

UAS Activities at the Conrad Blucher Institute at TAMUCC



An update:
Scientific Committee for Oceanographic Aircraft Research
November 2, 2023

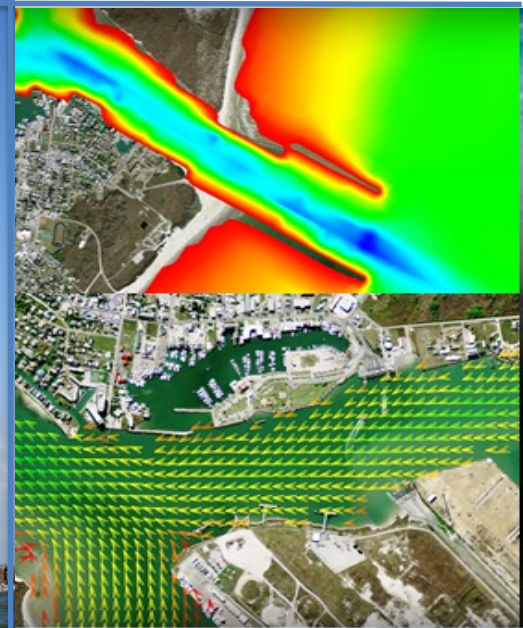
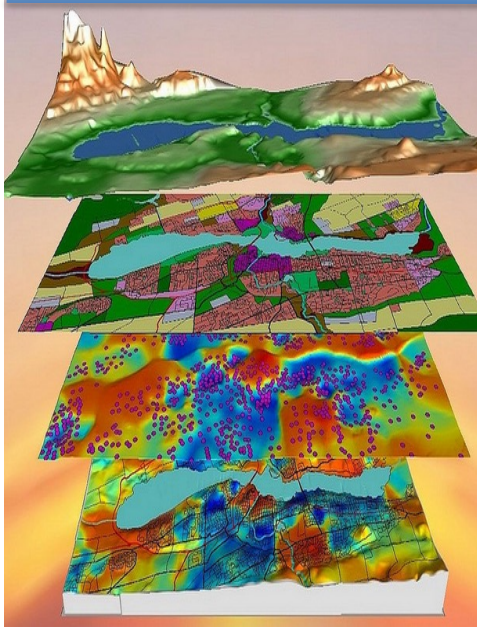
Michael J. Starek

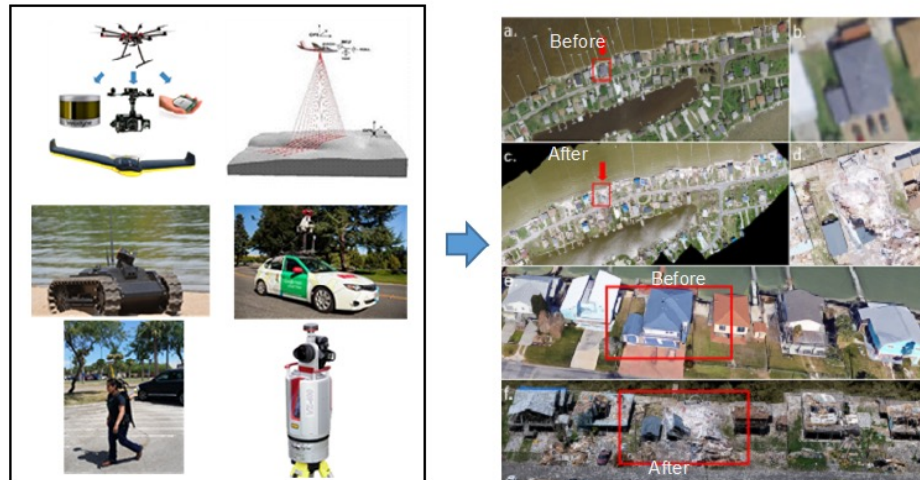
Professor of Geospatial Systems Engineering
Chair of Remote Sensing & Autonomous Systems at CBI

Conrad Blucher Institute for Surveying & Science



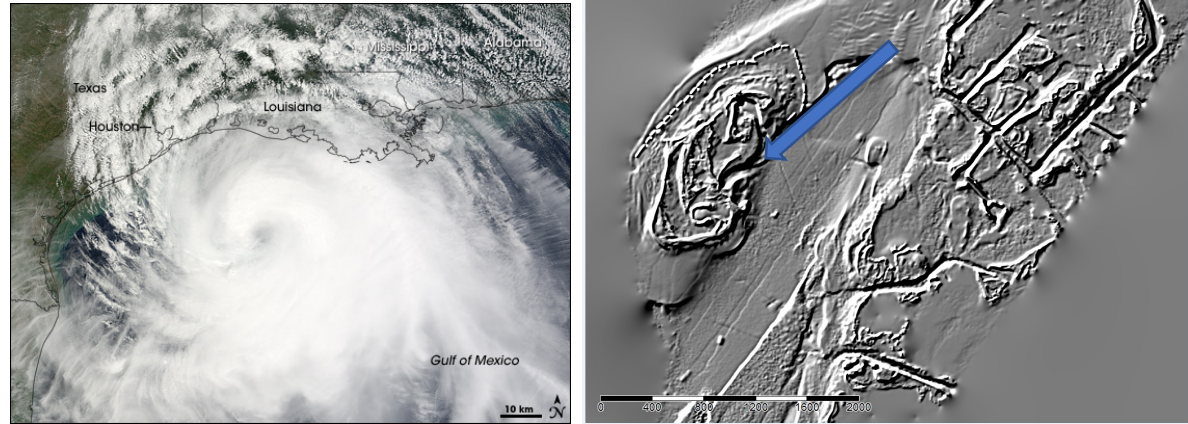
- Dedicated May 1987 - Blucher Family: surveyors of South Texas (1882-1954)
- Support of academic programs (BS – MS – PhD)
- Research in geomatics, UAS, GIS, coastal observation & modeling, coastal AI
- Work supports coastal management, navigation, emergency response...



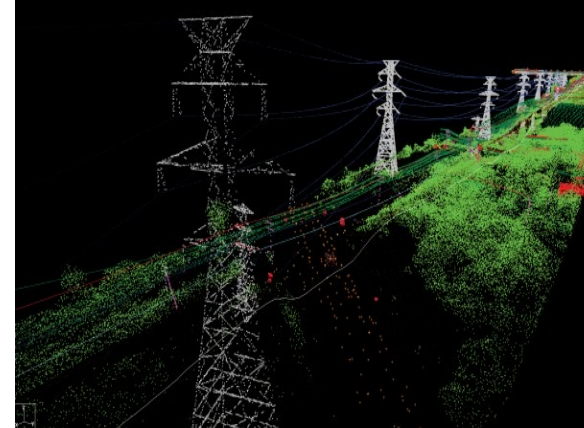


MANTIS explores the merging of geomatics, remote sensing, and geospatial computing to aid science and engineering decision-making through improved measurement and analytics.

