MACHINE LEARNING AUGMENTATION & DATA FUSION USING CM-SCALE FLUID LENSING FOR ENHANCED CORAL REEF ASSESSMENT

EARTH SCIENCE TECHNOLOGY FORUM 2017

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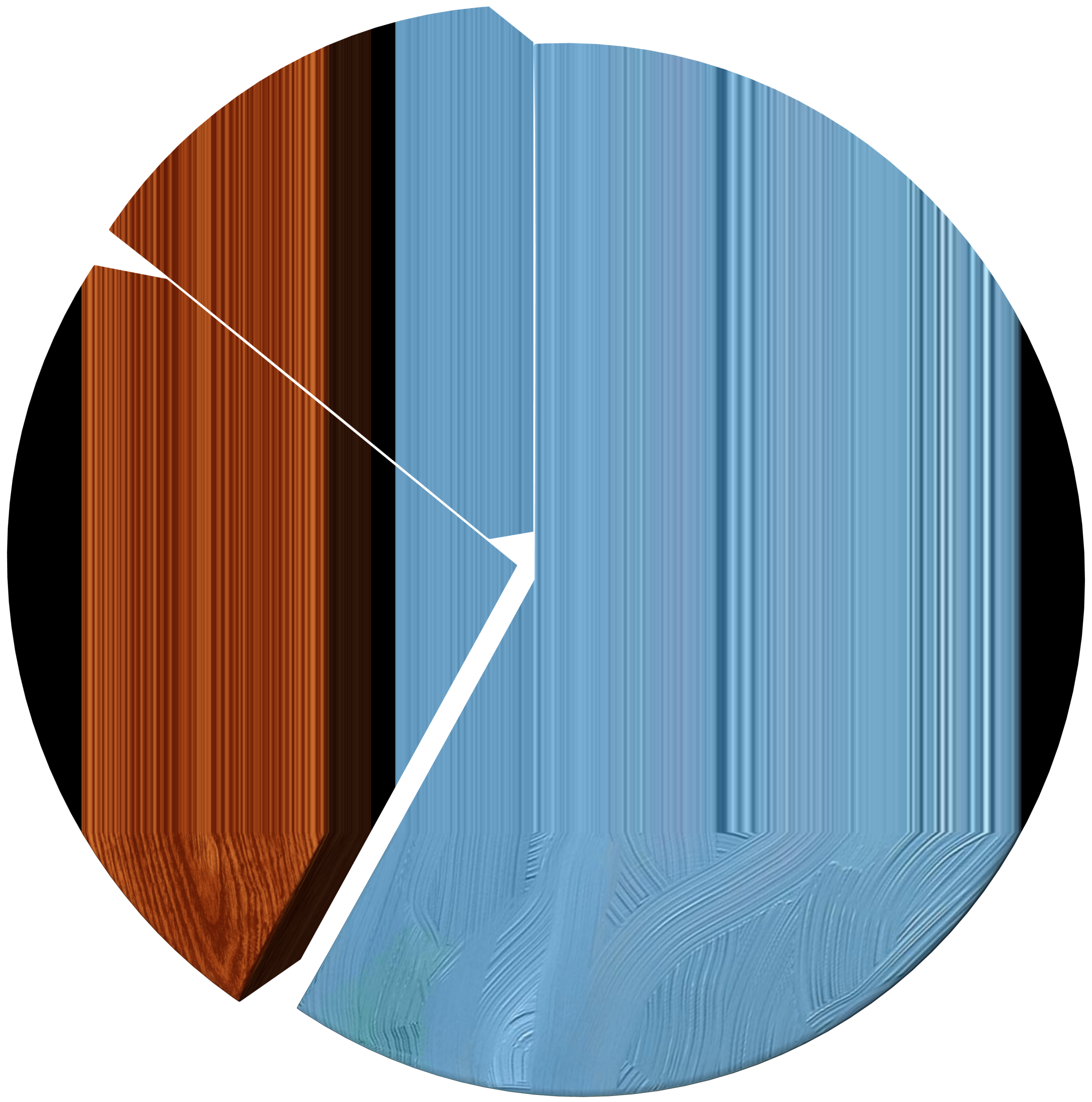
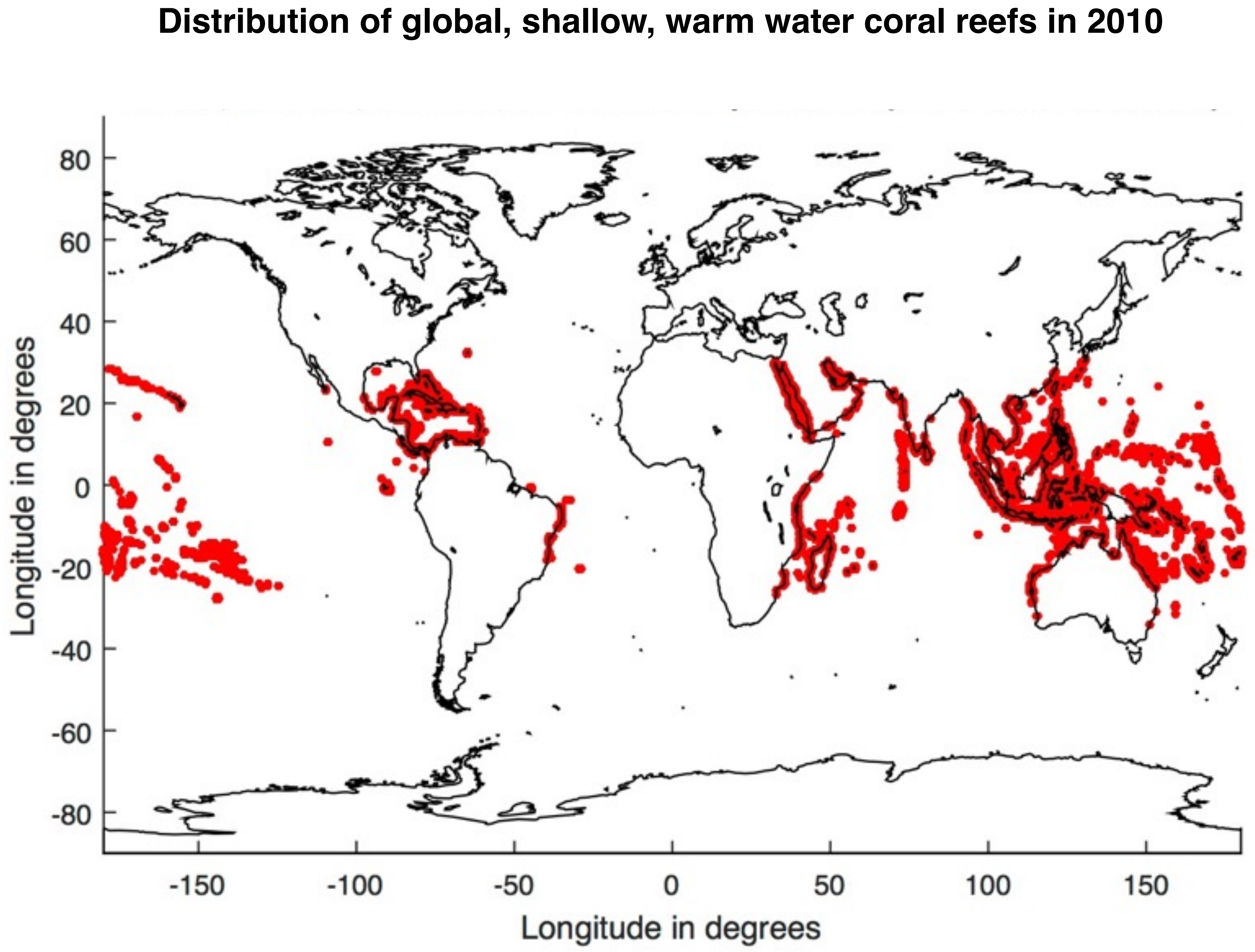
LAB FOR ADVANCED SENSING
NASA AMES RESEARCH CENTER

CORAL REEFS

Modern Global Oxygen Production





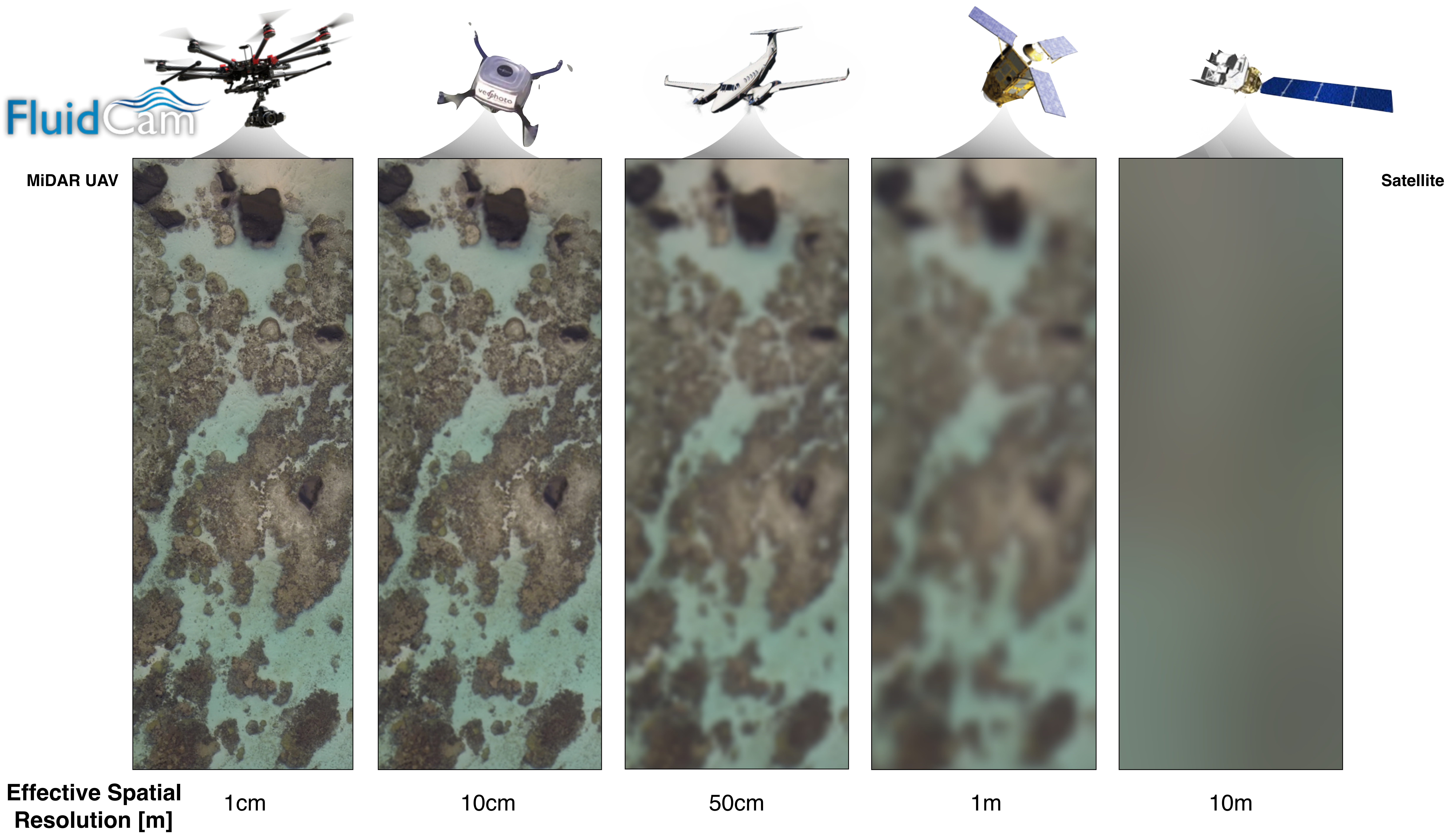
Value

- Shoreline protection
- Economic value
- Highest biodiversity
- Medical applications

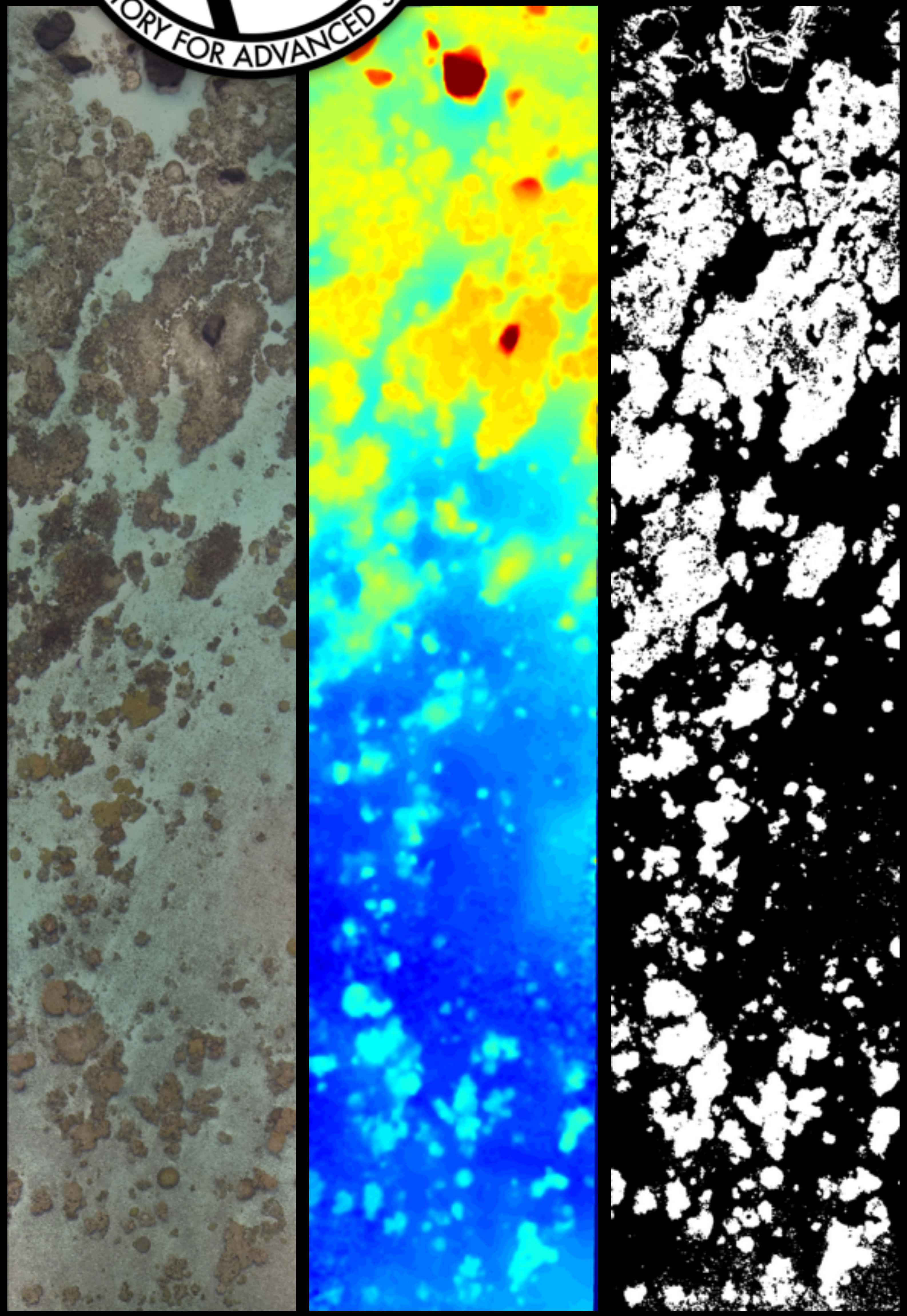
Pressures

- Climate Change
- Ocean Acidification
- Pollution, run-off
- Human Impact

Data: Scripps Oceanographic Institute, NOAA, NASA, UNEP


FluidCam
MiDAR UAV
Satellite
vexphoto
Effective Spatial Resolution [m]
1cm
10cm
50cm
1m
10m

NOVEL INSTRUMENT TECHNOLOGIES

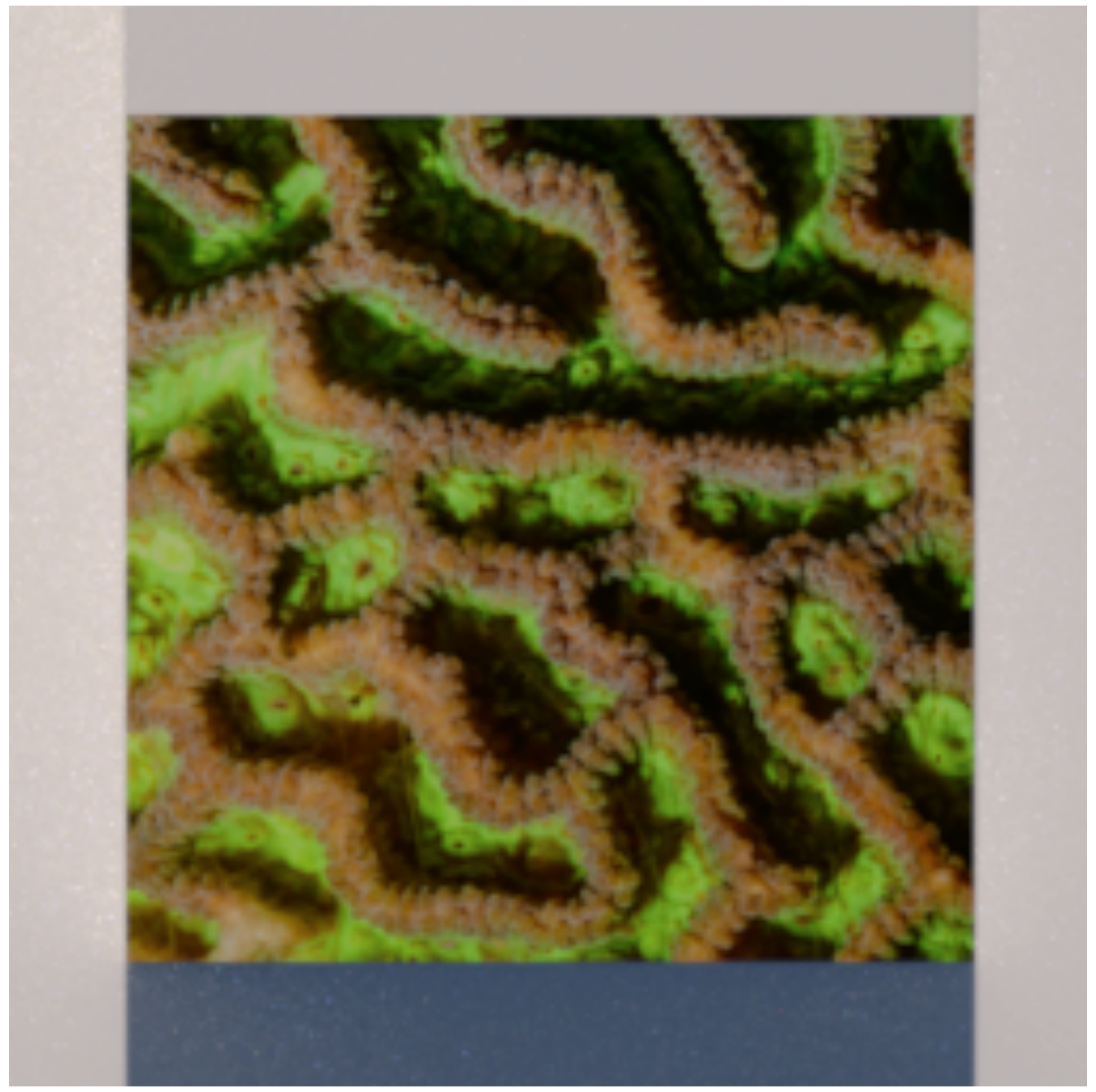


Science	Remote Sensing Measurements	Technologies
Physical oceanography, understand shallow coastal environment, transport, flow and storm surge	Bathymetry, sea surface temperature, salinity	FluidCam
Biological oceanography, determine health, extent and coverage of marine life	High-resolution, multispectral image of underwater environment	MiDAR

