Robots in the Wild — Collaborative Exploration and Mapping

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Kanna Rajan
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John Ryan

Reza Ehsani

UCMERCED

Ramon Arrowsmith

M B A R I

ASU School of Earth and Space Exploration
Arizona State University

Psyche mission

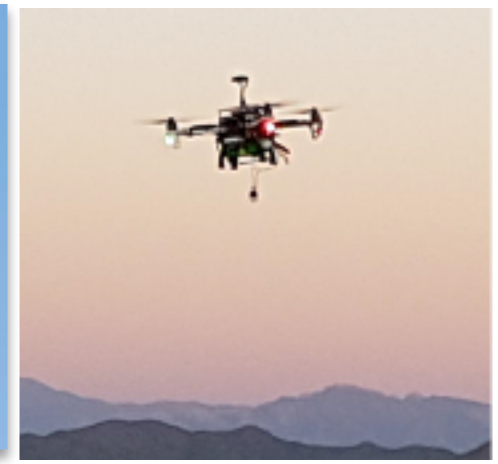
Dirty Dull Dangerous

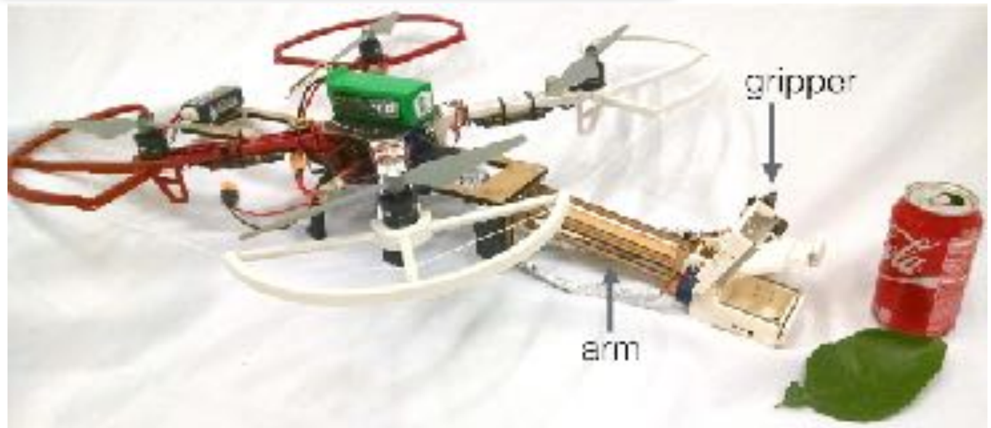
Motivation

Solve grand challenges (food, water, environment) with robotics technology

Is there a toxinogenic algae bloom close to the coast, and will it hit the beach during a busy holiday weekend?

Can a crop disease be detected before it spreads across an agricultural field?





USC Viterbi School of Engineering

ROBOTIC EMBEDDED SYSTEMS LABORATORY

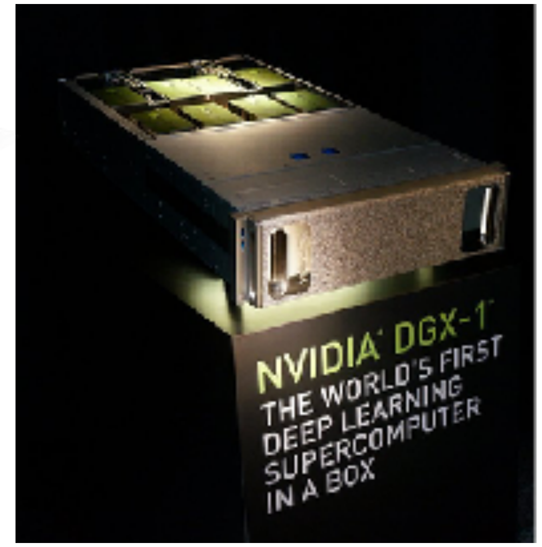
M B A R I

Penn Engineering GRASP LABORATORY General Robotics, Automation, Sensing & Perception Lab

Interests

- Robotics, machine learning, autonomous systems, precision agriculture, environmental monitoring — **extreme environments**
- Closing the loop on information collection
  - Systems and algorithms that efficiently observe properties of interest through *both* in-situ and ex-situ labeling of samples
    - Adaptivity and opportunism in sampling missions
    - Performance guarantees

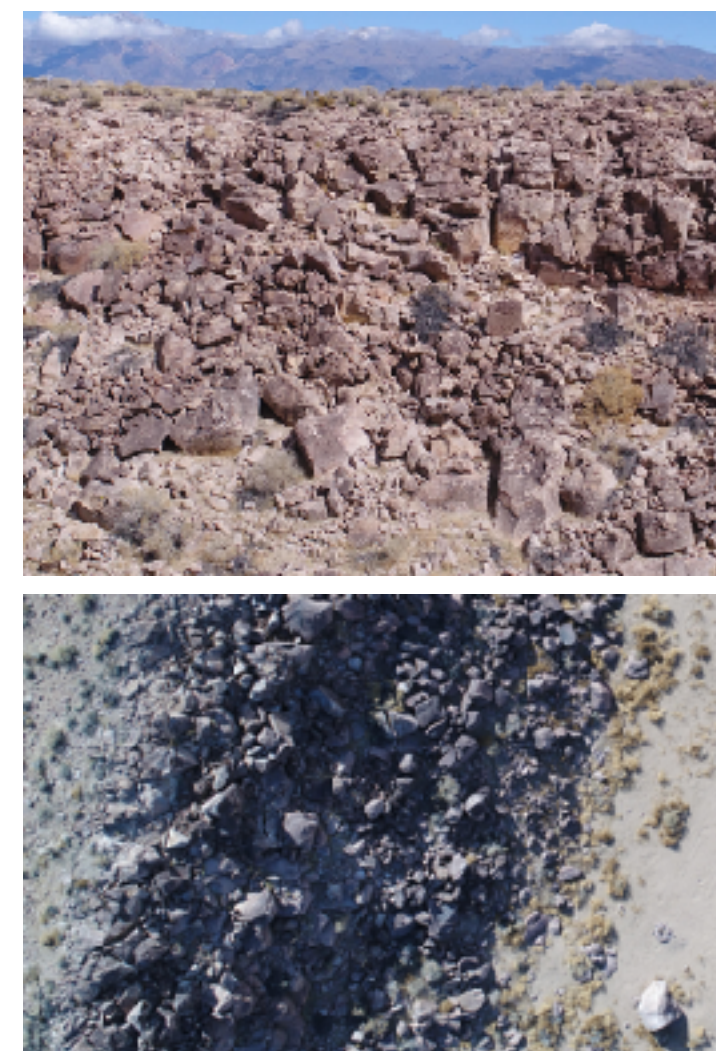
The Annotation Game



Hannah Kerner

	In-situ	Ex-situ
Sampling	measurement	specimen
Analysis	features	big-data

Chelsea Scott, Ramon Arrowsmith



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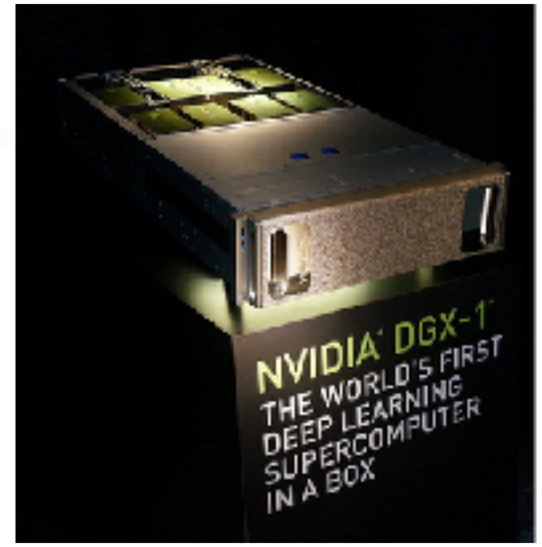

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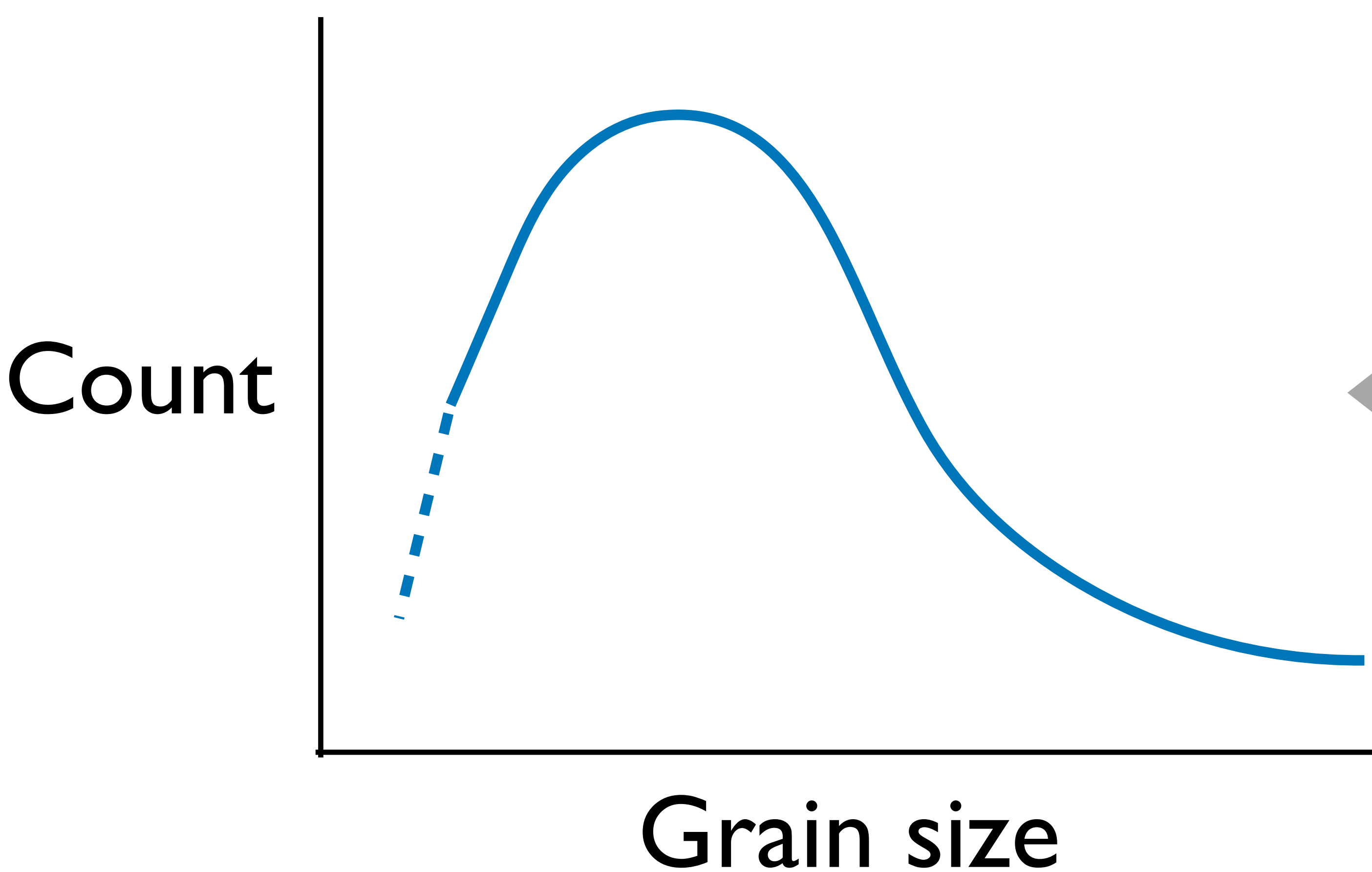

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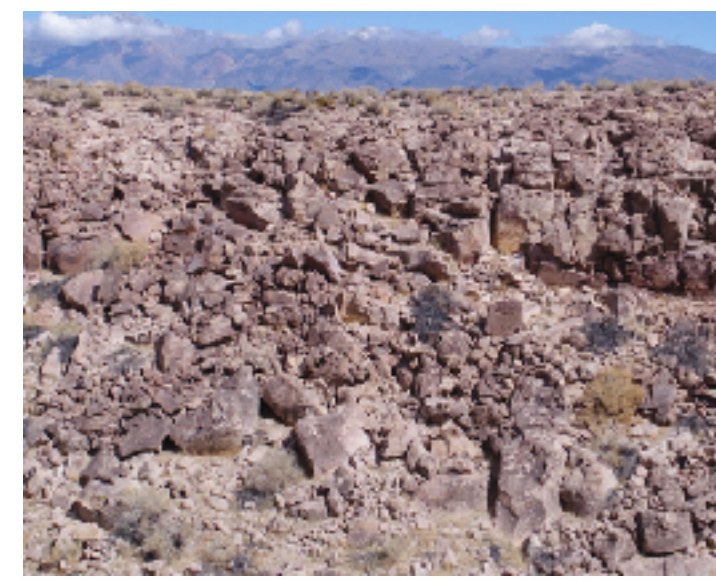

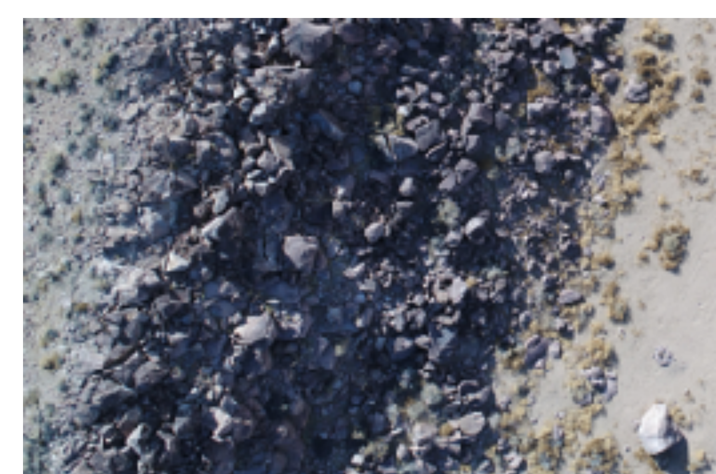

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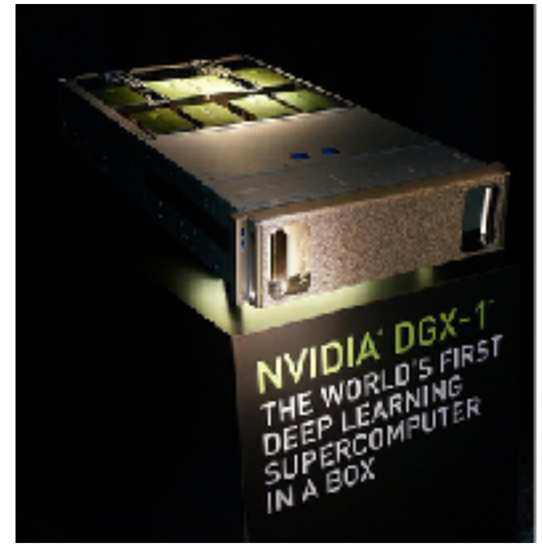

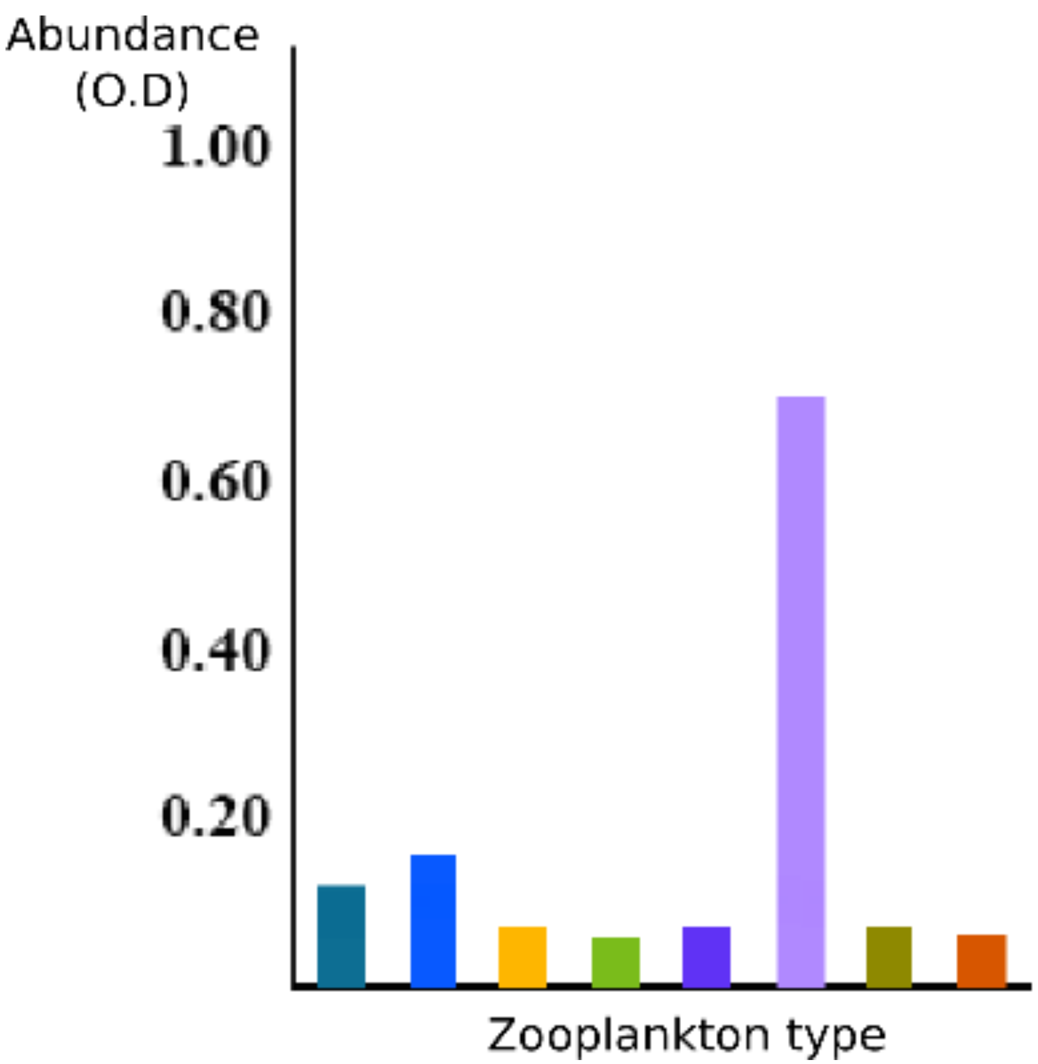

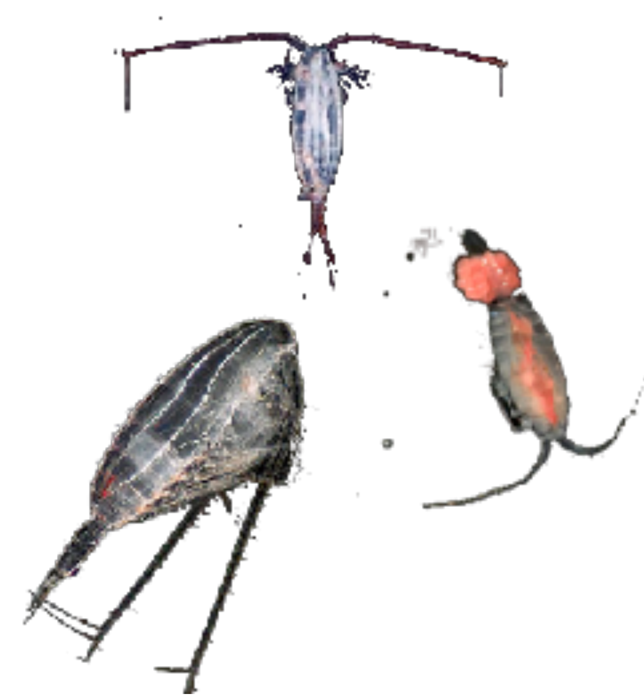

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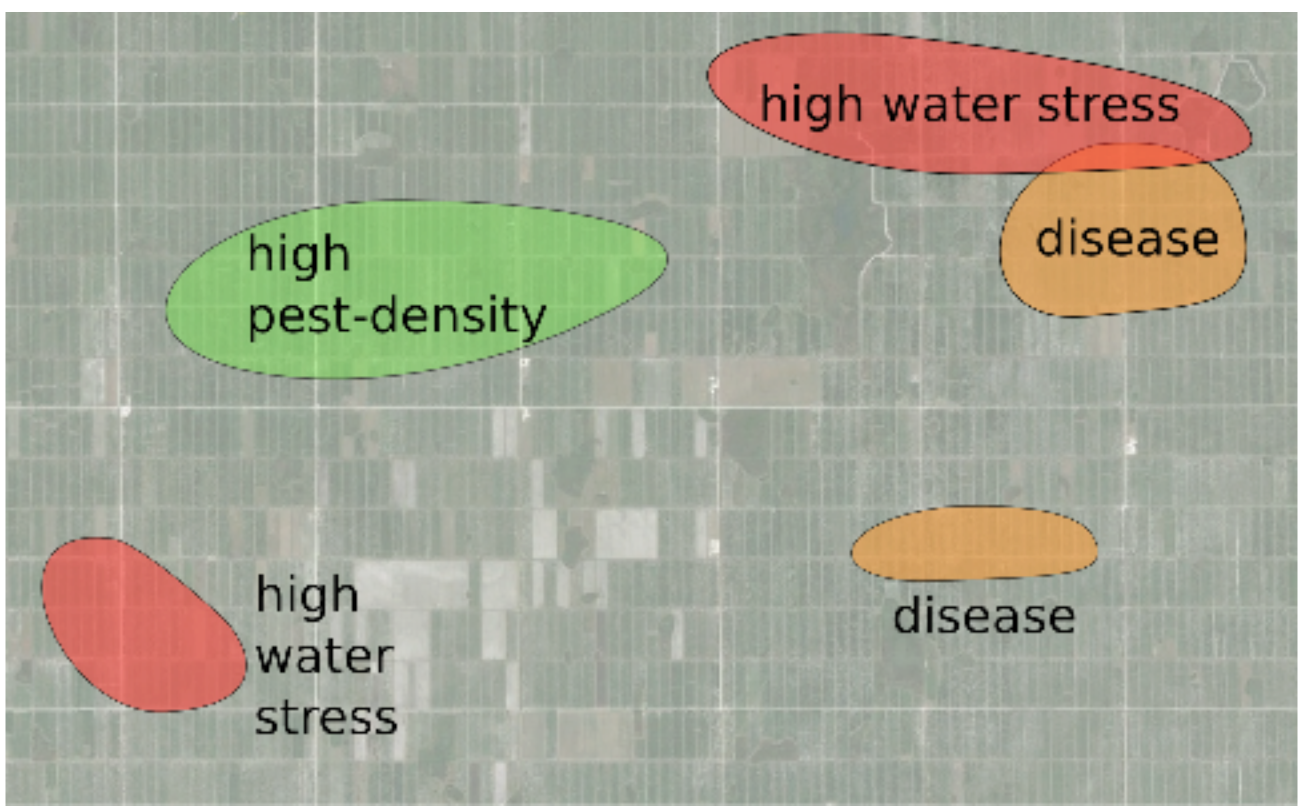
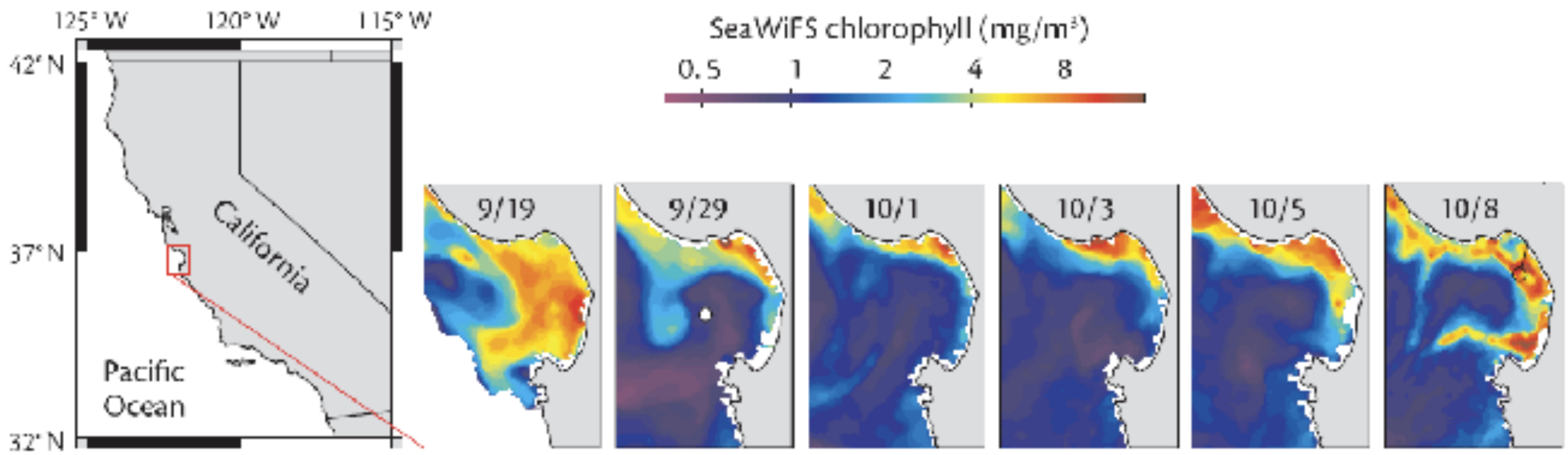
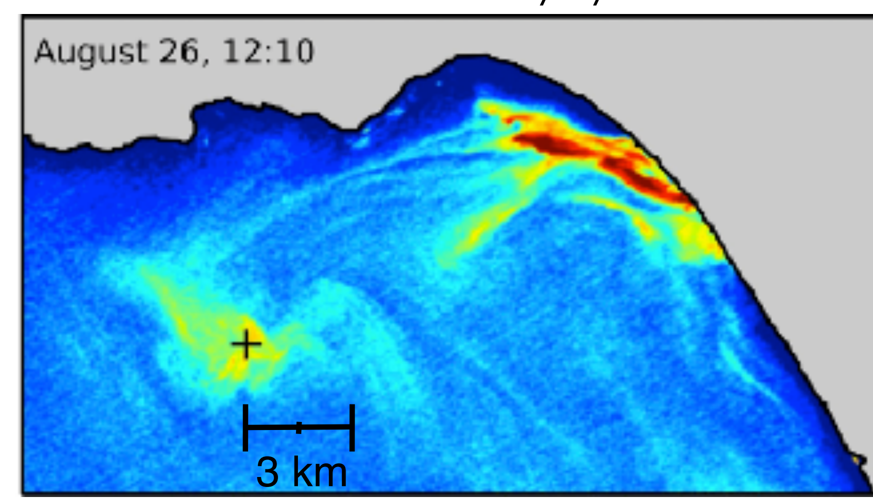


The water planet

Ocean life - Heterogeneous and Dynamic

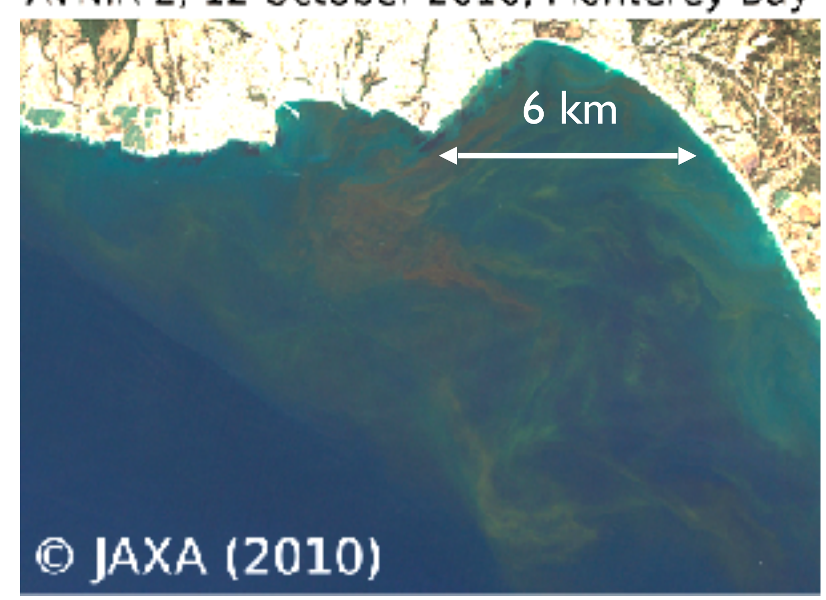


North Monterey Bay



- Sparse
- Mobile (advection)
- Large spatio-temporal extent (km-days)
- Variable correlation scales
- Multi-dimensional measurements

AVNIR-2, 12 October 2010, Monterey Bay



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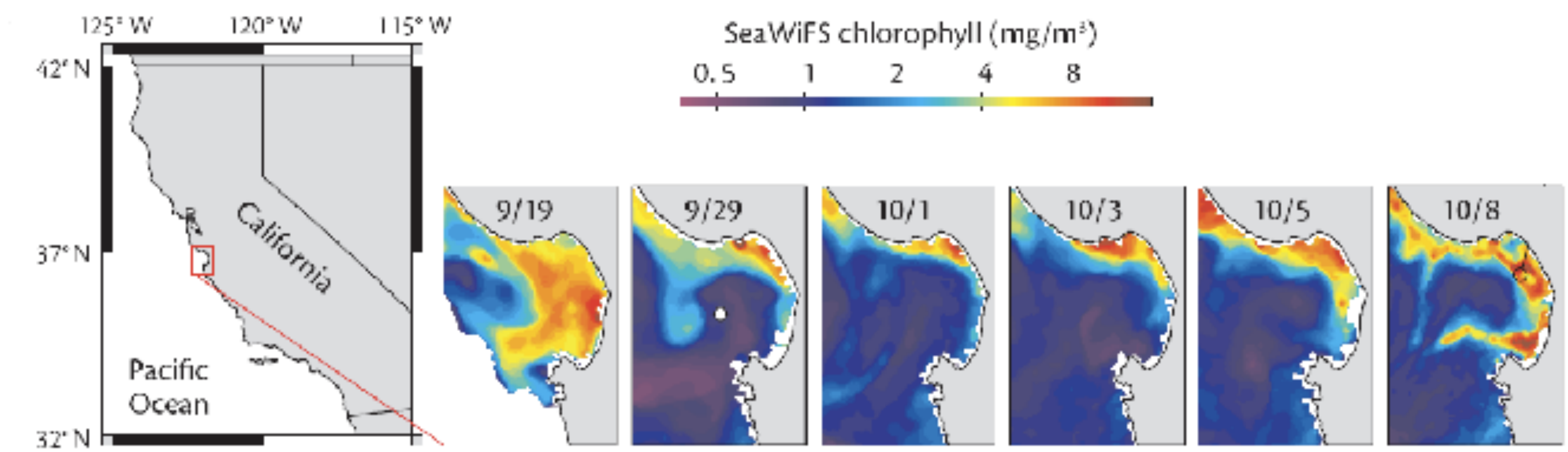

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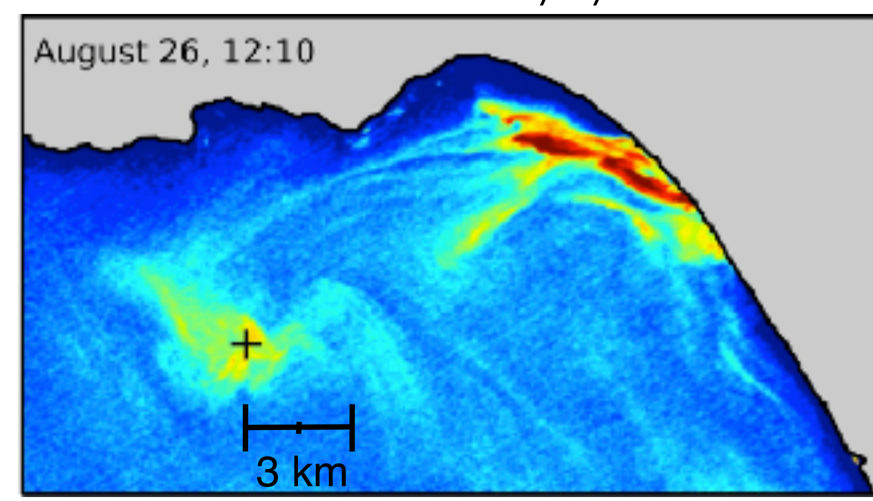

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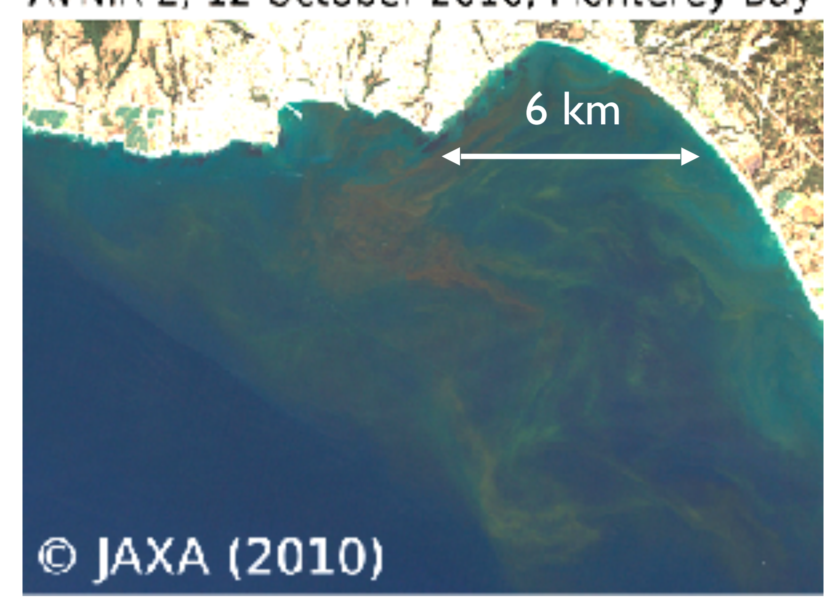

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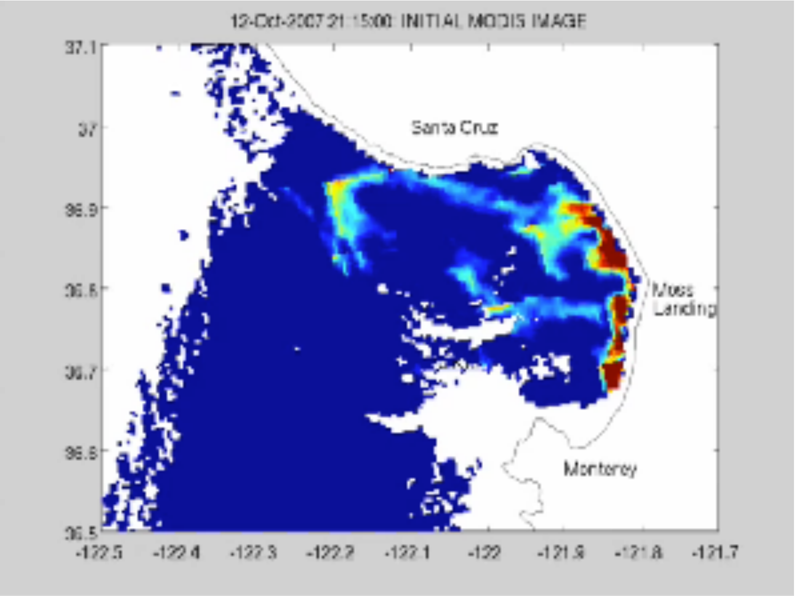
Sampling Marine Blooms



	Goal	Characteristics	Approach	
Deployment planning	Detect	Heterogeneous, Multi-scale	Remote-sensing, land based HF Radar	Macro
	Track	Mobile, coherent	Lagrangian surveys using GPS tracked drifters - tag and track	↓
Autonomous sampling	Sample	Online, adaptive	Data-driven acquisition of biological samples	Micro
Tools	Oceanographic Decision Support System (ODSS)	Web-based	Enables marine scientists as end-users, helps guide asset use	

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Macro

Micro

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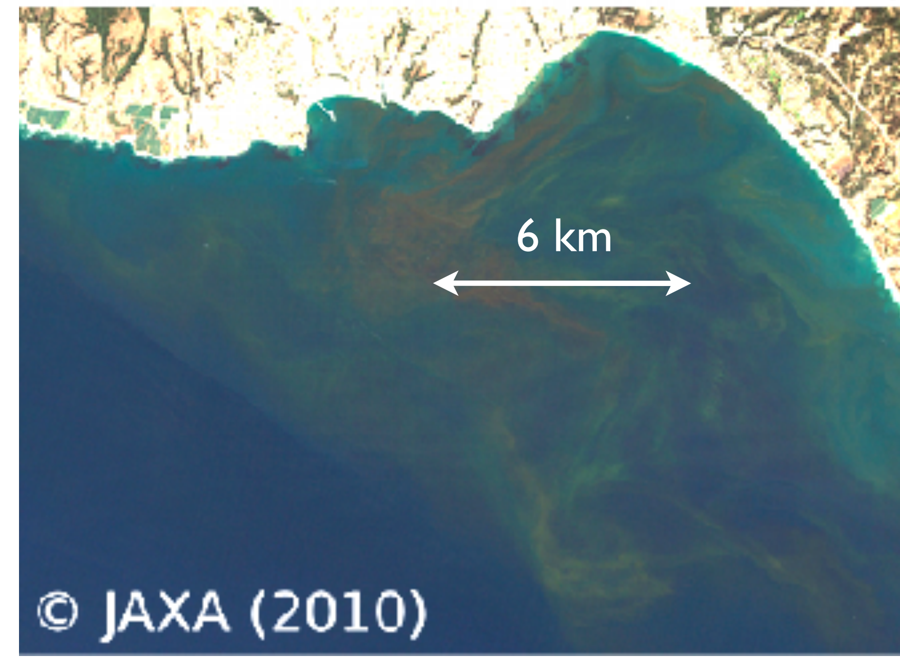

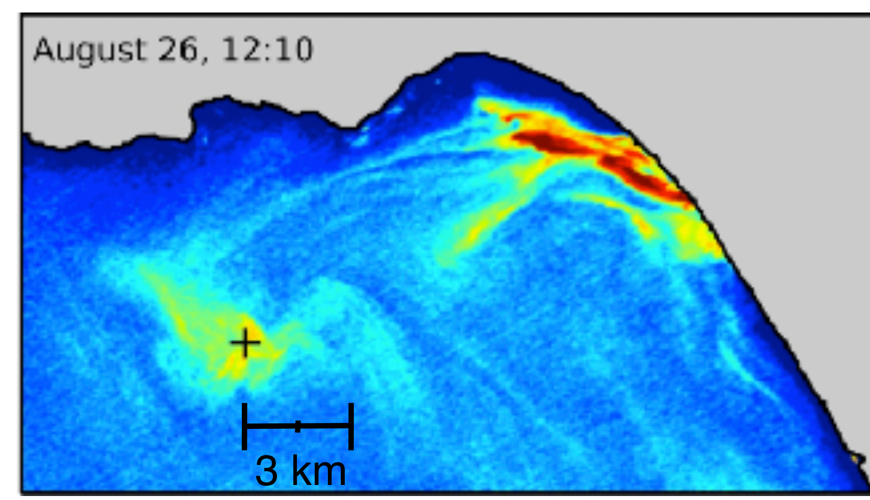

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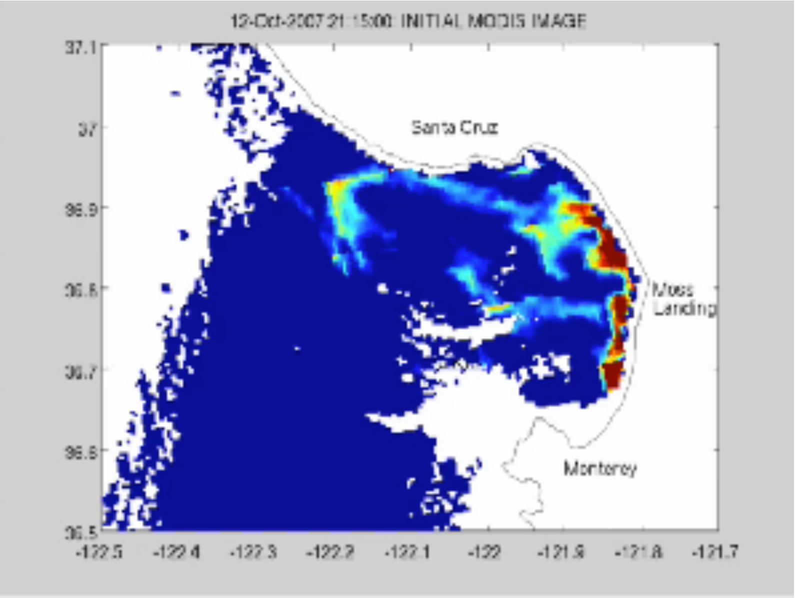

Algae bloom detection and advection over 2 days using remote sensing and hourly HF radar data

J. Das et. al, "Towards Marine Bloom Trajectory Prediction for AUV Mission Planning", In *IEEE International Conference on Robotics and Automation*, May 2010.

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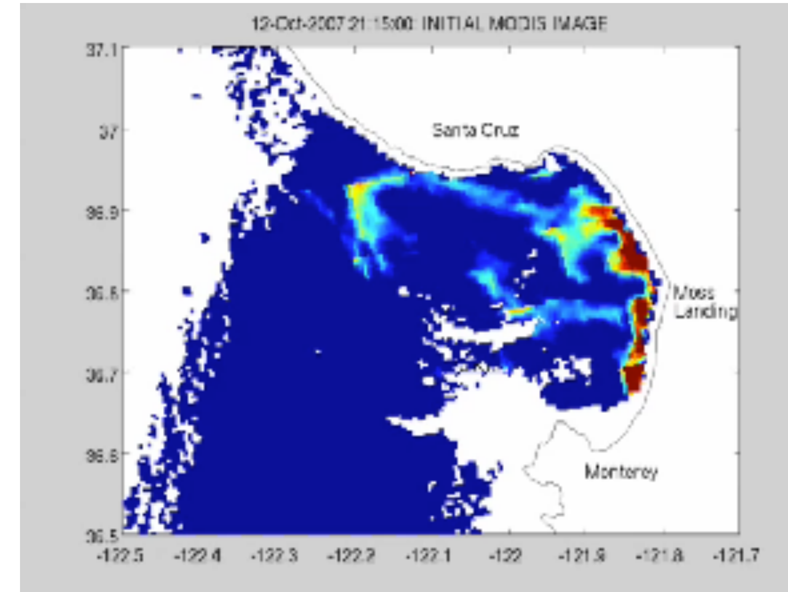

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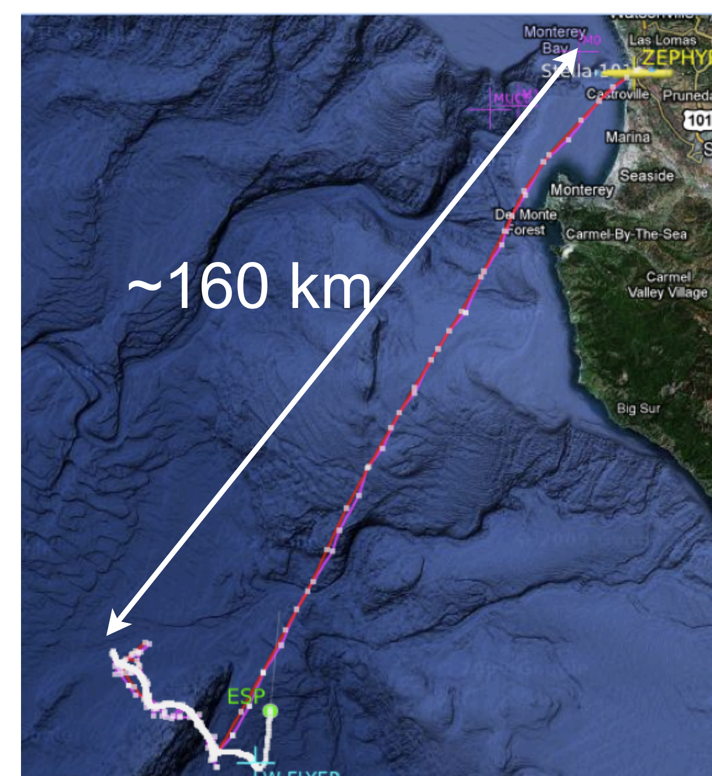

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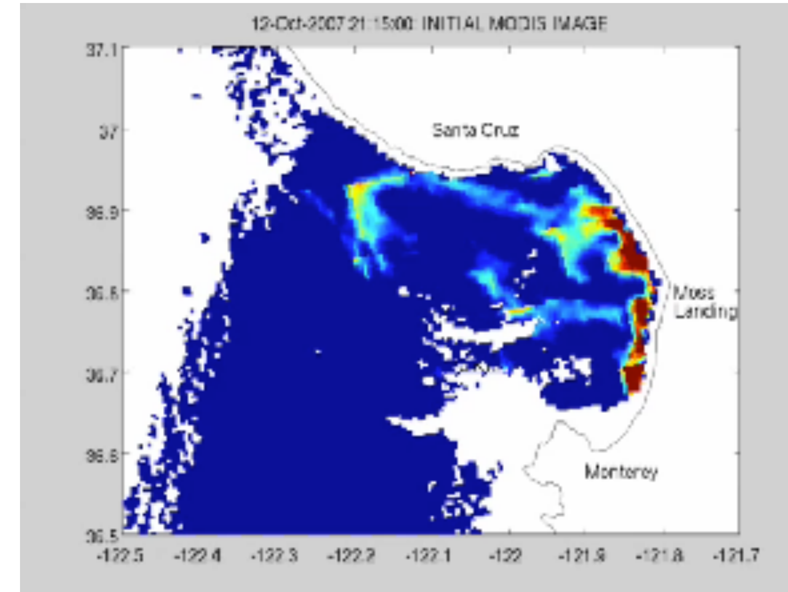

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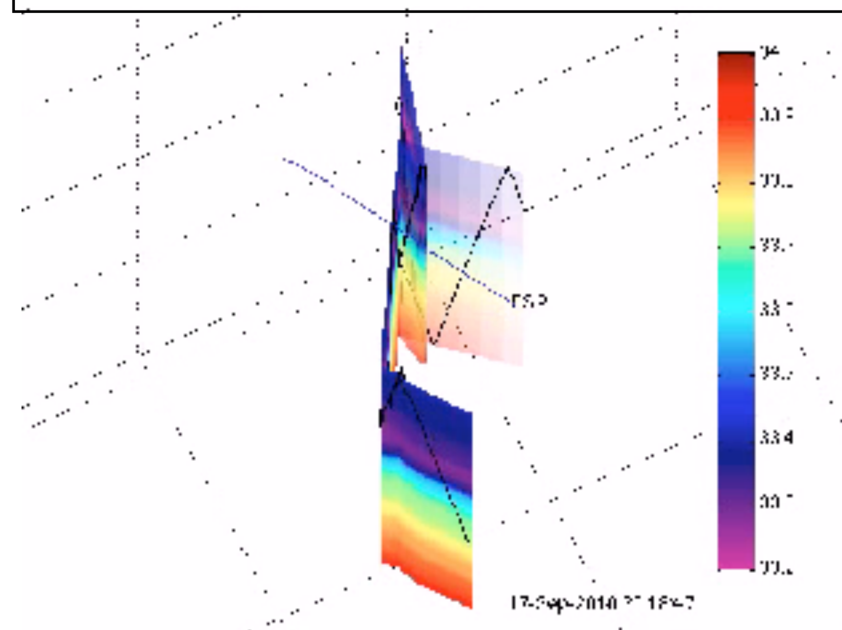

AUV carrying out Lagrangian surveys in a patch of water tagged with a GPS-tracked drifter,

J. Das et. al, "Coordinated Sampling of Dynamic Oceanographic Features with AUVs and Drifters", in International Journal of Robotics Research (IJRR), 2012.

Autonomous Underwater Vehicles (AUVs)

- Sensor suite to log scientific data, water sample collection system
- Limited communication

Slocum Glider

Dorado AUV

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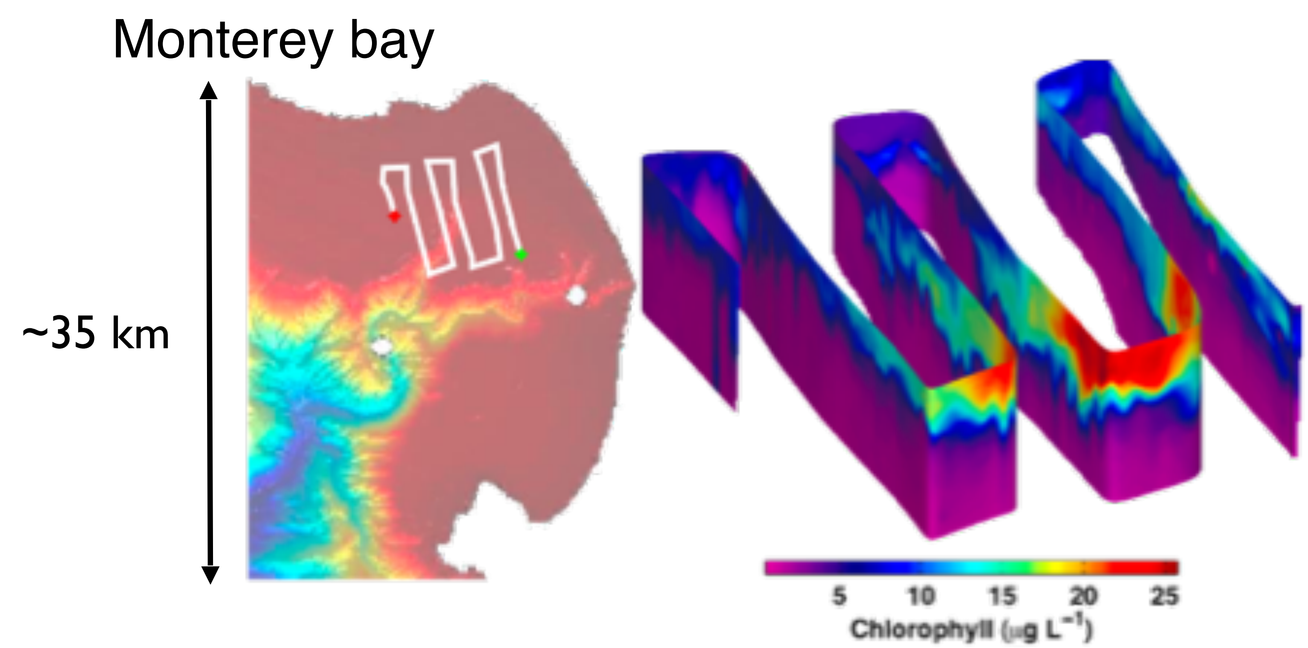
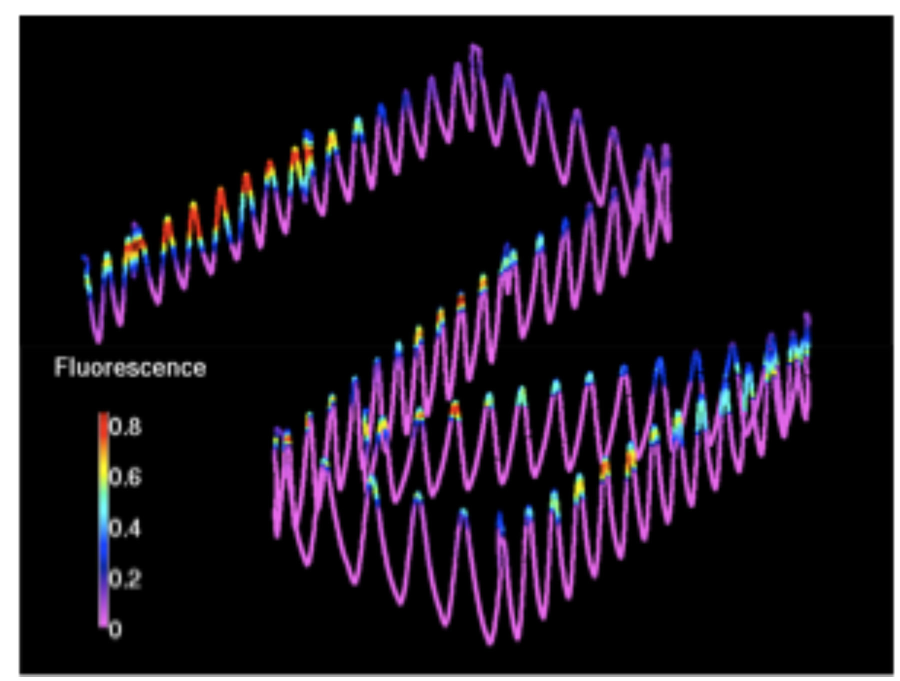
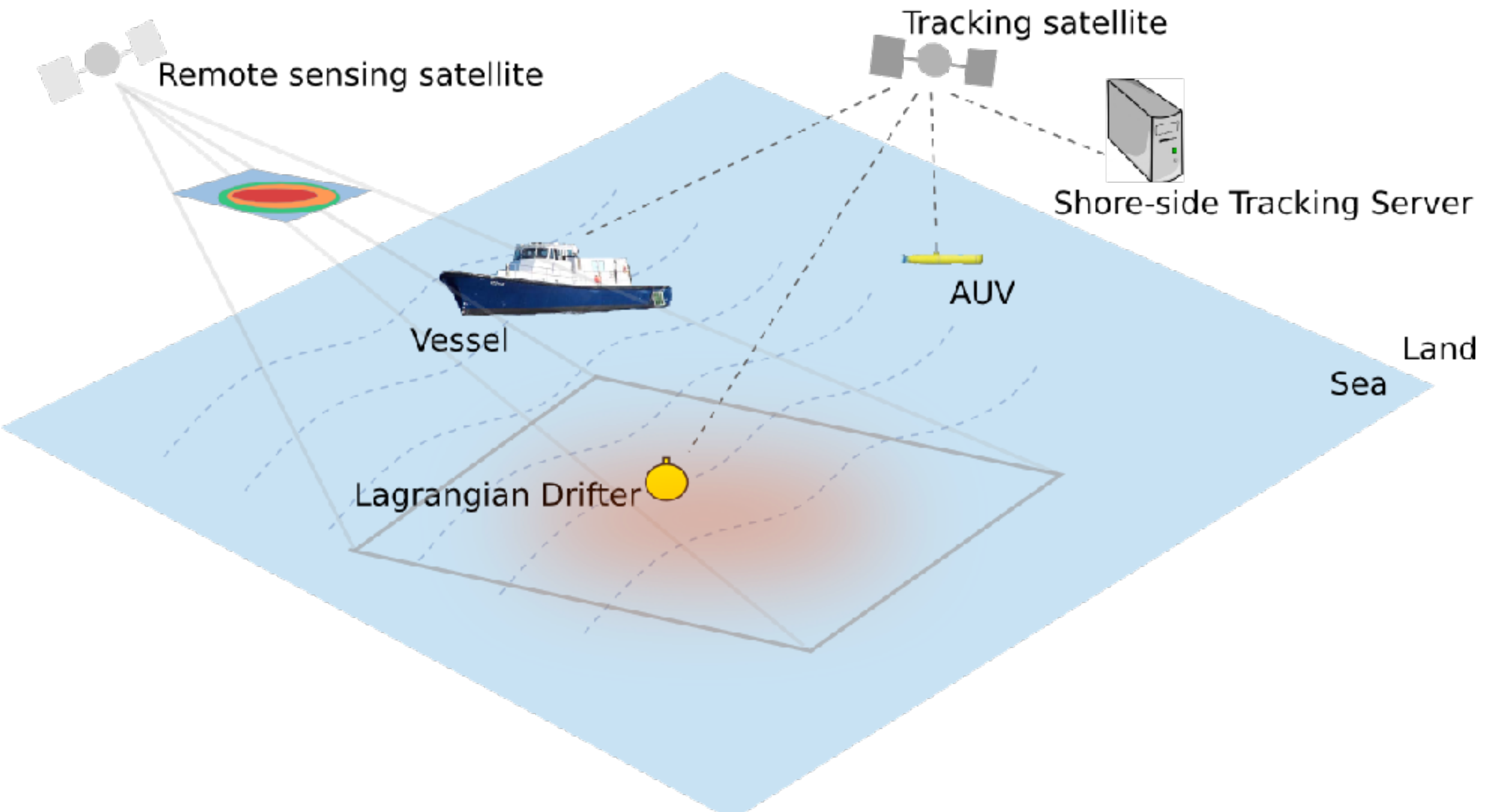