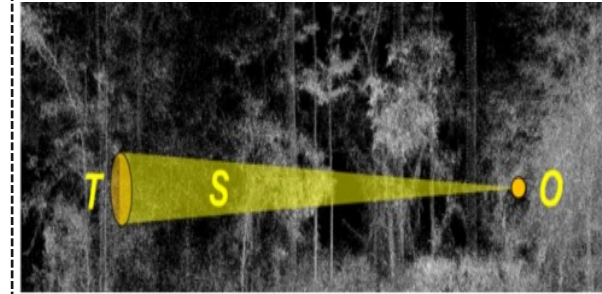
Coastal Zone Monitoring and Resiliency



Infrastructure and Transportation



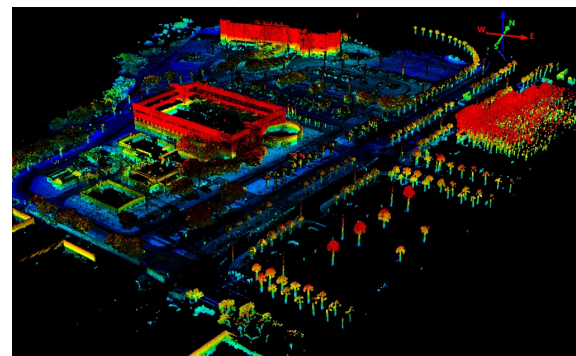
Geospatial Intelligence/Military



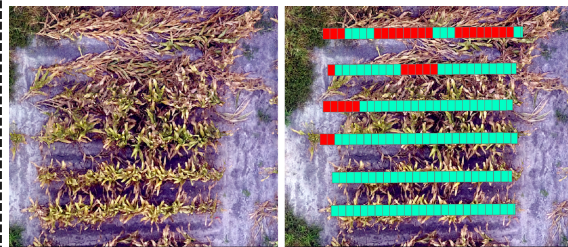
Expertise

- LiDAR
- Photogrammetry
- Computer Vision
- InSAR
- AI and GIS

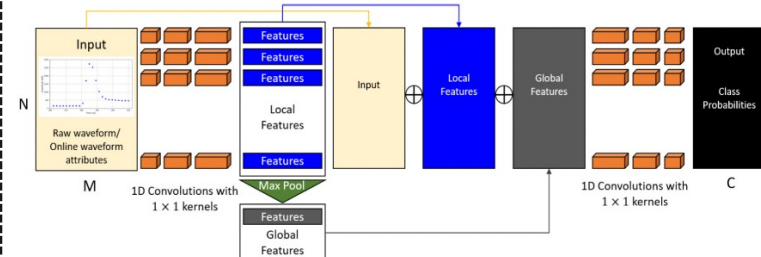
3D Scanning & Mapping



Agriculture

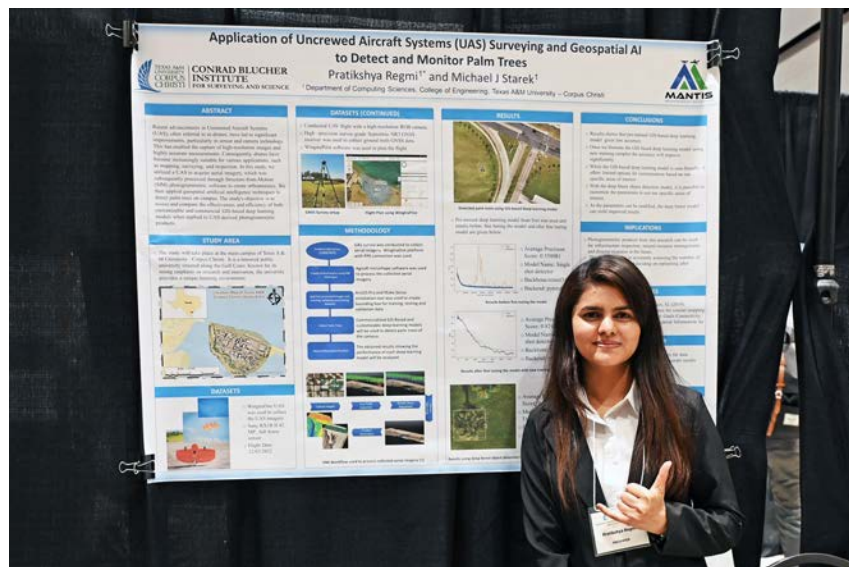
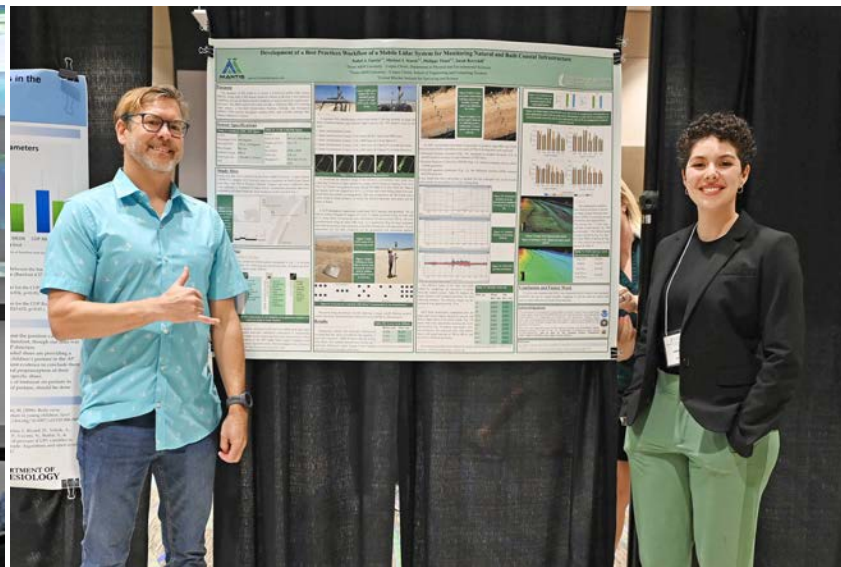


Geospatial AI



Instruments





Evaluation of Different GNSS Solutions on UAS-SfM Accuracy for Shoreline Surveying
 José Pilarles-Congo¹, Dr. Michael J. Starek², LCDR Damian Manda²

(#16464 2020)
¹ Conrad Blucher Institute for Surveying and Science, Texas A&M University-Corpus Christi
² Office of Coast Survey, National Oceanic and Atmospheric Administration, USA

Objective

Examine the applicability of different GNSS solutions as optimal alternatives to GPS for conducting surveys using Uncrewed Aircraft Systems (UAS). Evaluate the impact of Structure from Motion (SfM) software utilized for data processing on model accuracy, 3D point clouds, digital surface and terrain models, and orthorectified. Ultimately, use findings to promote optimized data collection/processing workflows.

Study Area / Hardware

GNSS Solution Results


National Recognition of Students

- ASEE Postdoc. Fellowship (ASEE) to US NRL
- Blue Marble Geographics Award 2020
- ASPRS Paul Wolf Award 2019
- HENAAC Best Poster Award 2018
- USDA HIS Best Poster Award 2017

TEXAS A&M UNIVERSITY CORPUS CHRISTI
 CONRAD BLUCHER INSTITUTE FOR SURVEYING AND SCIENCE

MANTIS

UAS Campus Survey Project

A photograph of a drone flying over a dirt road. The road is flanked by green and yellow vegetation on the left and a flat, sandy area on the right. A series of utility poles with power lines runs along the road into the distance. The sky is clear and blue. A drone is visible in the upper right portion of the frame.