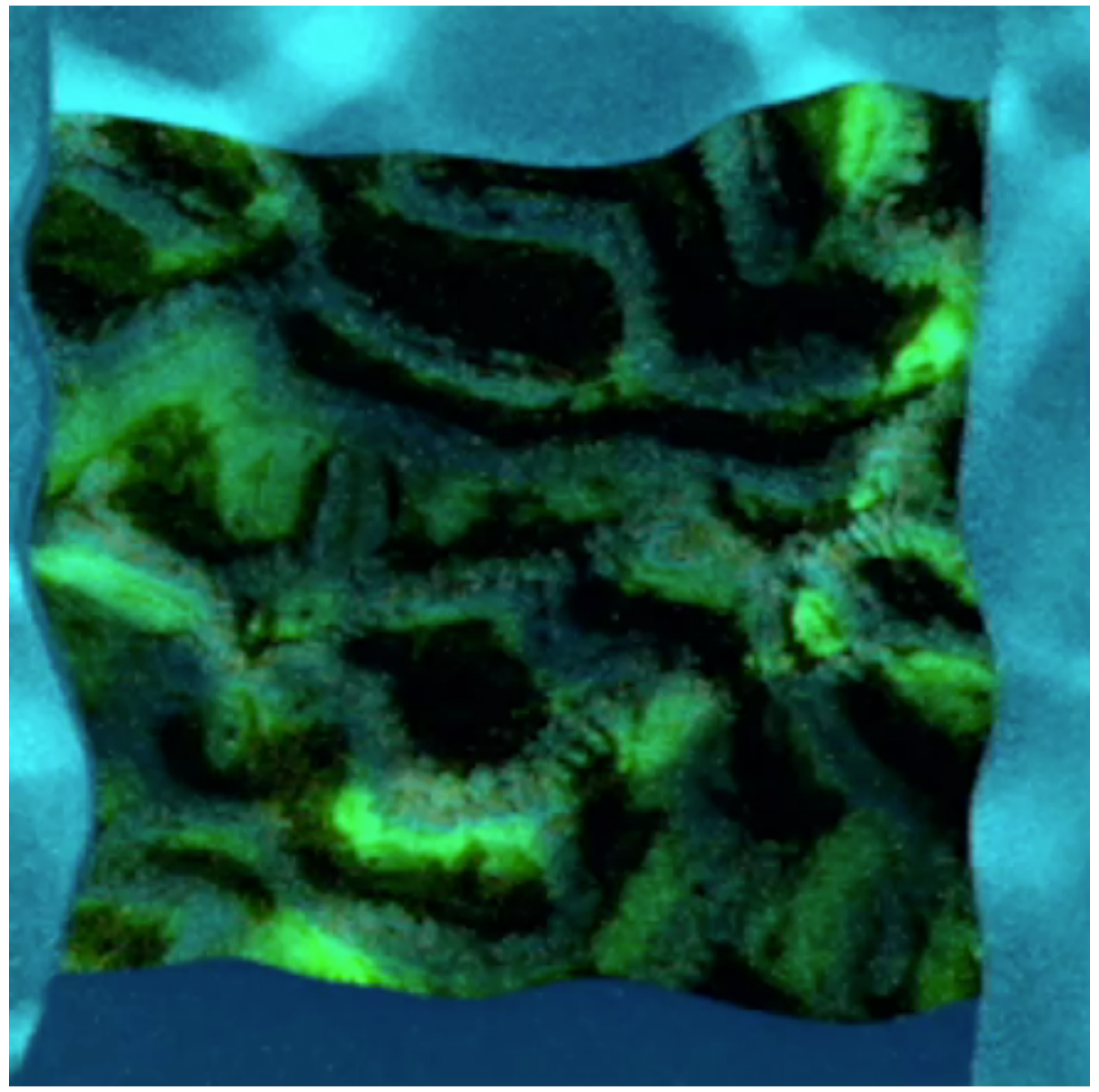
FluidCam

2D Fluid Lensing Results, Coral Image Test Target, Test Platforms 11, Depth = 4.5m, MSL

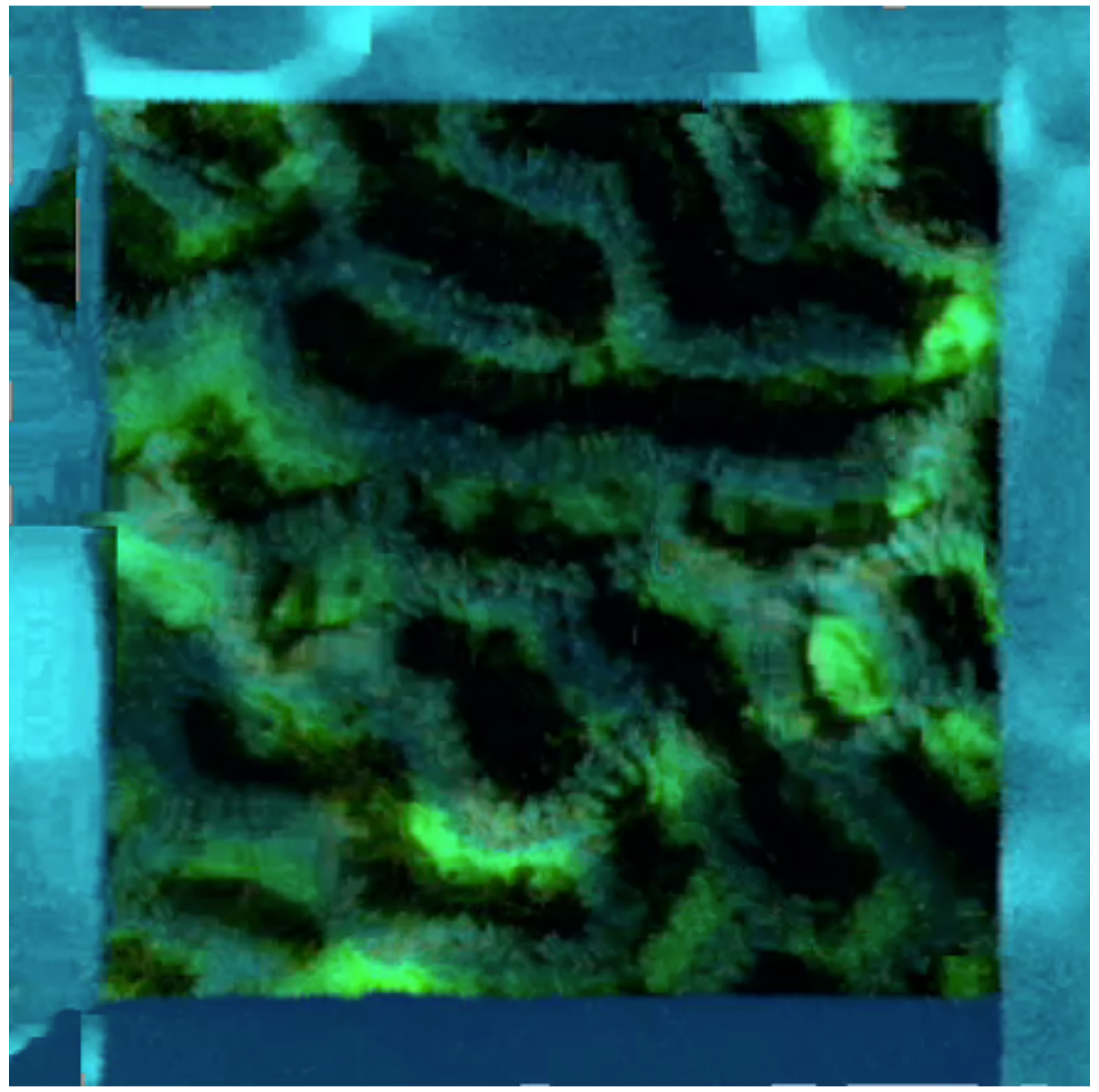
No Fluid



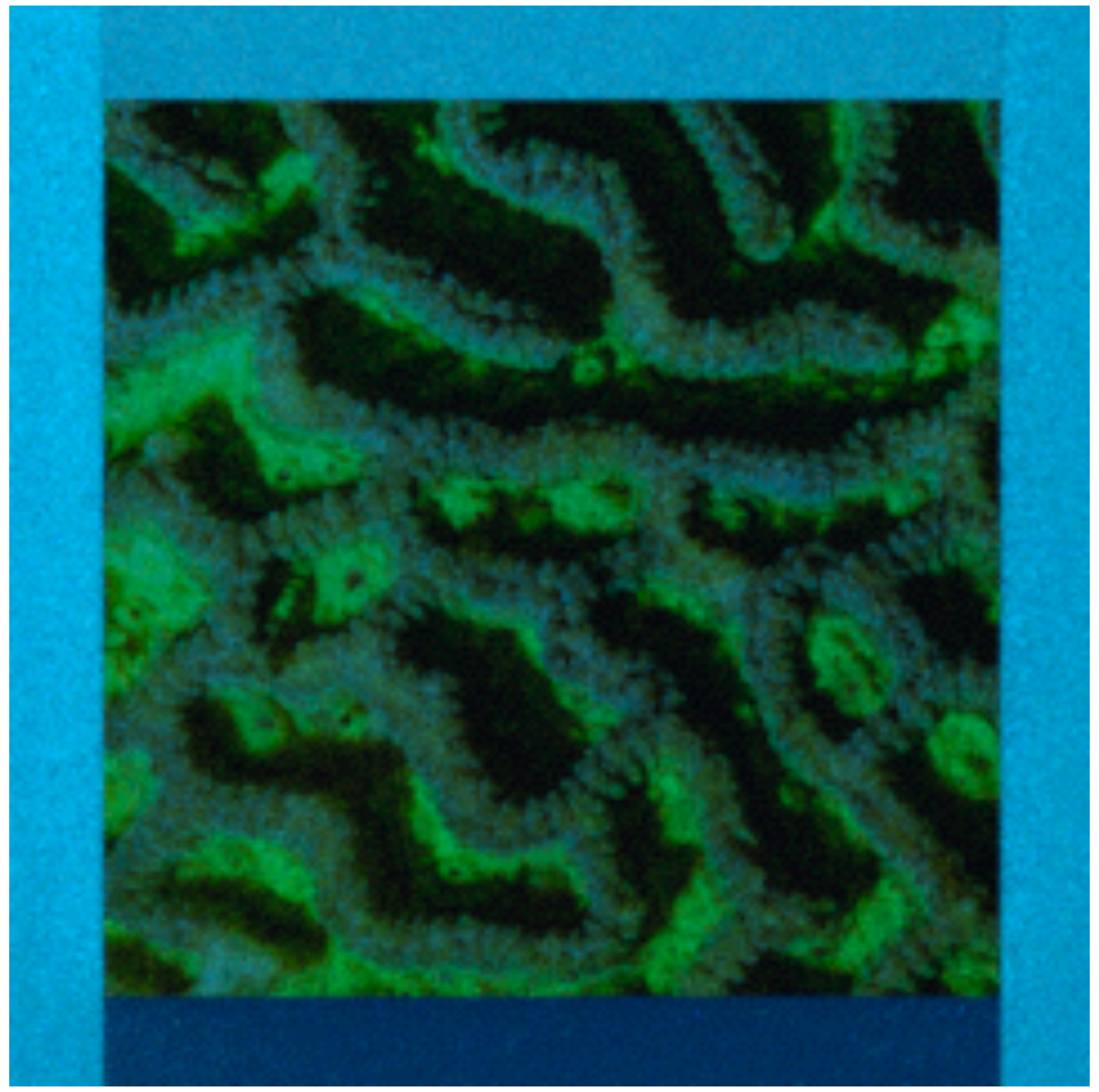
Raw Distorted Frames



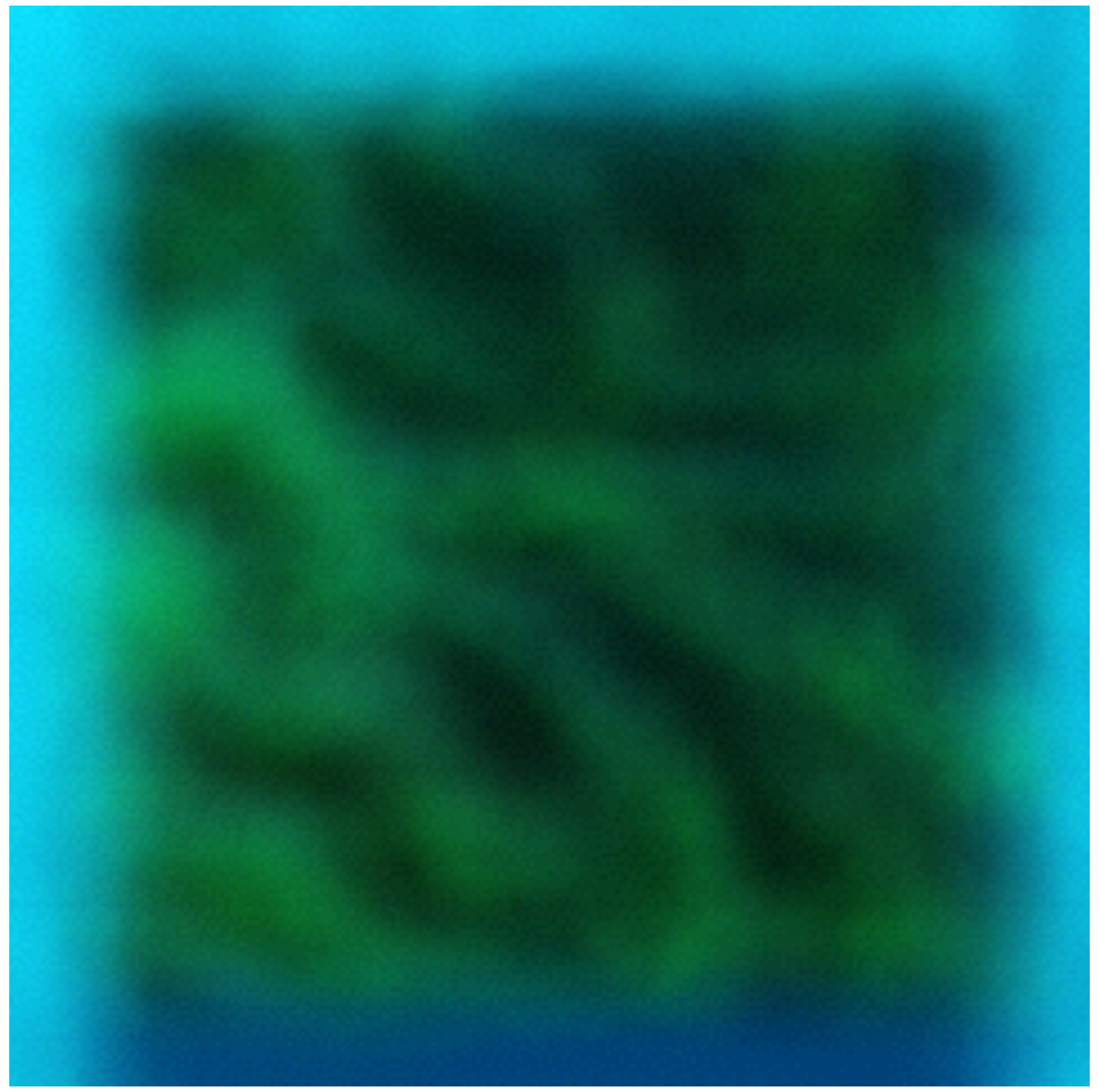
2D Fluid Lensing Results



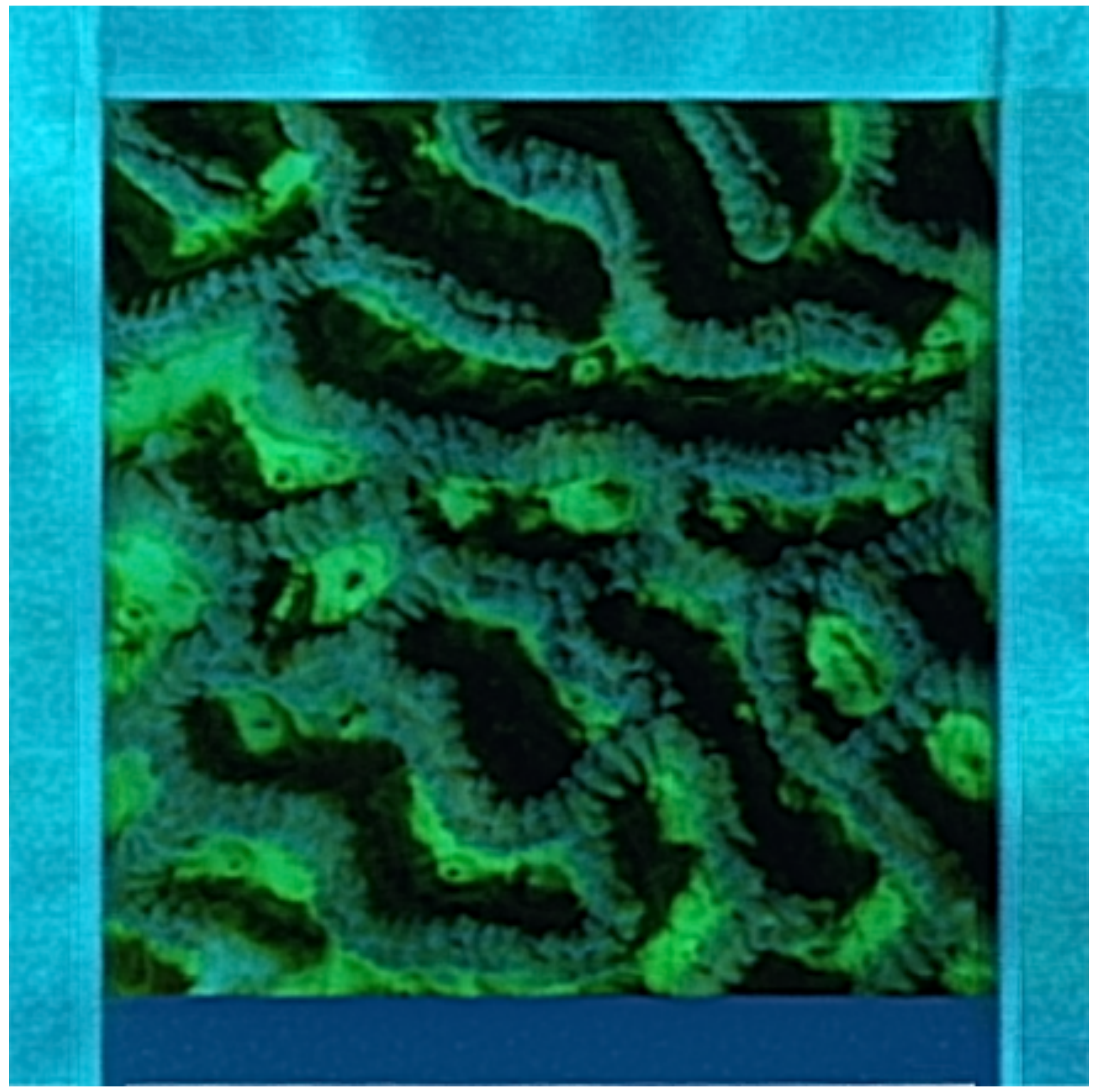
Flat Fluid



Mean Image (600 frames)



2D Fluid Lensing Integration (90 frames)

