



Improving The Science Returns on Coastal Sensor Webs Using Autonomous Predictive Control and Resource Management

Ashit Talukder/Jet Propulsion Laboratory

Alan Blumberg, Thomas Herrington,
Nickitas Georgas, Anand Panangadan

NASA ESTC-2008



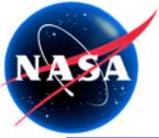
Outline



- Goals and Science Objectives
- NYHOPS Coastal Sensor Web Overview
- Autonomous Sensor Web Control and Resource Management Theory
- Sensor Web Adaptive Control Results
- Ongoing and Future Work



CARDS Goals and Science Objectives



Specific Goals



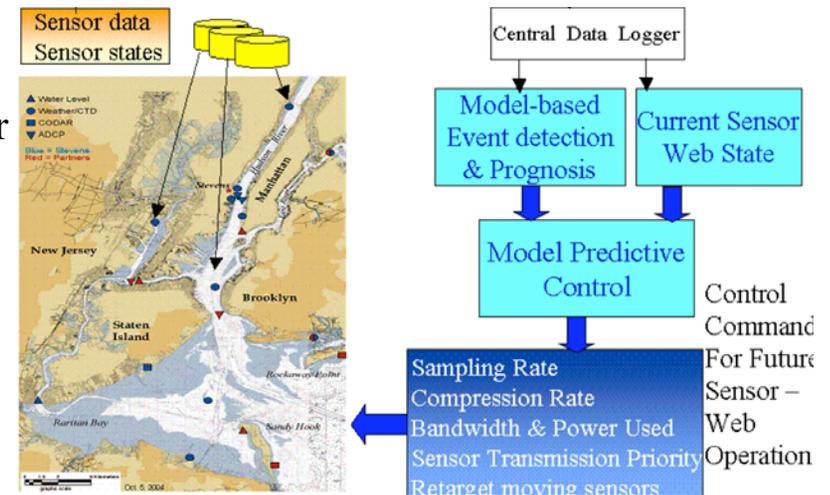
Technical Objectives

- Develop new techniques for *adaptive* in-situ control, operation, and management of multiple resources in heterogeneous spatially distributed sensor webs
- Event detection and prognosis from distributed sensor measurements

Science Goals

- Validate above technologies on coastal New York Harbor Observation and Prediction System (NYHOPS) to improve science returns
- Off-line science validation of NYHOPS sensor web operational autonomy and control with CARDS
- Adapt coastal sensor web to study plumes and coastal storm surges for faster, advanced and improved warning, prediction and modeling
- Reduce response time, increase data quality and scientific value
- Explore opportunities with other ongoing sensor web projects

Concept for Control and Resource Workflow Mgmt. of Sensor Webs

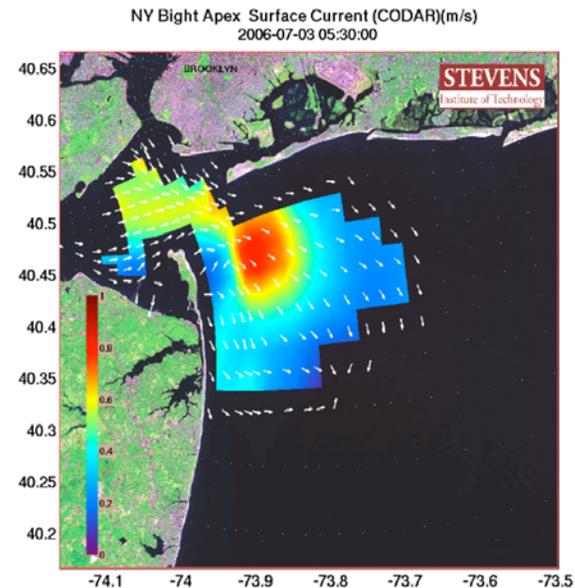




Science Objectives



- Existing operational predictive models of the natural environment cover broad spatial and temporal scales
 - Difficult to identify and capture the onset and evolution of small-scale extreme events (e.g., discharges into coastal waters, anoxia)
- Need for rapid identification and forecasting of events
- Event detection must be automated through model-sensor decision support architecture for 24/7 monitoring.

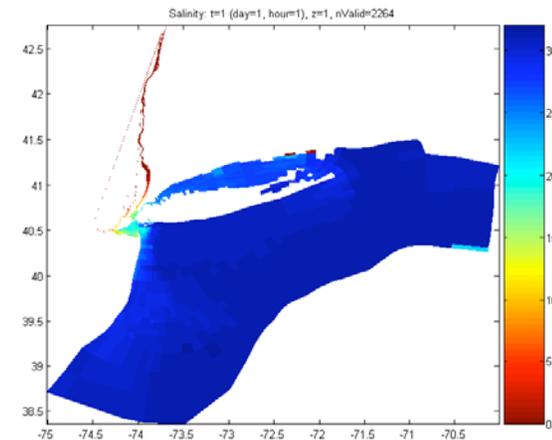
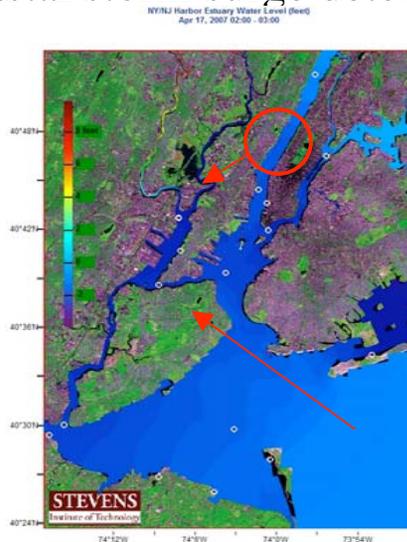




Science Goals



- Detected events and anomalies outside of modeled range can be used to trigger adaptive operation (faster sampling, communication) automatically
 - Adaptive control of sensor network supporting model can provide high-resolution event modeling & detection for **improved knowledge** and **faster (immediate) response**:
 - Plume detection and tracking
 - Coastal storm surge detection and tracking





New York Harbor Observation and Prediction System (NYHOPS) Sensor Web



NY Harbor Observation and Prediction System (NYHOPS)



Real-time observation and model forecast system designed to:

- Develop an awareness of present and future conditions in the NY Harbor and Bight
- Provide knowledge of the natural environment that can be used to assess variances in measured data for threat detection.

STEVENS
Institute of Technology

Funding Agencies

Partners and Collaborators

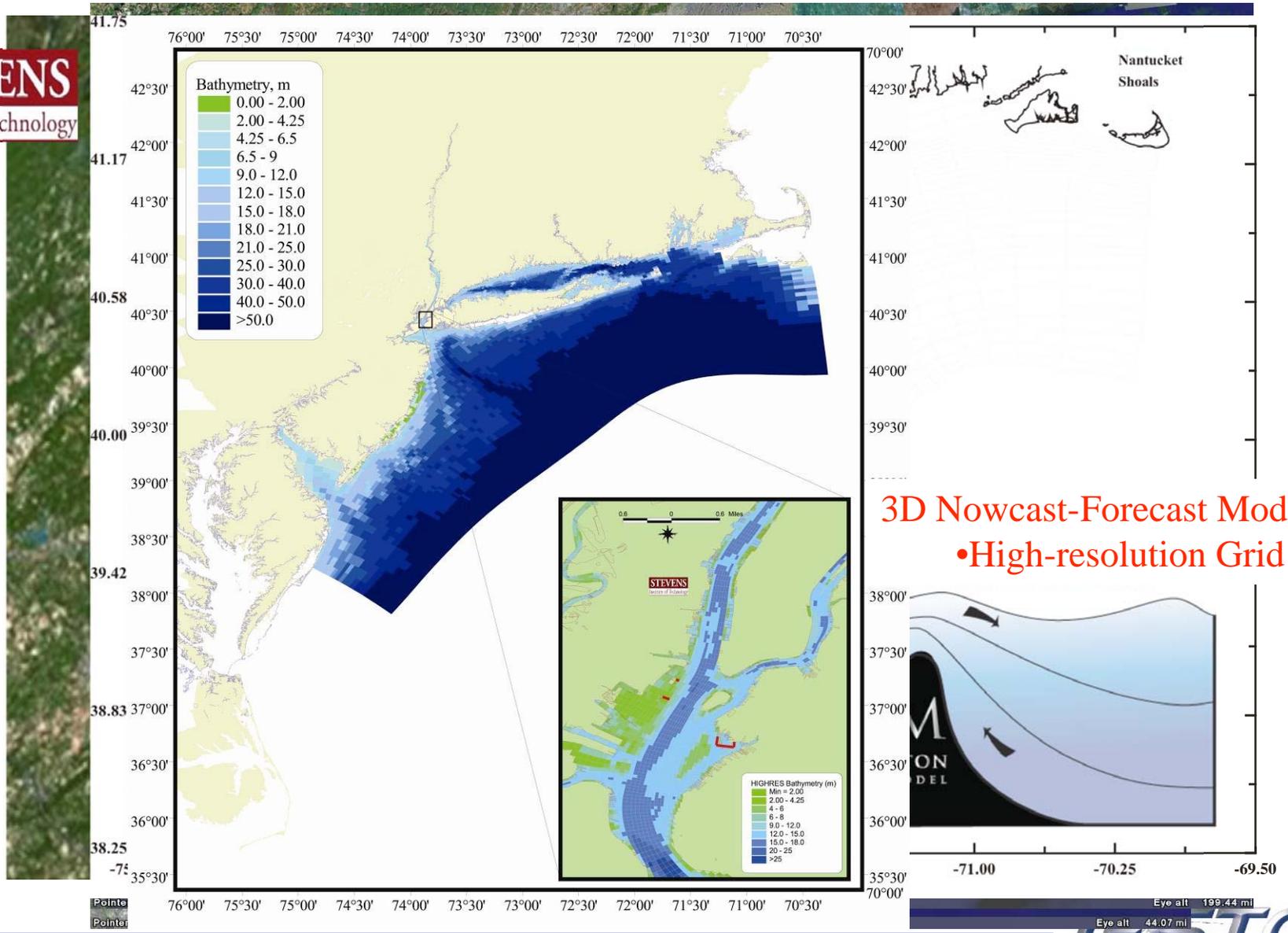




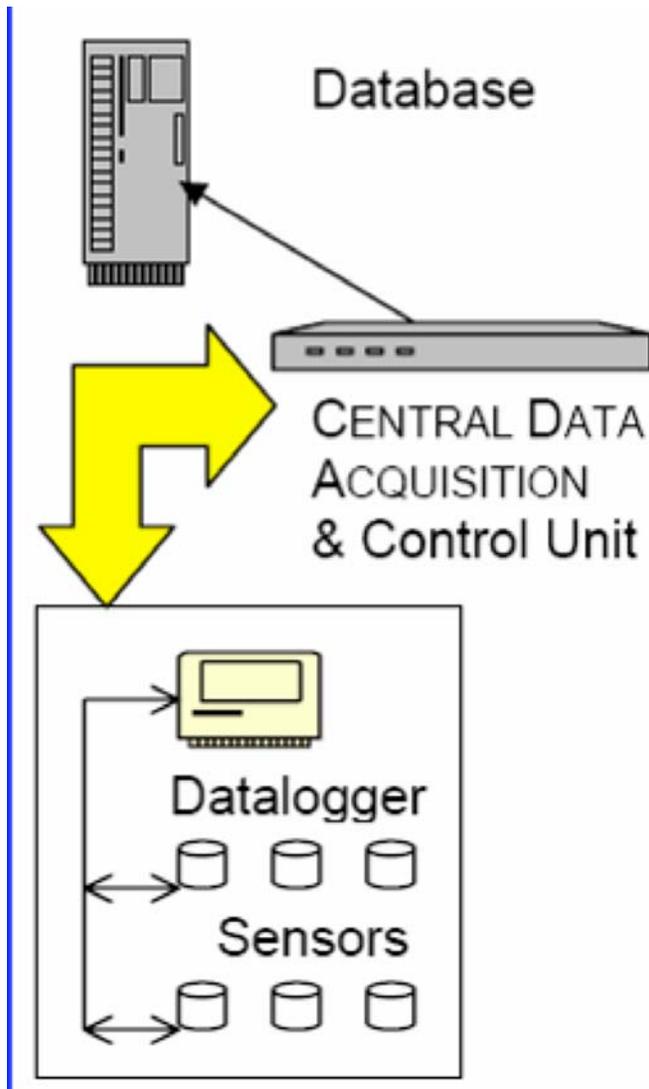
NYHOPS



STEVENS
Institute of Technology



3D Nowcast-Forecast Models
• High-resolution Grid



Network Architecture

- Instrument Platforms
 - Contain Multiple Sensors
 - Recorded on station logger
- Data Transmission
 - RF, Cellular, Internet
- Central Acquisition Unit
 - Pulls data into database
 - Model accesses database



Sensor Networks: Static & Mobile Sensors

Buoys

Mobile sensors on ships/cruise liners

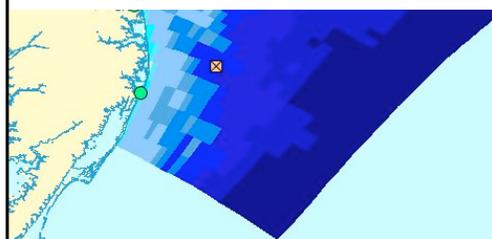
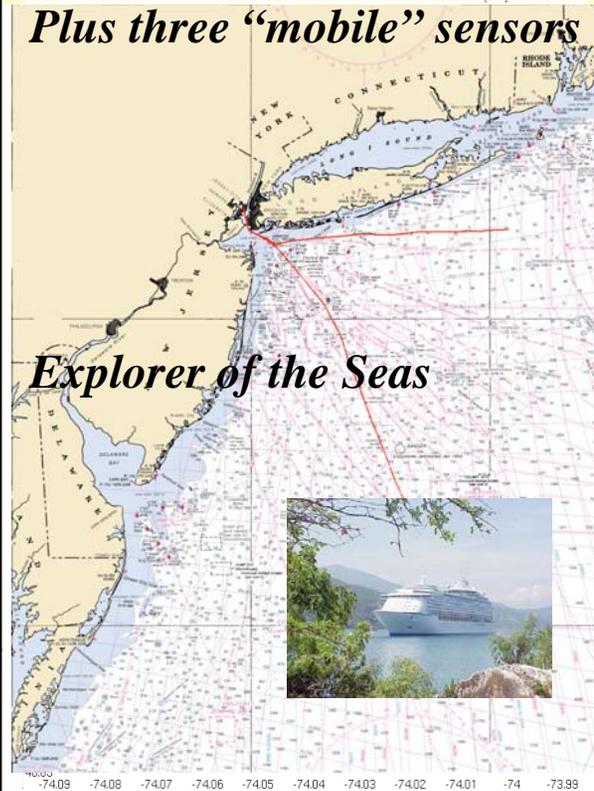
UUVs

Sensor network includes:

- Point Observations,
- Mobile non-controllable sensors
- Mobile controlled sensors

“Point” measurements:
Water Level, T, S, met, etc.