UAS-LiDAR Sensor Evaluation (Example Results)

Data Collection Equipment: UAS-LiDAR



RIEGL VUX-1 LR

- NIR wavelength (1550 nm)
- Max Pulse Rate = 820 kHz
- Max Effective Range = 1540 m @ 80% albedo
- Ranging Accuracy = 1 cm
- Max Number of Returns = 12
- Rotating scanner, FOV = 360°
- **Rotating mirror scanner**



Livox Avia

- NIR wavelength (905 nm), **MEMS IMU**
- Max Pulse Rate = 240 kHz (single returns)
- Max Effective Range = 320 m @ 80% albedo
- Ranging Accuracy = 2 cm
- Max Number of Returns = 3
- Line scanner (2 modes), FOV = 70.4°
- **Risley prism beam steerer**

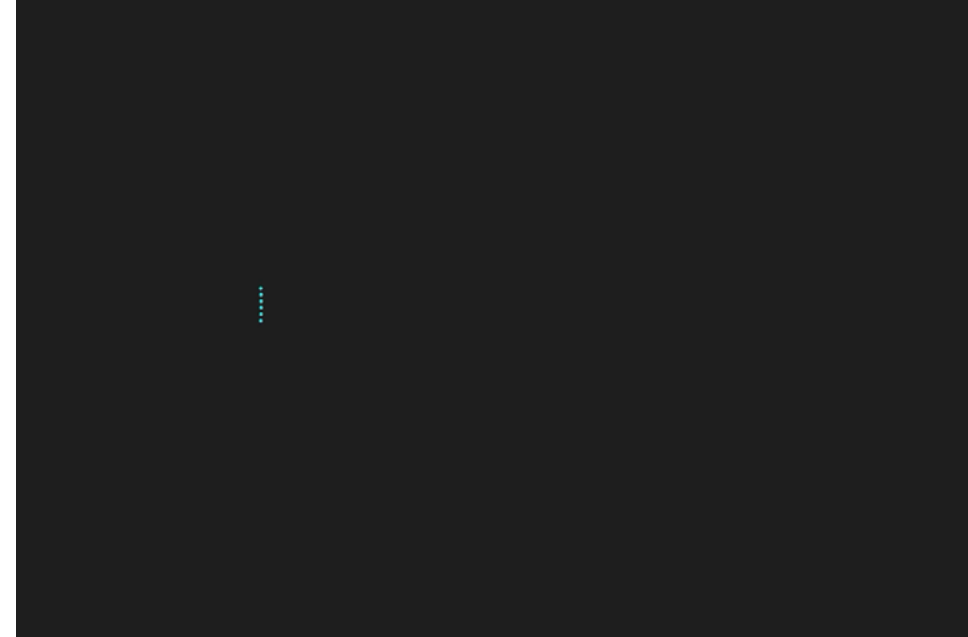


Livox Avia LiDAR Sensor



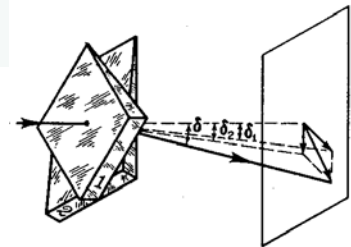
Non-repetitive Circular Scanning

In the non-repetitive scanning mode, as more time is provided for the system to scan the area, the coverage area ratio increases, thus improving the detection of objects and details within the FOV.



Repetitive Line Scanning

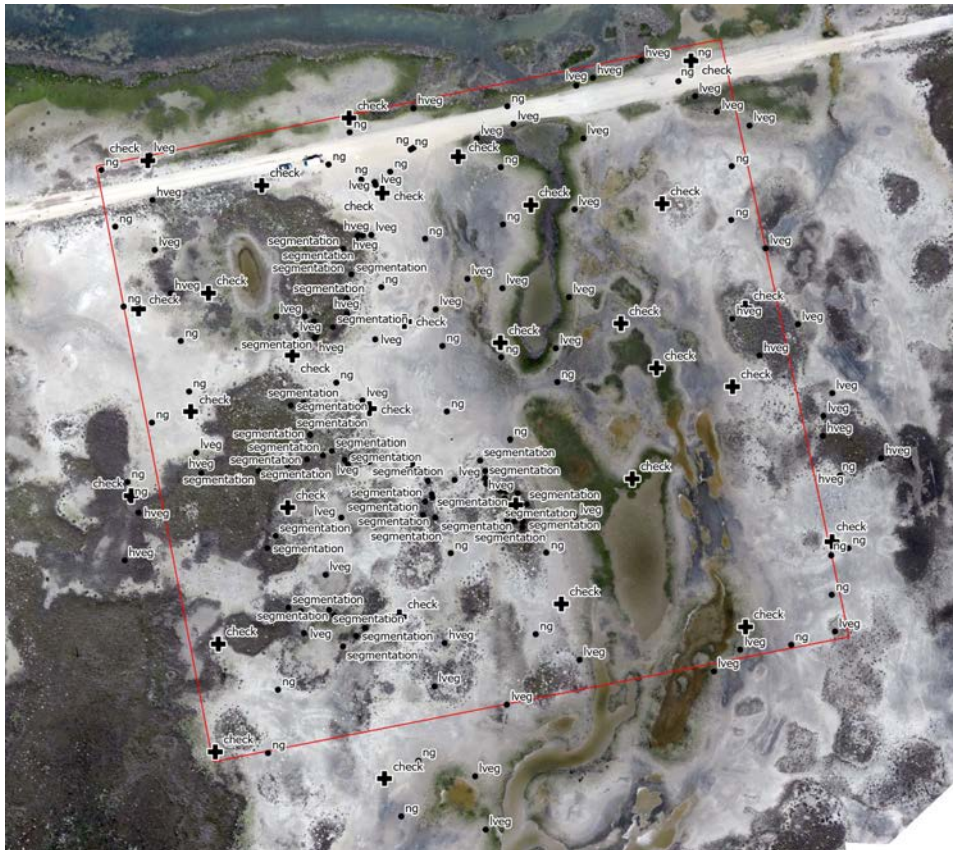
The repetitive scanning mode enables the Livox Avia to operate more efficiently in mapping scenarios that require high precision and point cloud distribution, such as the mapping of agricultural fields, forests and hill slopes, as well as the inspection of construction sites.



Data Collect: Mustang Island (MUI) Wetland Site

Date: 04/01/2023

Purpose: elevation accuracy, impact of altitude & density, SfM versus LiDAR



10 acre historical study area

Flights Completed

UAS-LiDAR

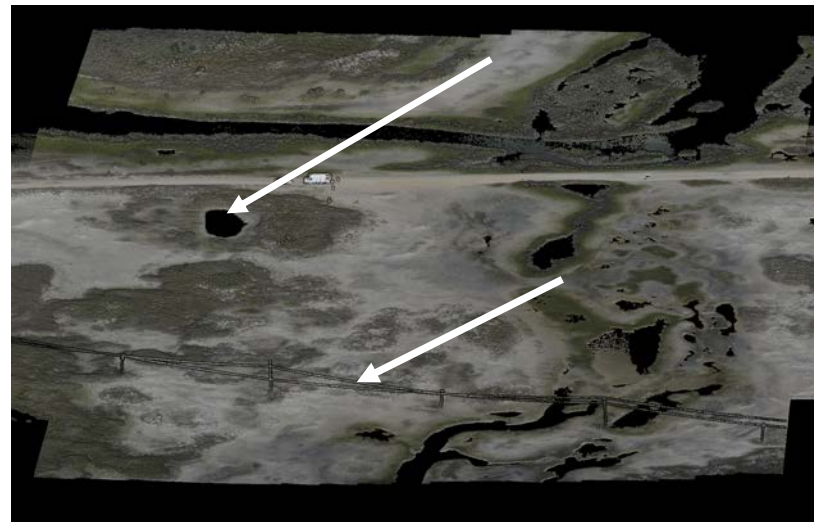
- REIGL VUX-1 LR @ 600kHz @ 120 m AGL
 - 163 points per meter square average
- REIGL VUX-1 LR @ 600 kHz @ 90 m AGL
 - 409 points per meter square average