Coordinated Sampling of Blooms



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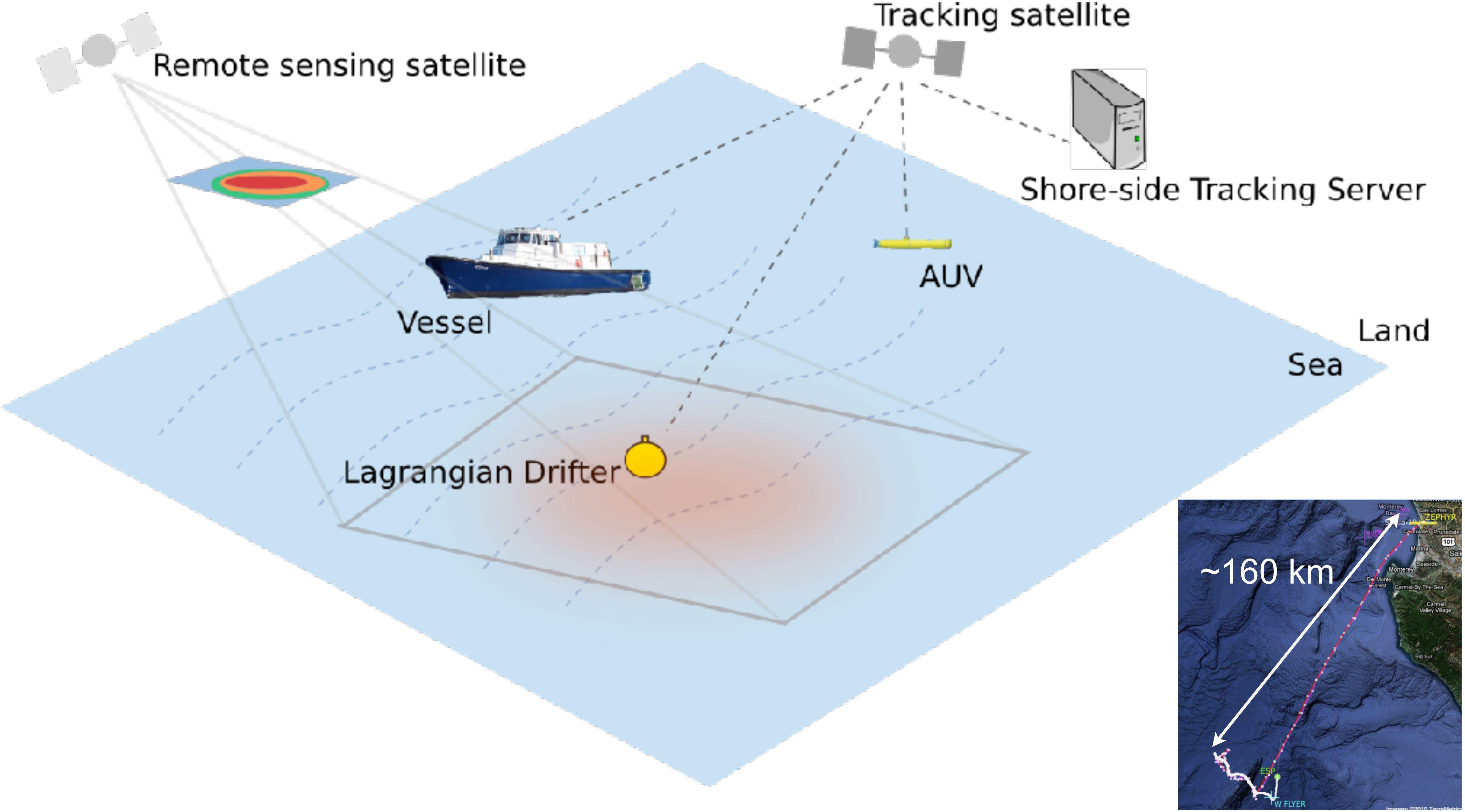

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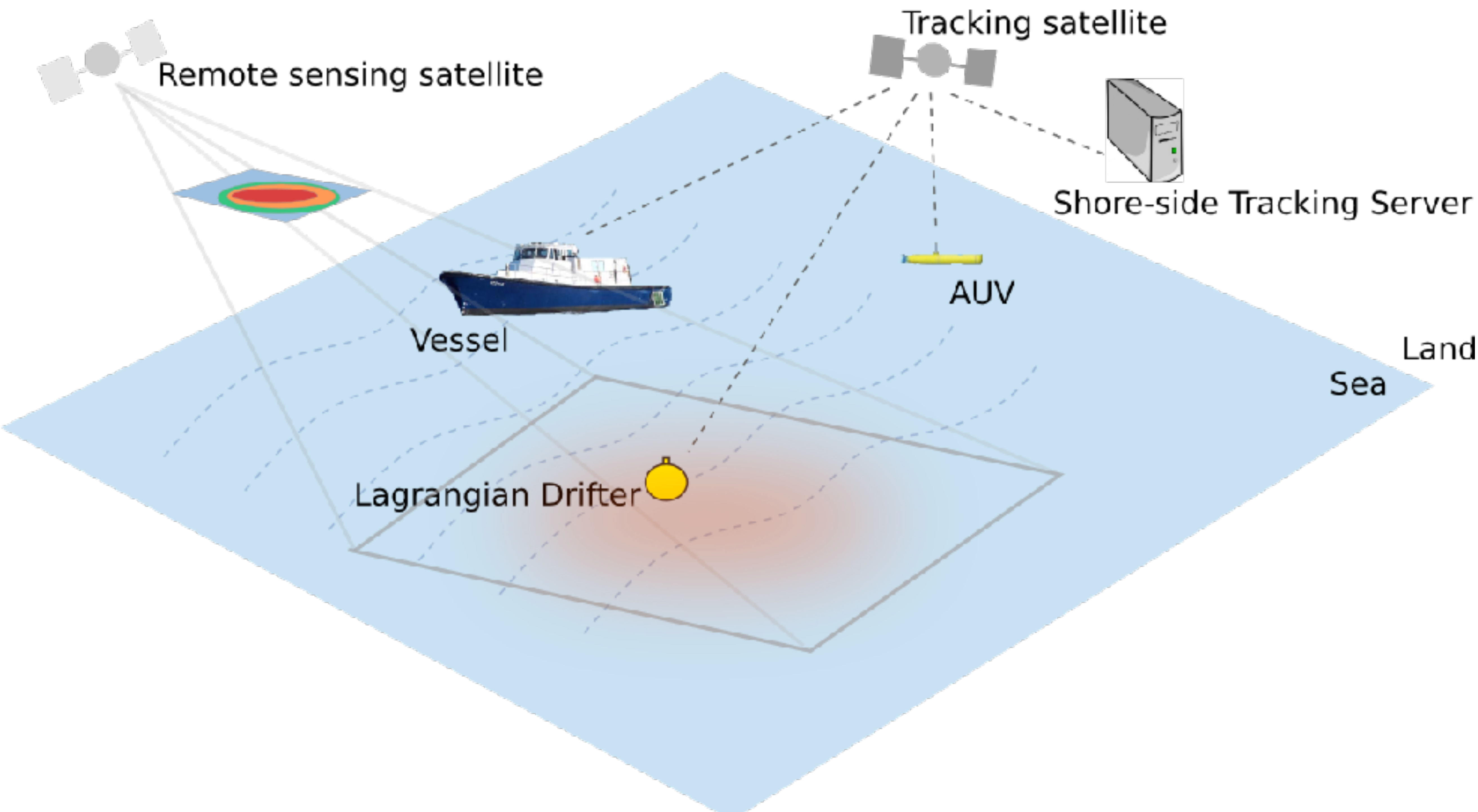

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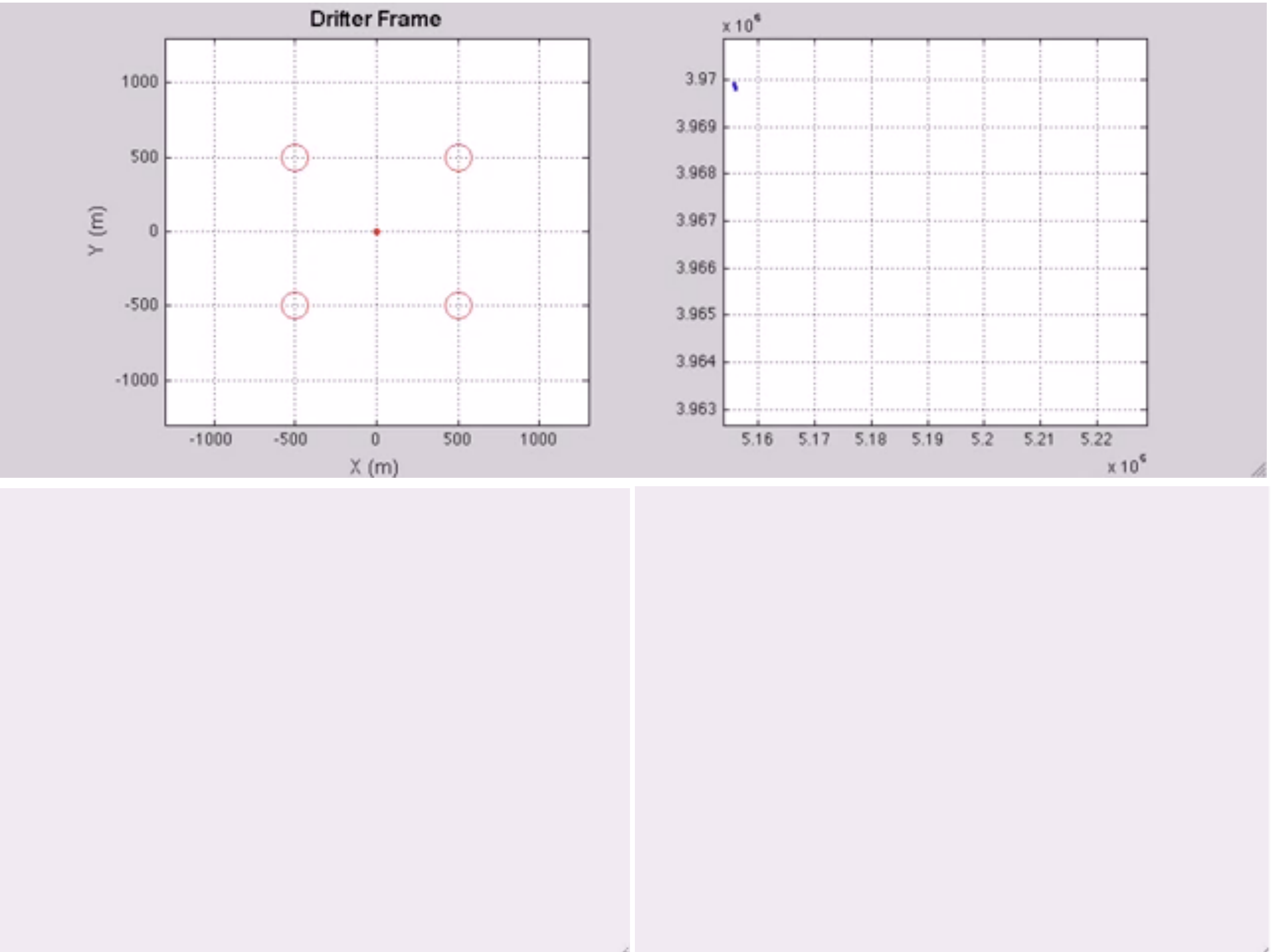

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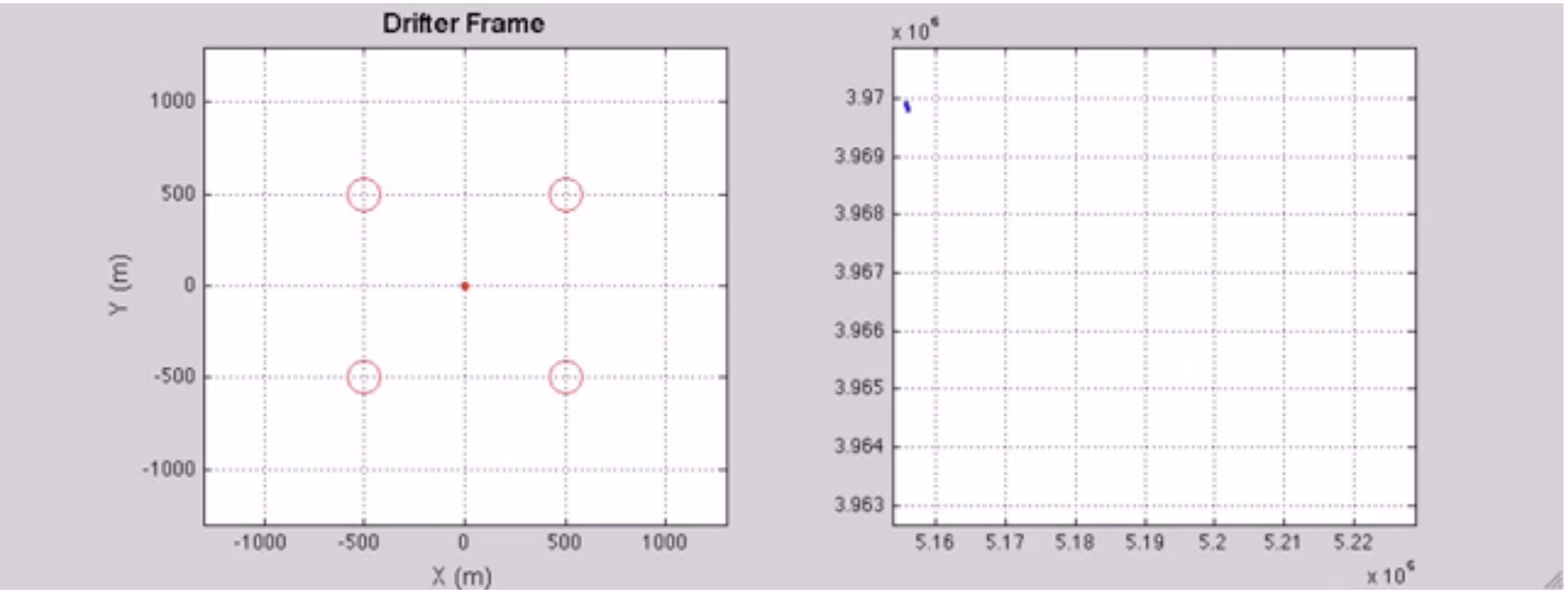

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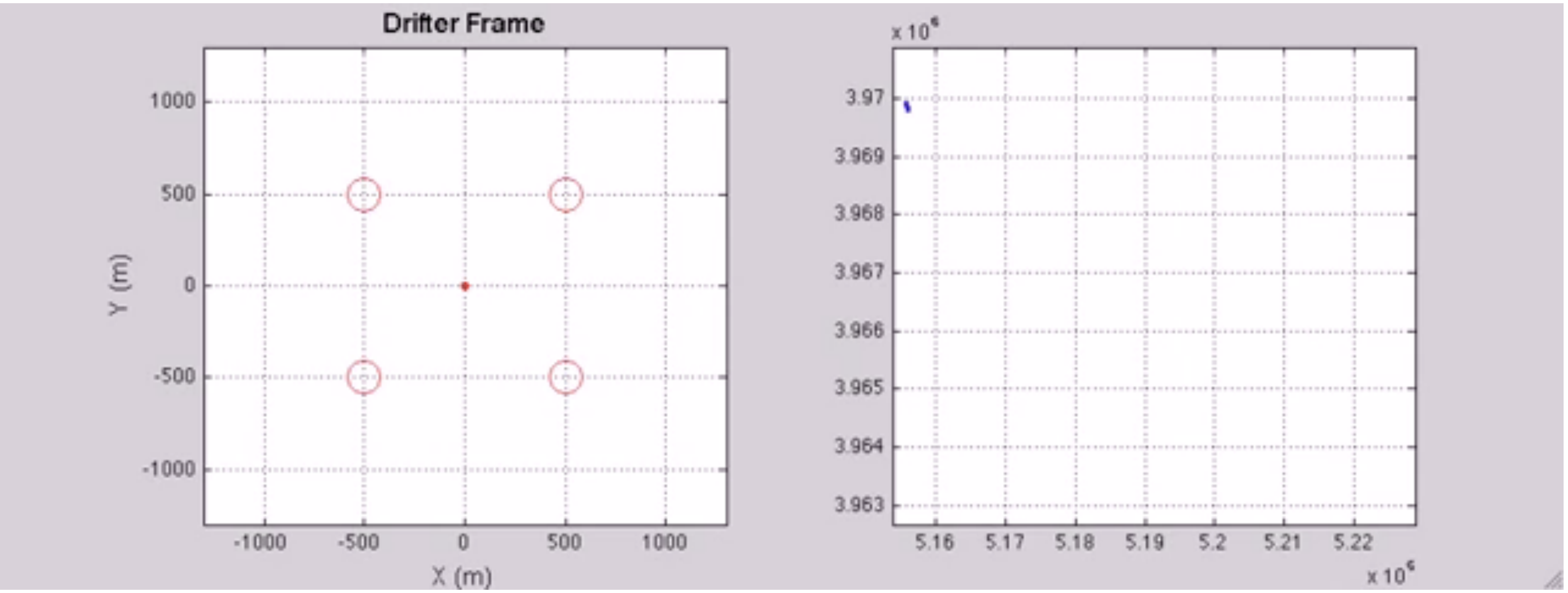

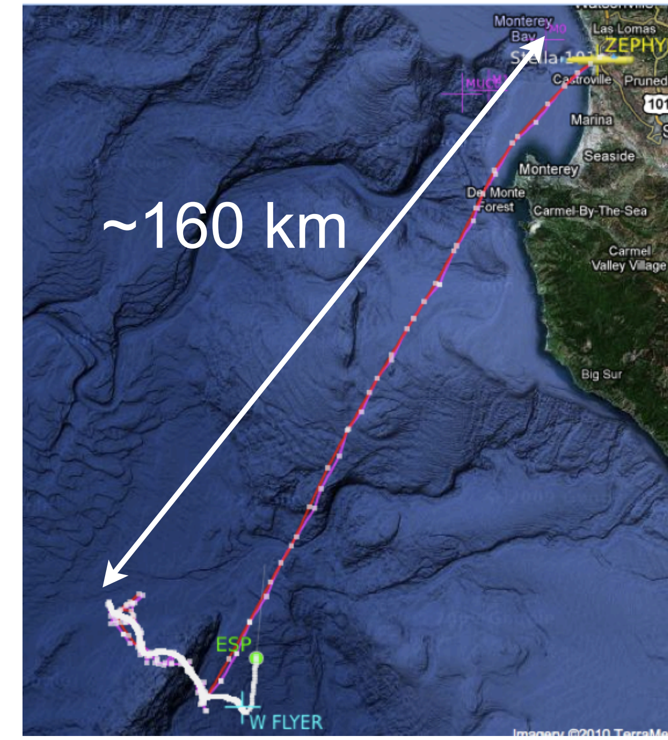

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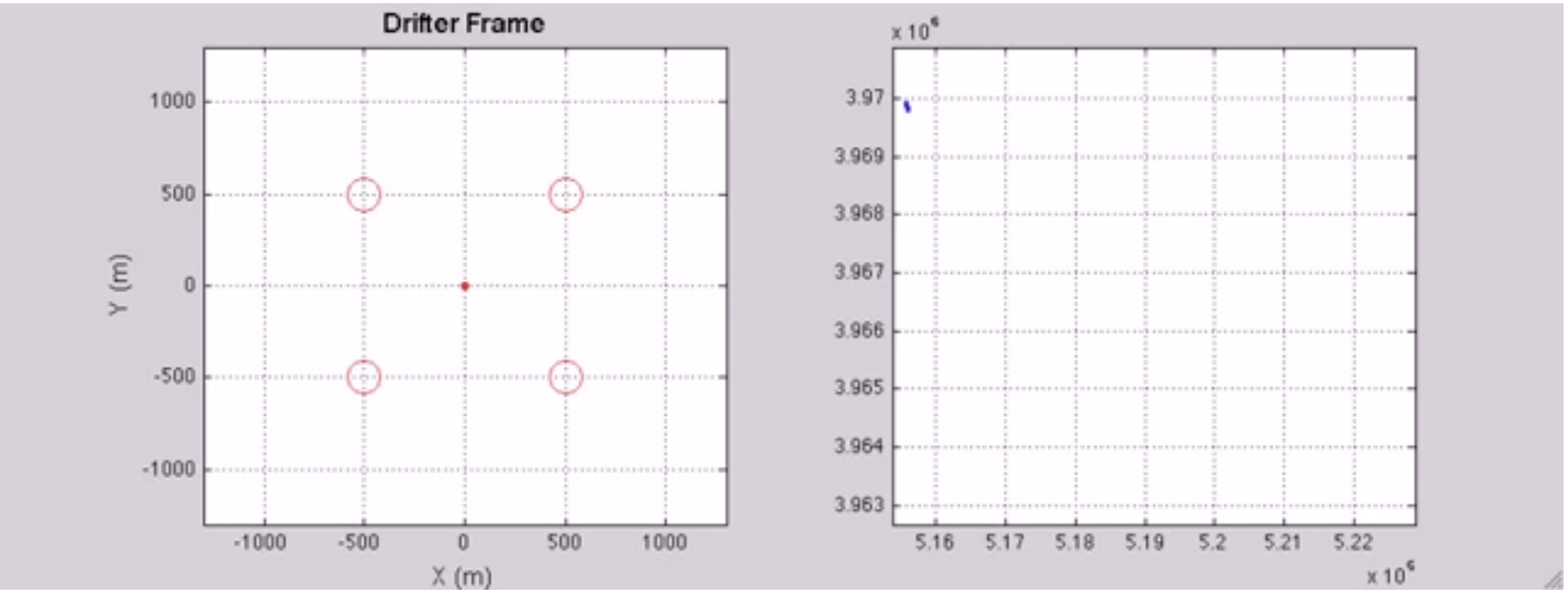

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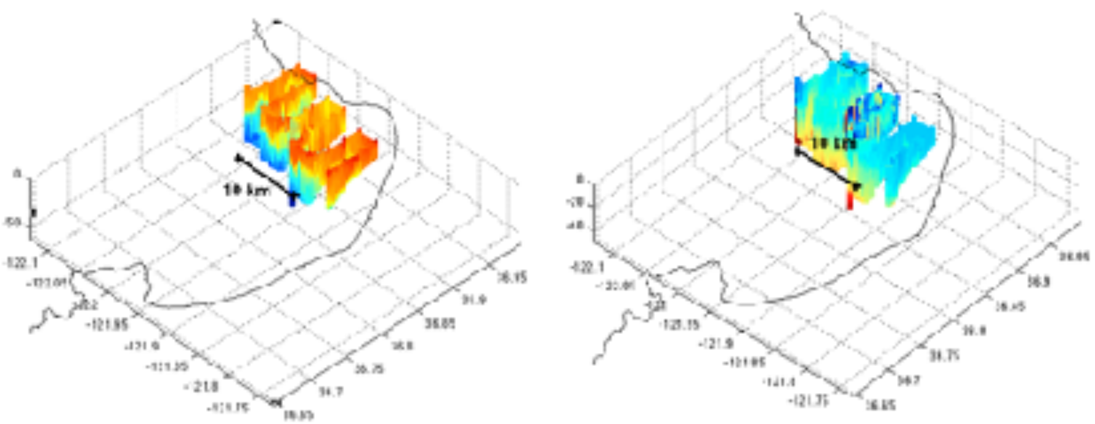
Limitations of In-situ Sampling

MBARI's Dorado AUV

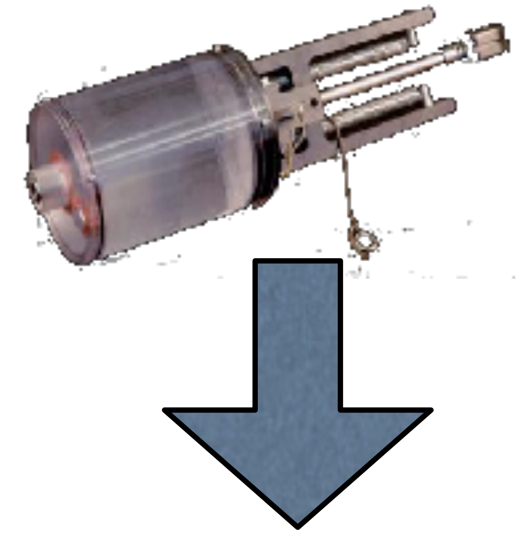
in-situ



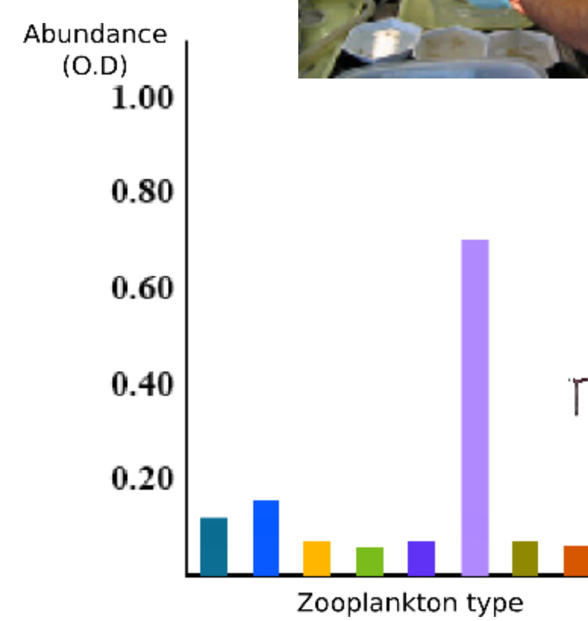
<temperature, salinity,...>

environmental context

Ten 1.8 L gulpers



lab analysis



organism abundance

Limitations of In-situ Sampling

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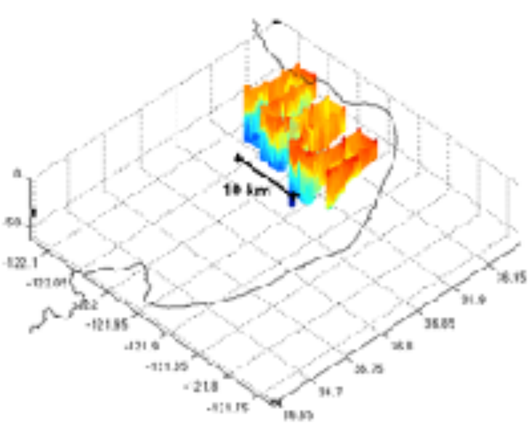

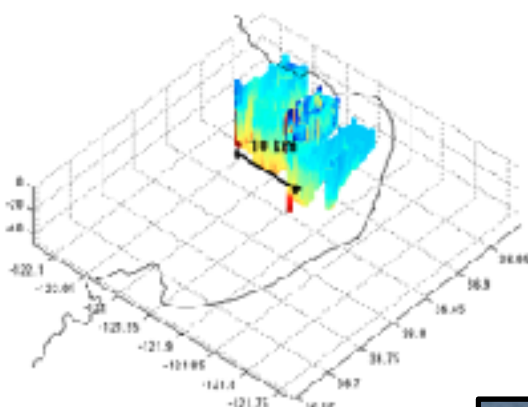

<temperature, salinity,...>

environmental context

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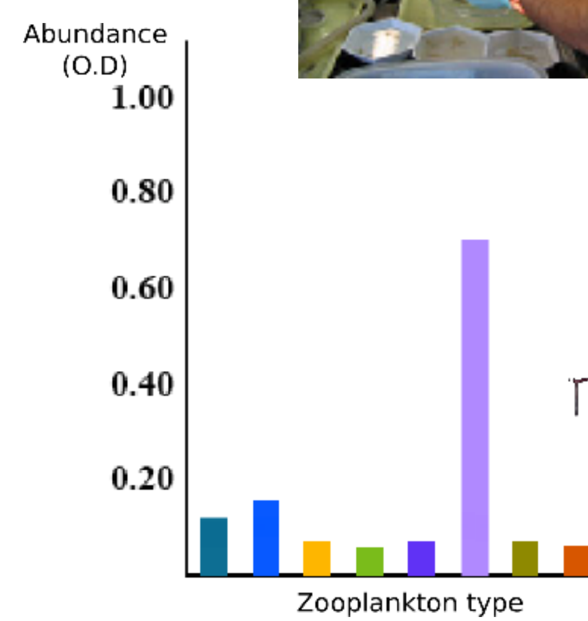
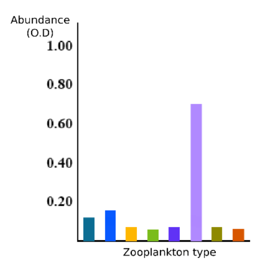


organism abundance

Acquiring Water Samples Adaptively

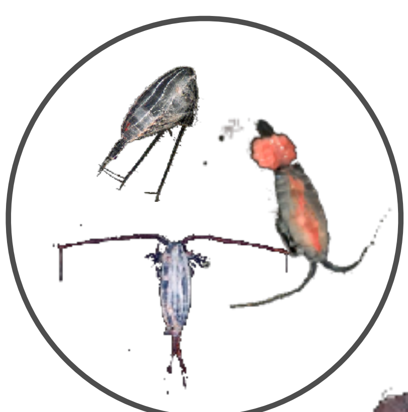
Sampling Policy

Training data
[temp, salinity,...][b]



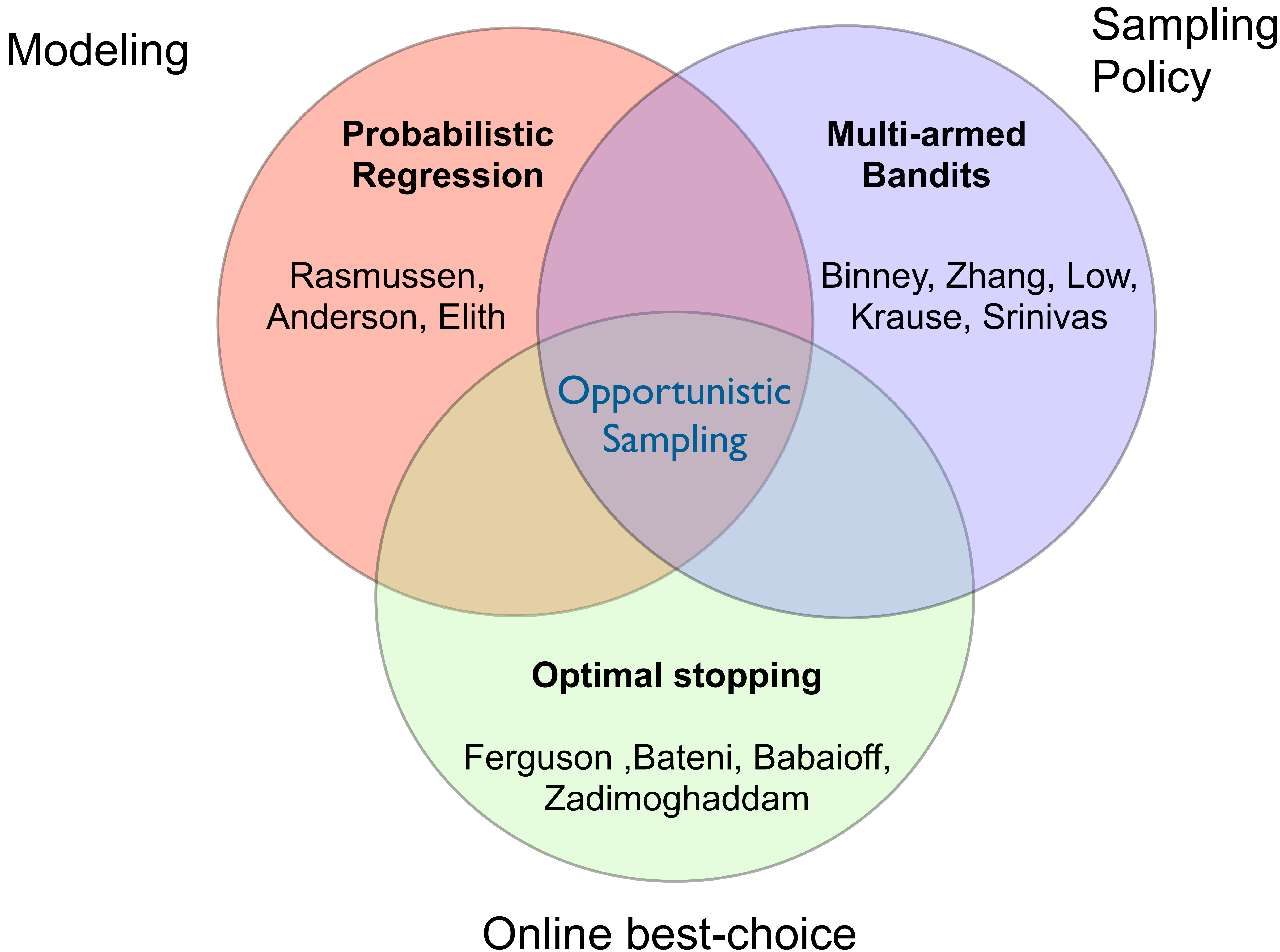
(re)learn organism abundance model

Organism niche model

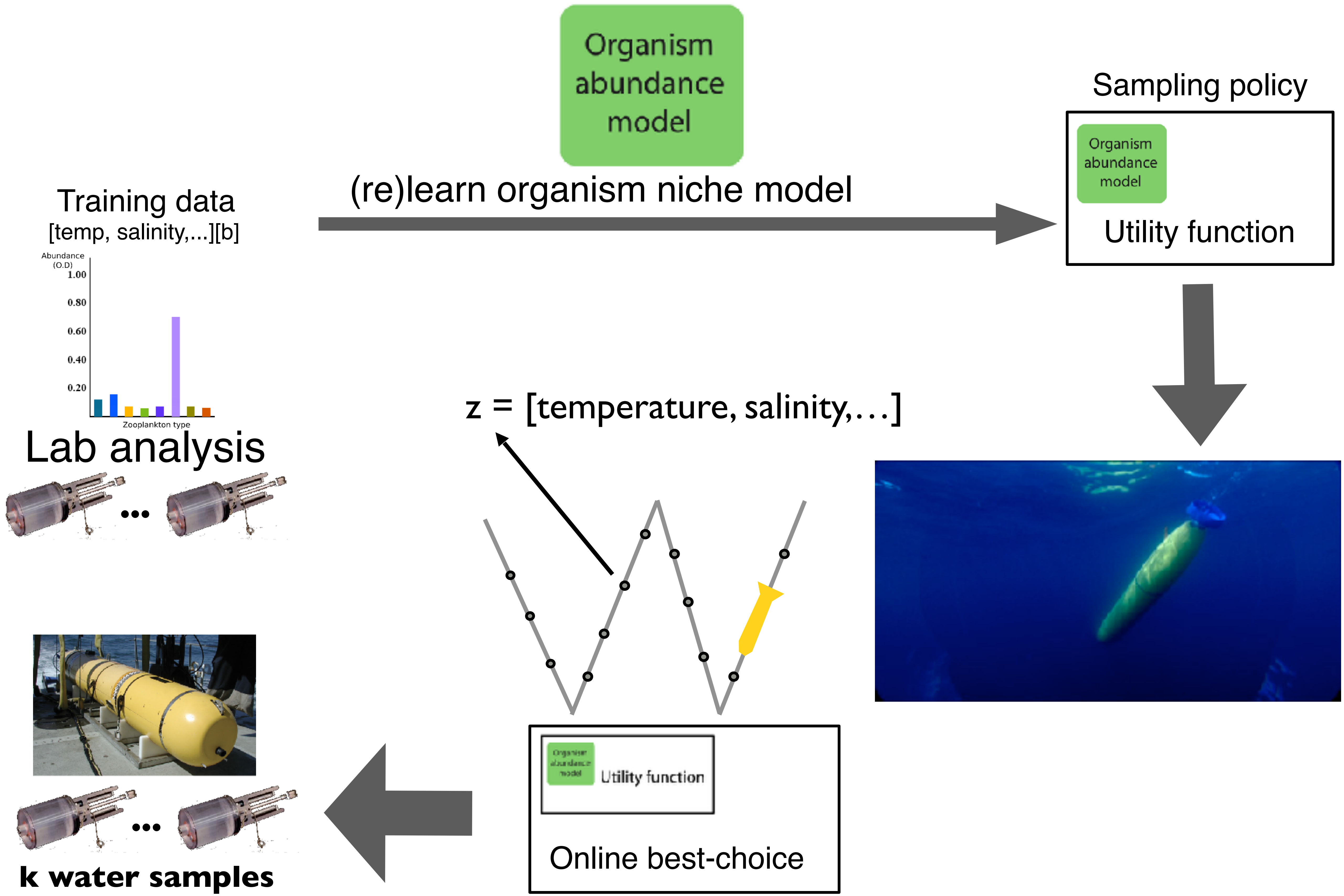


Lab analysis

Adaptive water sampling


Modeling
Sampling
Policy
Probabilistic
Regression
Rasmussen,
Anderson, Elith
Multi-armed
Bandits
Binney, Zhang, Low,
Krause, Srinivas
Opportunistic
Sampling
Optimal stopping
Ferguson ,Bateni, Babaioff,
Zadimoghaddam
Online best-choice

Opportunistic Sampling



Problem Formulation

Environmental feature vector $\mathbf{z} = [\text{temperature, salinity,...}] \in \mathbb{R}^D$

Training dataset $\mathbf{T} \ = \ < \mathbf{z}_1, b_1 >, < \mathbf{z}_2, b_2 >, ..., < \mathbf{z}_M, b_M >$

Probabilistic model
for organism abundance

$$b = g(\mathbf{z}) + \epsilon, b \in \mathbb{R}$$

$$\mu(\mathbf{z}), \sigma^2(\mathbf{z})$$

AUV samples **z** at geographic
locations

$$\mathbf{x} = [\text{latitude, longitude, depth}] \in \mathbb{R}^3$$

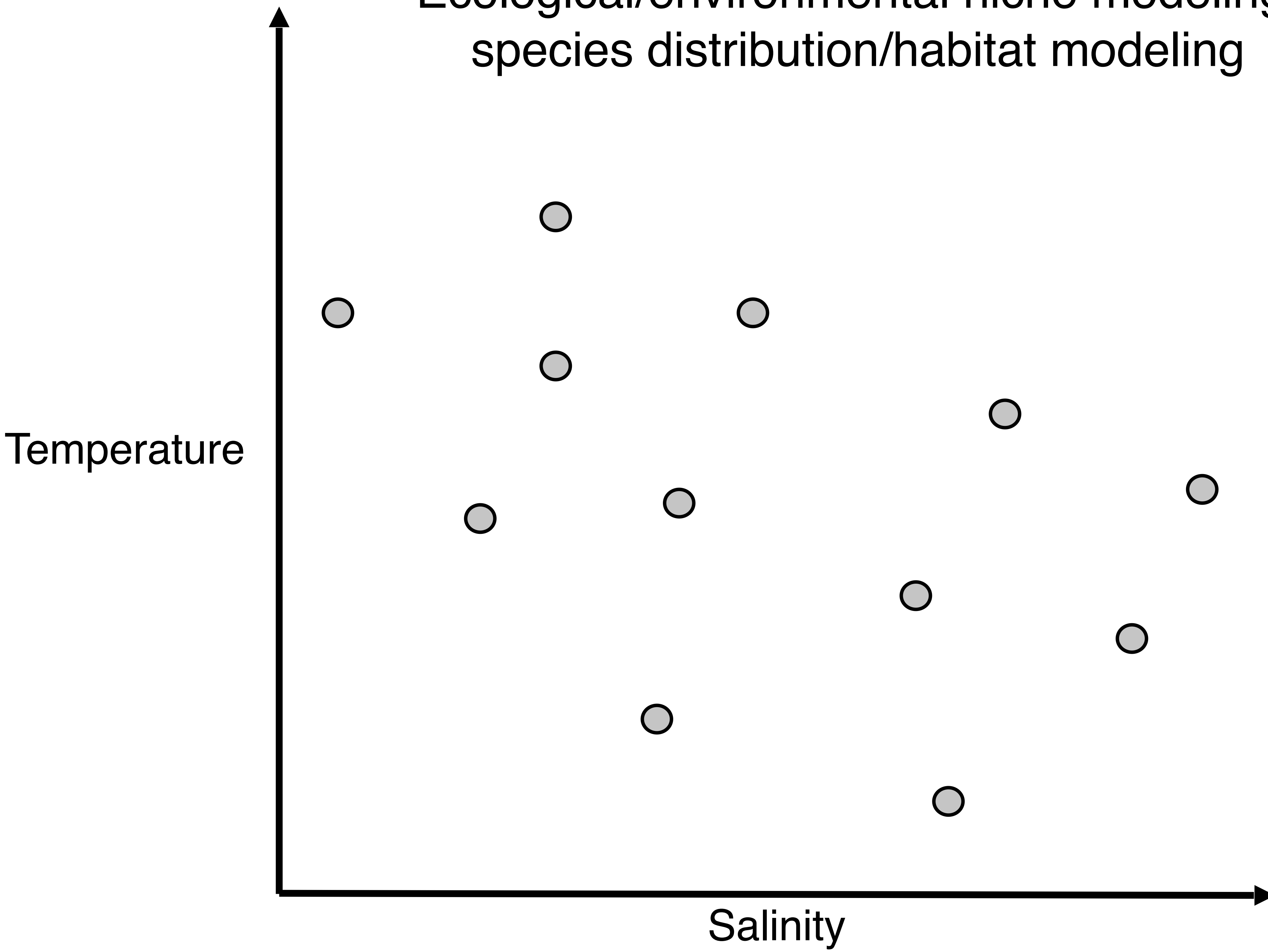
Bayesian sequential optimization
: utility function

$$u = h(\mu(\mathbf{z}), \sigma^2(\mathbf{z}))$$

Goal : Acquire samples that maximize utility, *online*

Organism Abundance Model

Ecological/environmental niche modeling,
species distribution/habitat modeling



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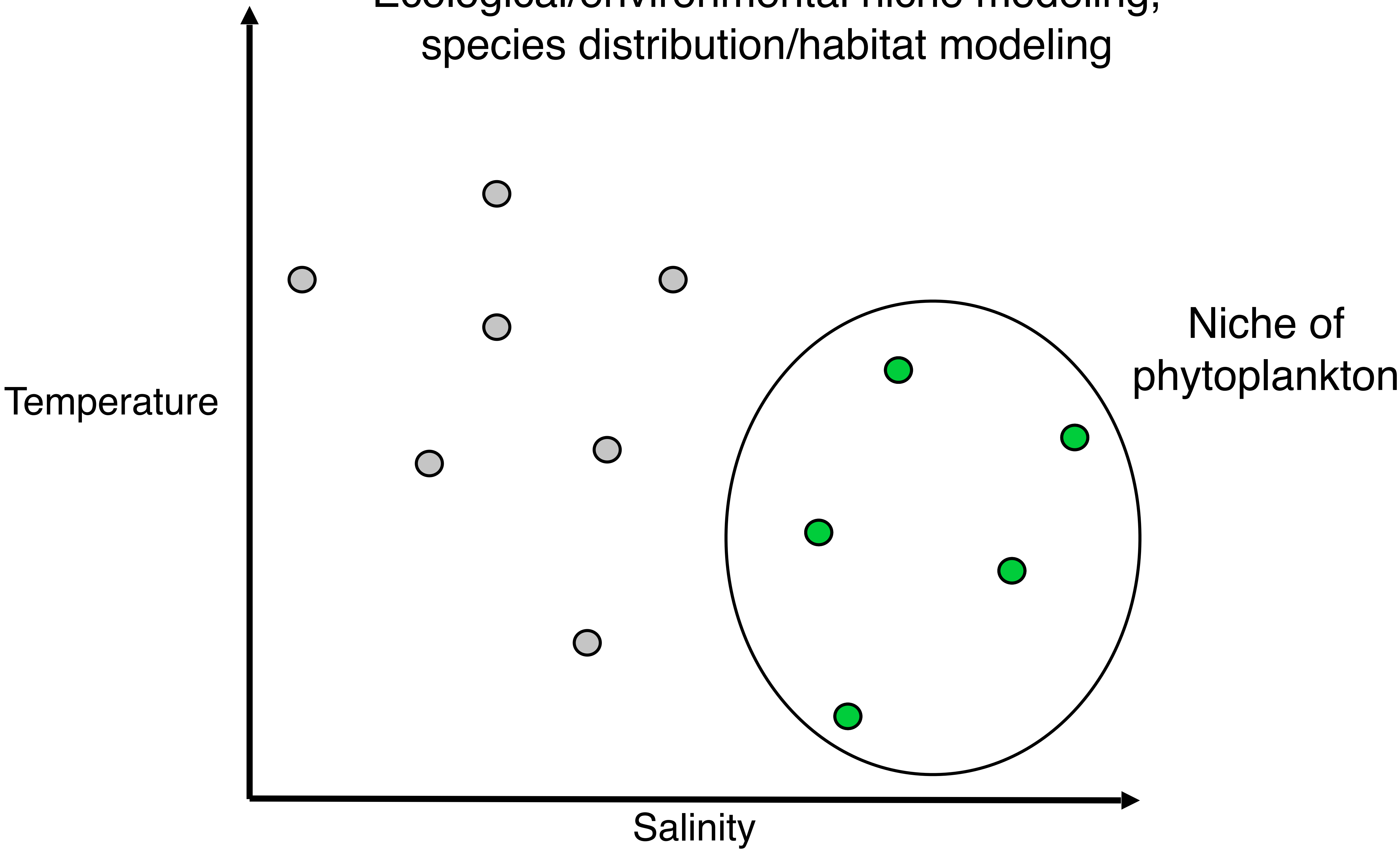

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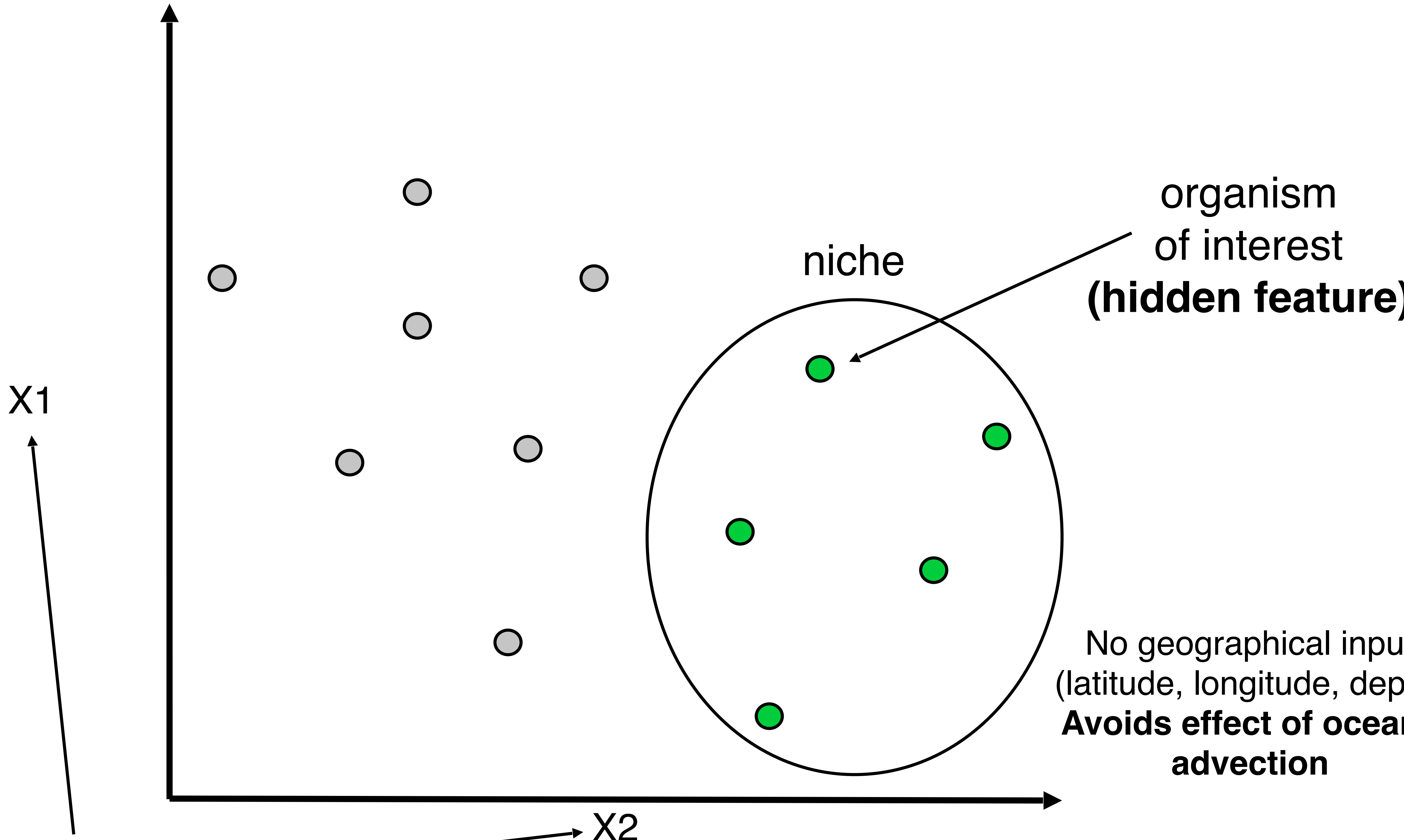


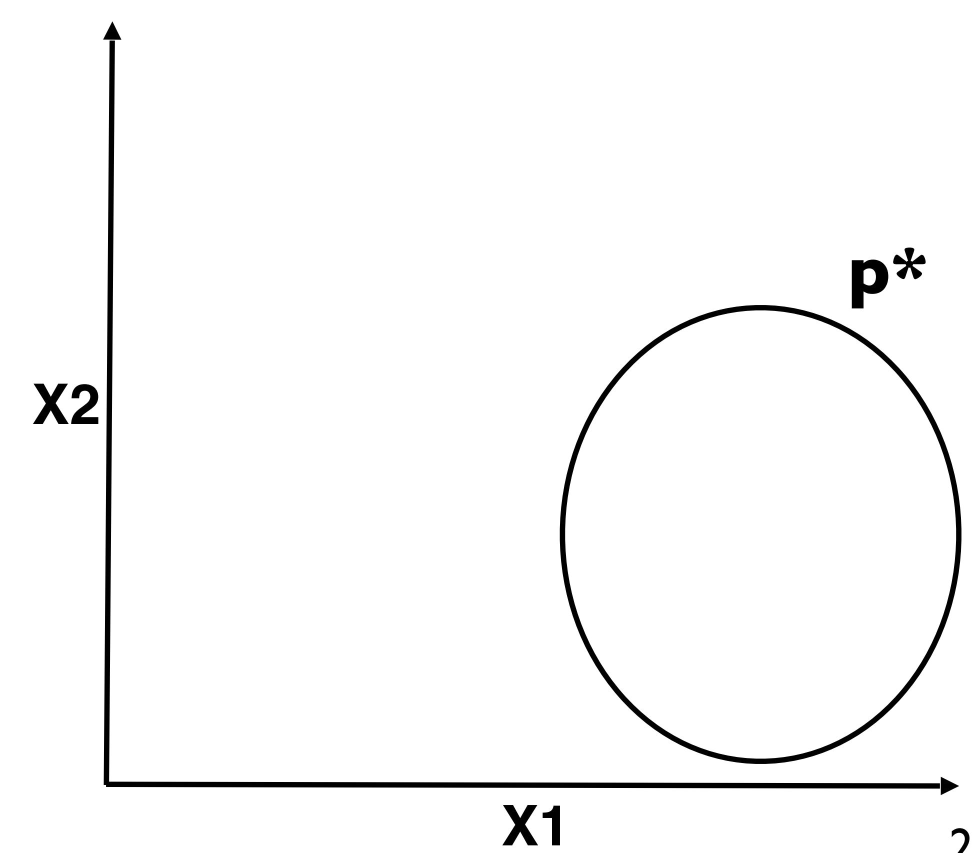
No geographical input
(latitude, longitude, depth)
Avoids effect of oceanic advection

input features

in-situ measurements:
temperature, salinity, chlorophyll fluorescence, backscatter, ...