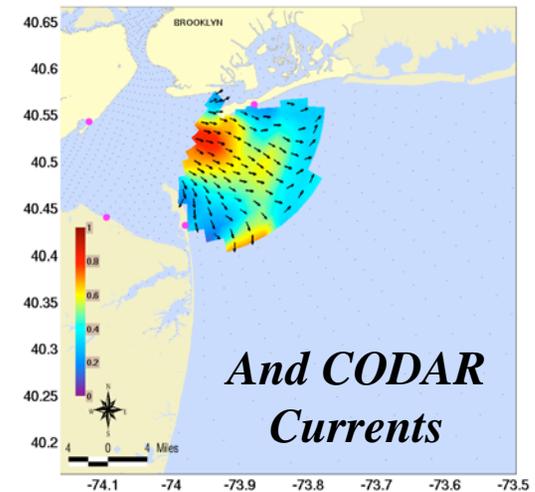
Plus three “mobile” sensors



Two Nekton UUVs



NY Bight Apex SURFACE CURRENT: HF RADAR (m/s)
November.26.2007 14:30:00 EDT

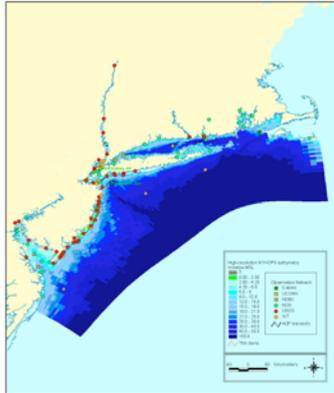




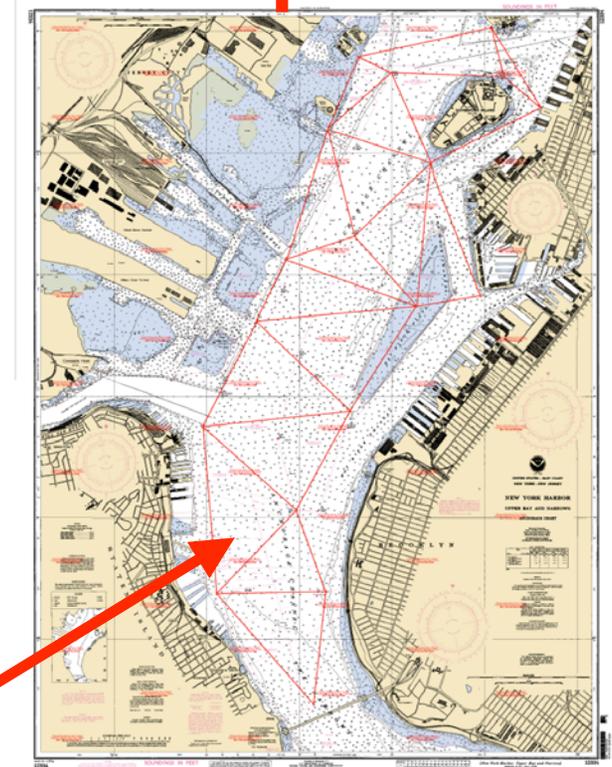
Need for Adaptive In-Situ Sampling



Ocean forecast model

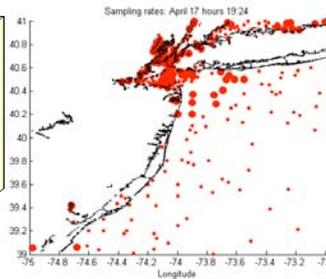
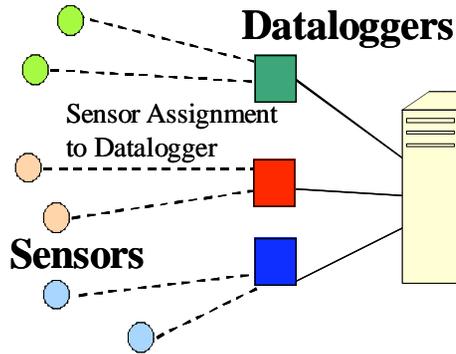


Data assimilation, model improvement



Event Estimation
Threat assessment
(environment, intel)

Adaptive Predictive Controller
Mobile robot tasking
Static sensor operation
Comm. Management



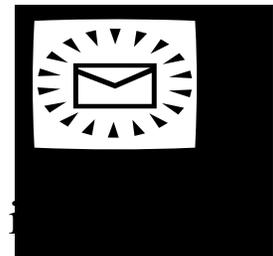
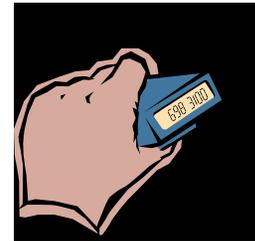
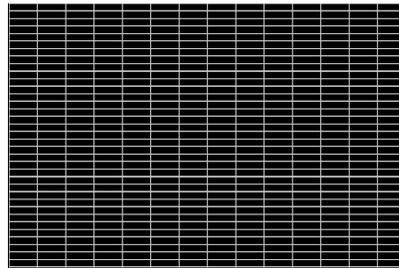
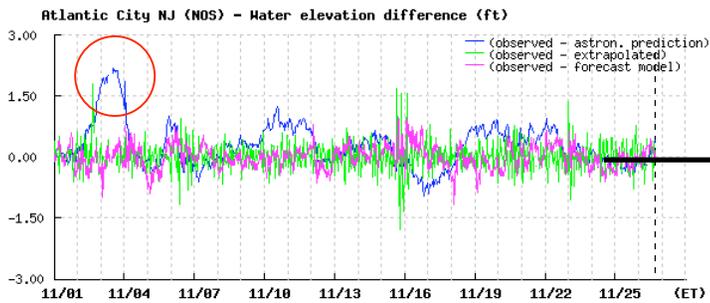
Dynamic Assignment

Adaptive sampling of Static Sensors

Adaptive sampling: UUV coordination



NYHOPS-supported Storm Surge Warning System



If surge levels are predicted
To exceed minor, moderate,
or severe flood level...

.. a database of emergency
management contact
information is accessed and ...

.. a tailored text message
transmitted via pager, text
message and email



Sensor Web Control and Resource Management Solution



Sensor Web Adaptive Control



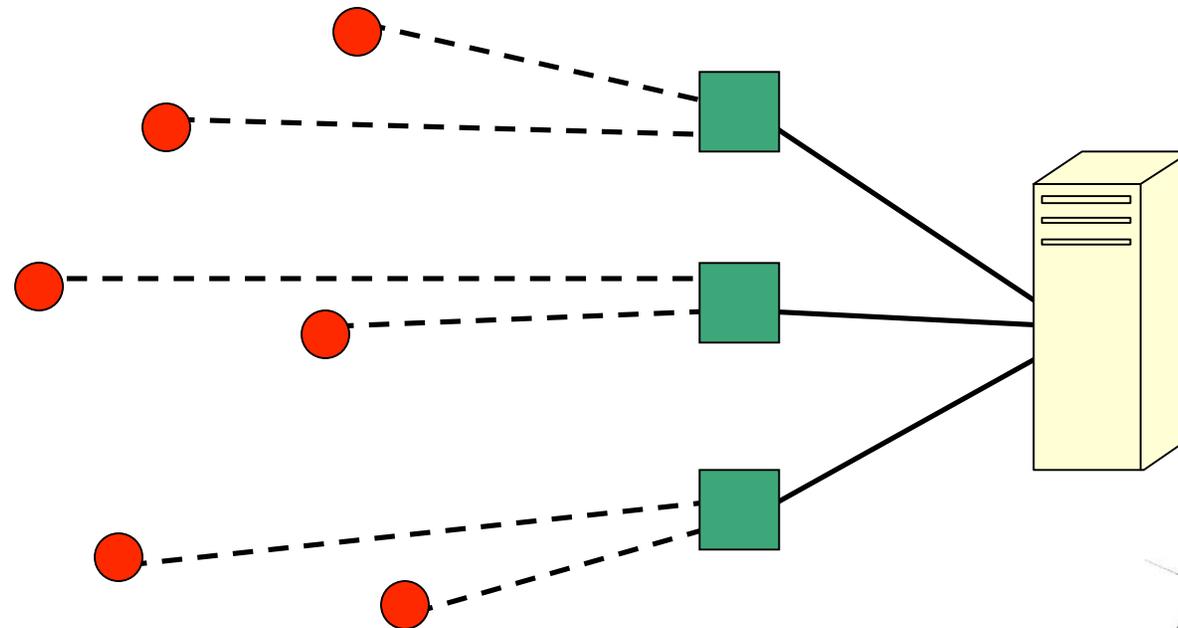
- Goal: Increase model accuracy at events of interest
 - For example, for better plume tracking
- Assumption: Increasing spatial and temporal resolution of sensors near area of interest improves model accuracy
 - Improve interpolation step that feeds the model
- System Constraints
 - Limited power (sensors cannot operate at highest sampling rate at all times, or transmit high amounts of data at all times)
 - Limited bandwidth (too much data at high sampling rate will overload communication system)
 - Mobile nodes very limited in supply (few in number), speed constrained



Communication Network for NYHOPS



- Two level hierarchical network
 - sensor → relay nodes → central computer
- Assignment of sensors to relay nodes dynamic

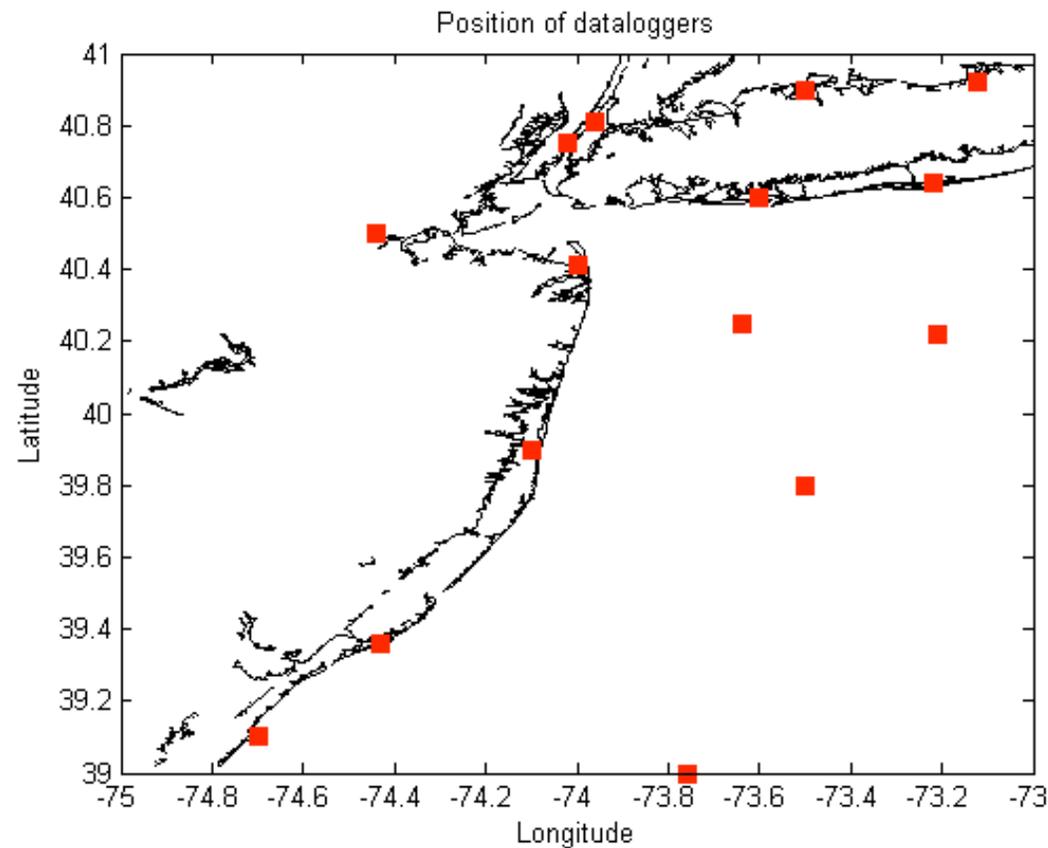




Relay Nodes/Dataloggers



- 15 locations
 - Most along coast and at local universities
 - Few in open ocean to reduce wireless transmission distance





