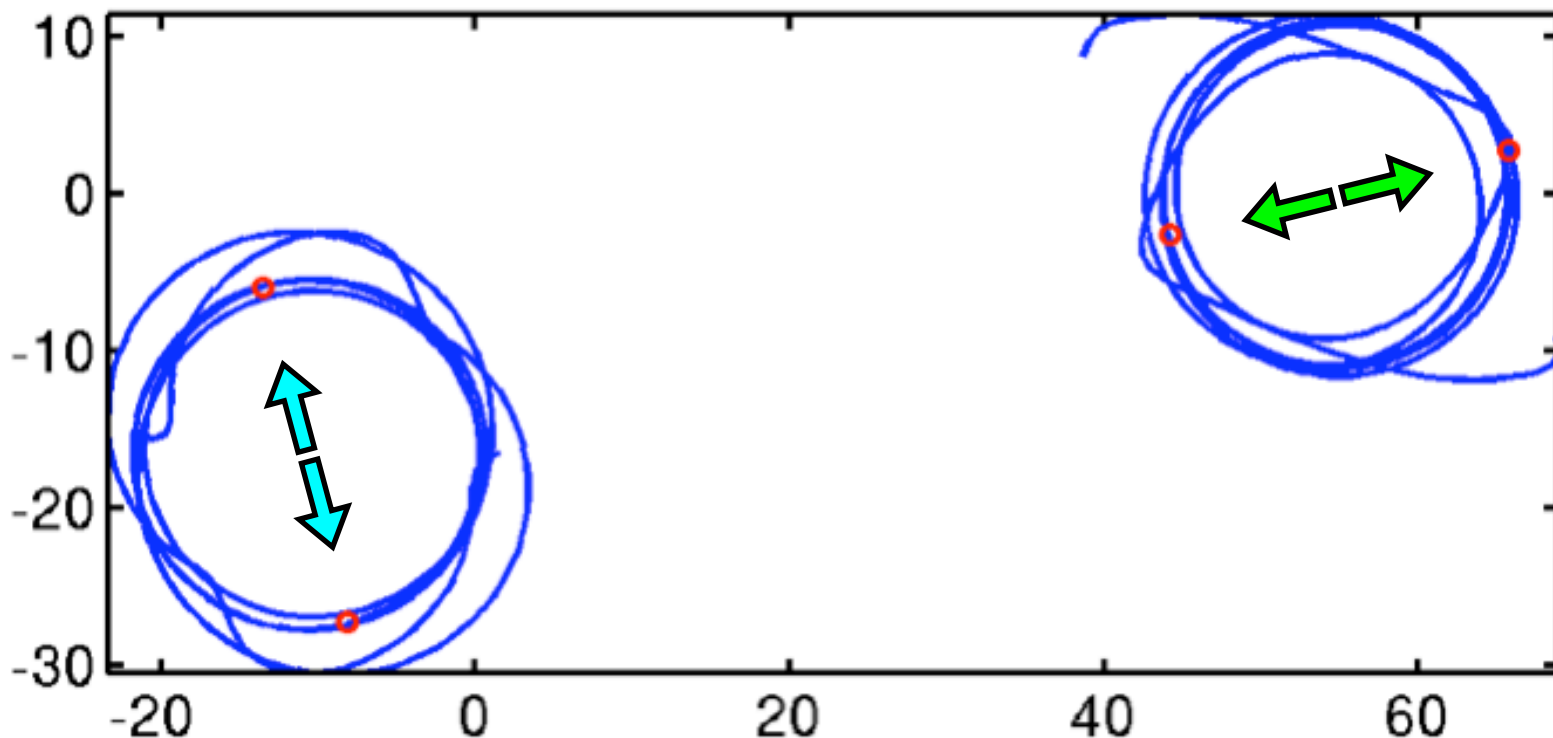


$$N = 10, \rho_o = 10$$

Extension: Topology Changes

Modify network **adjacency matrix** to form subgroups, while preserving **splay state** over all particles:

$$N = 4, \rho_o = 10, A =$$




Overview of Research Topics

- Feedback control laws for stabilization of collective motion
- Quantitative metrics for evaluation/planning of measurement distributions
- Sensor network design for adaptive oceanographic sampling

Objective Analysis

[Gandin, 1965]

[Bretherton, Davis and Fandry, 1976]

Used to compute a gridded **error map** of an estimate formed from noisy measurements of scalar field:

$$\theta(X) = \phi(X) + v$$

$$\hat{\phi}(x) = B\theta(X), \quad x, X \in \mathbb{R}^2 \times \mathbb{R}^+$$

$$\varepsilon^2(x) = \overline{\left(\phi(x) - \hat{\phi}(x)\right)^2}$$

Gauss-Markov Theorem

[Liebelt, 1967]

Theorem provides a linear **minimum variance** unbiased estimator:

$$\mathbf{x} \in (\mathbb{R}^2 \times \mathbb{R}^+)^P, \mathbf{X} \in (\mathbb{R}^2 \times \mathbb{R}^+)^M$$

$$\mathbf{e}(\mathbf{x}) = \phi(\mathbf{x}) - \hat{\phi}(\mathbf{x}) \implies C_{\mathbf{e}} = E(\mathbf{e}\mathbf{e}^T)$$

$$C_{\mathbf{e}} = C_{\mathbf{x}} - C_{\mathbf{x}\mathbf{X}}(C_{\mathbf{X}} + C_{\mathbf{v}})^{-1}C_{\mathbf{x}\mathbf{X}}^T$$

Autocorrelation Function

[Lermusiaux, 1999]

Assume **homogeneous**, isotropic, stationary field:

$$C_{xX} = F(\xi, \eta)$$

$$\xi = \|(x_1 - X_1, x_2 - X_2)\|, \eta = |x_3 - X_3|$$

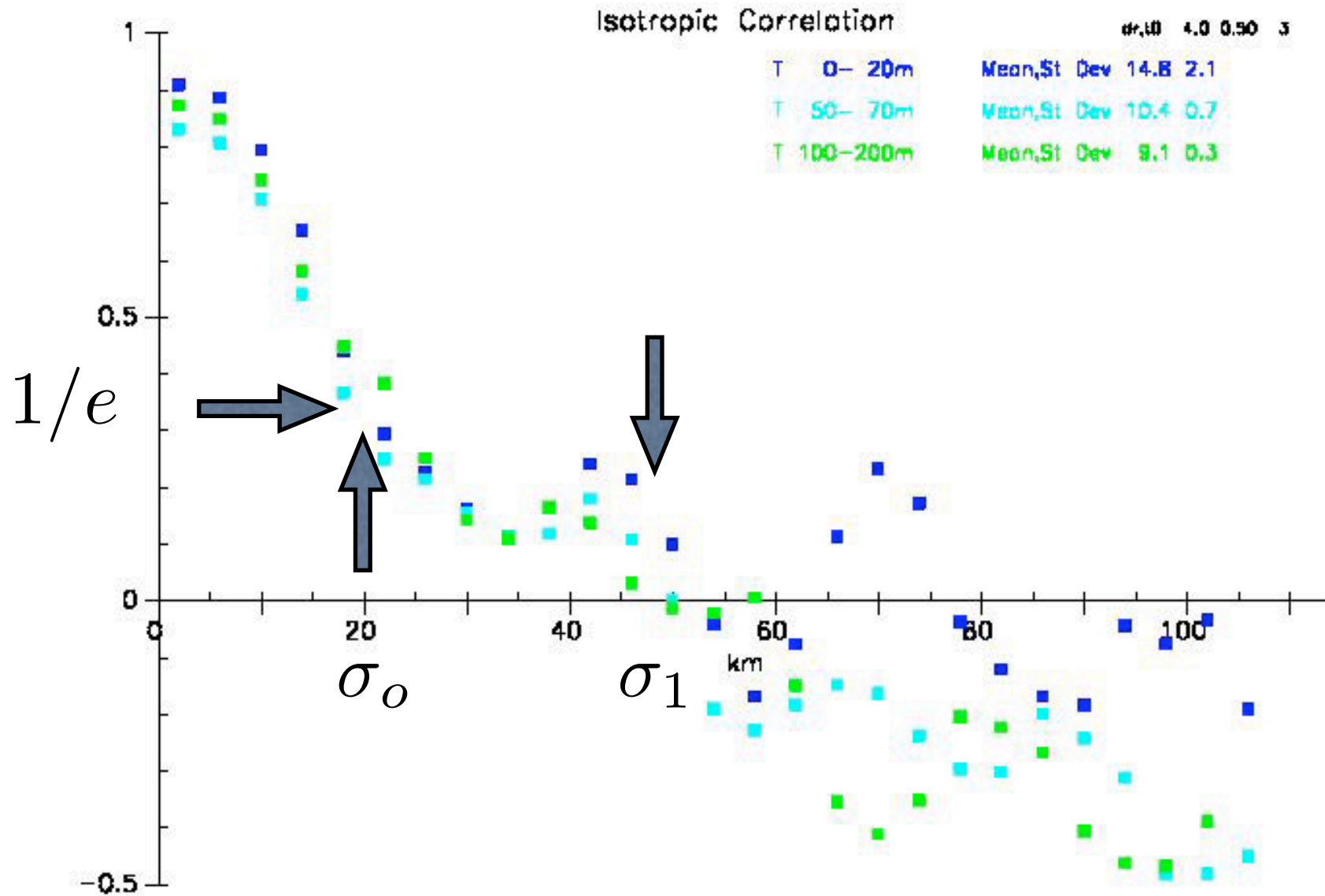
$$F(\xi, \eta) = \left(1 - \frac{\xi^2}{\sigma_1^2}\right) \exp\left[-\frac{1}{2} \left(\frac{\xi^2}{\sigma_o^2} + \frac{\eta^2}{\tau^2}\right)\right]$$