Sequential Sampling

- Organism observed from unknown true niche p*
- Goal: acquire high abundance samples for ecological studies

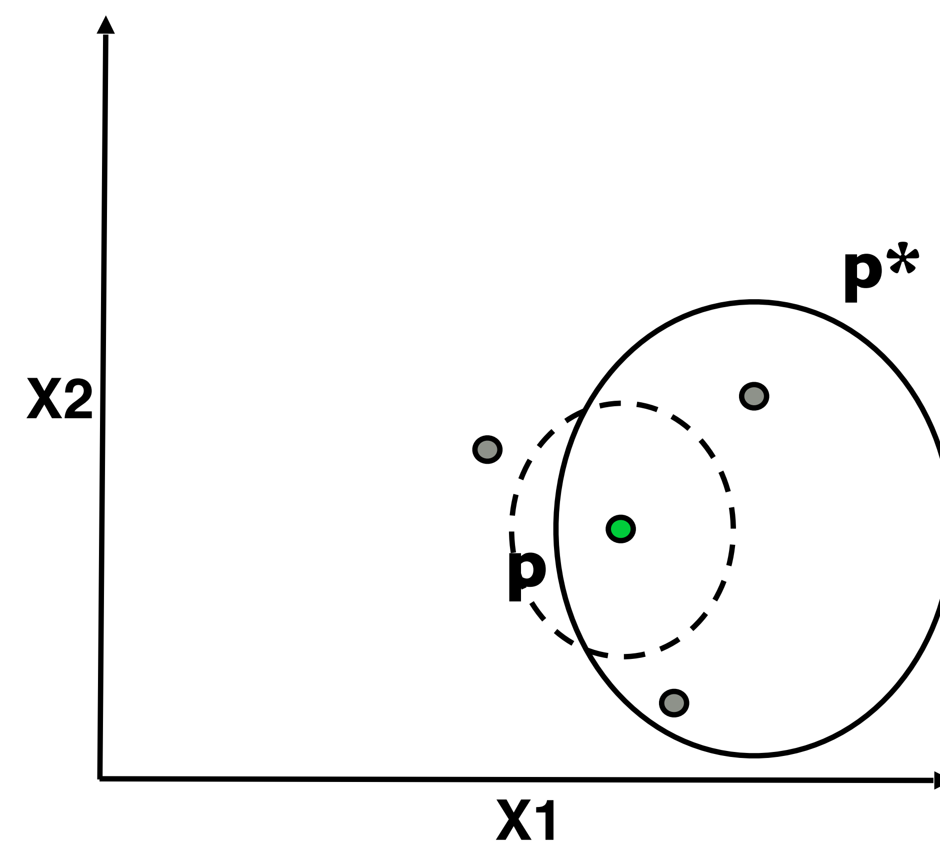


Sequential Sampling

- Organism observed from unknown true niche p*
- Goal: acquire high abundance samples for ecological studies

steps

1. Robot samples from p* randomly
2. Oracle reveals organism abundance of samples
3. Model learns distribution p (an estimate of p*)



Sequential Sampling

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- Goal: acquire high abundance samples for ecological studies

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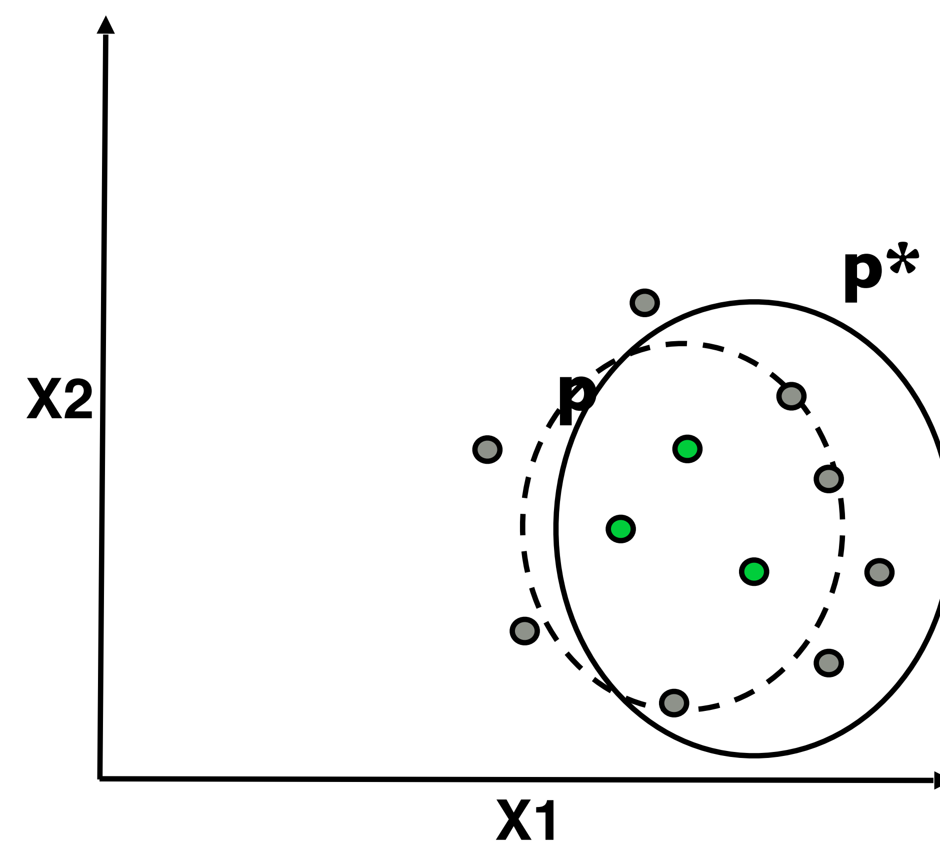
4. Sequential sampling policy uses p to determine new samples to acquire
5. Repeat 2 - 4



Sequential Sampling

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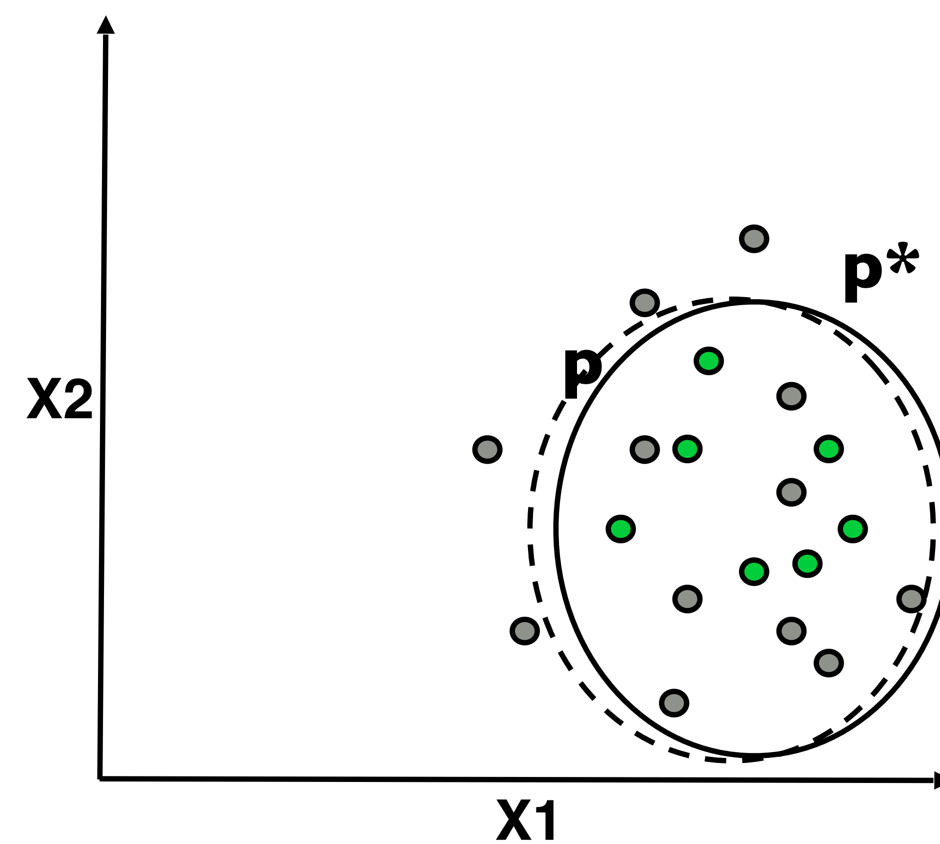


Gaussian Processes Regression

- Non-linear (expressive), probabilistic (introspective)

$$\mu(\mathbf{z}^*) = \mathbf{k}(K + \sigma_n^2 I)^{-1}\mathbf{b}$$

$$\sigma^2(\mathbf{z}^*) = k(\mathbf{z}^*, \mathbf{z}^*) + \mathbf{k}(K + \sigma_n^2 I)^{-1}\mathbf{k}$$

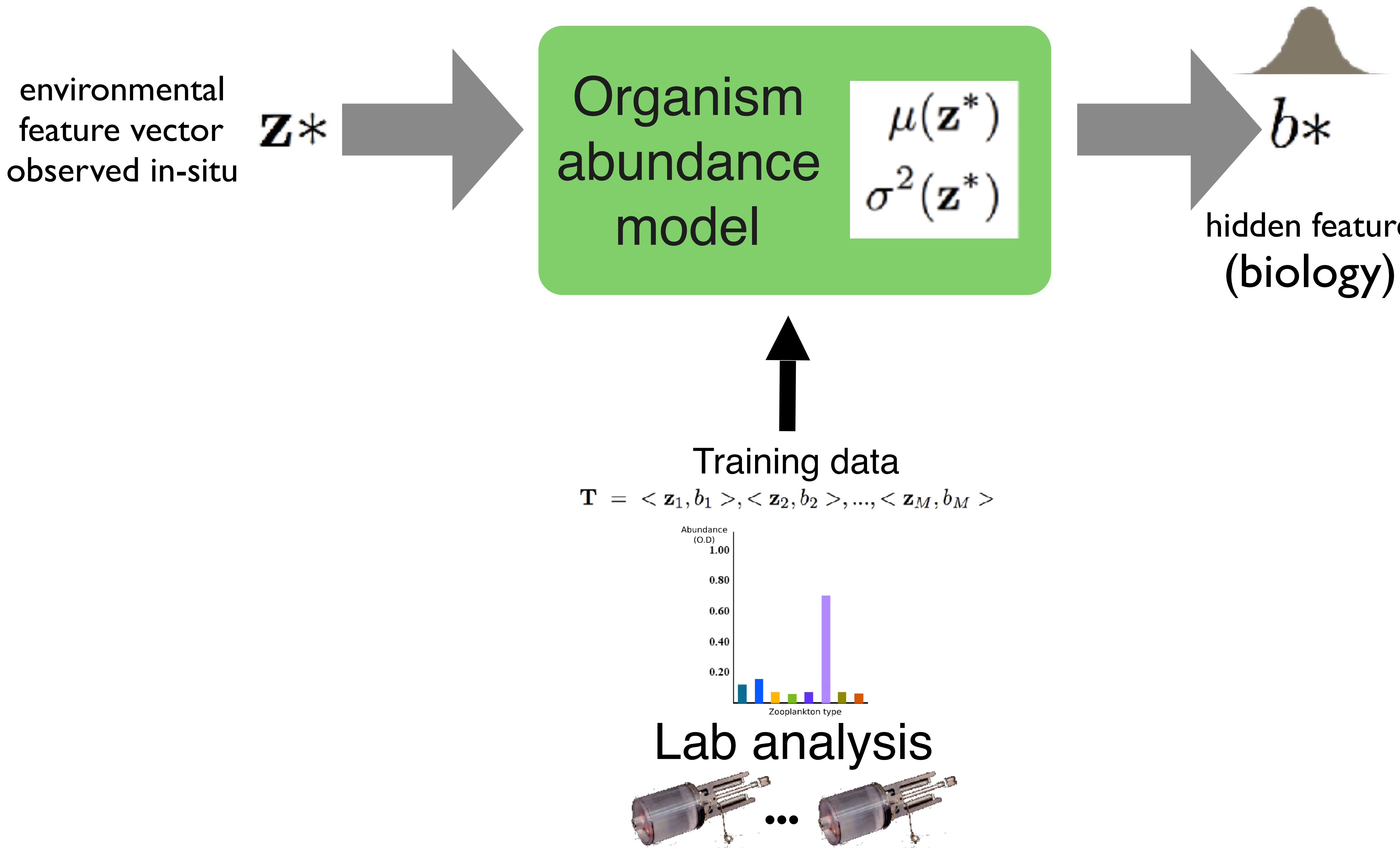
- K is the covariance (or Gram) matrix, generated using a kernel function (squared exponential for this work)

$$k(\mathbf{z}_p, \mathbf{z}_q) = e^{-\frac{1}{2\lambda^2}|\mathbf{z}_p - \mathbf{z}_q|^2}$$

- Train model on shore - make predictions on robot, in real time

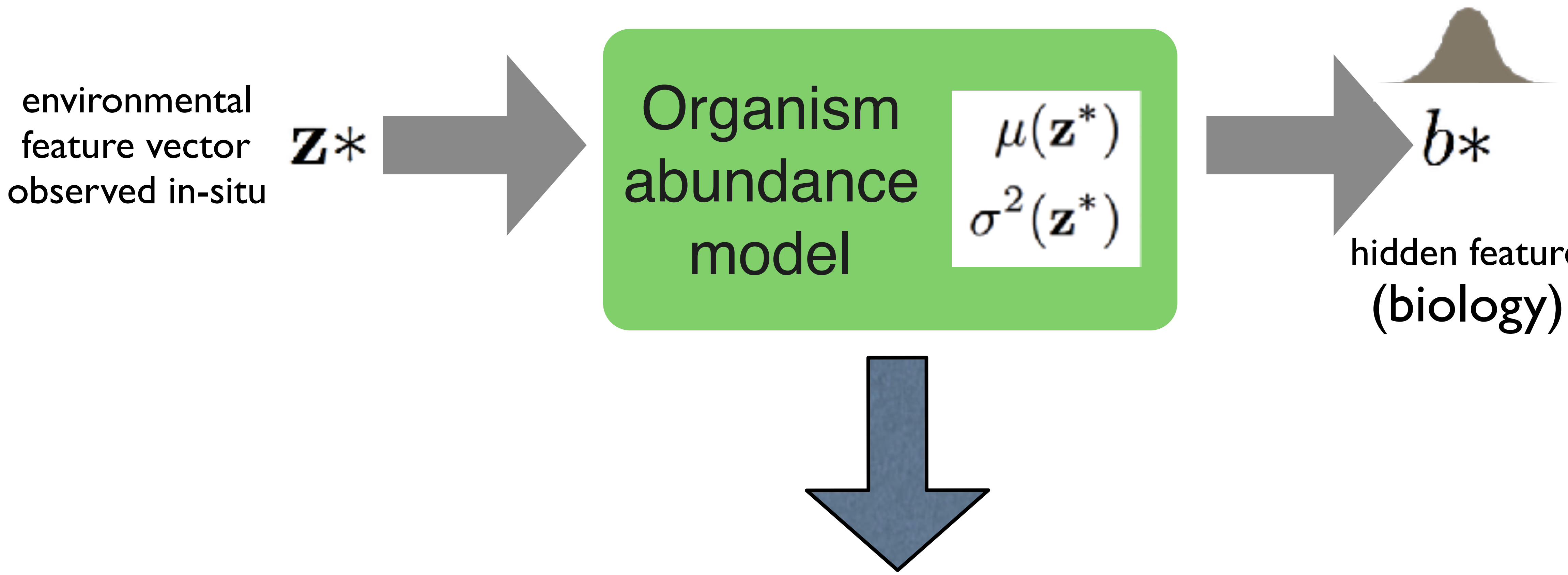
“Gaussian Processes for Machine Learning”, C. Rasmussen and C. Williams., The MIT Press, 2006.

Probabilistic Model



"Hierarchical Probabilistic Regression for AUV-based Adaptive Sampling of Marine Phenomena", **J. Das**, J. Harvey, F. Py, H. Vathsangam, R. Graham, K. Rajan and G. S. Sukhatme. In International Conference on Robotics and Automation (ICRA), May 2013.

Probabilistic Model



Predict organism abundance, and associated uncertainty in real-time

"Hierarchical Probabilistic Regression for AUV-based Adaptive Sampling of Marine Phenomena", **J. Das**, J. Harvey, F. Py, H. Vathsangam, R. Graham, K. Rajan and G. S. Sukhatme. In International Conference on Robotics and Automation (ICRA), May 2013.

Sampling Policy

next best sample to improve model?

environmental feature vector observed in-situ $\mathbf{z}*$ → Organism abundance model $\mu(\mathbf{z}^*)$ $\sigma^2(\mathbf{z}^*)$ $u = h(\mu(\mathbf{z}), \sigma^2(\mathbf{z}))$ Utility function → u utility

J. Das, F. Py, J. B. Harvey, J. P. Ryan, A. Gellene, R. Graham, D. A. Caron, K. Rajan, and G. S. Sukhatme, “Data-driven robotic sampling for marine ecosystem monitoring,” The International Journal of Robotics Research, vol. 34, no. 12, pp. 1435–1452, 2015.

Exploration-exploitation Tradeoff

$$\mu(\mathbf{z}^*) = \mathbf{k}(K + \sigma_n^2 I)^{-1}\mathbf{b}$$
$$\sigma^2(\mathbf{z}^*) = k(\mathbf{z}^*, \mathbf{z}^*) + \mathbf{k}(K + \sigma_n^2 I)^{-1}\mathbf{k}$$

- Maximize sum of organism abundance from acquired samples : **reward**
- Balance **exploitation** of known high valued regions, and **exploration** of unknown parts of input space
- Minimize long term **regret** $r = b(\hat{\mathbf{z}}) - b(\mathbf{z}_t)$

Exploration-exploitation Tradeoff

$$\mu(\mathbf{z}^*) = \mathbf{k}(K + \sigma_n^2 I)^{-1}\mathbf{b}$$
$$\sigma^2(\mathbf{z}^*) = k(\mathbf{z}^*, \mathbf{z}^*) + \mathbf{k}(K + \sigma_n^2 I)^{-1}\mathbf{k}$$

- Multi-armed bandit - maximize rewards from unknown distributions, i.e. improve model locally (mean driven)
- Experiment design (active learning) - improve model globally (variance driven)

Utility function : $u = h(\mu(\mathbf{z}), \sigma^2(\mathbf{z}))$

Exploration-exploitation Tradeoff

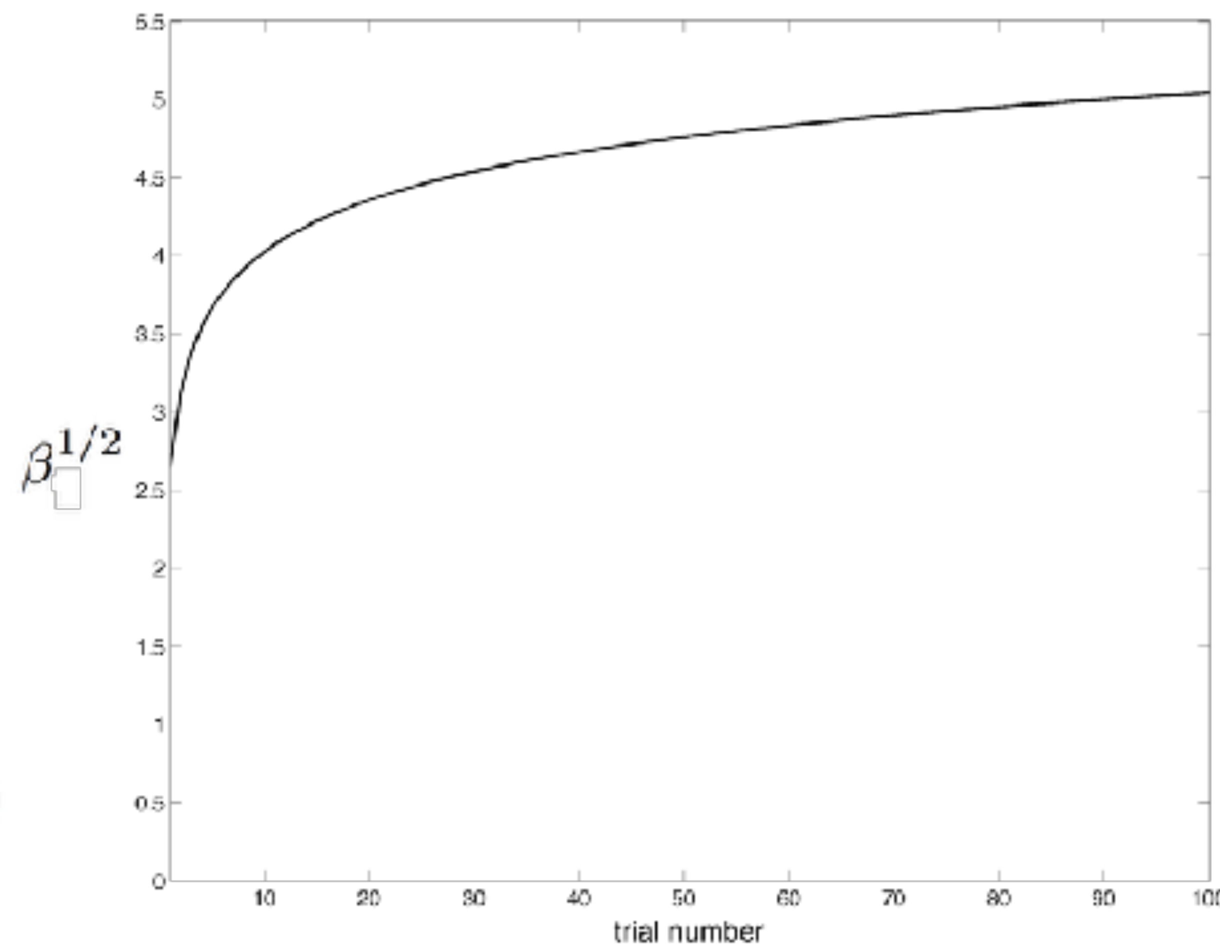
- Upper confidence bound - Auer et. al (JMLR 2002)
- GP upper confidence bound (GP-UCB) - Srinivas et. al (2010)
- Minimize cumulative average regret over *t* trials

$$z_t = \arg\max_{z \in D} \mu_{t-1}(z) + \beta_t^{1/2} \sigma_{t-1}(z)$$

$$\beta_t = 2 \log\left(\frac{|D| t^2 \pi^2}{6\delta}\right)$$

$$\Pr\left\{R_T \leq \sqrt{C_1 T \beta_T \gamma_T} \quad \forall T \geq 1\right\} \geq 1 - \delta.$$

$$where\ C_1 = 8/\log(1 + \sigma^{-2}).$$



Increasing rate of exploration, that eventually stabilizes

"Information-Theoretic Regret Bounds for Gaussian Process Optimization in the Bandit Setting", N. Srinivas, A. Krause, S. M. Kakade, and M. W. Seeger. IEEE Transactions on Information Theory (2012)

Batch-update GP-UCB

- Our goal : Acquire top k peaks of the utility function from a deployment
- Model update happens at the end of the deployment, i.e. in batches of k samples

Algorithm 1: Batch-update GP-UCB algorithm

Data: Input dimension D, GP Prior $\mu = 0$, σ_0, k

for $t \leftarrow 1$ **to** T **do**

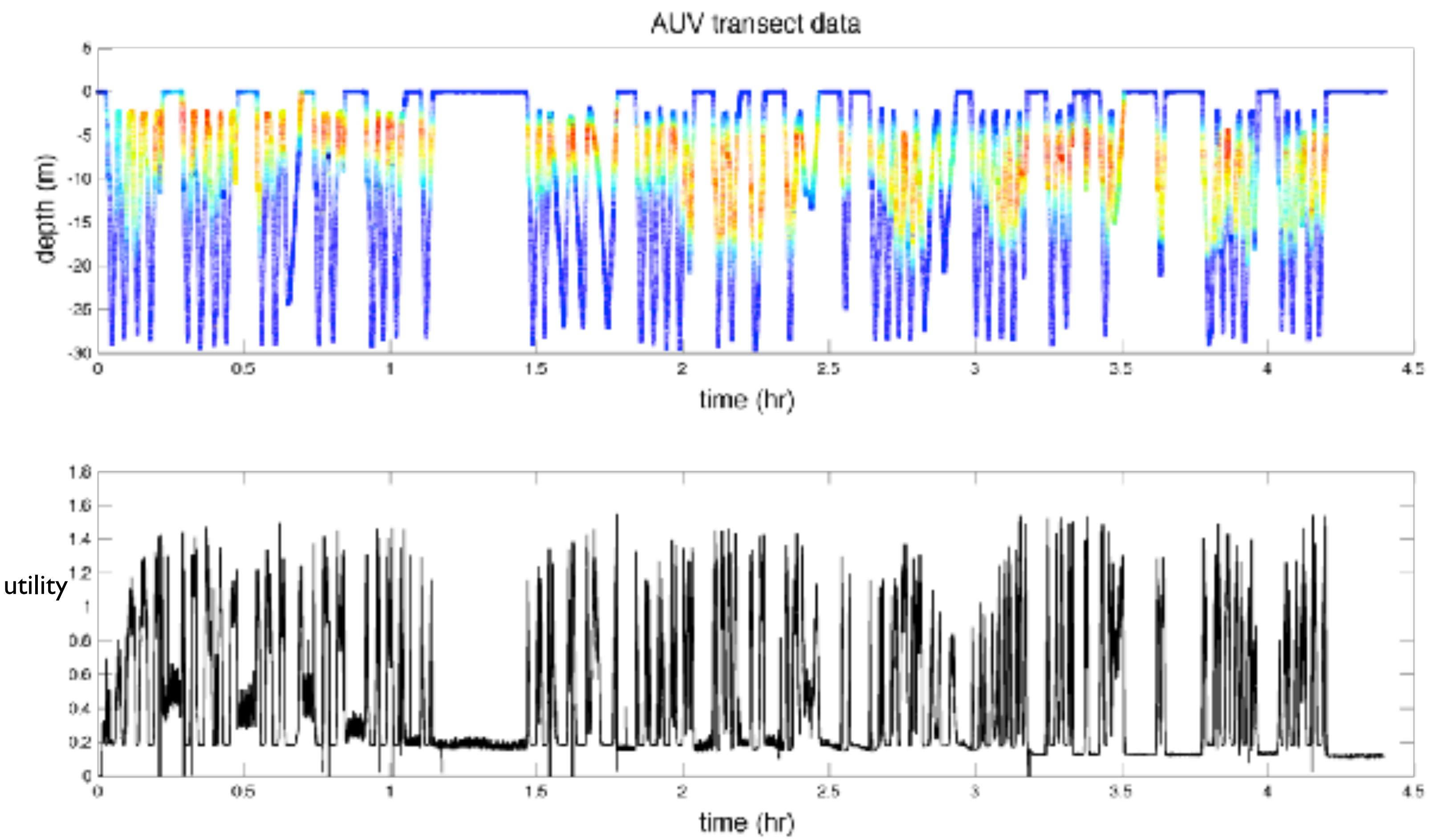
  Choose top k arguments $Z_t = z_1 ... z_k$ corresponding to top k peaks of $\mu_{t-1}(z) + \beta_t^{1/2}\sigma_{t-1}(z)$;

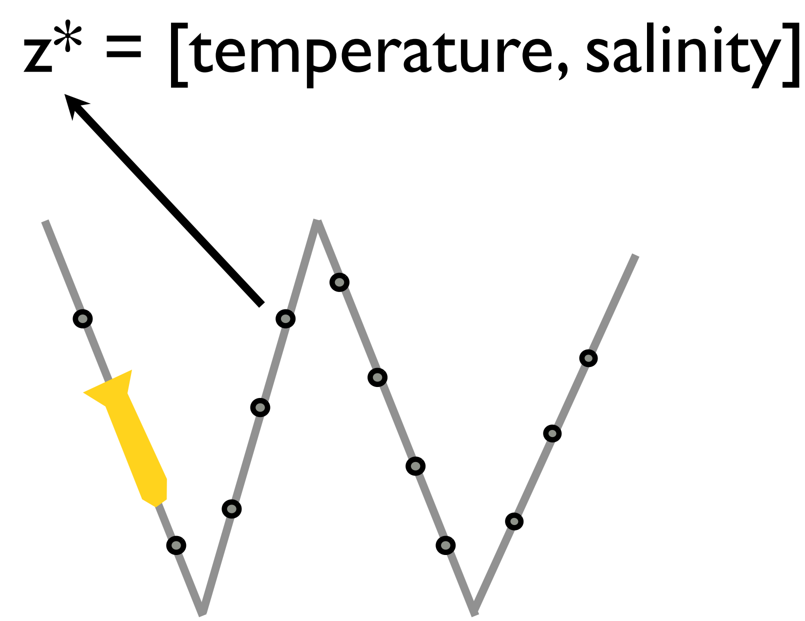
  Sample set $B_t = g(Z_t) + \epsilon_t$;

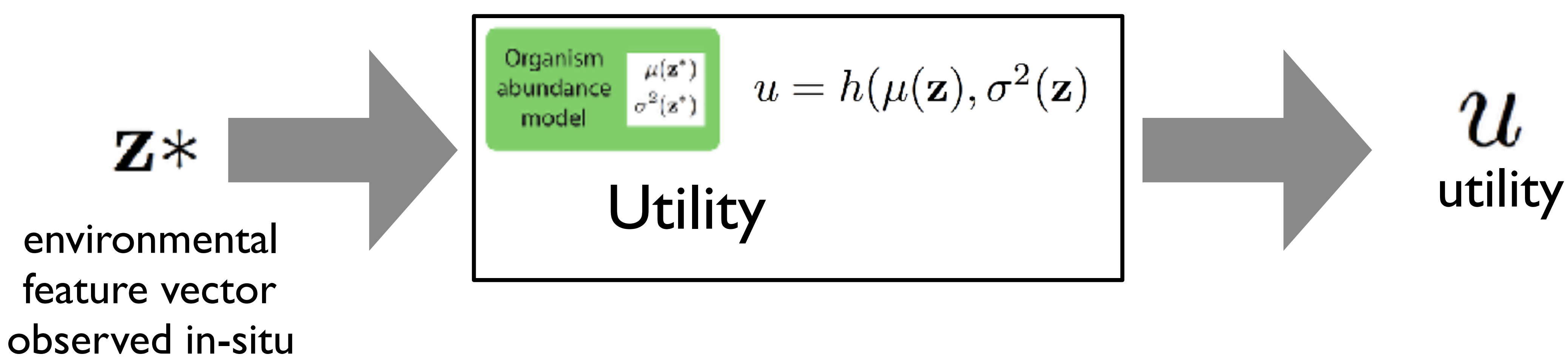
  Perform Bayesian update to obtain μ_t and σ_t;

end

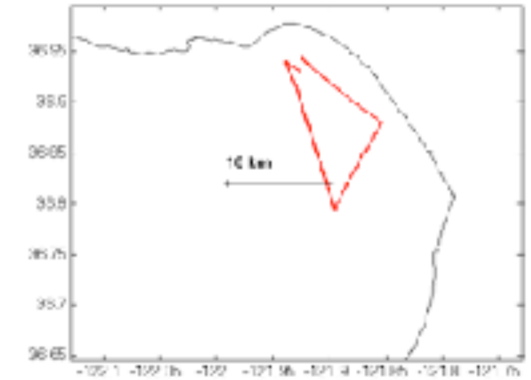
Online Best-choice Problem

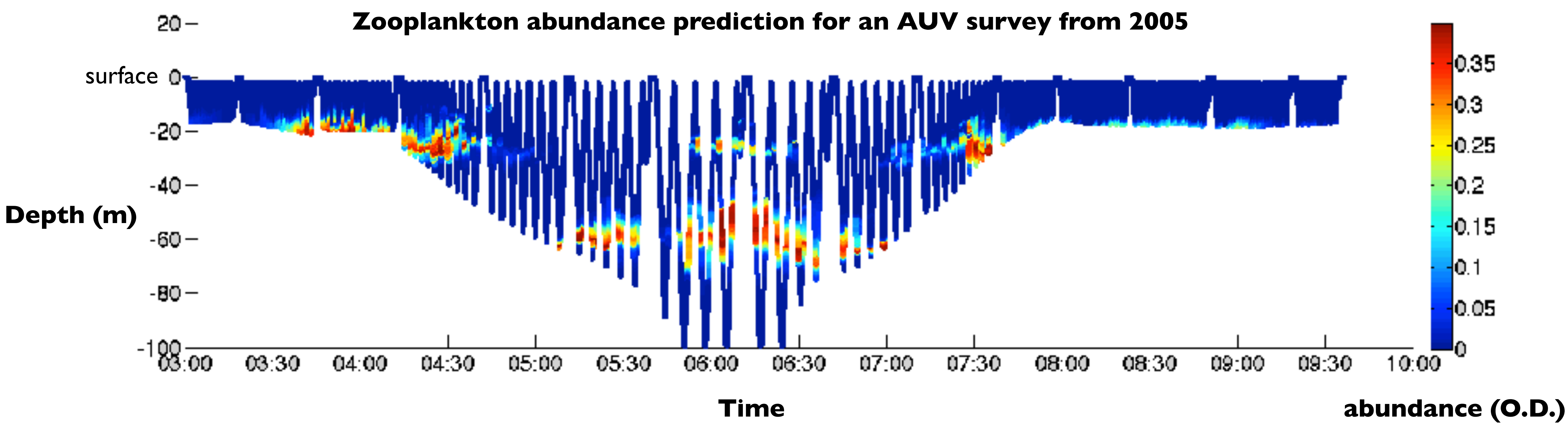






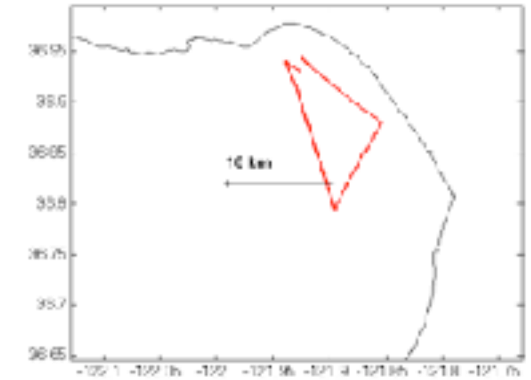
Online Best-choice Problem

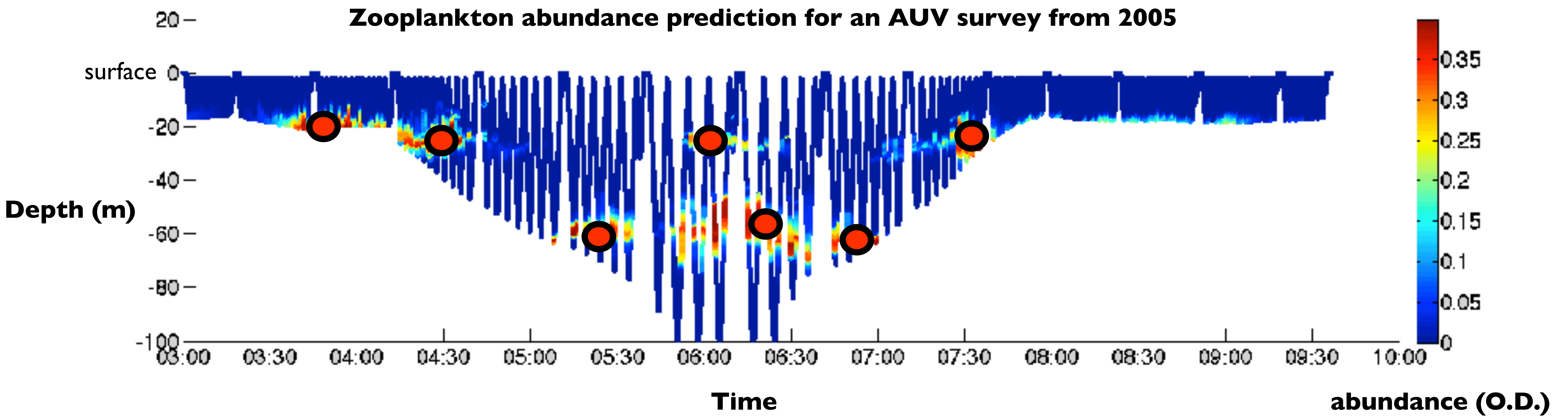




How to choose k samples to maximize the the sum of utility from all samples?

Online Best-choice Problem





How to choose k samples to maximize the the sum of utility from all samples?

Challenges

- Missing out on potential future hotspots
  - too greedy
- Coming back with few samples
  - too conservative
- Having to set thresholds
  - undesirable

Optimal Stopping Theory

Problem of choosing a time to take a particular action

Optimal
Stopping Theory

Hiring (or secretary) problem

- N candidates arrive for an interview i.i.d, and ranked
- Goal: choose best candidate, online
- Hiring decision irrevocable

“Who Solved the Secretary Problem?“, T. Ferguson, Statistical Science, Vol. 4 (1989)

Optimal
Stopping Theory

Hiring (or secretary) problem

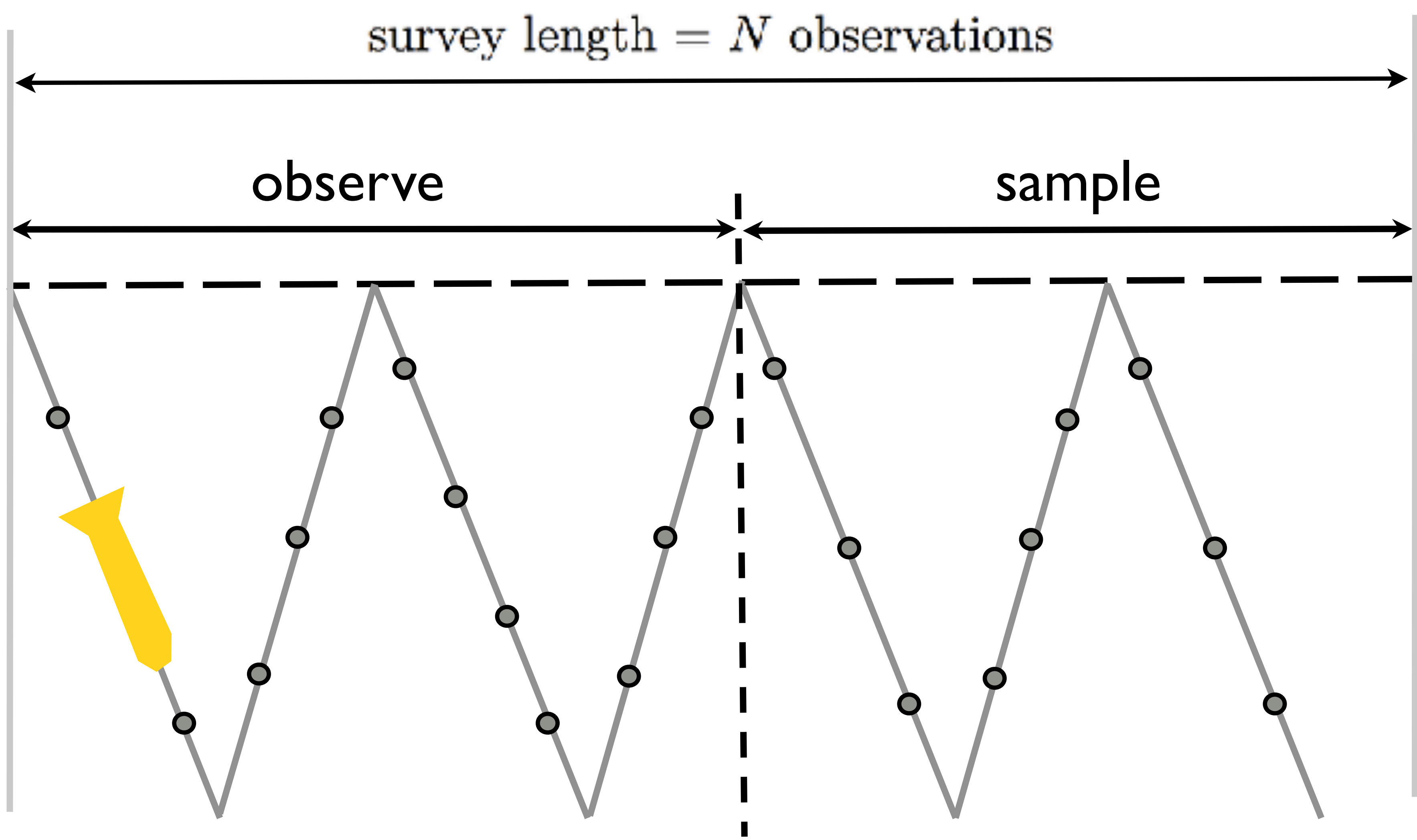
- N candidates arrive for an interview i.i.d, and ranked
- Goal: choose best candidate, online
- Hiring decision irrevocable

Solution

- Observe first N/e (36.7 %) candidates, hire next best
- If no better candidate, hire last person
- Probability of choosing best candidate = 1/e (~36.7 %)

“Who Solved the Secretary Problem?“, T. Ferguson, Statistical Science, Vol. 4 (1989)

Hiring Problem



$$N_w = \frac{N}{s}$$

$s=$ stopping parameter

Selecting k Candidates Online

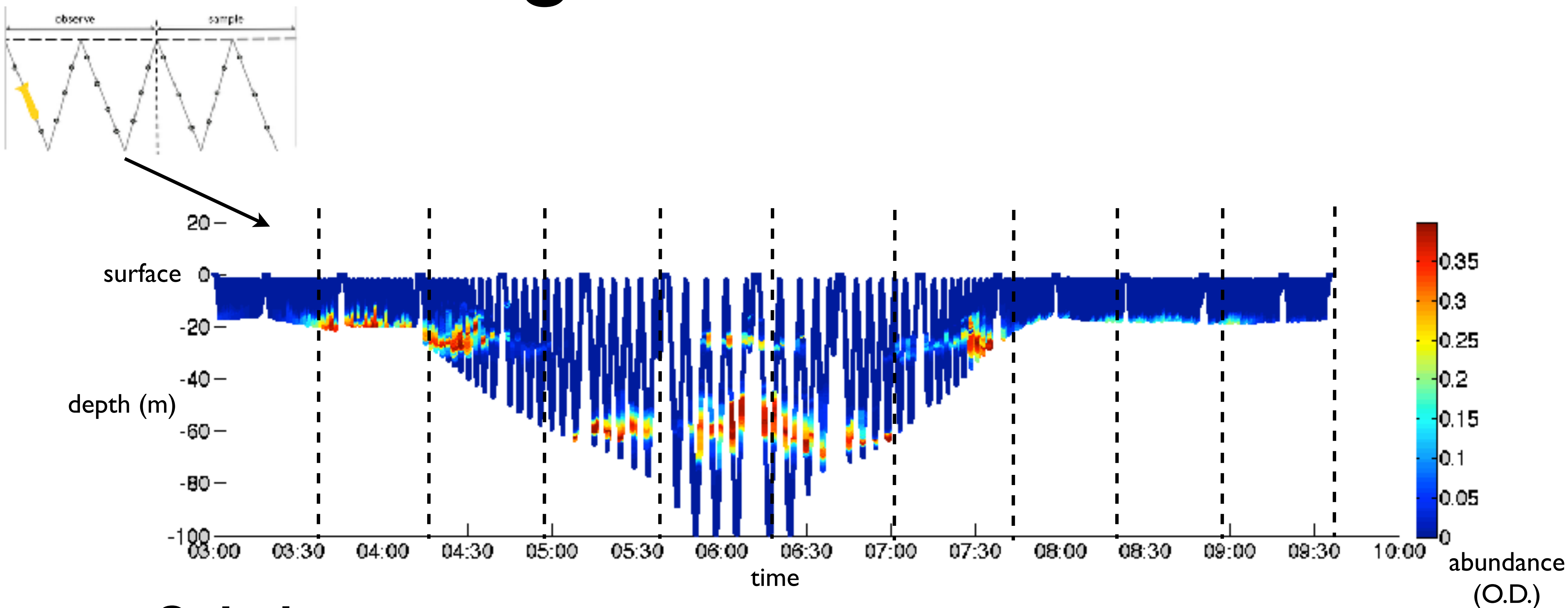
- **Submodular secretary problem**
    - N candidates arrive for an interview, i.i.d, and ***rated***
    - Goal: choose ***best k*** candidates, online (best sum of rating)
    - Hiring decisions irrevocable

Selecting k Candidates Online

- **Submodular secretary problem**
  - N candidates arrive for an interview, i.i.d, and ***rated***
  - Goal: choose ***best k*** candidates, online (best sum of rating)
  - Hiring decisions irrevocable
- **Solution**
  - Split total window into k segments
  - Apply secretary algorithm in each segment
  - Guaranteed competitive-ratio of at least (1 - 1/e)/11, ~0.05

"Submodular secretary problem and extensions," M. Bateni, M. Hajiaghayi, and M. Zadimoghaddam, in APPROX-RANDOM (2010)

Selecting k Candidates Online



- **Solution**
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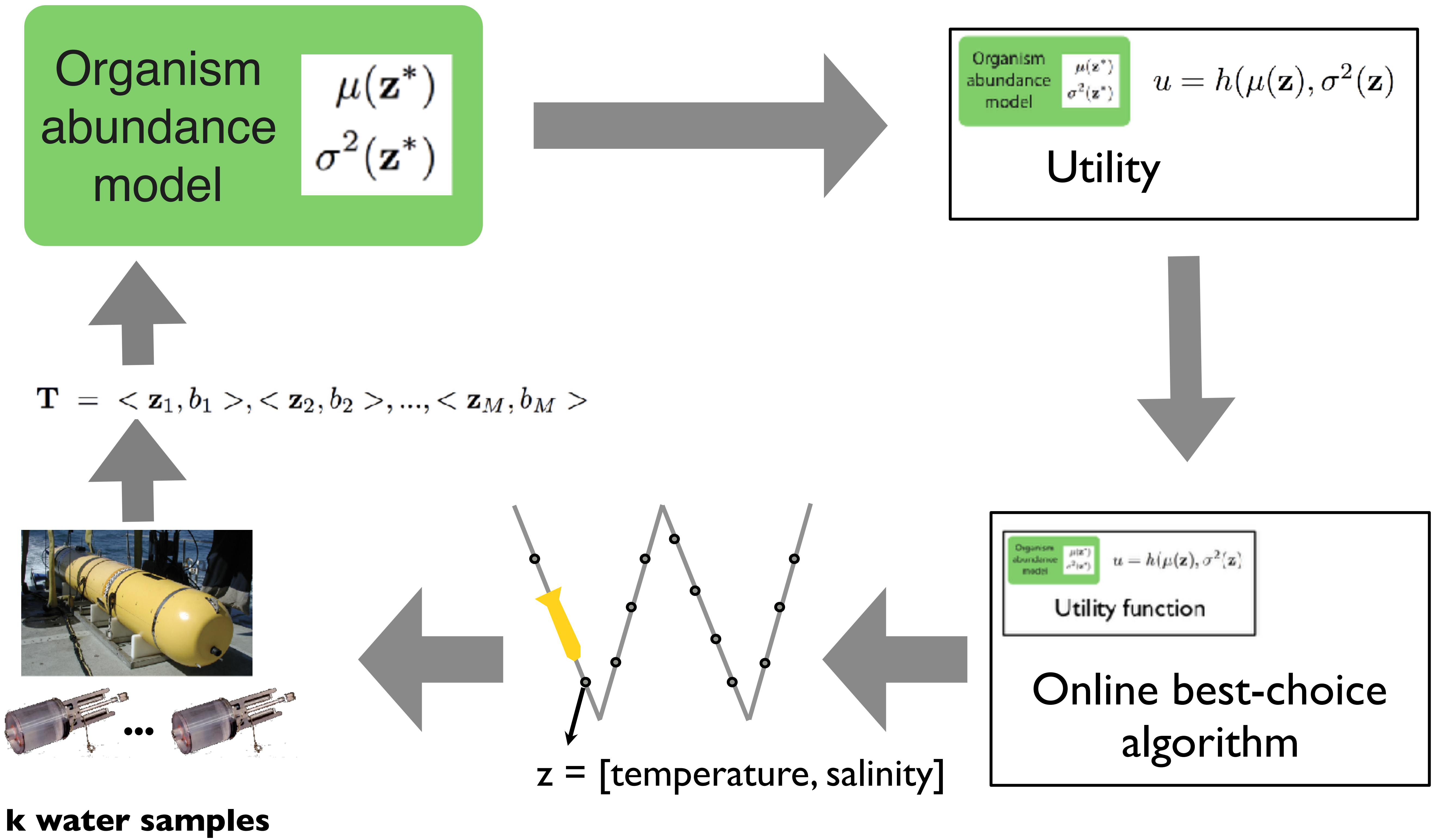
“Submodular secretary problem and extensions,” M. Bateni, M. Hajiaghayi, and M. Zadimoghaddam, in APPROX-RANDOM (2010)

Workflow



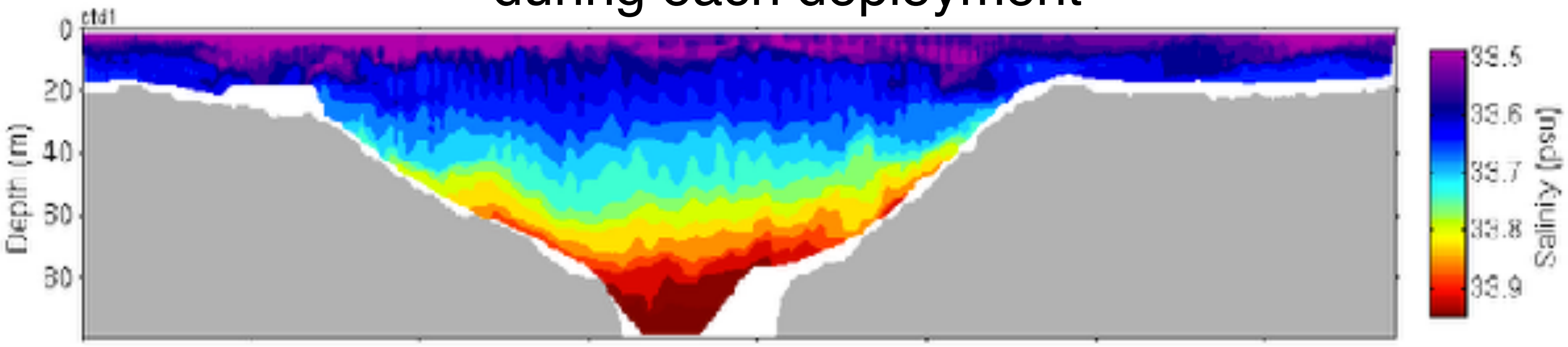
Organism abundance model
$\mu(\mathbf{z}^*)$
$\sigma^2(\mathbf{z}^*)$
$u = h(\mu(\mathbf{z}), \sigma^2(\mathbf{z}))$
Utility
Utility function
Online best-choice algorithm
z = [temperature, salinity]
$\mathbf{T} = <\mathbf{z}_1, b_1>, <\mathbf{z}_2, b_2>, ..., <\mathbf{z}_M, b_M>$
...
k water samples

Evaluation

- Framework to test methodology on real data
  - Campaign : 17 Dorado AUV deployments in Monterey bay over 8 days from August 2005
  - Logged in-situ - temperature, salinity, optical backscatter, chlorophyll fluorescence, nitrate conc., dissolved oxygen
  - Chlorophyll fluorescence - proxy for phytoplankton (algal) biomass, measured by a fluorometer
- Goal: Acquire **simulated gulps** of high abundance phytoplankton samples

Methodology

Measured by AUV
during each deployment



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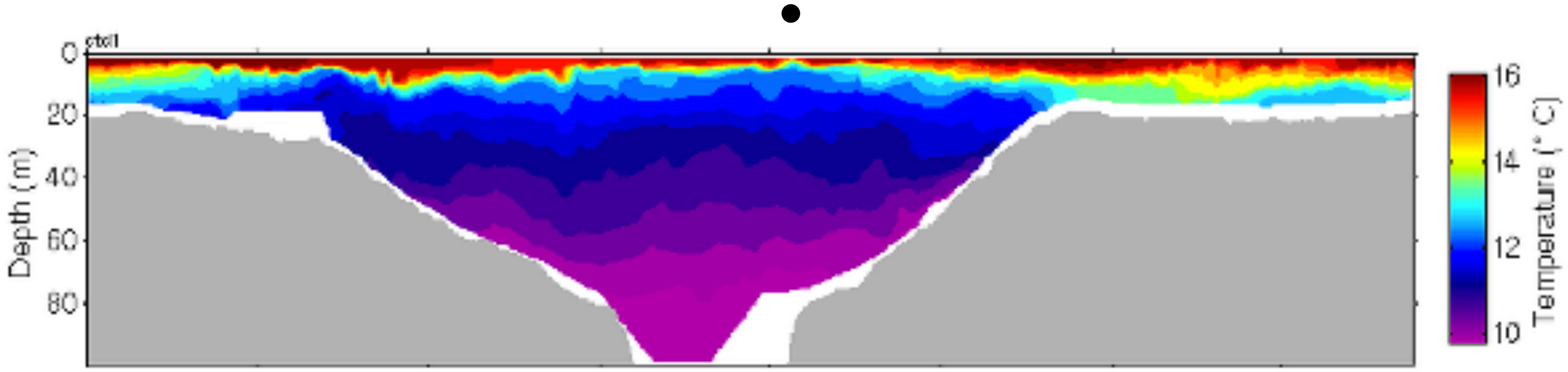

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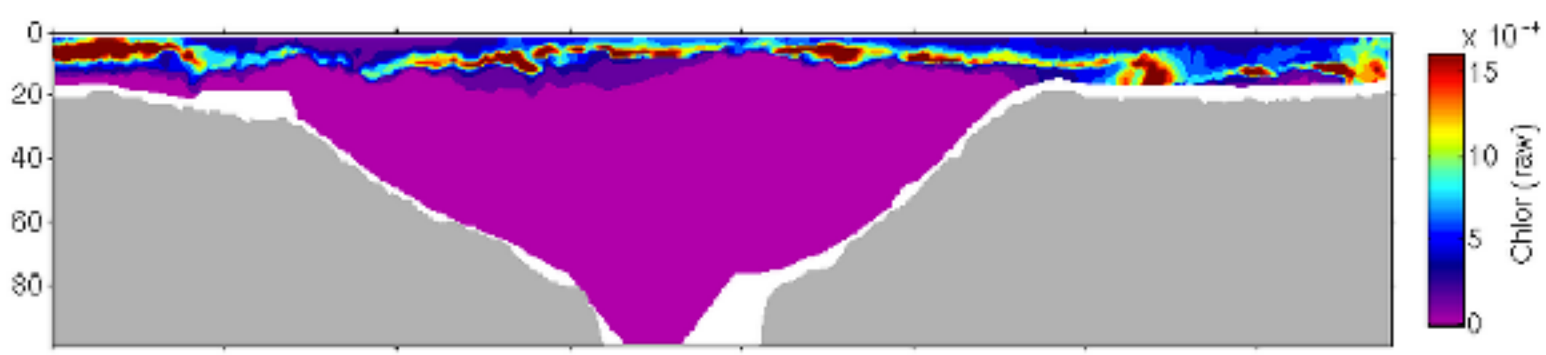
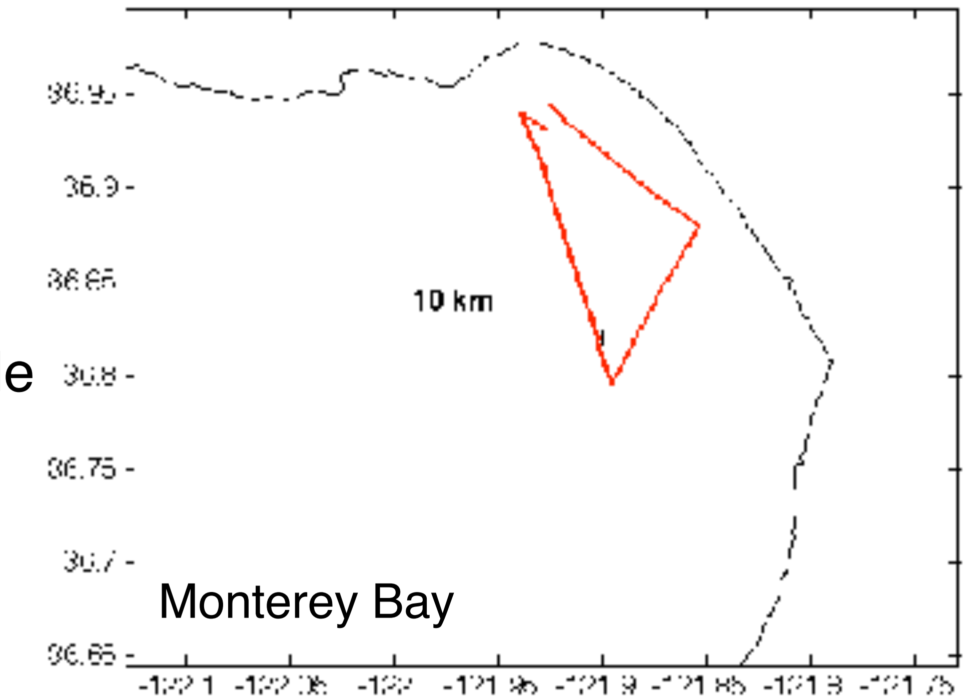


latitude

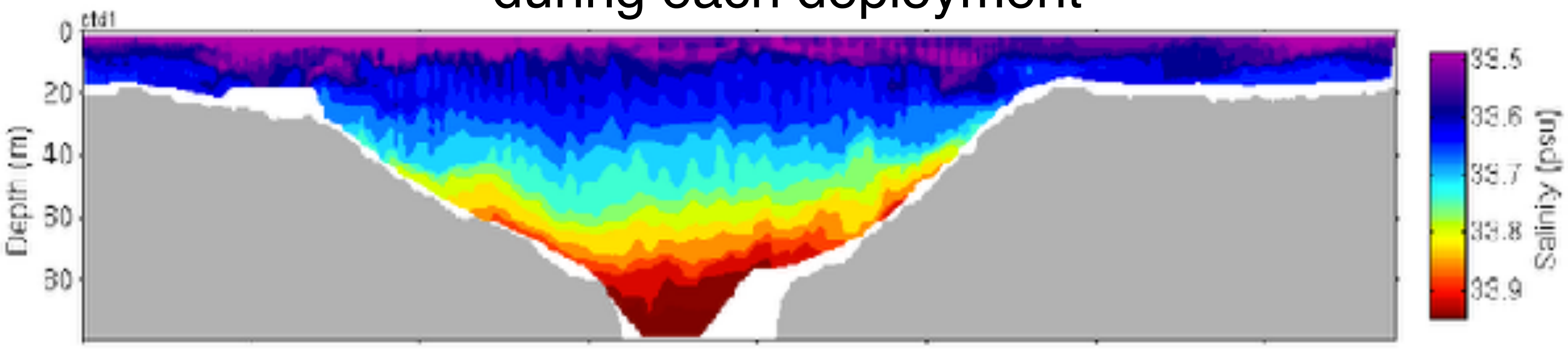


longitude

•17 deployments, ~ 7 hr each
•8 days (2005)
•~ 45,000 measurements per deployment
•No gulps

Methodology

Measured by AUV
during each deployment



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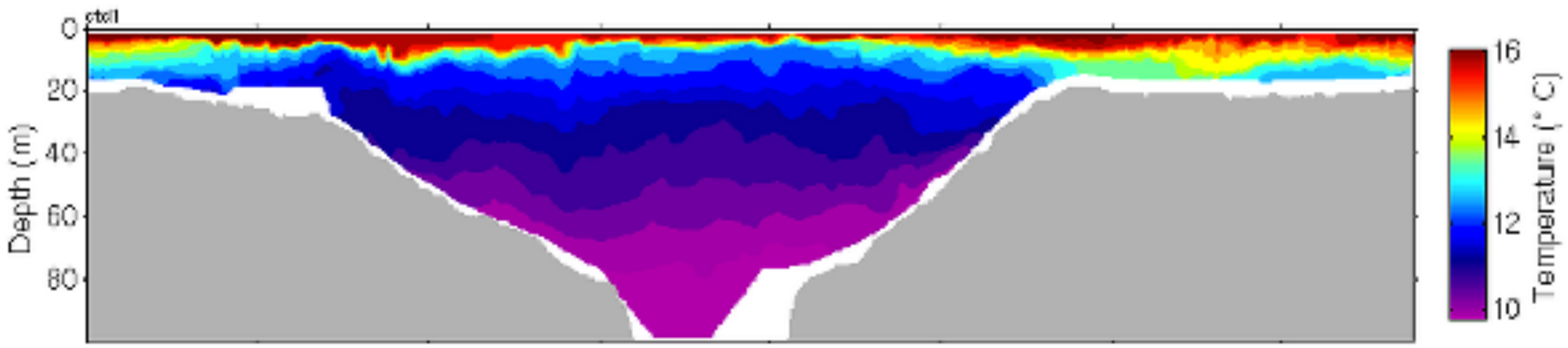
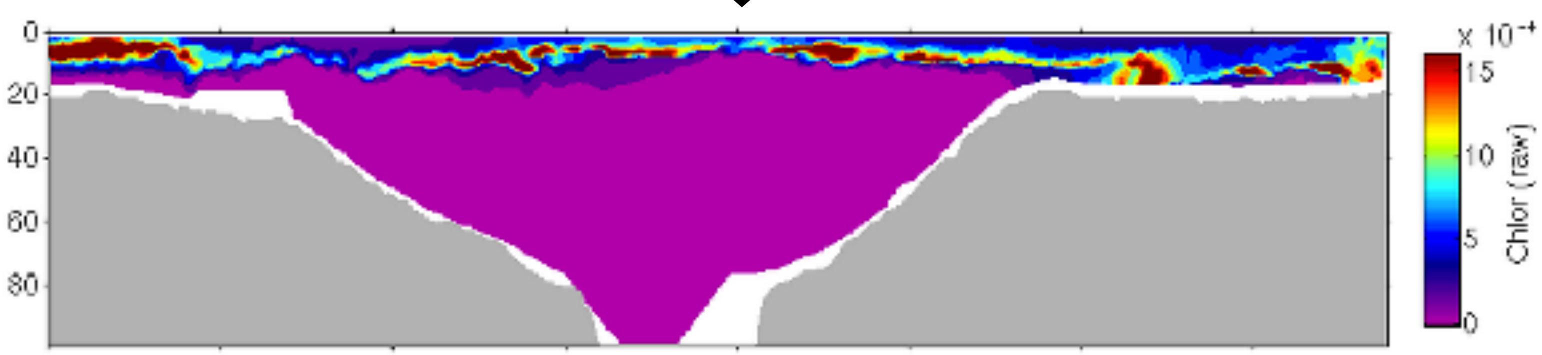
latitude