Types of Sensors



- Static sensors
 - CODAR, satellite imagery are also modeled as a collection of static sensors
 - Control sampling rate of physical sensors
- Mobile UUVs
 - Confined to harbor or continental shelf
 - Control position of individual UUVs taking into account position of other UUVs and points of interest
- Passing cruise ships
 - *Pioneer, Osprey, Explorer of the Seas*
 - Not controlled, but sensor measurements available



Rutgers UUV





System Overview



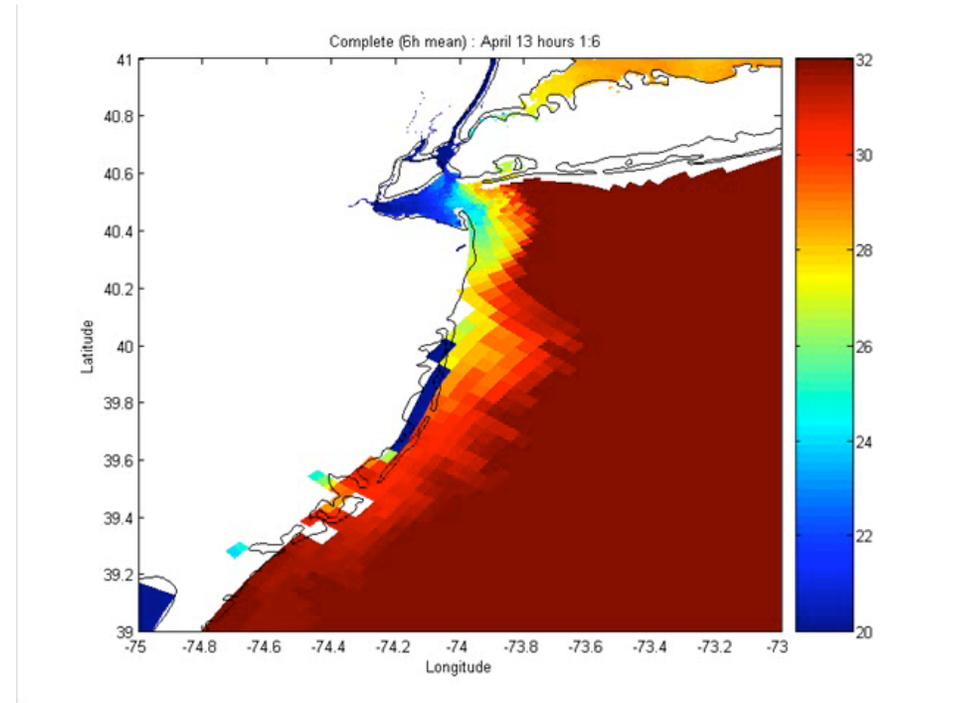
- Improve accuracy of the NYHOPS measurements via adaptive sampling
- Minimize resource utilization by adaptive sensor network control
 - Resources: energy, bandwidth
 - Model Predictive Control (MPC)
- Incorporate a variety of sensor types in one framework
 - Static sensors, UUVs, ships



Coastal Storm Surge & Plume



- 2007 “Tax day” flooding
 - Unusually high rainfall in mid-April 2007 caused a freshwater plume
 - Not predicted by historic models
 - Use real-time data from sensors to update model predictions
 - Use adaptive control to optimally allocate limited resources between sensors

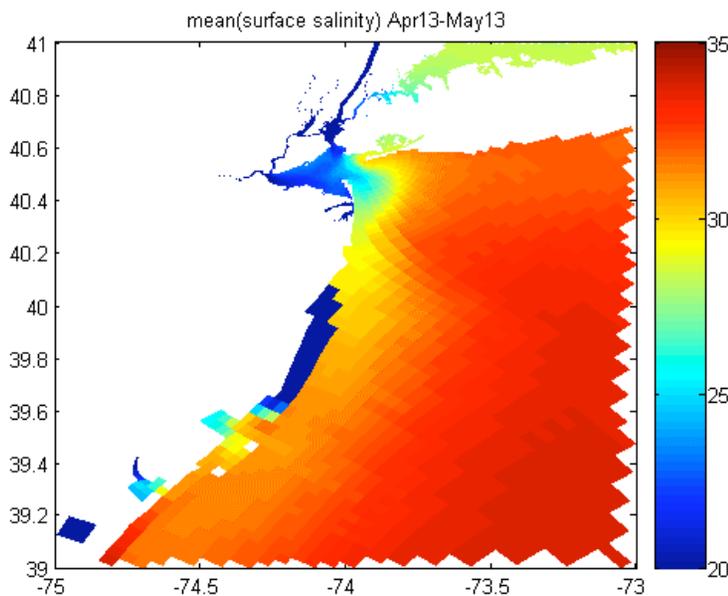




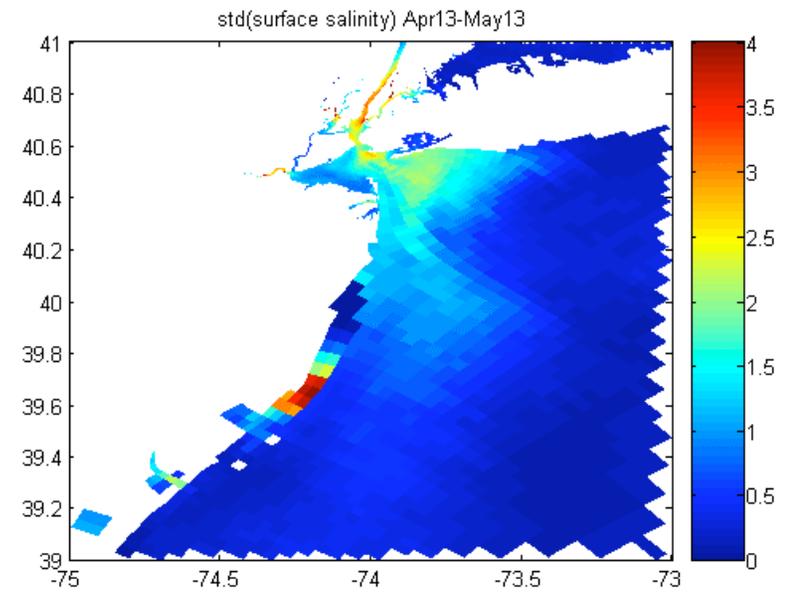
Event detection



- We assume a Gaussian distribution of sensor measurements
- Difference between surface salinity and corresponding historic mean gives confidence interval of expected measurements

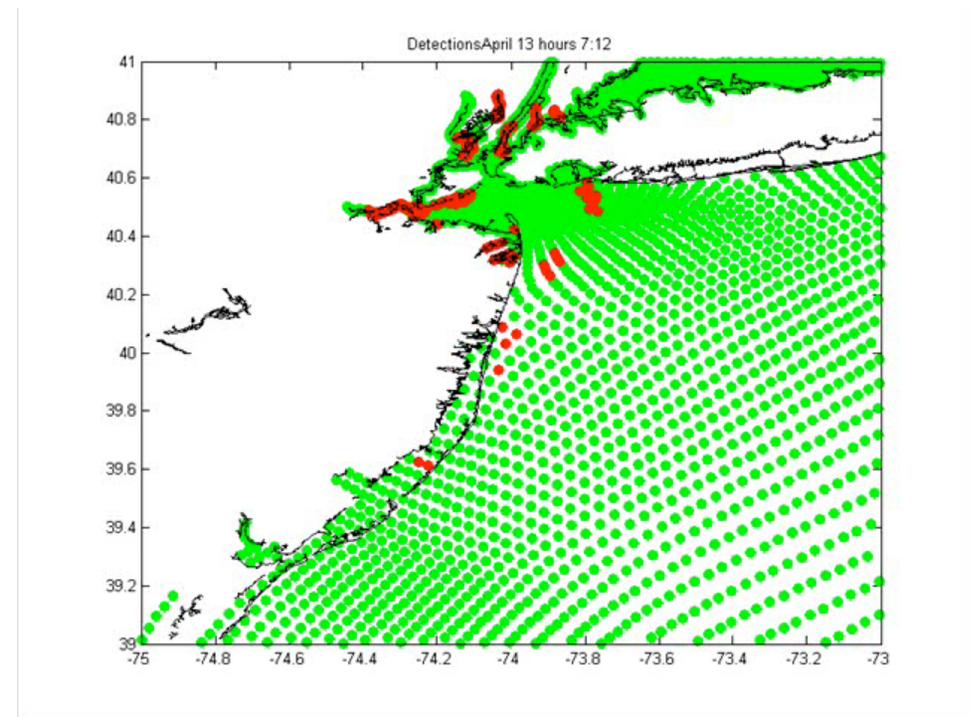


Mean of compromised data

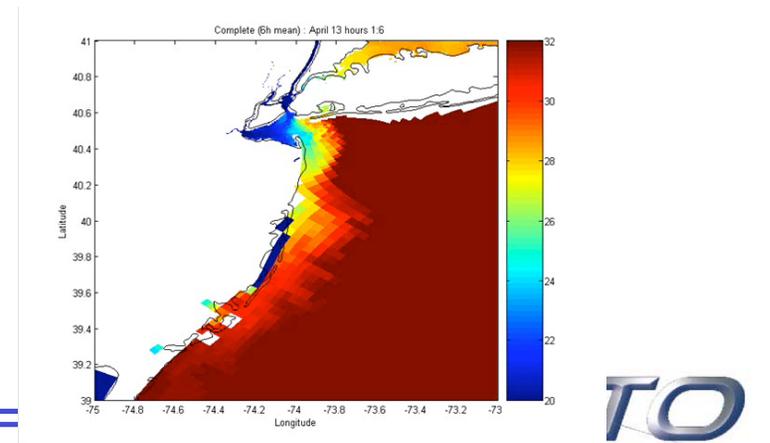


Std. dev of compromised data

- Historic means and deviations calculated from compromised dataset
 - Denote by μ_p the historic mean at location p
- Sensor location will not match exactly with any of the precomputed locations
 - Match sensor s to nearest location with known mean
- Event(s) = 1 if
 - $|x_s - \mu_p| > \text{Threshold}$
 - x_s is the measurement at sensor s



Detected events





Need for Sensor Network Control



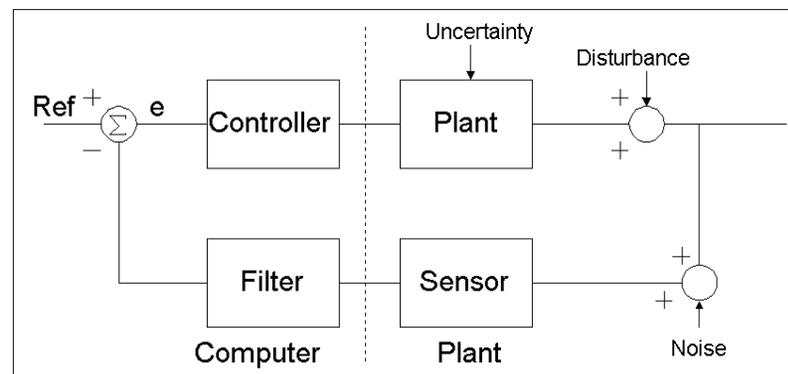
- Goal achieved if all sensors sample at maximum rate
- However
 - sensors are limited in their energy capacity
 - network is limited by bandwidth
 - sensors prone to failures
- Approach
 - Adapt system resources in real-time to changing regions of importance
- Solution: Model Predictive Control
 - Mathematical optimization based controller framework



Control Methodologies



- Model-based control
 - Assume that a mathematical model of the system is available
 - Given system control inputs, the corresponding outputs can be calculated
 - Evaluate the quality of different system control inputs
 - MPC output is that system control which has the best relative quality
- Popular control framework for large industrial plants
- Distributed variants are also possible

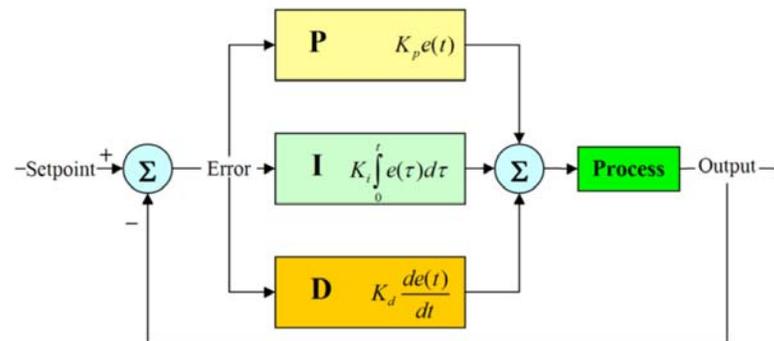




Control Methodologies



- Non model-based control
 - Control output is analytically calculated from current system outputs and desired setpoint
 - No model available that relates inputs to outputs
 - No explicit optimization of future control steps
 - Controller results can be obtained quickly
- Popular control framework for systems with short control periods or weak computational resources
 - Robotics, embedded systems
- If an accurate model of the system is available, model-based controller can generate optimal control quickly compared to non-model based controllers

