Utilizing NASA's MiDAR Fluid Lensing and NeMO-Net for Automated Airborne Detection, Localization, and Characterization of Underwater Military Munitions

MR24-4534

Ved Chirayath

Aircraft Center for Earth Studies, University of Miami

In-Progress/ Final Review Meeting

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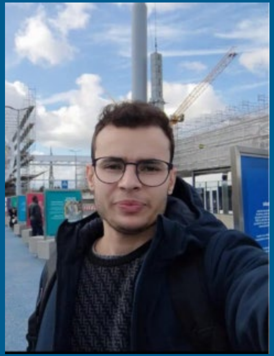
Project Team

Ved Chirayath

Drew Christensen

Soufyane Bouchelaghem



Imad Tibermacine

Isaiah Wang

Aircraft Center for Earth Studies, University of Miami

Bottom Line Up Front

- **Demonstrated new capability**: First use of airborne Fluid Lensing and MiDAR imaging with automated detection using a modified NeMO-Net architecture to successfully locate all deployed UXO in shallow, cluttered waters.
- **Strong results**: Achieved high precision (0.8–0.9) across modalities; however, recall remains moderate (~0.71) due to dataset and environment limitations.
- **Clear Path Forward**: Broader validation requires additional funding to support more campaigns that expand UXO types, environments, and improve machine learning methods for deployment.

Technical Objective

- **Objective:** Demonstrate the feasibility of using airborne 10-band multispectral Fluid Lensing (passive) and 8-band MiDAR (active) technologies, combined with a YOLO-based machine learning detector adapted from NASA's NeMO-Net, to detect, localize, and characterize underwater unexploded ordnance (UXO). This research is essential because shallow-water UXO pose significant risks to human safety, marine ecosystems, and coastal infrastructure, yet traditional acoustic methods are limited in water depths less than 10 meters and ship speeds.
- **Goal:** Deliver a scalable, UAV-based detection pipeline capable of operating effectively in cluttered, shallow environments with high precision.

SERDP

Technical Approach

Field Deployment and Imaging

- Finalize vessel and Unmanned Aircraft System (UAS) operational plans.
- Identify and receive inert munitions at the University of Miami.
- Establish modified NeMO-Net Convolutional Neural Network (CNN) workflow.
- Complete necessary permitting and field operations plans.
- Test and document the spectral reflectance of munitions.
- Deploy munitions in the field.
- Image the munitions using airborne Fluid Lensing and MiDAR

Data Processing

- Process all field data into georectified 3D images.

NeMO-Net Training and Analysis

- Classify the georectified 3D images using modified detector.
- Perform an accuracy assessment of NeMO-Net outputs for submerged munitions.