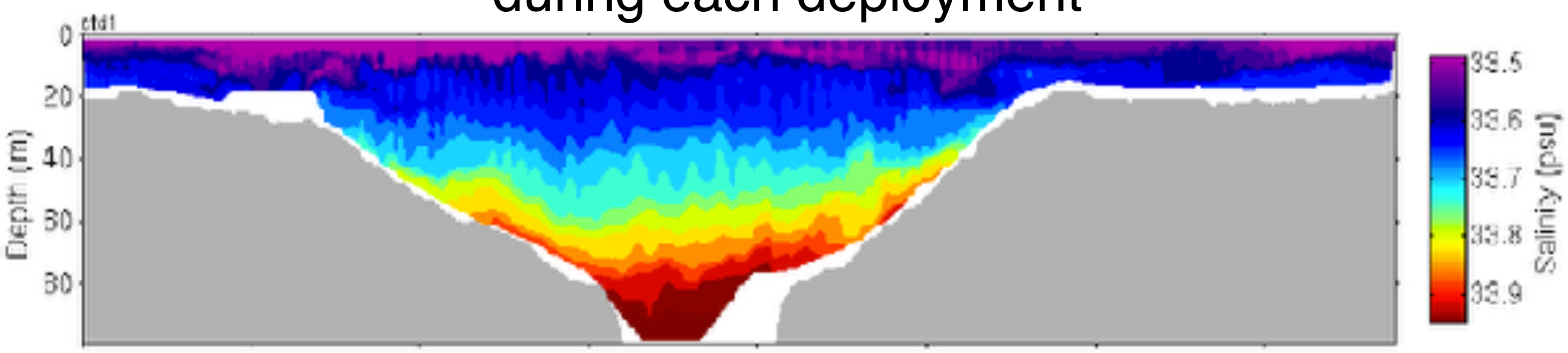




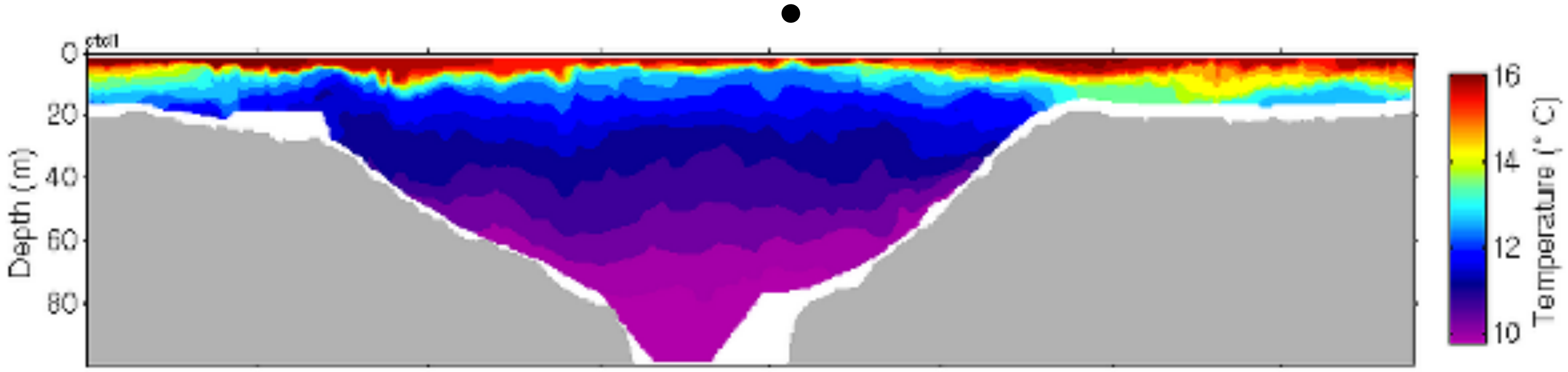
Hidden from AUV
during the mission

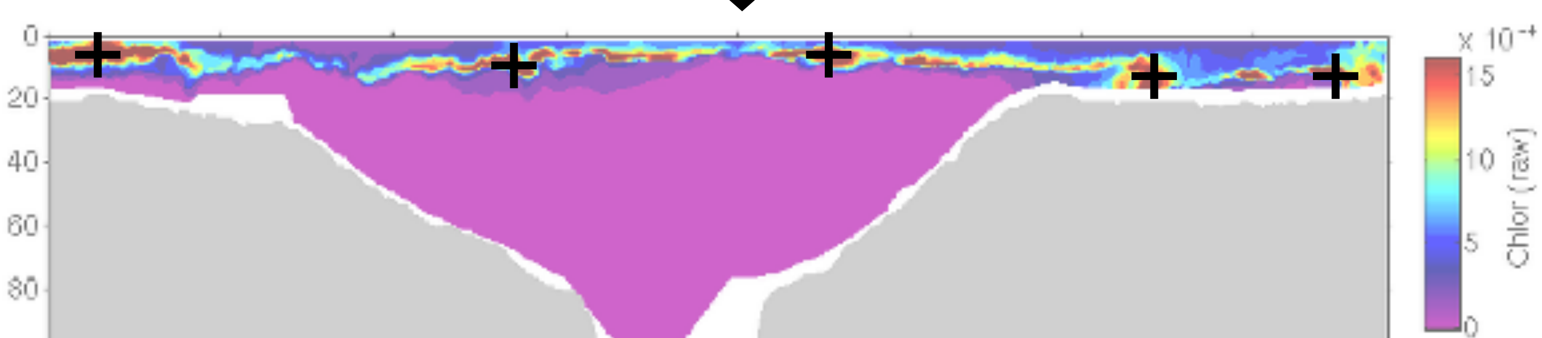
Methodology

Measured by AUV
during each deployment



latitude





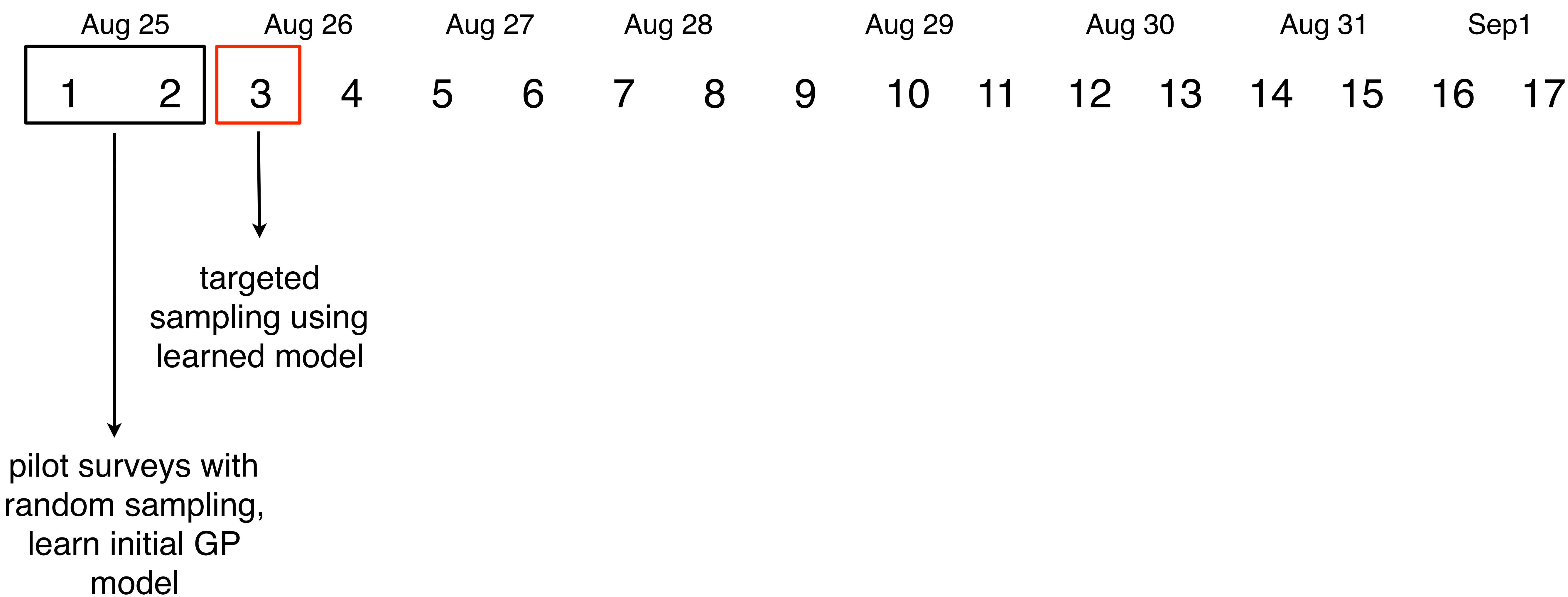
Hidden from AUV
during the mission

Methodology

Aug 25		Aug 26		Aug 27		Aug 28			Aug 29		Aug 30		Aug 31		Sep1	
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17

pilot surveys with random sampling, learn initial GP model

Methodology



Methodology

Aug 25 Aug 26 Aug 27 Aug 28 Aug 29 Aug 30 Aug 31 Sep1

$\boxed{1 \quad 2 \quad 3}$ 4 5 6 7 8 9 10 11 12 13 14 15 16 17

Update
GP model

Methodology

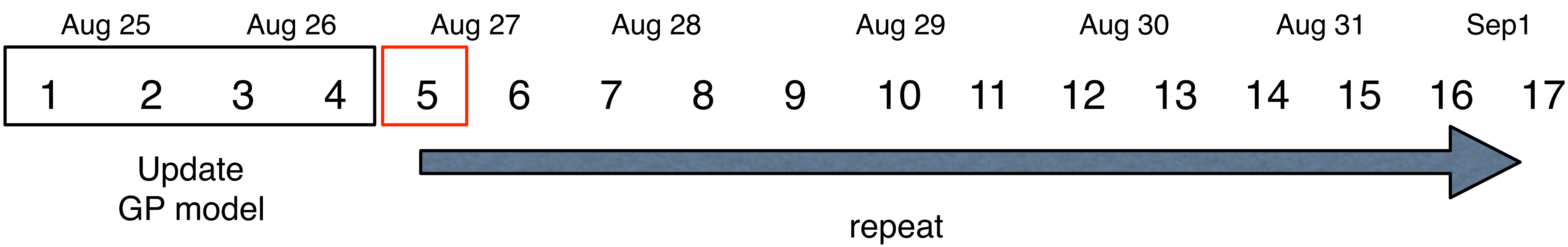
Methodology

Aug 25 Aug 26 Aug 27 Aug 28 Aug 29 Aug 30 Aug 31 Sep1

$\boxed{1 \quad 2 \quad 3 \quad 4}$ 5 6 7 8 9 10 11 12 13 14 15 16 17

Update
GP model

Methodology



Methodology

Aug 25 Aug 26 Aug 27 Aug 28 Aug 29 Aug 30 Aug 31 Sep1

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17

Campaign

Methodology

Aug 25 Aug 26 Aug 27 Aug 28 Aug 29 Aug 30 Aug 31 Sep1

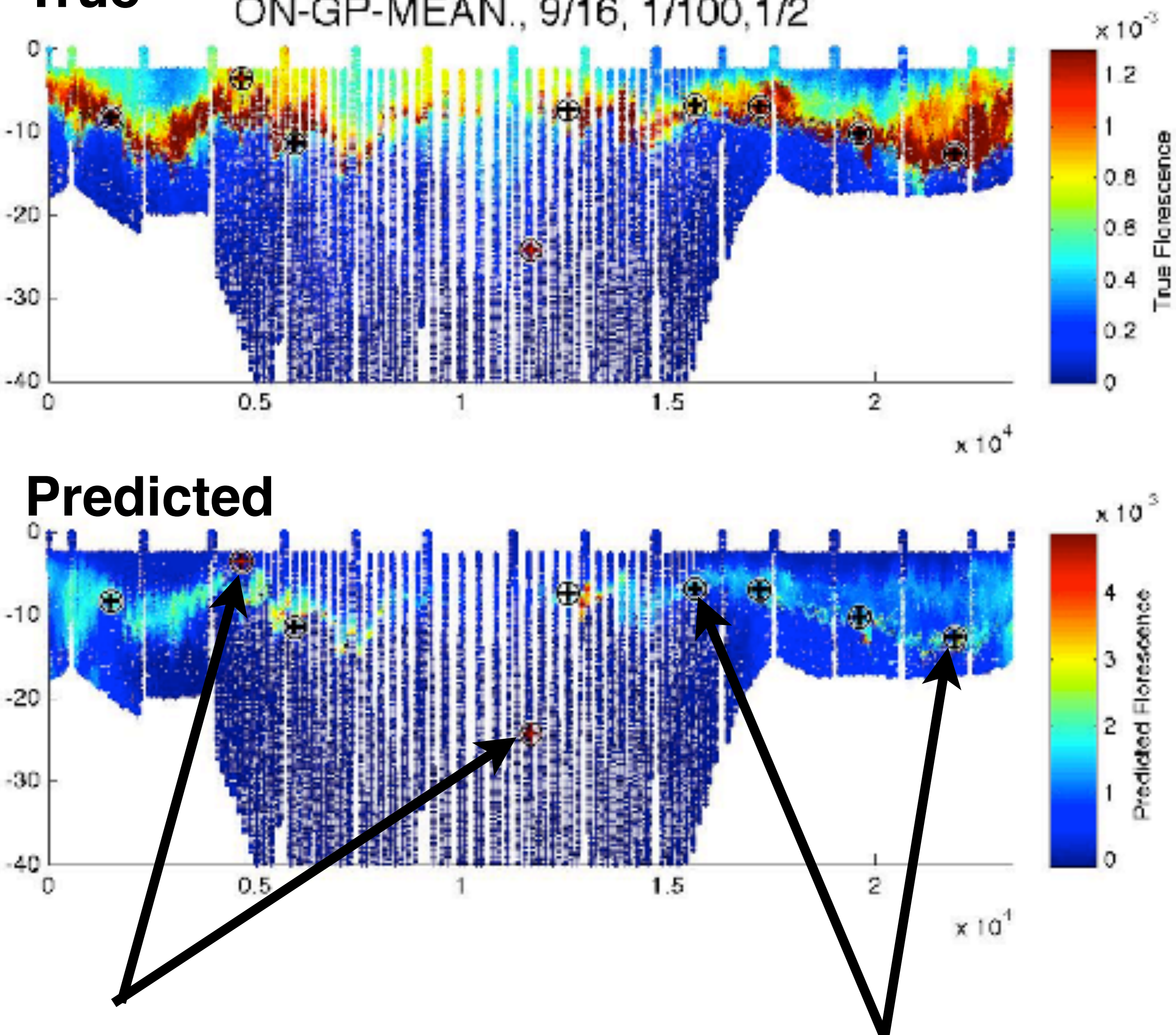
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17

Campaign (repeat 100 times)

random restarts
(k = 10 of ~40,000 samples, 0.02%)

Simulation Snapshot

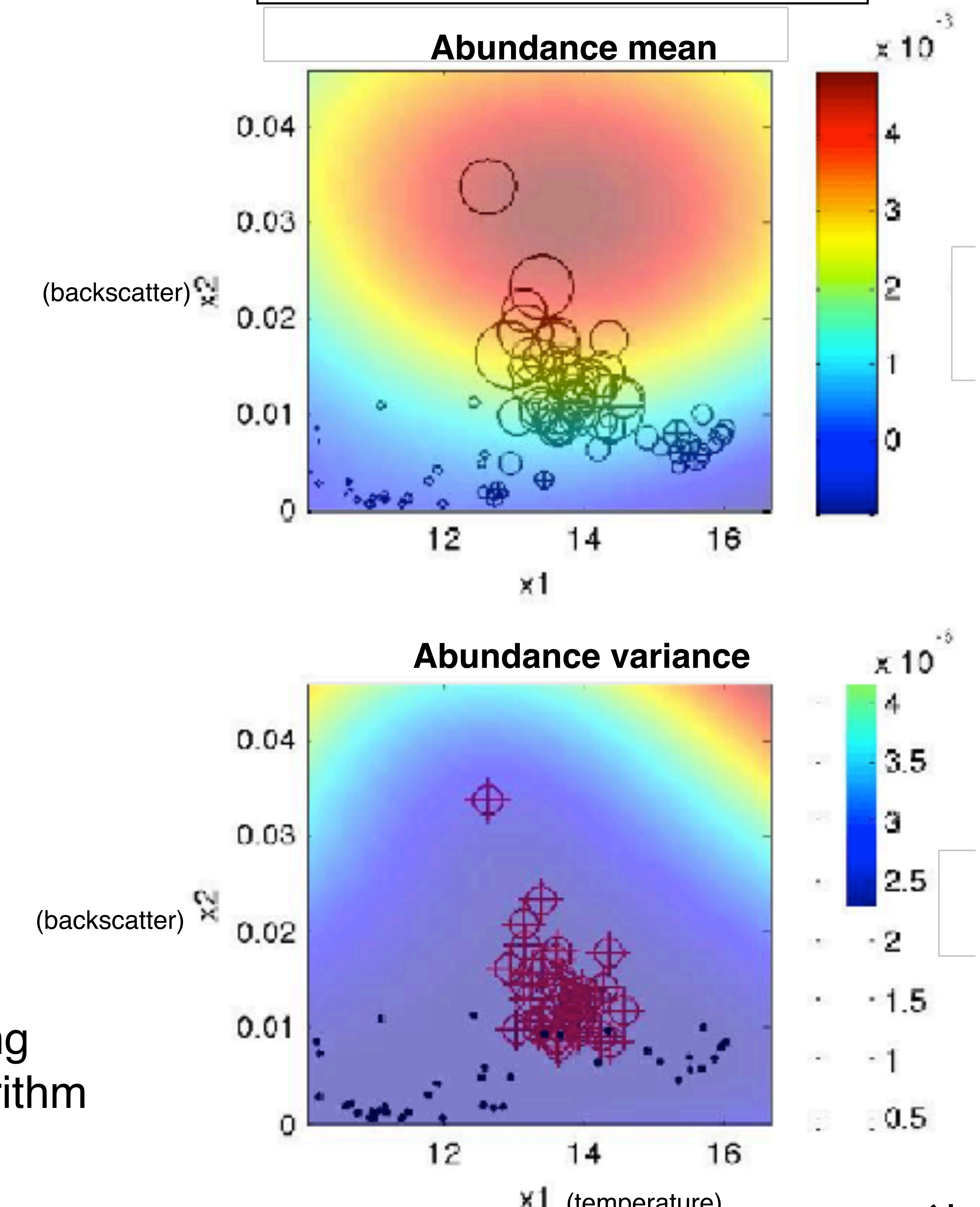
AUV transect and simulated gulps



Gulps at segment-end for lack of better candidates

Gulps within segments using submodular secretary algorithm

Learned probabilistic Organism Model



Evaluation

Aug 25 Aug 26 Aug 27 Aug 28 Aug 29 Aug 30 Aug 31 Sep1

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17

- Data size
  - First two, previous two, and all deployments
- Sampling policy
  - Mean, variance, GP-UCB
- Offline vs online

Evaluation

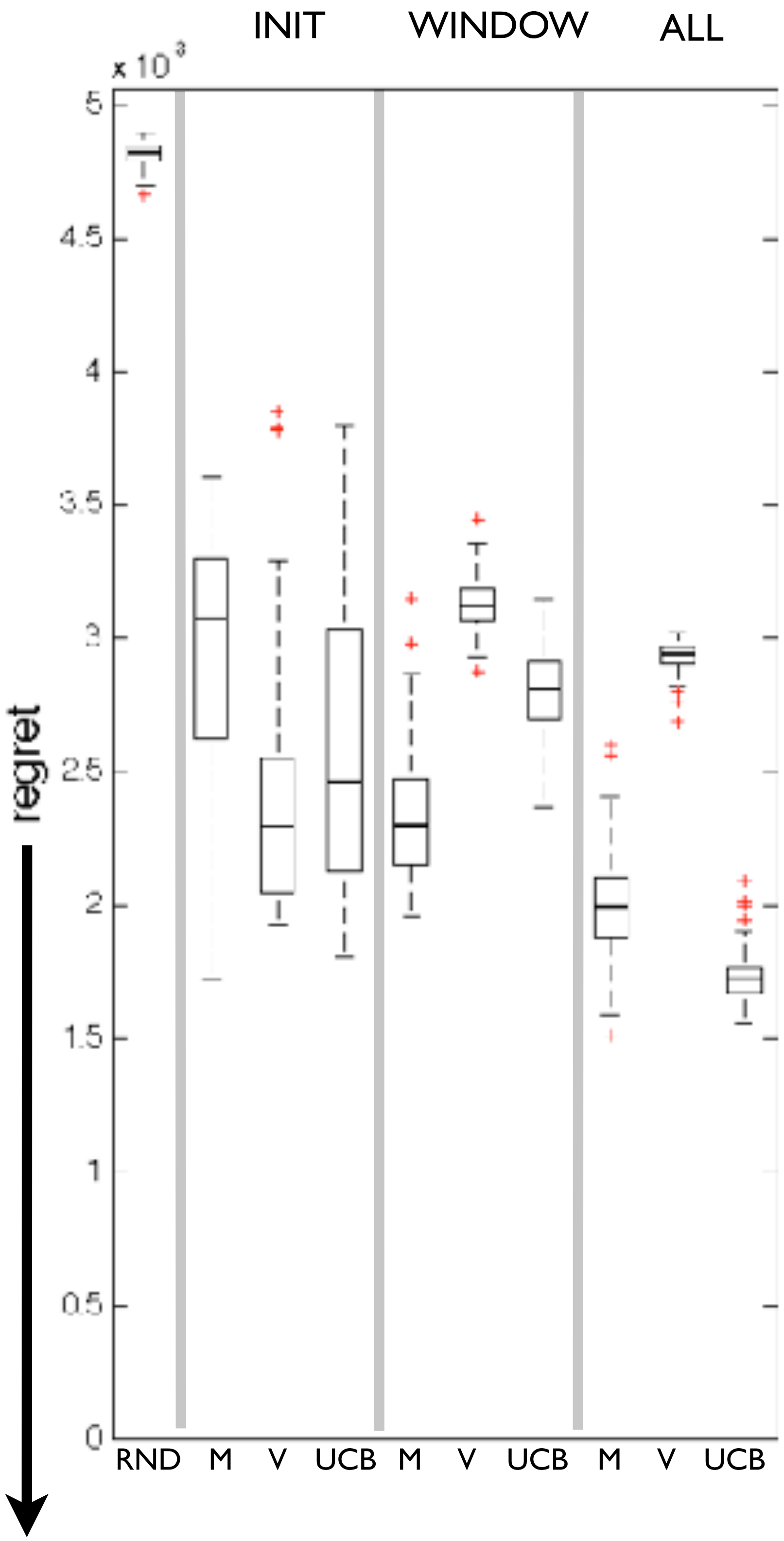
Methods

- Data size
  - First two, previous two, and all deployments
- Sampling policy
  - Mean, variance, GP-UCB
- Offline vs online

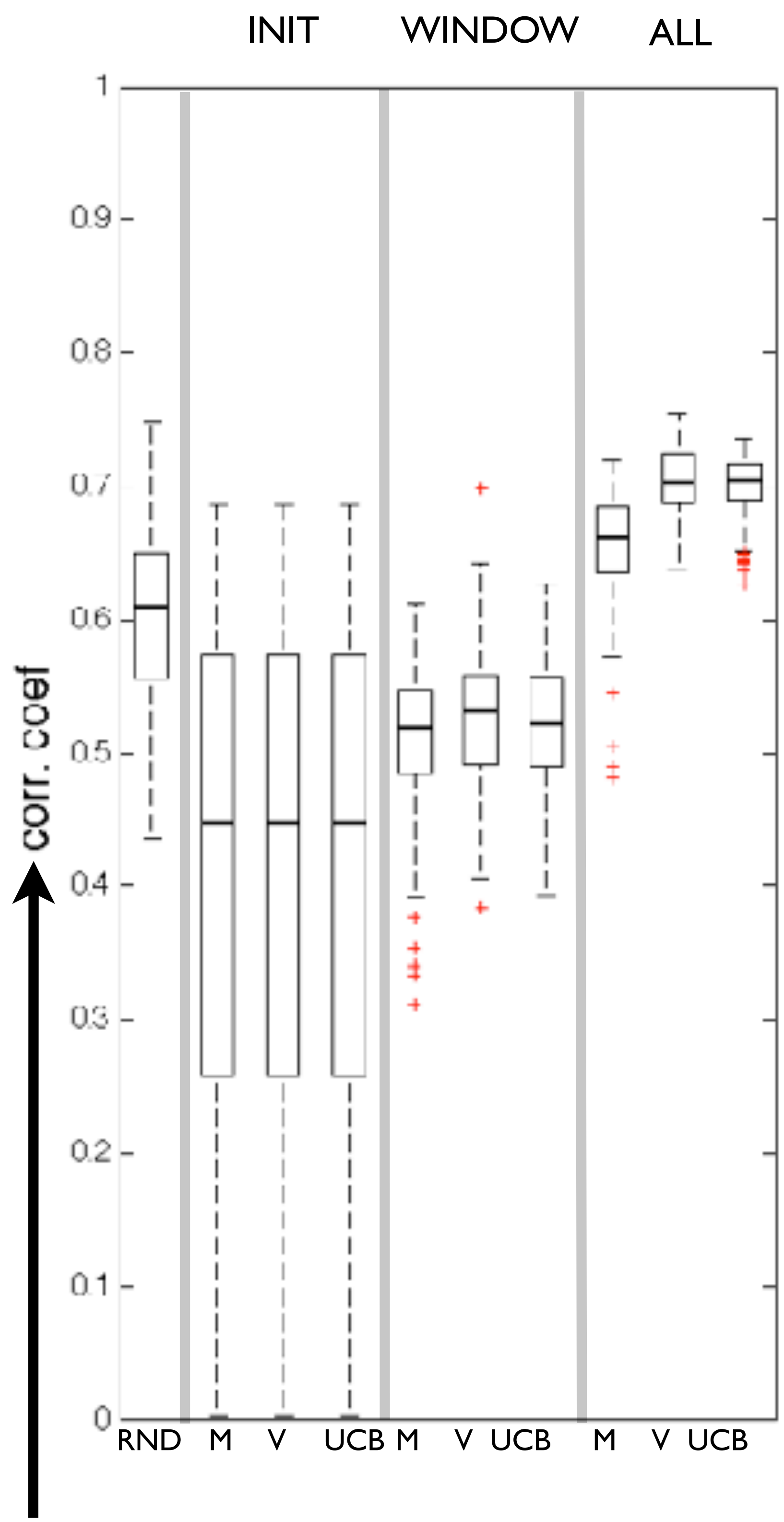
Metrics

- Regret
- Correlation coefficient

Results (offline policy)



Regret : LOWER is better



Corr. coeff. : HIGHER is better

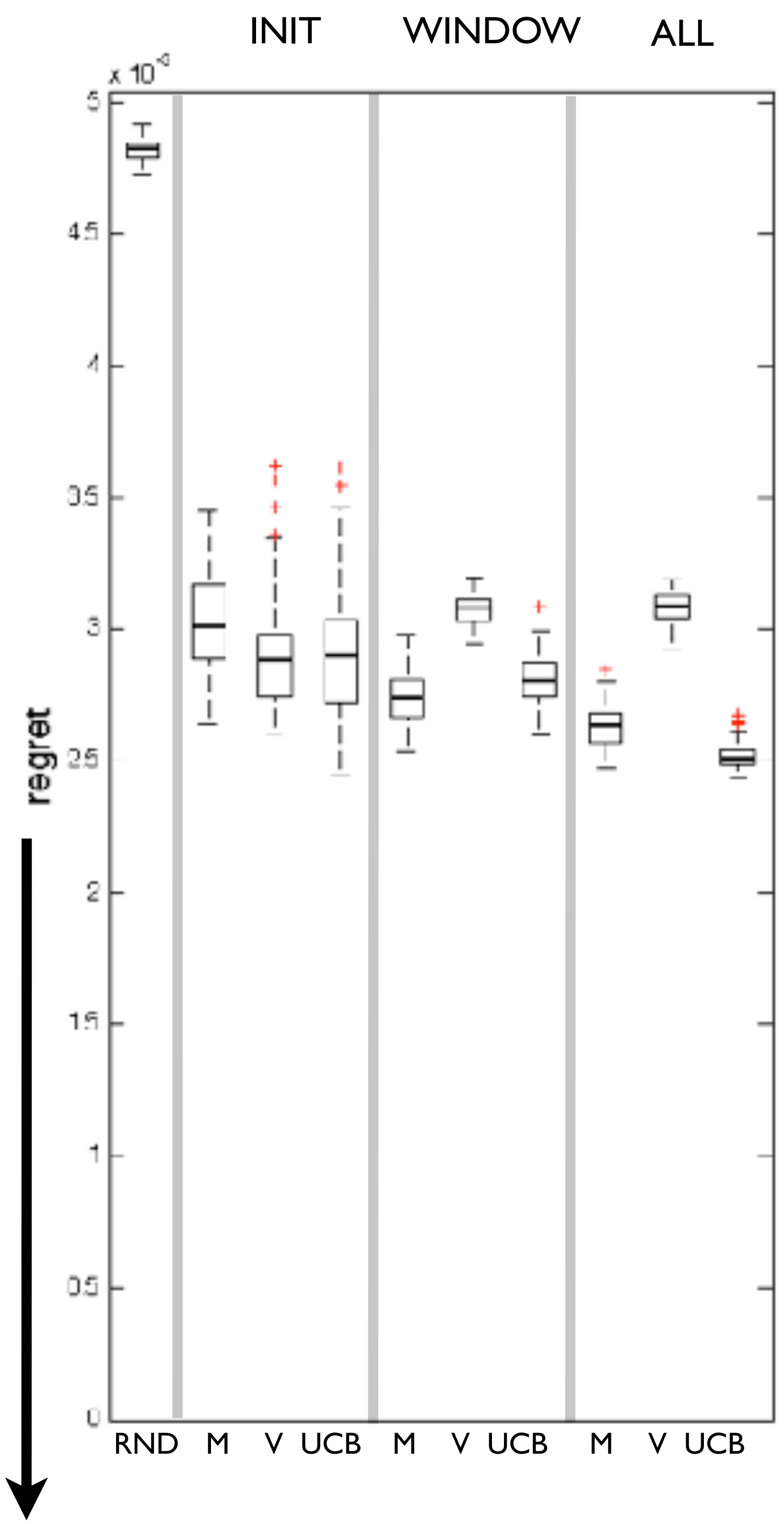
Data
INIT: initial 2 surveys
WINDOW : previous 2 surveys
ALL : all surveys

Regret - lowest median and variance for GP-UCB, with all data

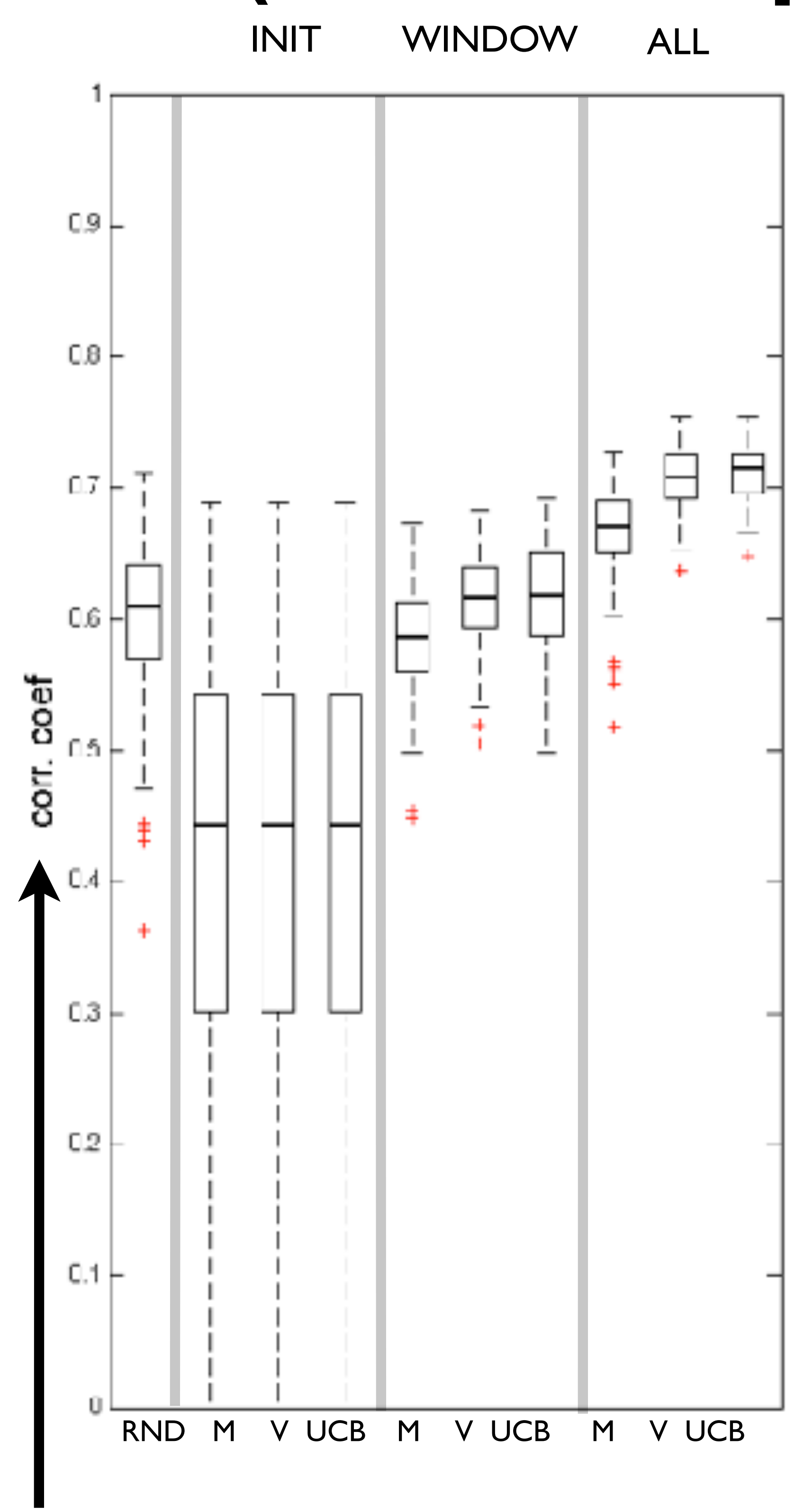
Corr. coefficient - GP-UCB competitive with variance sampling, with all data

Sampling
RND : random
M : mean driven
V : variance driven
UCB : GP-UCB

Results (online policy)



Regret : LOWER is better



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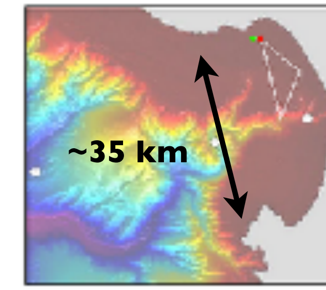
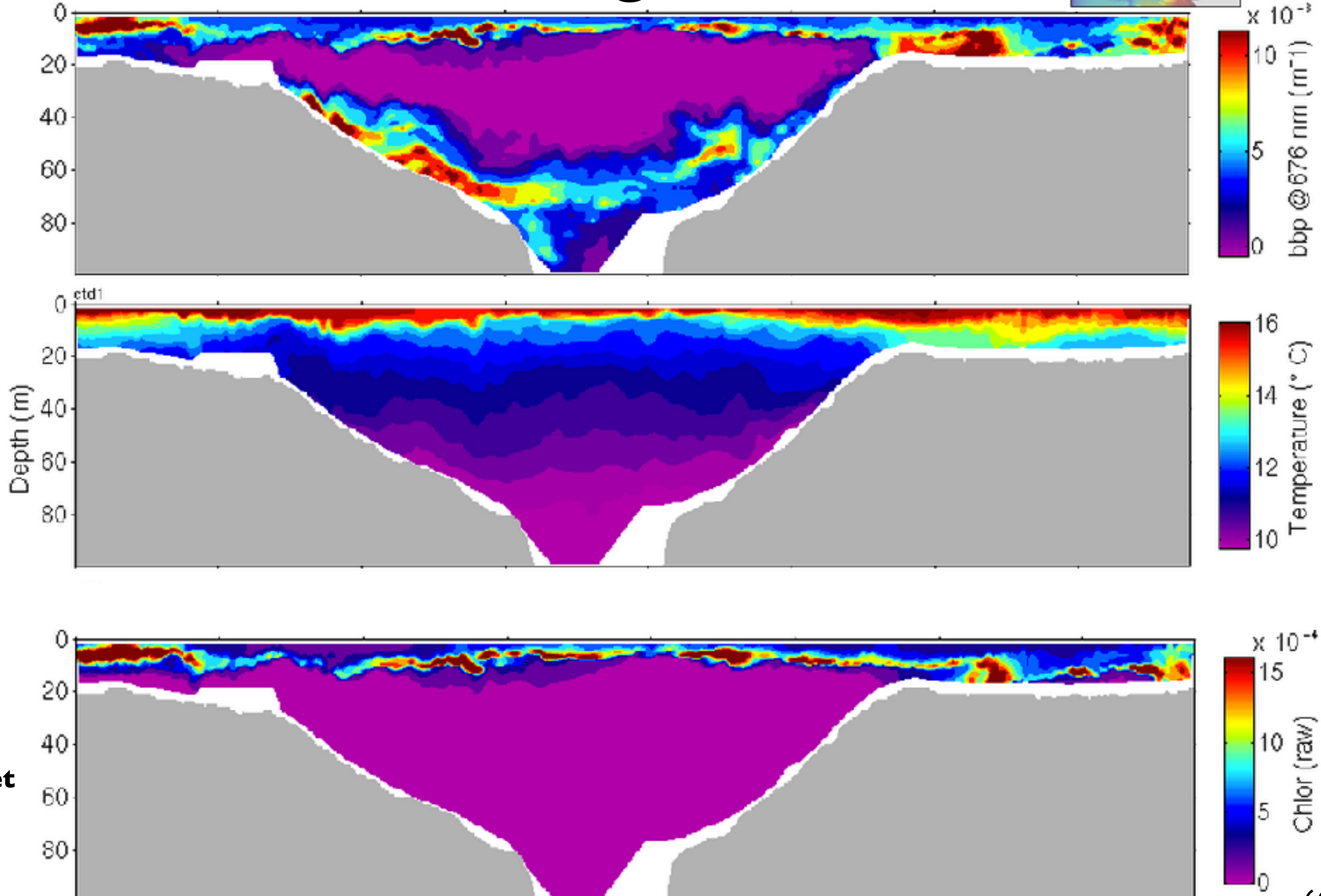
Sampling
RND : random
M : mean driven
V : variance driven
UCB : GP-UCB

Insights



Input

Target

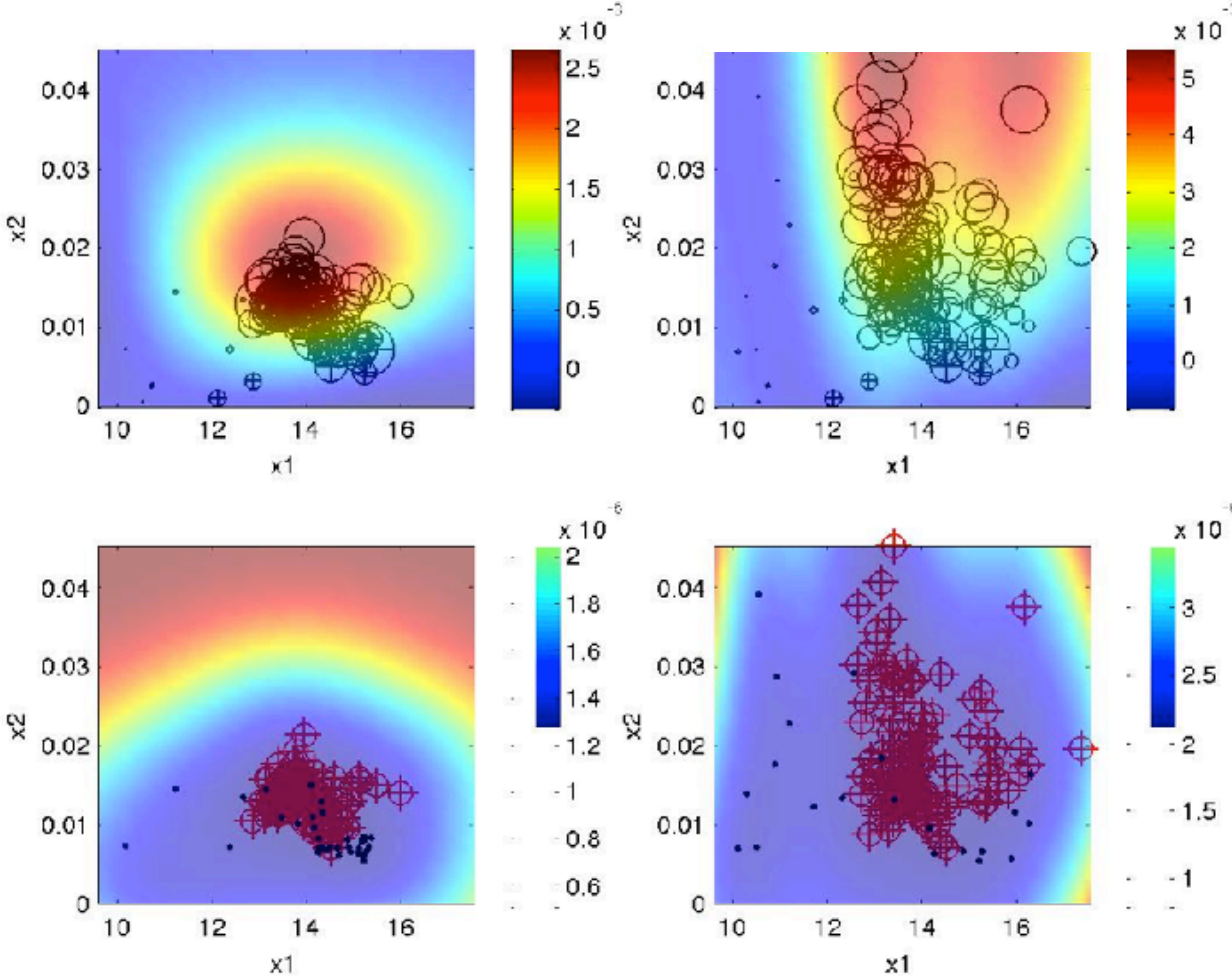


Learned Algae Model

Deployment 16/17 - (temperature,backscatter)

Mean
(abundance)

Variance
(uncertainty)



Mean-driven
(exploiter)

GP-UCB
(explorer-exploiter)

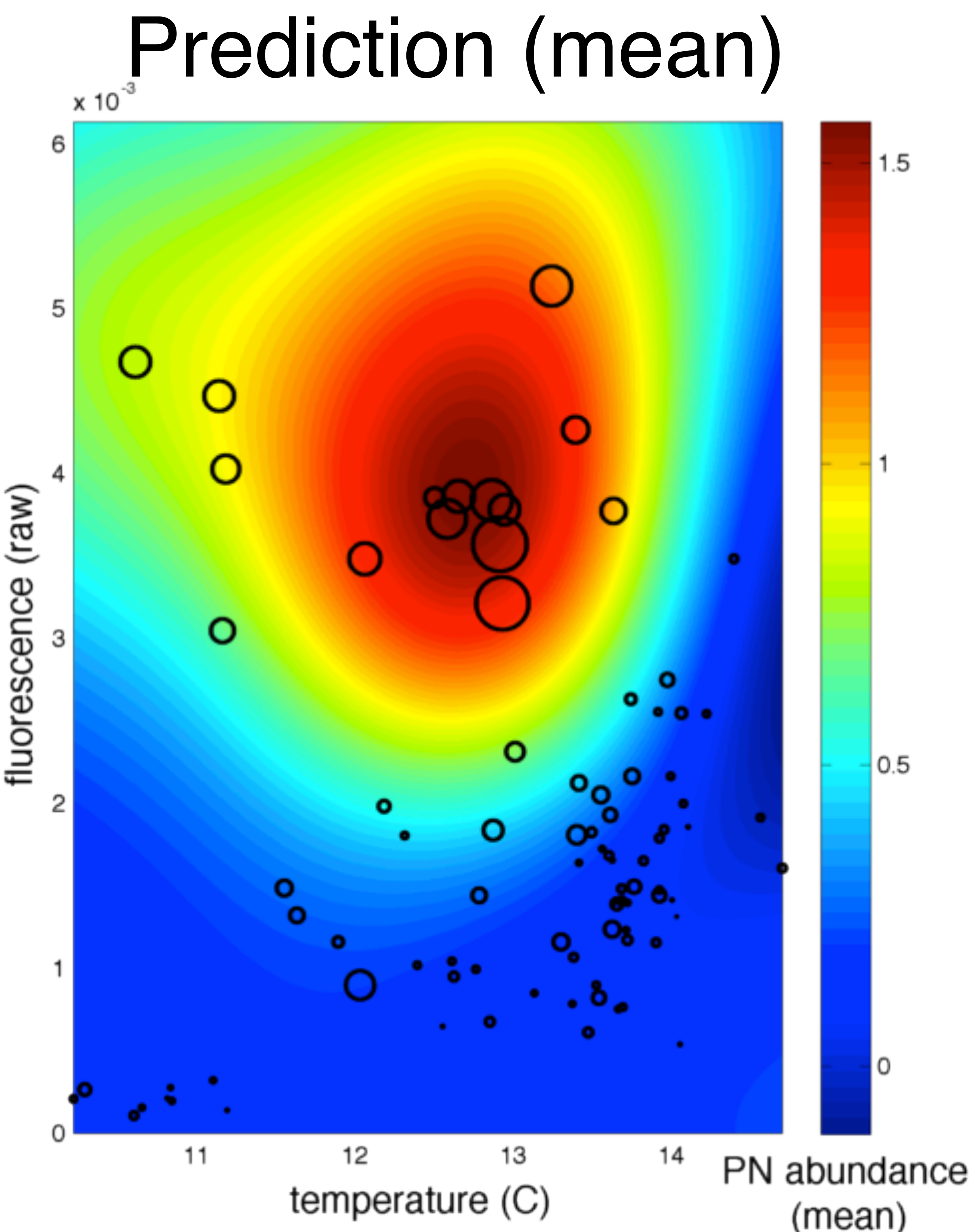
Higher backscatter (particle size)

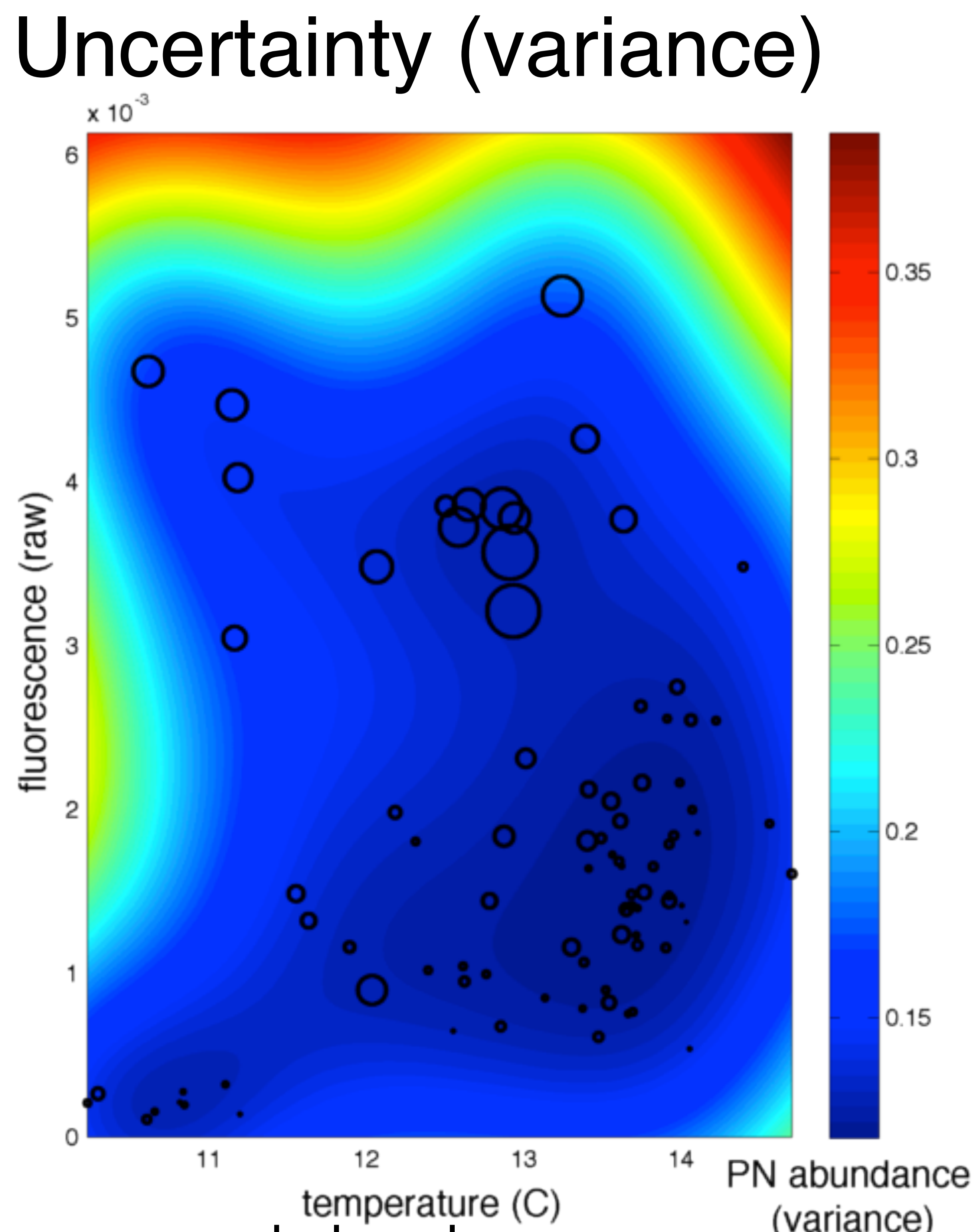
Higher temperature (near the surface)

Field Trial

- **Goal : Acquire high abundance samples of pseudo-nitzschia (PN), a potentially toxinogenic algae**
- 87 analyzed samples from October 2010 CANON experiment used to learn niche model for pseudo-nitzschia
- Cross-validation to pick input variables and kernel parameter
- Mission in north Monterey bay to acquire 9 samples (1 gulper non-functional)