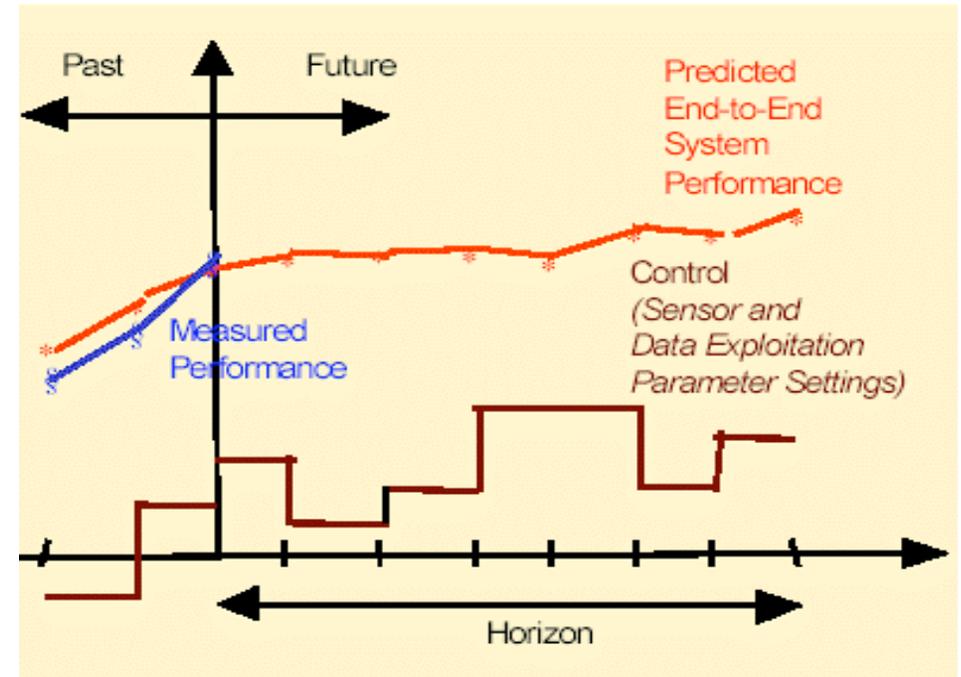




Model Predictive Control



- The *objective function* models the quality of a candidate control
- *Constraints* model the physical and resource limits of the system
- Optimal control is obtained by constrained minimization of the objective function at every control step (*Horizon*)



`OptimalControl = argmin (objectiveFunction(control))`
subject to

Constraints: system resource and physical limitations



Features of MPC



- Lookahead capability
 - *Moving horizon control*: The objective function can make use of a predictive model of the system to optimize future control steps
 - Environmental model of a spreading plume can be used to determine where higher resolution sensing will be required *in the future*
- Online execution
 - Optimal control is determined for a finite number of steps in the future, but only the first is executed
- All aspects of the system are modeled either as part of the objective function or constraints
 - The optimization problem can be easily updated to account for modifications to the system



MPC for NYHOPS



- Spatiotemporal sensor web control
- All system components and parameters form part of the optimization problem
 - Control variables
 - MPC output
 - Objective functions
 - Mathematical model of quality of a set of control variables
 - Constraint equations and inequalities
 - Define feasible values of control variable
- NYHOPS resources
 - Static sensors
 - Mobile sensors (UUVs)
 - Communication network (sensors to dataloggers)



NYHOPS Control



1. Sampling rate of sensors

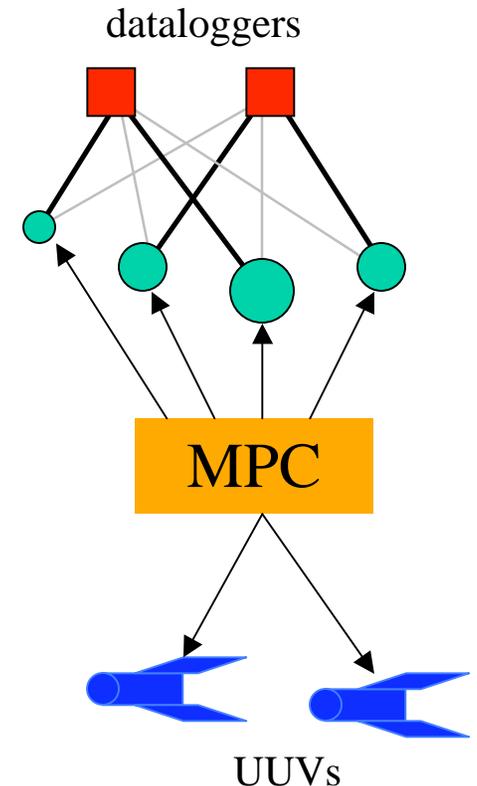
- Adapts sensor resolution to environment model output
- Intuitively: sensors close to interesting areas sample at a higher rate

2. Position of mobile controllable sensors

- Maximize utilization of network bandwidth
- Intuitively: move UUVs to locations with high variance

3. Assignment of sensors to dataloggers

- Maximize utilization of network bandwidth
- Intuitively: sensors associate to closest relay nodes in order to minimize energy needed for wireless transmission





NYHOPS Constraints



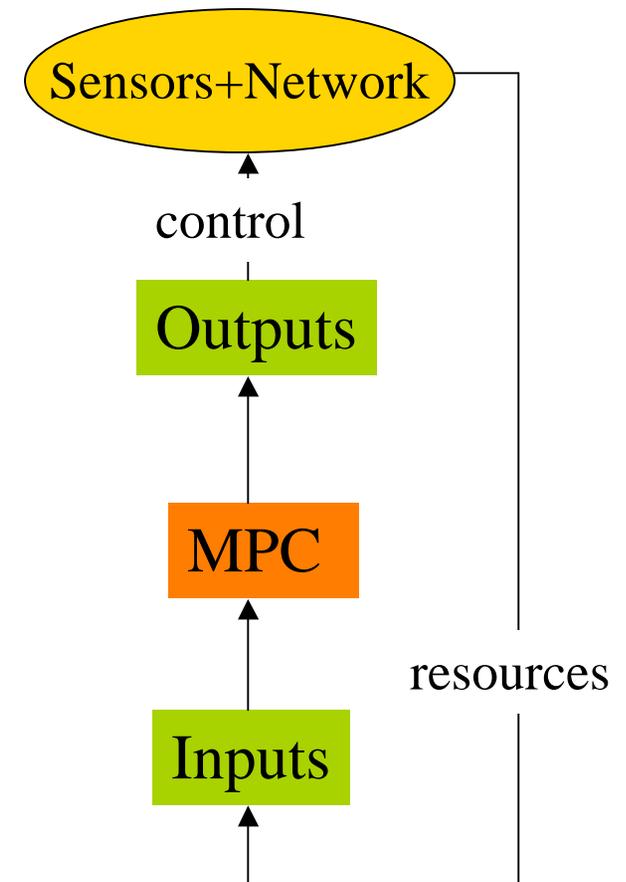
1. Minimum and maximum sensor sampling rates
2. Speed of UUVs
3. Area navigable by UUVs
 - NY harbor, continental shelf
4. Energy expended in moving UUVs
5. Bandwidth of each datalogger
 - Global limit on sensor sampling rate
6. Energy expended in wireless data transmission from sensors to dataloggers



NYHOPS MPC Inputs and Outputs



- Input
 - Location of sensors
 - Critical locations (output of event detection)
 - Energy consumption rates of sensors
 - Number and physical characteristics of UUVs
 - Location of dataloggers
 - Bandwidth of dataloggers
- Output
 - Sampling rates of static sensors
 - Positions of mobile sensors
 - Assignment of static sensors to dataloggers

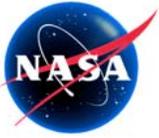




Objective functions for optimization



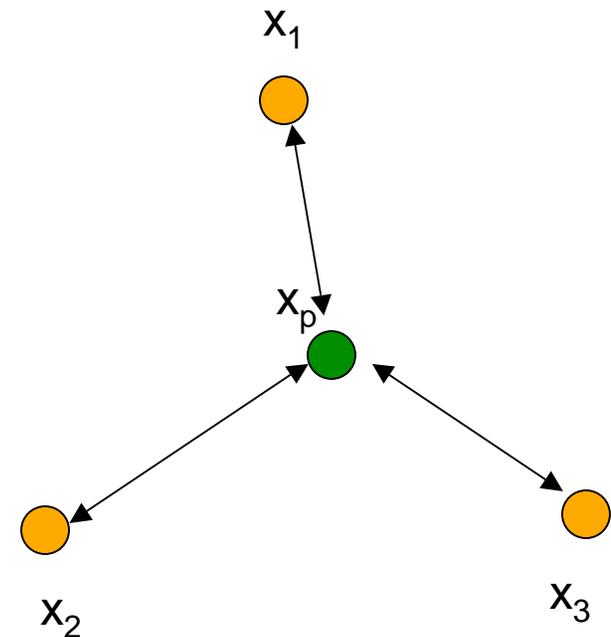
- Multi-objective optimization
 - A single objective function cannot model all system features
- MPC outputs (system control) are the solutions to a series of objective functions:
 1. Minimize static sensor fusion uncertainty
 - $f_1(\mathbf{u}_{\text{static}})$
 2. Minimize UUV data fusion uncertainty
 - $f_2(\mathbf{x}_{\text{UUV}})$
 3. Minimize UUV energy expenditure
 - $f_3(\mathbf{x}_{\text{UUV}}; \mathbf{x}_{\text{UUV}}^{t-1})$
 4. Minimize wireless data transmission energy expenditure
 - $f_4(\mathbf{A}_{\text{SxM}}; \mathbf{x}_{\text{static}}, \mathbf{x}_{\text{dataloggers}}, \mathbf{u}_{\text{static}})$



Objective function for sensor uncertainty



- Optimal fusion of correlated sensors
 - Kalman filter
- Multiple (homogeneous) sensors sample the same environmental parameter simultaneously
 - x_p denote the true state, $x_1, x_2 \dots$ sensor measurements
 - $[x_1 \ x_2 \ x_3]^T = Hx_p + v$
 - Assume $H=[1 \ 1 \ 1]^T$
 - v is the measurement noise with covariance matrix \mathbf{R}
 - distance from event and distance between sensors determine the covariance of the measurement noise





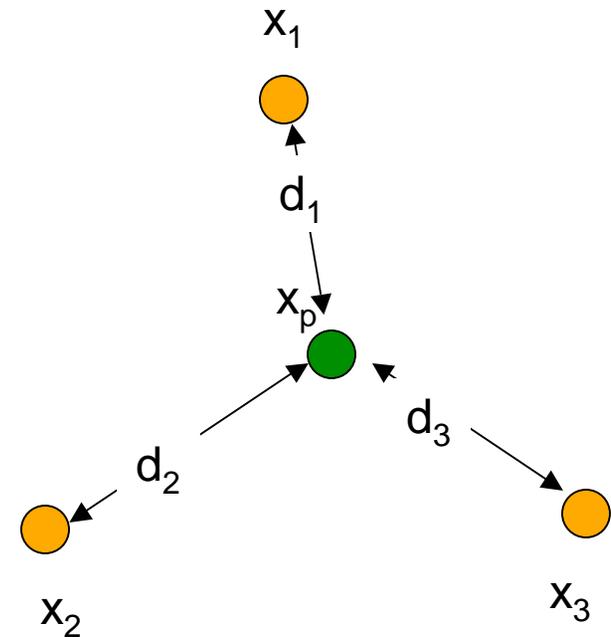
Objective function for sensor uncertainty



- Assume that local region is wide-sense stationary for short durations
 - constant mean, correlation depends only on distance
- Error covariance of a sensor i depends on sampling rate and distance from point of interest
 - Denote by R error covariance

$$R_{i,i} = \frac{\sigma_s^2 + kd(p, s_i)}{u_{s_i}}$$

- σ^2 denotes the intrinsic noise in the sensor
- Noise decreases with increasing sampling rate



$d(p,s)$: distance between sensor s and critical point p

u_s : sampling rate of sensor s



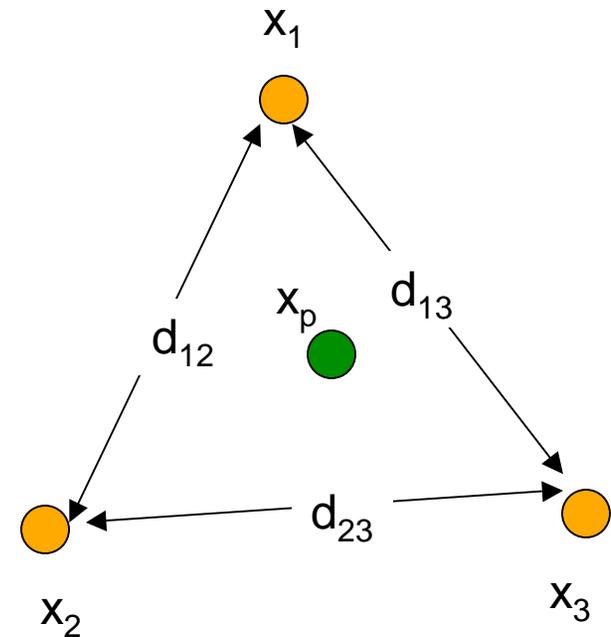
Objective function for sensor uncertainty