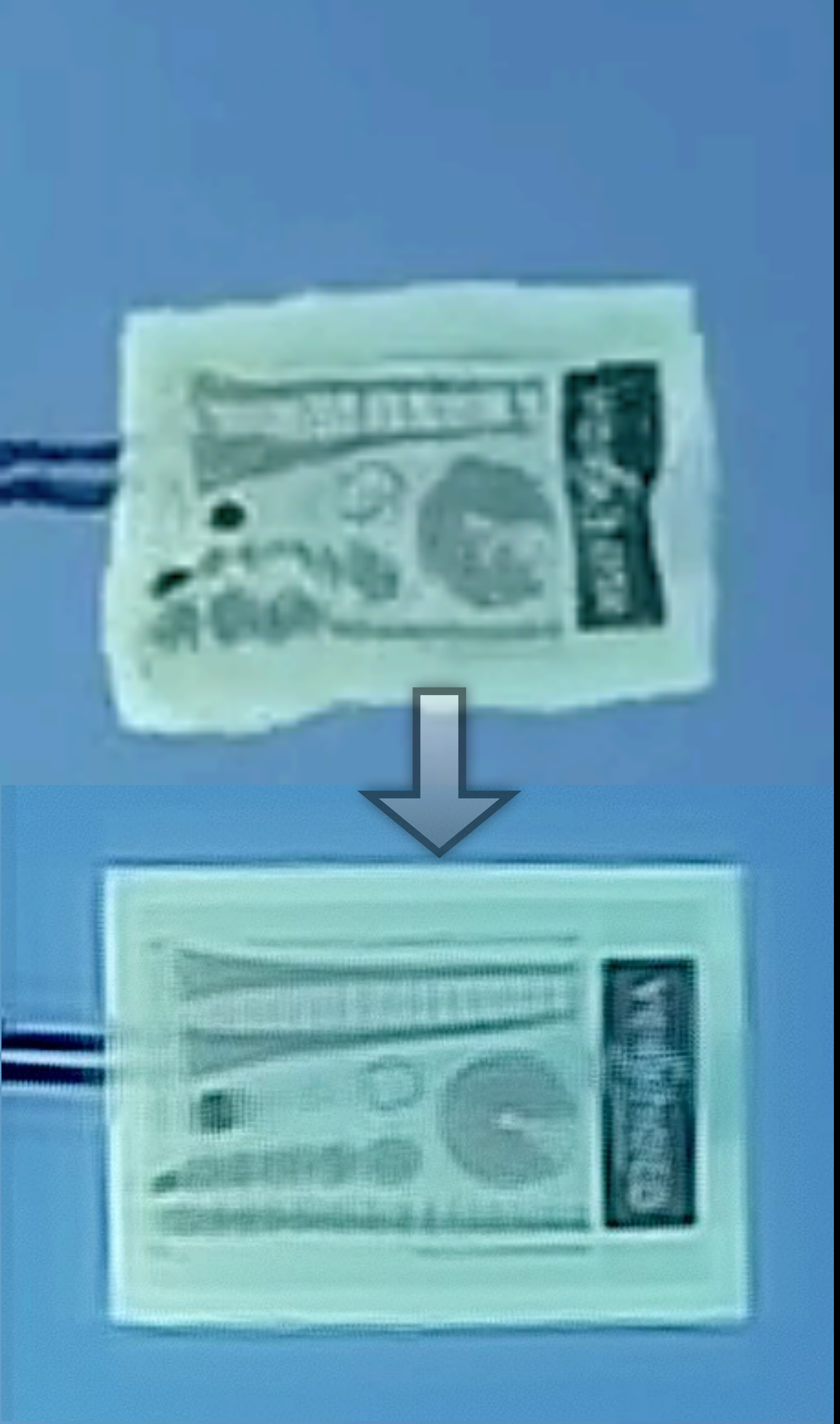


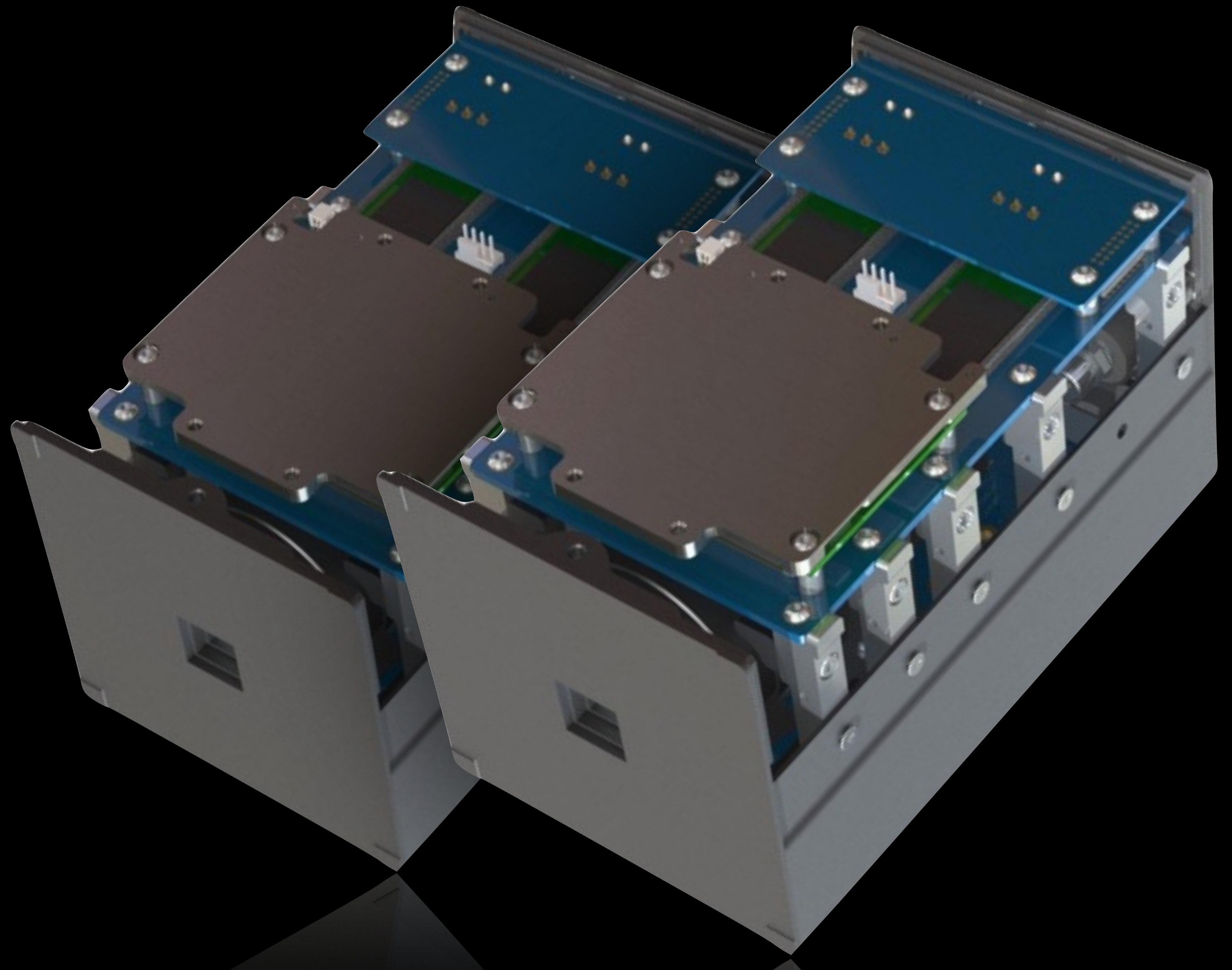
www.nasa.gov/ames/las

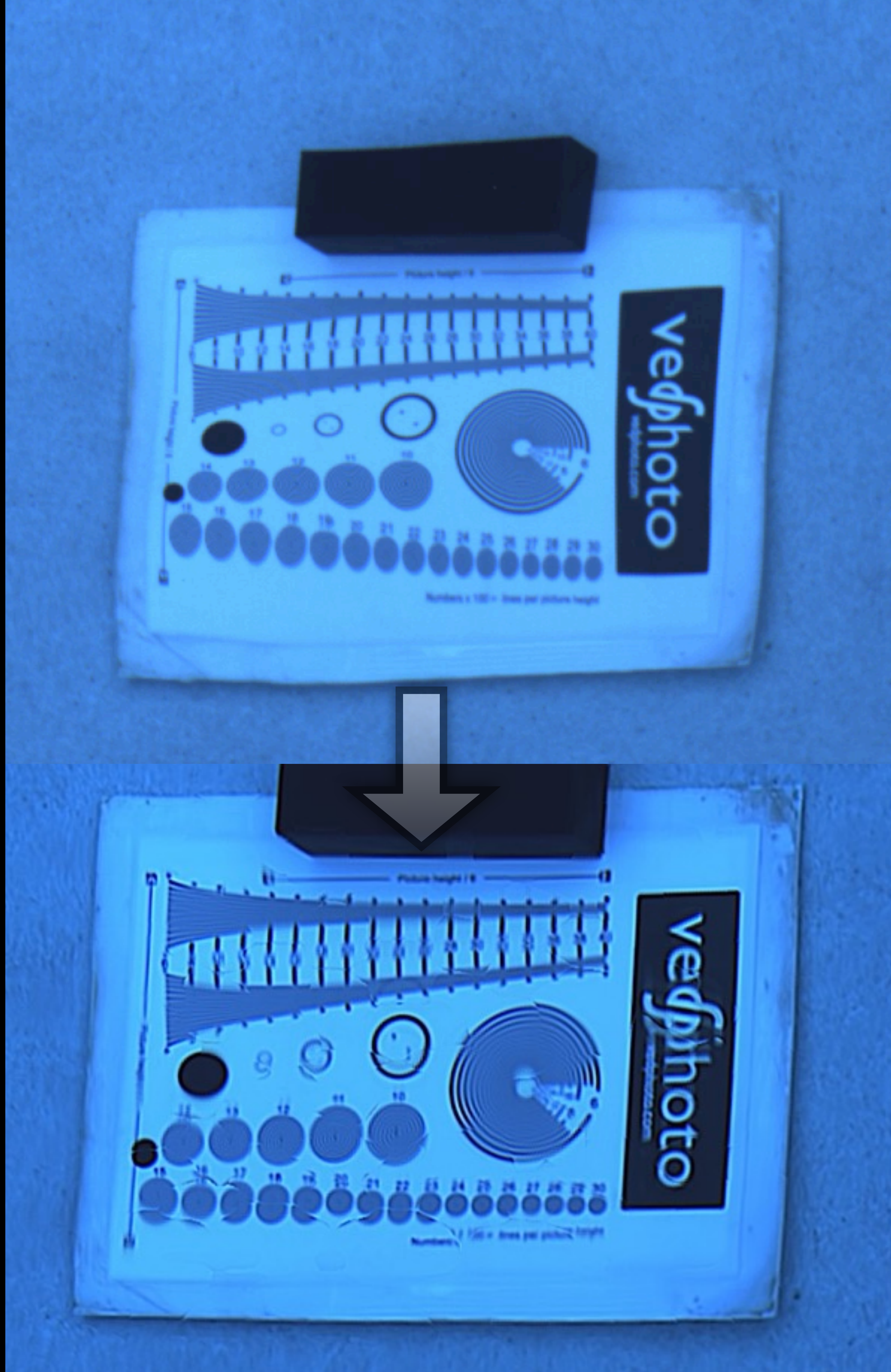
Original sensor 2013

FluidCam

FluidCam Color 2016







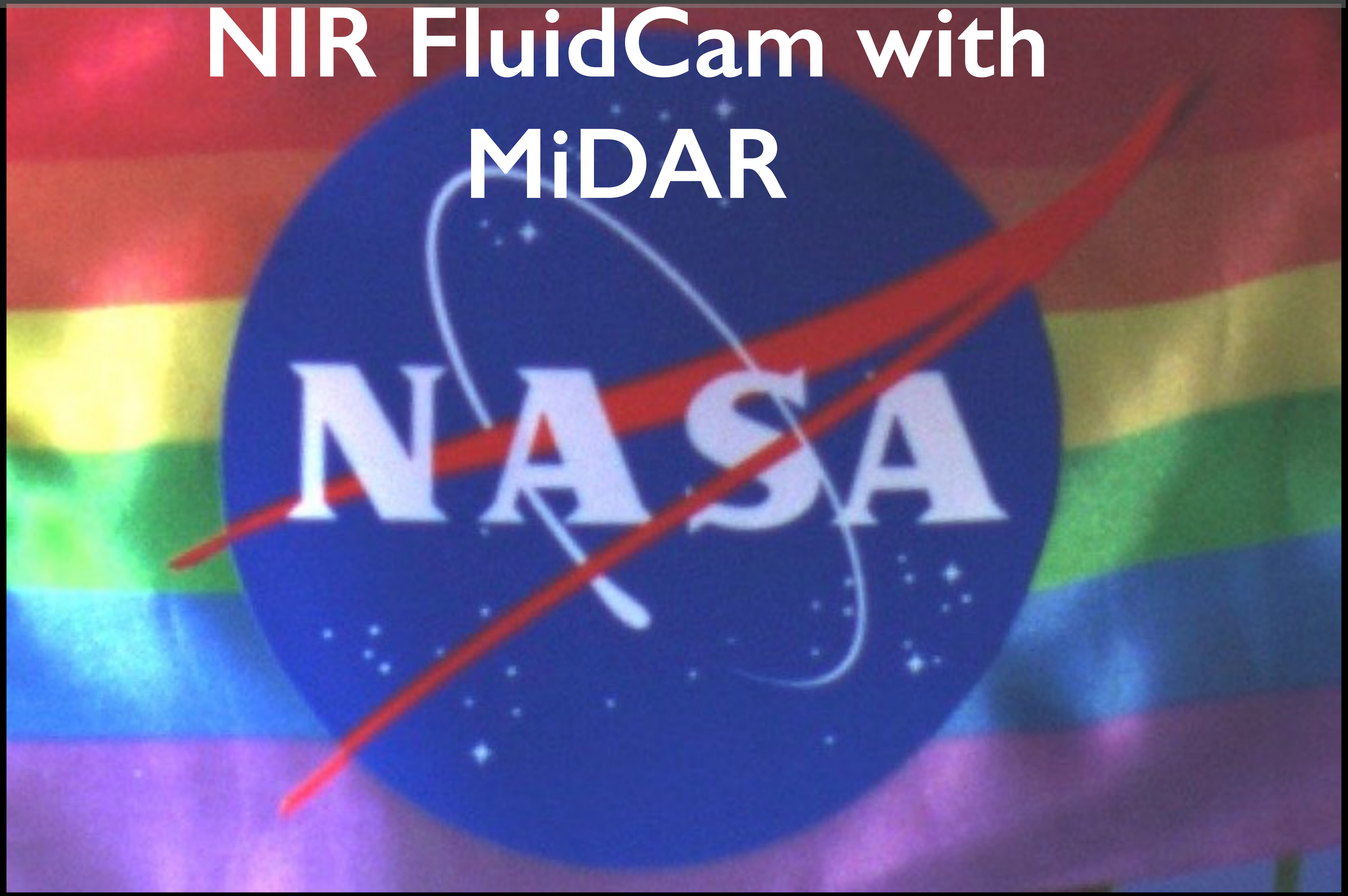
FluidCam 1&2 offer more than a 10x improvement over previous Fluid Lensing instruments in resolution, data bandwidth, spectral range, SNR, and onboard compute capability.