and uncorrelated, zero mean noise:

$$C_v = E\mathbf{I}$$

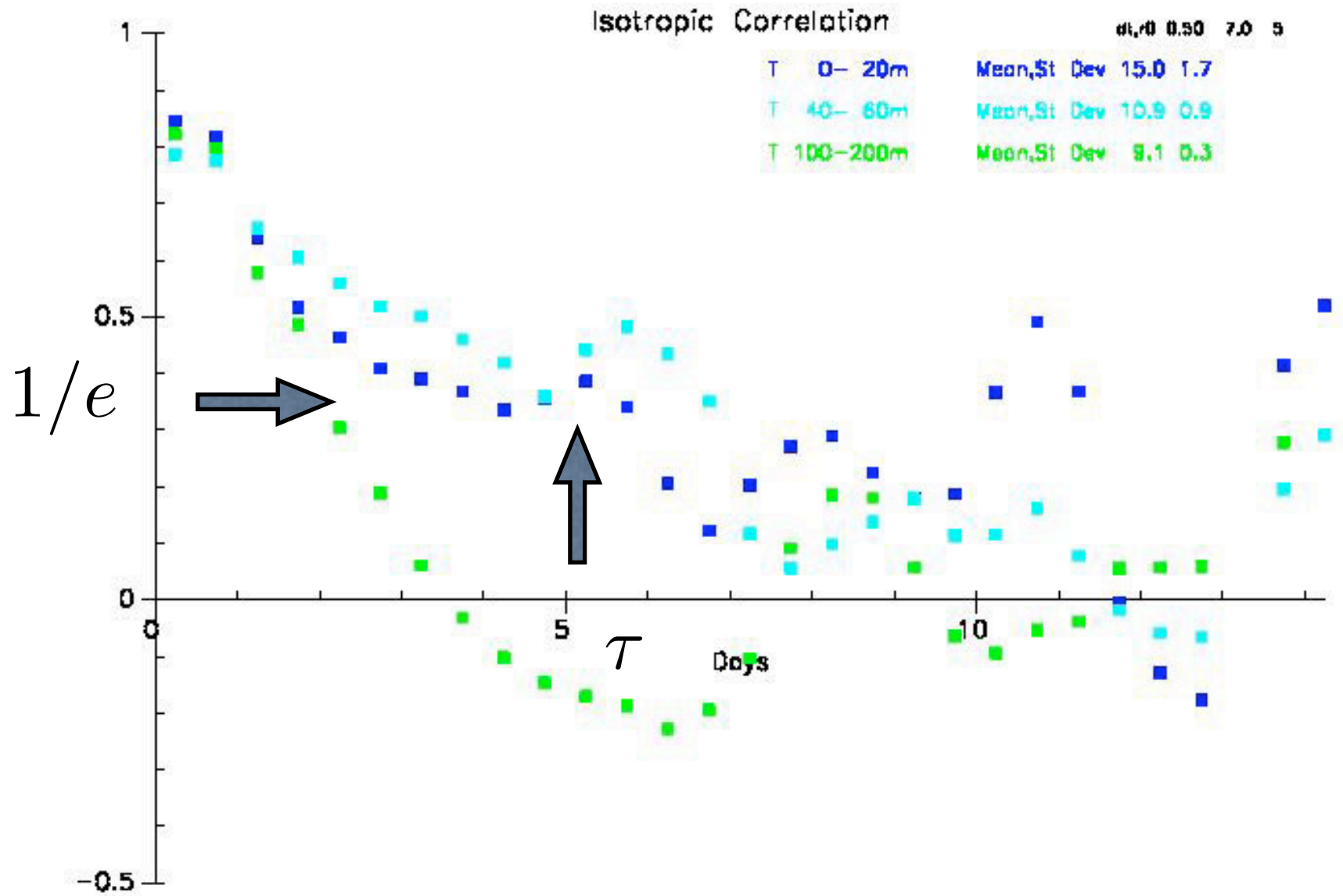
Temperature Correlation vs. Distance

[Davis, 2003]

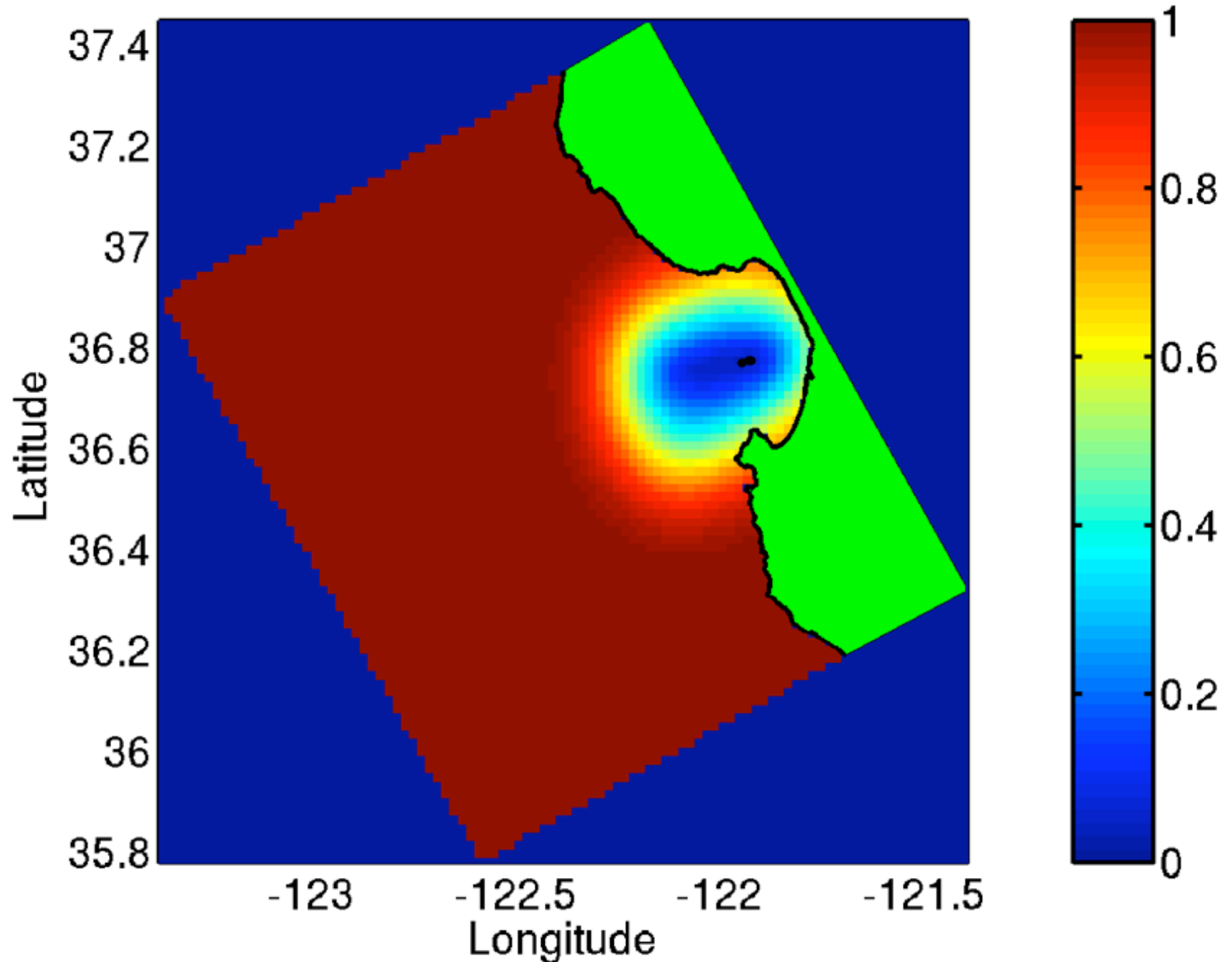


Temperature Correlation vs. Time

[Davis, 2003]