Reporting

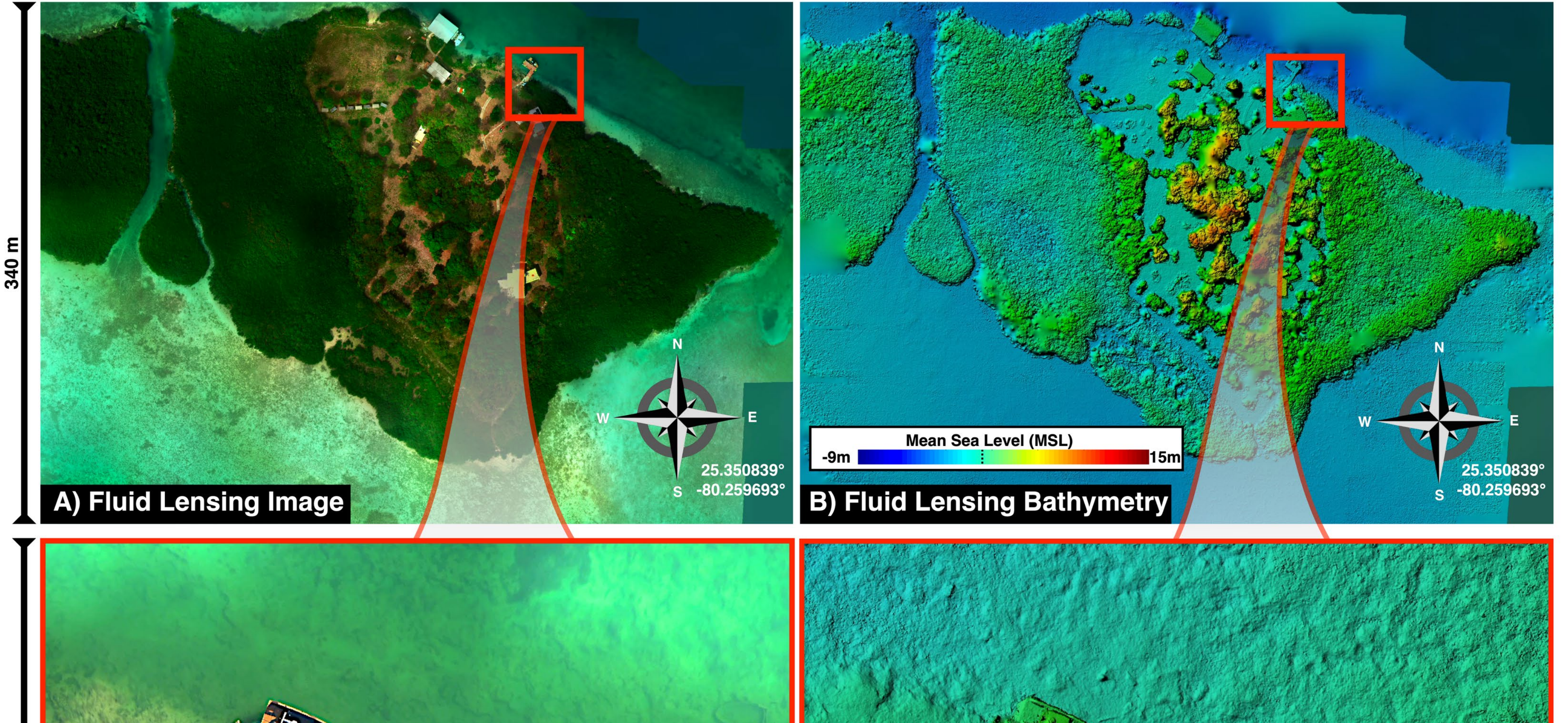
- Capture findings in a peer-reviewed publication.
- Final report.