UAS-SfM (Photogrammetry)

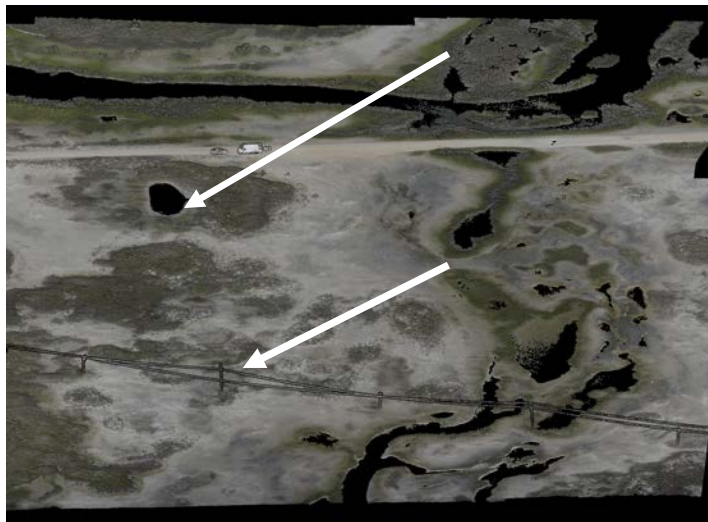
- WingtraOne Gen II @ 120 m AGL
 - 1.6 cm/pixel GSD
 - North-South, East-West
- WingtraOne Gen II @ 60 m AGL
 - 0.8 cm/pixel GSD
 - North-South, East-West



Colorized Point Cloud Examples



VUX-1 LR @ 120 m AGL (LiDAR)

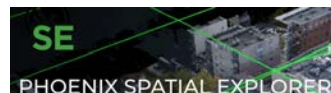


VUX-1 LR @ 90 m (LiDAR)



WingtraOne @ 60 m (SfM)

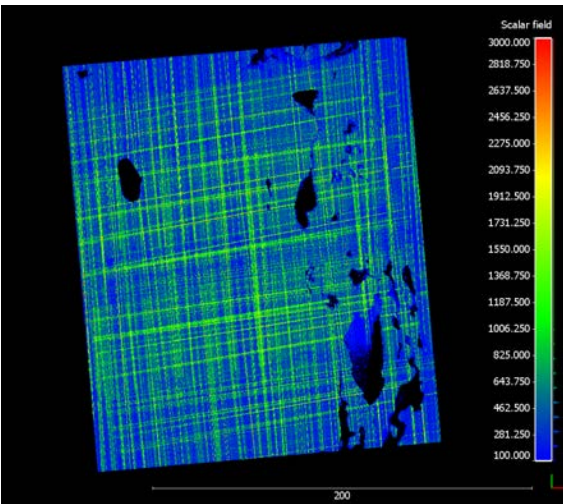
Inertial Explorer®
NovAtel Inertial Explorer®



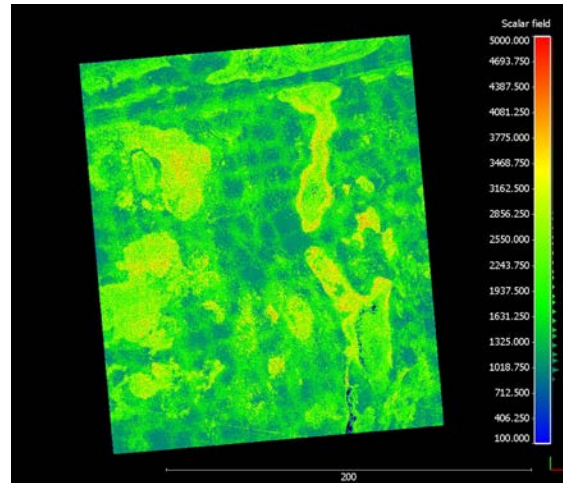
Results @ MUI

Point Cloud Density & Accuracy

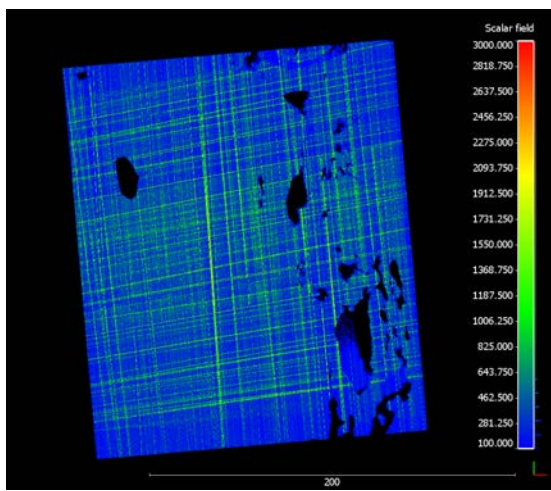
VUX LiDAR (90m)