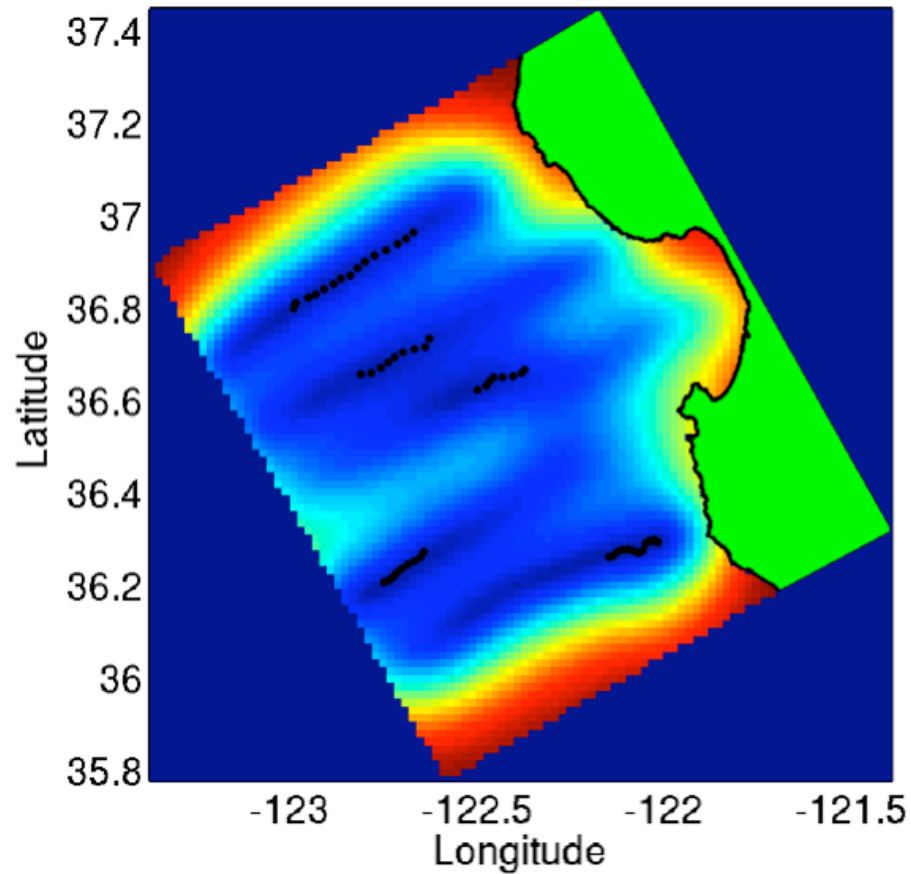
Error Map Day 204, $l=0.056665$, 91 profiles