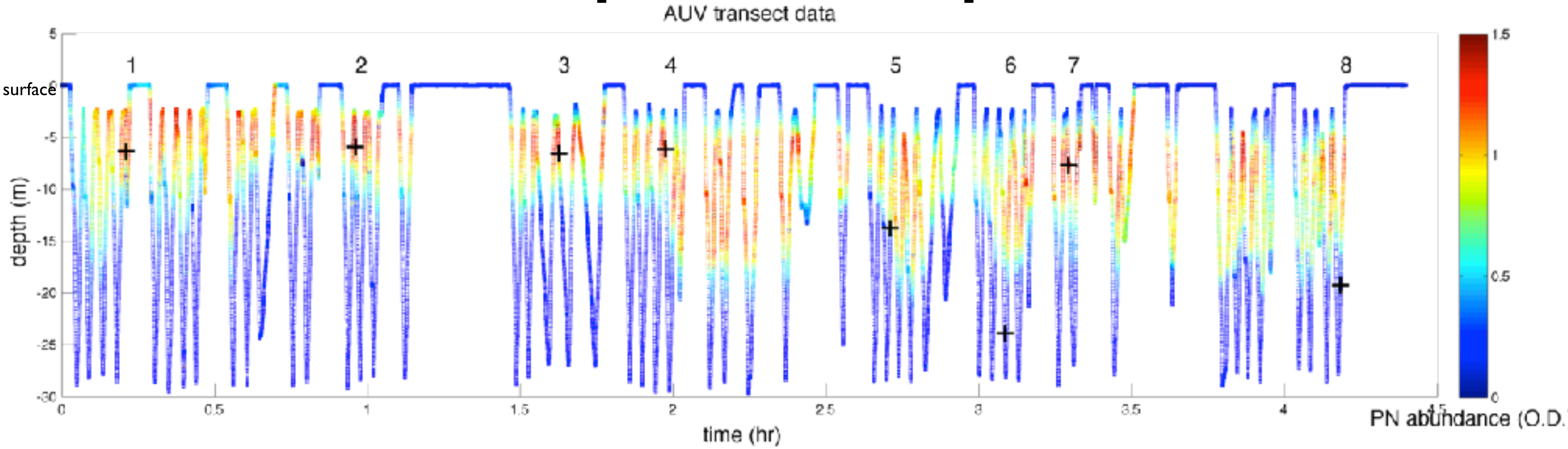
Trained PN Model

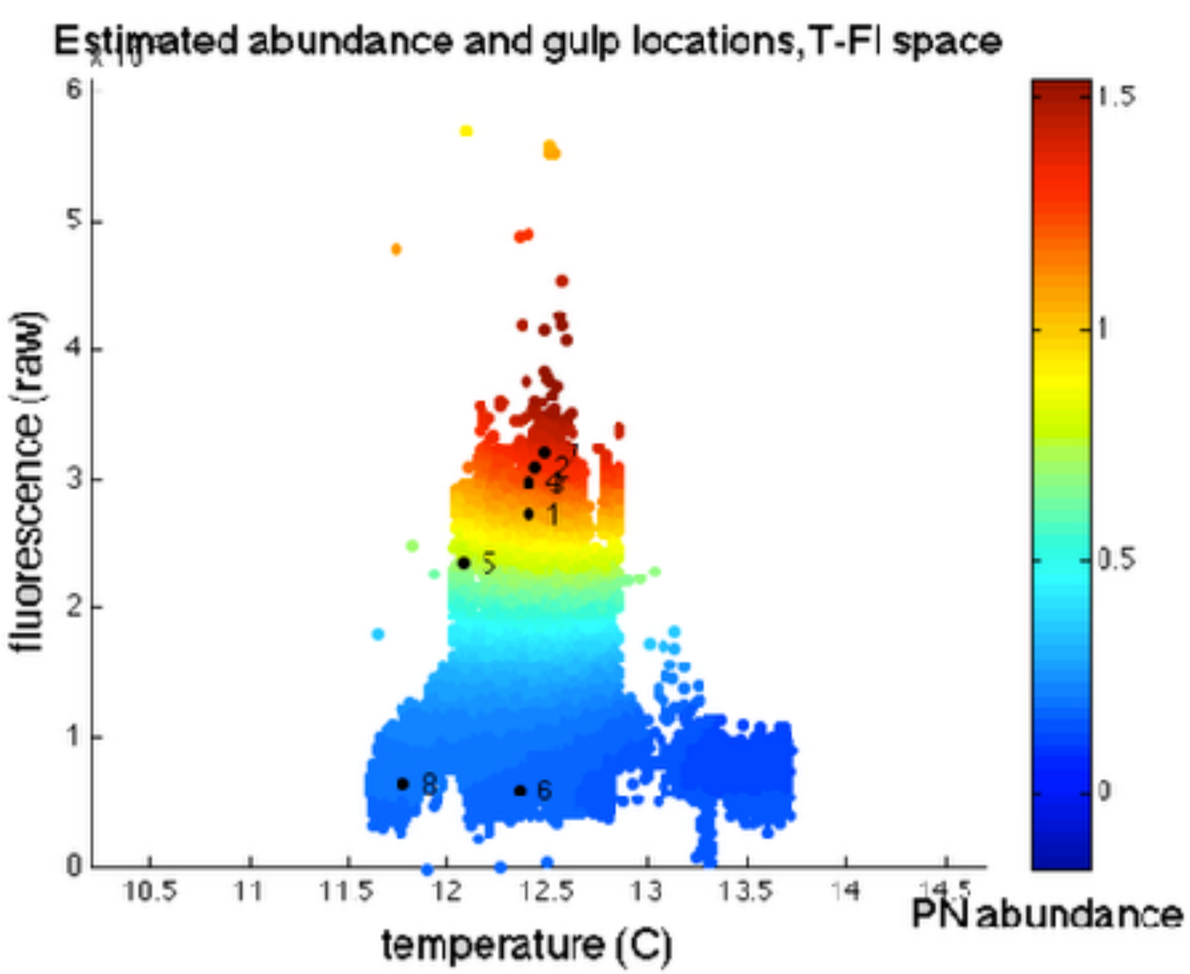


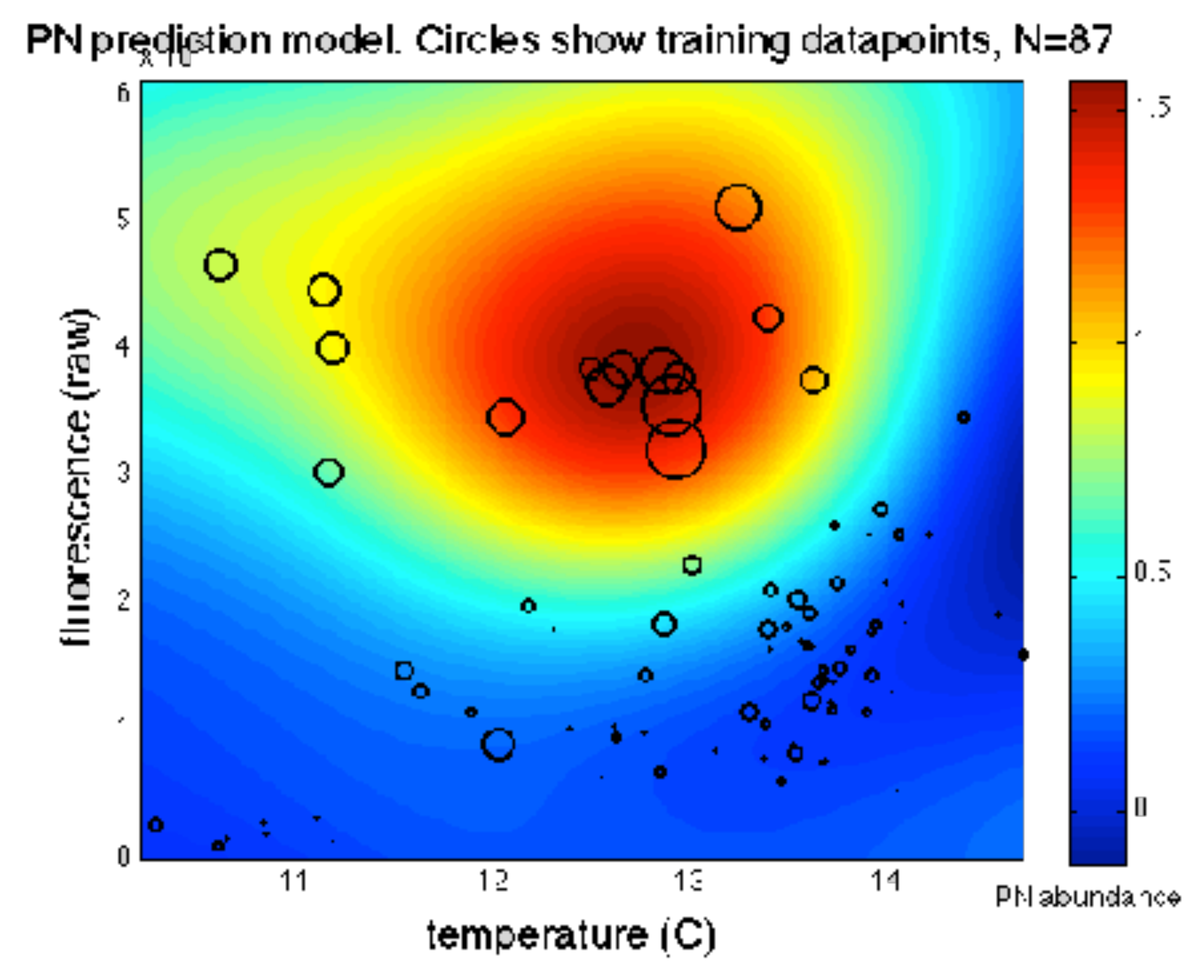


circle size proportional to measured abundance

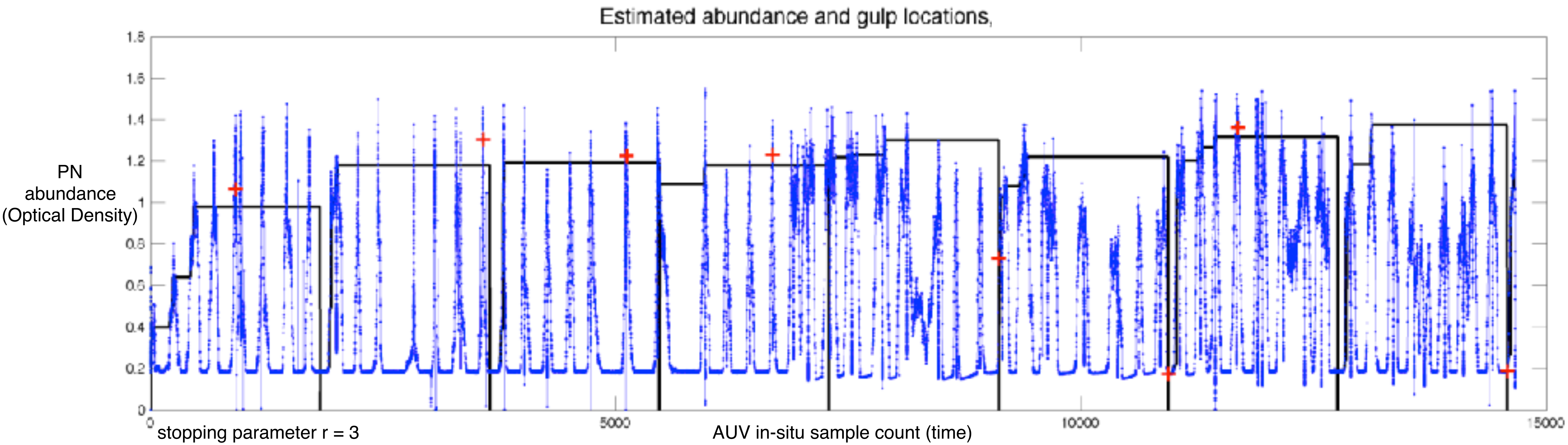
Samples Acquired



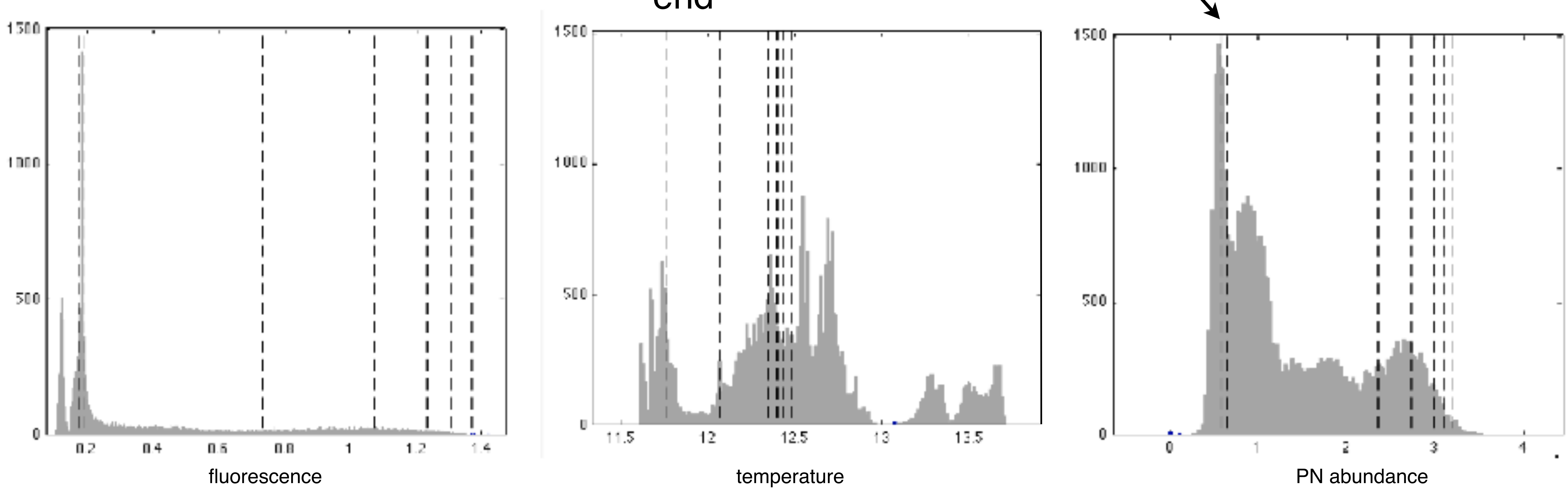




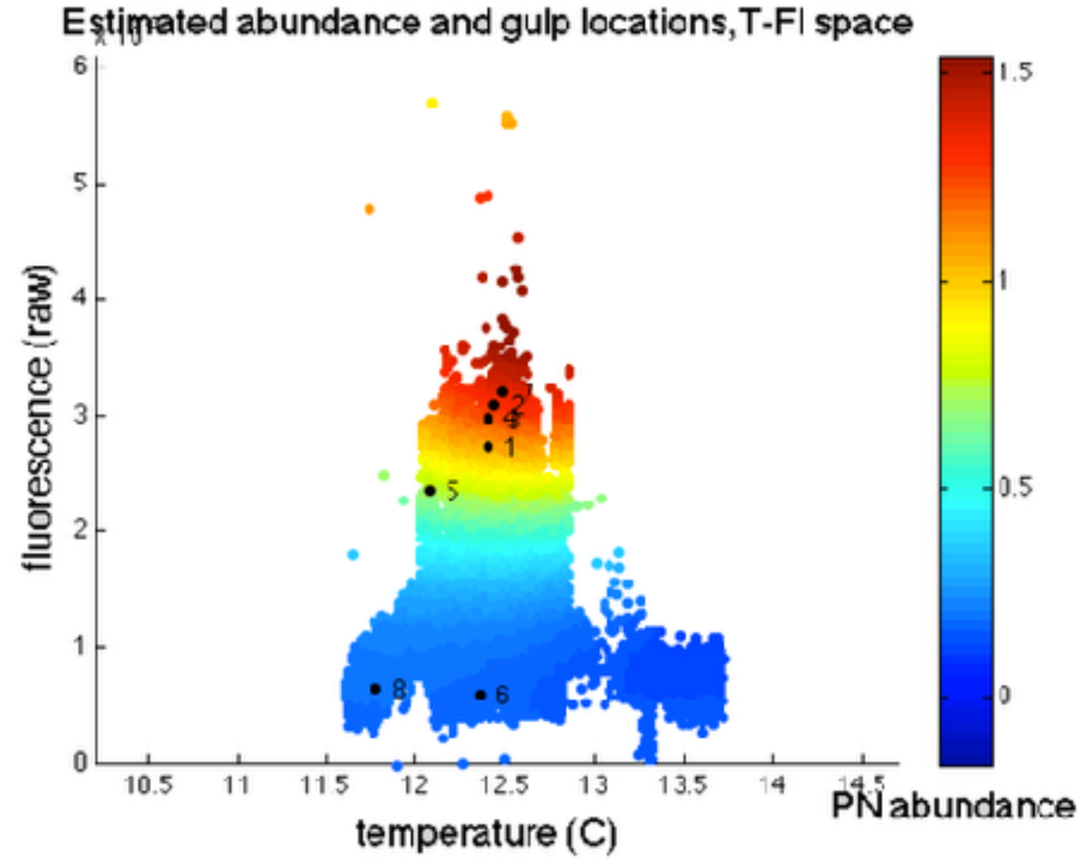
Samples Acquired



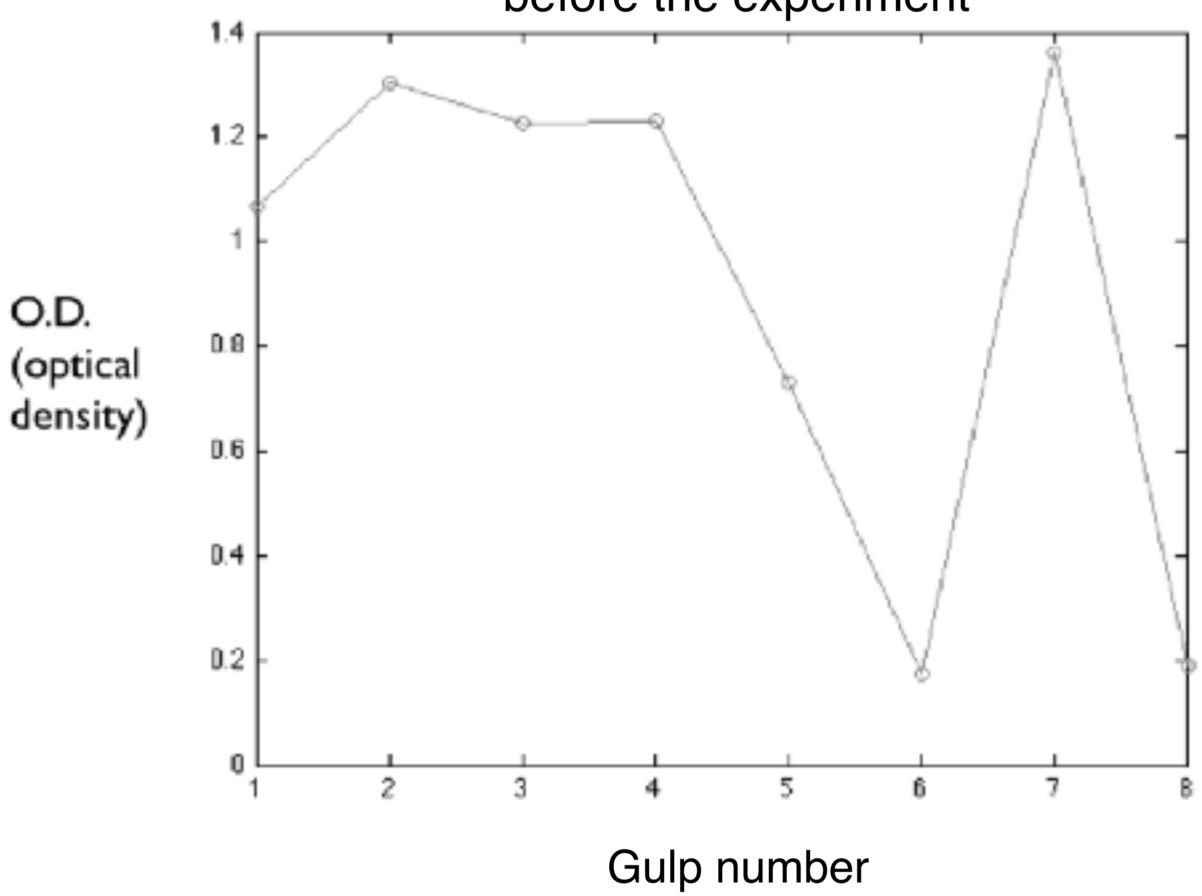
Control samples due to (random) triggering at segment end



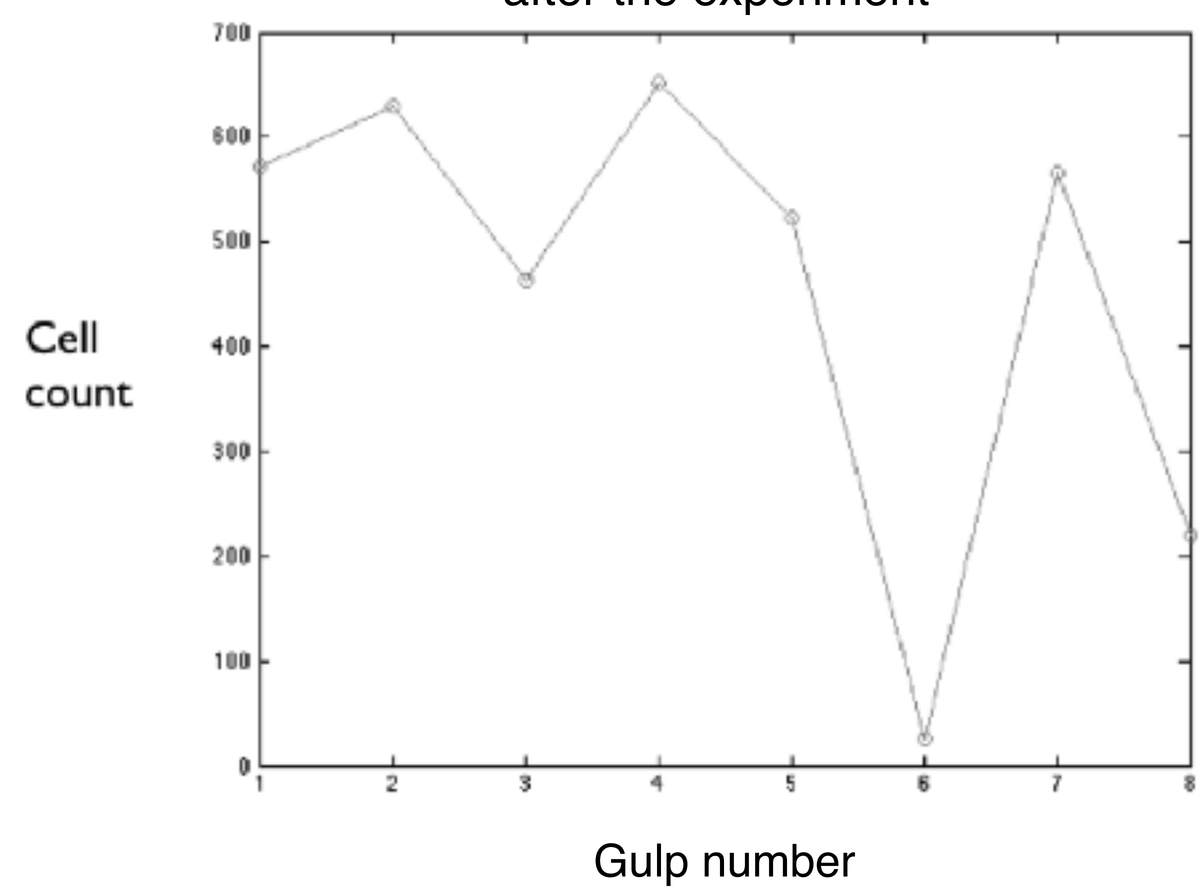
Ex-situ Sample Analysis



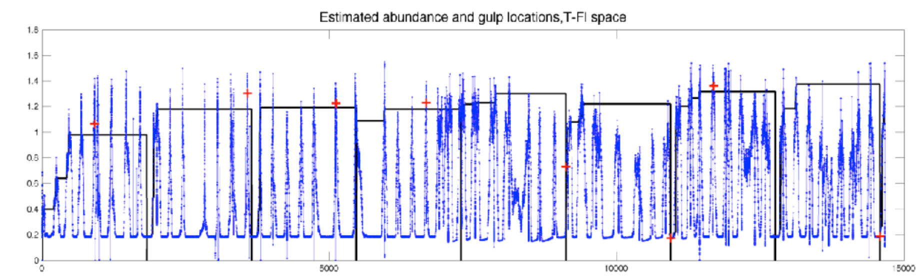
predicted PN seriata
from model trained on molecular analysis data
before the experiment



measured PN seriata
from morphological analysis
after the experiment



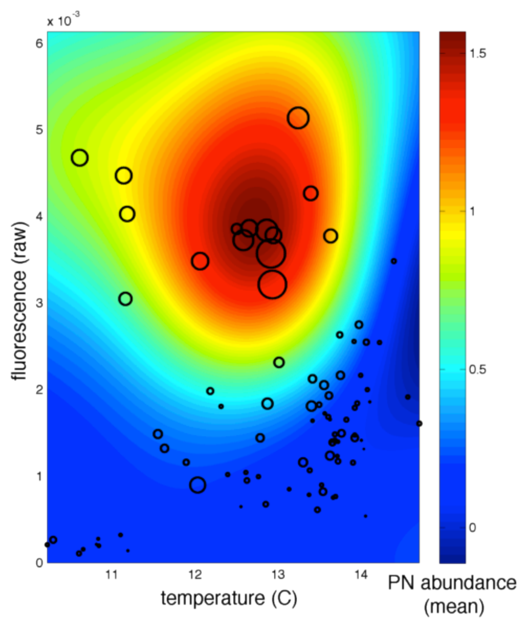
Summary



Sampling Policy

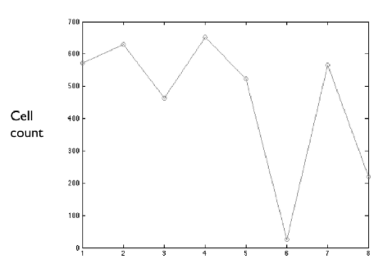
relearn organism abundance model

Organism niche model



Training data

[z1, z2, ...] [b]



Lab analysis

Adaptive water sampling

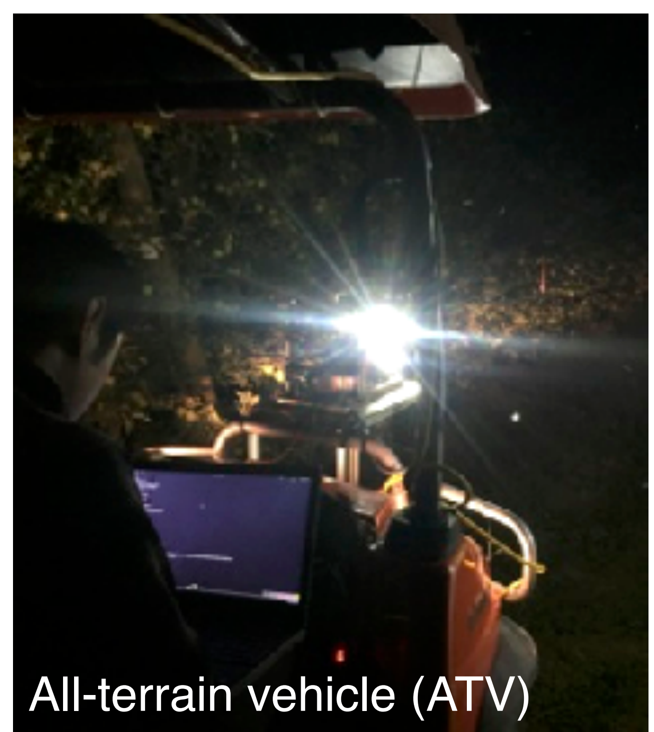
Precision Agriculture

Accurate estimation of fruit count and sizes	Dense 3-D reconstruction of canopy	Detection and monitoring of crop stress and disease
Yield	**Morphology**	**Health**
Labor and storage planning, harvest timing, pricing	*Leaf area, canopy height, pruning management*	*Water, fertilizer, and herbicide management*

Crops Citrus, watermelon, apples, grapes

Platforms Versatile, self-contained, lightweight sensor suite

Harnessed camera stabilizer

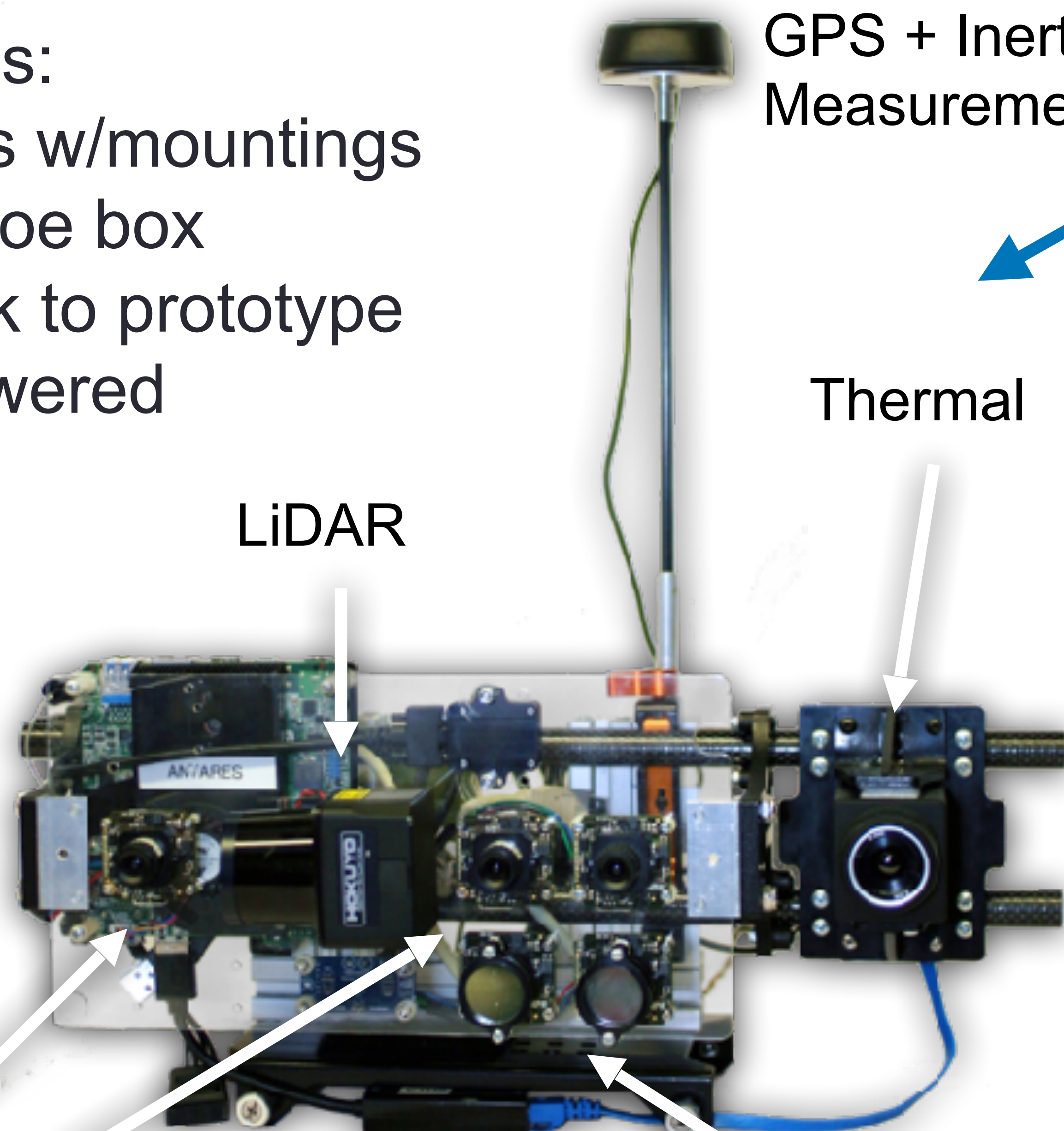


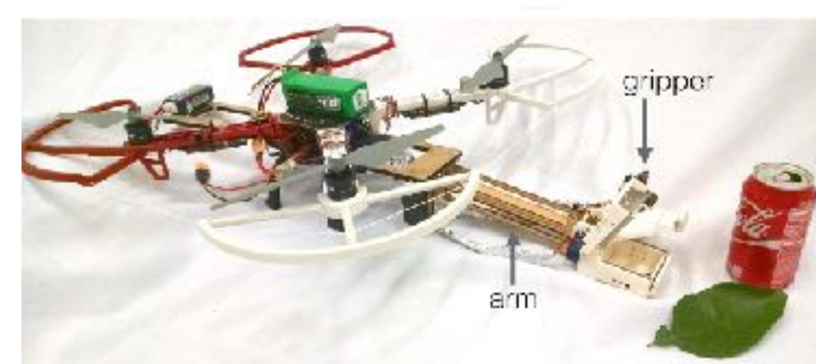
All-terrain vehicle (ATV)

UAV

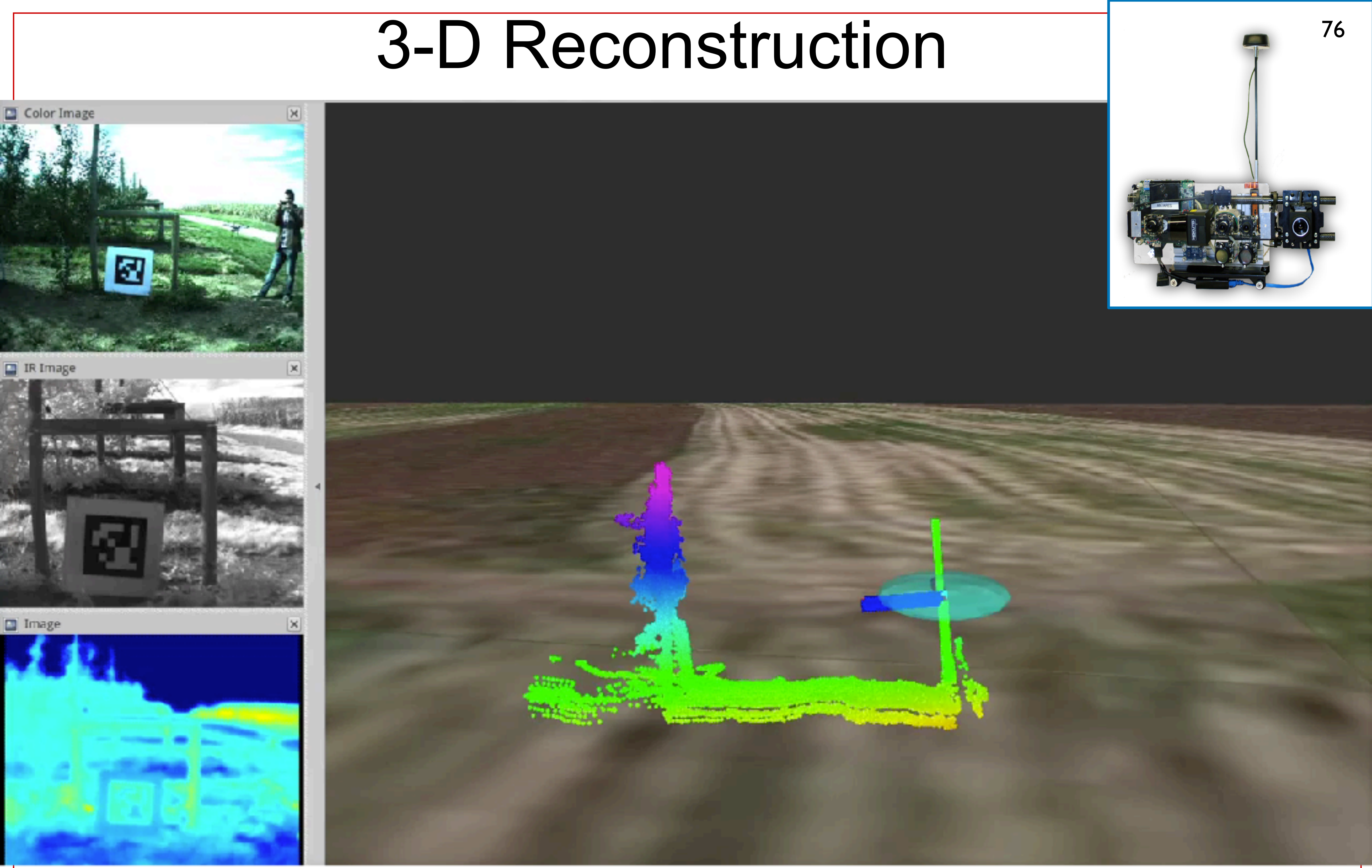
Precision Agriculture

Specifications:
- 1.5kg mass w/mountings
- Fits in a shoe box
- Under $20k to prototype
- Battery powered



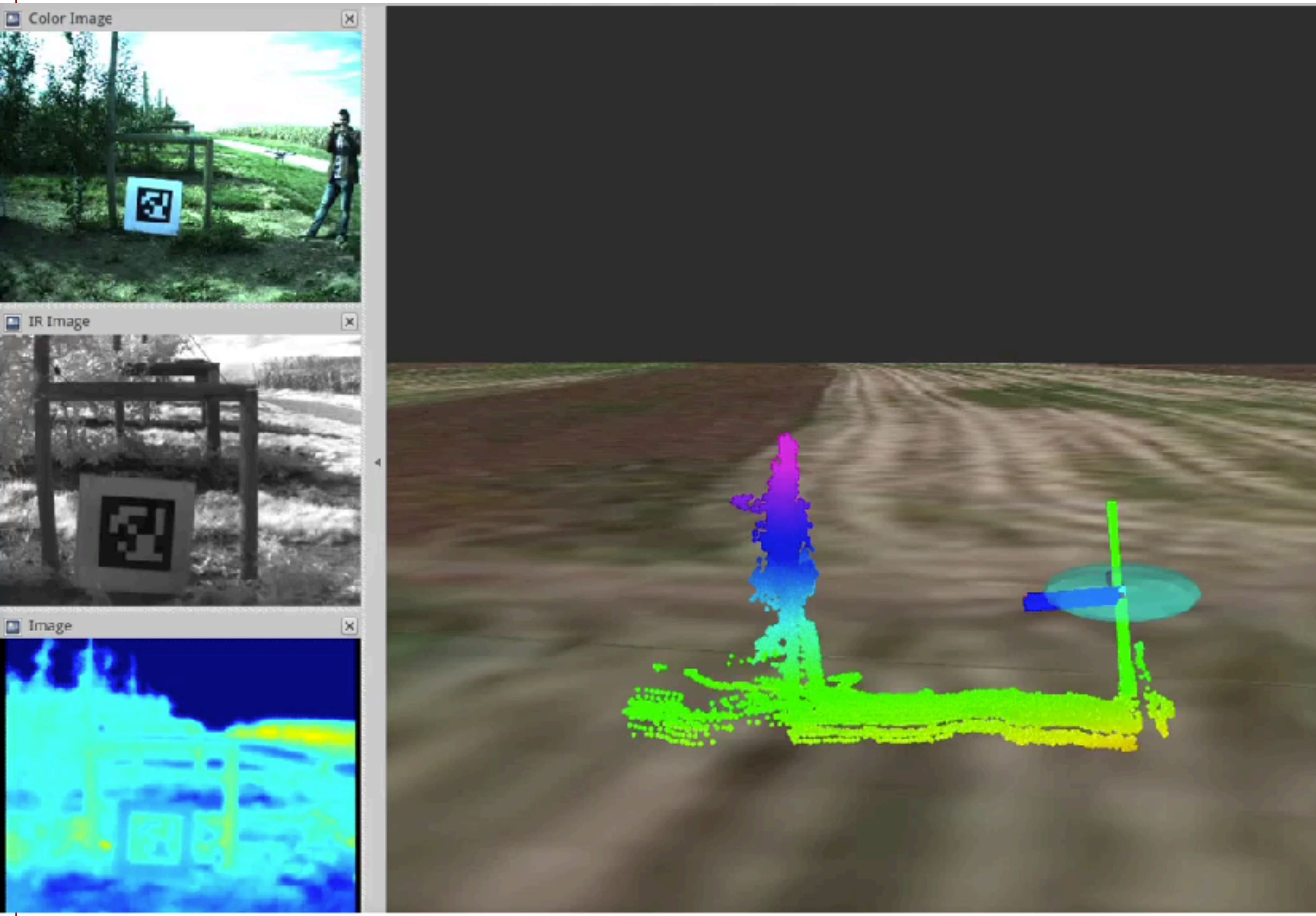


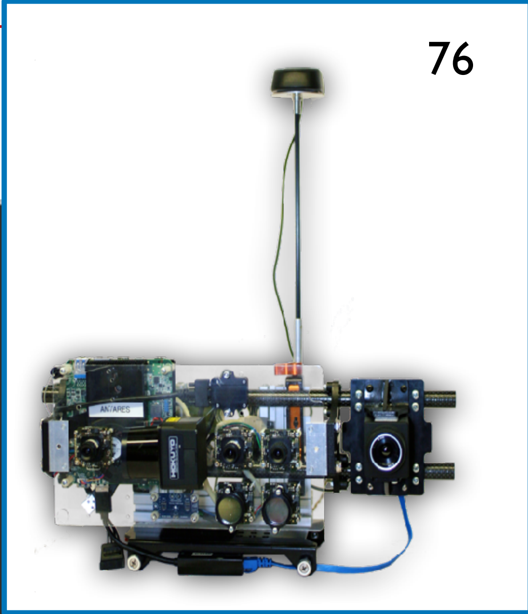
3-D Reconstruction



J. Das, G. Cross, C. Qu, A. Makineni, P. Tokekar, Y. Mulgaonkar, and V. Kumar, “Devices, systems, and methods for automated monitoring enabling precision agriculture,” in 2015 IEEE International Conference on Automation Science and Engineering (CASE). IEEE, Aug 2015, pp. 462–469.

3-D Reconstruction





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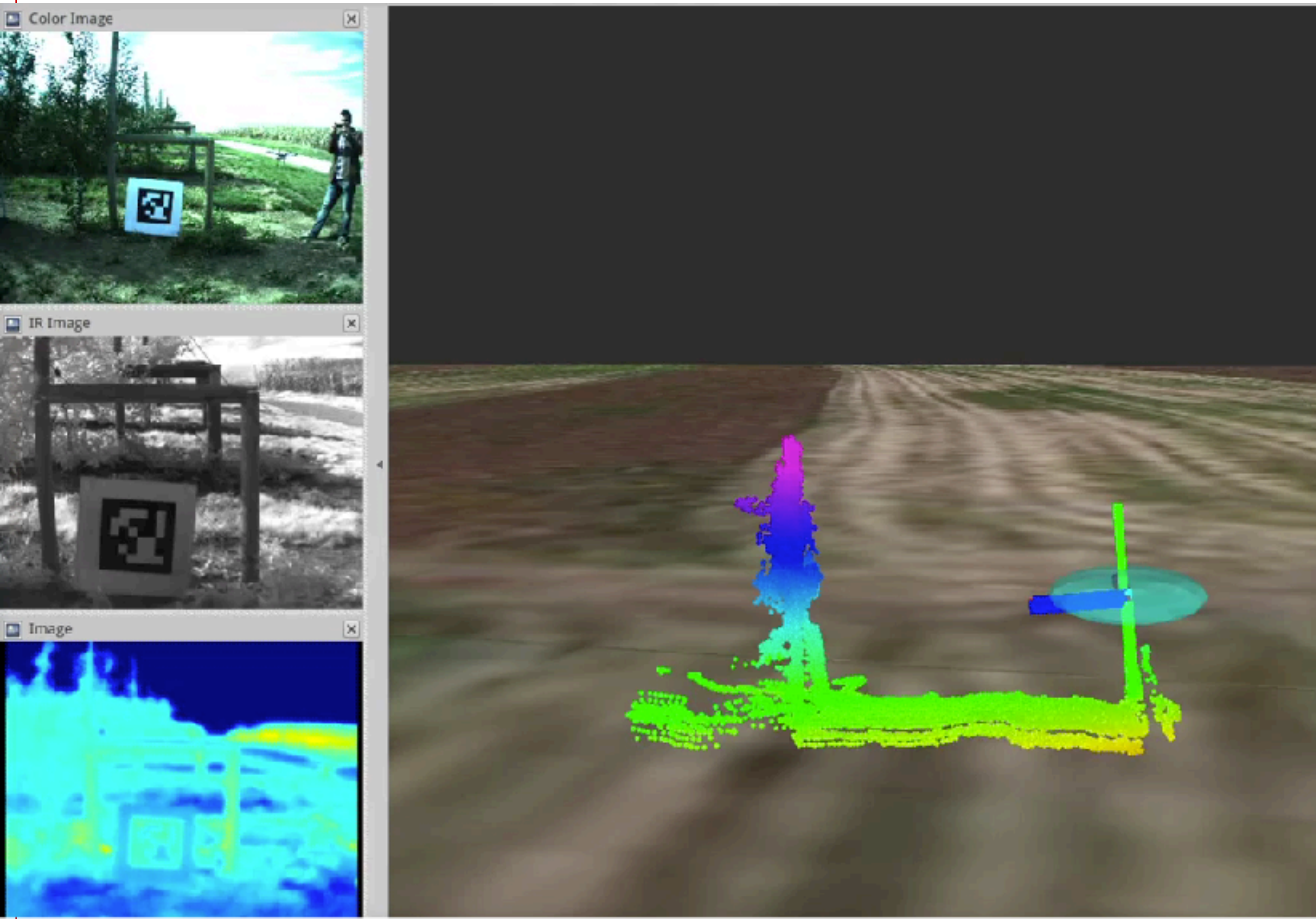
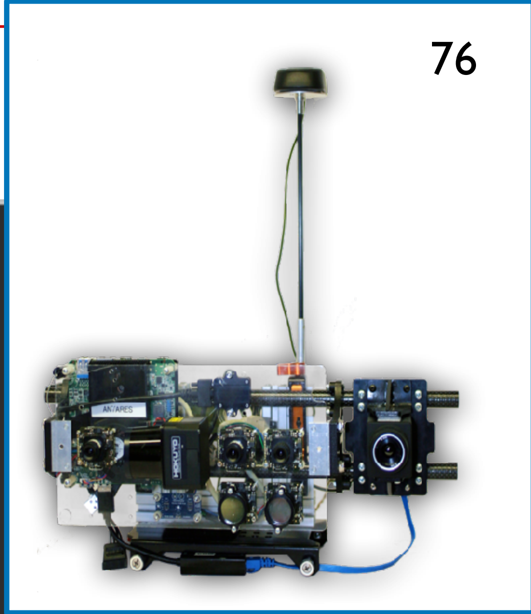
3-D Reconstruction





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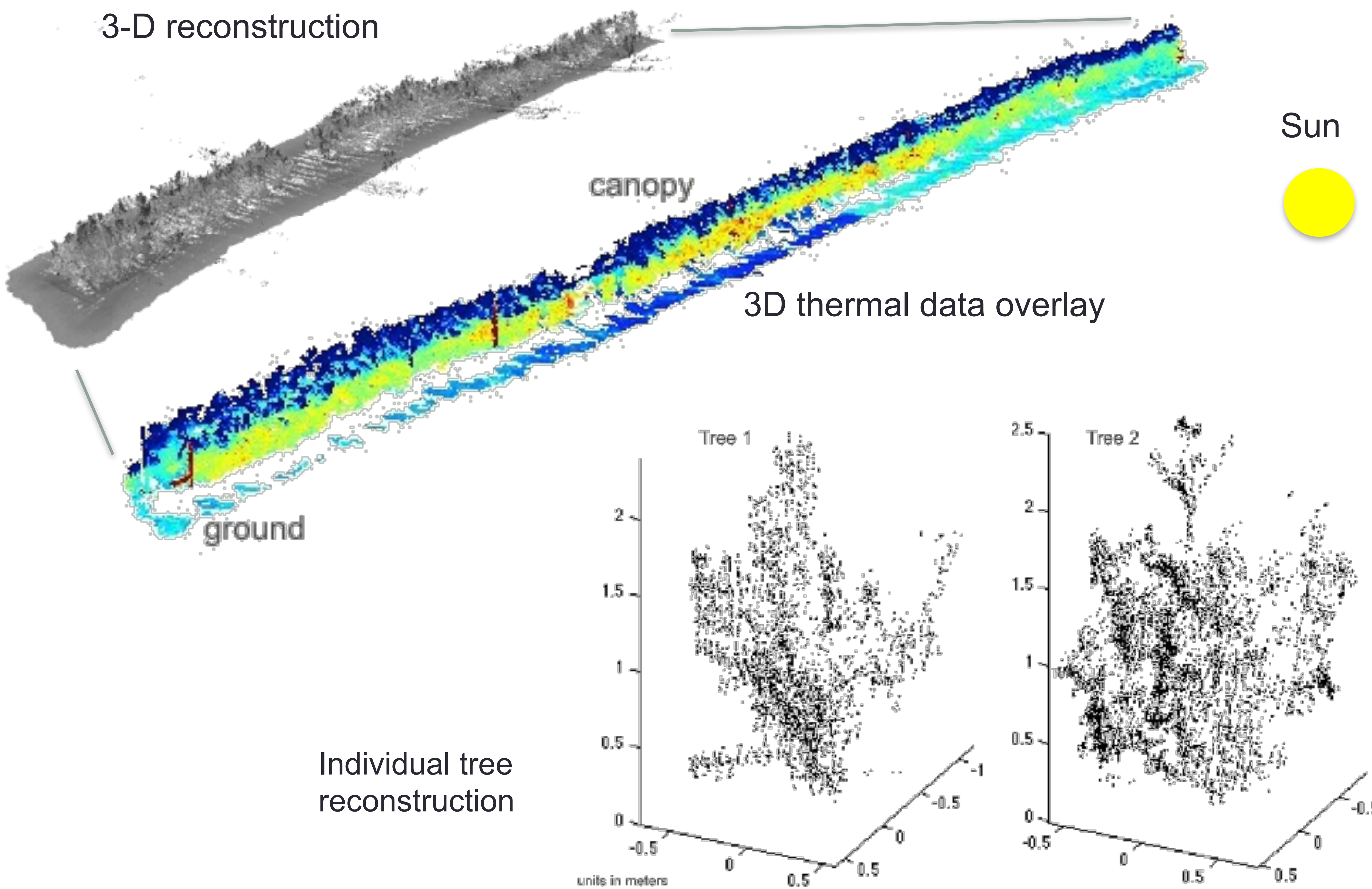
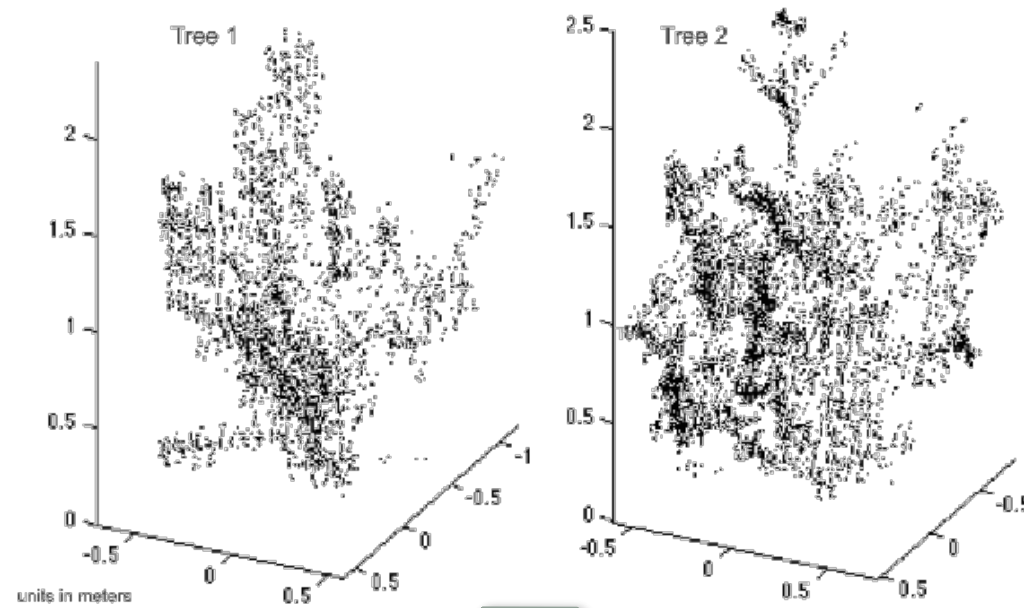
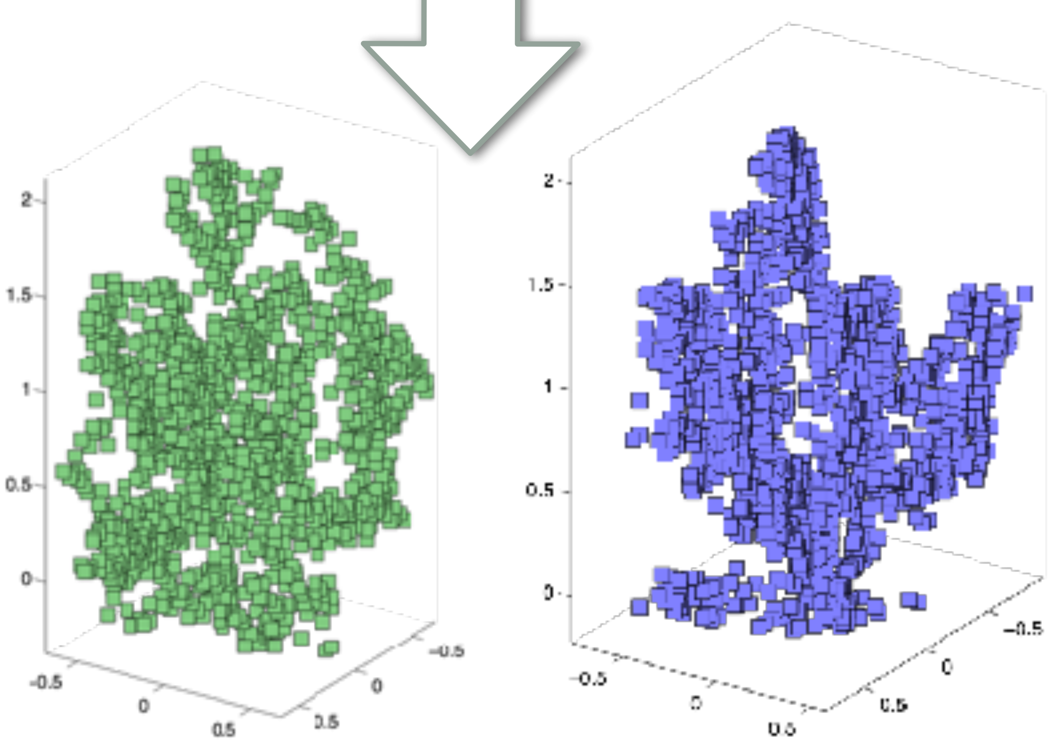
3-D Reconstruction



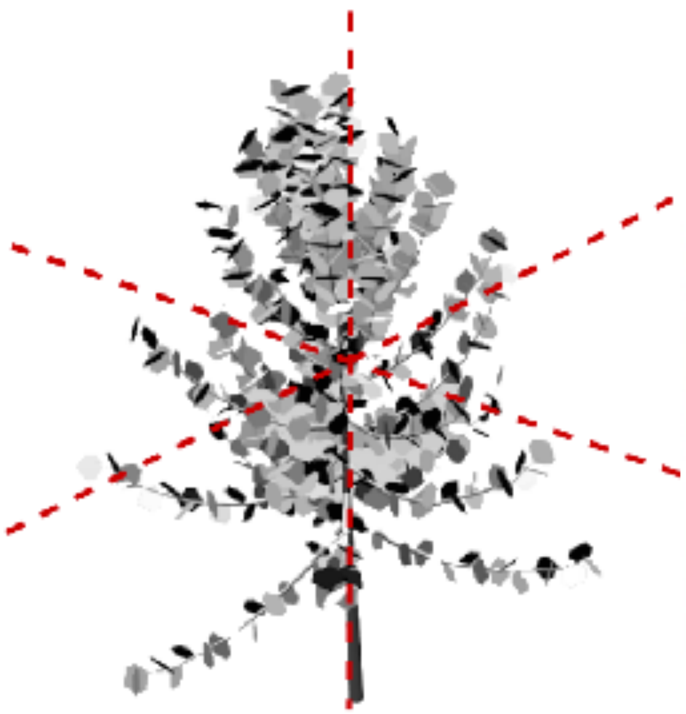
Automatic Extraction of Leaf Area

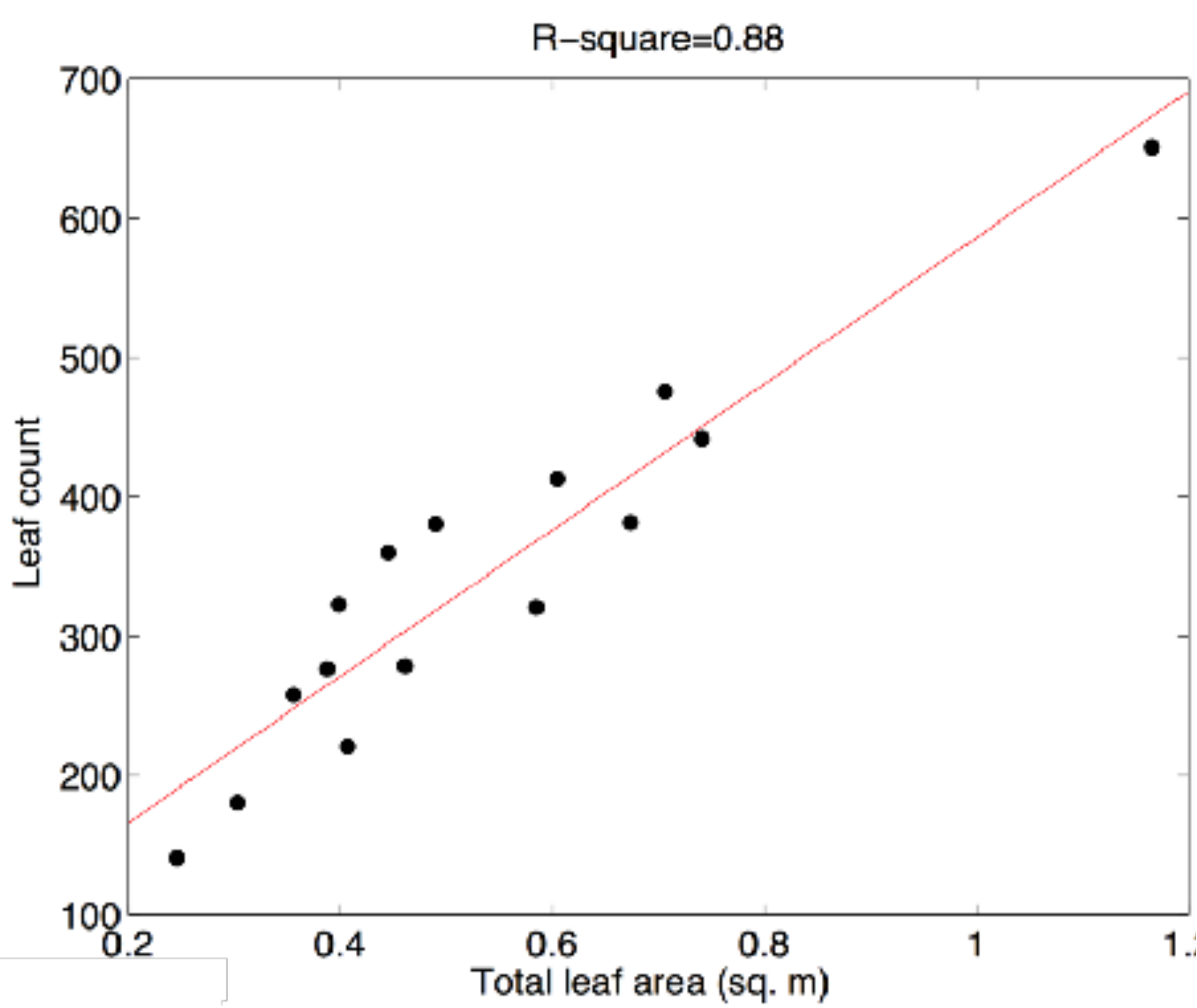


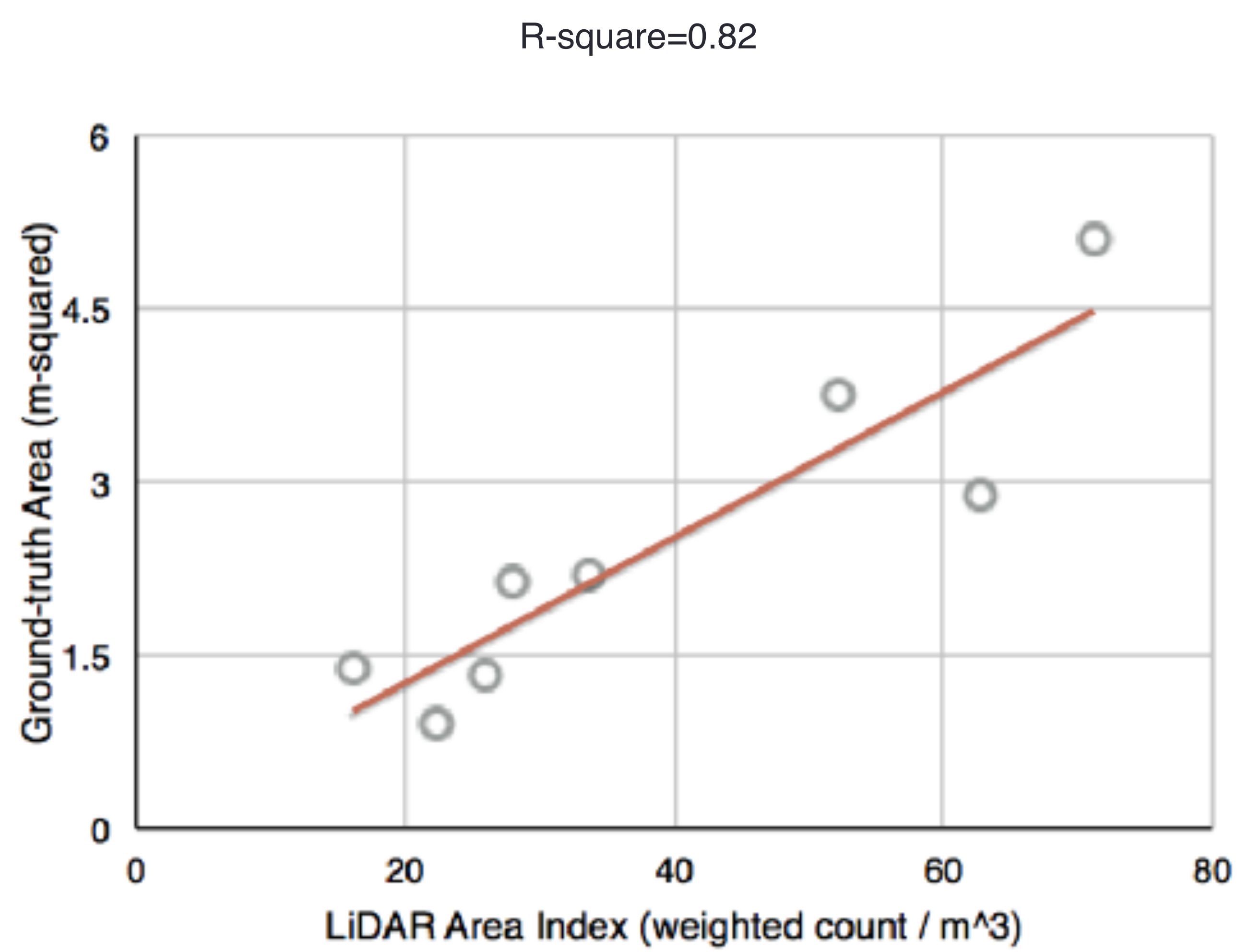


Leaf Area Index

Leaf Area Analysis



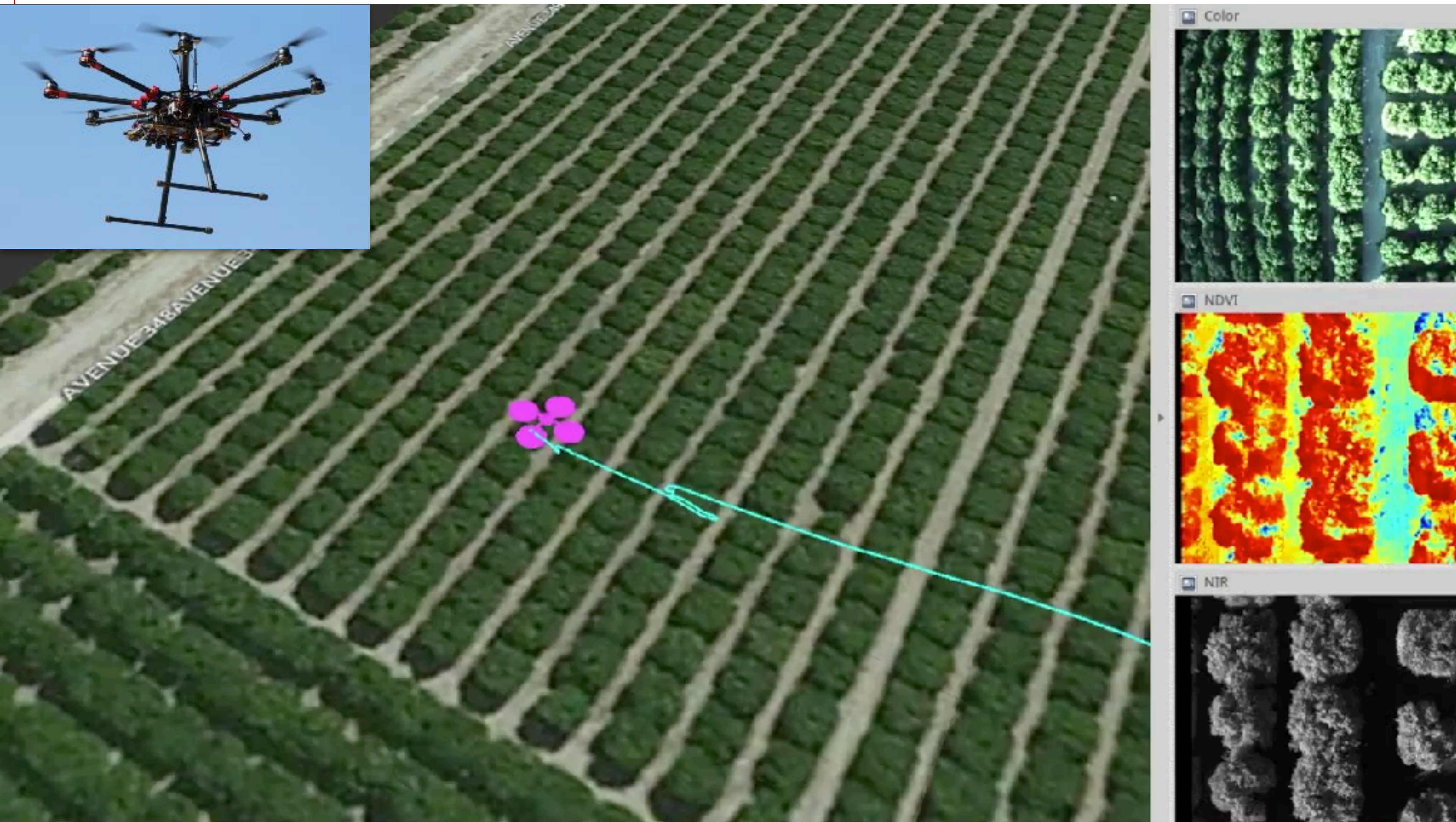




Crop Stress

J. Das, G. Cross, C. Qu, A. Makineni, P. Tokekar, Y. Mulgaonkar, and V. Kumar, “Devices, systems, and methods for automated monitoring enabling precision agriculture,” in 2015 IEEE International Conference on Automation Science and Engineering (CASE). IEEE, Aug 2015, pp. 462–469.