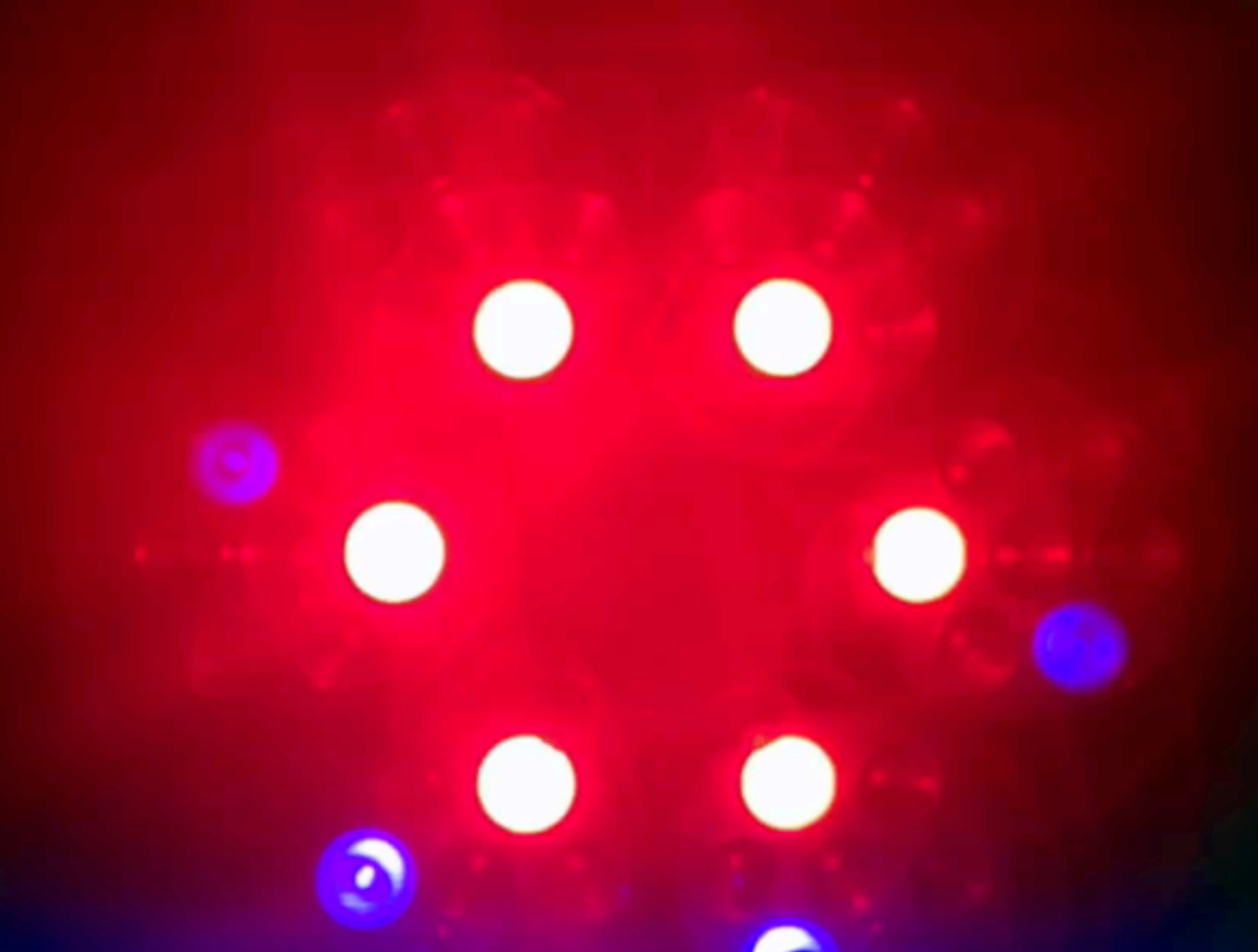
MiDAR REMOTE SENSING

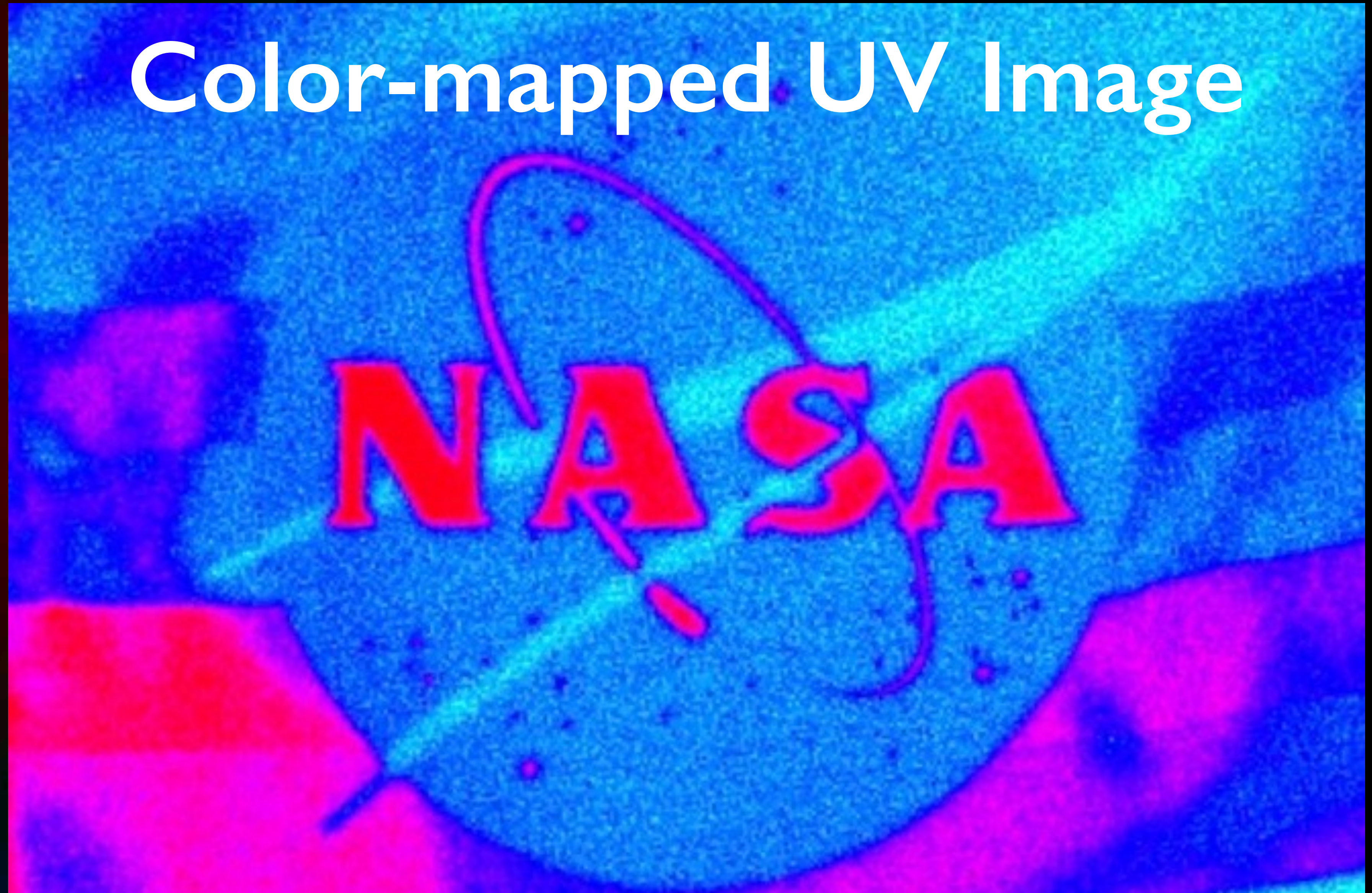
MiDAR

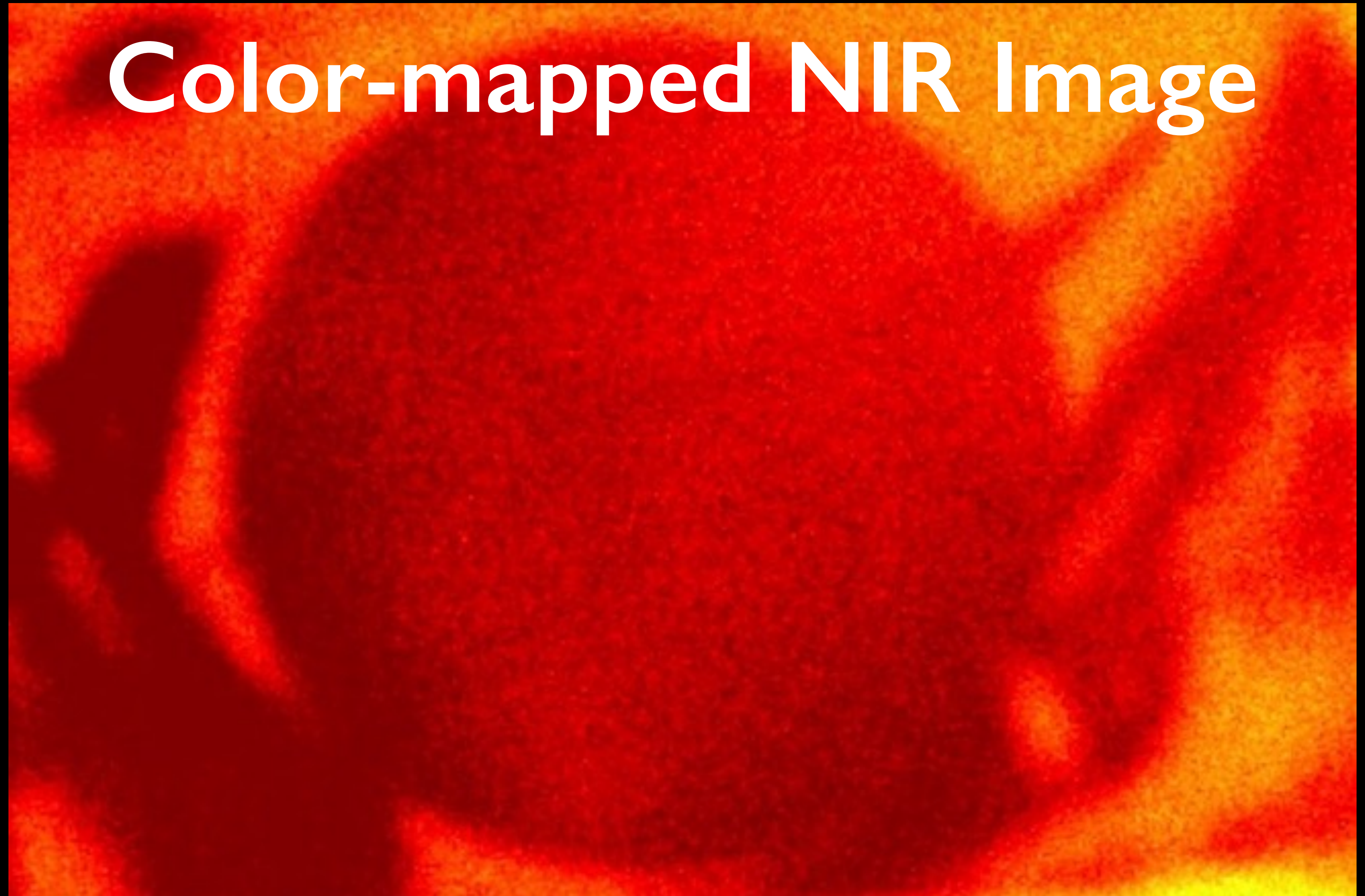

NASA


Color FluidCam Image
NASA


NIR FluidCam with MiDAR
NASA

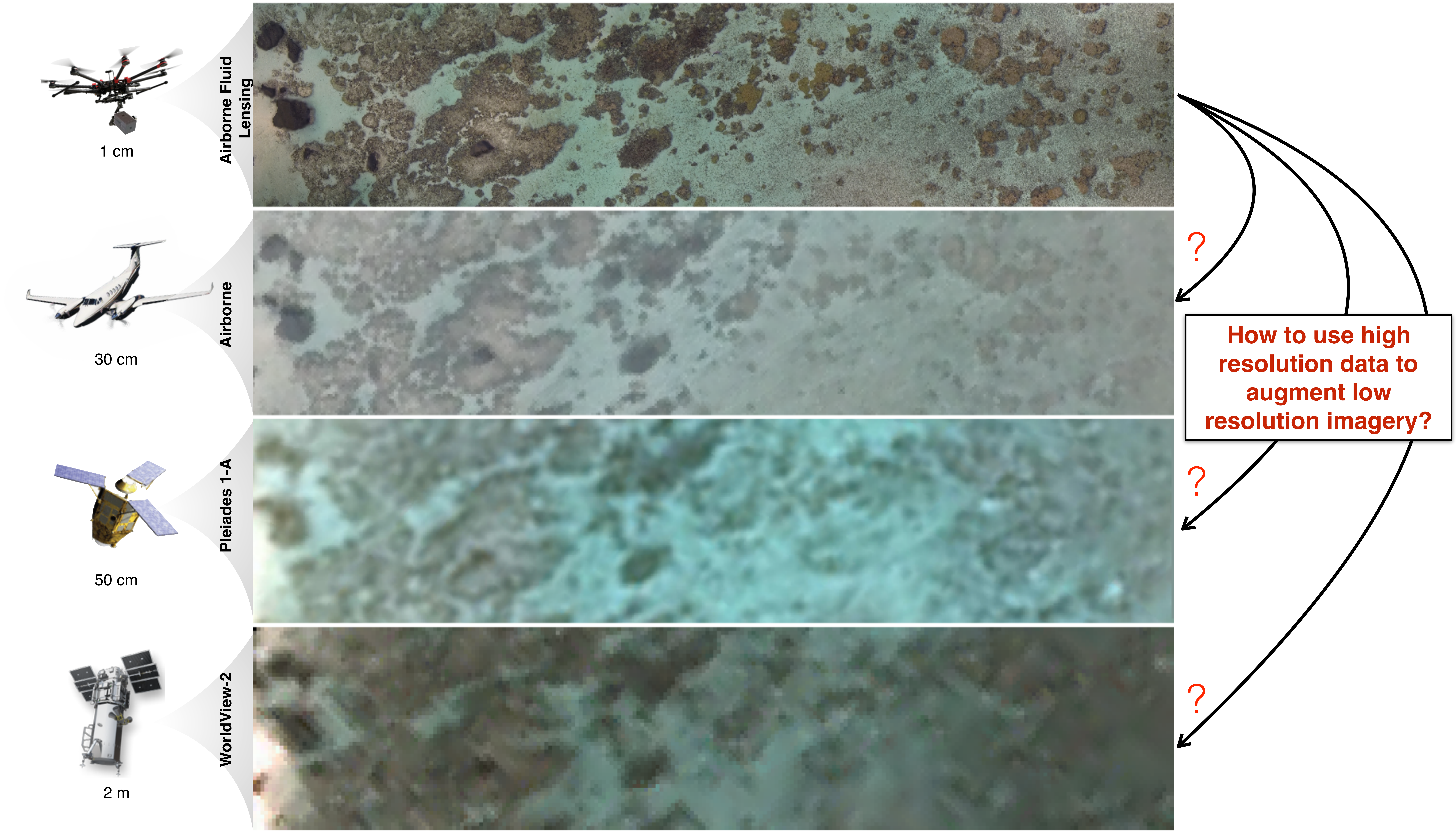



Color-mapped UV Image
NASA


Color-mapped NIR Image

MACHINE LEARNING WITH FLUIDCAM & MIDAR

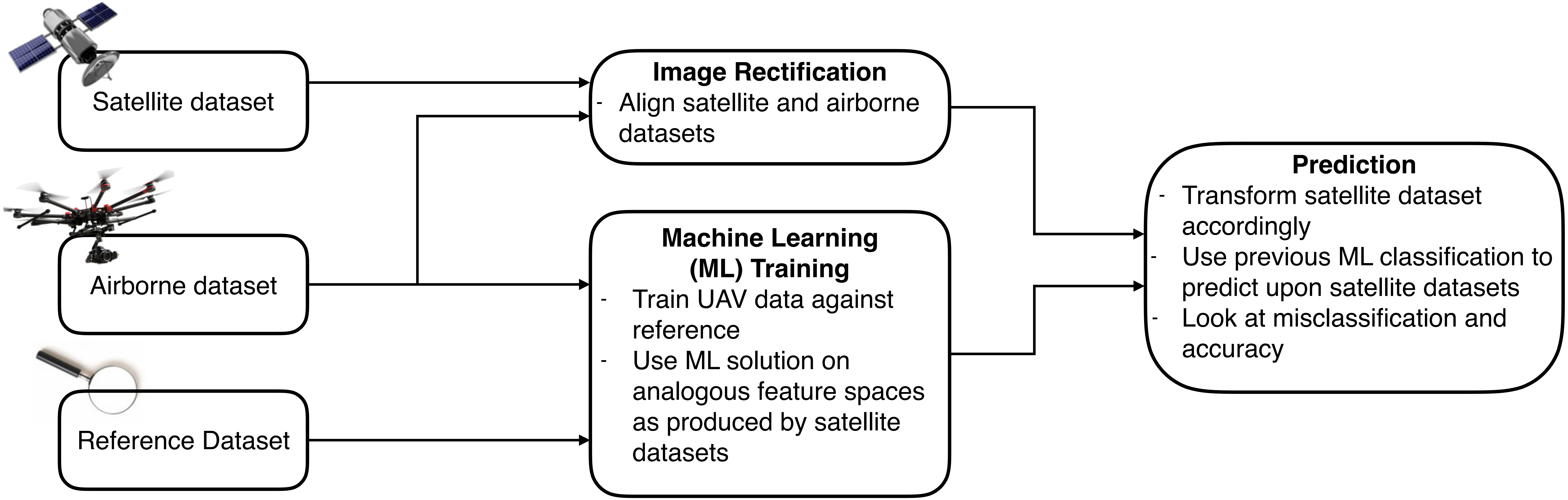

Best Satellite Image
Fluid Lensing on UAV
FL + SFM Depth
Manual ID
Automated Morphology ID
Automated Percent Cover ID
5m
25m
-3m
1.8m
Sand/Other
Branching
Mounding
Rock
8% total error in Morphology ID
Living Structure
Nonliving Structure
5% total error in Percent Cover ID vs 30% in literature


1 cm
Airborne Fluid Lensing
30 cm
Airborne
50 cm
Pleiades 1-A
2 m
WorldView-2
?
?
?
How to use high resolution data to augment low resolution imagery?

Is there a method to autonomously relate these feature spaces?

Goal: To use high resolution data from UAVs augment low resolution datasets captured by higher altitude and satellite platforms.

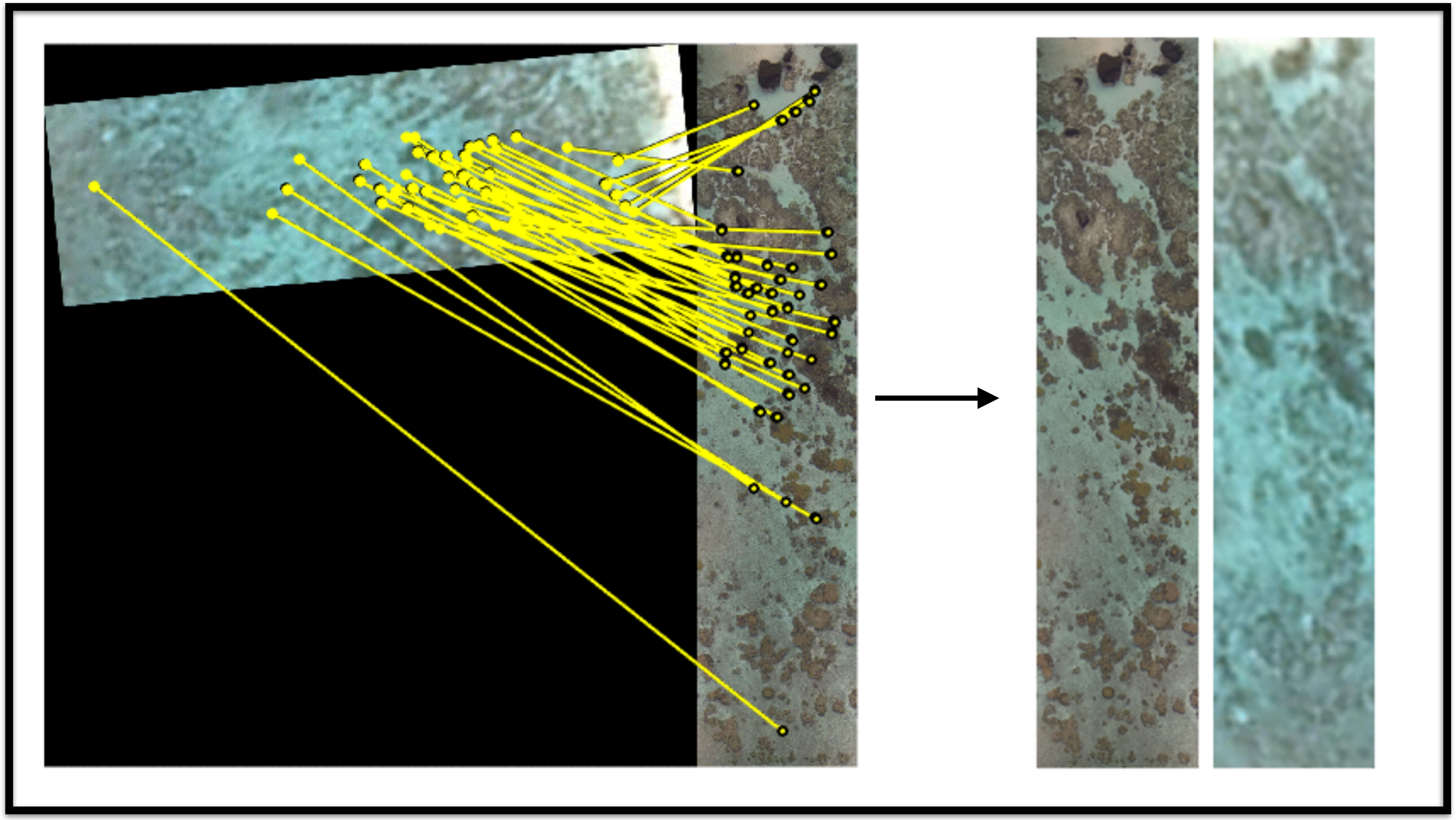
General Approach



Idea: Leverage airborne data, which offers high resolution imagery of reef systems close to the source which gives the best representation of the feature space

Concept: Train UAV dataset against the reference dataset using supervised machine learning. Take this classification criteria and apply it to a transformed version of the satellite dataset.

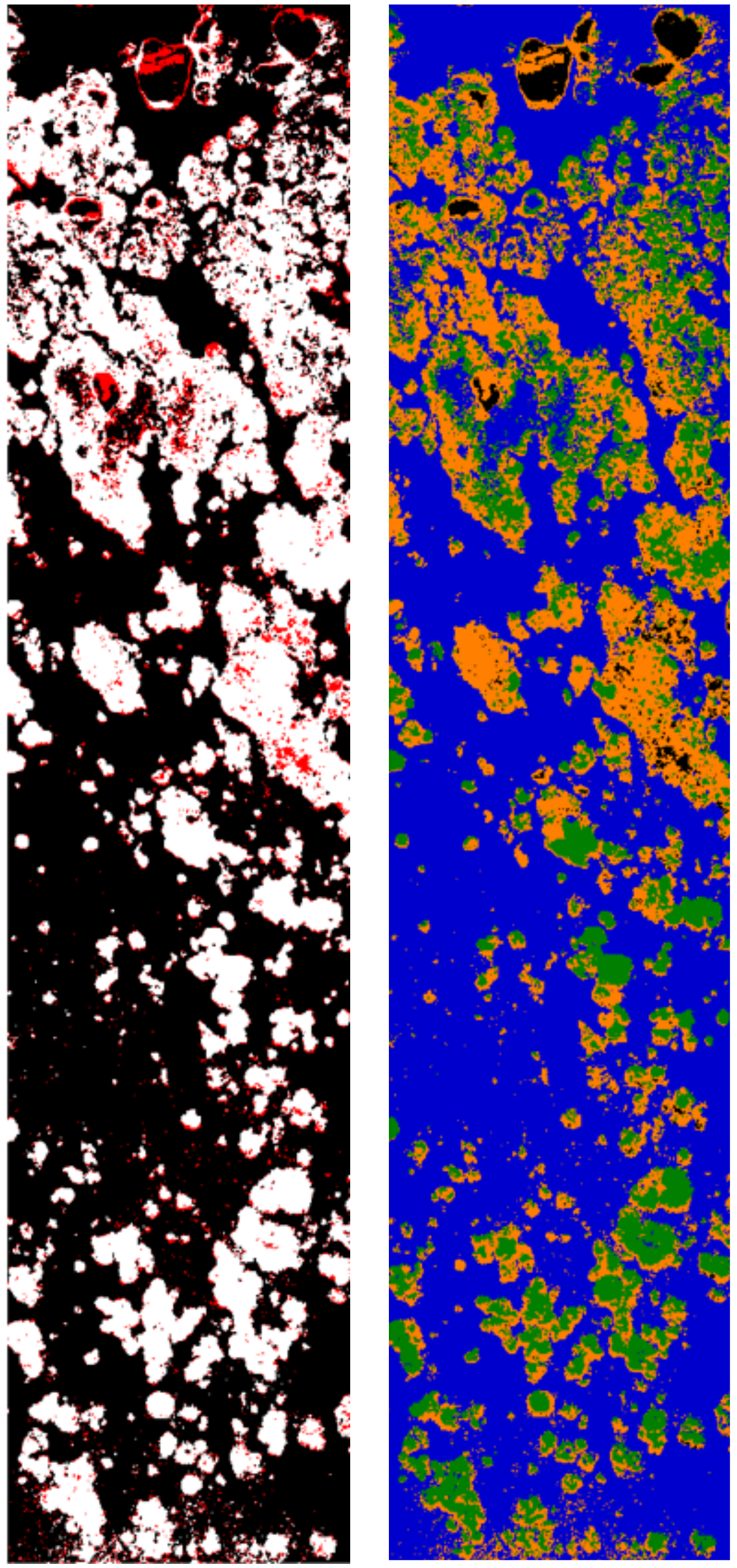
Image Rectification



- Align images and resolutions:
  - Scale Invariant Feature Transform (SIFT)
  - Random Sample Consensus (RANSAC)
- Finds the optimal homography transform