$\sigma_o = 20$ km, $\sigma_1 = 40$ km, $\tau = 5$ days, $E = 0.1$

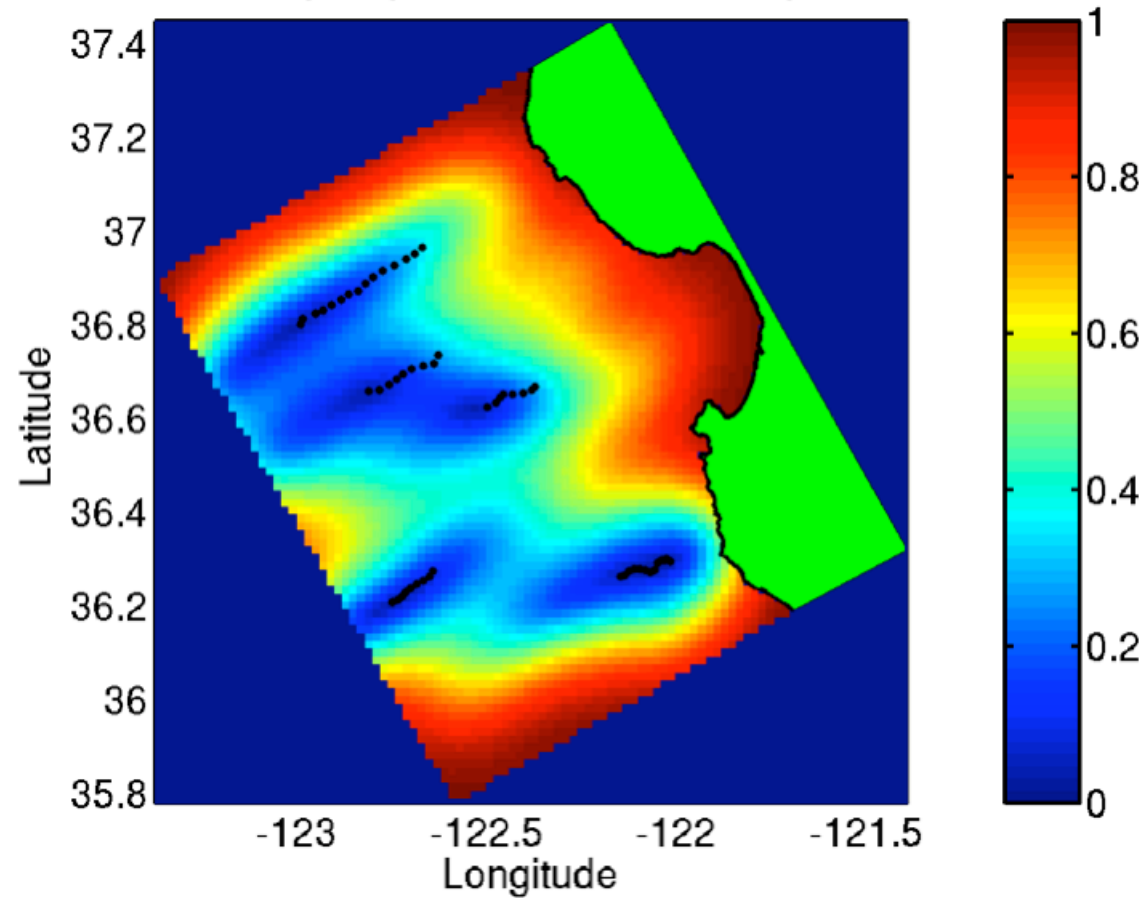
Sensitivity to Parameters

Error Map Day 225, $I=0.86033$, 533 profiles



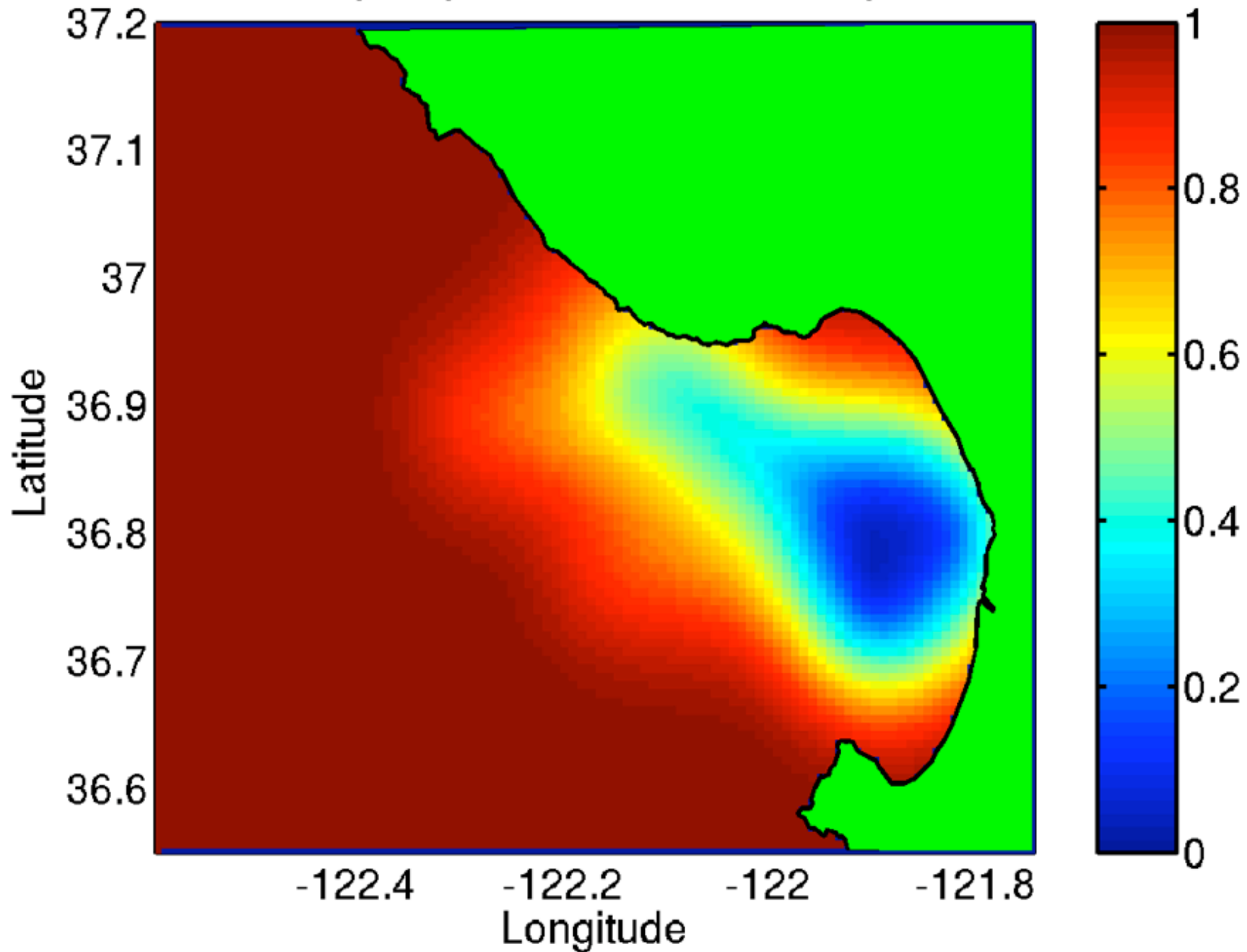
$\tau = 5$ days

Error Map Day 225, $I=0.51683$, 262 profiles



$\tau = 2.5$ days

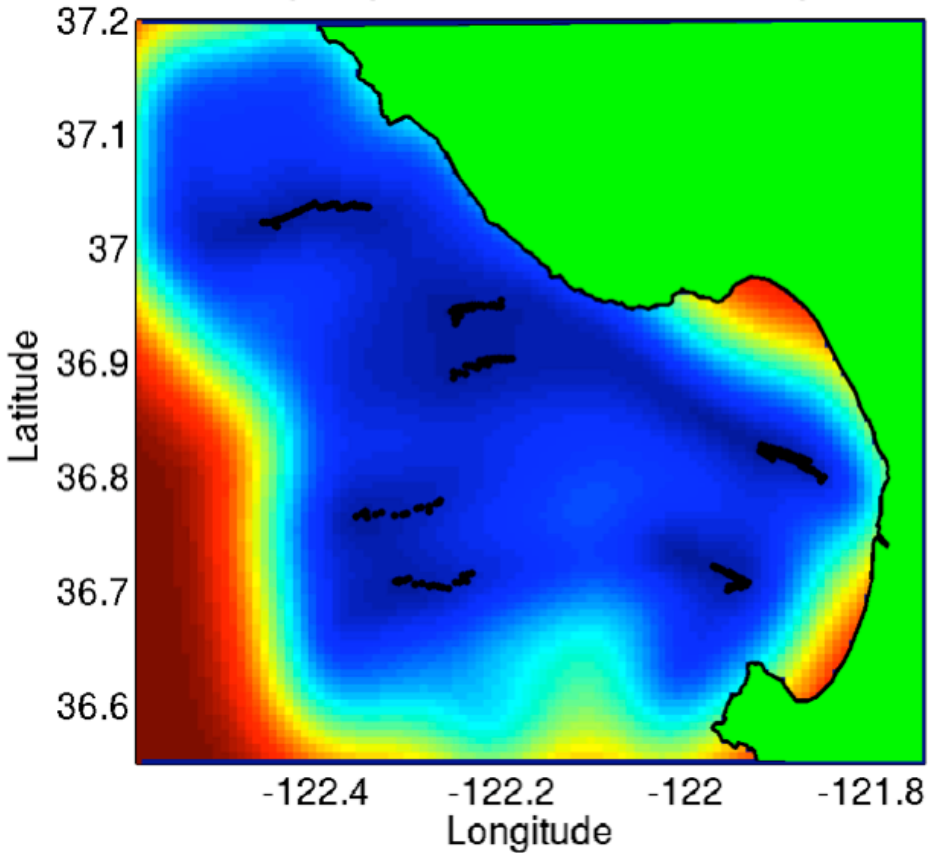
Error Map Day 210, $l=0.11472$, 496 profiles



$$\sigma_o = 10 \text{ km}, \sigma_1 = 20 \text{ km}, \tau = 2.5 \text{ days}, E = 0.1$$