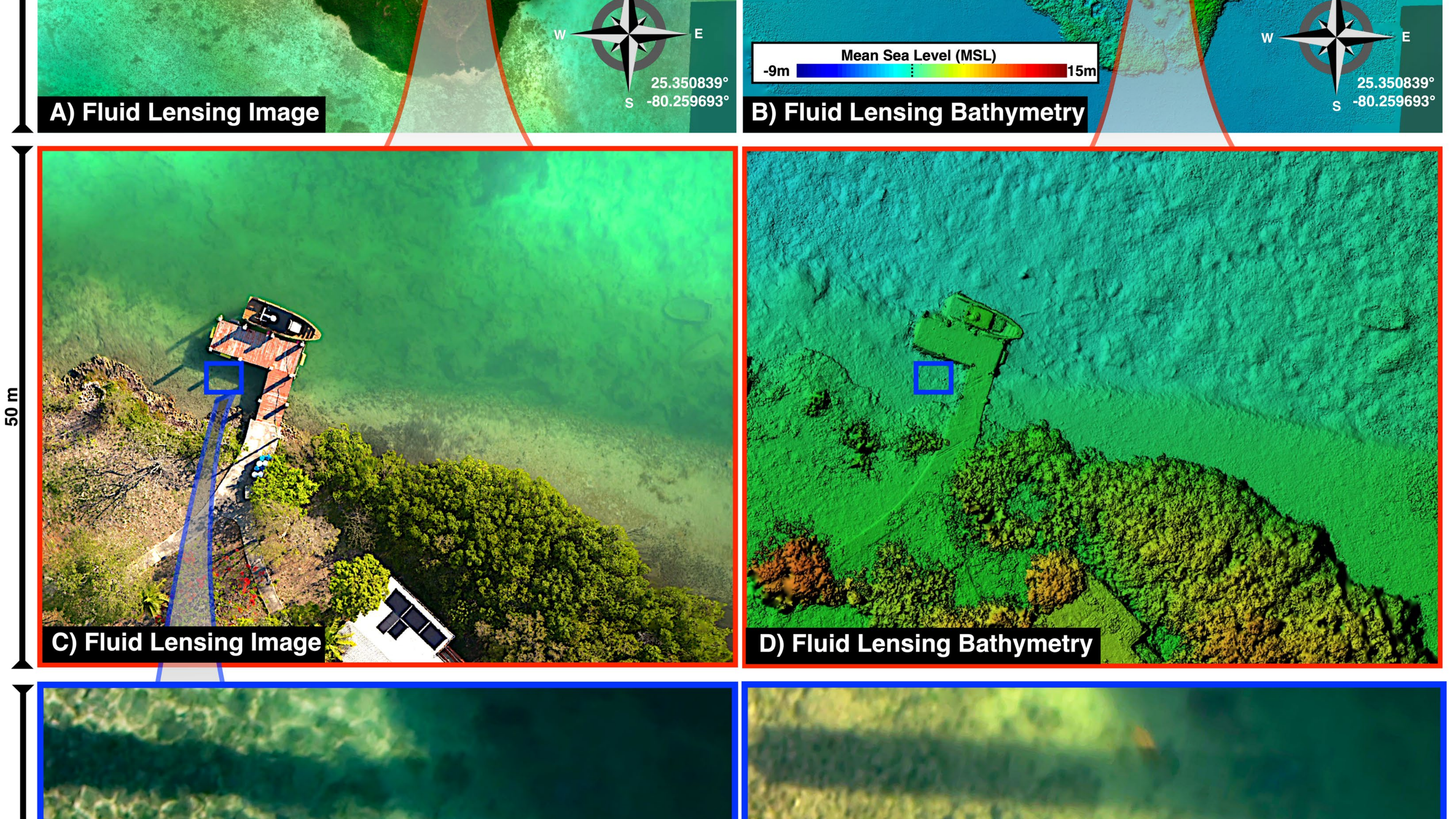
Results

- **Detection Performance**: Successfully detected and localized all 14 inert UXO and discriminated against nipples.
- **Methods and Techniques**: UAV-based Fluid Lensing and MiDAR imaging at cm-scale resolution; dataset expanded via augmentation (2,700 synthetic samples); YOLO-based detector adapted from NeMO-Net.
- **Key Outcomes**:
  - High precision across modalities (MiDAR: 0.8–0.9; 3-band: 0.73–0.89; 10-band: 0.71–0.74).
  - Moderate recall (~0.71) due to turbidity, vignetting, and dataset scope.
  - Demonstrated cross-modal generalization without re-training, validating scalability.