Augmented Machine Learning Training

Reference Data



PCA + SVM

PCA

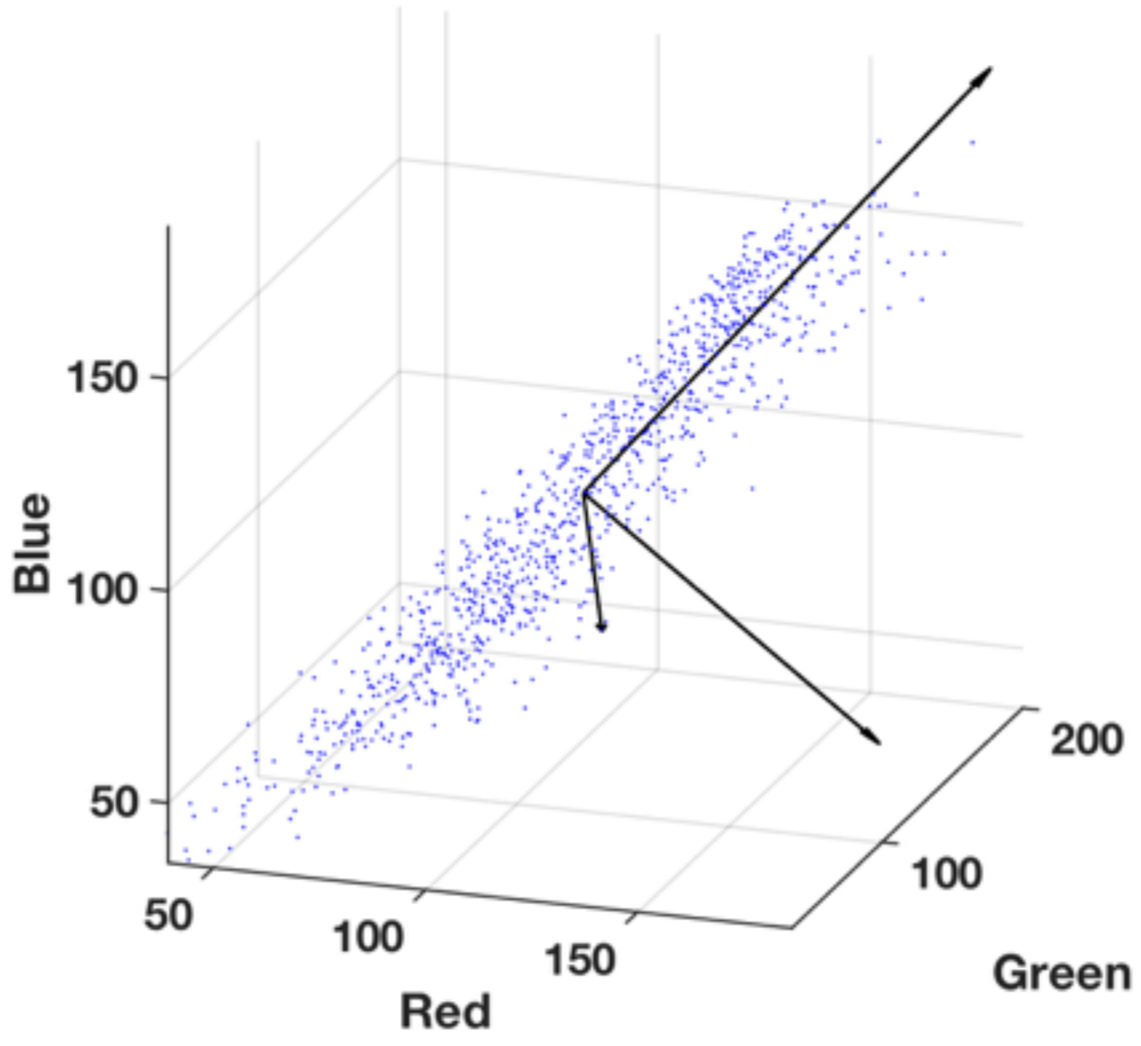
$$\mathbf{x}_{PCA} = \begin{bmatrix} \mathbf{p}_1^T \\ \mathbf{p}_2^T \\ \dots \\ \mathbf{p}_n^T \end{bmatrix} (\mathbf{x}_\lambda - \mathbf{x}_{\lambda,\mu})$$

$\mathbf{x}_{PCA}$ - Data point in PCA space

$\mathbf{p}_i^T$ - i^{th} principal unit vector

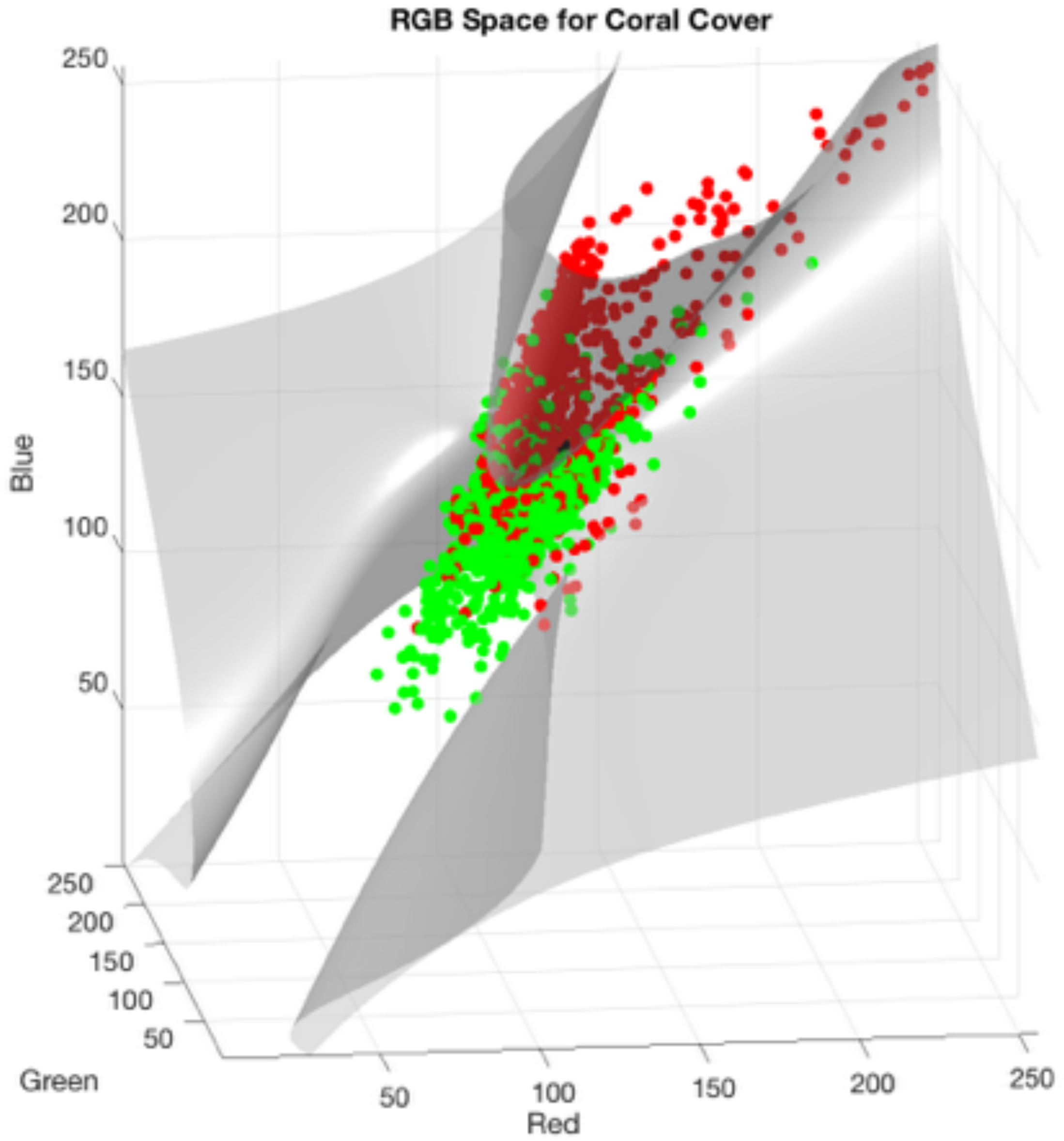
$\mathbf{x}_\lambda$ - Data point in original space

$\mathbf{x}_{\lambda,\mu}$ - Mean of $\mathbf{x}_\lambda$

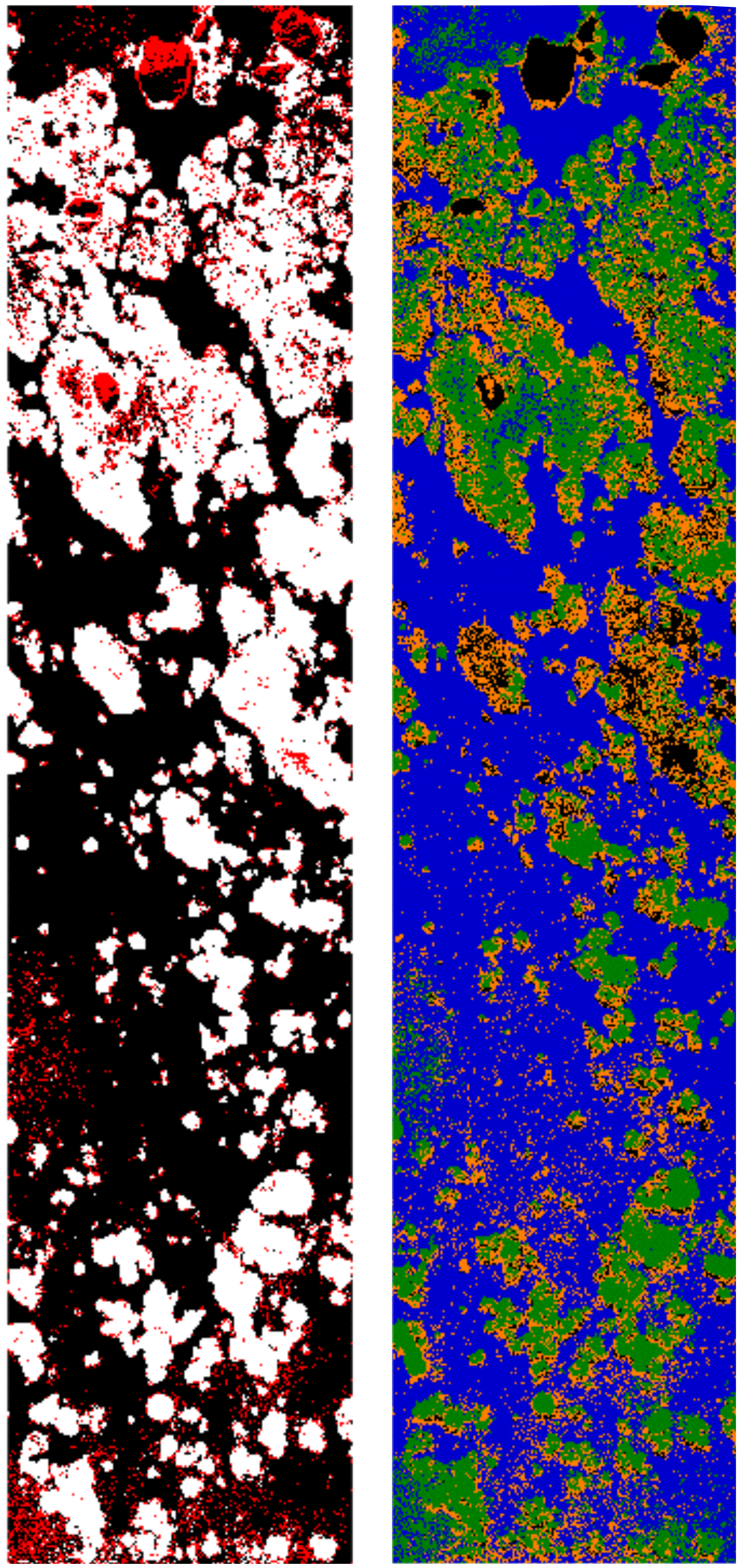


SVM

- 3rd order polynomial SVM fit to $\mathbf{x}_{PCA}$
- Separation into *k* classes via one-versus-one classification



SVM Classification Result

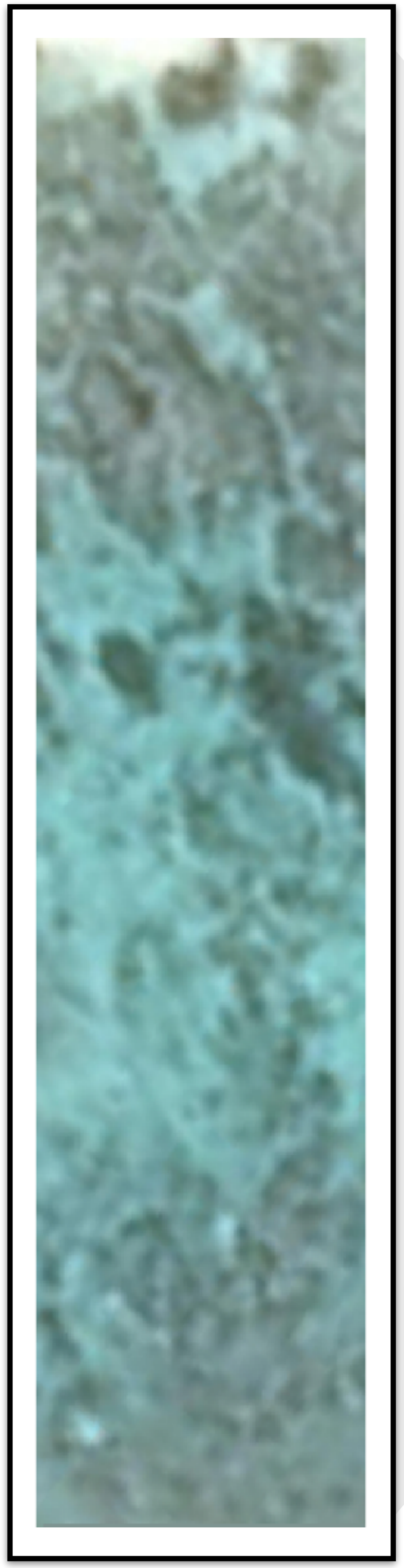


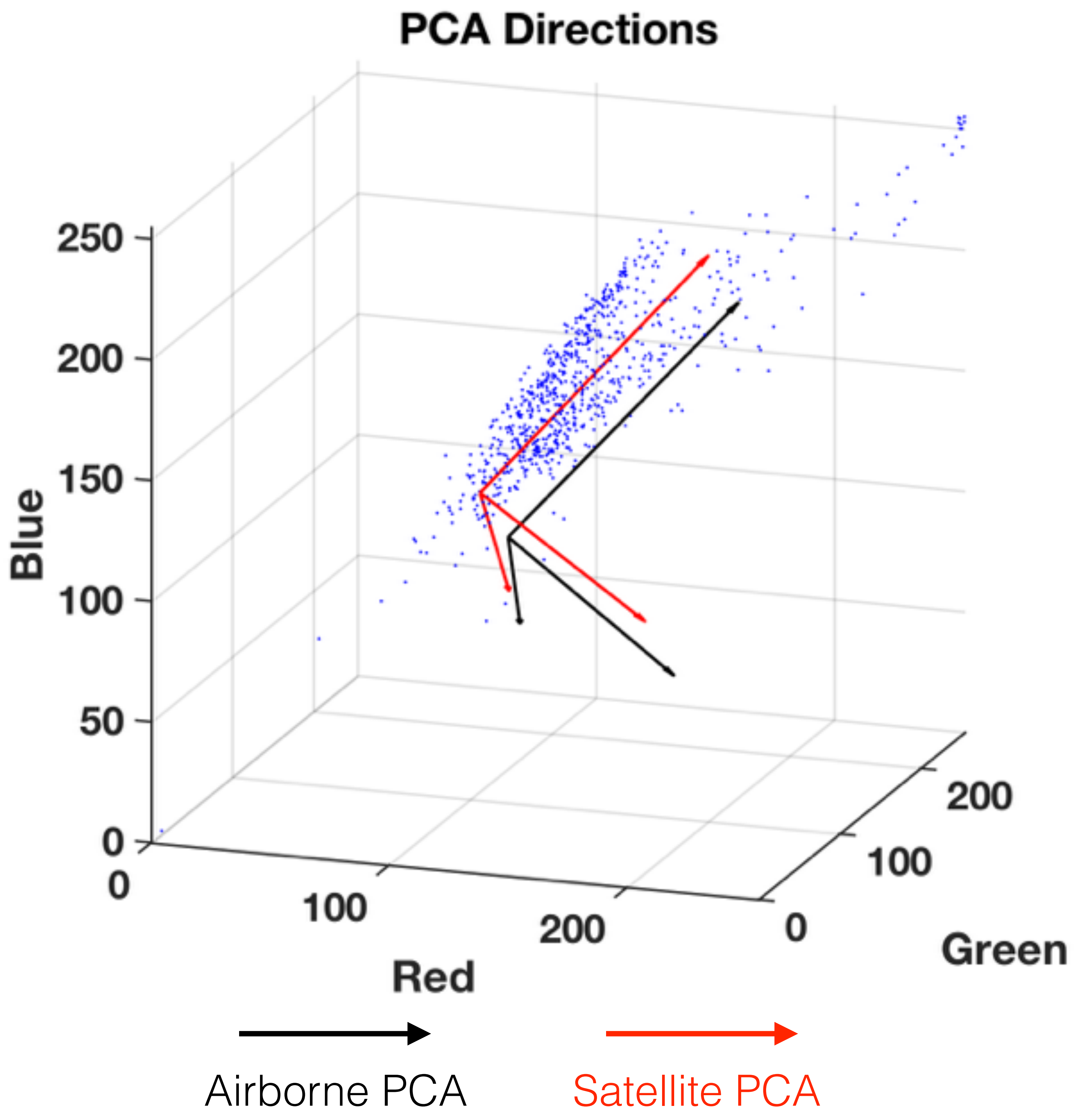
Organic Inorganic Error

Rock Branching Mounding Sand

Prediction Methodology

Satellite





Transform solution in **Airborne feature space** to apply to **Satellite feature space**

Augmentation Algorithm:

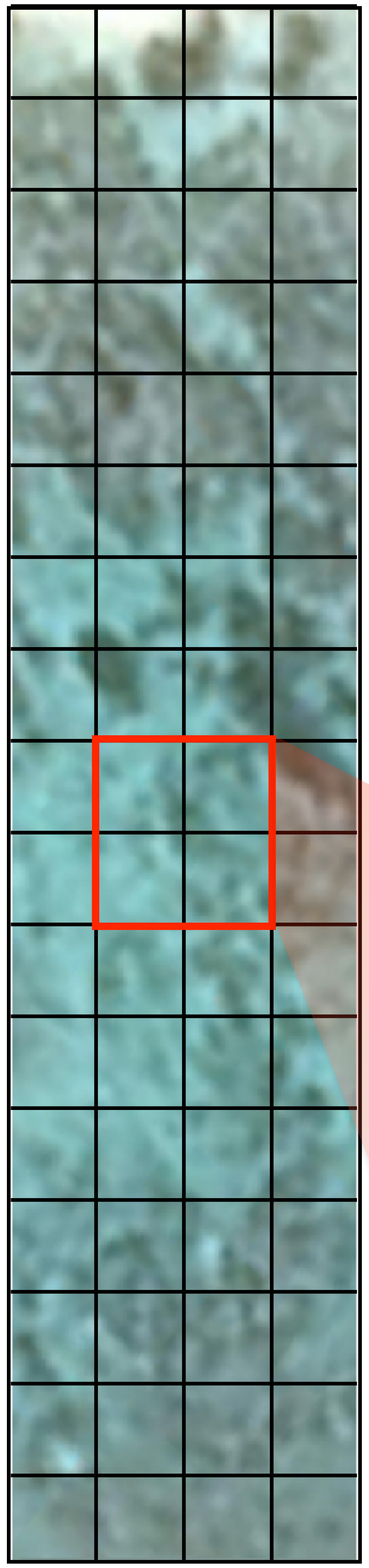
1) **Partition** image into various sections