Crop Stress



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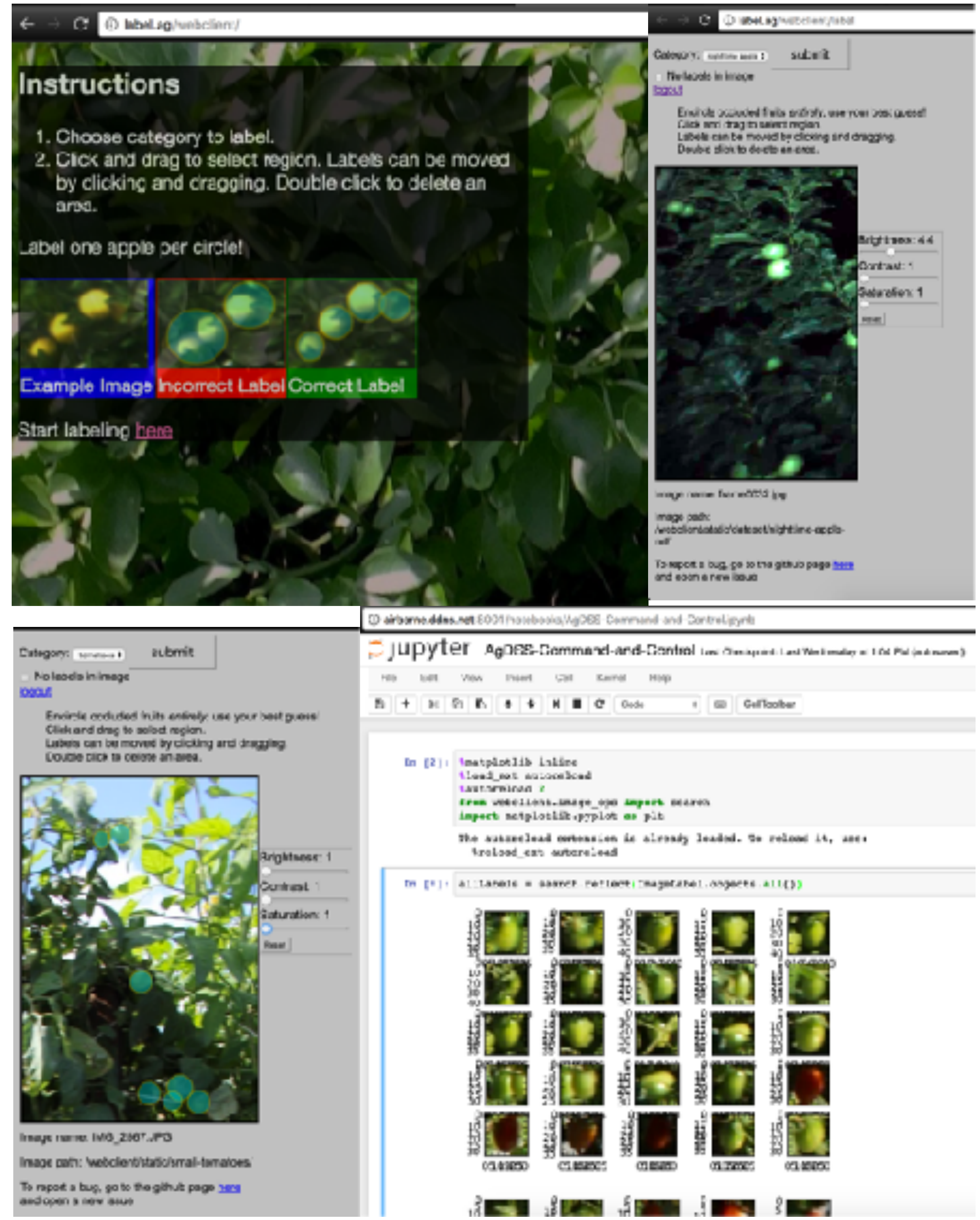
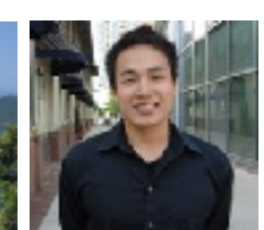
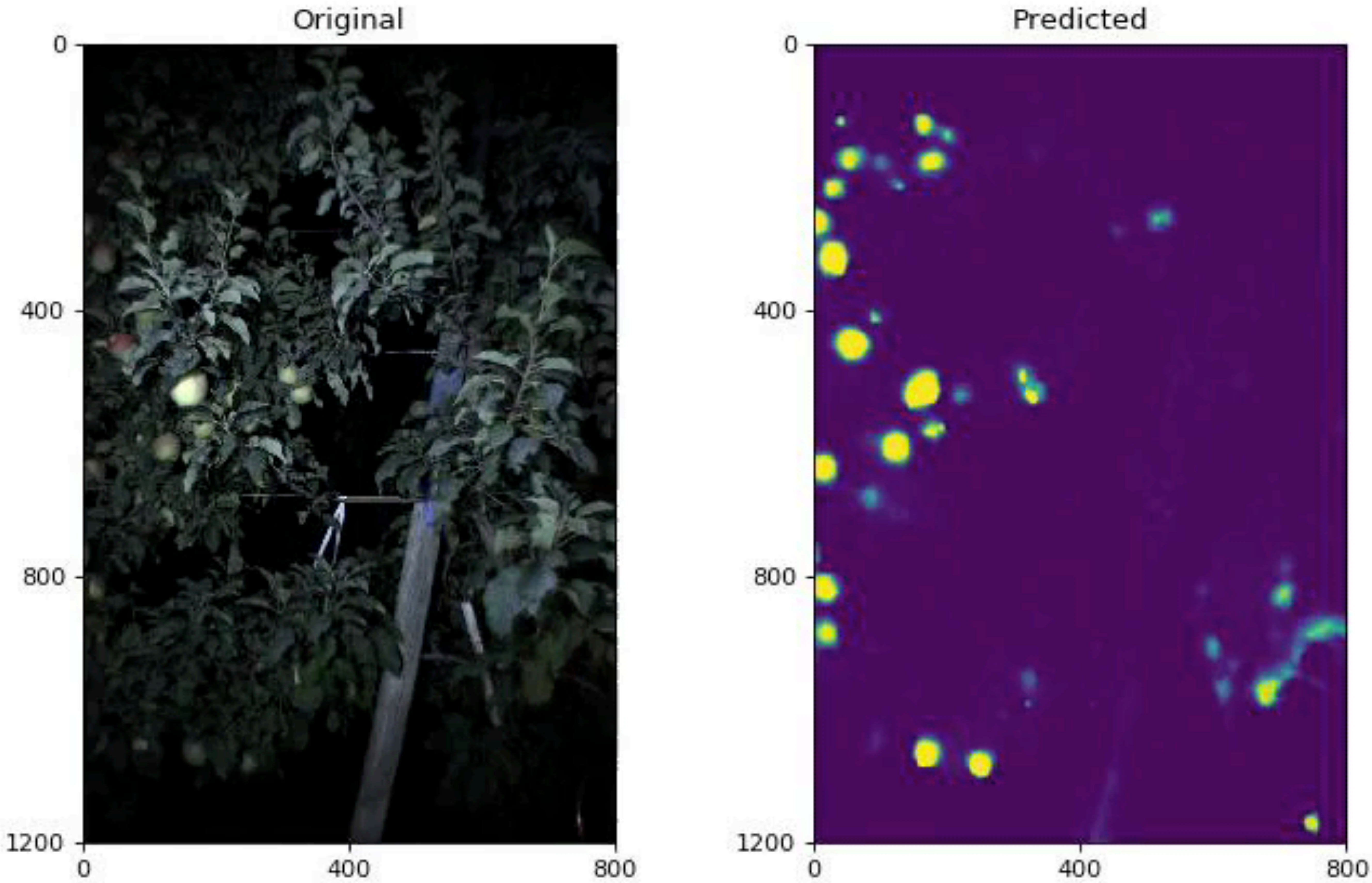
Fruit Counting

- Automatic fruit counting using low SWaP technologies and deep learning
- https://annotate.label.ag - open-source annotation tool
  - 22 labelers, 5000+ labeled images in two weeks
  - dataset released! https://label.ag
- Allows growers to quickly annotate data, train models, and deploy on their own

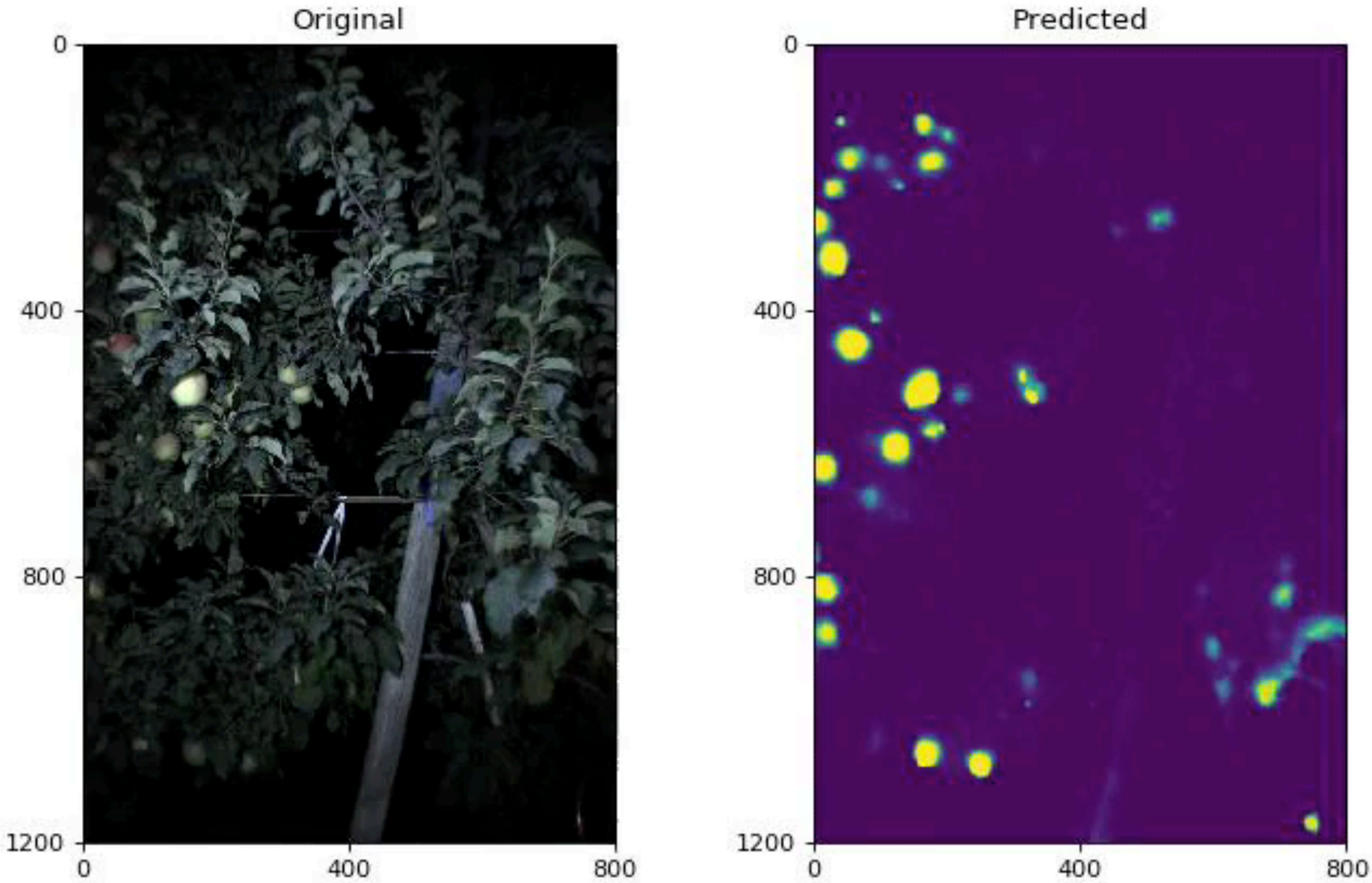




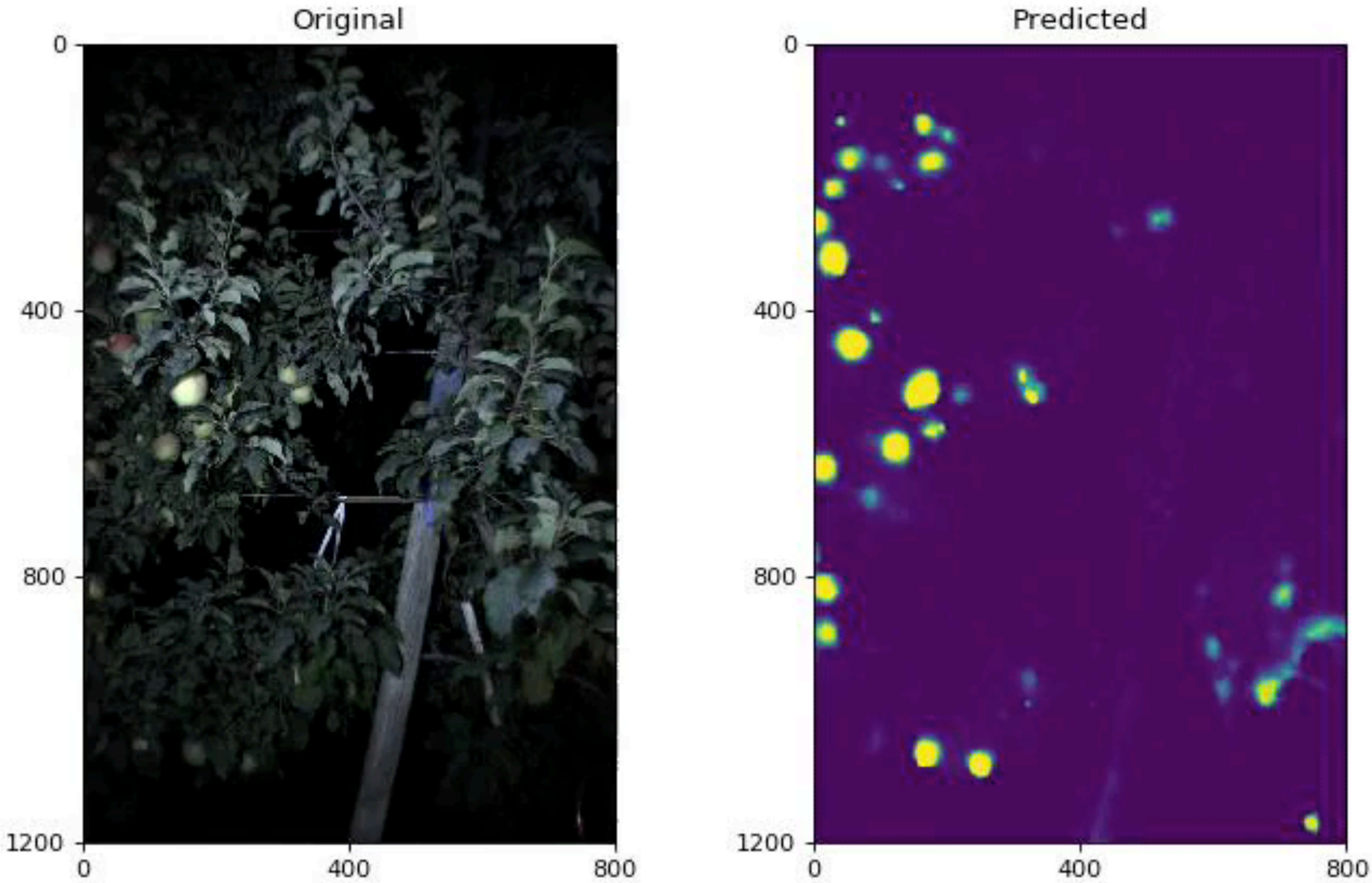
Fruit Detection



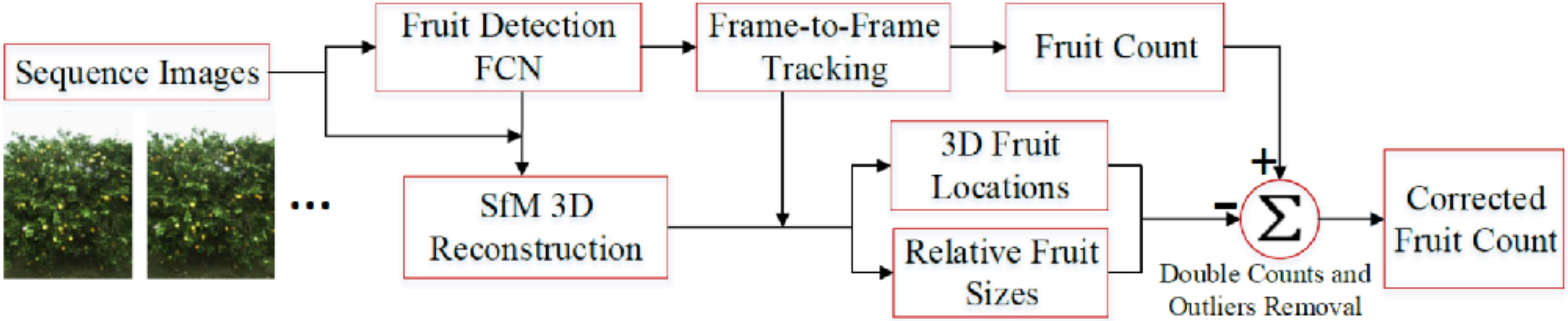
Fruit Detection

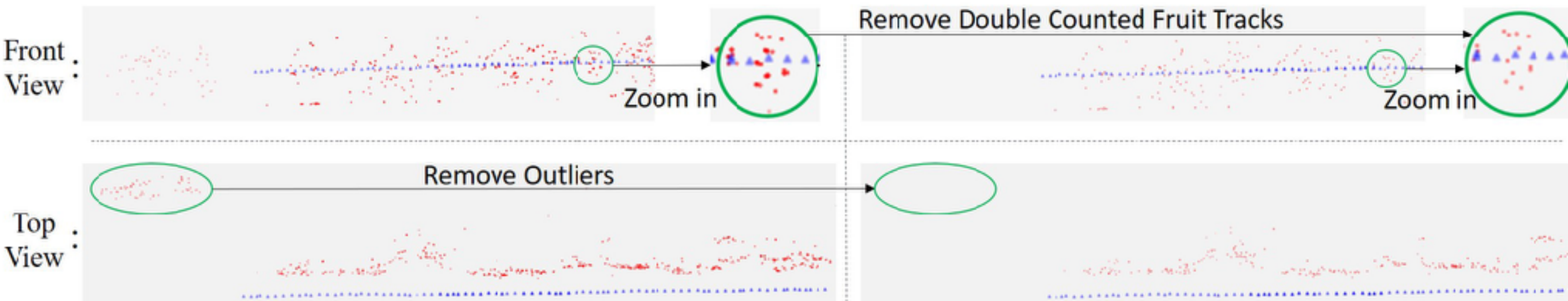


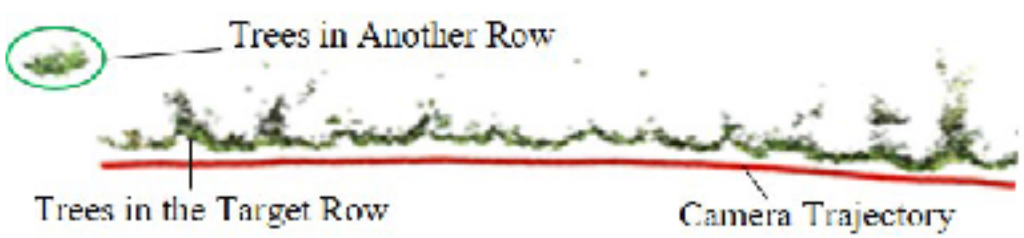
Fruit Detection

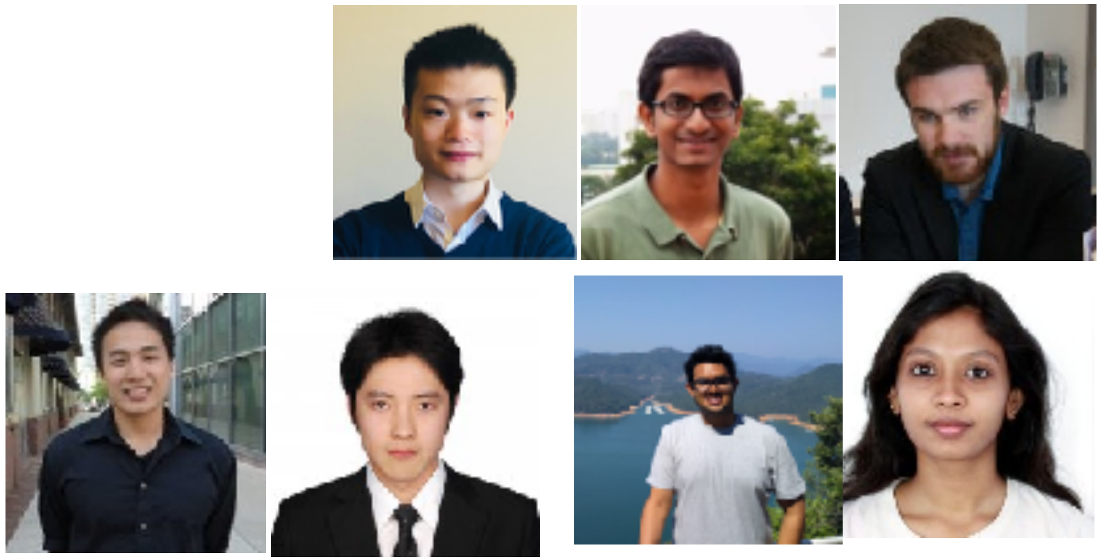


Fruit Mapping

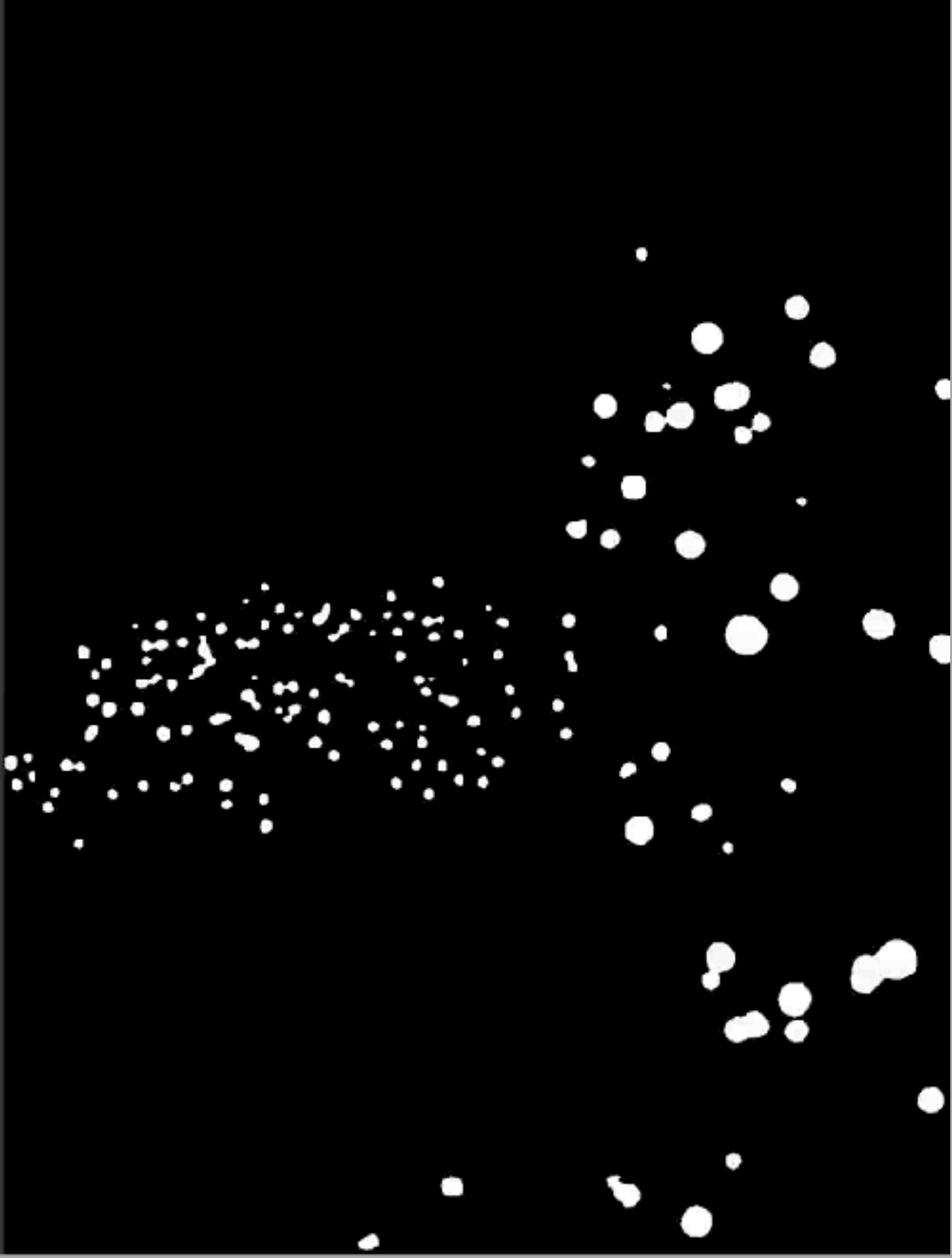








Xu Liu, Steven W. Chen, Shreyas Aditya, Nivedha Sivakumar, Sandeep Dcunha, Chao Qu, Camillo J. Taylor, Jnaneshwar Das, and Vijay Kumar, "Robust Fruit Counting: Combining Deep Learning, Tracking, and Structure from Motion", in International Conference on Intelligent Robots and Systems (IROS) 2018



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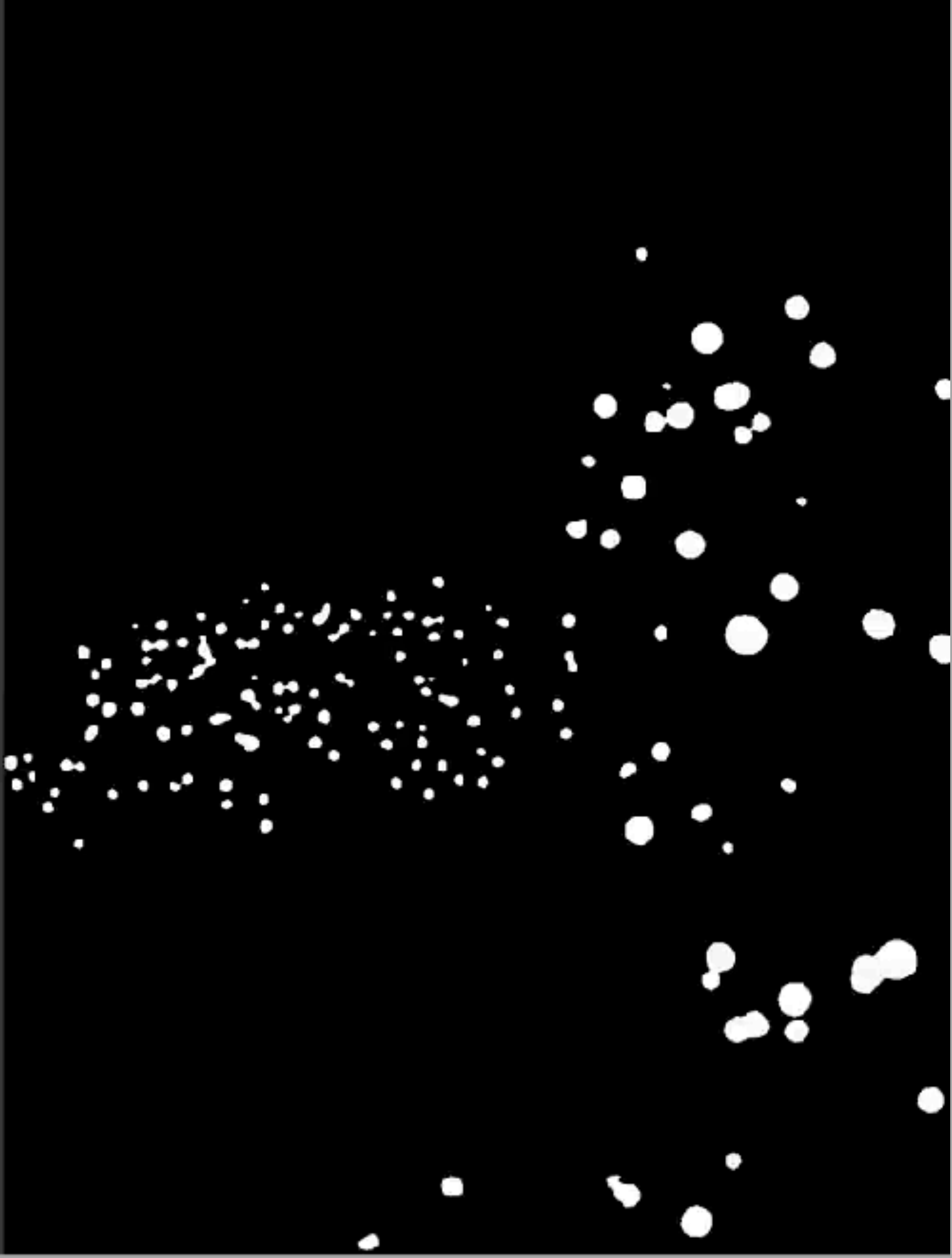

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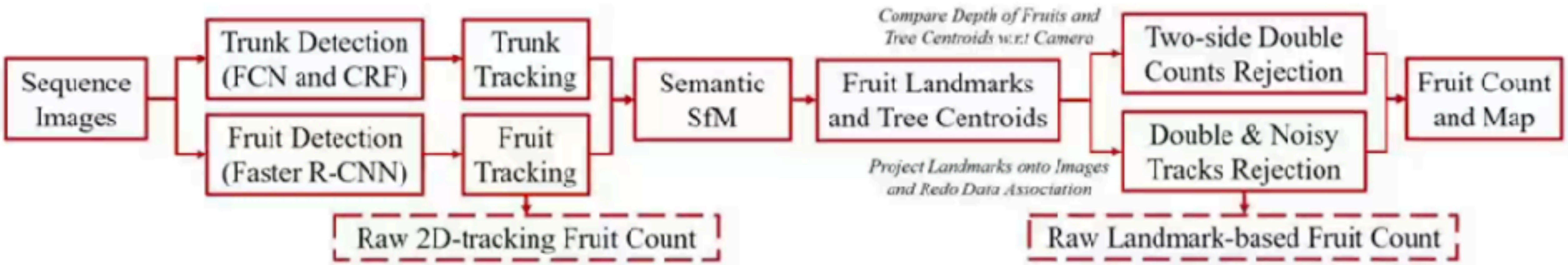
Monocular Camera Based Fruit Counting and Mapping with Semantic Data Association



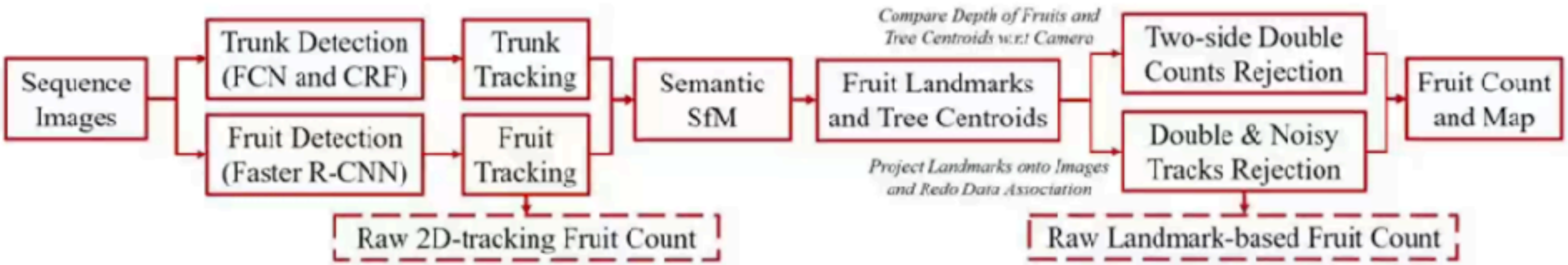
Xu Liu, Steven W. Chen, Chenhao Liu, Shreyas S. Shivakumar, Jnaneshwar Das, Camillo J. Taylor, James Underwood, Vijay Kumar

Penn Engineering GRASP LABORATORY

USDA

THE UNIVERSITY OF SYDNEY
Australian Centre for Field Robotics

Monocular Camera Based Fruit Counting and Mapping with Semantic Data Association



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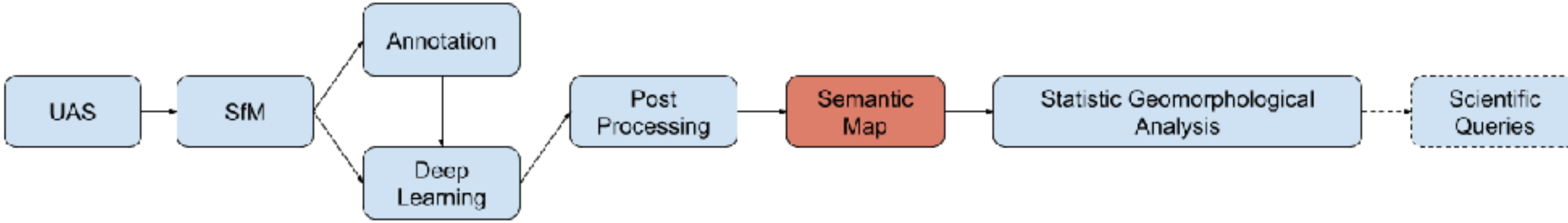
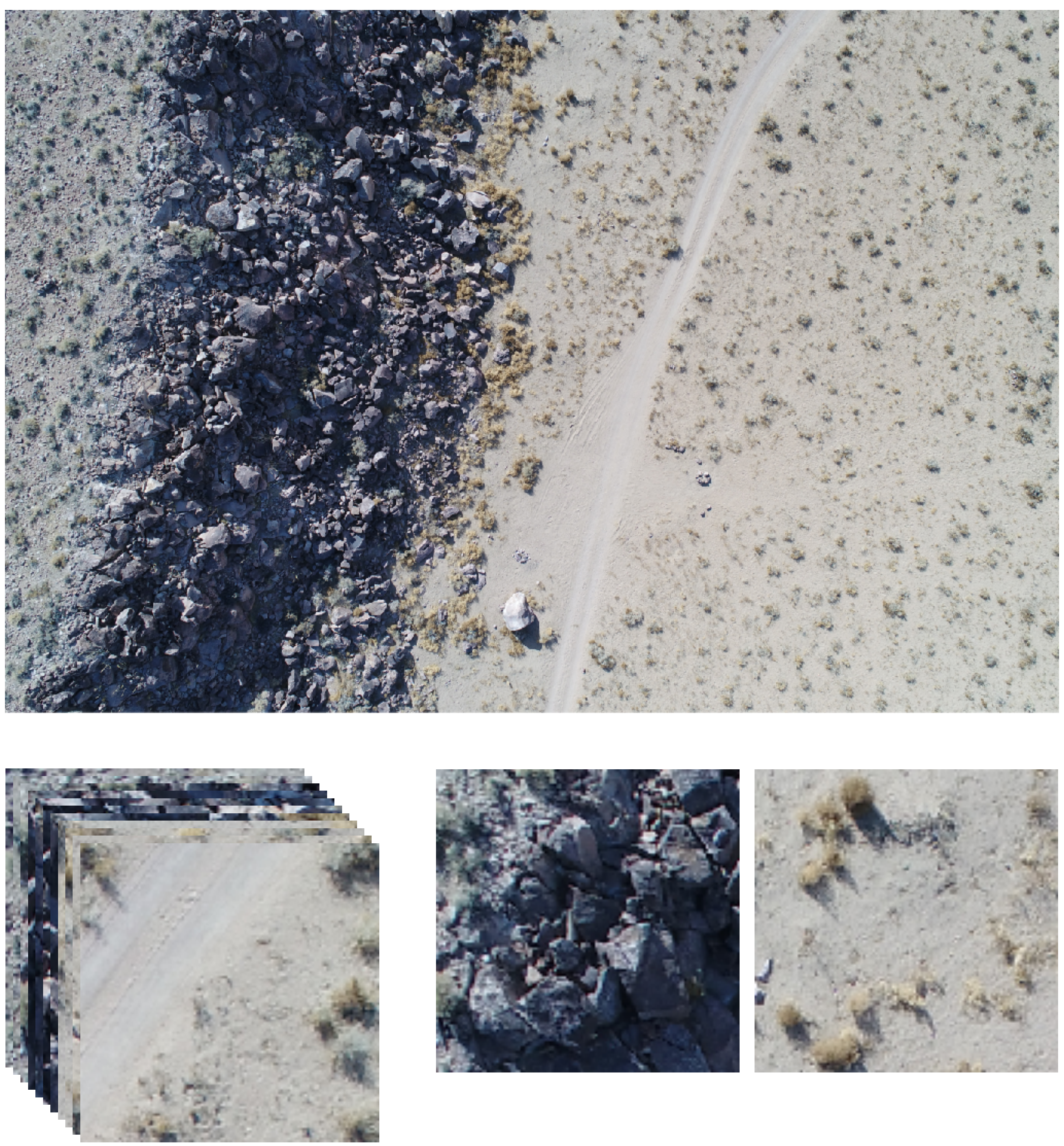
Penn Engineering GRASP LABORATORY
USDA
THE UNIVERSITY OF SYDNEY Australian Centre for Field Robotics