- Error covariance between sensors is inversely proportional to distance between them

$$R_{i,j} = \frac{1}{kd(p, s_i)}$$

- If sensors are far apart, their noise is uncorrelated (covariance matrix becomes diagonal)
- If multiple sensors are close together, the information extracted is comparable to that of a single sensor





Objective function for sensor uncertainty



- Variance after optimal fusion given by the Kalman filter equations
 - Denote by P_{t-1} the *a priori* estimate variance
 - Residual covariance $S = HP_{t-1}H^T + R$
 - Kalman gain $K = P_{t-1}H^T S^{-1}$
 - Updated estimate variance $P_t = (I - KH)P_{t-1}$
- Assuming zero information initially
 - Estimate variance $P_t = H^T R^{-1}H$
- Use estimate variance as objective function
$$f(\mathbf{u}, \mathbf{x}) = H^T R^{-1}H$$
 - R is calculated from \mathbf{u} and \mathbf{x}



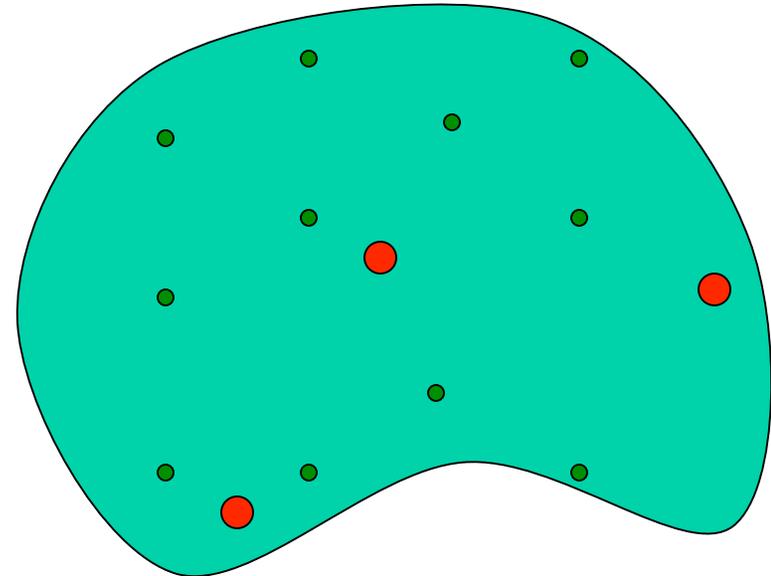
Objective function for sensor uncertainty



- The sensor fusion uncertainty will be used as the objective function to evaluate a set of sampling rates and sensor positions
- Earlier defined for a single point of interest p
- Now extend to multiple points of interest
 - Mean uncertainty over all critical points

$$f(\mathbf{u}, \mathbf{x}) = \sum_p H^T R_p^{-1} H$$

- Critical points determined by event detection algorithm



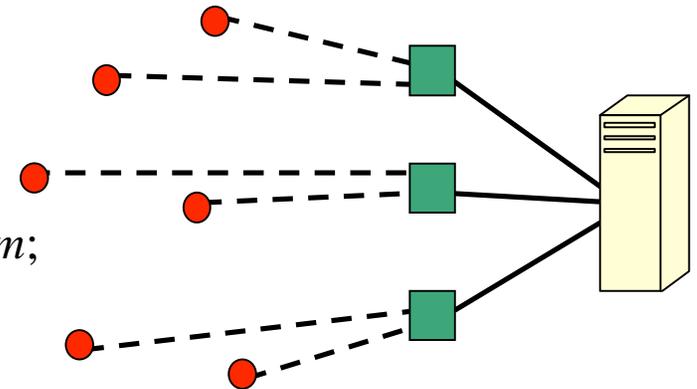
- Sensor
- points of interest



Modeling Two-Level Communication



- Dynamic sensor to datalogger assignment
- To determine $a(s,m)$
 - $a(s,m)=1$ iff sensor s is assigned to datalogger m ;
= 0 otherwise
- Additional goal:
 - Minimize energy spent in wireless transmissions between sensors and relays
 - Both goals can be optimized by using multi-objective optimization techniques
- Additional constraints:
 - Total amount of data transmitted to a datalogger m should not exceed its bandwidth B_m
$$\sum_s u_s a(s,m) < B_m, \forall m$$
 - A sensor associates to exactly one relay node
$$\sum_m a(s,m) = 1, \forall s$$





Modeling communication



- Power expended in wireless communication
 - proportional to square of distance between transmitter and receiver
 - sensor and datalogger
 - proportional to volume of data transmitted
 - sampling rate
 - Hence total power consumed is

$$\sum_s \sum_m u_s a(s, m) d^2(s, m)$$

- a denotes assignment of sensors to dataloggers, u the sensor sampling rates, and d the distance between a sensor – datalogger pair



Modeling UUVs



Two conflicting objective functions

1. Minimize sensor fusion uncertainty

- Use objective function used for static sensors but control the UUV locations (instead of sampling rates)
- Estimate variance of optimal sensor fusion
- $f_2(\mathbf{x}_{\text{UUV}}) = \Sigma \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H}$
- On-diagonal terms in covariance matrix \mathbf{R} proportional to distance of UUV from each point of interest
- Off-diagonal terms in covariance matrix inversely proportional to distance between UUVs

2. Minimize energy spent in moving

- Assume proportional to distance moved
- Depends on past location: $f_3(\mathbf{x}_{\text{UUV}}; \mathbf{x}_{\text{UUV}}^{t-1})$





Multi-objective optimization



- Multiple objective functions conflict with each other
 - Maximize sampling rate to reduce measurement uncertainty but this also increases energy expenditure
- All the objective functions cannot be simultaneously optimized
- Must use a multi-objective optimization technique
 - Goal optimization
 - Assign weights to different objective functions and minimize the weighted sum; then solve as a single objective optimization
 - Determining weights is not obvious
 - Objective function values have to be appropriately scaled
 - Lexicographic optimization
 - Can be used if the objective functions have a pre-defined priority, i.e., one is strictly more important than the other



Multi-objective optimization



- Lexicographic optimization
 - Minimize the objective functions one after the other, starting with the most “important”
 - At every successive optimization, add previously obtained minimum objective value as a constraint
 - Not necessarily pareto-optimal
- NYHOPS function priorities
 1. Optimize sampling rate of static sensors
 - $f_1(\mathbf{u}_{\text{static}})$
 2. Determine locations of UUVs
 - $f_2(\mathbf{x}_{\text{UUV}}) + w f_3(\mathbf{x}_{\text{UUV}}; \mathbf{x}_{\text{UUV}}^{t-1})$
 3. Assign sensors to dataloggers
 - $f_4(\mathbf{A}_{\text{SxM}}; \mathbf{x}_{\text{static}}, \mathbf{x}_{\text{dataloggers}}, \mathbf{u}_{\text{static}})$



NYHOPS AIST



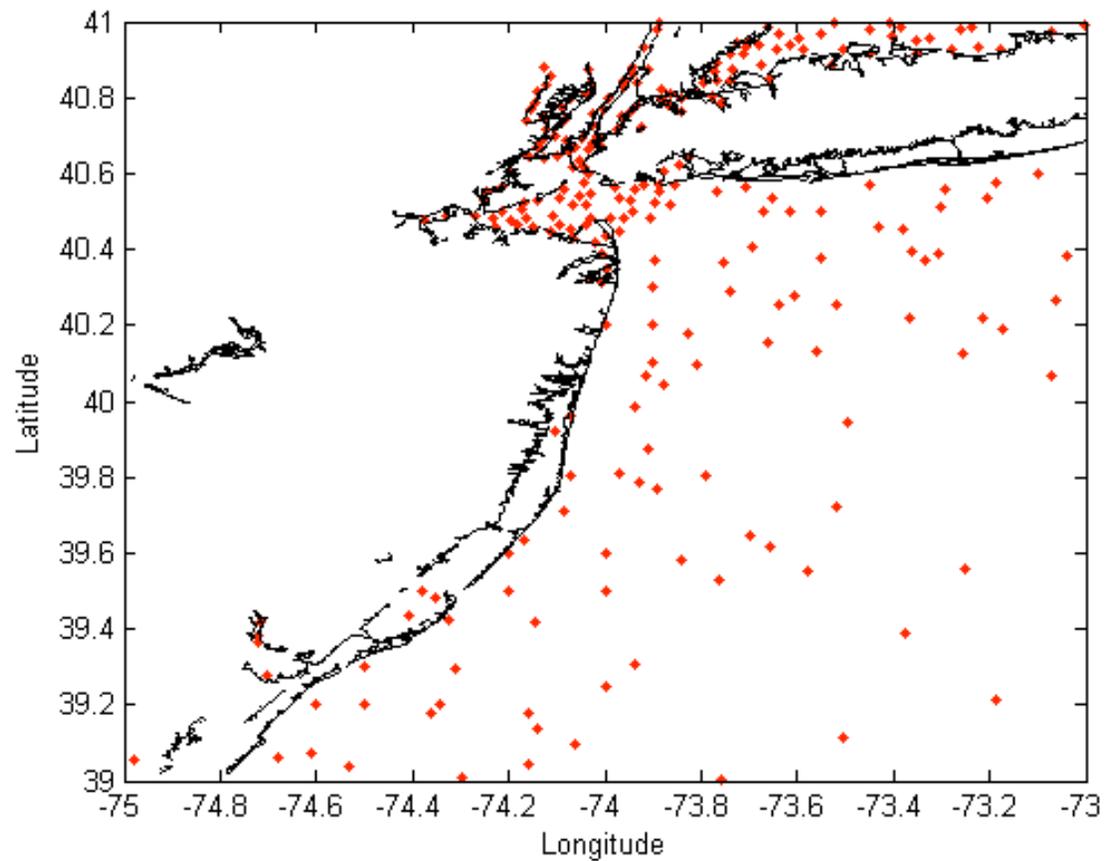
- System overview
- Event detection
- MPC control
- Nudging
- **Results**
- Future Work



Sensor locations



- 250 static sensors
- Most sensors are close to the coast

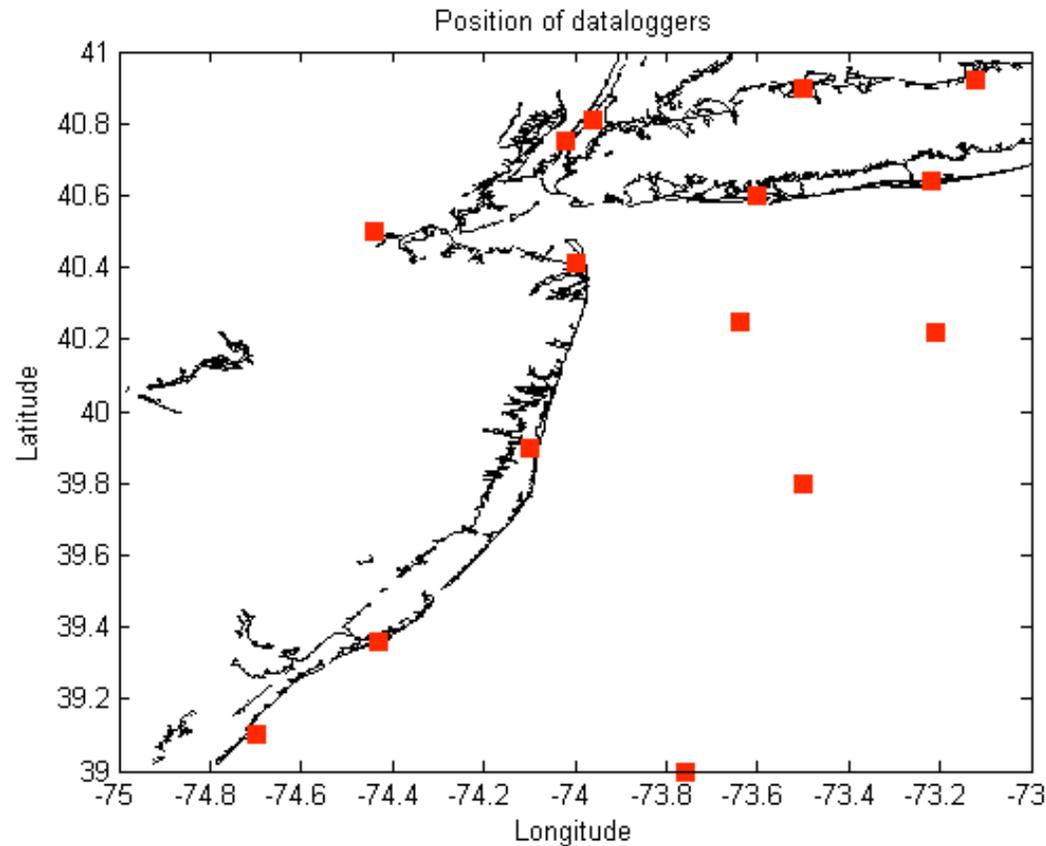




Dataloggers / Relay Points



- 15 locations
 - Most along coast and at local universities
 - Few in open ocean to reduce wireless transmission distance