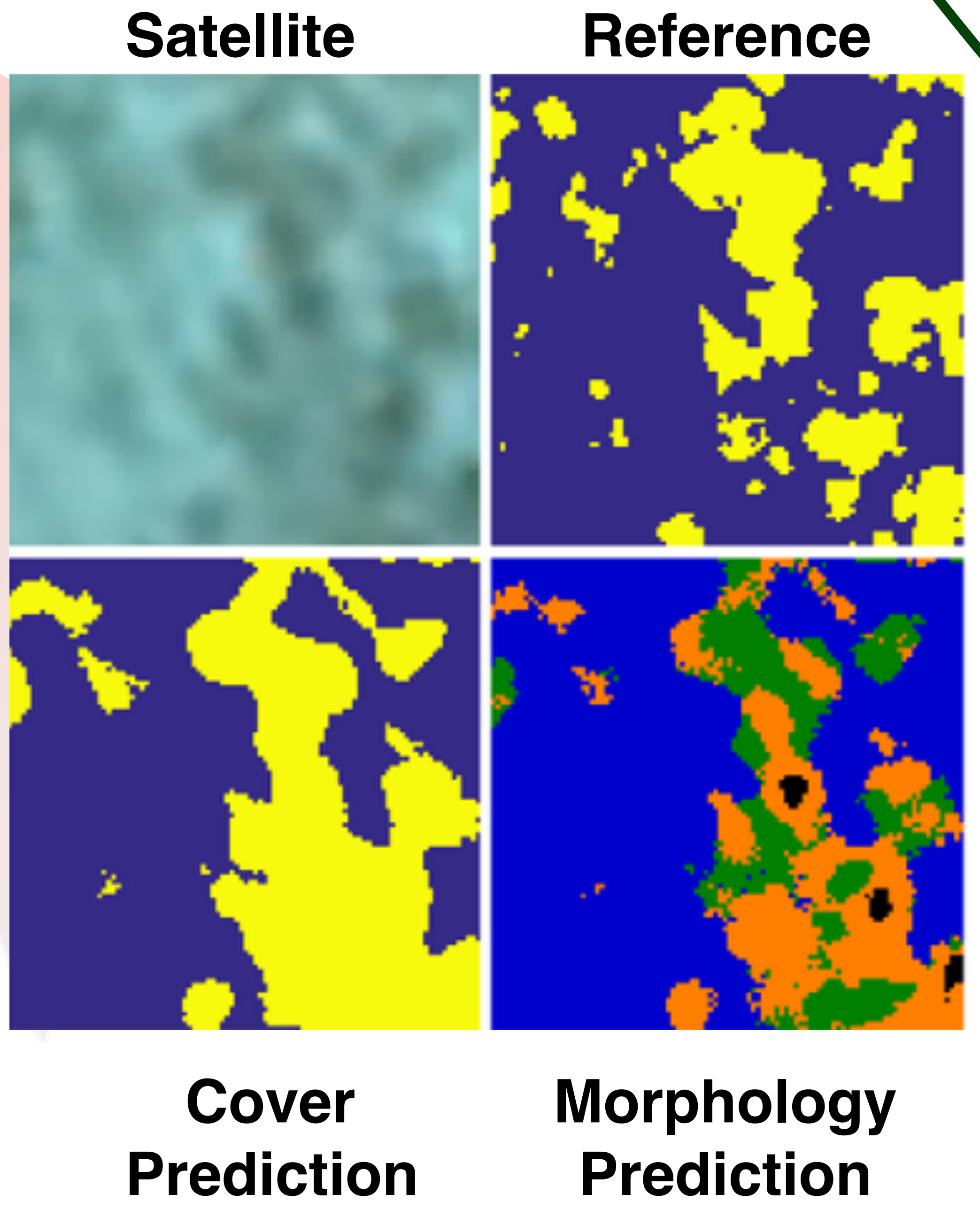
2) **Translate, rotate** and **scale** auxiliary dataset with reference to original SVM solution
   - **Translate**: Determined by mean of classes
   - **Rotate**: Determined by PCA directions
   - **Scale**: Determined by covariance of classes

3) **Predict** upon partitioned image using previous SVM solution
   - **Repeat** over all partitions
   - **Overlap** areas to build **Consensus**

Prediction Methodology

Image Partition





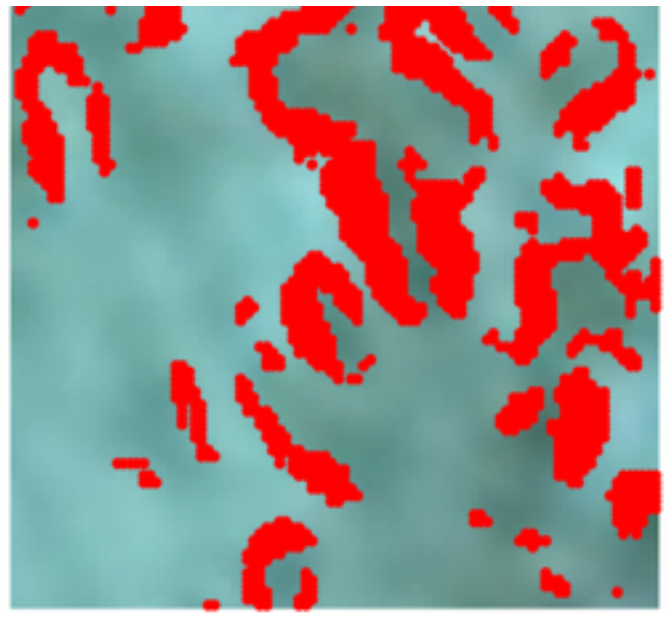
- $\mathbf{z}_{PCA}$ - Scaled result
- Σ_x - Covariance of x (reference data)
- Σ_y - Covariance of y (satellite data)
- $\mathbf{q}_i$ - Estimated i^{th} principal unit vector
- $\mathbf{y}_\lambda$ - Satellite data in original space
- $\hat{\mathbf{y}}_{\lambda,\mu}$ - Estimated mean of $\mathbf{y}_\lambda$

$$\mathbf{z}_{PCA} = \mathrm{diag}(\Sigma_x)[\mathrm{diag}(\Sigma_y)]^{-1} \begin{bmatrix} \mathbf{q}_1^T \\ \mathbf{q}_2^T \\ \cdots \\ \mathbf{q}_n^T \end{bmatrix} (\mathbf{y}_\lambda - \hat{\mathbf{y}}_{\lambda,\mu})$$

Translate

Gradient analysis (2 class)

- Identify regions of high gradients
- Perform clustering by DBSCAN
- Assign labels on adjacent points in relation to clustered points



Rotate

Rotate by mapping onto PCA vectors

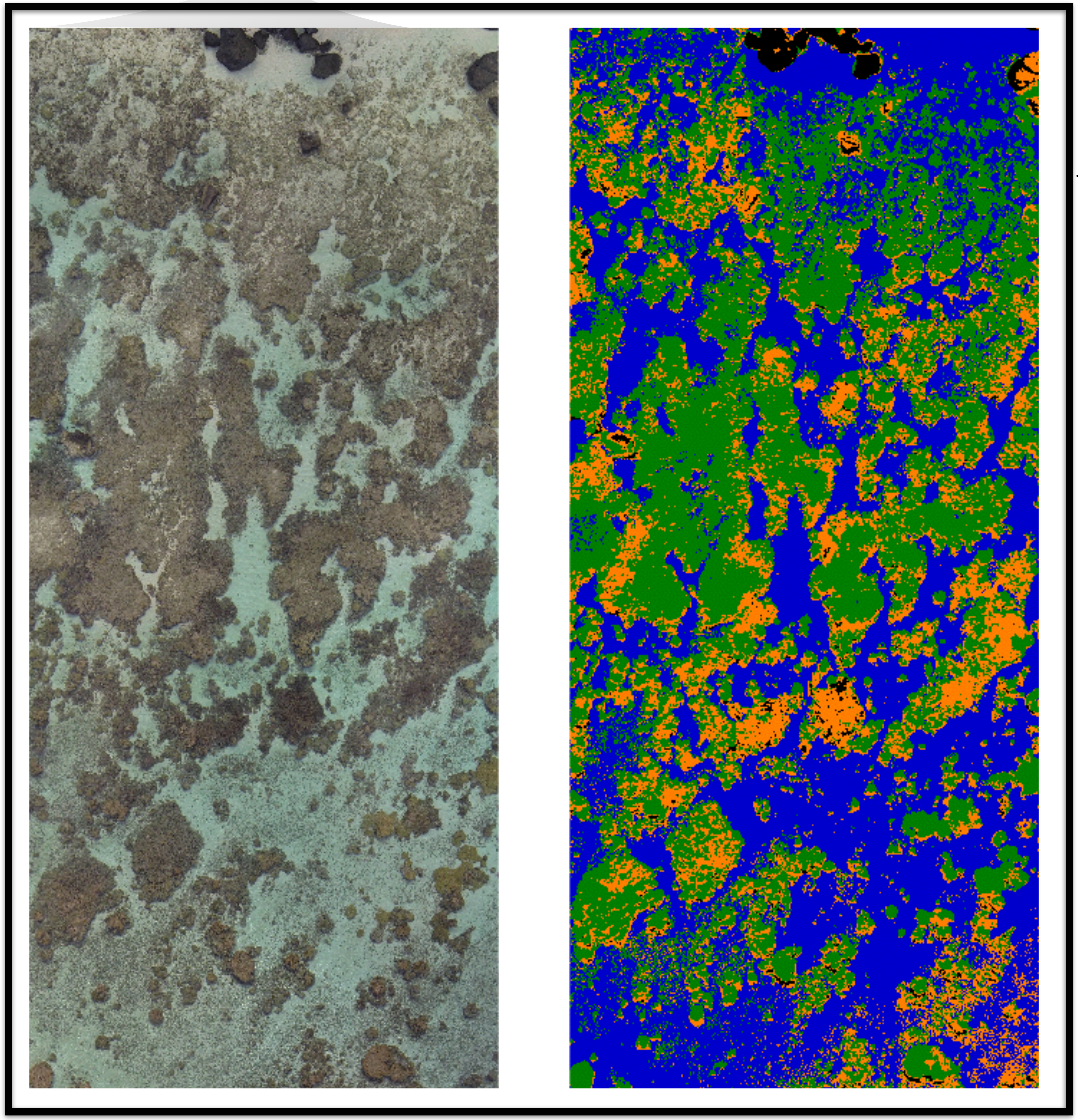
Scaling

Scale by covariance matrix

Results: 2-m scale Imagery

Robustness

MAP Estimate



What if we learn upon an **entirely different region**?

1) Take MAP estimate as reference
2) Learn upon these data
3) Predict on original transect

Coral Cover Prediction Accuracy

Method	0.3 m	0.5 m	2 m
K-Means	67%	71%	66%
SVM	74%	74%	63%
Previous Augmented	84%	79%	71%
Augmented	**83%**	**77%**	**69%**

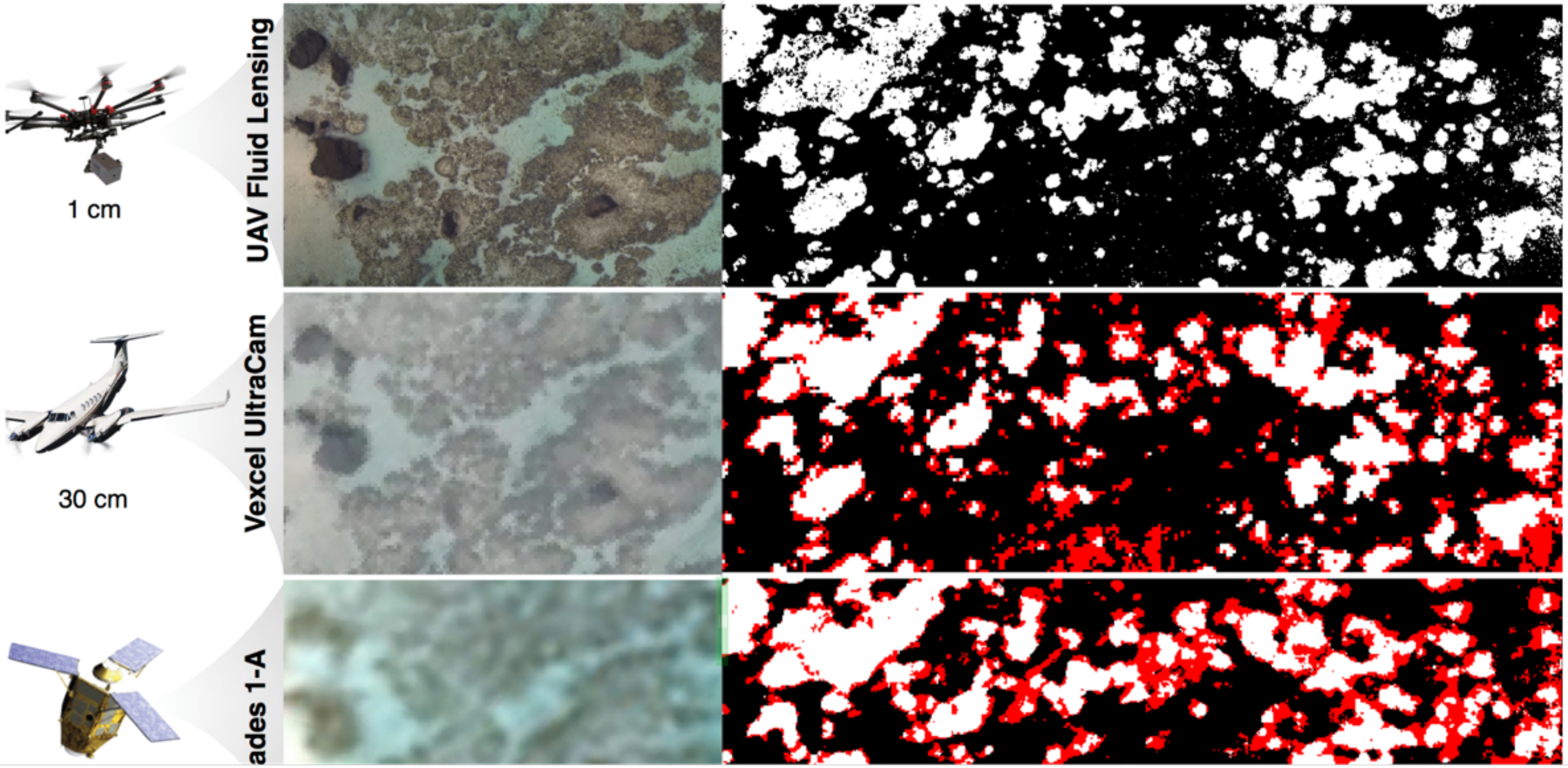
Morphology Prediction Accuracy

Method	0.3 m	0.5 m	2 m
SVM	59%	61%	38%
Previous Augmented	69%	62%	57%
Augmented	**70%**	**68%**	**60%**

AUGMENTED MACHINE LEARNING TOOLBOXES

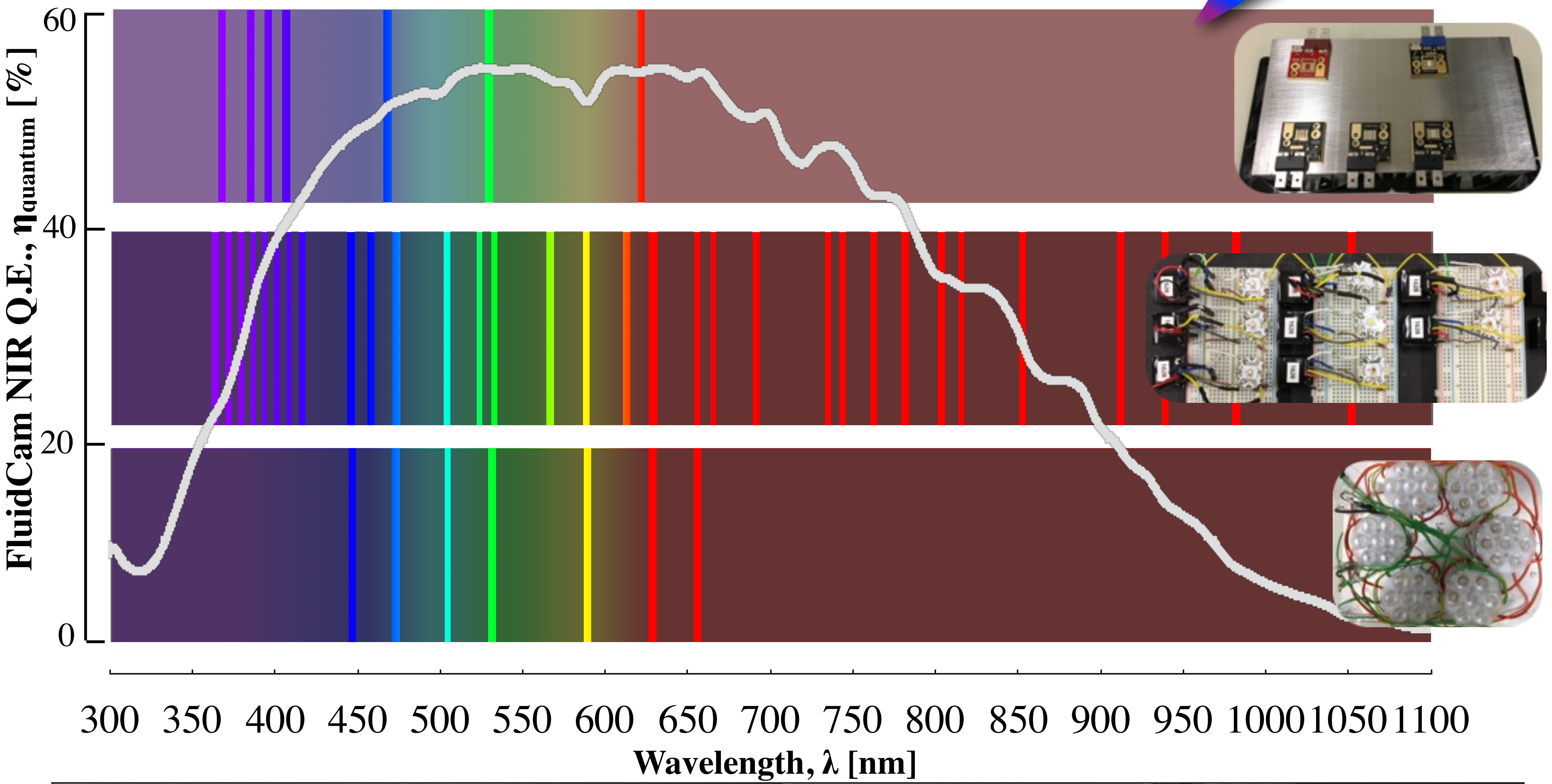
and (2) discrimination by morphology (sand, rock, branching coral, or mounding coral). The method is based upon Principal Component Analysis (PCA) to remap and rescale existing datasets upon a known Support Vector Machine (SVM) solution within analogous principal spaces.This supervised method is able to autonomously compensate for changing water depth and illumination conditions, with errors for coral cover and morphology classification derived from aerial imagery at approximately 16% and 31%, respectively. Classification error for data derived from the highest resolution commercial satellite imagery available (Pleiades-1A) is approximately 21% for coral cover and 38% for morphology. Although classification accuracy is improved across both phases, morphology discrimination suffers more acutely from lower resolution and noise effects. However, the method shows promise for future work where UAVs may observe multispectral or hyperspectral data, further increasing the speed and accuracy of classification and enhancing datasets taken at higher altitudes.