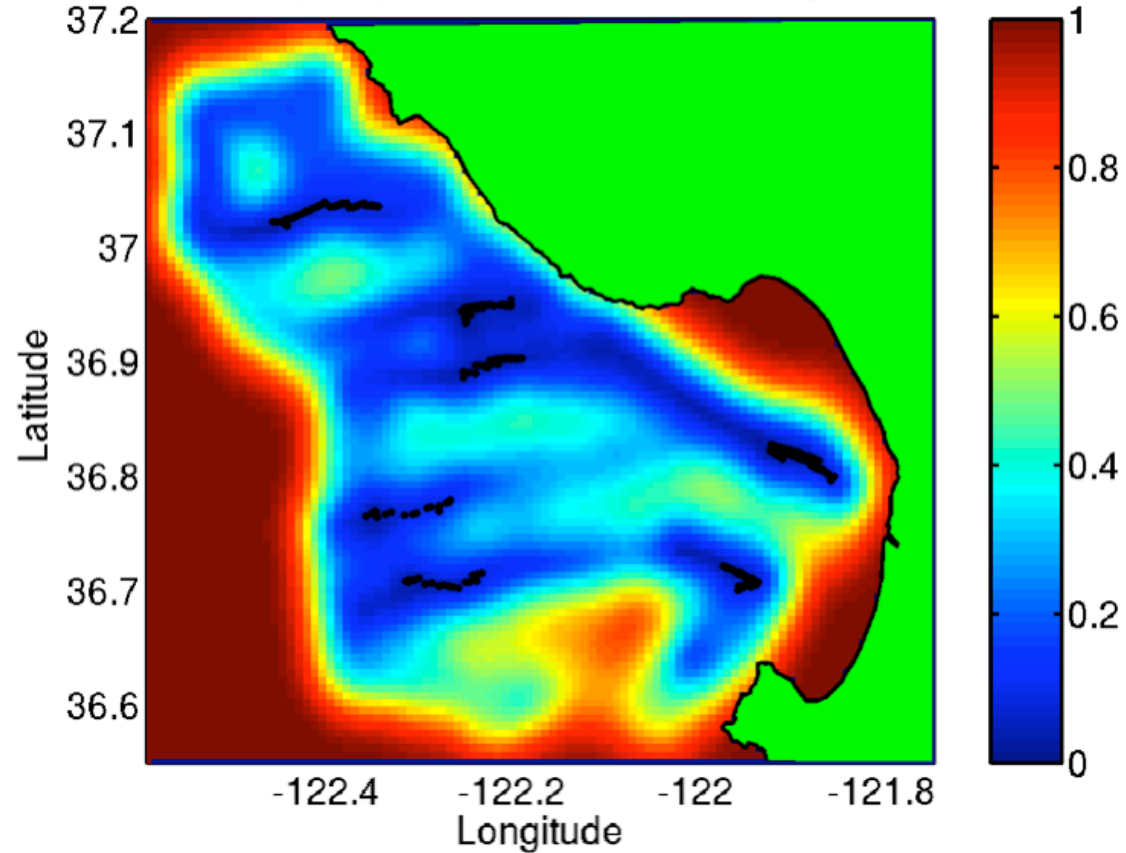
Sensitivity to Parameters II

Error Map Day 224.5, $l=0.88759$, 2524 profiles



$$\sigma_o = 10 \text{ km}, \sigma_1 = 20 \text{ km}$$

Error Map Day 224.5, $l=0.49491$, 2524 profiles



$$\sigma_o = 5 \text{ km}, \sigma_1 = 10 \text{ km}$$

Scalar Entropy Metric

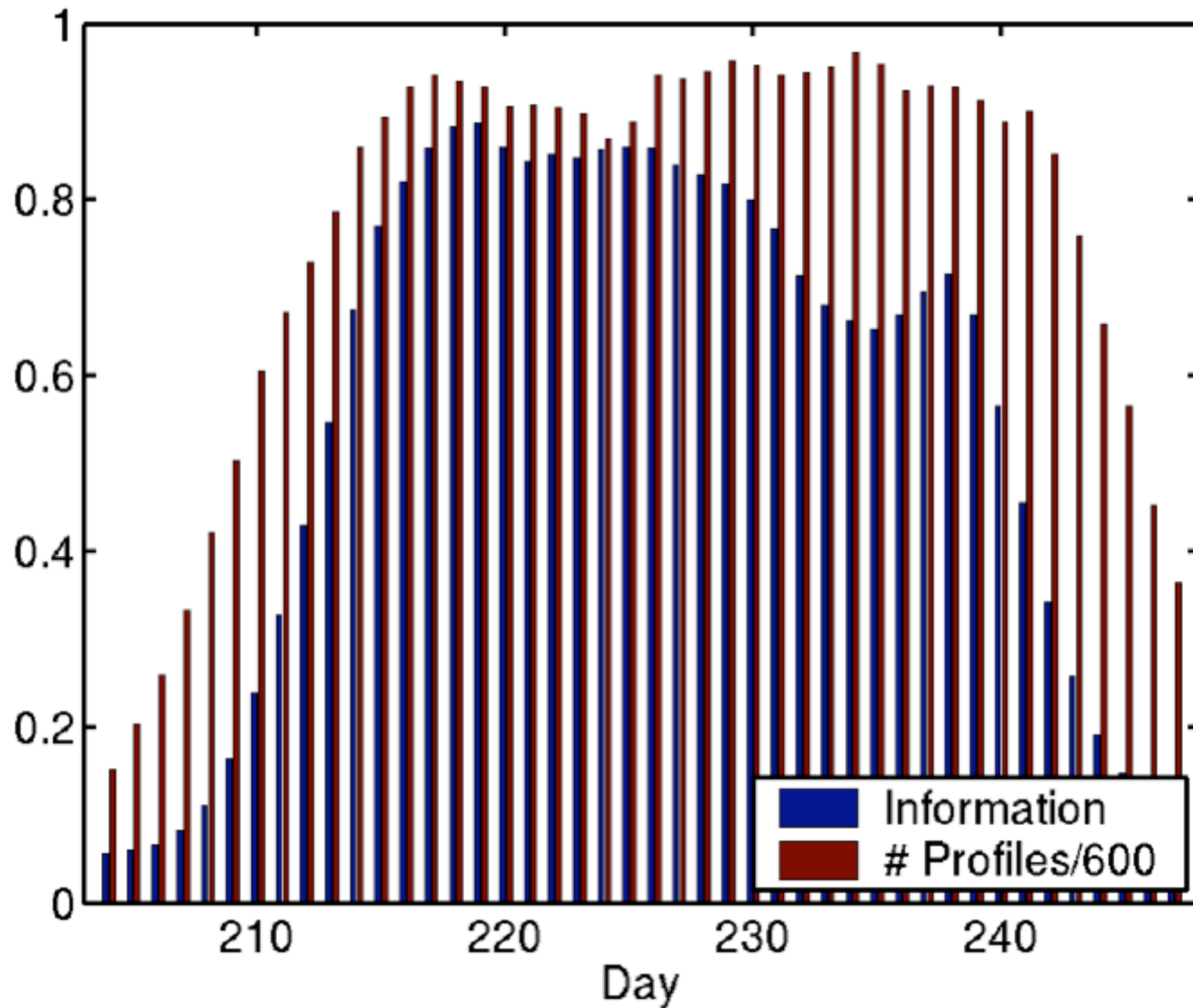
$$H(\mathbf{e}) = -E(\log Pr(\mathbf{e})) \quad [\text{Papoulis, 2002}]$$

$$H(\mathbf{e}) = \frac{1}{2} \log [(2\pi e)^P |C_{\mathbf{e}}|] \quad [\text{Cover, 1991}]$$

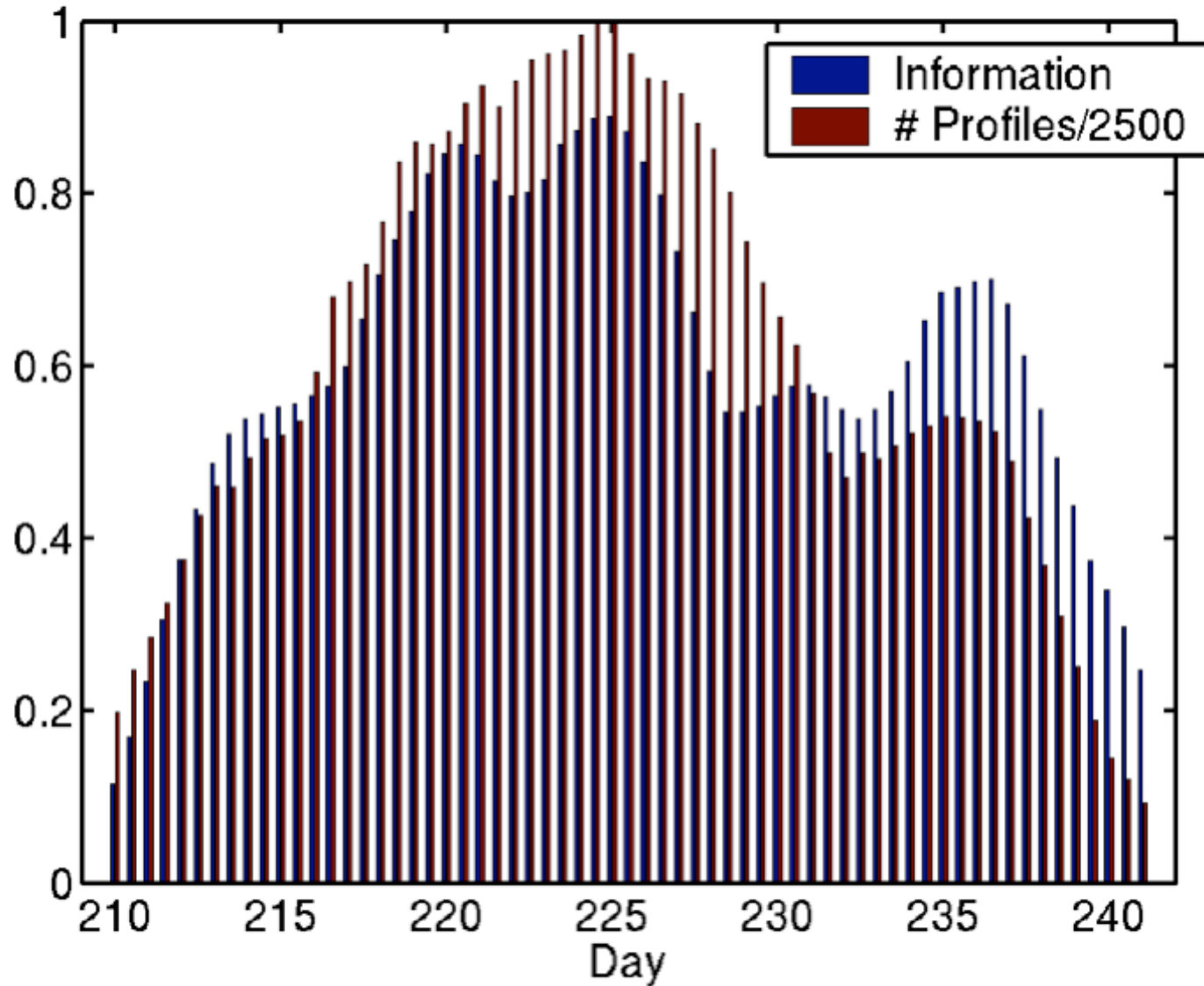
$$H(\mathbf{e}) \leq \frac{1}{2} \log \left[(2\pi e)^P \frac{\text{tr}(C_{\mathbf{e}})}{P} \right]$$

$$I(\mathbf{e}) + c \geq -\log \sqrt{\frac{\text{tr}(C_{\mathbf{e}})}{P}}$$

AOSN-II SIO Glider Performance Profile



AOSN-II WHOI Glider Performance Profile



Overview of Research Topics

- Feedback control laws for stabilization of **collective motion**
- Quantitative **metrics** for evaluation/planning of measurement distributions
- **Sensor network design** for adaptive oceanographic sampling