Rock trait mapping

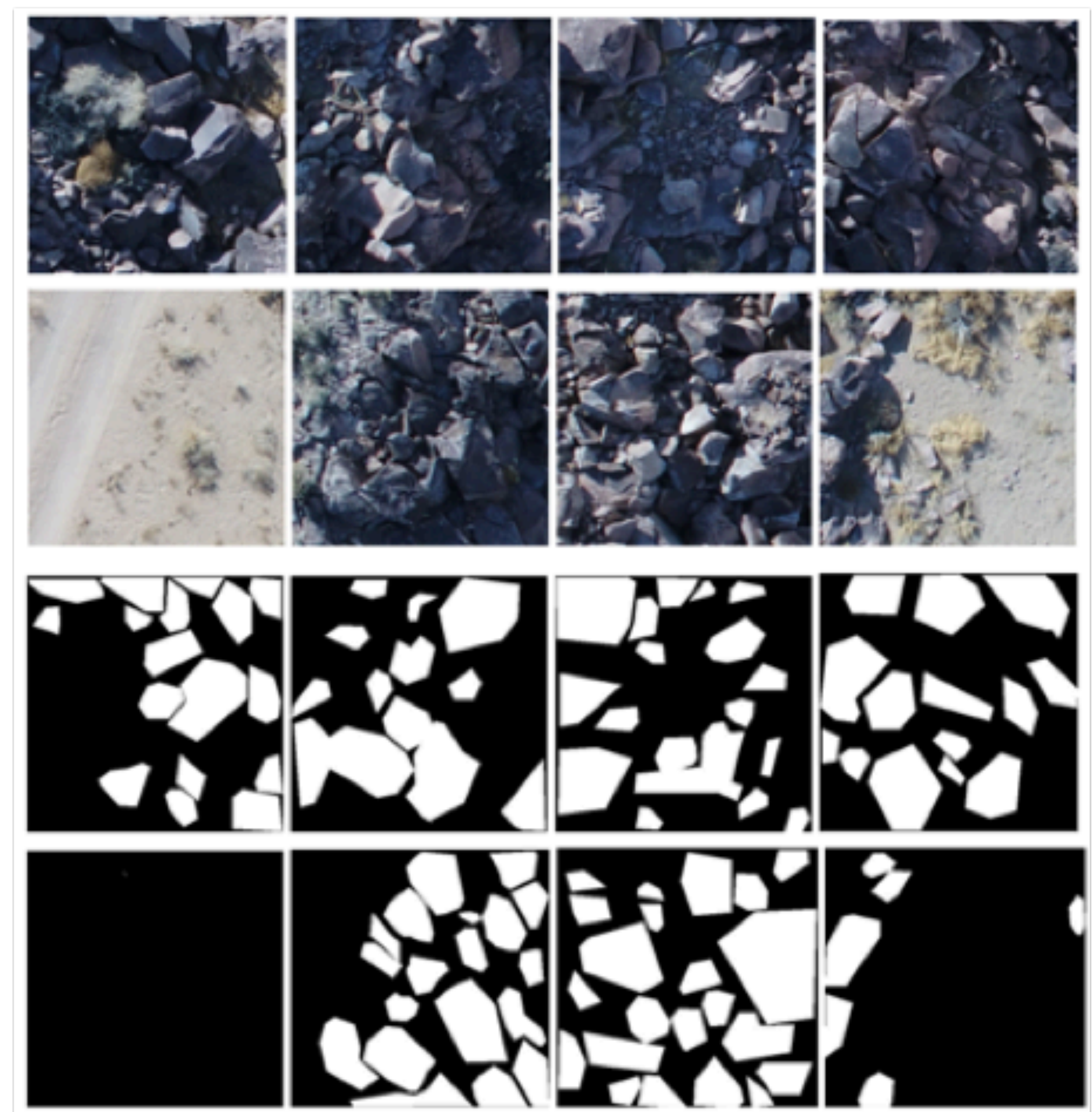
Rock trait mapping



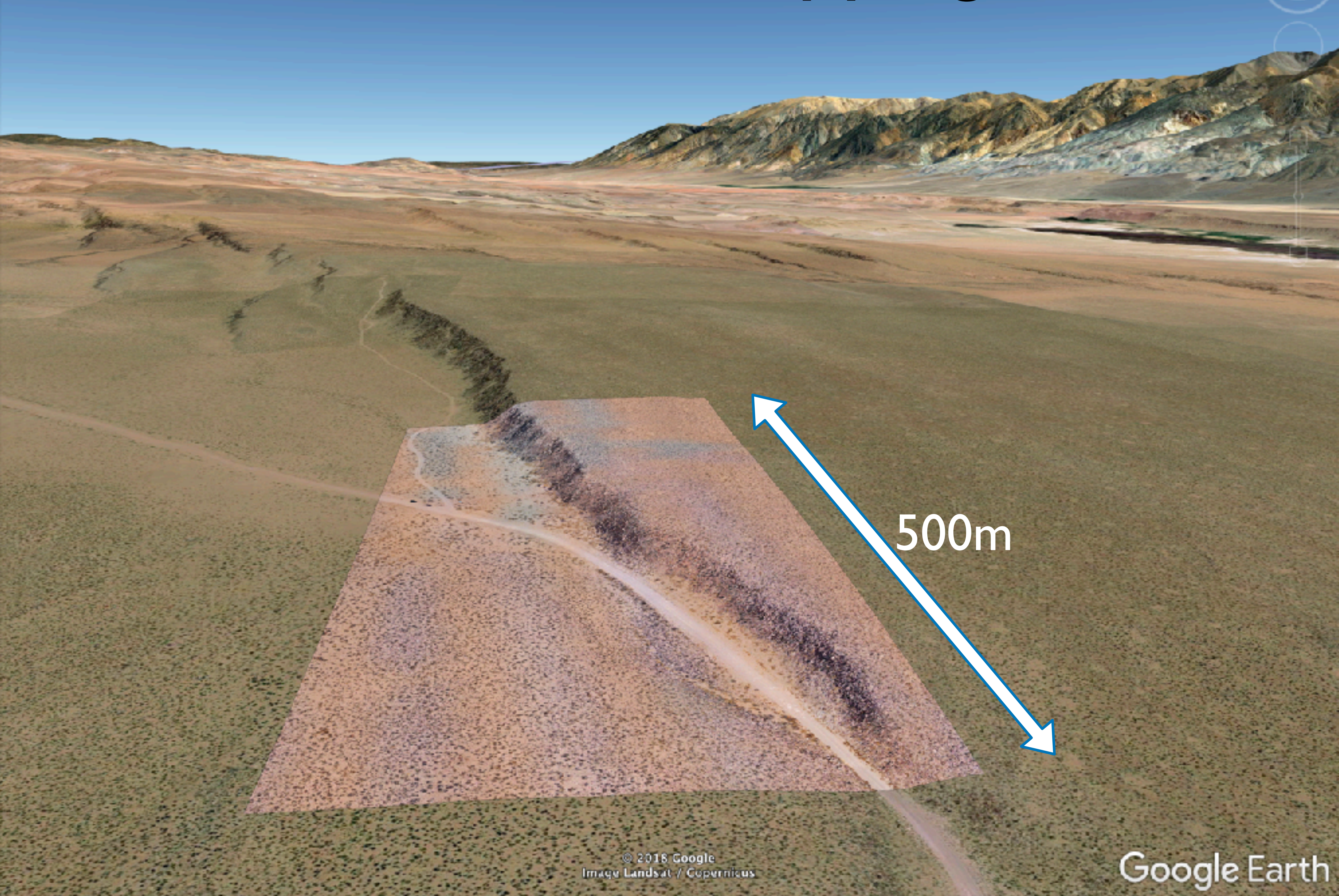
training set

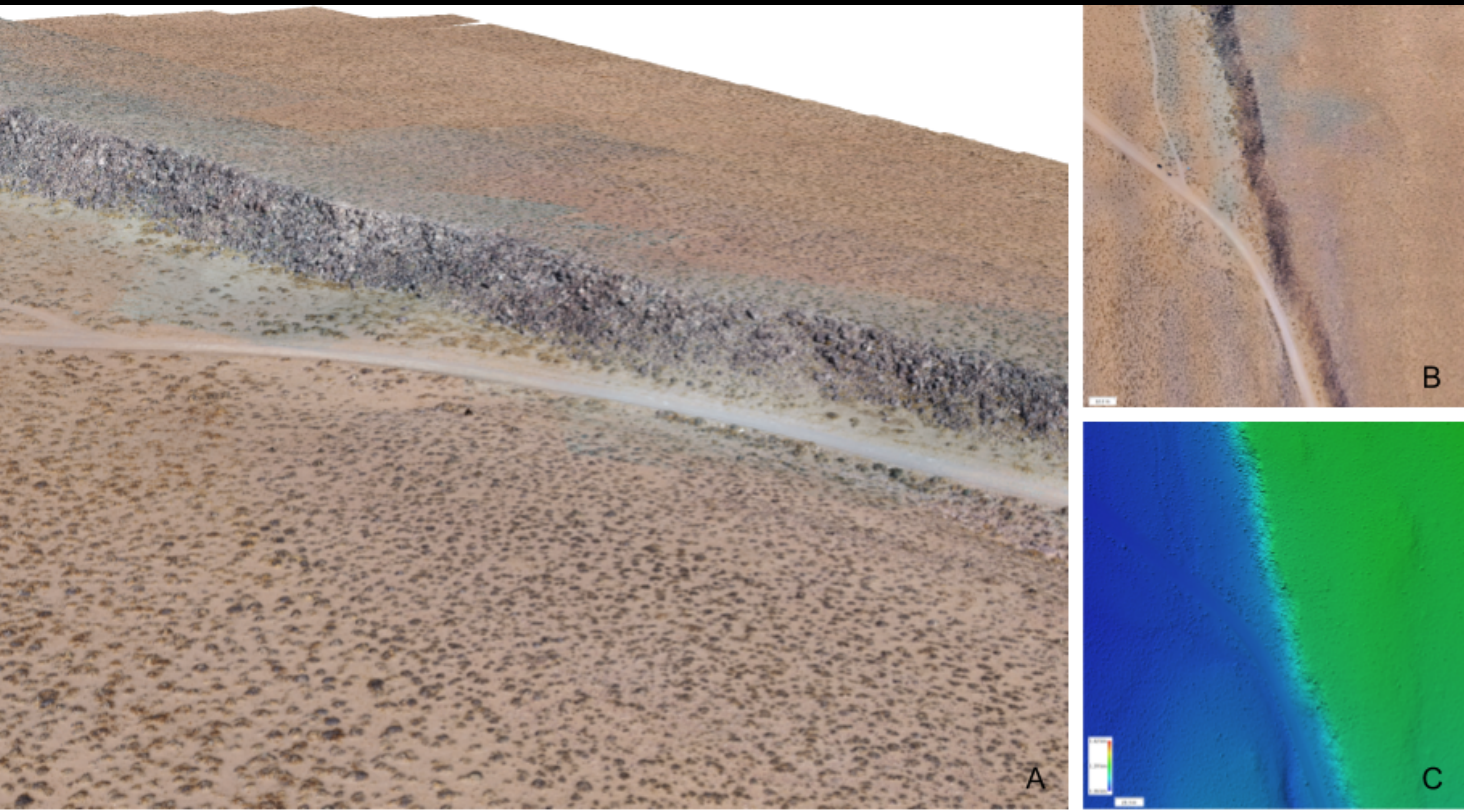


human annotation

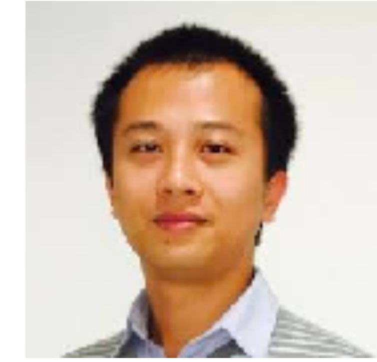


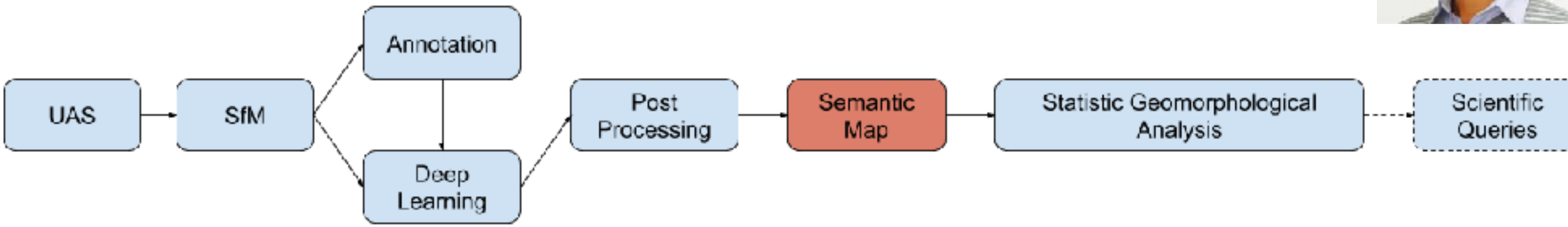
Rock trait mapping



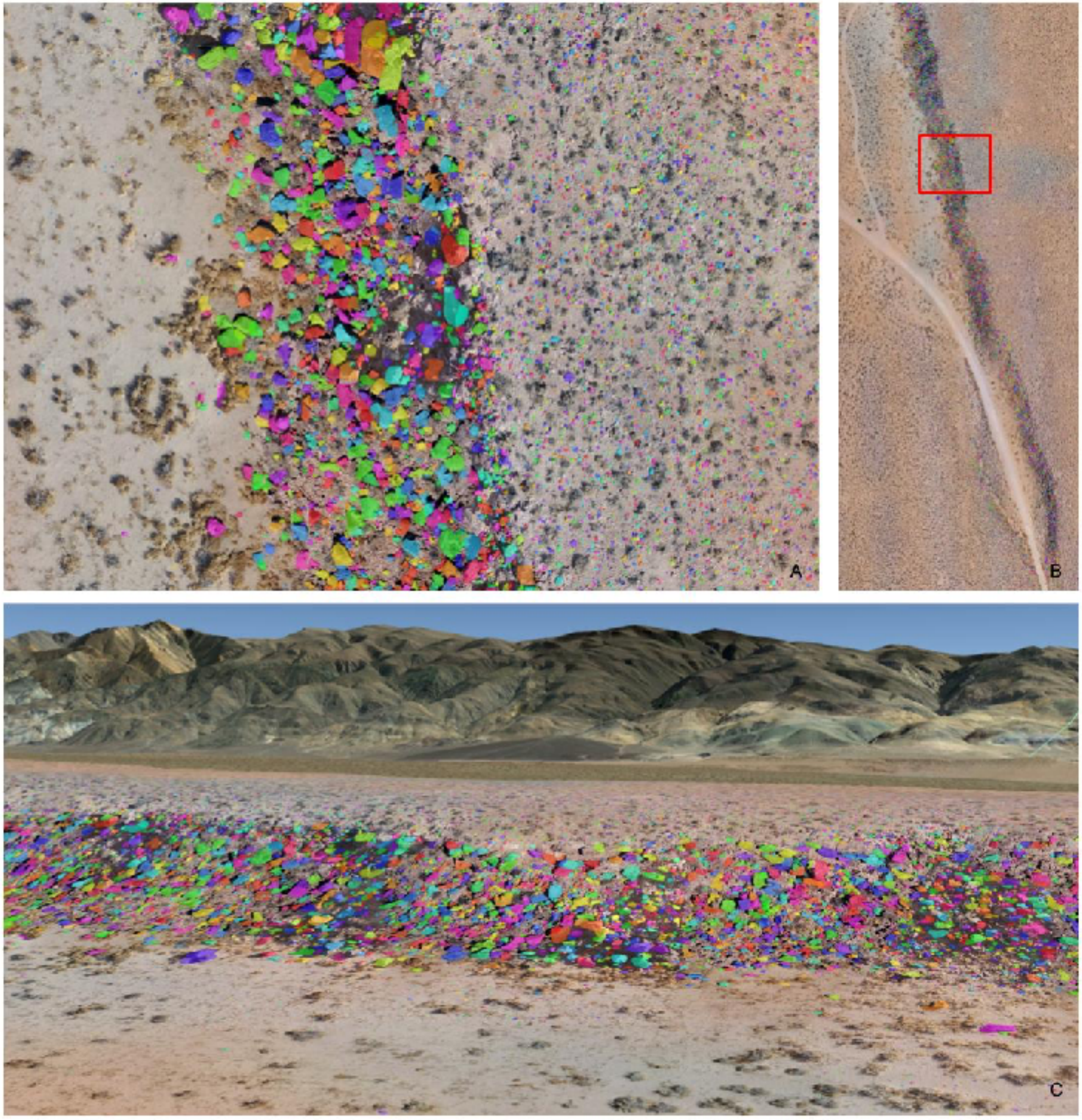

A
B
C

Rock trait mapping

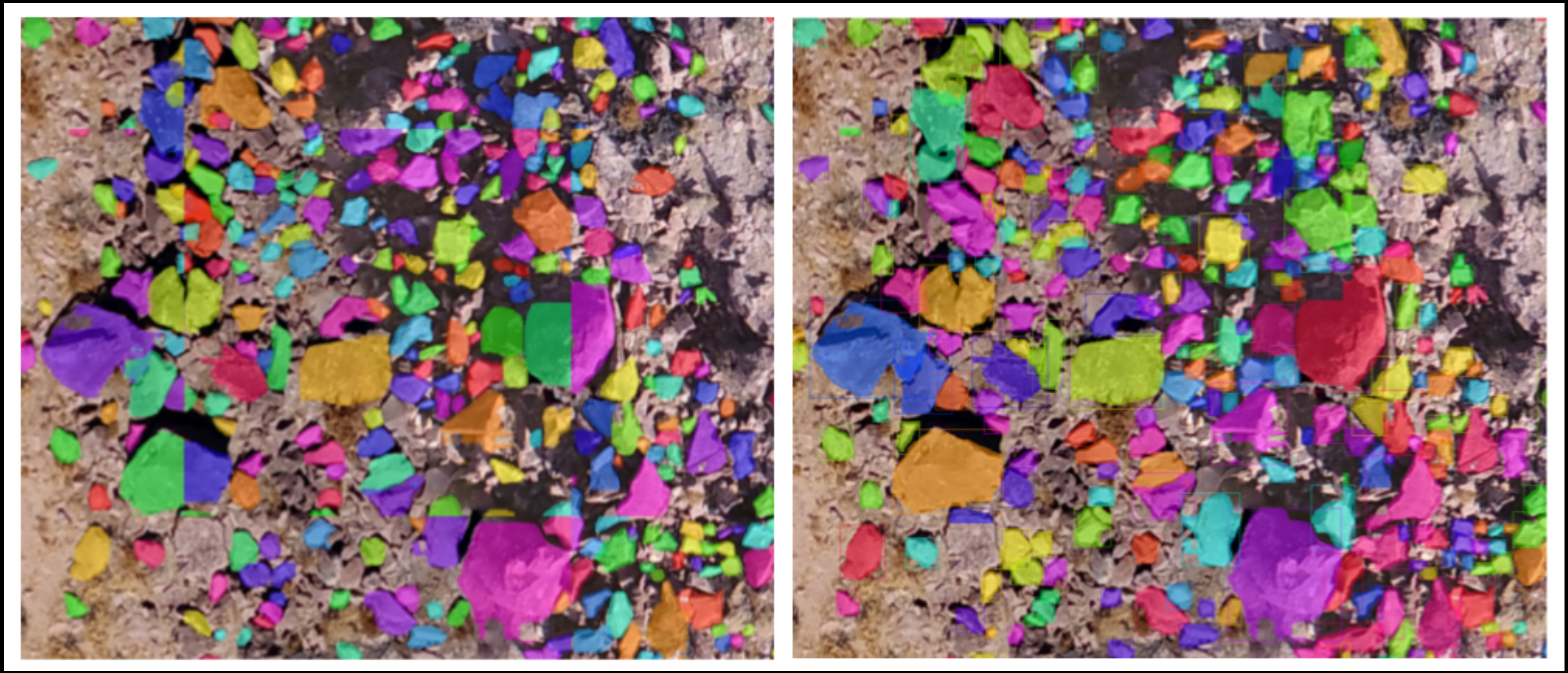




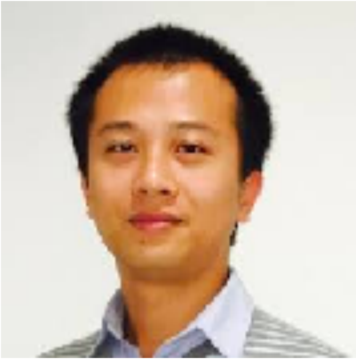
Mask RCNN results


A
B
C

Removing tile boundaries

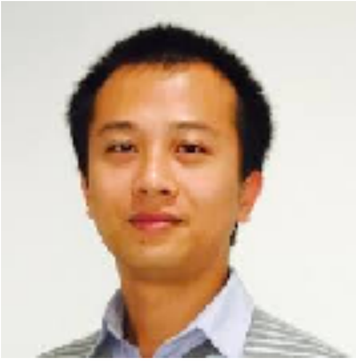


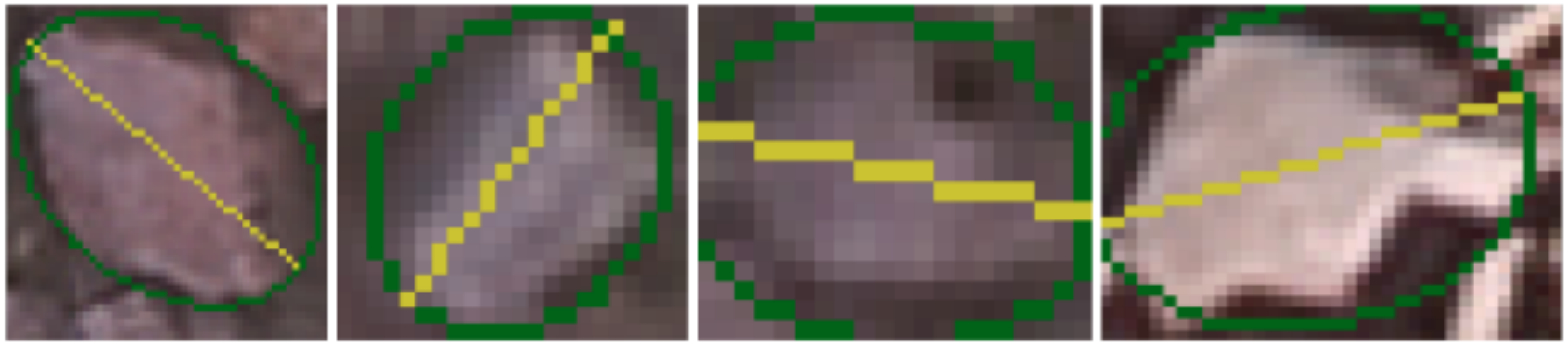
Rock trait mapping



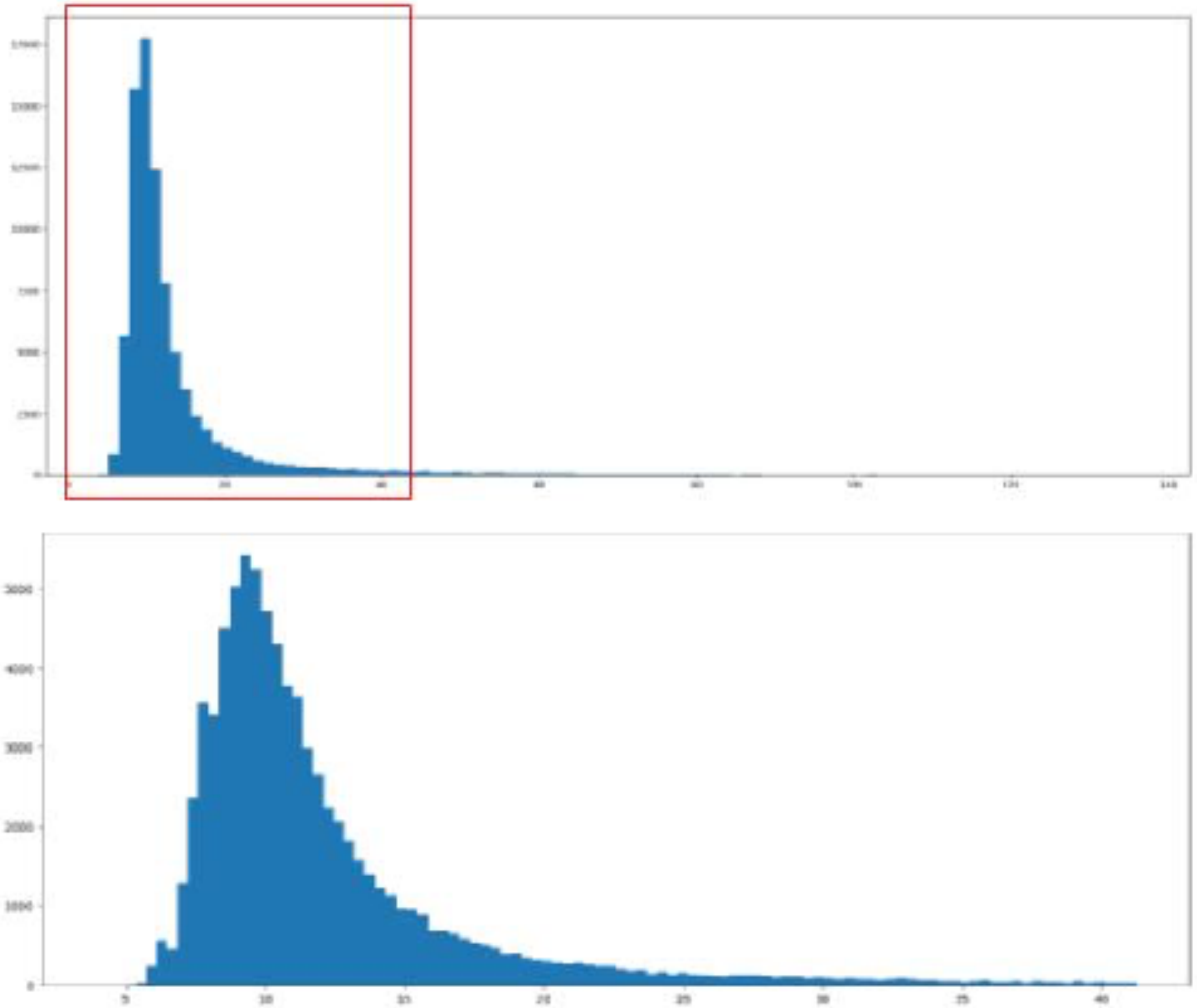
Filtering

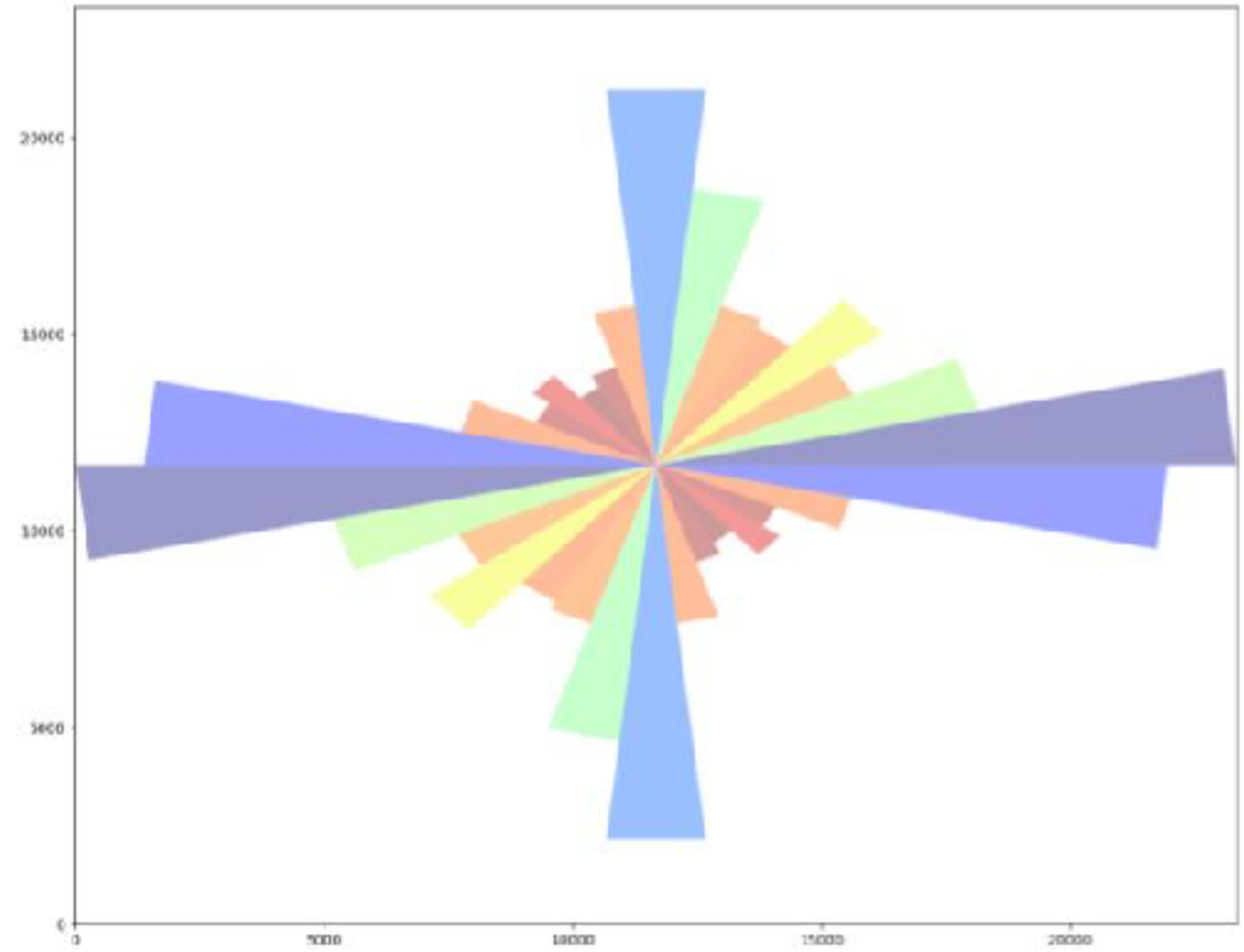
Rock trait mapping





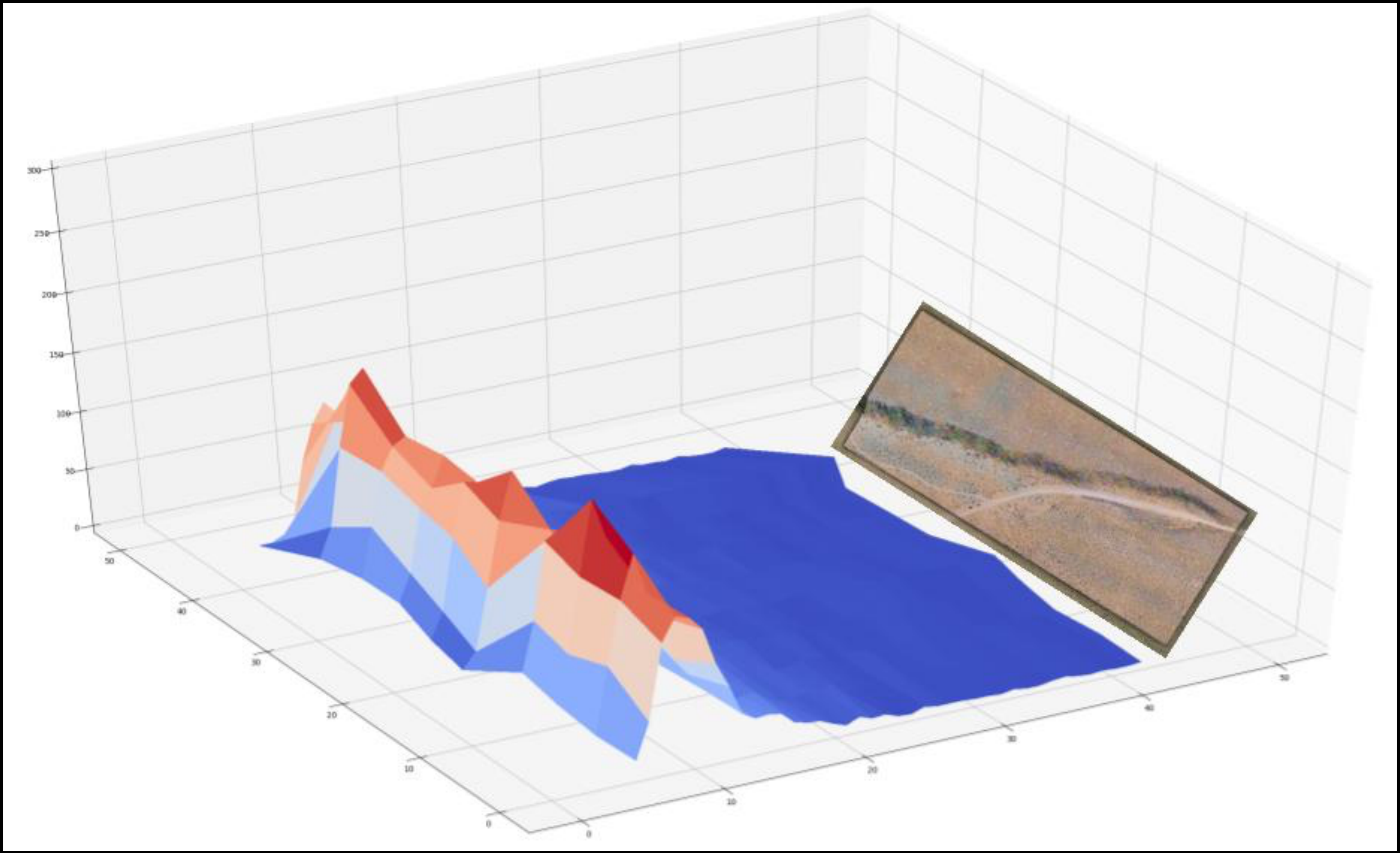
ellipse fitting

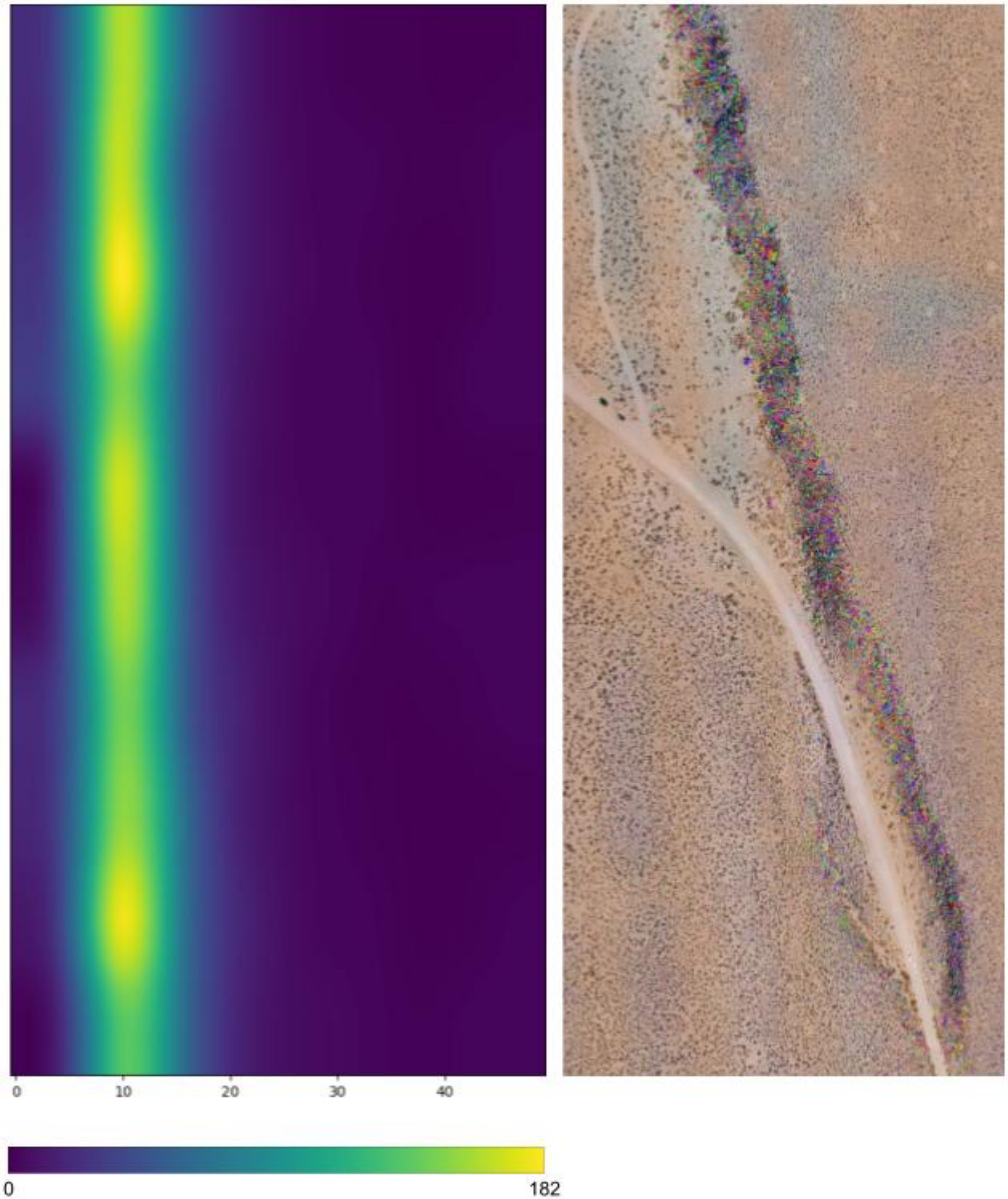




Major-axis length

Major-axis orientation

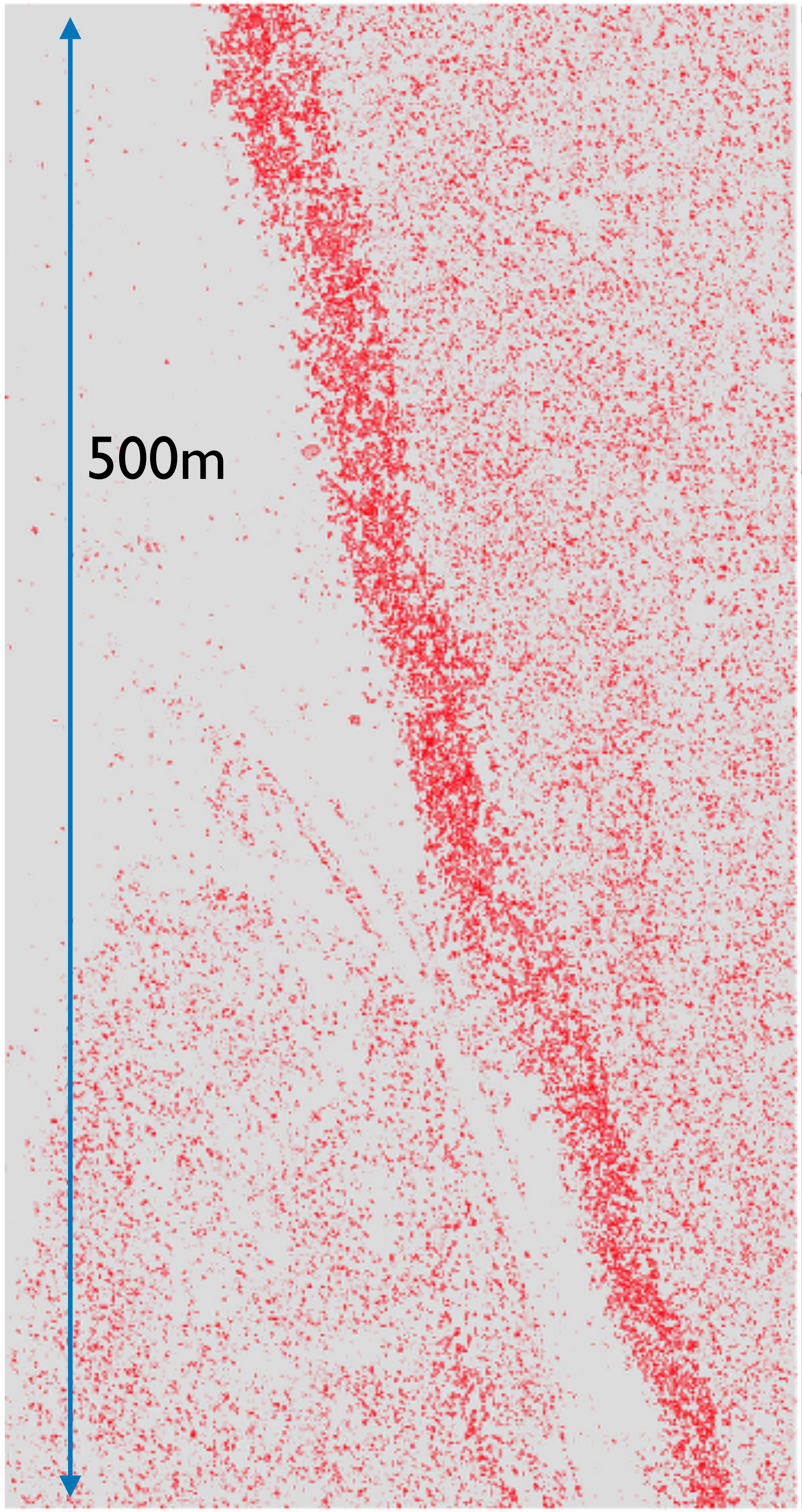

300
250
200
150
100
50
0
50
40
30
20
10
0
0
10
20
30
40
50



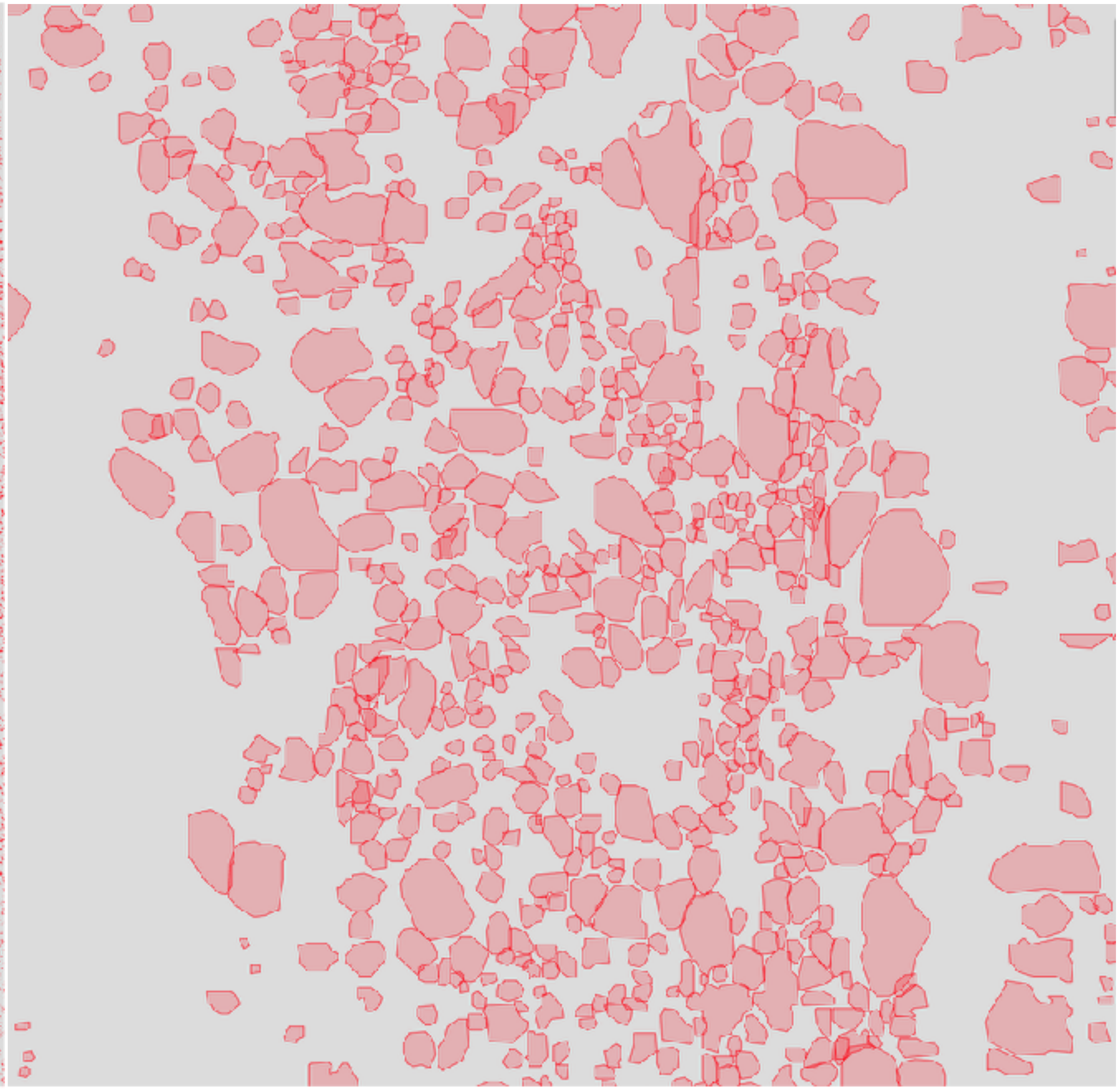
0
10
20
30
40
0
182

Rock trait mapping

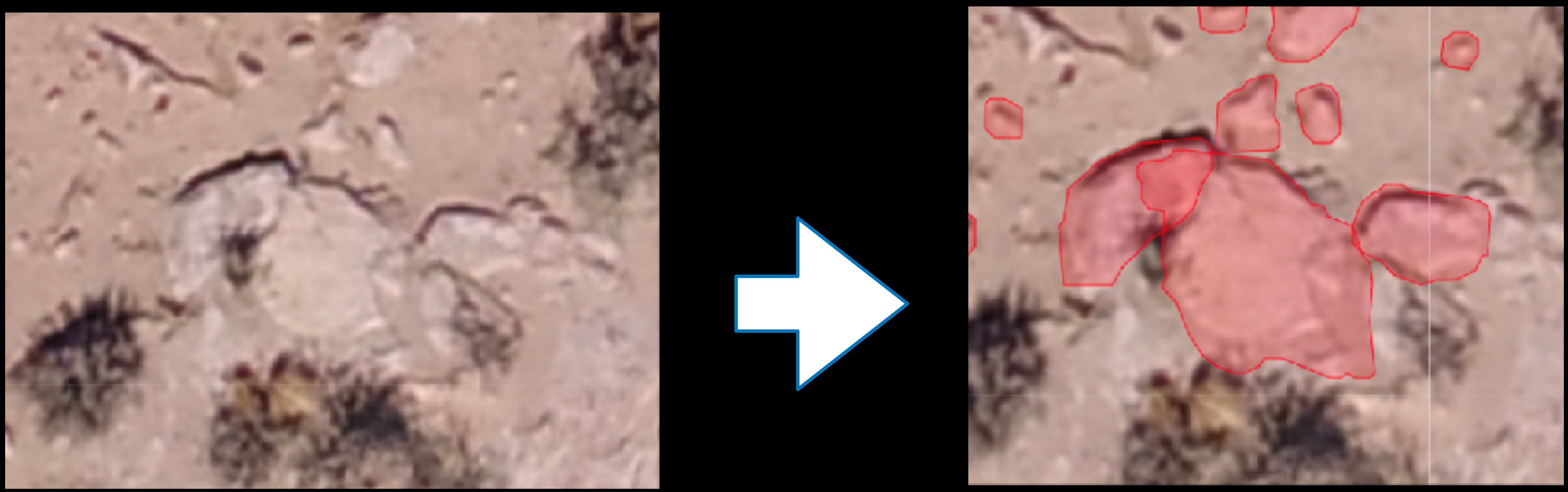
~80,000 rocks



zoomed in



?



Physical Sample Collection

Phytobiopsy

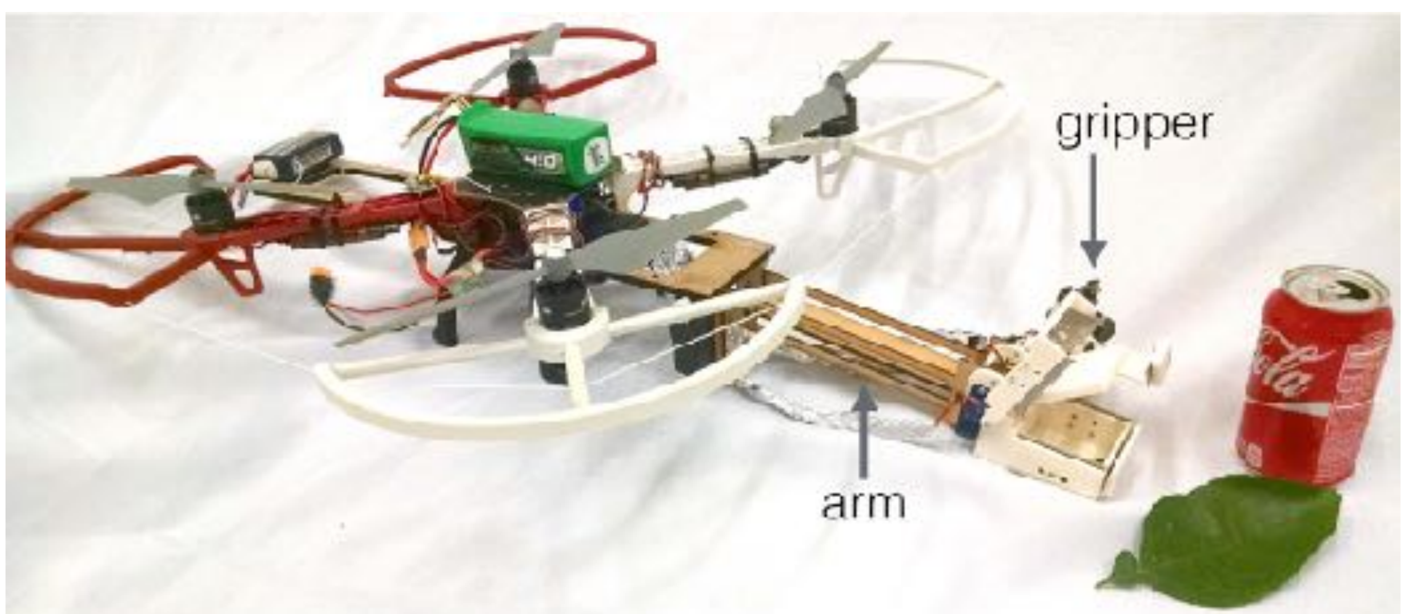
Leaf samples for ex-situ analysis

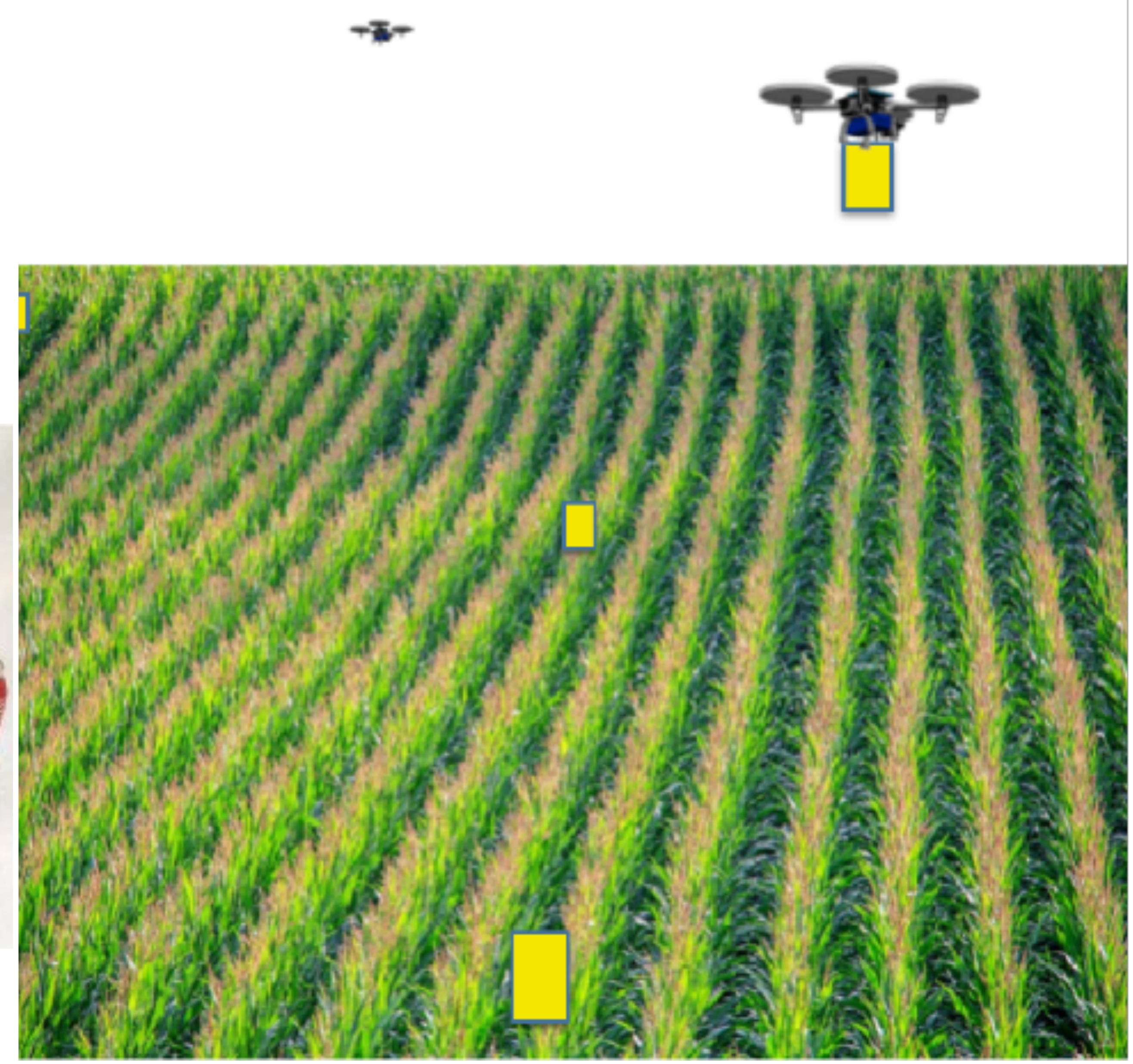
Low dwell-time (seconds)

Environmental probe

Air, soil, pest sample collection

High dwell-time (hours to days)



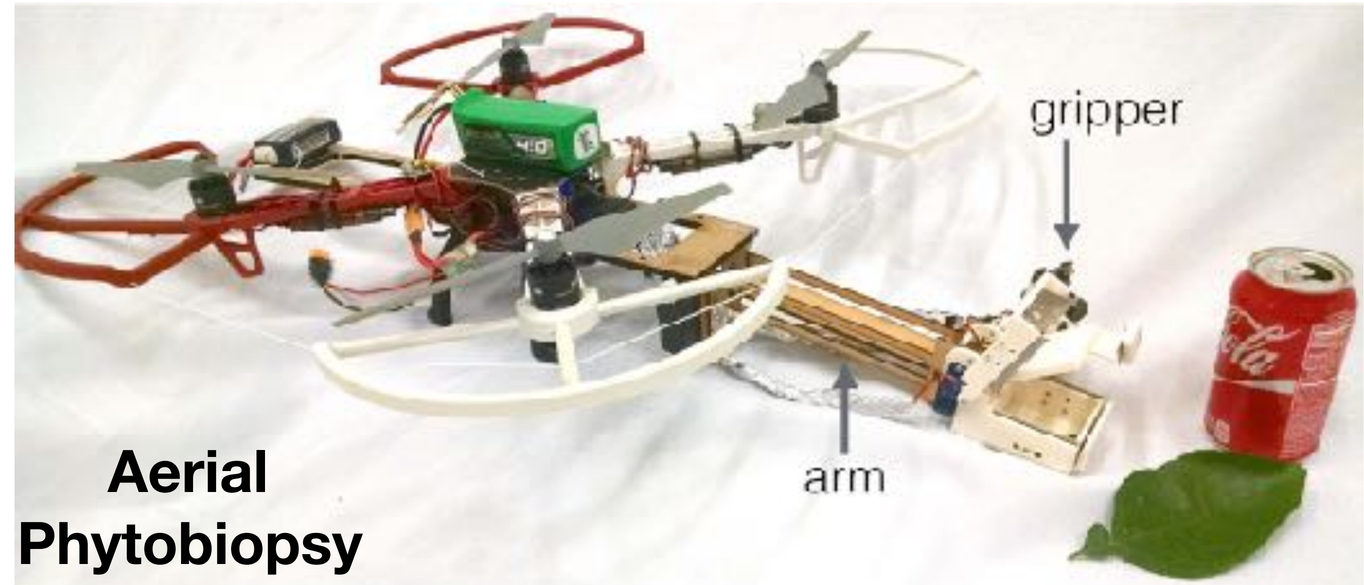


Crop Disease Detection

In-situ analysis

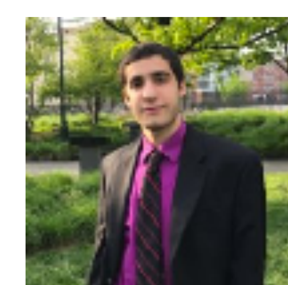
Ex-situ analysis

Aerial Phytopathology



Aerial Phytobiopsy

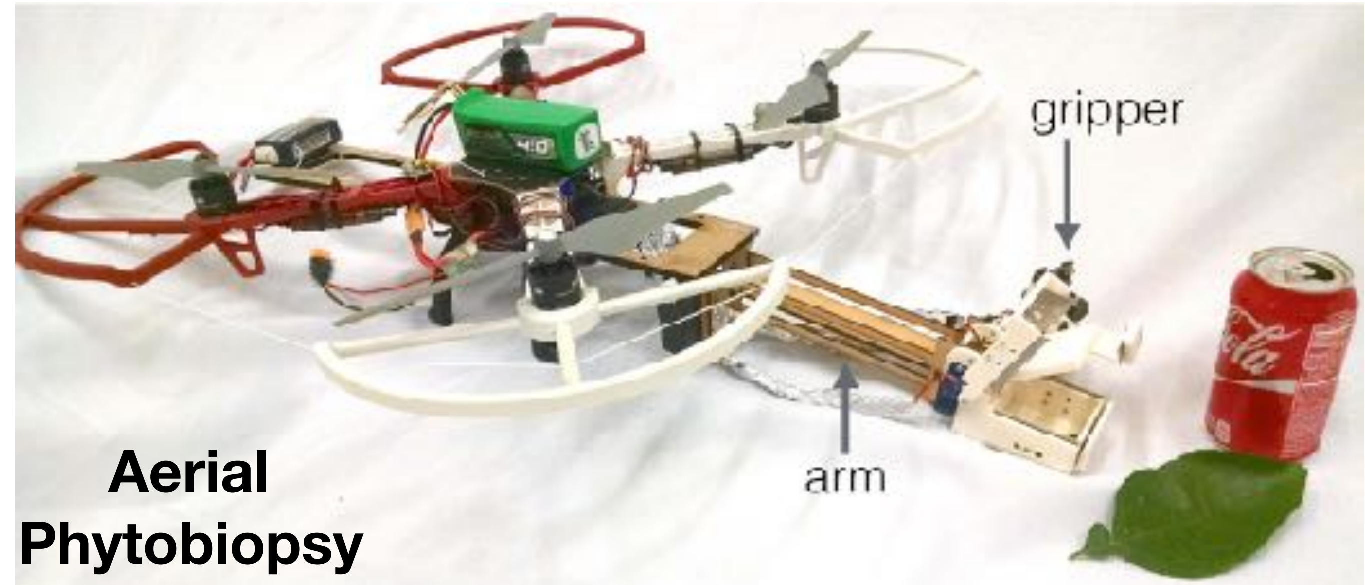
- S. K. Sarkar, J. Das, R. Ehsani and V. Kumar, ”Towards autonomous phytopathology: Outcomes and challenges of citrus greening disease detection through close-range remote sensing,” 2016 IEEE International Conference on Robotics and Automation (ICRA), Stockholm, 2016, pp. 5143-5148.
- D. Orol, J. Das, L. Vacek, I. Orr, M. Paret, C.J. Taylor, V. Kumar, ”An aerial phyto- biopsy system: Design, evaluation, and lessons learned,” 2017 International Conference on Unmanned Aircraft Systems (ICUAS), Miami, FL, USA, 2017, pp. 188-195.



Crop Disease Detection

In-situ analysis

Ex-situ analysis



Aerial Phytopathology

Aerial Phytobiopsy

- *S. K. Sarkar, J. Das, R. Ehsani and V. Kumar, "Towards autonomous phytopathology: Outcomes and challenges of citrus greening disease detection through close-range remote sensing," 2016 IEEE International Conference on Robotics and Automation (ICRA), Stockholm, 2016, pp. 5143-5148.*
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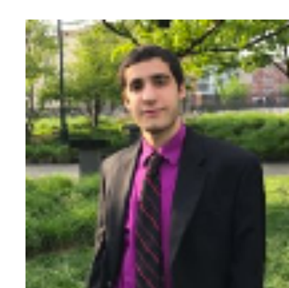
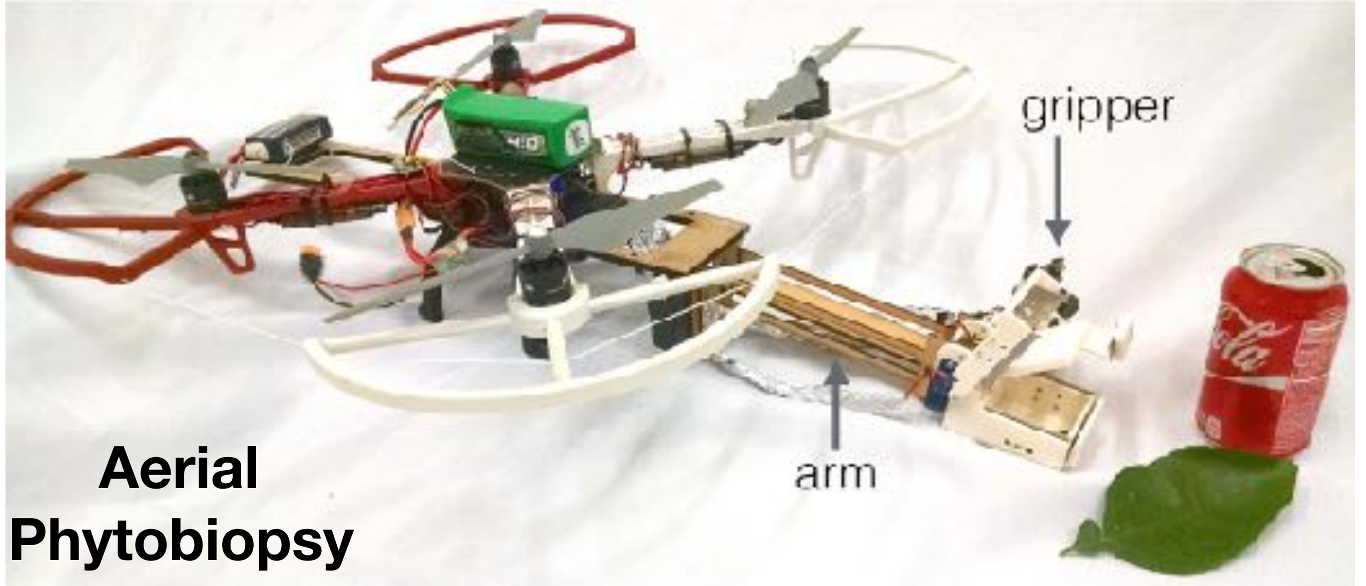


Crop Disease Detection

In-situ analysis

Ex-situ analysis

Aerial Phytopathology



Aerial Phytobiopsy

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Aerial Phytobiopsy

Samples retrieved during experiments

D. Orol, J. Das, L. Vacek, I. Orr, M. Paret, C. J. Taylor, and V. Kumar, “An aerial phytobiopsy system: Design, evaluation, and lessons learned,” in 2017 International Conference on Unmanned Aircraft Systems (ICUAS), June 2017, pp. 188–195.

UV Fluorescence Spectroscopy for Biogeochemical Mapping

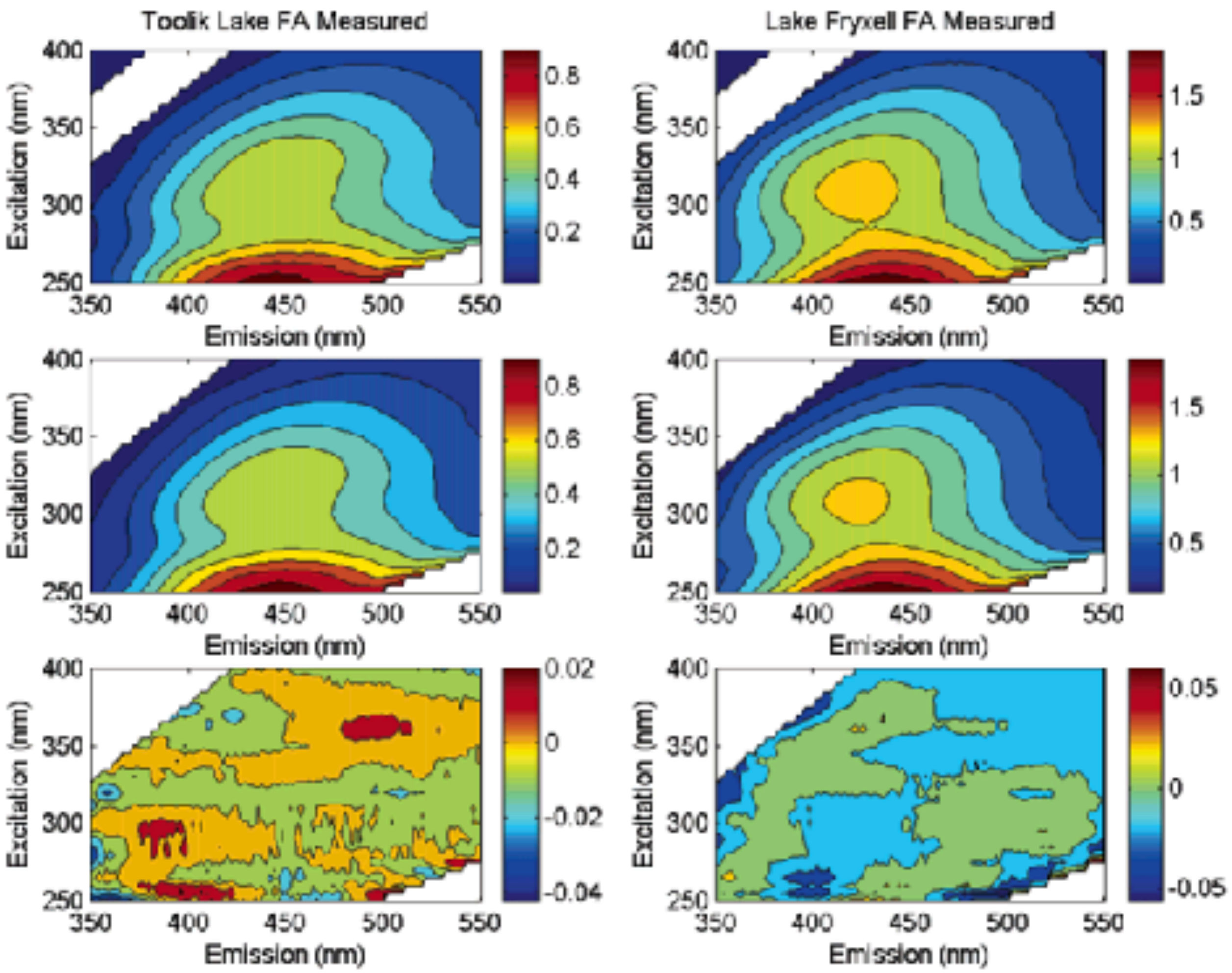


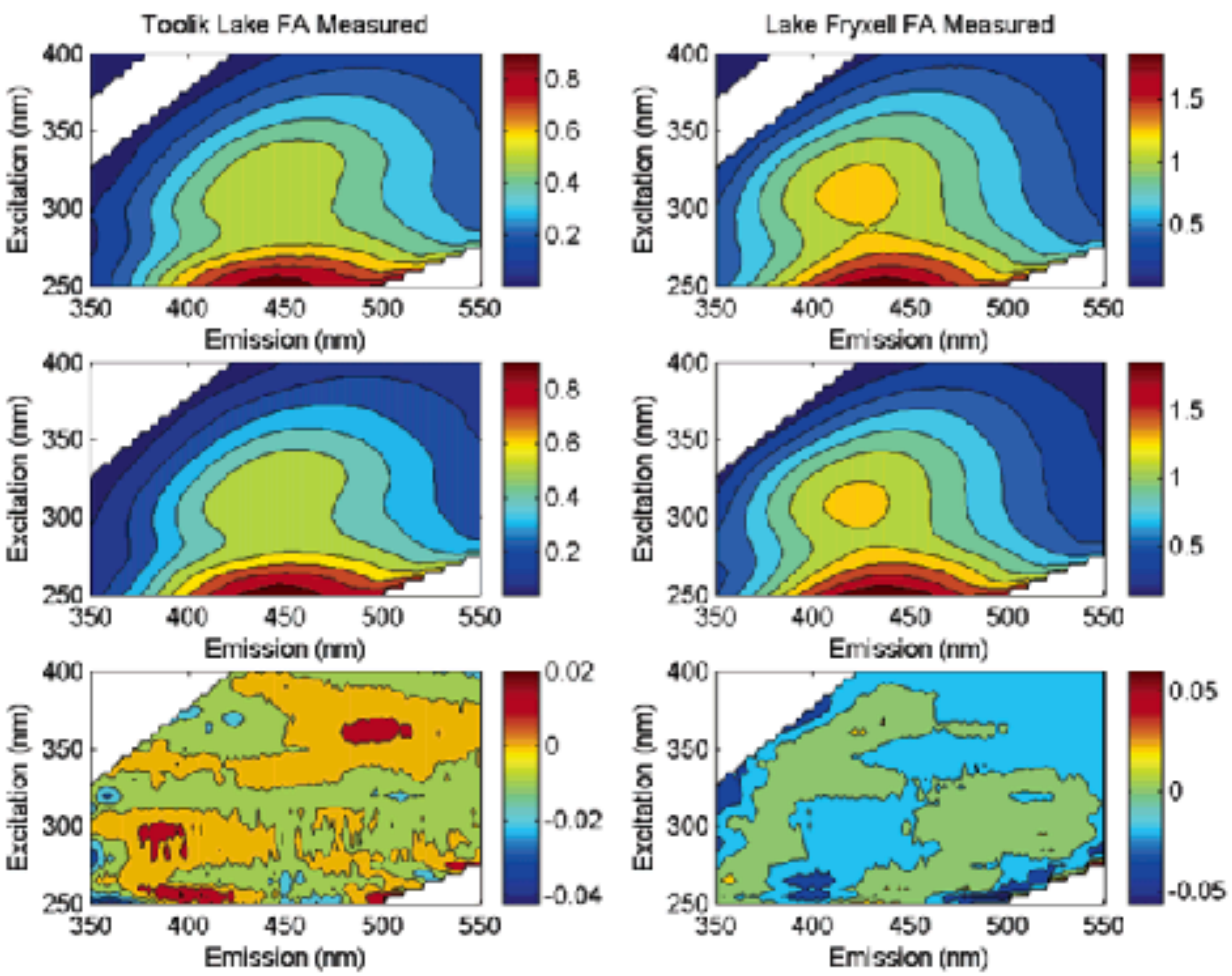
FIGURE 3. Comparison of the measured (top), modeled (middle), and residual (bottom) EEMs for two samples: Toolik Lake fulvic acid and Lake Fryxell fulvic acid. Intensities are in Raman units and are a function of the concentration of the prepared fulvic acid solution. Each contour plot was generated in Matlab using 10 contour lines.