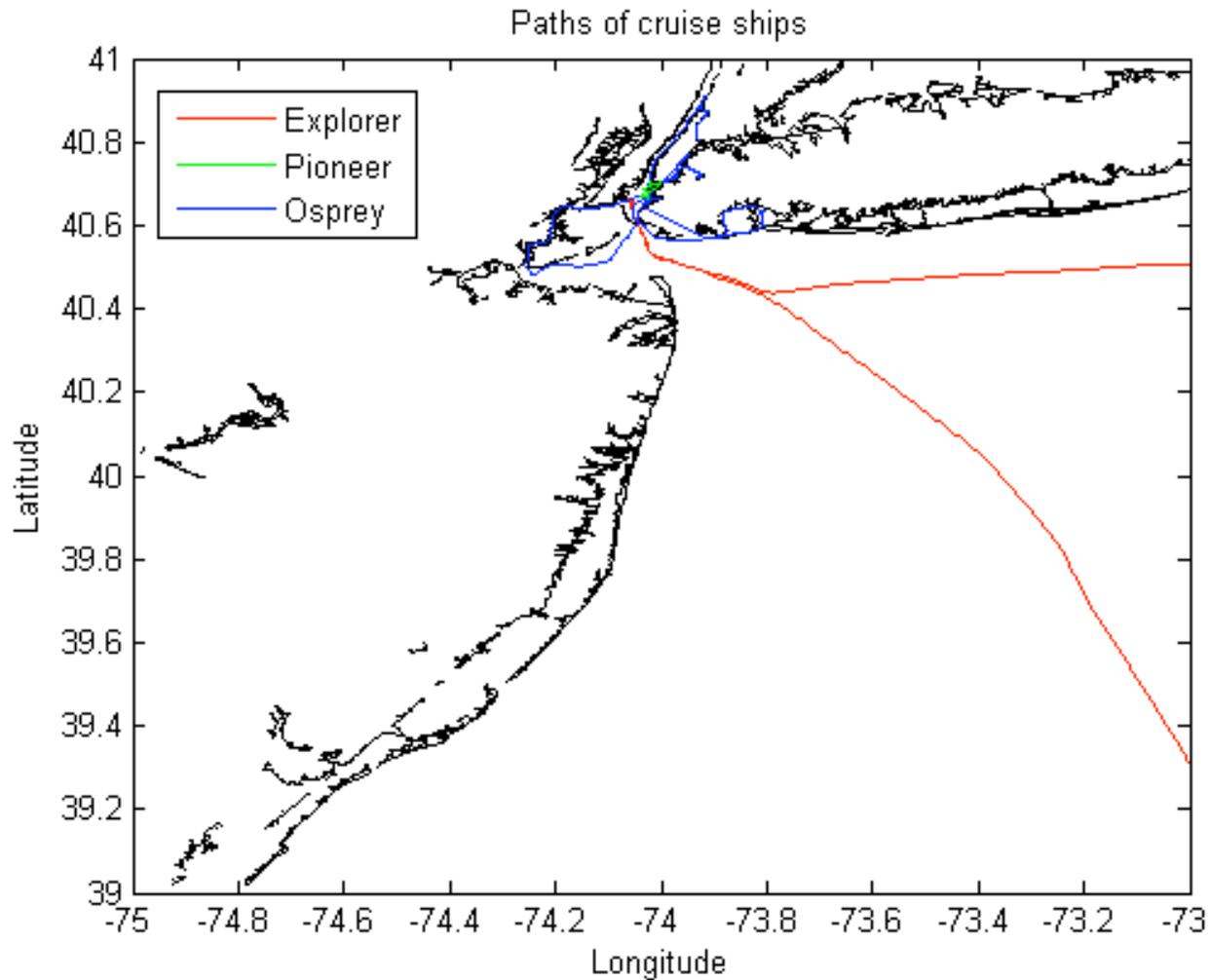




Paths of cruise ships

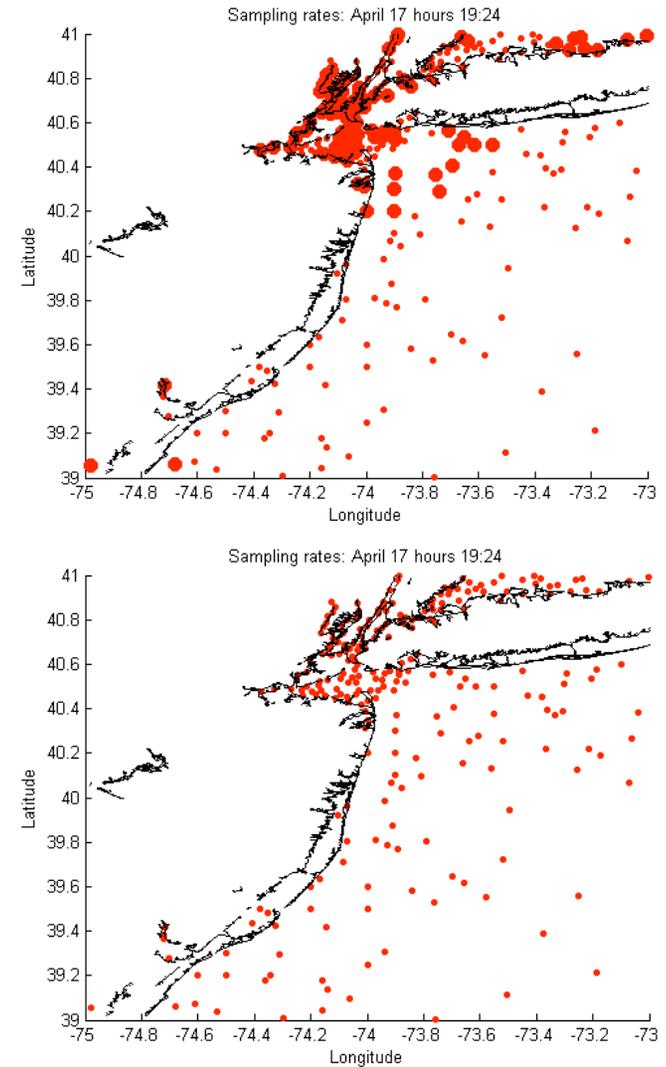
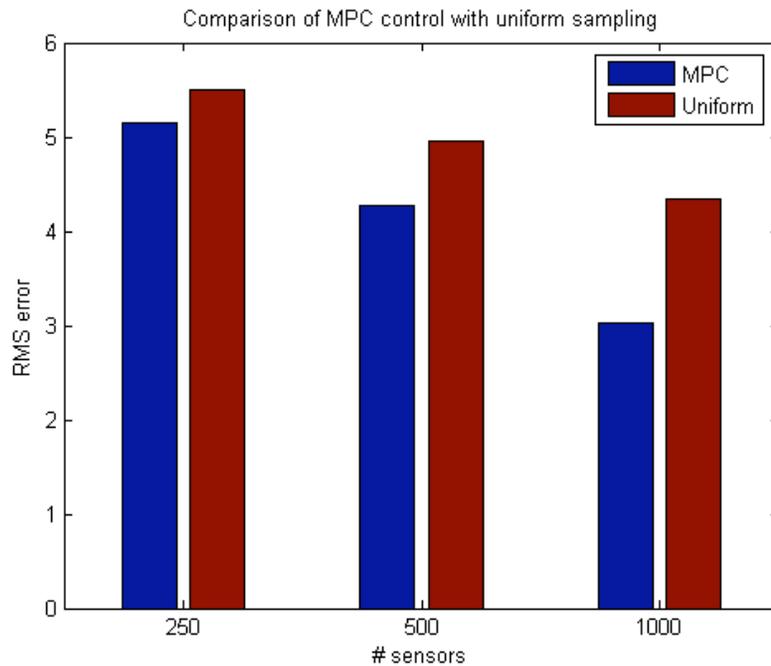