Dimensionless Parameters

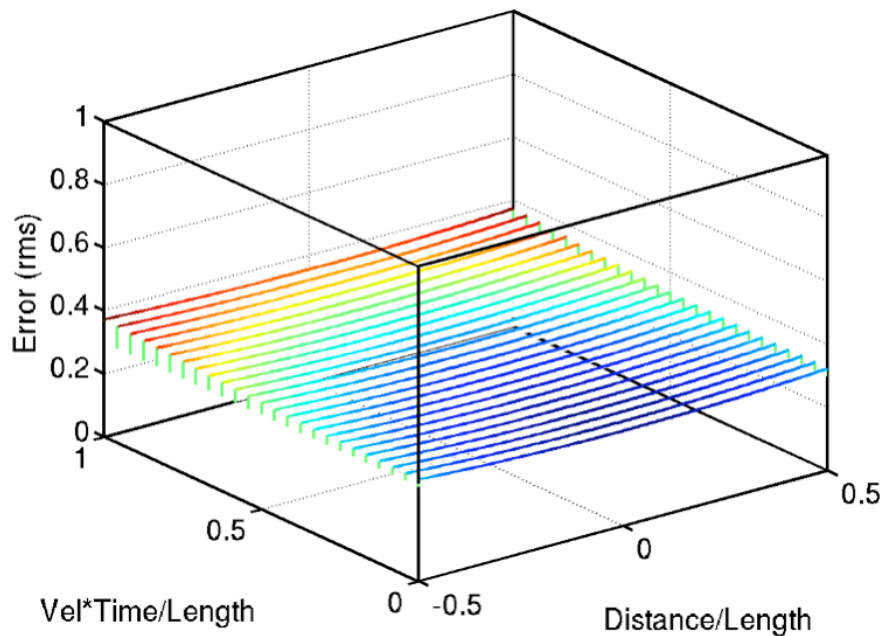
1D (space) plus time:

$$\begin{array}{l} x \rightarrow \frac{x}{L} \quad \lambda = \frac{\sigma}{L} \\ t \rightarrow \frac{vt}{L} \quad \gamma = \frac{v\tau}{\sigma} \end{array}$$

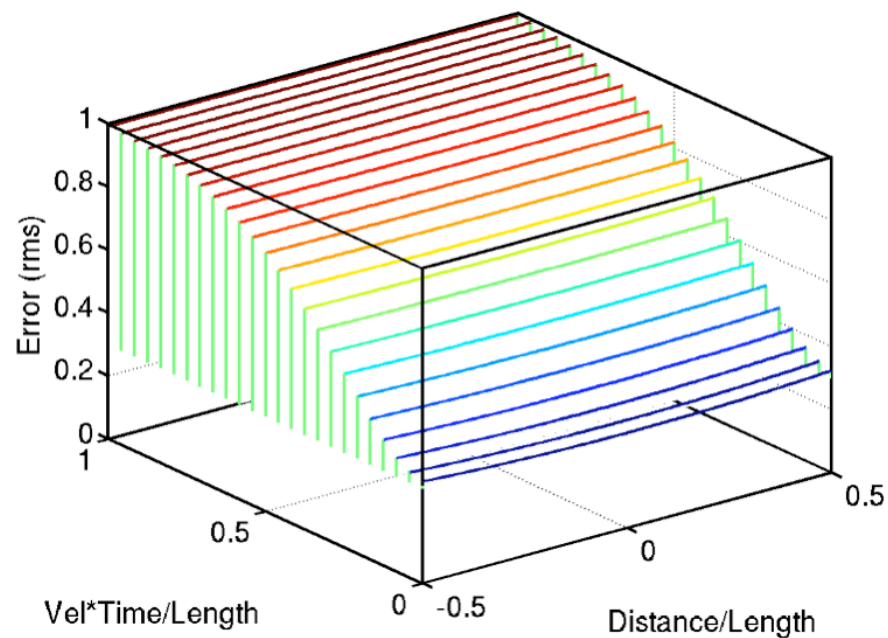
2D (space) and time:

$$L = 2a \quad e = \sqrt{1 - \frac{b^2}{a^2}}$$

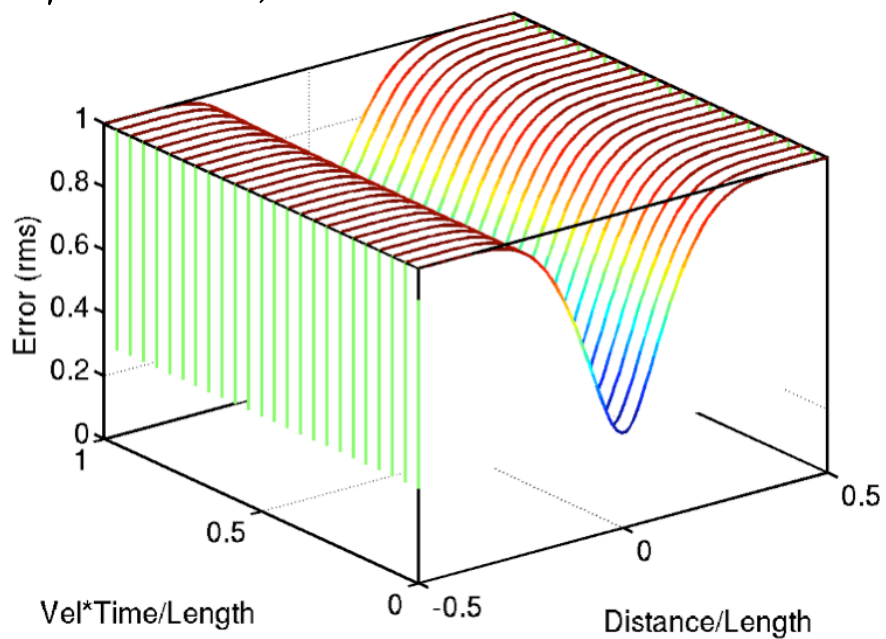
$$\gamma = 1, \lambda > 1$$



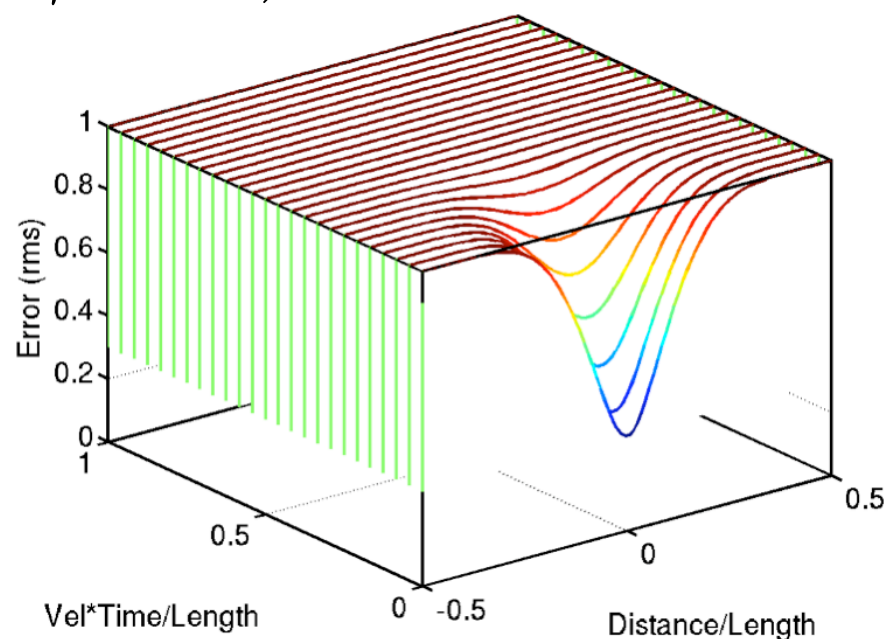
$$\gamma < 1, \lambda > 1$$



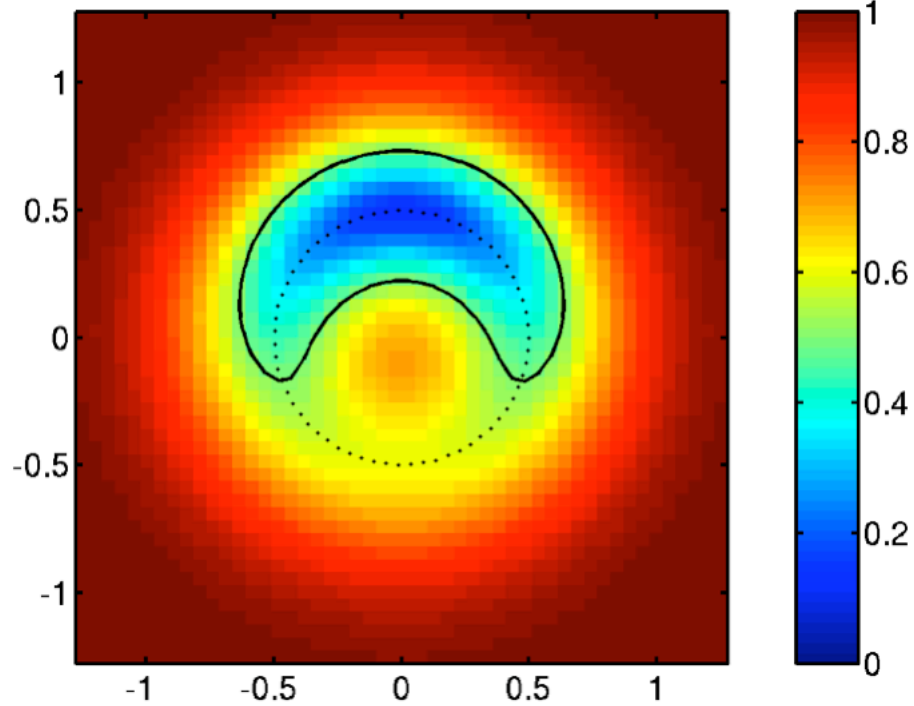
$$\gamma > 1, \lambda < 1$$



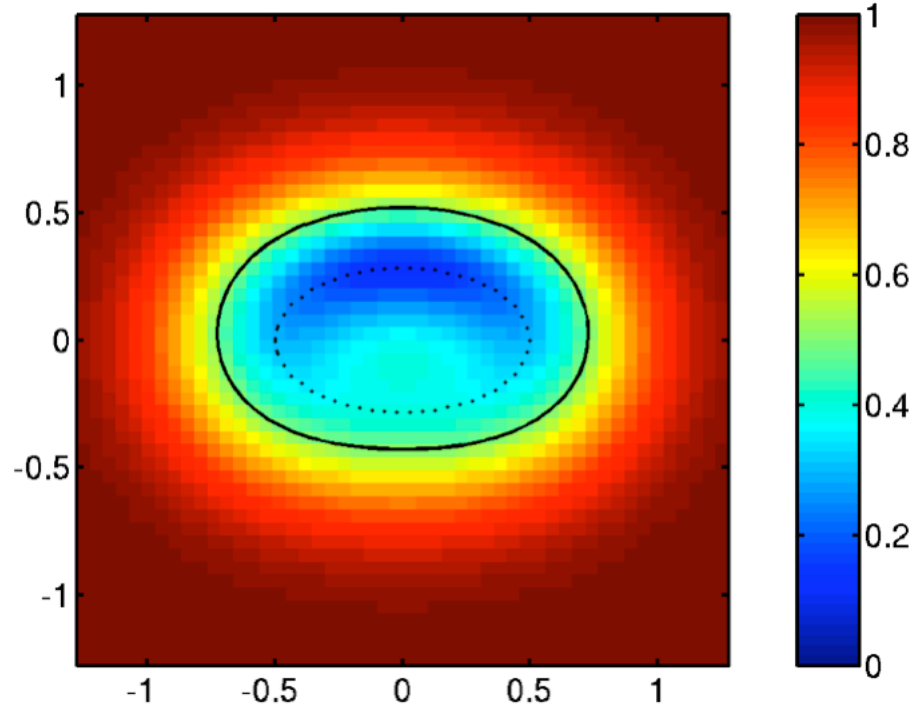
$$\gamma = 1, \lambda < 1$$



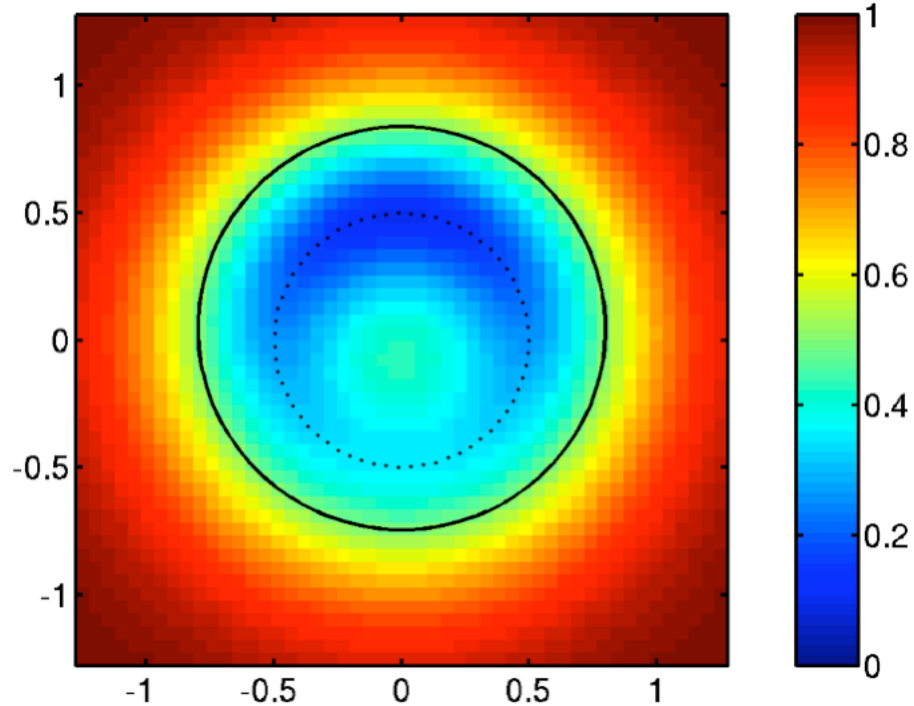
$\gamma=3, \lambda=0.5, e=0, A=0.71683$



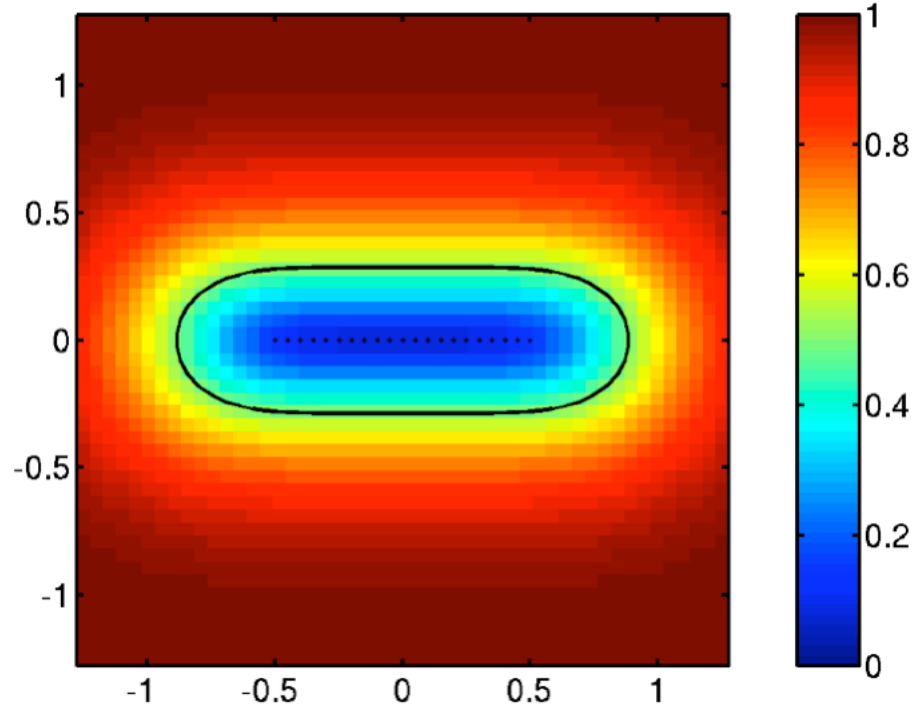
$\gamma=3, \lambda=0.5, e=0.8222, A=1.1114$



$\gamma=3, \lambda=0.6667, e=0, A=1.9832$



$\gamma=3, \lambda=0.6667, e=1, A=0.91133$



Optimal Shape and Size

- Choose eccentricity that maximizes sensor footprint **normalized** area
- Choose semi-major axis that maximizes the sensor footprint area:

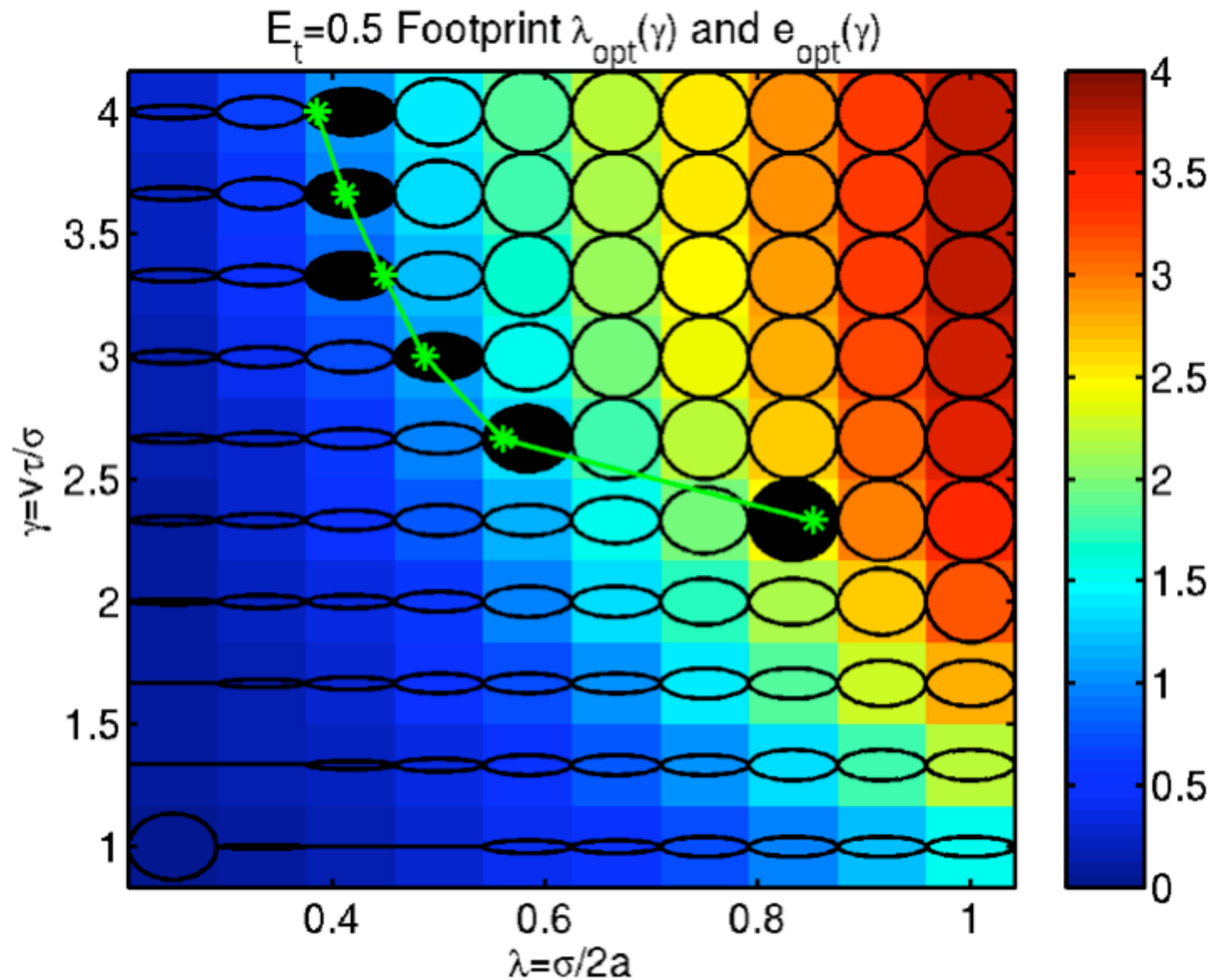
$$\frac{A}{4a^2} = p_1 \lambda^2 + p_2 \lambda + p_3$$

$$\frac{A}{\sigma^2} = p_1 + \frac{p_2}{\lambda} + \frac{p_3}{\lambda^2}$$

$$\frac{\partial A}{\partial \eta} = \sigma^2 (p_2 + 2p_3 \eta) = 0$$

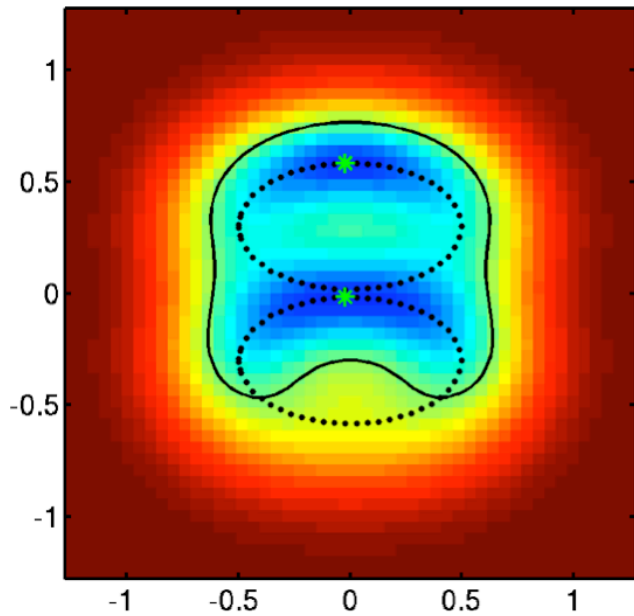
$$\lambda_o = \frac{1}{\eta_o} = \frac{-2p_3}{p_2}.$$

Optimal Shape and Size (N=1)



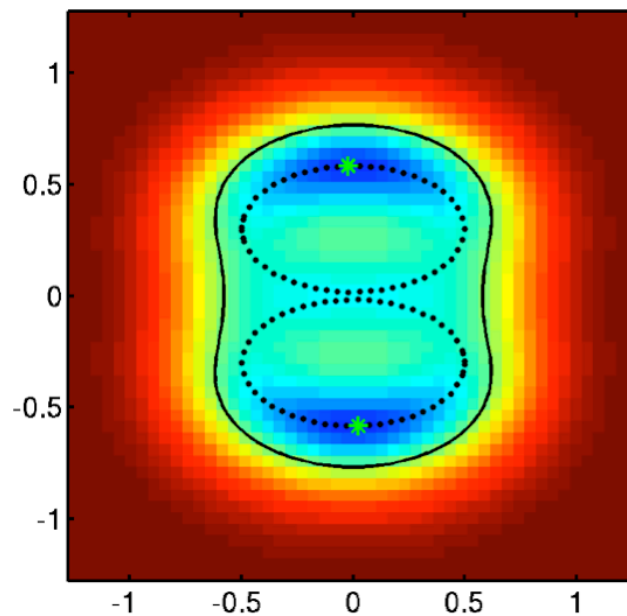
Phase-locked solutions (N=2)

$\gamma=3, \lambda=0.4, e=0.8222, A=1.3315$



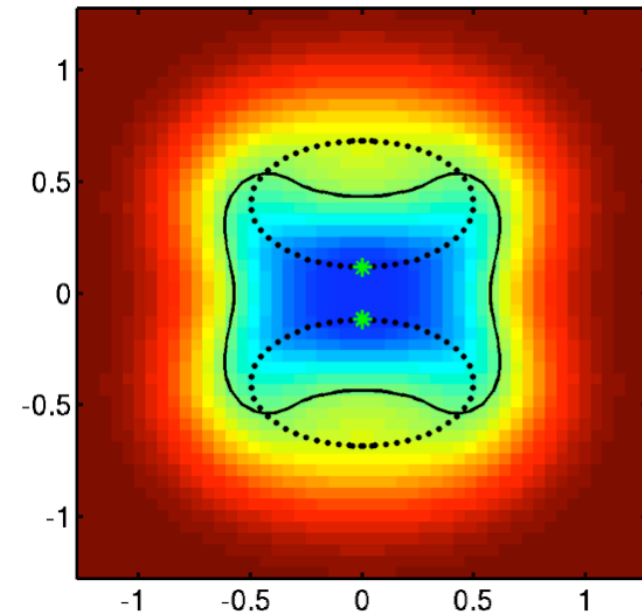
Sync

$\gamma=3, \lambda=0.4, e=0.8222, A=1.653$



Anti-Sync
(best)

$\gamma=3, \lambda=0.4, e=0.8222, A=1.1551$



Anti-Sync
(worst)

Future Work

- **Symmetry breaking** feedback controls to stabilize collective motion with drift, e.g.

$$\dot{\mathbf{r}}_k = \mathbf{f}(\mathbf{r}_k) + e^{i\theta_k}$$

- Study utility of **Fisher information** matrix eigenstructure for non-periodic trajectories
- Consider **non-homogeneous** fields
- Optimal experiment design literature, e.g. **Ucinski, 2004**