Cory & McKnight (2005)
Fluorescence Spectroscopy Reveals Ubiquitous Presence of Oxidized and Reduced Quinones in Dissolved Organic Matter

USD 14,000

Excitation-emission matrix (EEM)
quinone, amino acid

UV Fluorescence Spectroscopy for Biogeochemical Mapping



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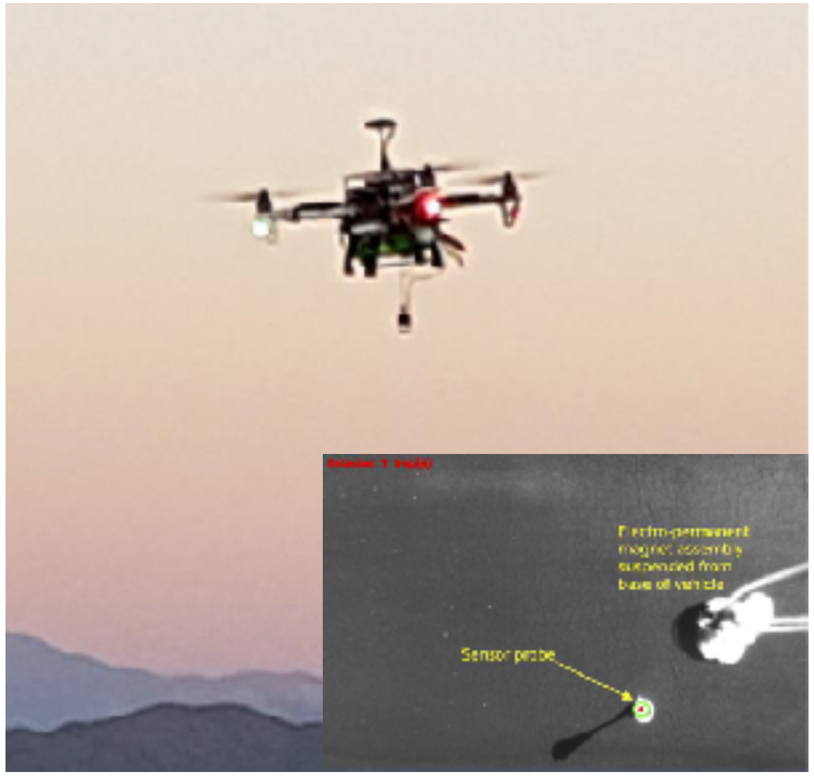
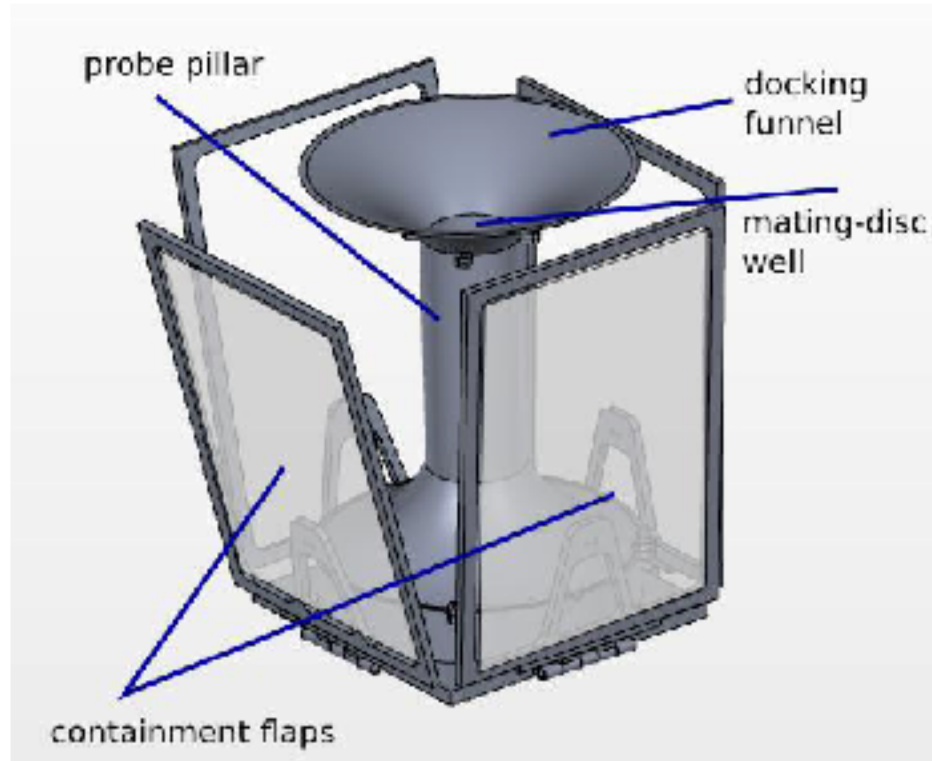
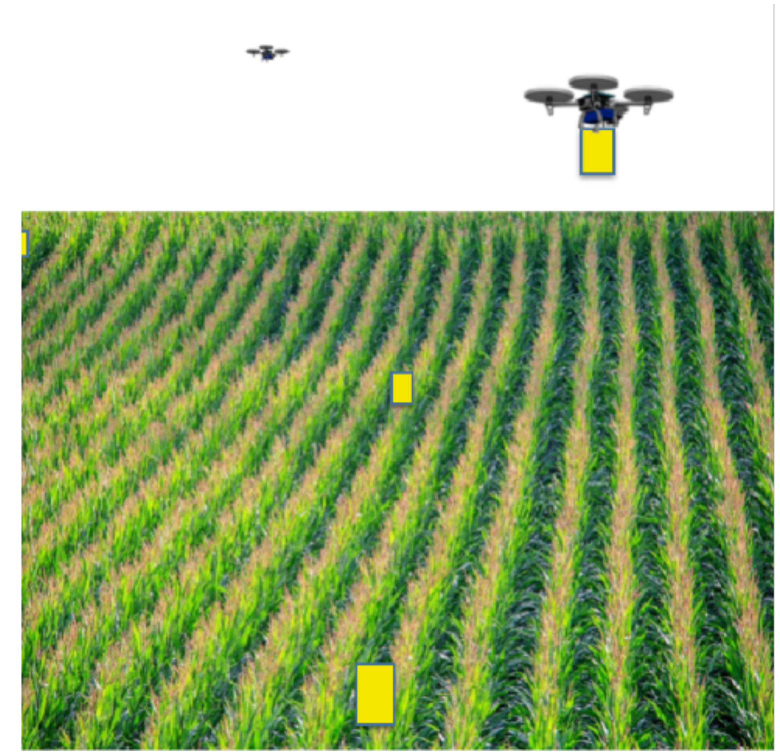
USD 4,000

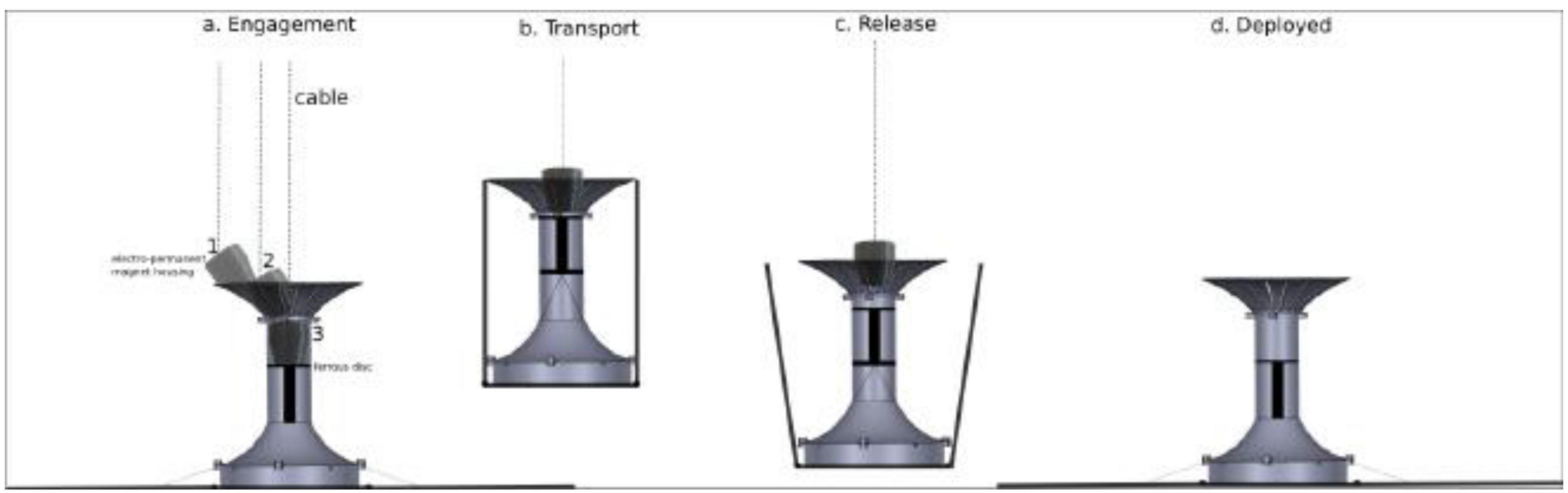
OceanOptics FLAME UV-VIS Spectrometer

Probe Deployment and Recovery

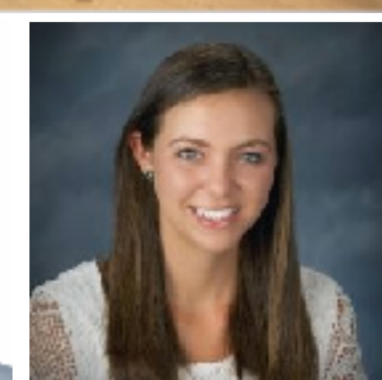


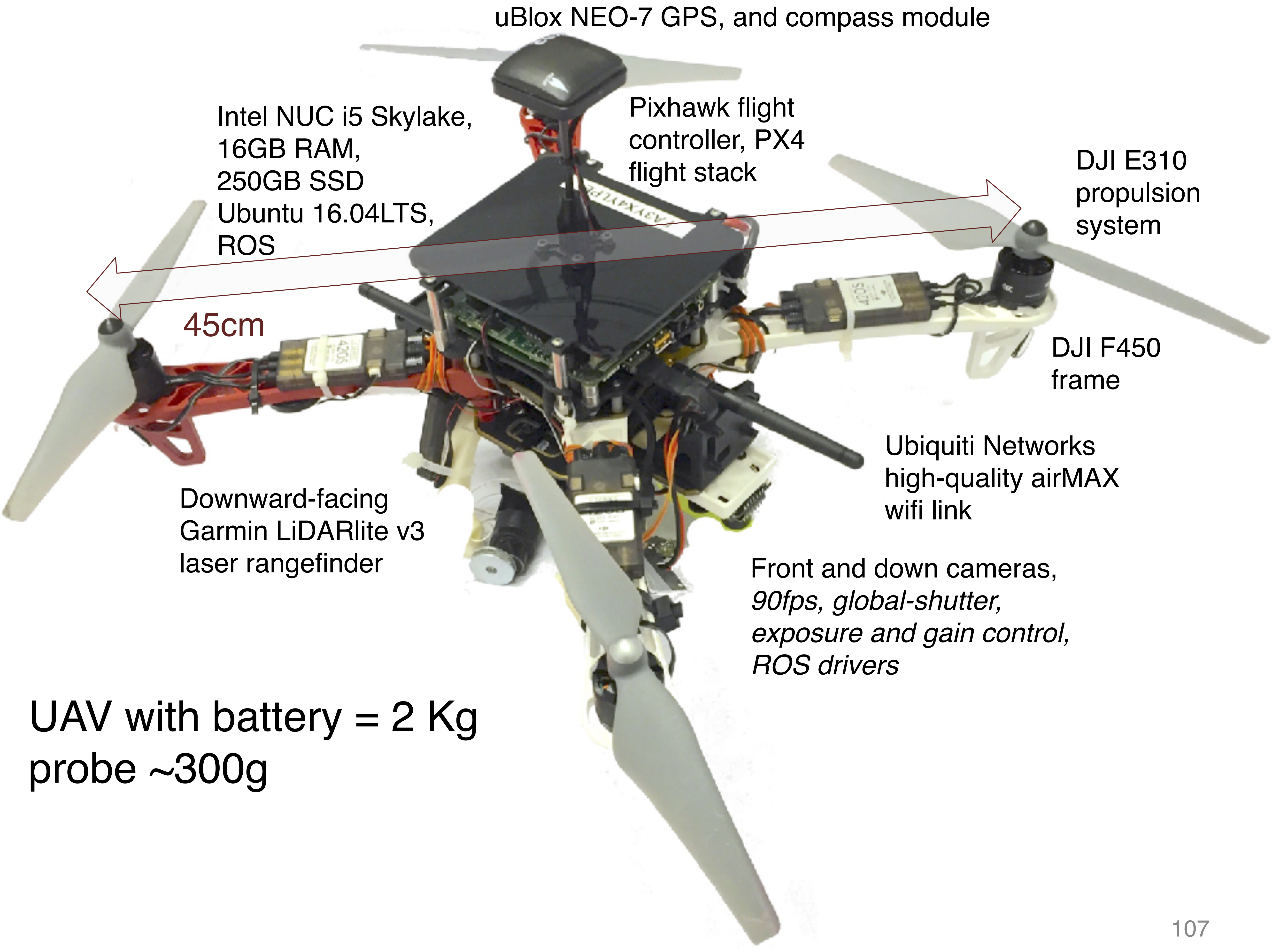






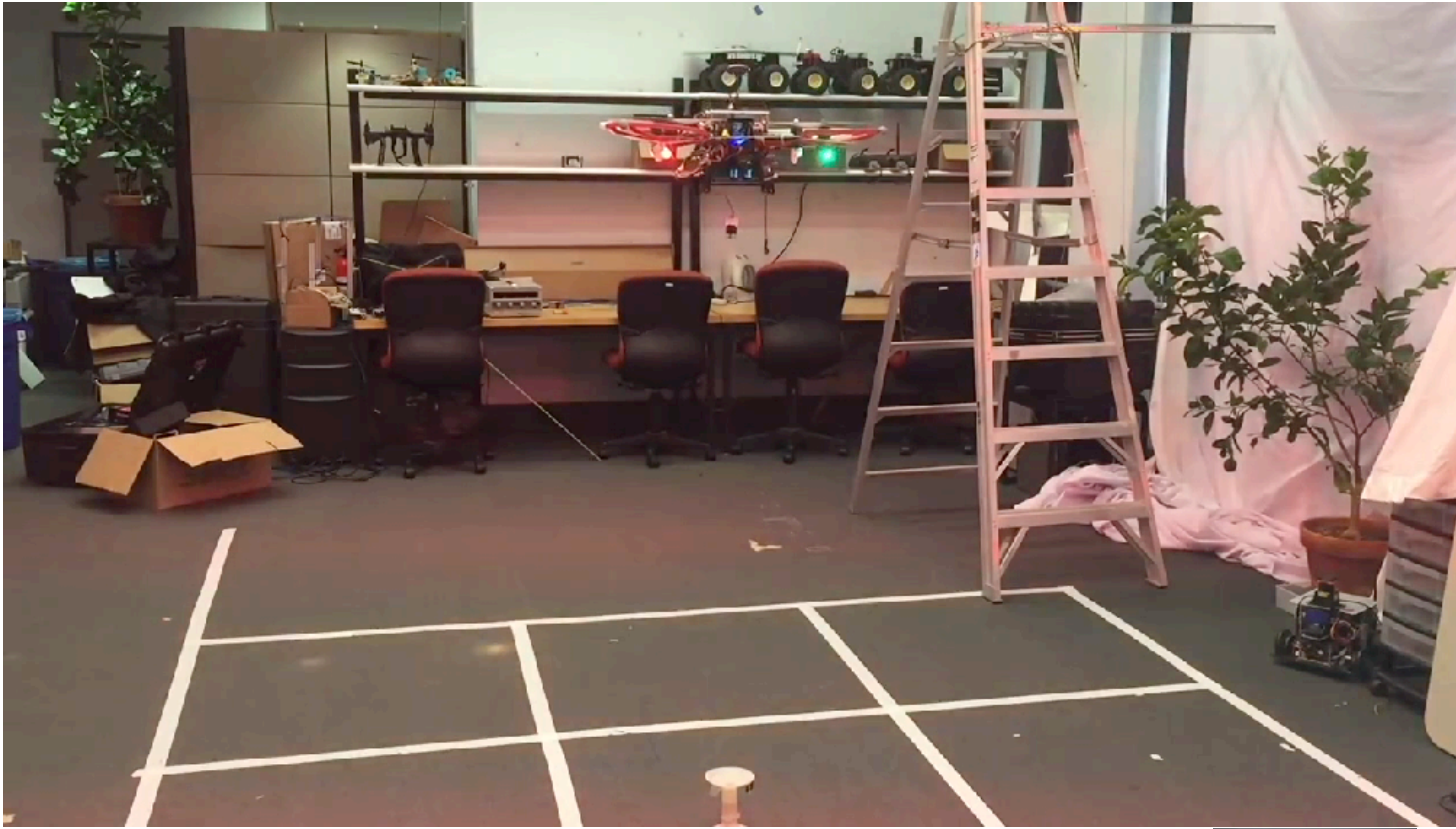
L. Vacek, E. Atter, P. Rizo, B. Nam, R. Kortvelesy, D. Kaufman, J. Das, and V. Kumar, “sUAS for deployment and recovery of an environmental sensor probe,” in 2017 International Conference on Unmanned Aircraft Systems (ICUAS), June 2017, pp. 1022–1029.





UAV with battery = 2 Kg
probe ~300g

Probe Deployment and Recovery



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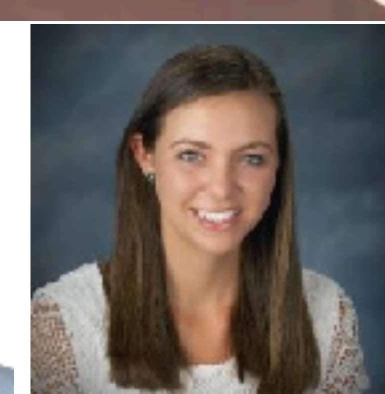
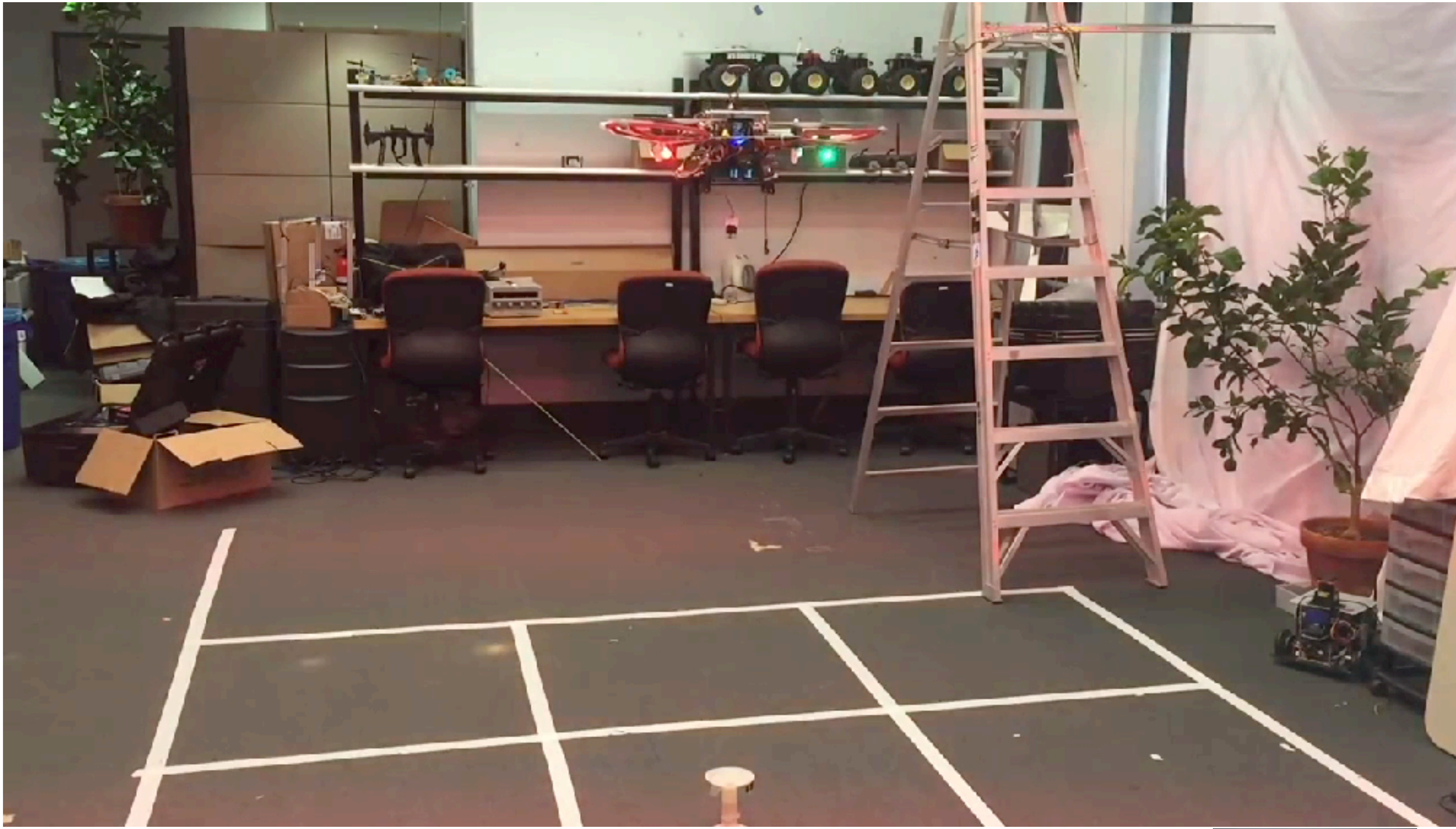


Probe Deployment and Recovery



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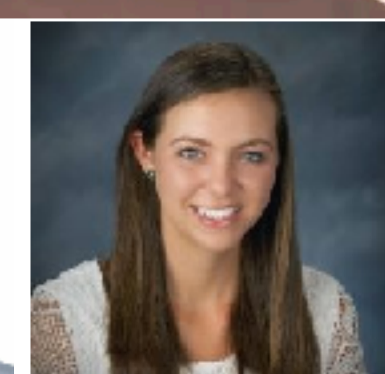

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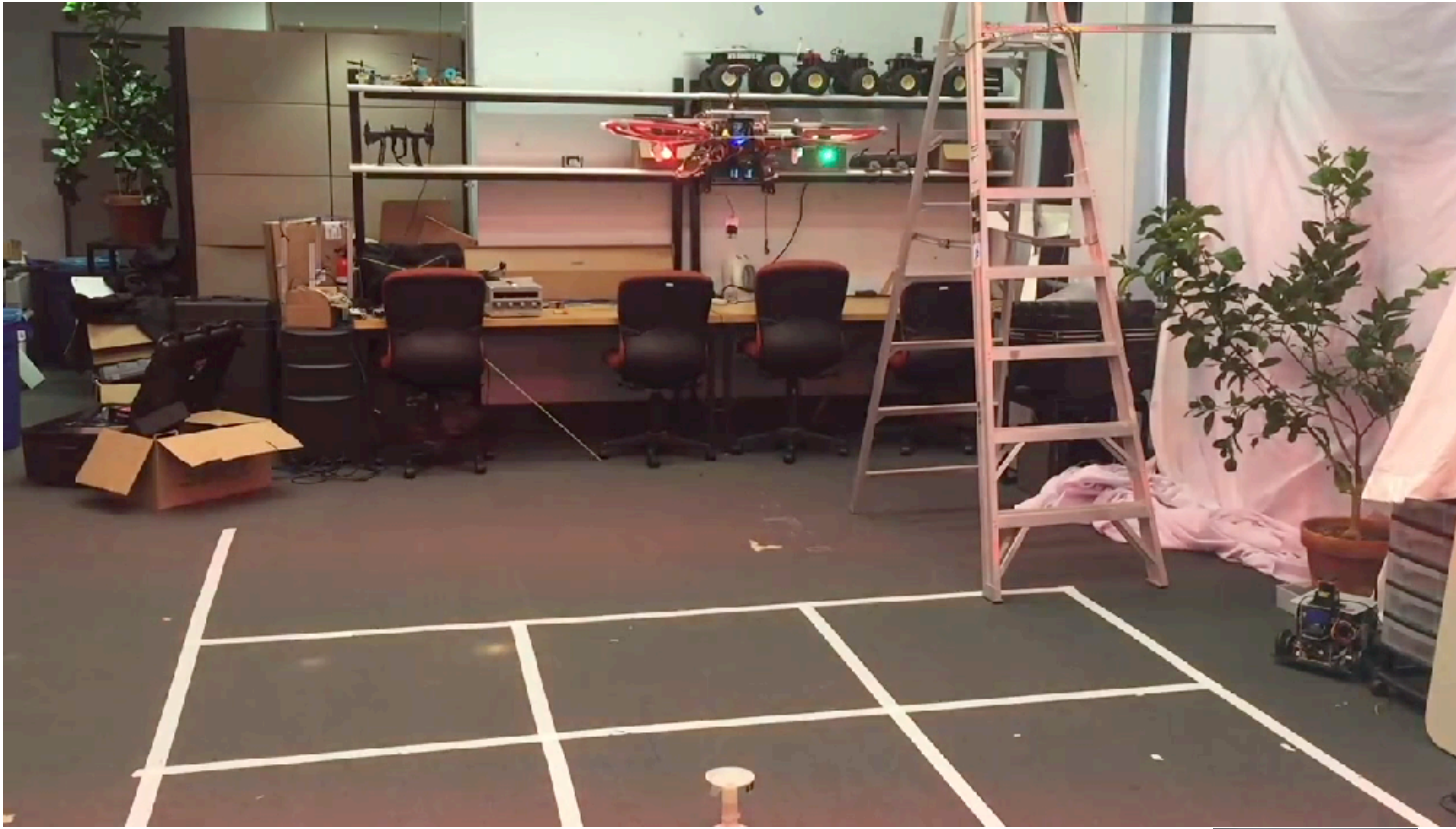

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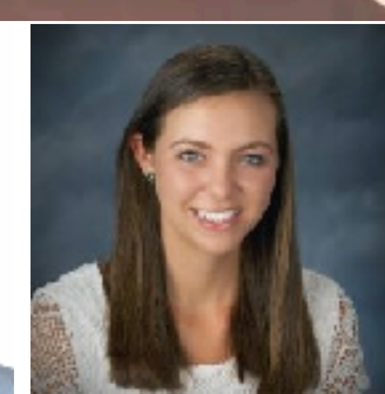
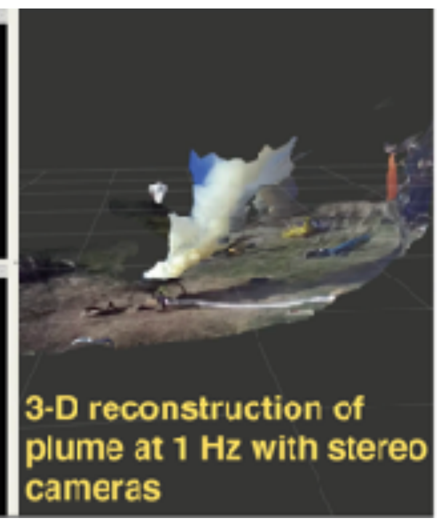
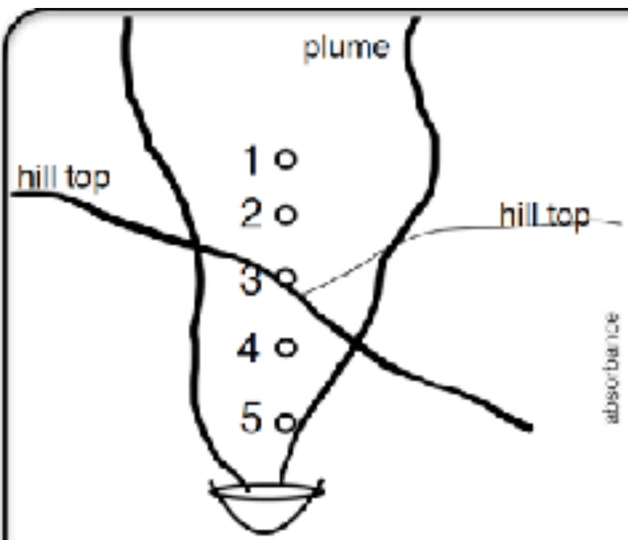
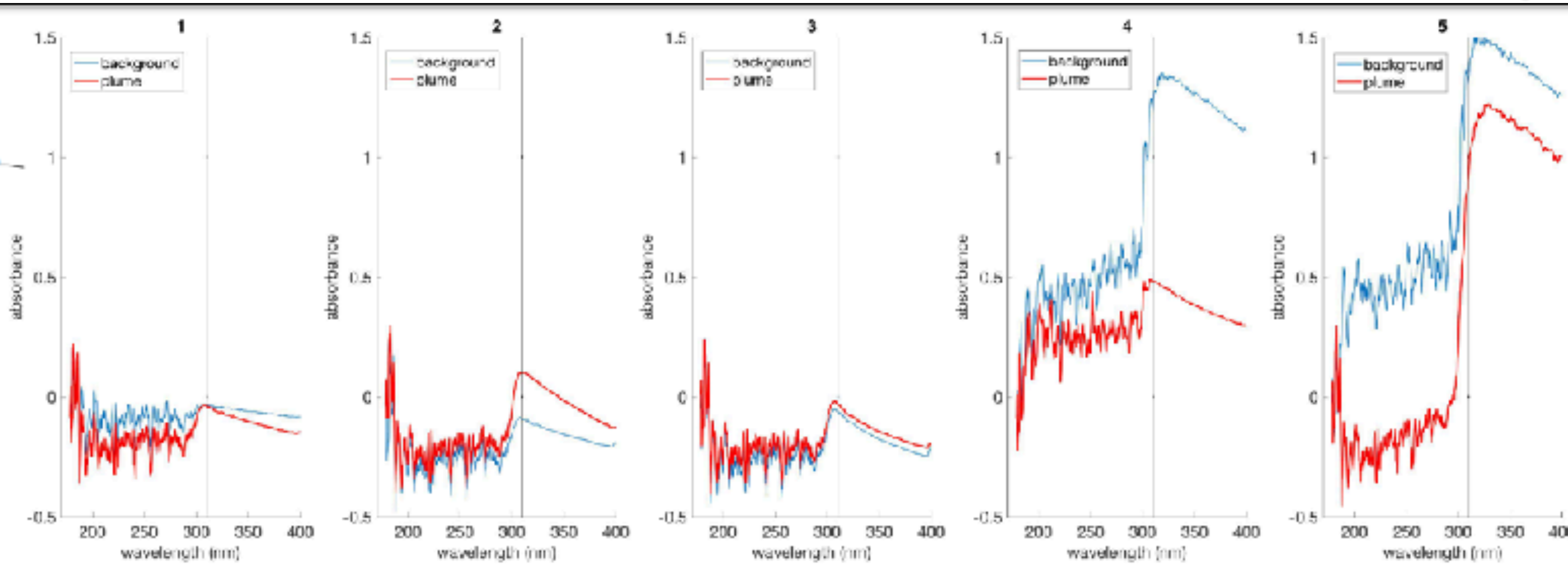


Small-scale Volcanology Tests





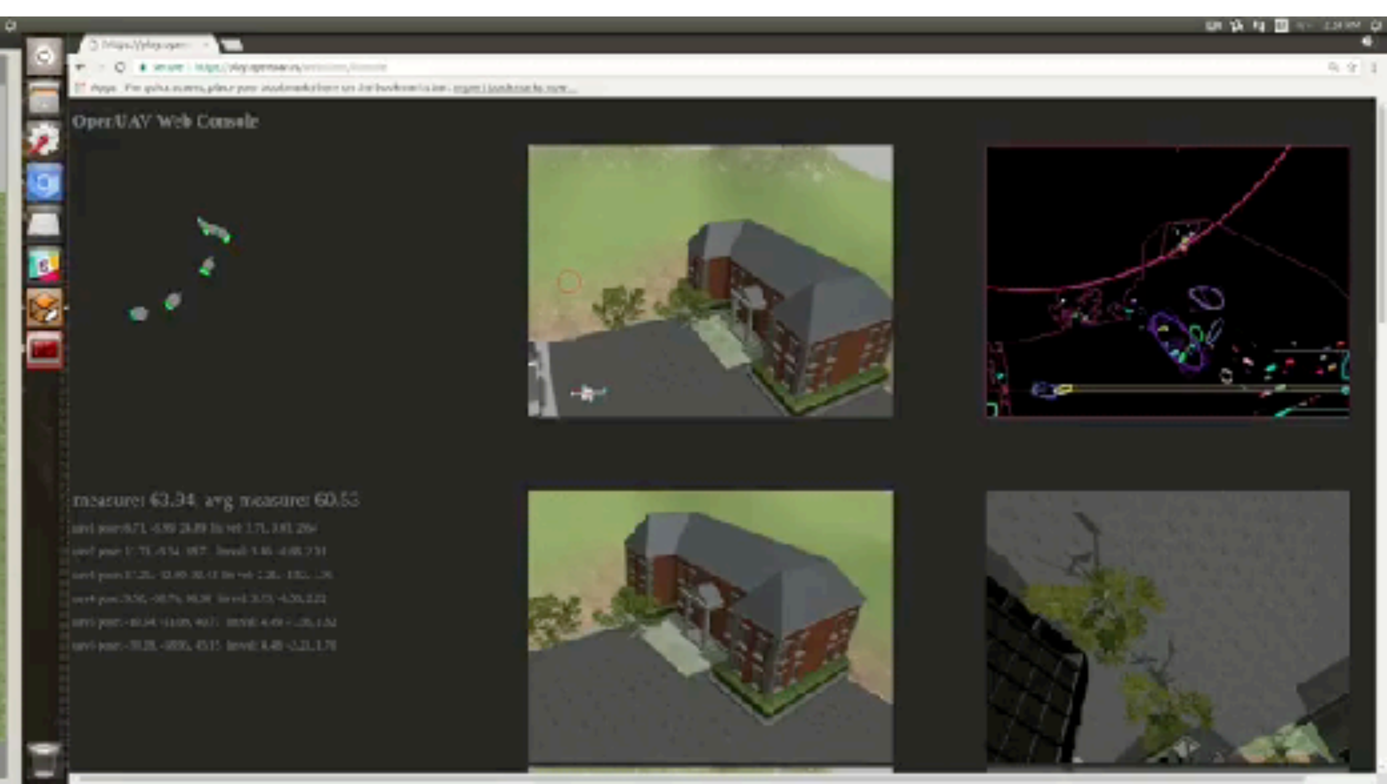


Absorbance for background points corresponding to sky and hills were acquired before starting the smoke plume.

Small-scale Volcanology Tests

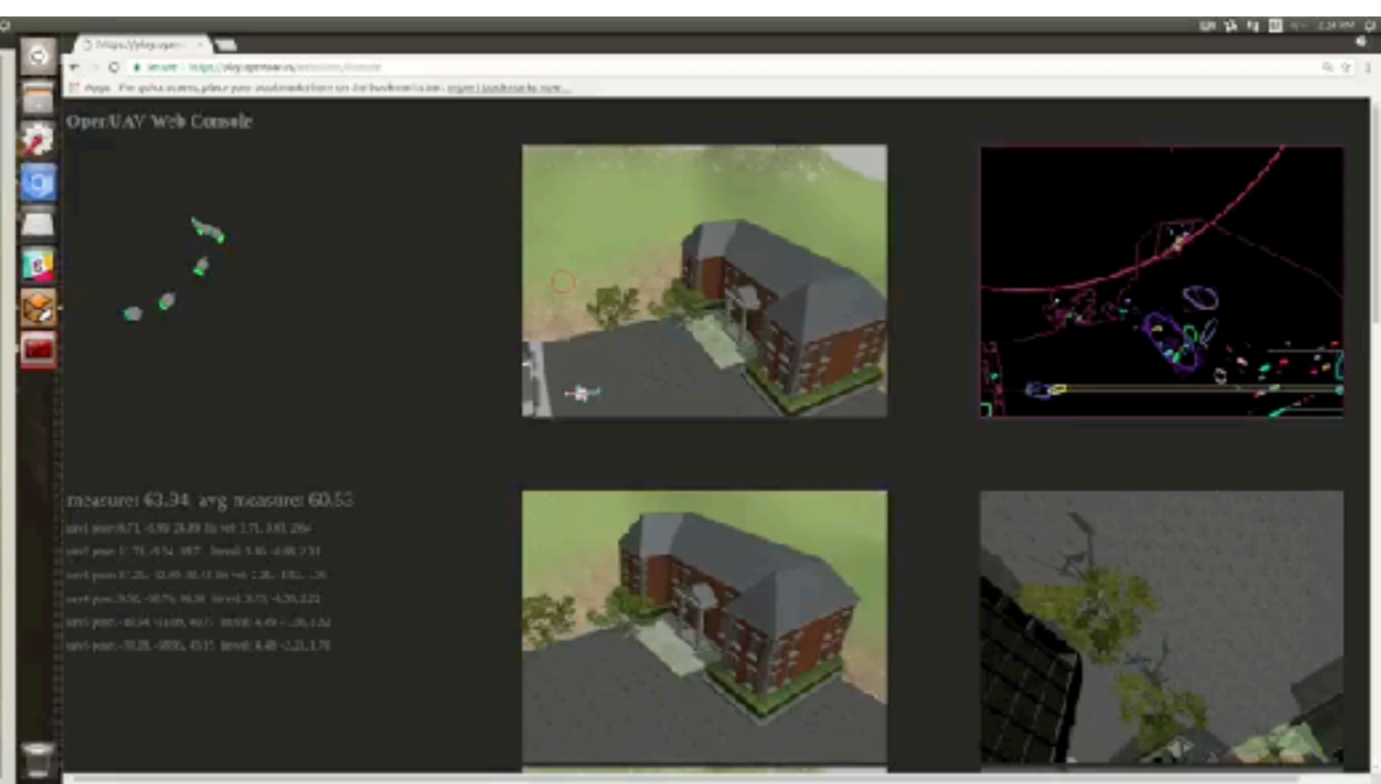
Small-scale Volcanology Tests

Simulations = gentle failures

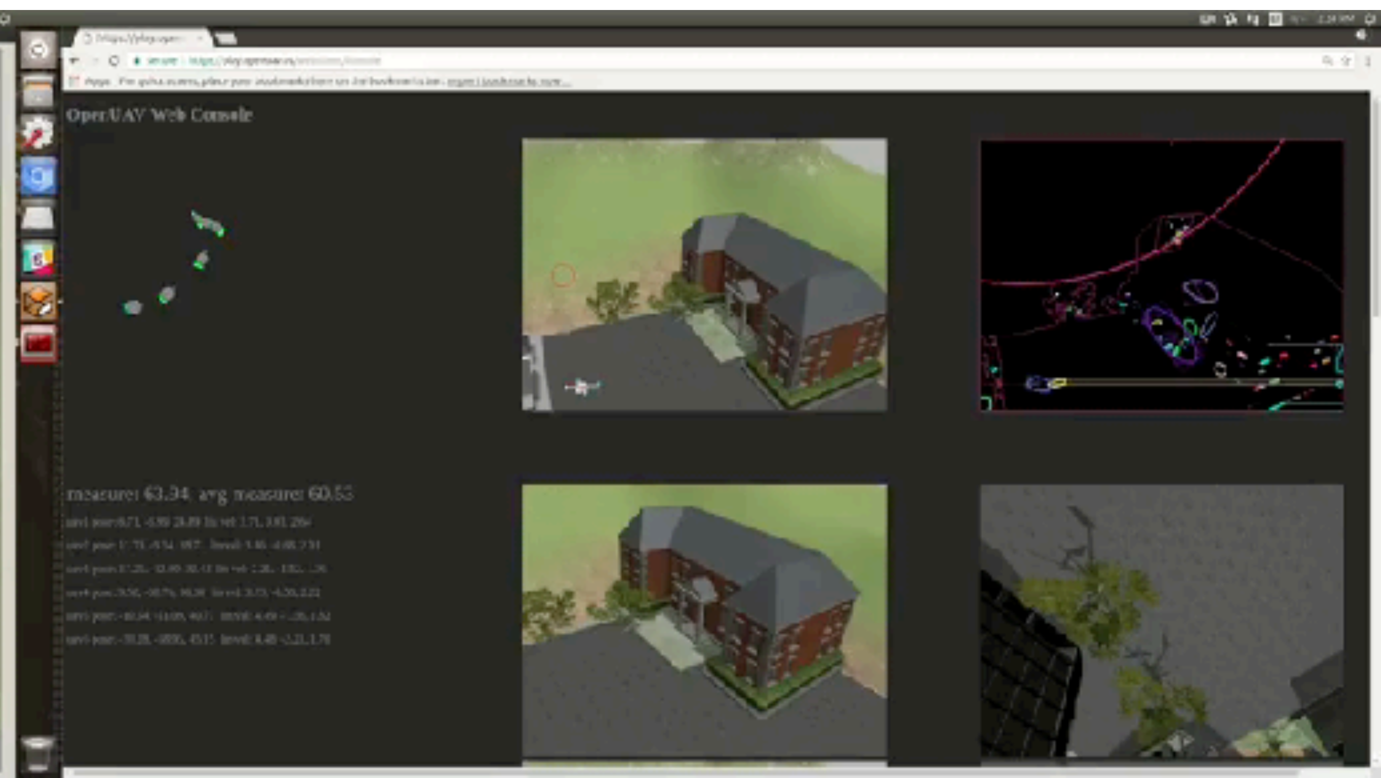


Simulations = gentle failures

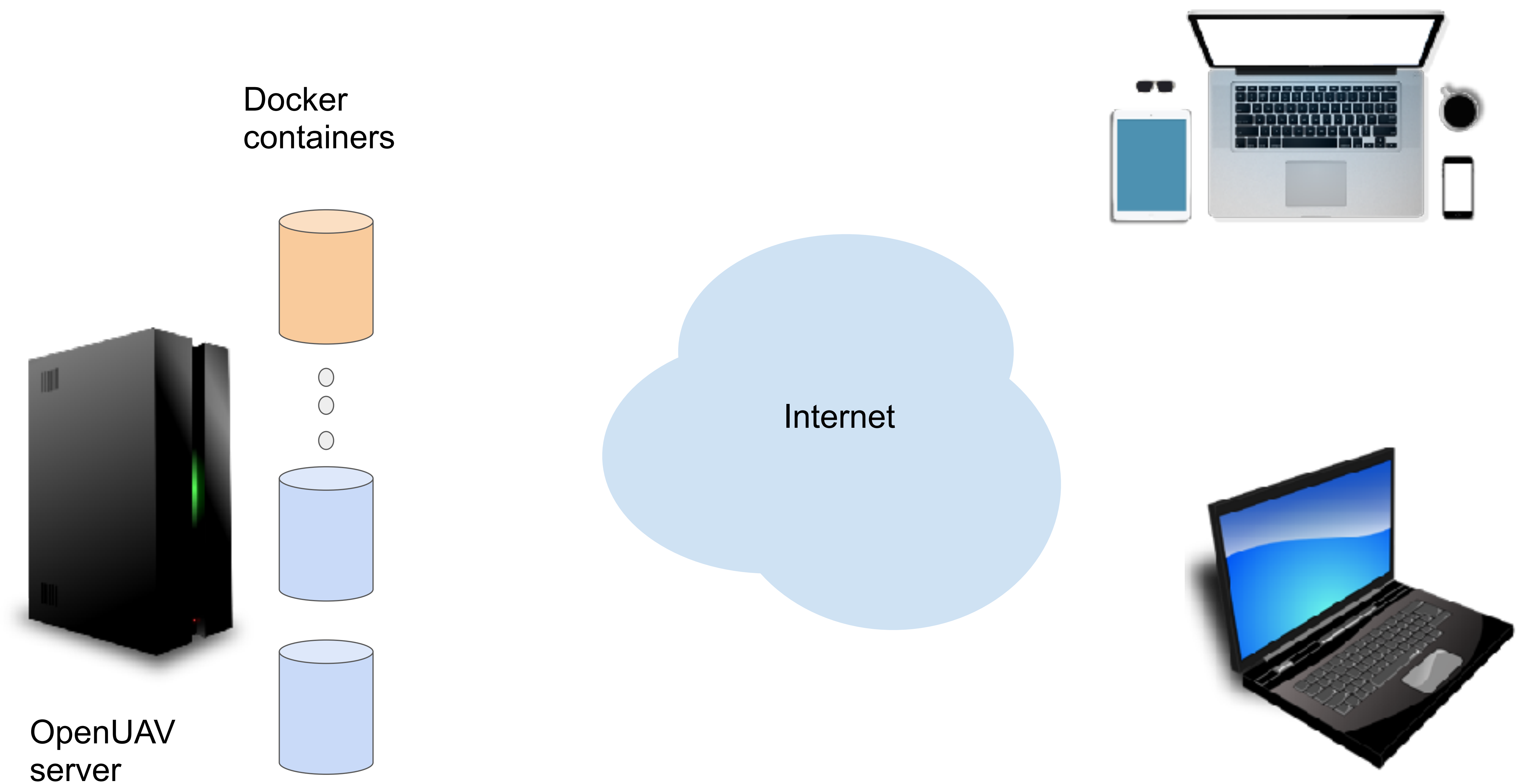


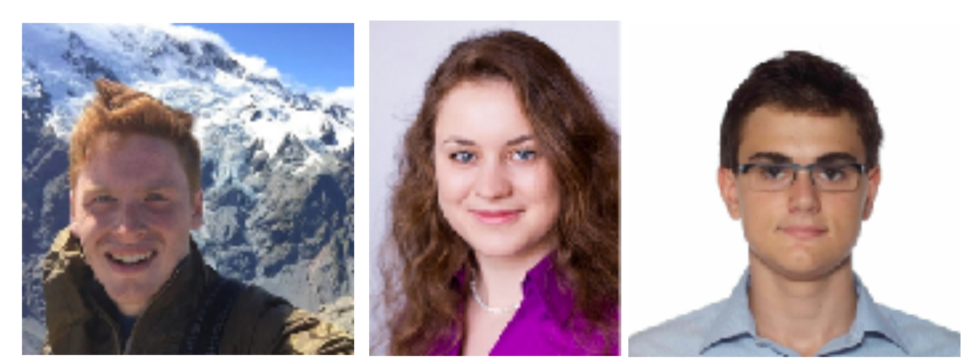
Simulations = gentle failures



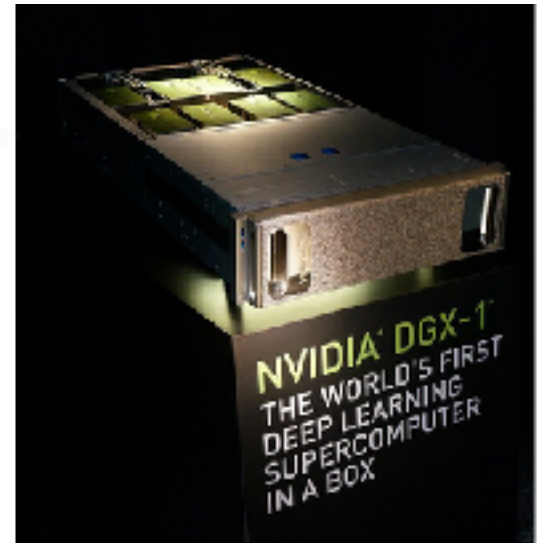
Swarm Testbed



M. Schmittle, A. Lukina, L. Vacek, J. Das, C. P. Buskirk, S. Rees, J. Sztipanovits, R. Grosu, and V. Kumar, “OpenUAV: A UAV Testbed for the CPS and Robotics Community,” in 2018 International Conference on Cyber-Physical systems (ICCPS)



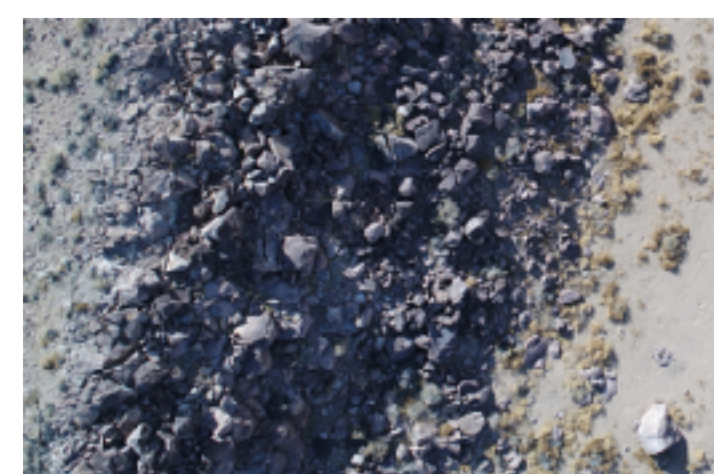
The Annotation Game



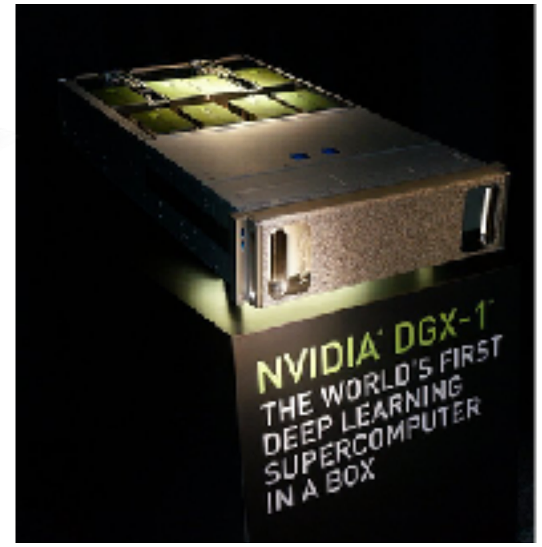
	In-situ	Ex-situ
Sampling	measurement	specimen
Analysis	features	big-data

Hannah Kerner

Chelsea Scott, Ramon Arrowsmith



The Annotation Game



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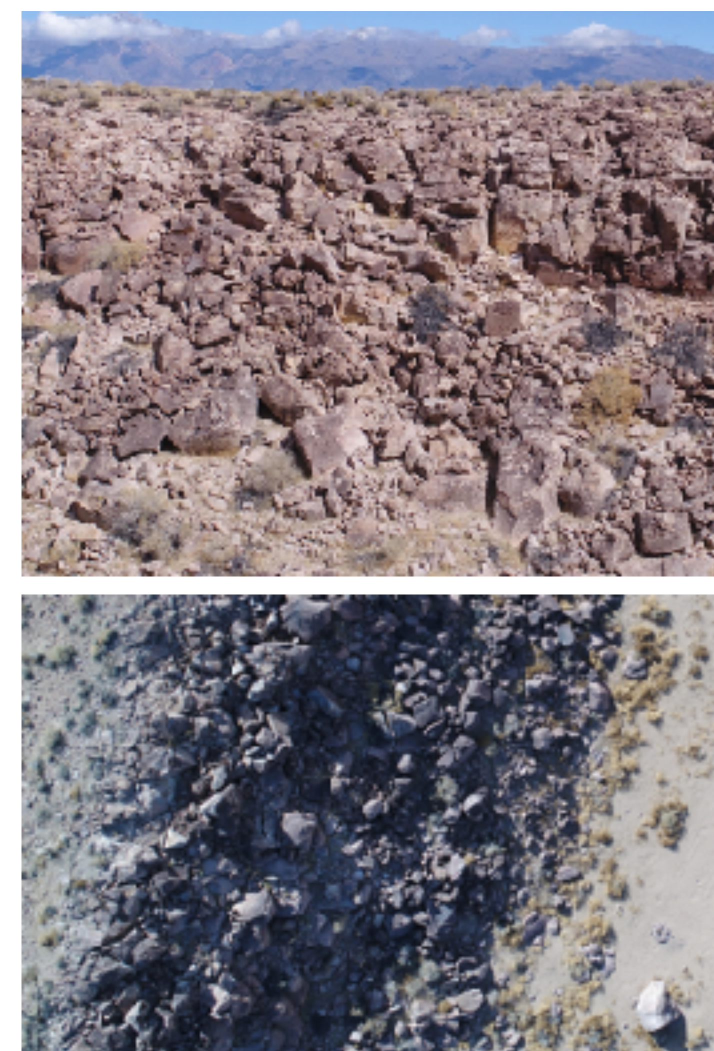
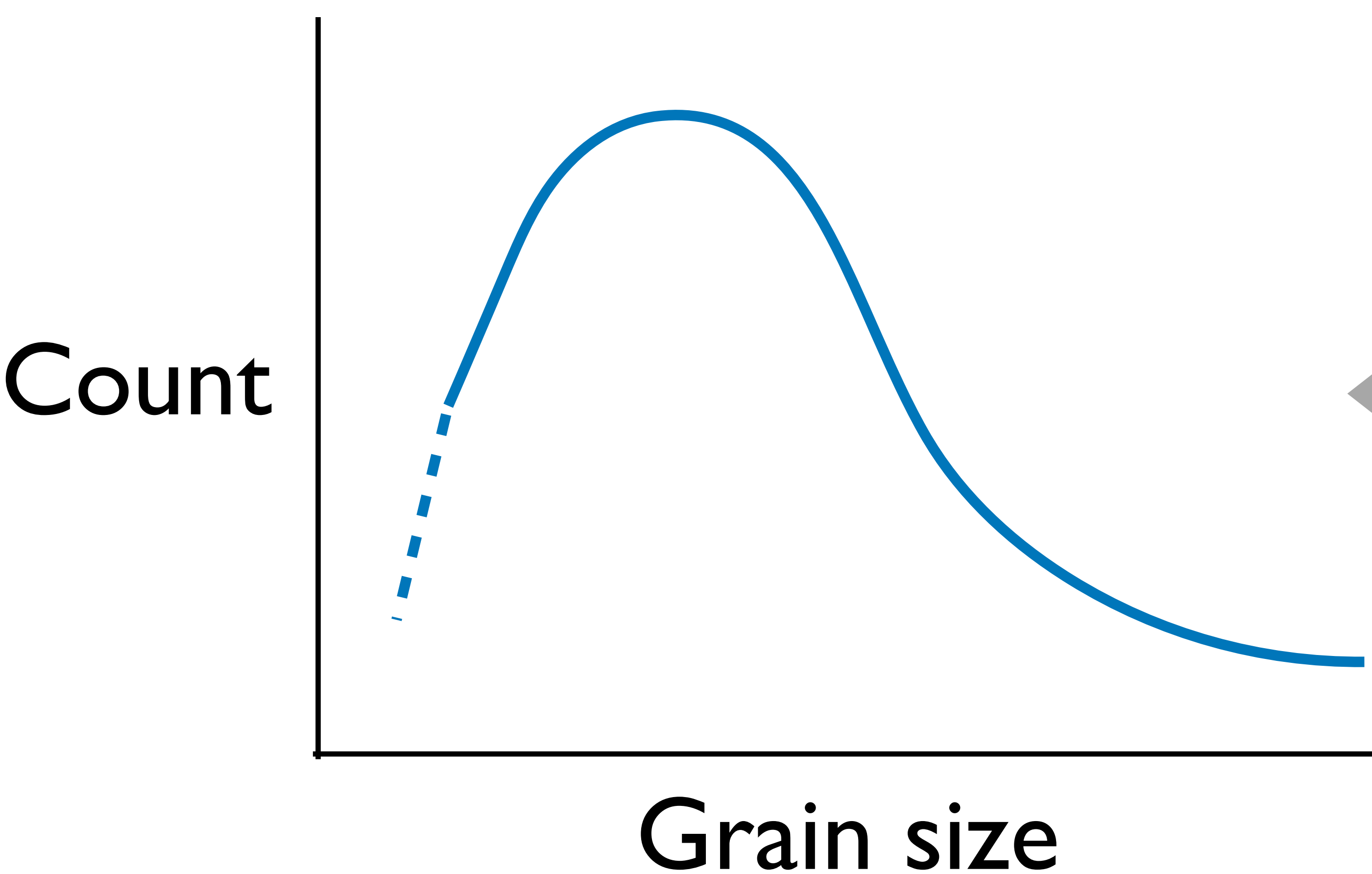




Where might AI help?
What are the challenges?

Precision agriculture
Geology, volcanology
Planetary sciences
Disaster response
Damage assessment

	In-situ	Ex-situ
Sampling	measurement	specimen
Analysis	features	big-data

Novelty
Anomaly
Change

2019 NSF CPS Challenge, May 14-16, TIMPA Airfield, TUCSON

IMAGINE

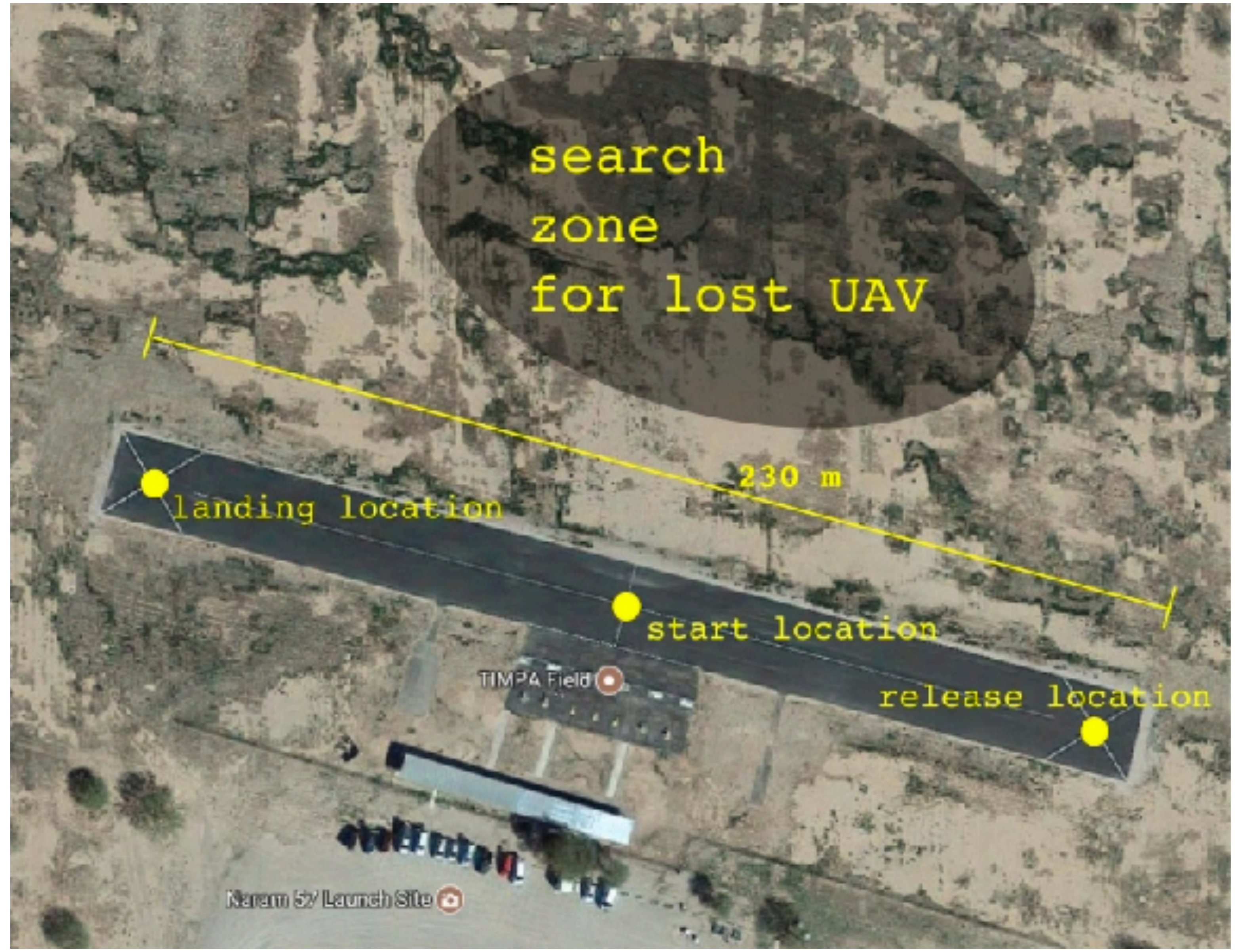
Your friend's quadrotor went down in a large field, and a storm is coming in.

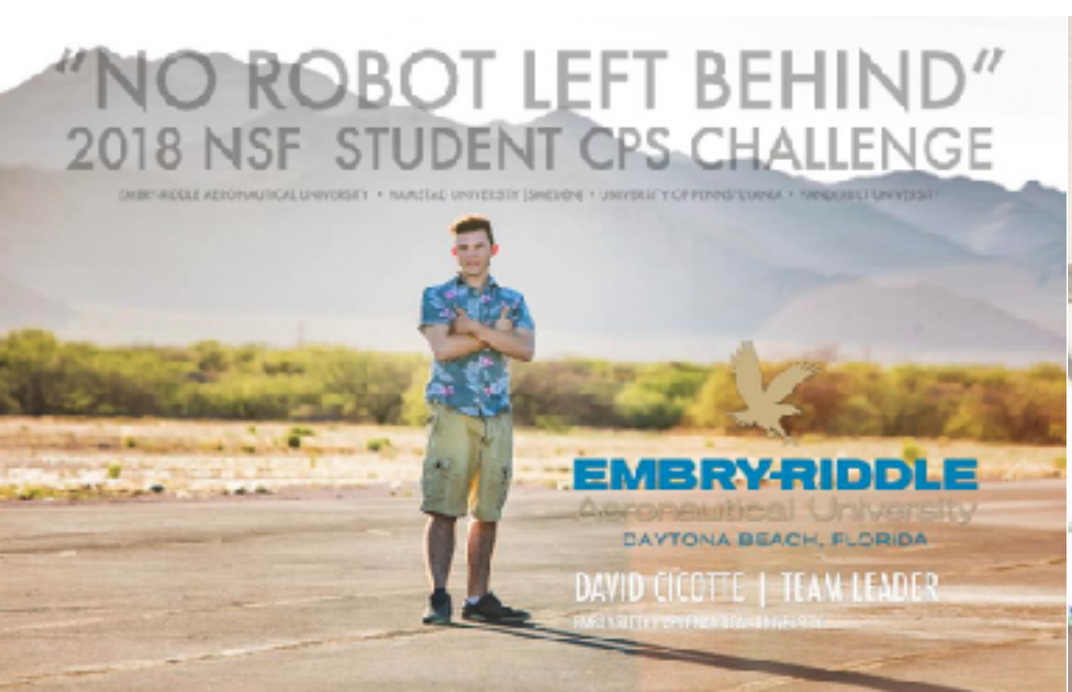
Looking for this lost drone needs a solution that could be repurposed to solve many other problems, like looking for a place to deploy an environmental sensor probe.

GOAL

The goal of this challenge is to use a quadrotor aircraft with downward facing camera, and possibly other sensors, to scan an area for a lost aircraft, and recover it safely back to base.

•





https://web.asu.edu/jdas
jdas5@asu.edu

https://cps-vo.org/group/CPSchallenge

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