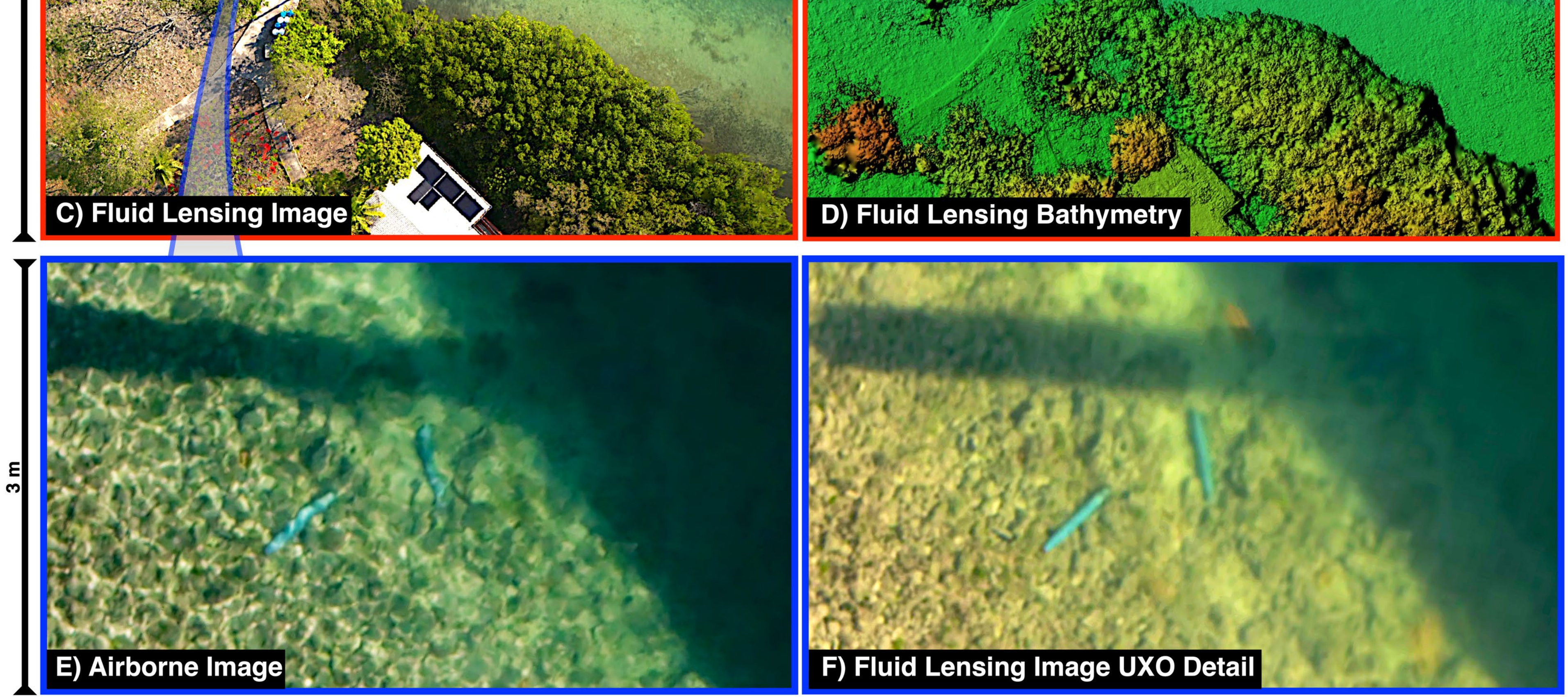
Results

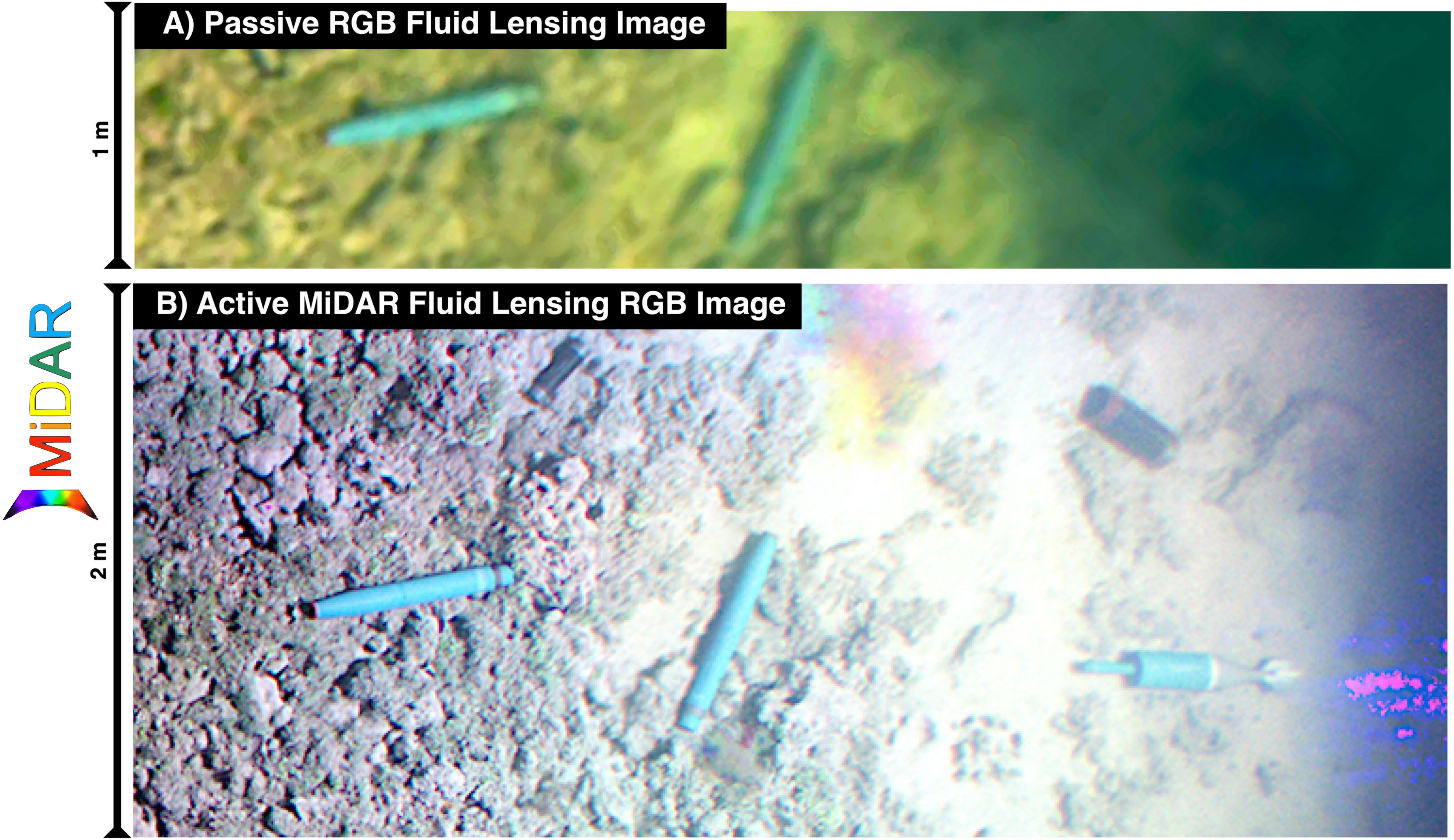
10-BAND MULTISPECTRAL PASSIVE FLUID LENSING