- Not controlled; assume that data available along path



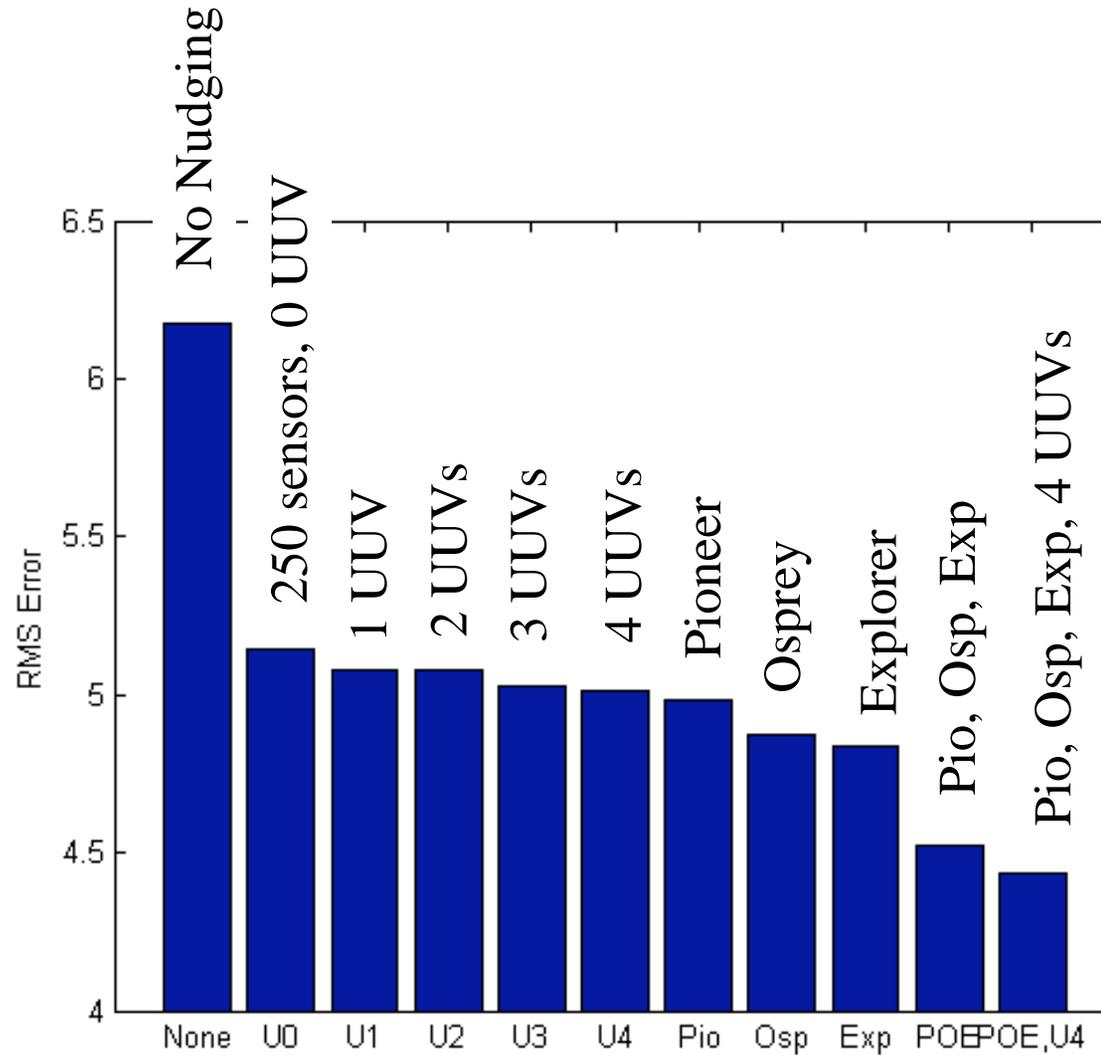


Comparison of uniform sampling and MPC with event detection



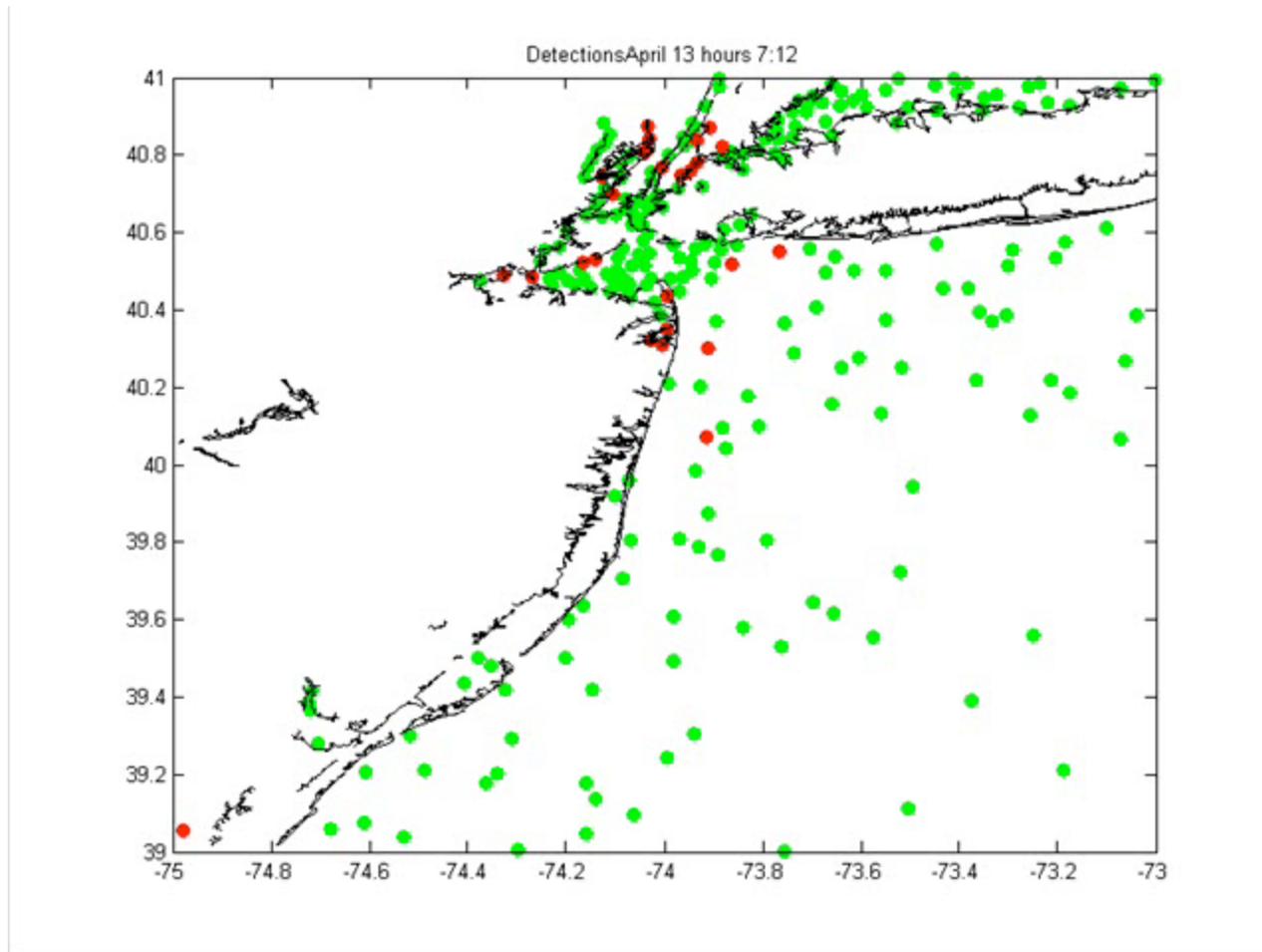


Effect of number of UUVs and ships



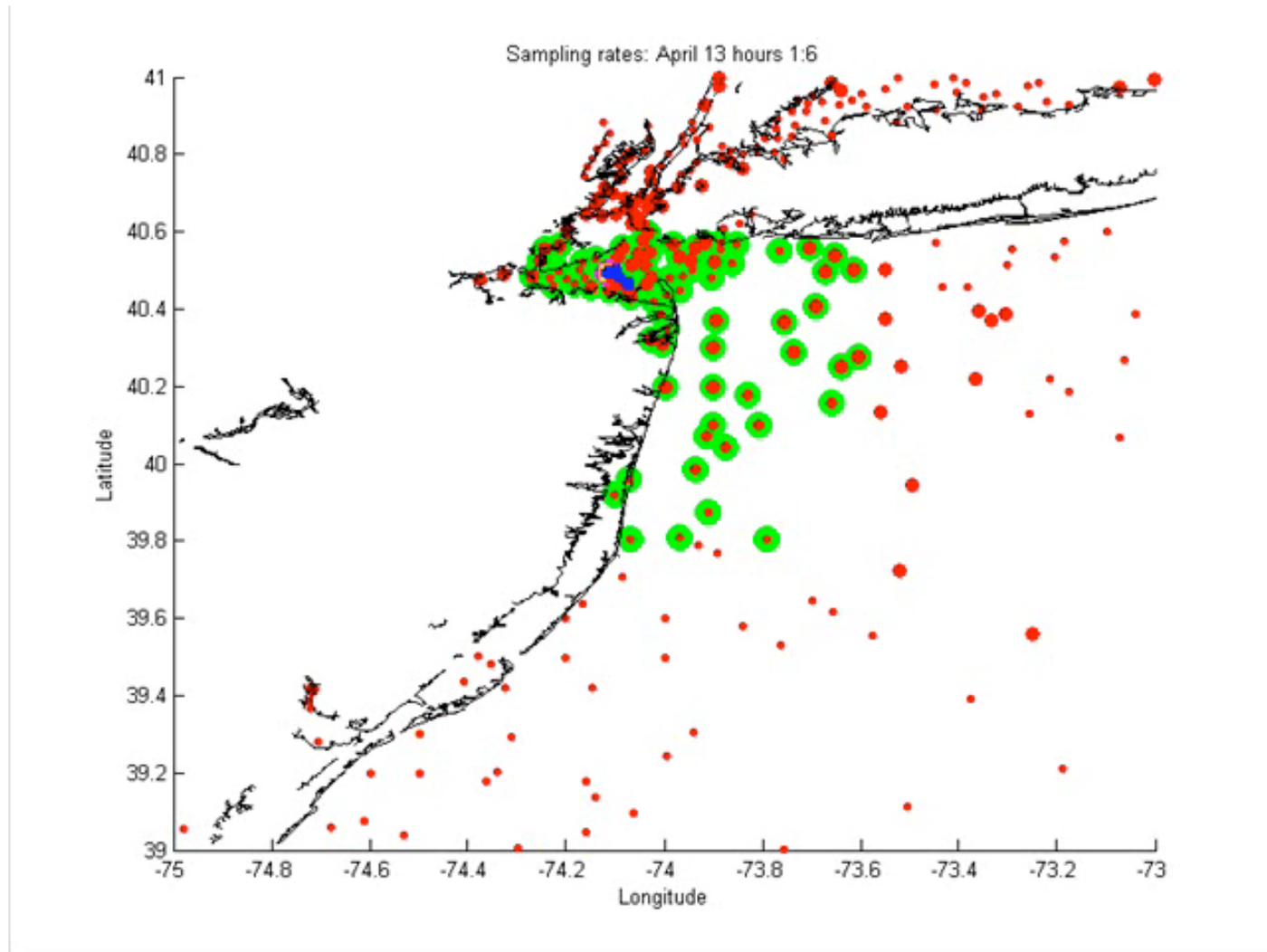


Event detections: 1 UUV



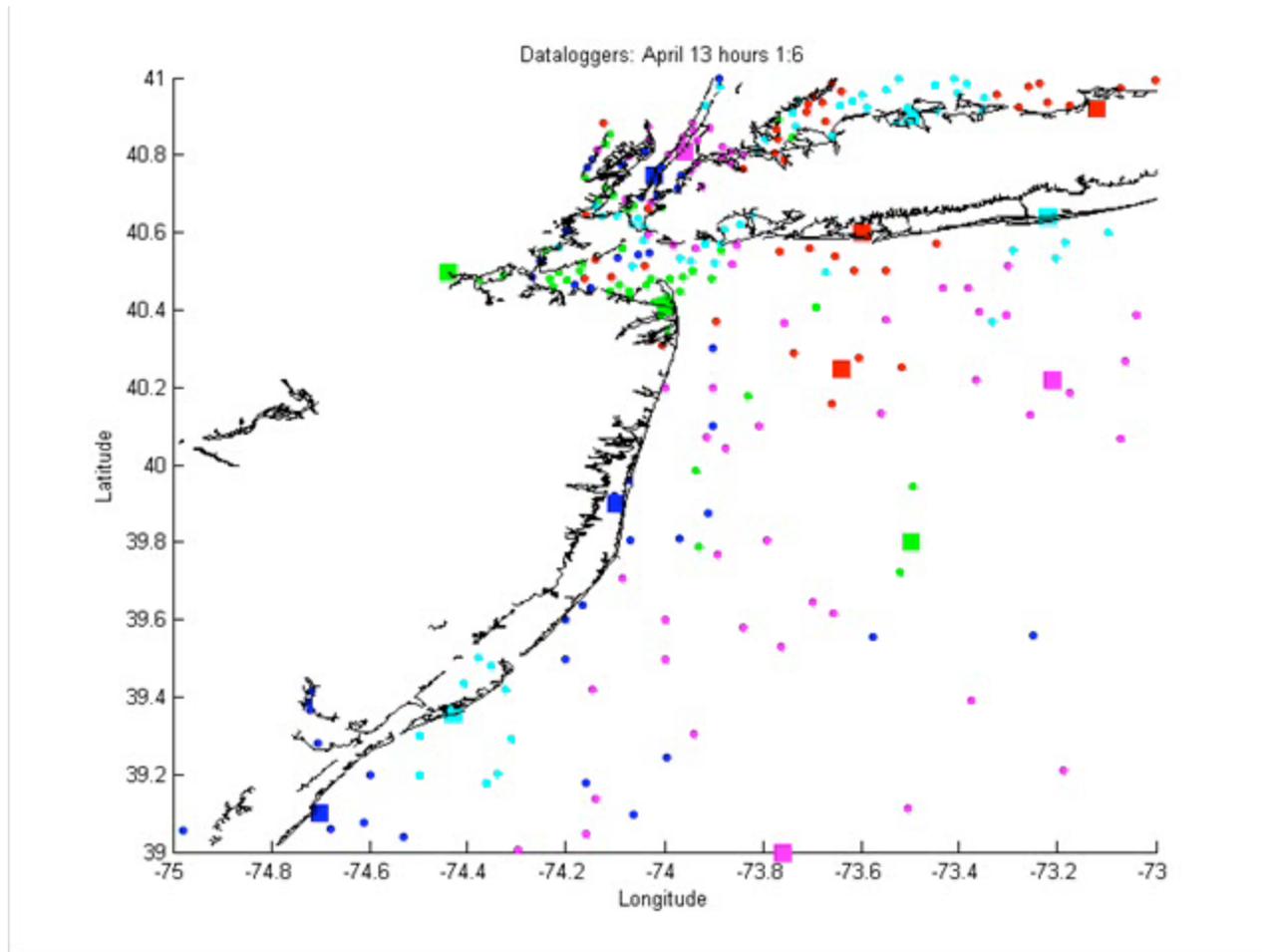


Sampling rates: 1 UUV



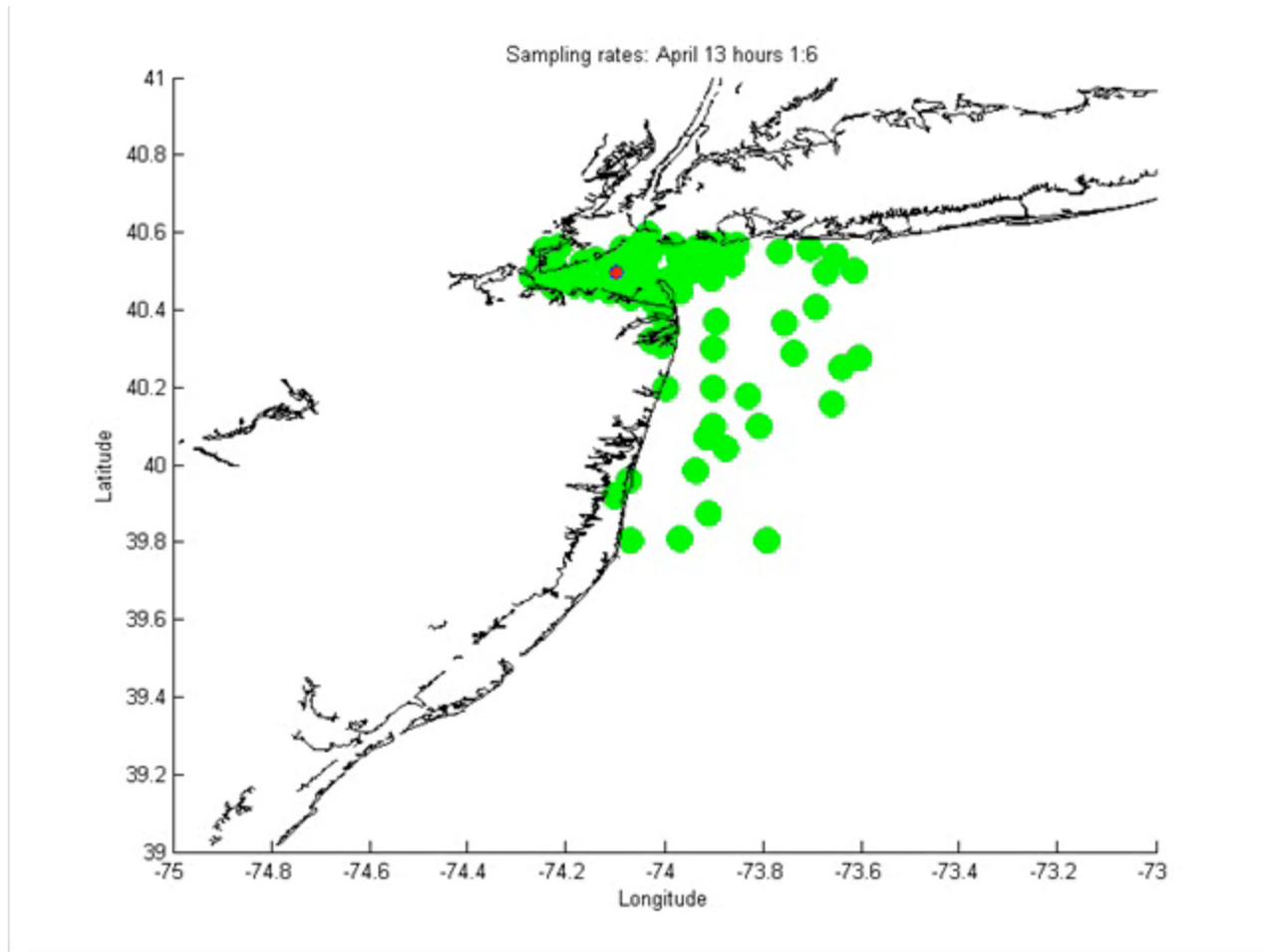


Assignment: 1 UUV



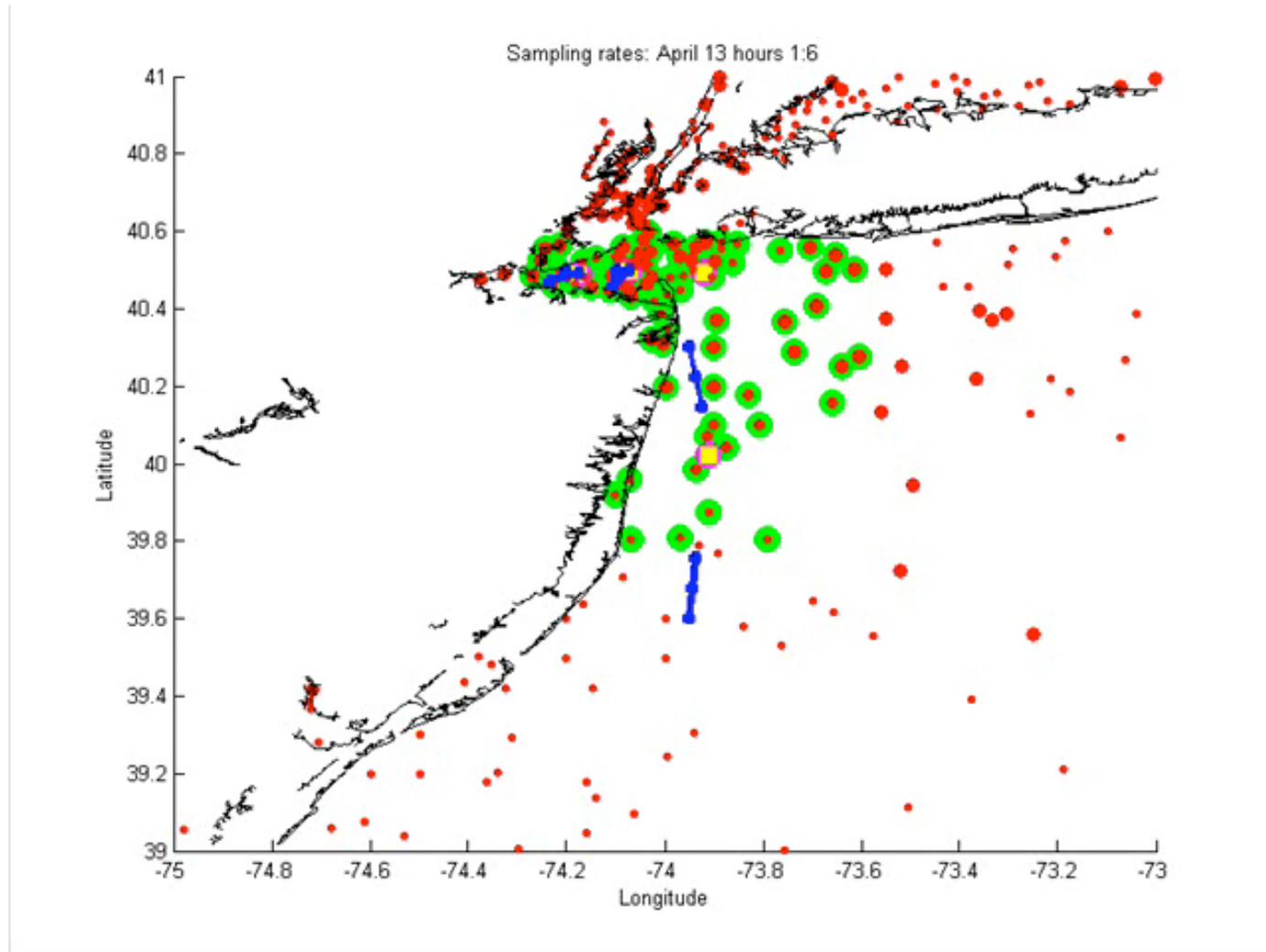


UUV Motion: 1 UUV



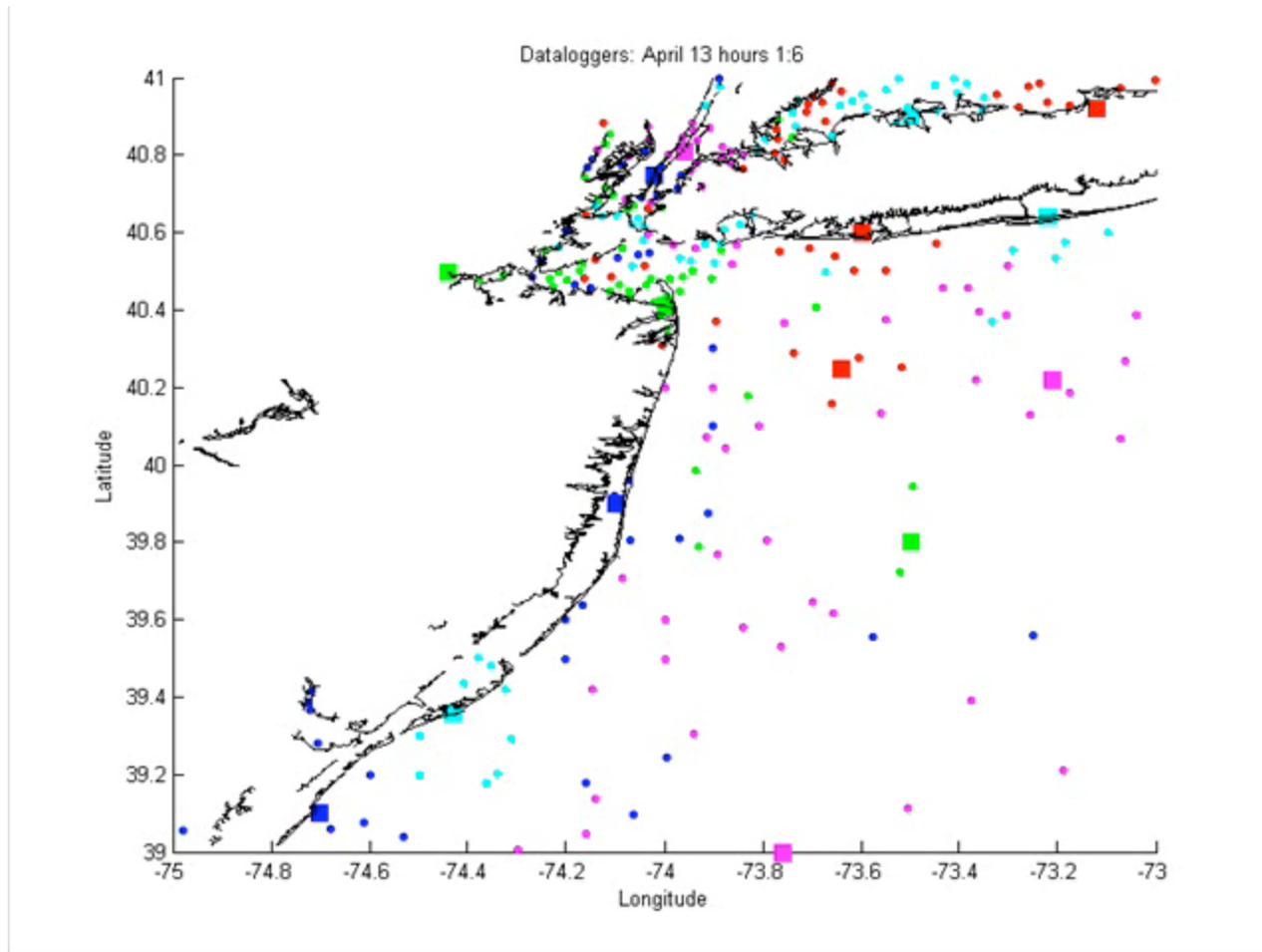


Sampling rates: 4 UUVs



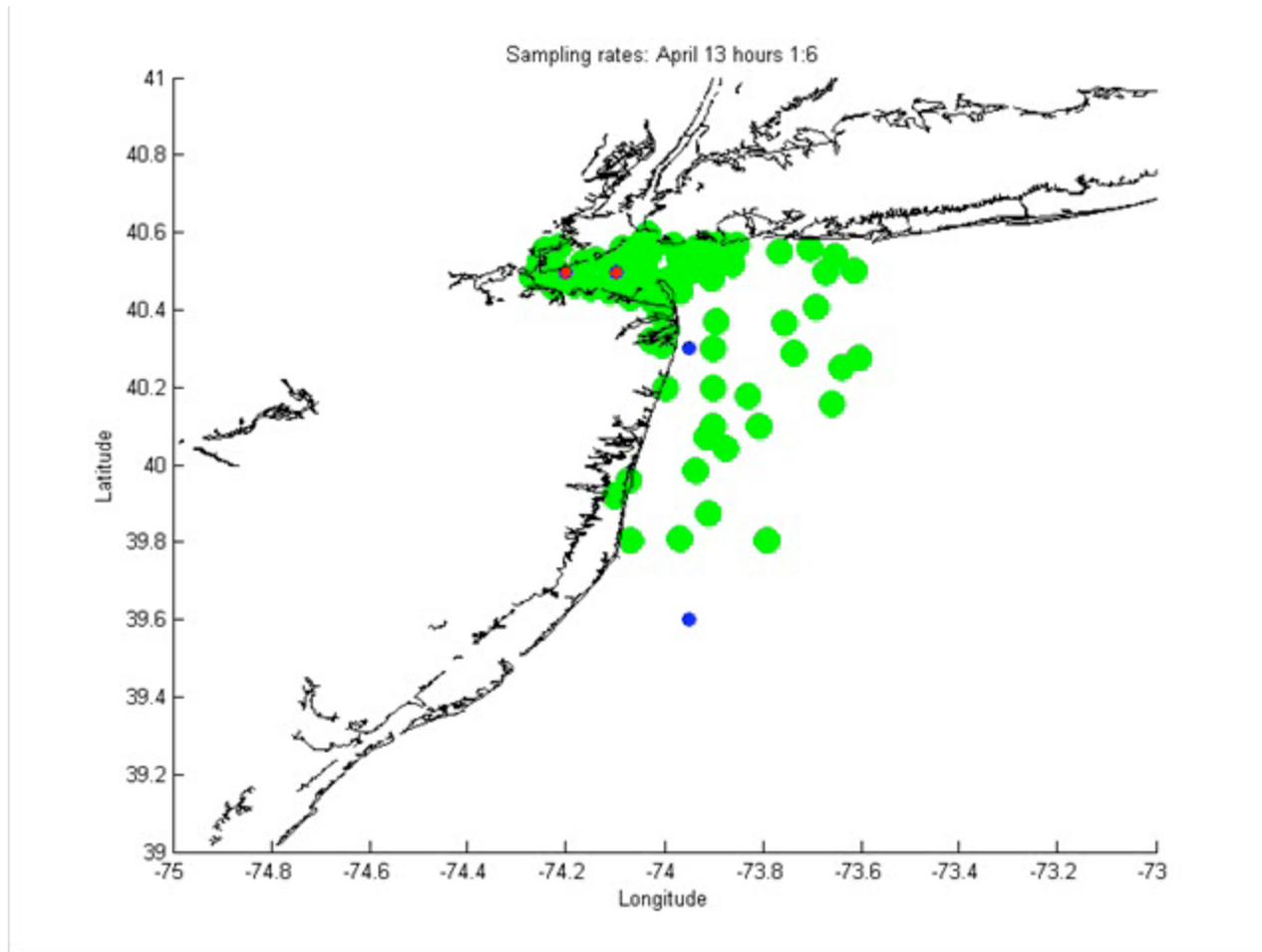


Assignment: 4 UUVs





UUV Motion: 4 UUVs





Google Earth NYHOPS Visualization





Future Sensor Web Work



- Incorporating other (remote and in-situ) data sources
 - The MPC framework general enough that different sensor sources can be incorporated into the mathematical model
 - Satellite data can be incorporated into the control framework. MPC controller can generate task lists for remote satellites
 - Incorporate satellite data to re-task in-situ instruments/sensors
- Distributed control and resource management
 - The current MPC formulation is centralized – all sensor and network parameters have to be available at a central location and resulting controls have to be transmitted back to the sensors.
 - In Distributed MPC, the minimization of the objective function is performed at multiple sites simultaneously. Each node processes its local portion of the objective function, only exchanging results with neighboring nodes



Future Sensor Web Work



- Real-time operation
 - The current implementation of the MPC framework is computationally expensive. Determining approximate solutions to the optimization problems will speed up the controller with a relatively small decrease in the quality of results
- Predictive control
 - One of the main advantages of MPC-based control is the ability to incorporate a predictive model of the system/environment into the controller's formulation. This enables resources to be optimized taking into account the locations of critical events that are expected to occur in the near future



Future Sensor Web Work



- Ongoing: Google Earth Interface for NYHOPS Website

- Integration of sensor web control into NYHOPS
 - Real-time tests