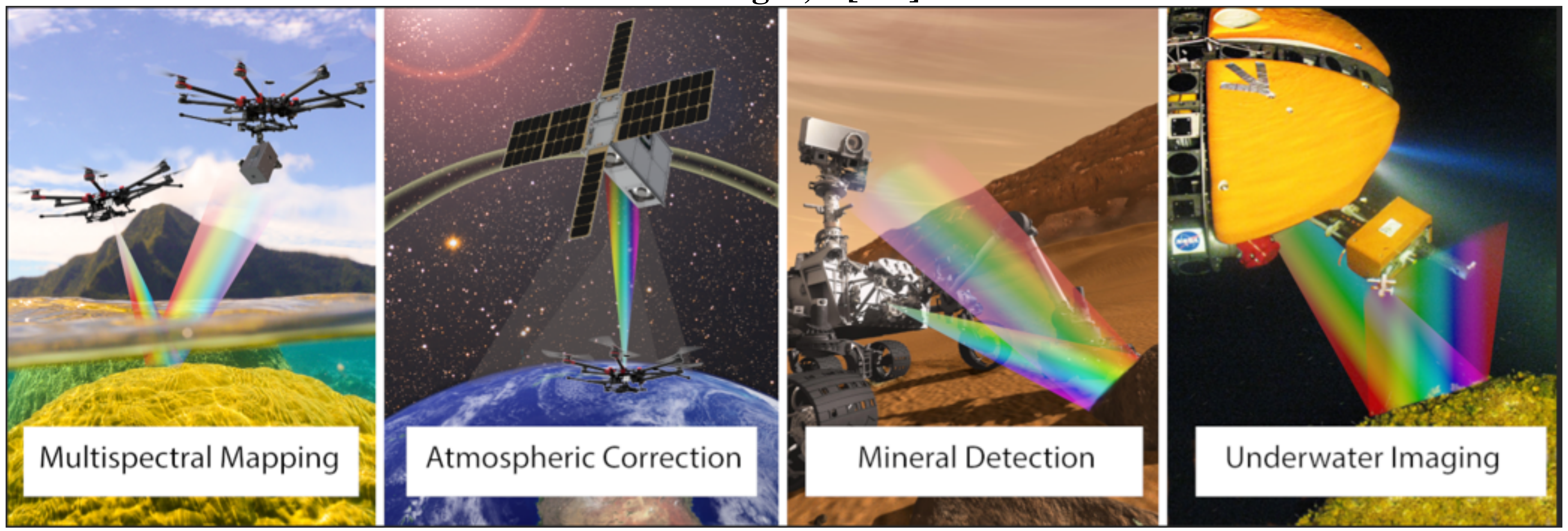
Classification of Coral Cover



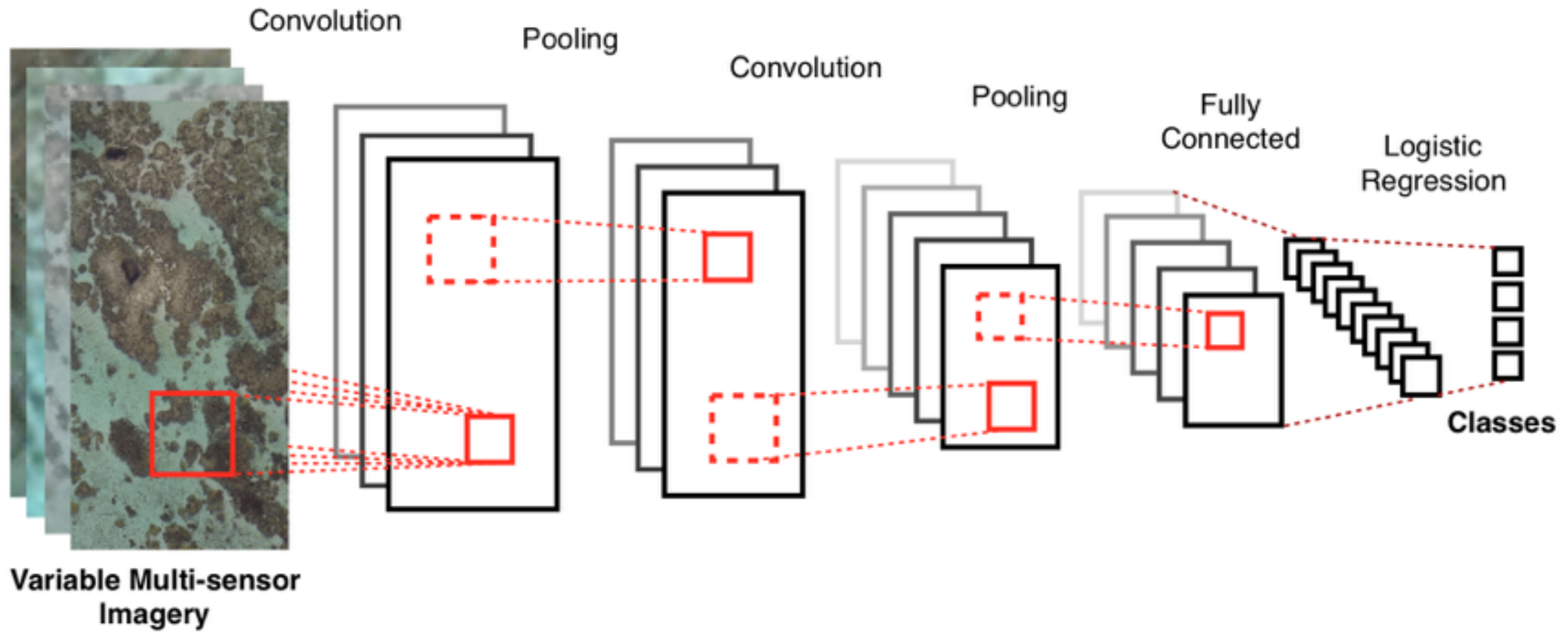
CURRENT & FUTURE WORK

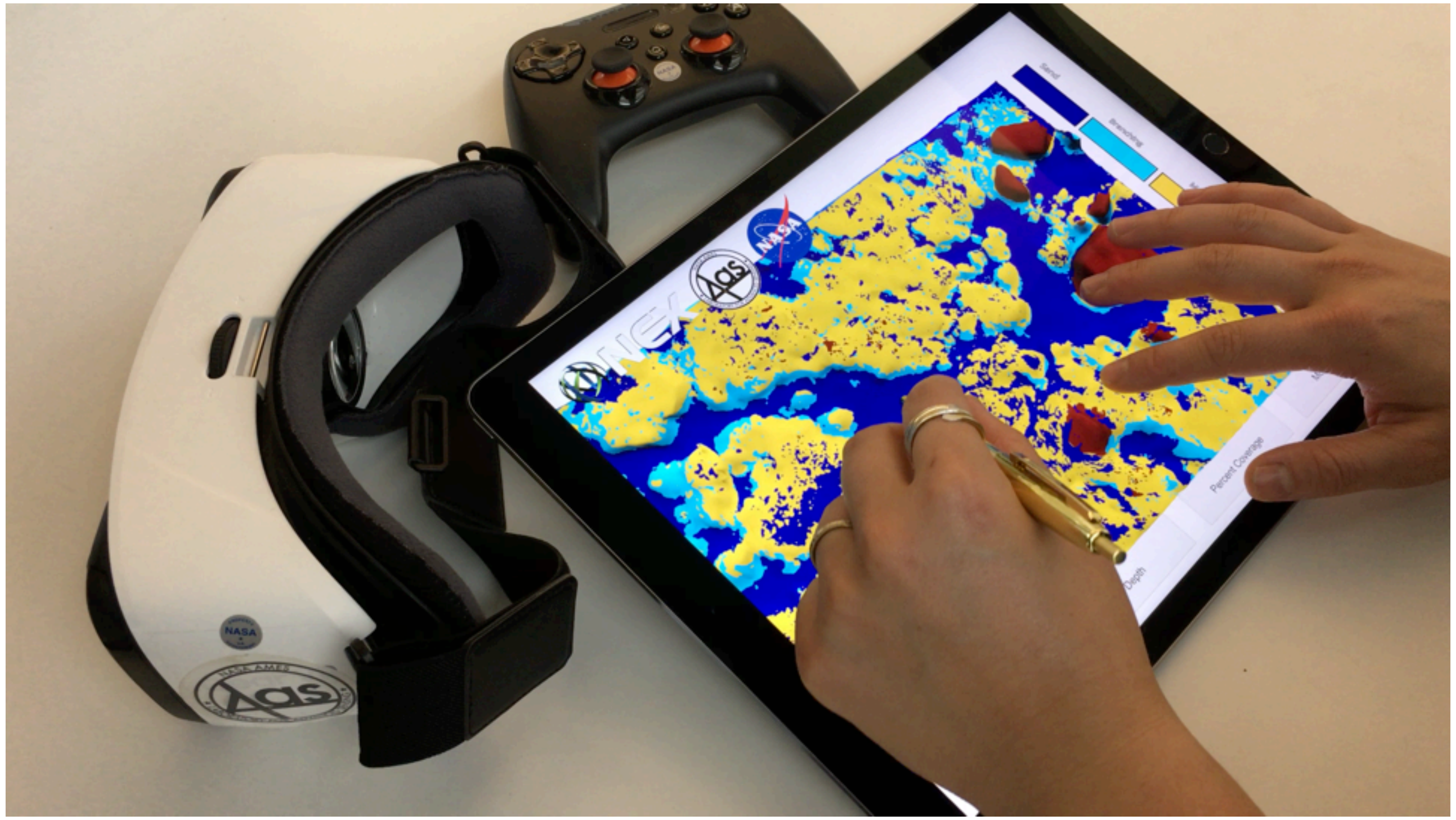
Airborne MiDAR-UV

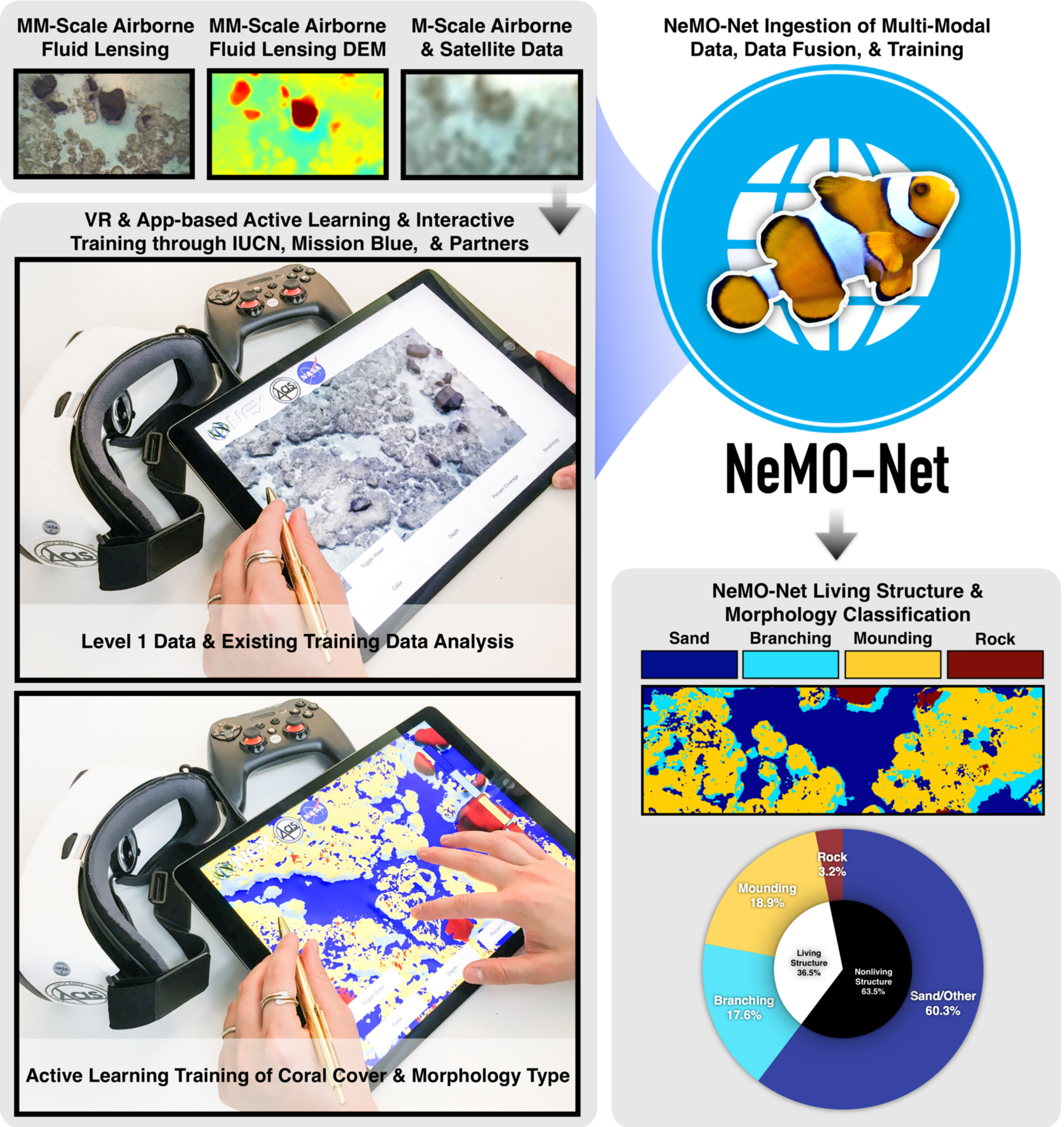




NEMO-NET - NEURAL MULTI-MODAL OBSERVATION & TRAINING NETWORK FOR GLOBAL CORAL REEF ASSESSMENT



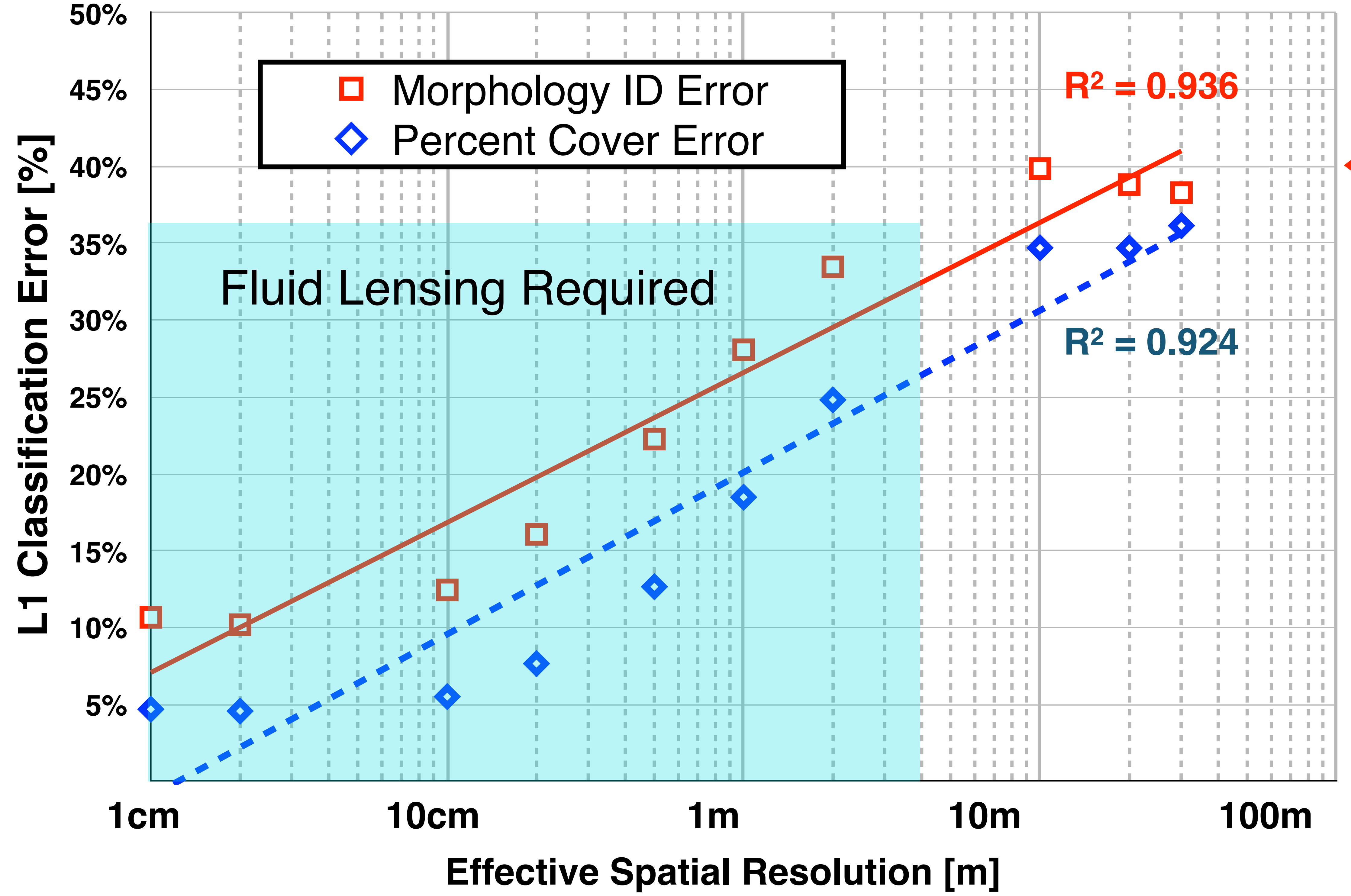


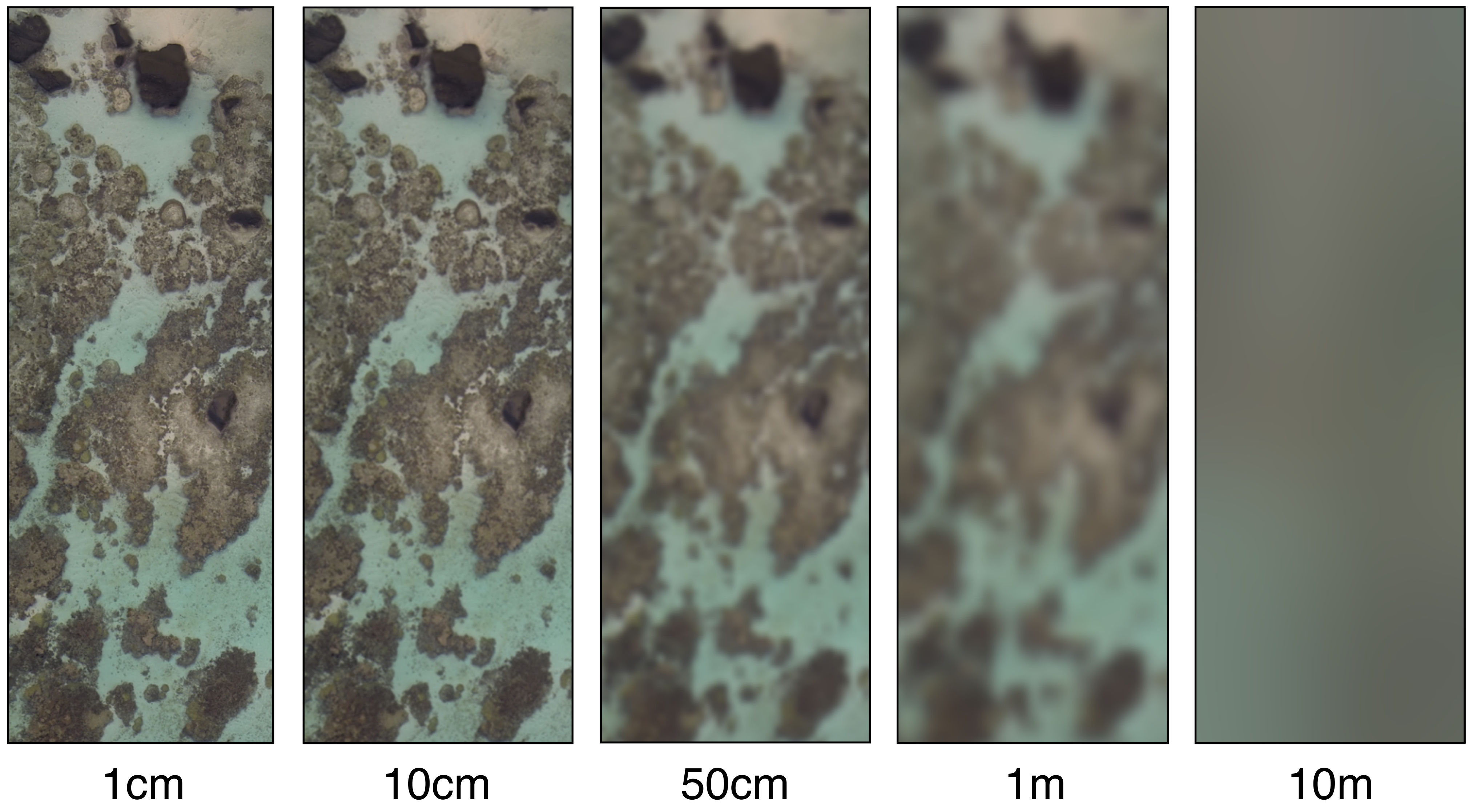


THANK YOU!