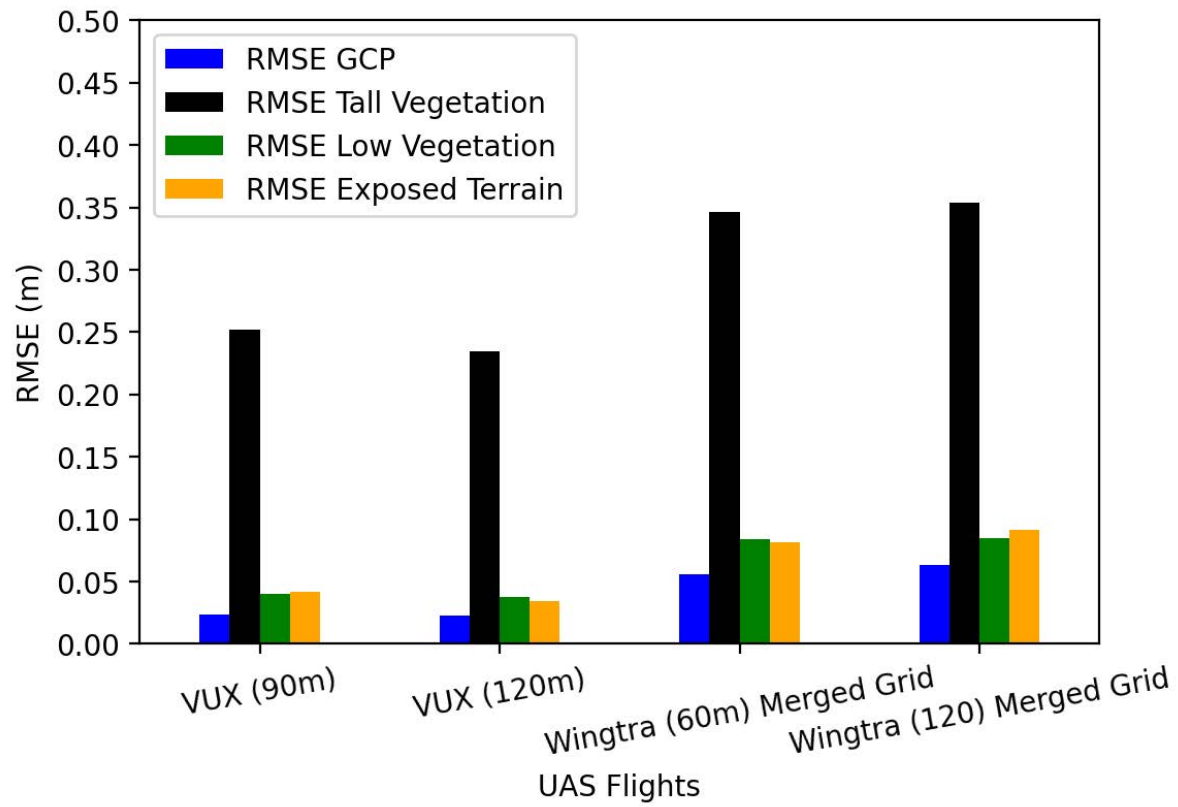
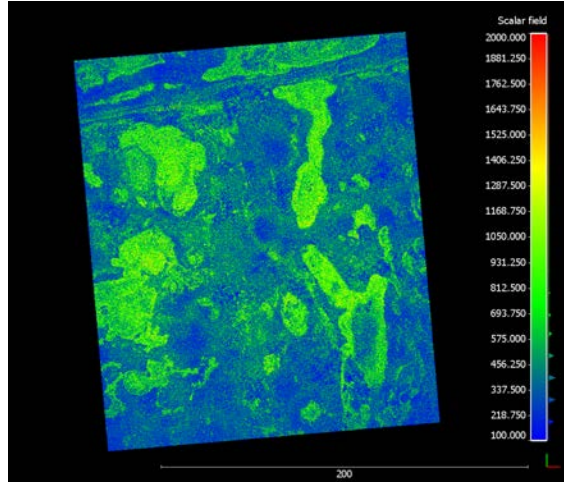
Wingtra SfM Merged (60m)



VUX LiDAR (120m)



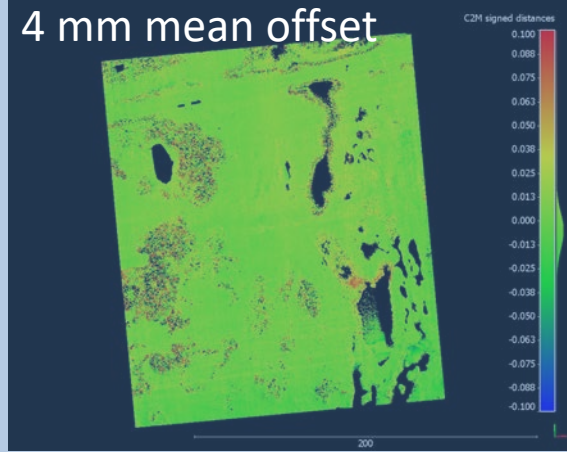
Wingtra SfM Merged (120m)



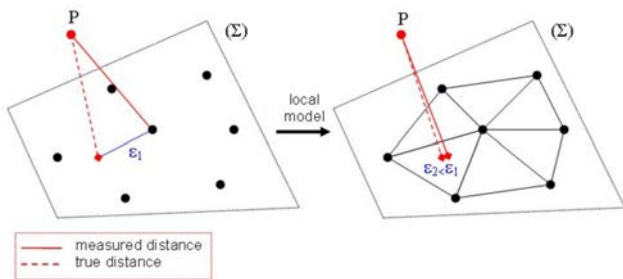
Cloud2Model Distance

VUX (90m)-VUX (120m)

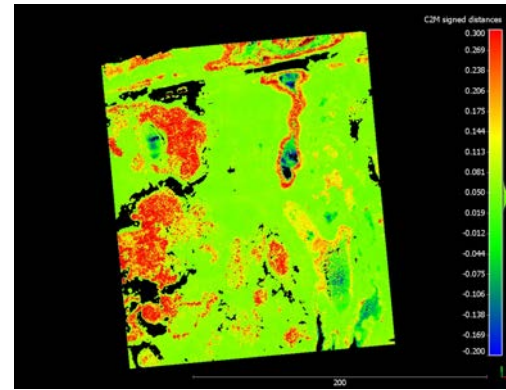
4 mm mean offset



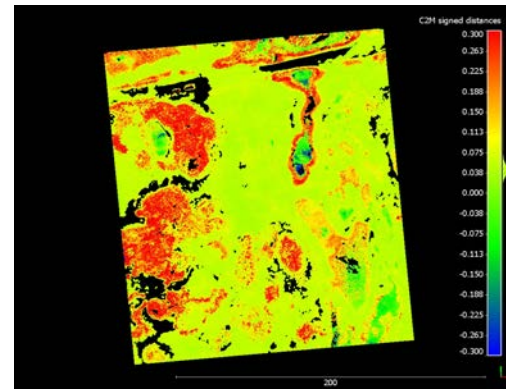
TIN created for **classified terrain points from VUX LiDAR (90m)**. Terrain points from different flights are compared with the TIN to calculate the offset distances.