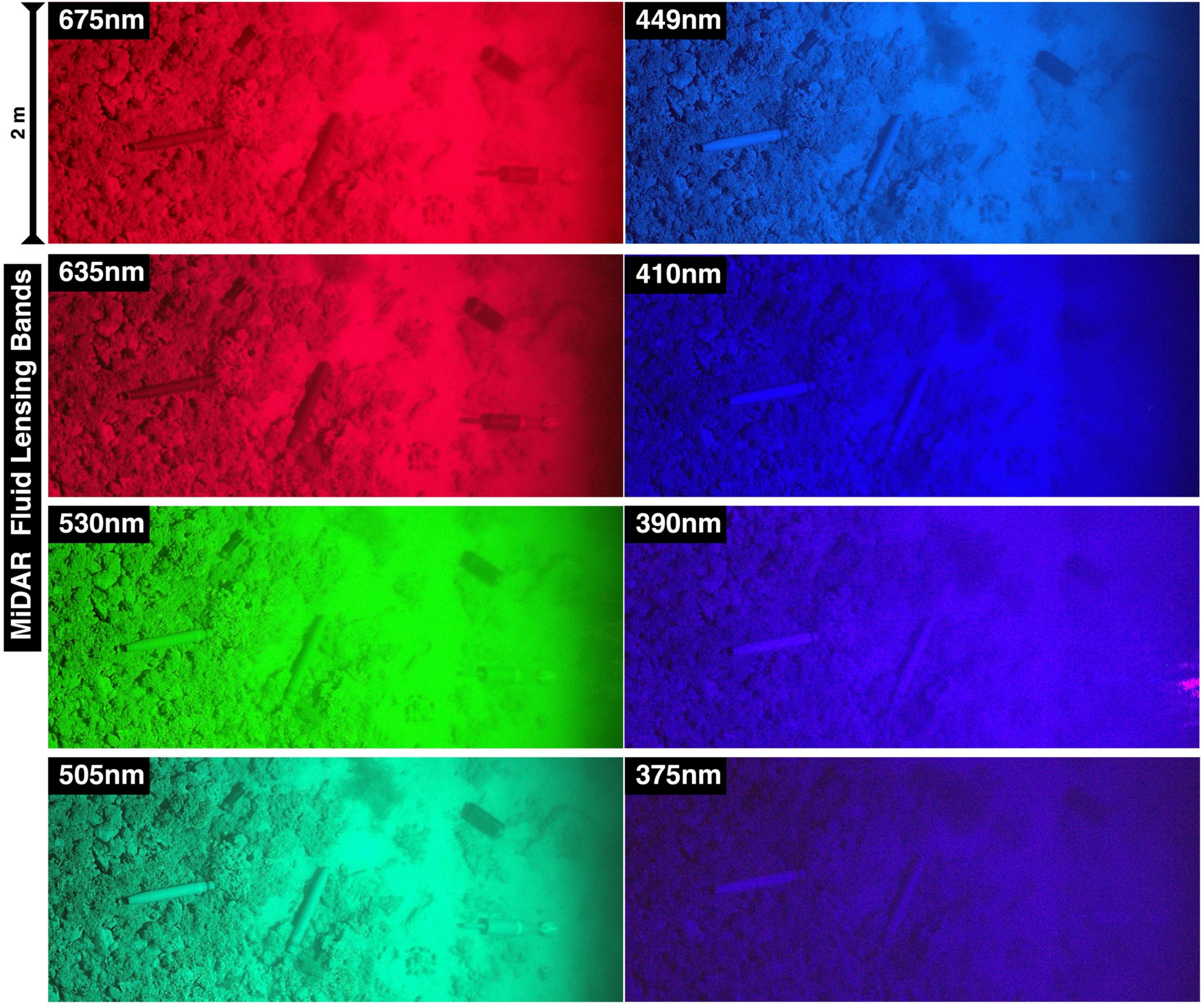




W
E
S
25.350839°
-80.259693°
A) Fluid Lensing Image
Mean Sea Level (MSL)
-9m
15m
B) Fluid Lensing Bathymetry
50 m
C) Fluid Lensing Image
D) Fluid Lensing Bathymetry