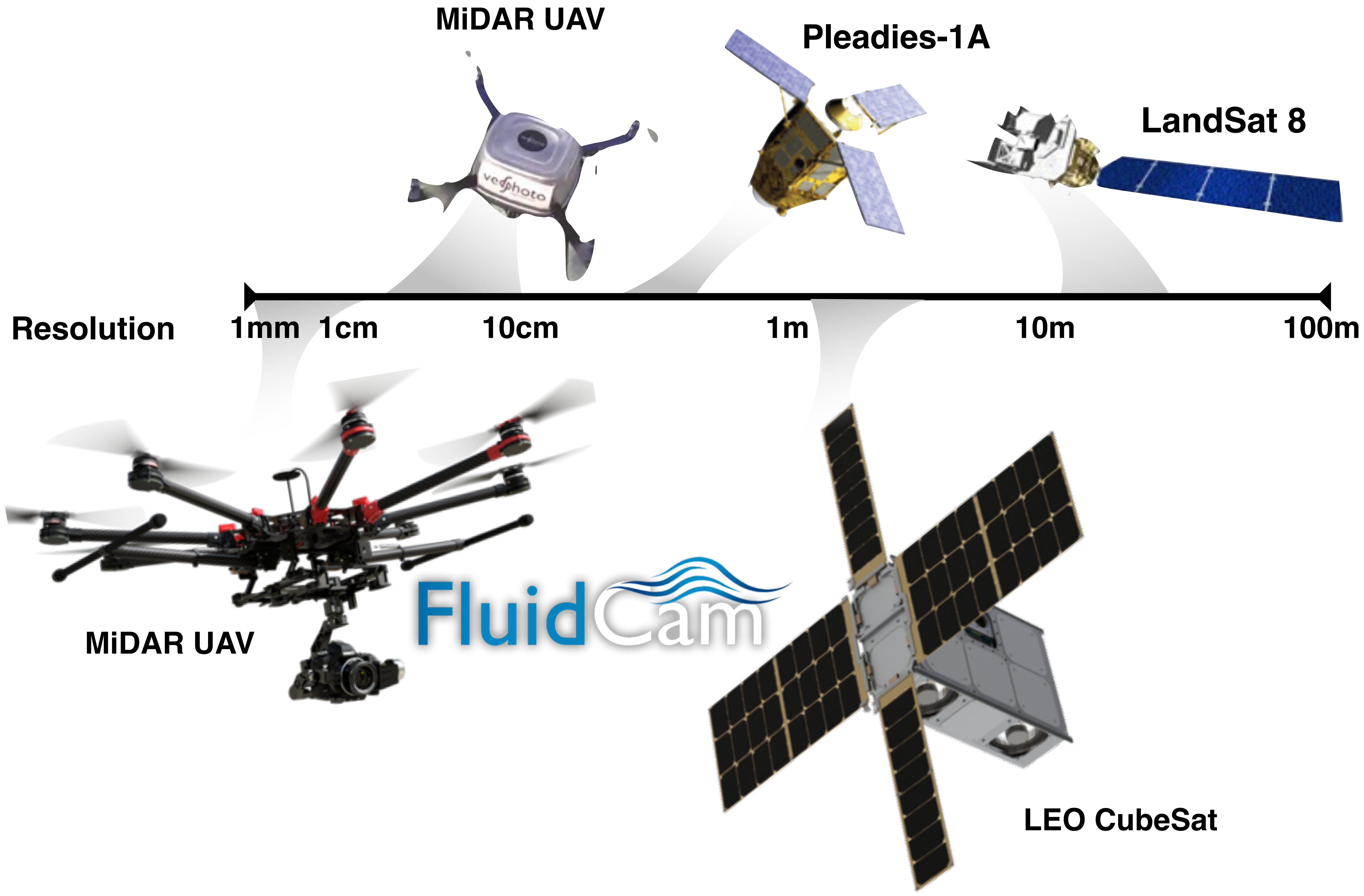
MiDAR DEMO

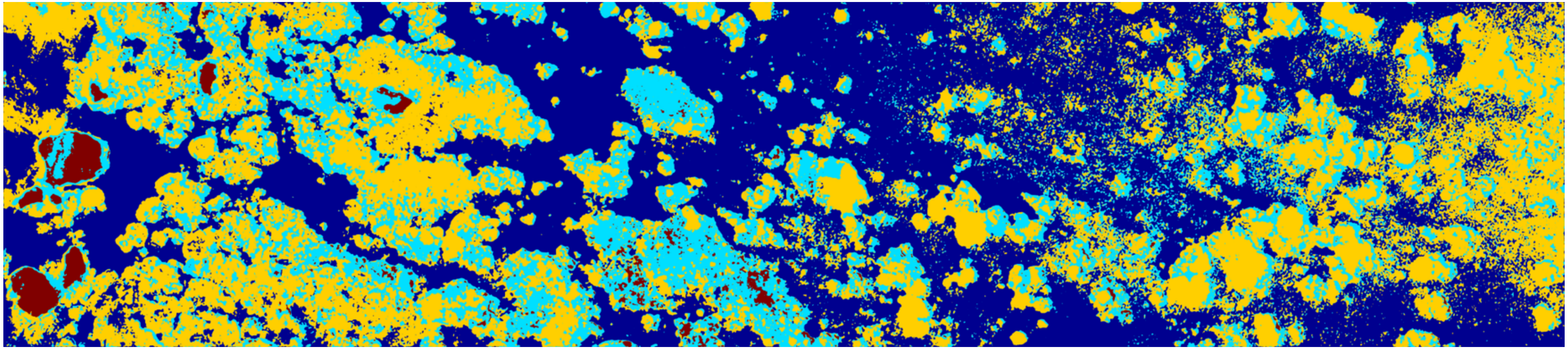
Morphology and Percent Cover Error vs. Effective Spatial Resolution

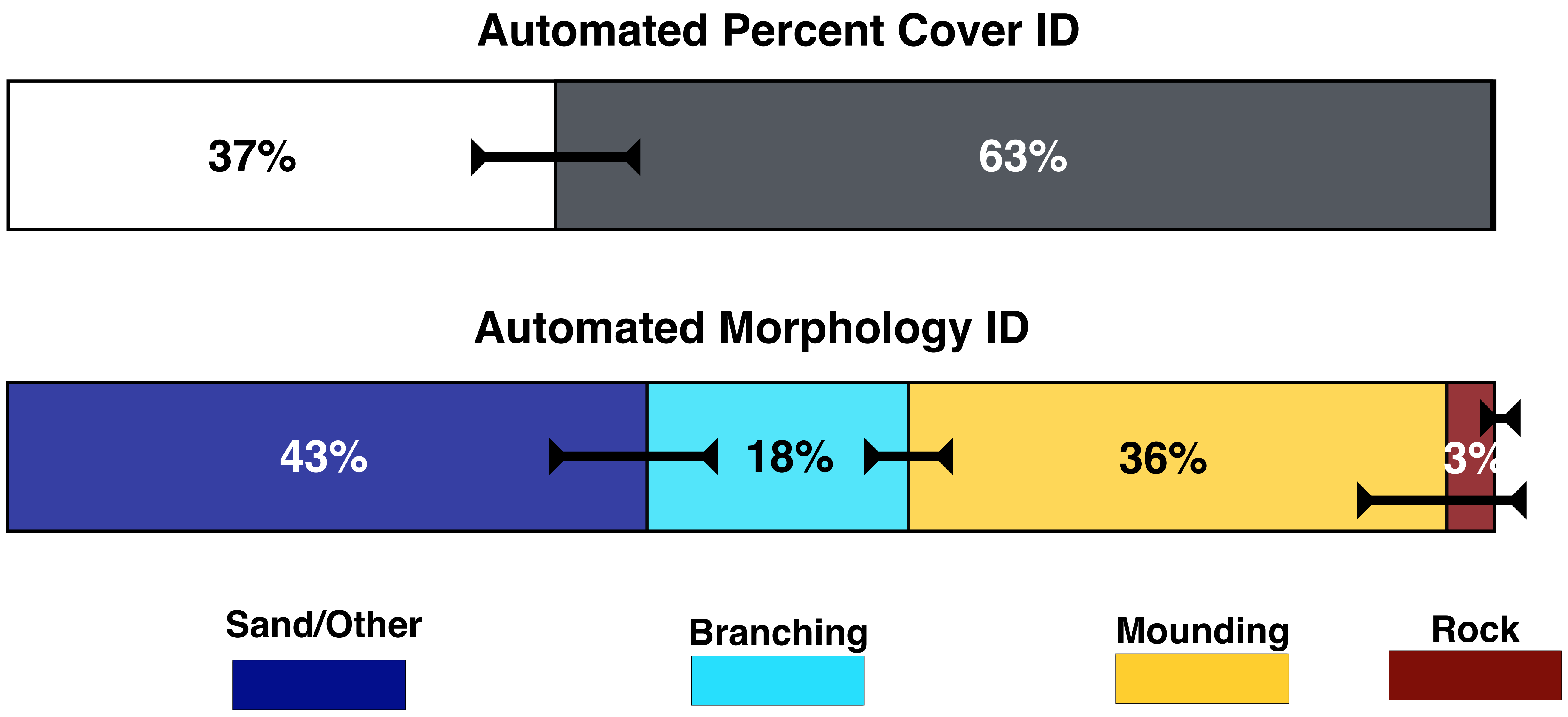


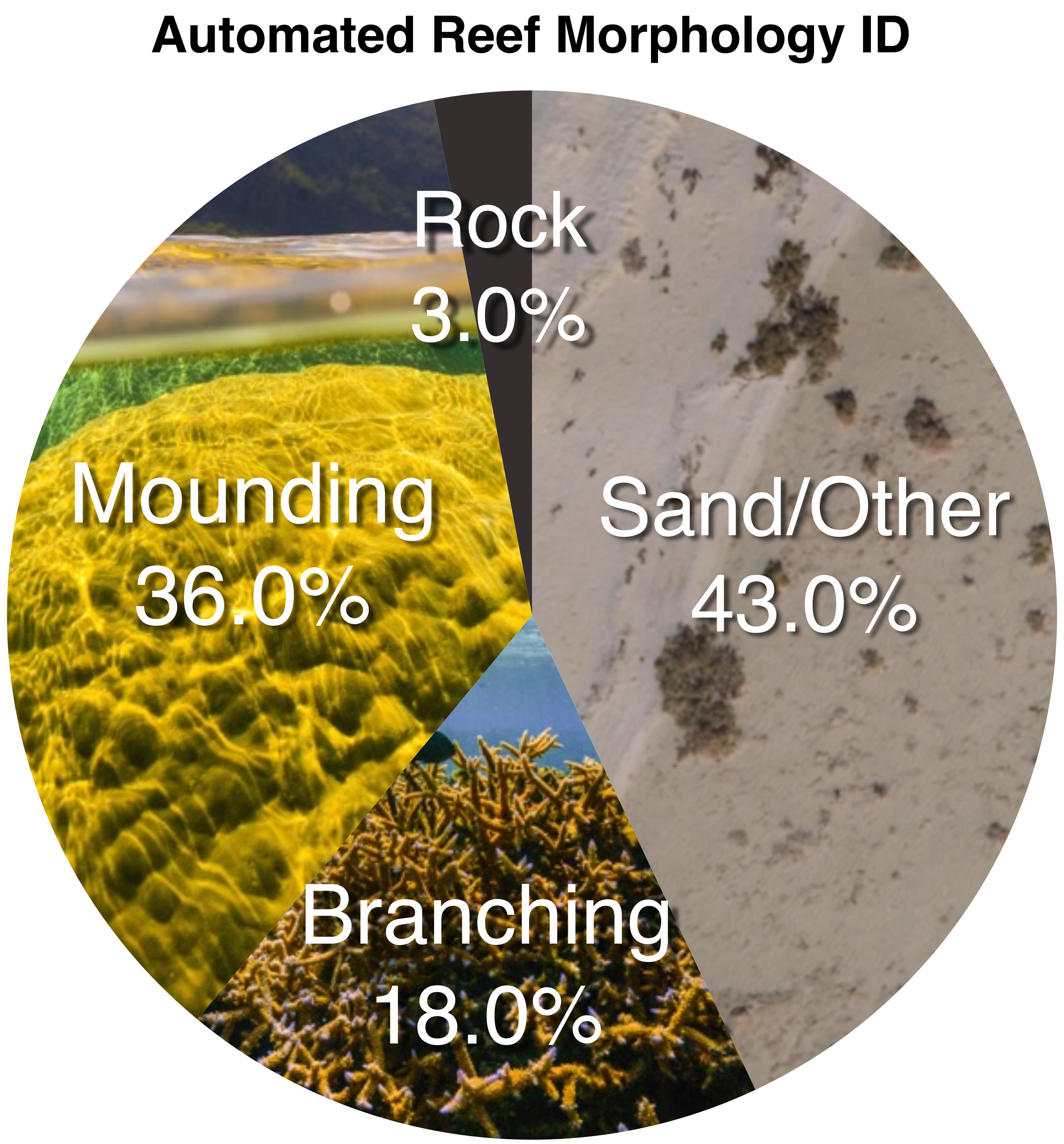


40% SHOCK!!!






Automated Percent Cover ID
37%
63%
Automated Morphology ID
43%
18%
36%
3%
Sand/Other
Branching
Mounding
Rock


Automated Reef Morphology ID
Rock
3.0%
Mounding
36.0%
Sand/Other
43.0%
Branching
18.0%

2016

FluidCam & MiDAR Fused Machine Learning & Dataset Augmentation

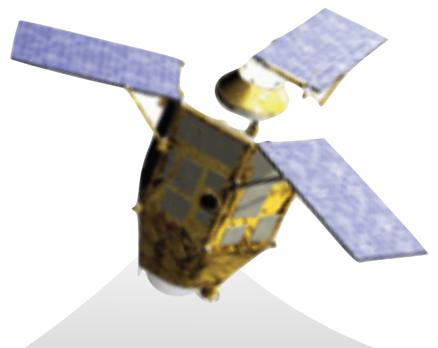
- Cm-scale dataset infusion
- Enhanced classification

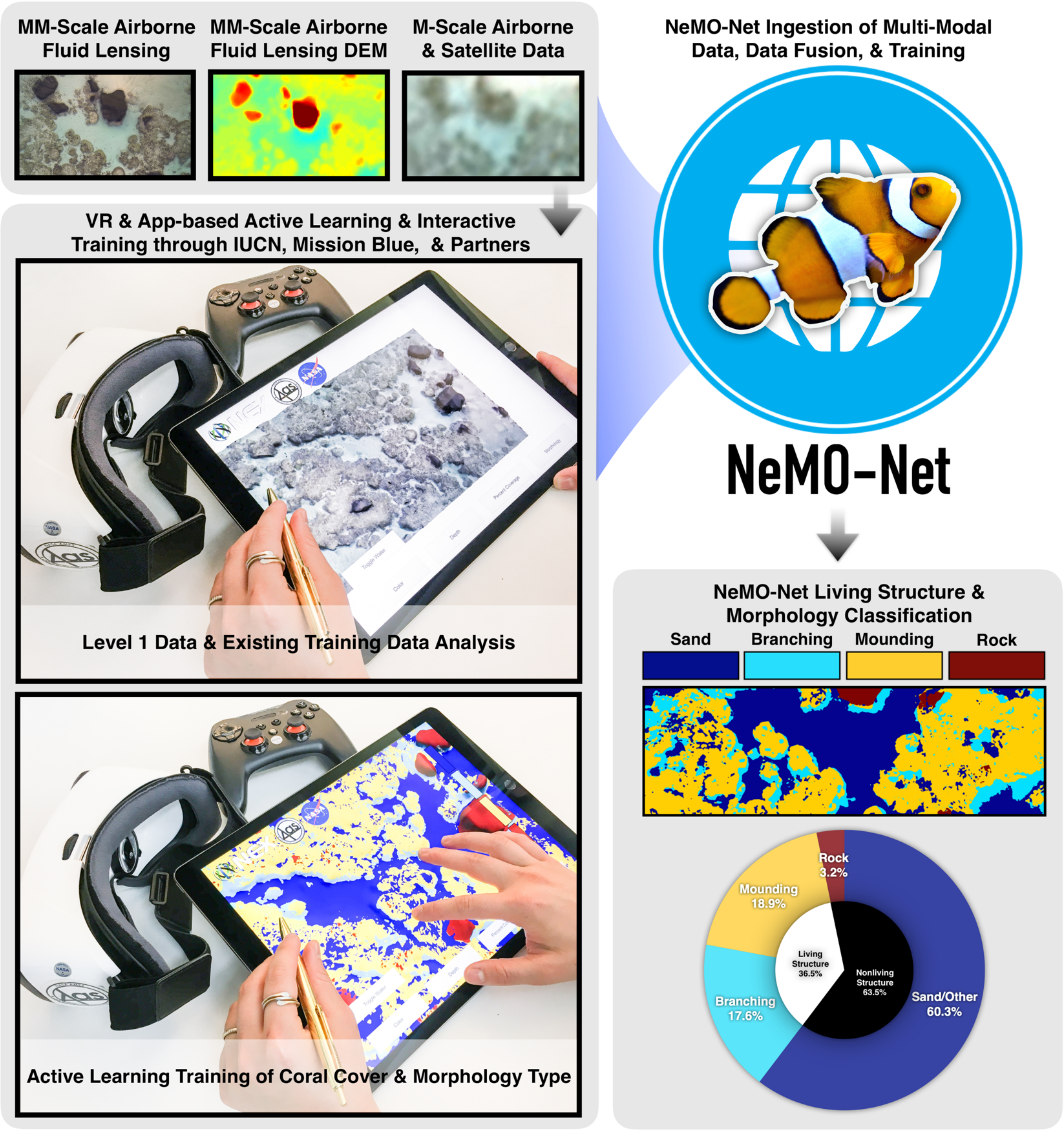
NASA AMES LABORATORY FOR ADVANCED SENSING

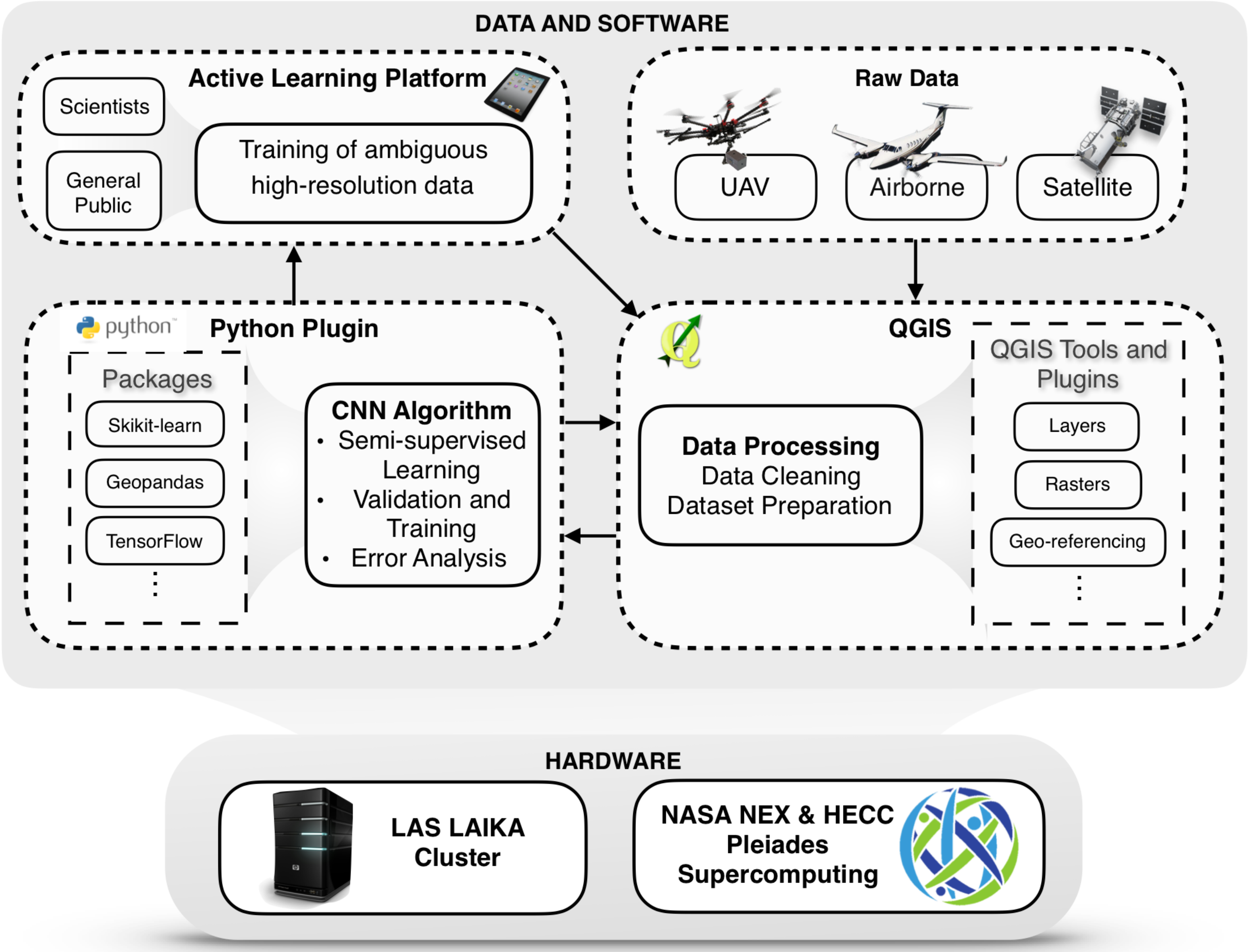
NASA


Results: 0.3-m scale Imagery
Reference
Organic
Inorganic
Error
Coral Cover
K-means
Direct SVM
Augmented
~67% Accuracy
~83% Accuracy
~84% Accuracy
Rock
Branching
Mounding
Sand
Morphology
Direct SVM
Augmented
~52% Accuracy
~69% Accuracy

Results: 0.5-m scale Imagery




MM-Scale Airborne Fluid Lensing
MM-Scale Airborne Fluid Lensing DEM
M-Scale Airborne & Satellite Data
VR & App-based Active Learning & Interactive Training through IUCN, Mission Blue, & Partners
Level 1 Data & Existing Training Data Analysis
Active Learning Training of Coral Cover & Morphology Type
NeMO-Net Ingestion of Multi-Modal Data, Data Fusion, & Training
NeMO-Net
NeMO-Net Living Structure & Morphology Classification
Sand
Branching
Mounding
Rock
Rock 3.2%
Mounding 18.9%
Branching 17.6%
Sand/Other 60.3%
Living Structure 36.5%
Nonliving Structure 63.5%


DATA AND SOFTWARE
Active Learning Platform
Scientists
General Public
Training of ambiguous high-resolution data
Raw Data
UAV
Airborne
Satellite
python
Python Plugin
Packages
Skikit-learn
Geopandas
TensorFlow
CNN Algorithm
• Semi-supervised Learning
• Validation and Training
• Error Analysis
QGIS
Data Processing
Data Cleaning
Dataset Preparation
QGIS Tools and Plugins
Layers
Rasters
Geo-referencing
HARDWARE
LAS LAIKA Cluster
NASA NEX & HECC Pleiades Supercomputing