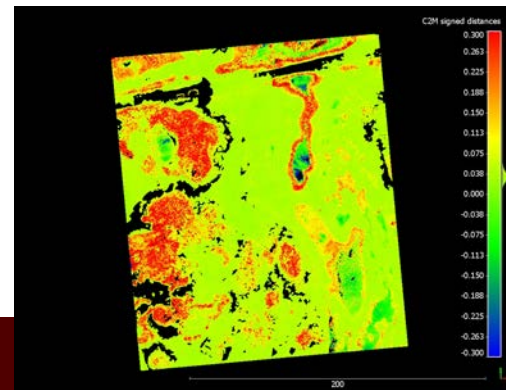
VUX (90m)-Wingtra (60)-East-West



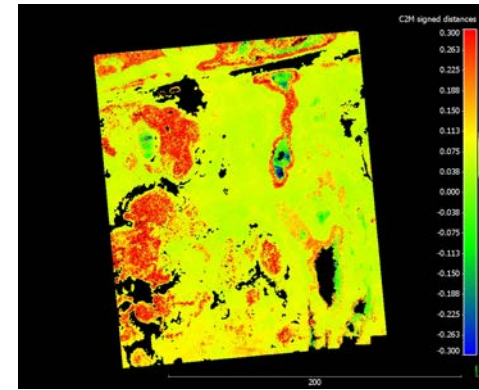
VUX (90m)-Wingtra (60)-Merged



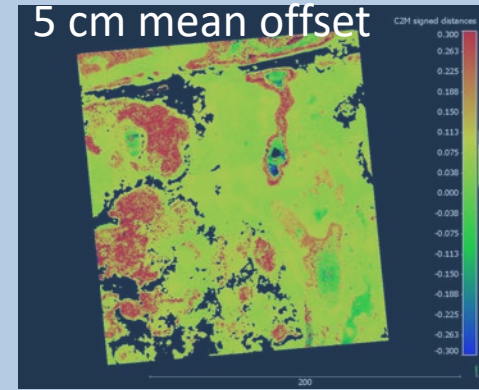
VUX (90m)-Wingtra (60)-North-South



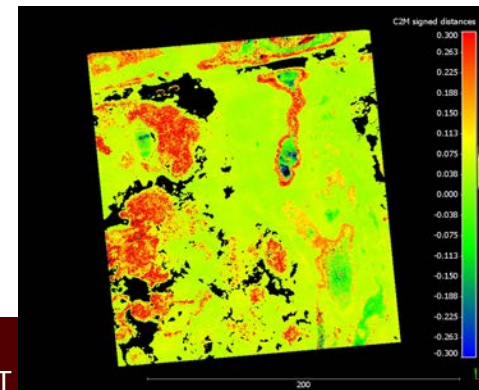
VUX (90m)-Wingtra (120)-East-West



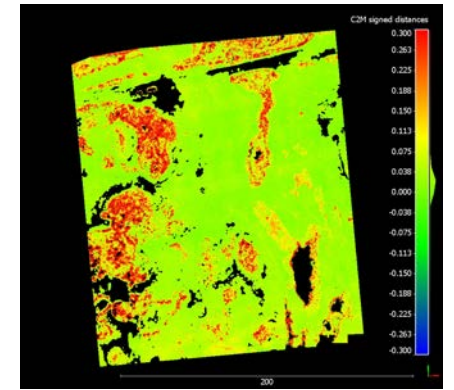
VUX (90m)-Wingtra (120)-Merged



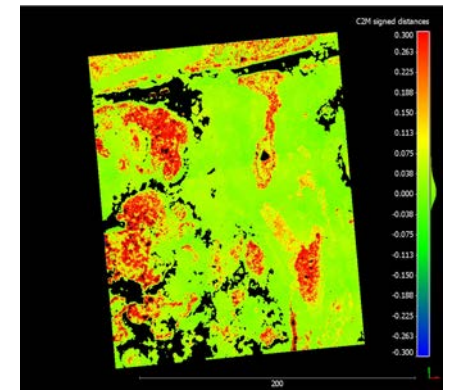
VUX (90m)-Wingtra (120)-North-South



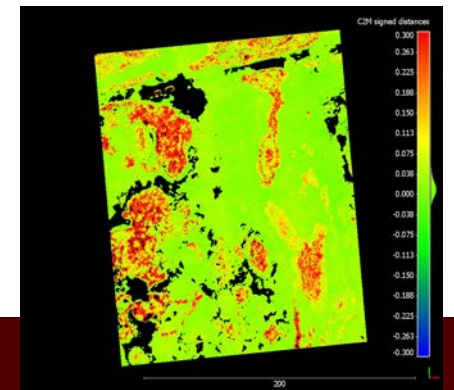
Wingtra (60)-Wingtra (120) -East-West



Wingtra (60)-Wingtra (120) -Merged



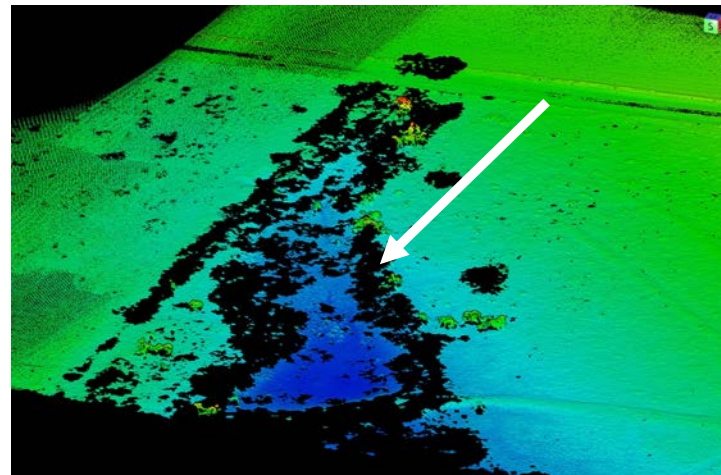
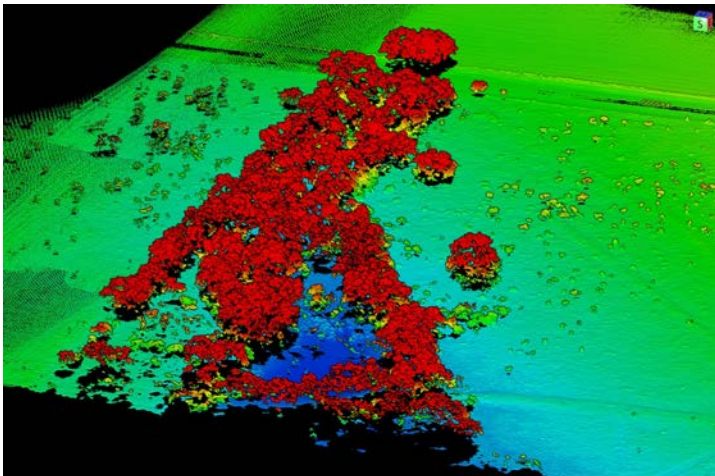
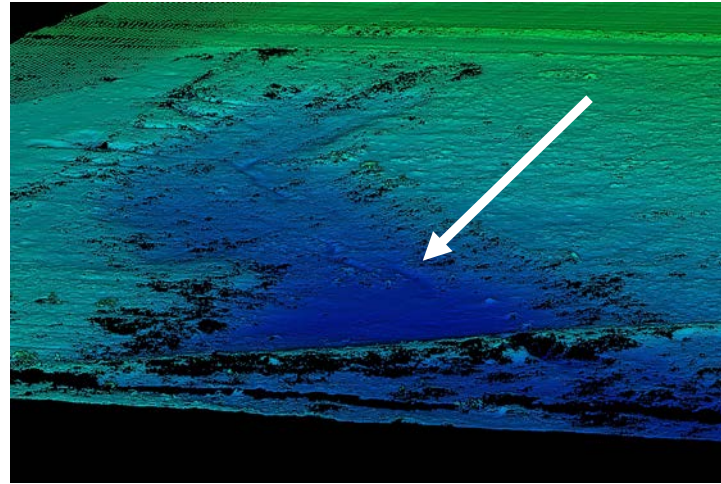
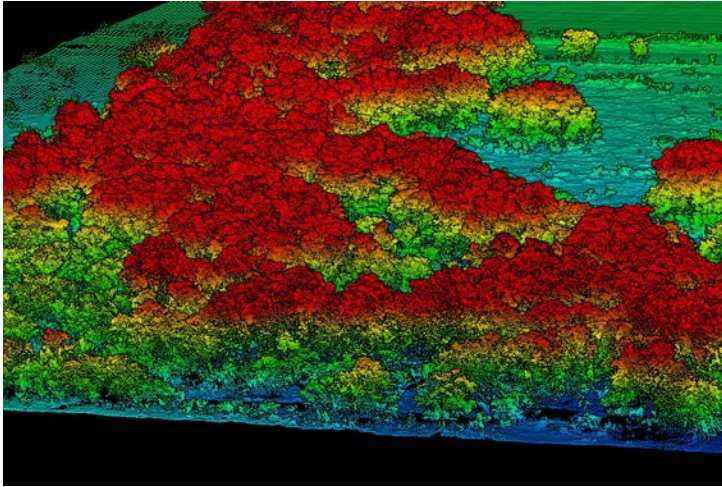
Wingtra (60)-Wingtra (120) -North-South