C) Fluid Lensing Image
D) Fluid Lensing Bathymetry
3 m
E) Airborne Image
F) Fluid Lensing Image UXO Detail


A) Passive RGB Fluid Lensing Image
1 m
B) Active MiDAR Fluid Lensing RGB Image
2 m
MiDAR


MiDAR Fluid Lensing Bands
2 m
675nm
449nm
635nm
410nm
530nm
390nm
505nm
375nm

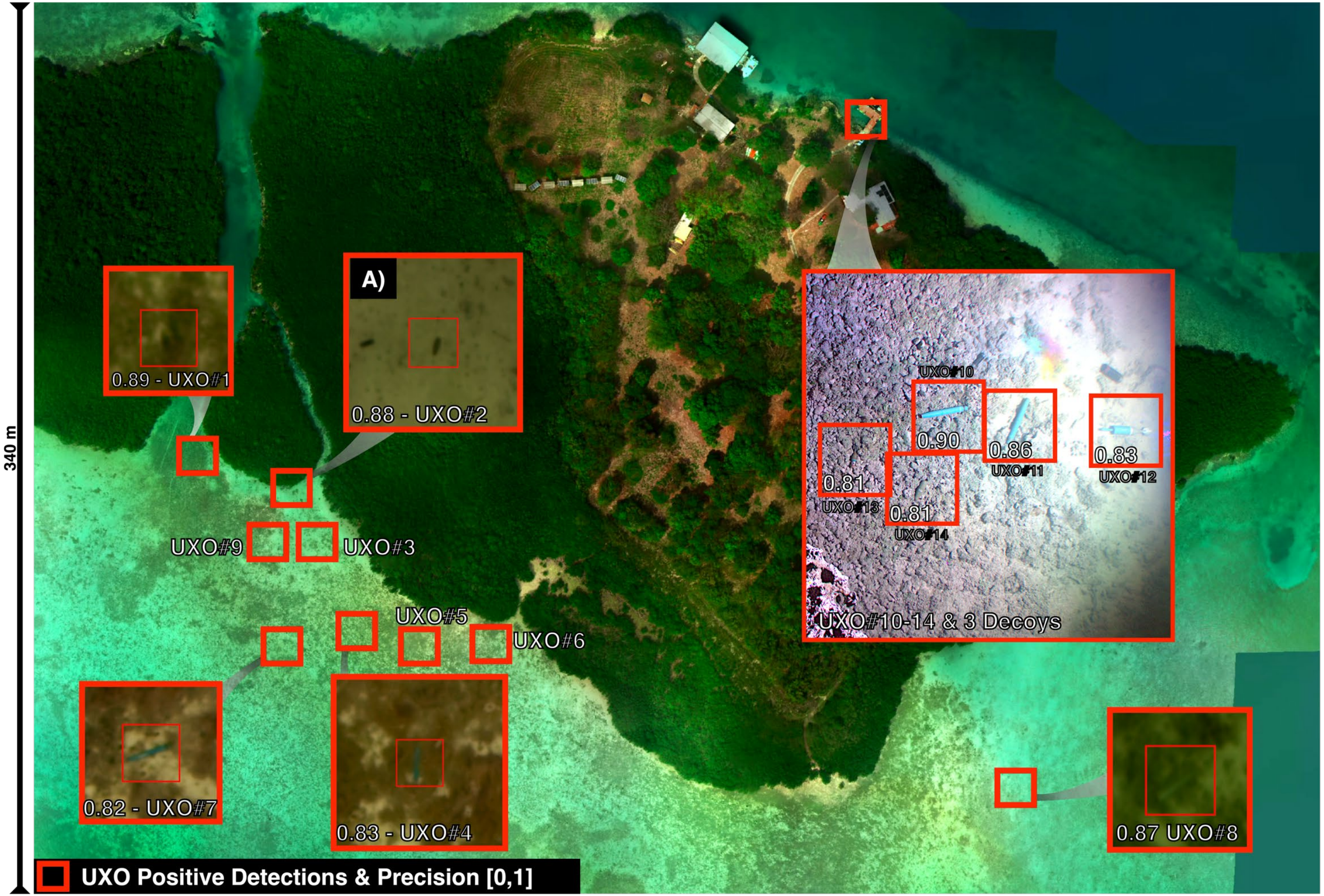


Figure 7 - UXO Positive Detections at Broad Key Research Station & Detection Precision. All UXO targets were successfully detected in the Fluid Lensing RGB image. All locations and detections are highlighted in red boxes with associated F1 (Dice) precision score in white. Note in A), the black nipple dummy target was not detected as UXO and several highlighted examples show detection against complex backgrounds.