Data Collect: Goliad Greenfield Site

Date: 04/13/2023

Purpose: LiDAR sensor evaluation



Flights Completed

UAS-LiDAR

- Avia Livox @ 120 m AGL
- REIGL VUX-1 LR @ 600 kHz @ 120 m AGL

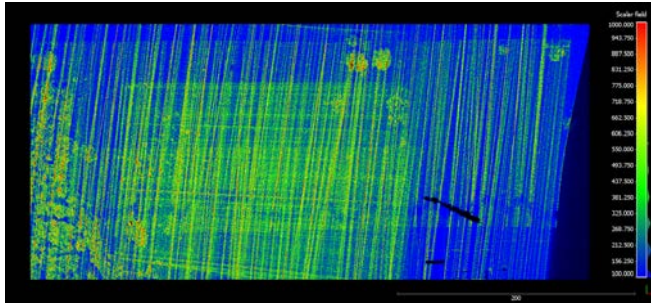
UAS-SfM

- WingtraOne Gen II @ 120 m AGL

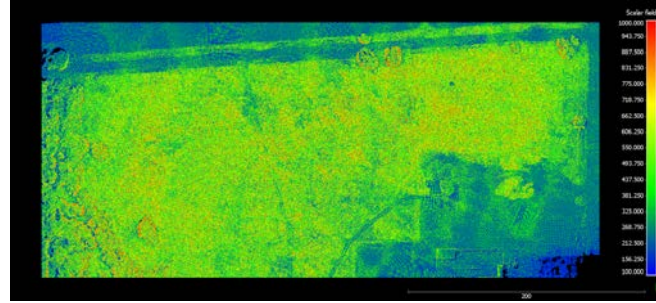
Preliminary Results @ Goliad

Point Cloud Density and Accuracy

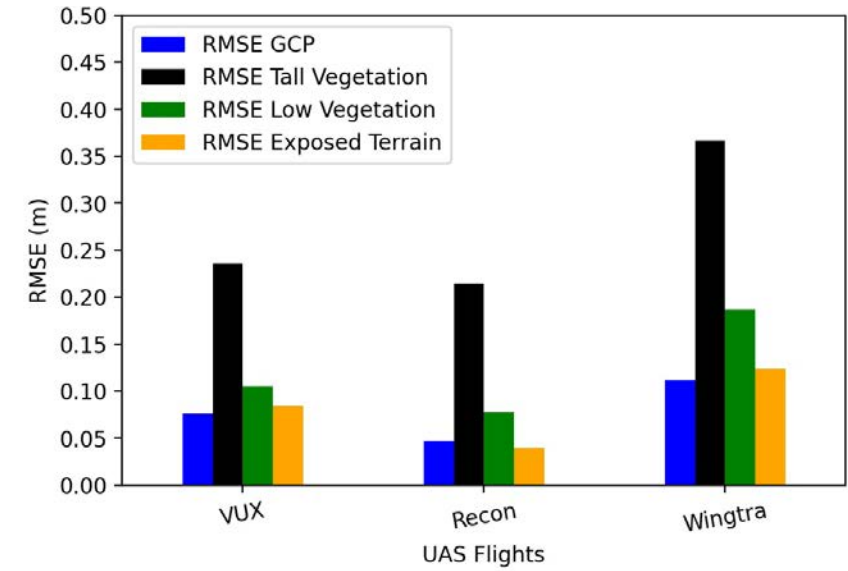
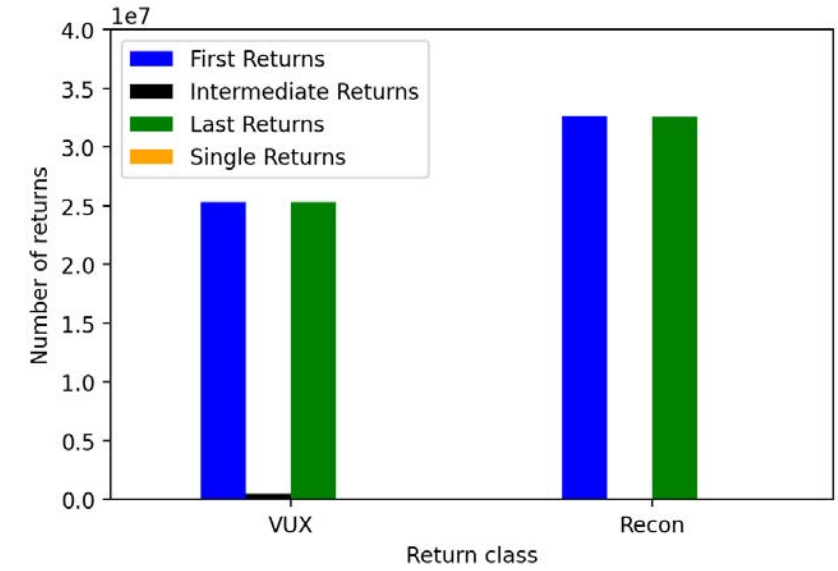
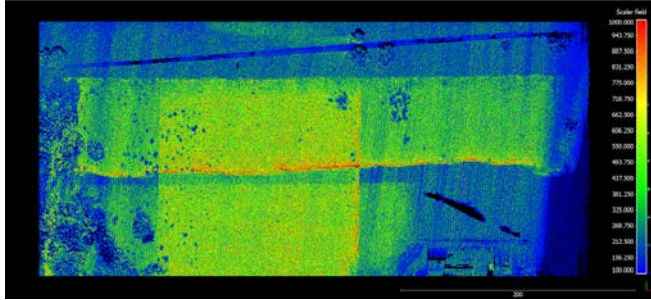
VUX



Wingtra



Recon

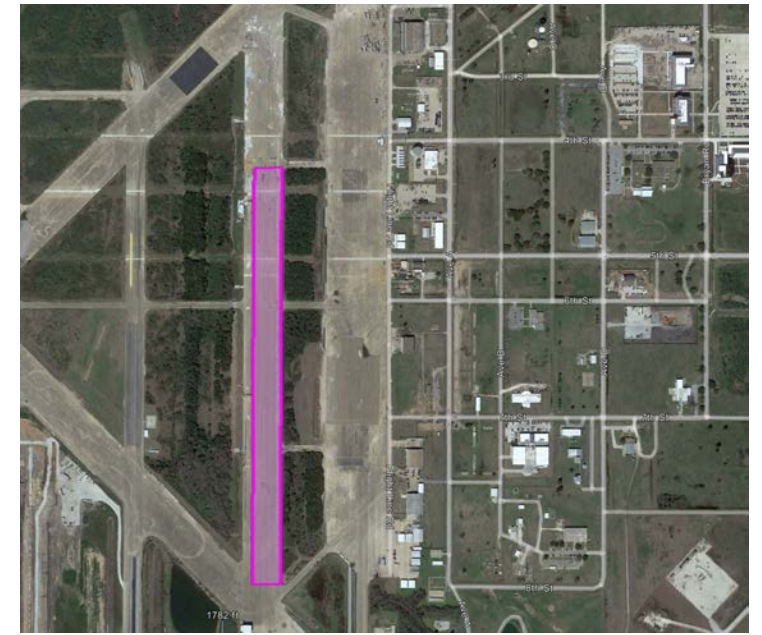


*Direct georeferencing/no GCPs

Data Collect: RELLIS TAMU Test Site

Date: 04/27/2023 – 04/30/2023

Purpose: Multi-day field experiment to assess repeatability, influence of control, and surface change detection error