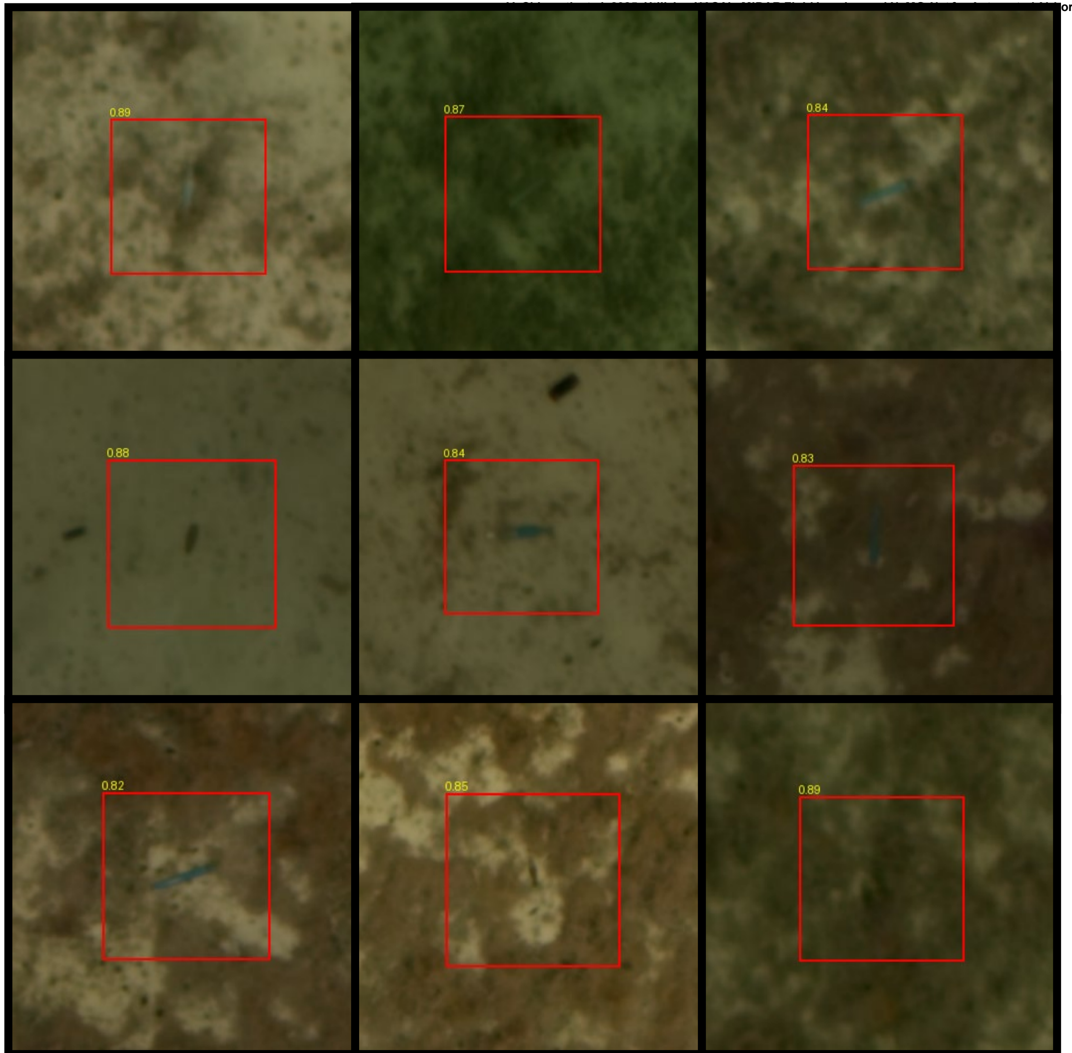
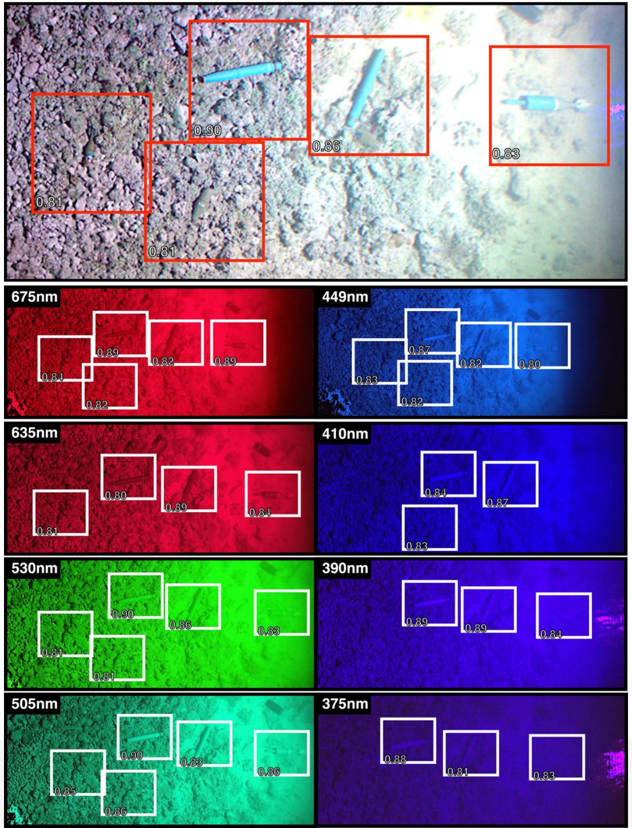


Figure 8 - Training Targets validation (training fold). Nine representative crops showing stable detections across turbidity and color cast. Confidence values range from 0.82 to 0.89; remaining errors are primarily slightly tight boxes under haze and isolated false positives on specular clutter.

Results



Detector results for MiDAR Fluid Lensing RGB composite (above) and per spectral band (below).

BACKUP MATERIAL

MR24-4534: Utilizing NASA's MiDAR Fluid Lensing and NeMO-Net for Automated Airborne Detection, Localization, and Characterization of Underwater Military Munitions

Performers

- *Ved Chirayath, Drew Christensen, Soufyane Bouchelaghem, Imad Tibermacine, Isaiah Wang*

Technology Focus

- *Utilize NASA Fluid Lensing and NeMO-Net to detect UXO*

Research Objectives

- *Use fluid lensing and MiDAR to image munitions and the novel NeMO-Net CNN to automate their detection in data.*

Project Progress and Results

- *The project demonstrated successful airborne detection and localization of all 14 inert UXO at Broad Key, including objects as small as 5 cm, using Fluid Lensing, MiDAR, and an AI detector adapted from NeMO-Net. Results showed high precision across modalities, but recall remained moderate and validation was limited by dataset size, munition diversity, and a single test environment.*

Technology Transition

- *Technologies are patented by NASA and already have licensing applications for use commercially.*

NOTE: This slide may used by the Program Office in future presentations to provide a brief overview of the project.

Plain Language Summary

- **Problem:** Unexploded munitions in shallow waters remain difficult to detect with current acoustic and diver-based methods, which are slow, hazardous, and ineffective in depths <10 m.
- **Approach:** Demonstrated an airborne solution utilizing NASA’s Fluid Lensing and MiDAR imaging technologies combined with an AI detector to automatically identify and localize UXO from UAVs.
- **Outcomes:** Successfully detected all deployed UXO, including objects as small as 5 cm, demonstrating that airborne optical methods can offer a safer, faster, and more precise alternative to sonar — pushing the boundaries of shallow-water UXO detection.

Impact to DoD Mission

The most significant progress has been the first airborne demonstration of successfully detecting and localizing all deployed UXO, including objects as small as 5 cm, in real-world shallow, cluttered waters.

This achievement is crucial because it confirms a new capability that existing sonar and diver-based methods cannot offer, providing a safer, faster, and scalable solution for shallow-water UXO detection.

By integrating NASA's Fluid Lensing and MiDAR imaging with AI detection, the project enhances DoD capabilities with a uniquely airborne toolkit that reinforces U.S. leadership in underwater sensing and facilitates broad-area coastal surveys vital for operational readiness.

Publications

- Provide a list of all publications, patents, awards, etc., resulting from this work.

1. Ved Chirayath, Imad Eddine Tibermacine, Isaiah Wang, Soufyane Bouchelaghem. “Automated Airborne Detection of Underwater Munitions using NASA Multispectral Passive & Active MiDAR Fluid Lensing.” 2025. In Review.

Literature Cited

- Provide a list of all the published work you cited in the presentation.

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