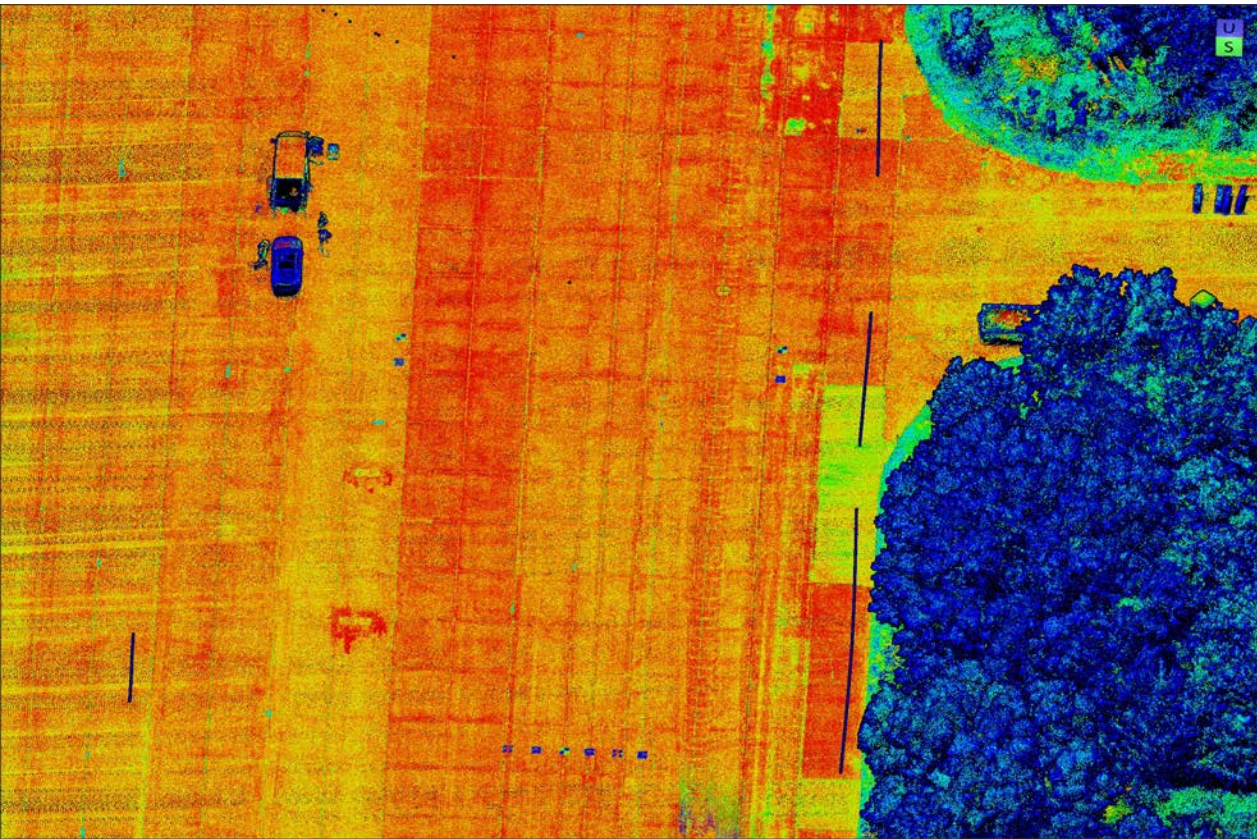


Flights Completed

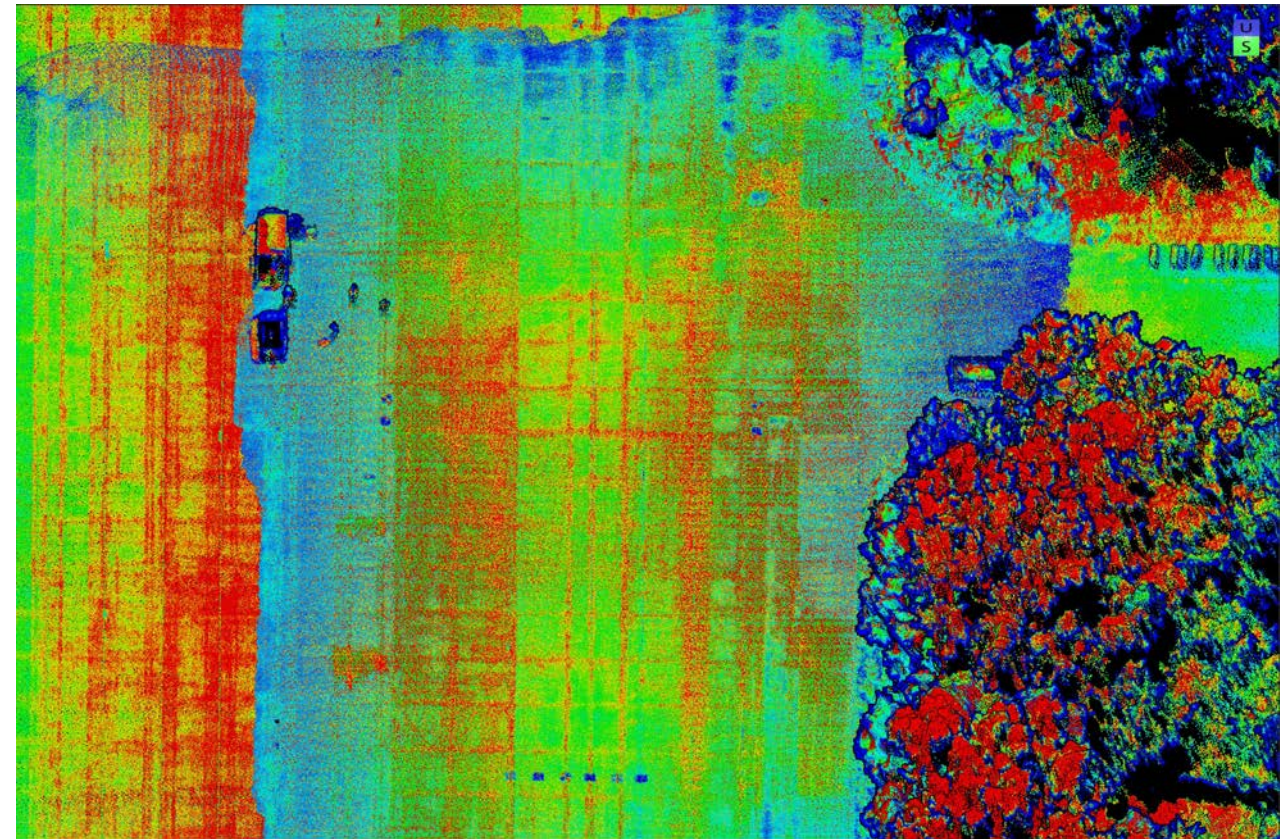
UAS-LiDAR

- 2 days x Avia Livox @ 60 m AGL,
 - 1300 points per square meter average
- 2 days x REIGL VUX @ 820 kHz @ 80 m AGL
 - 630 points per square meter average

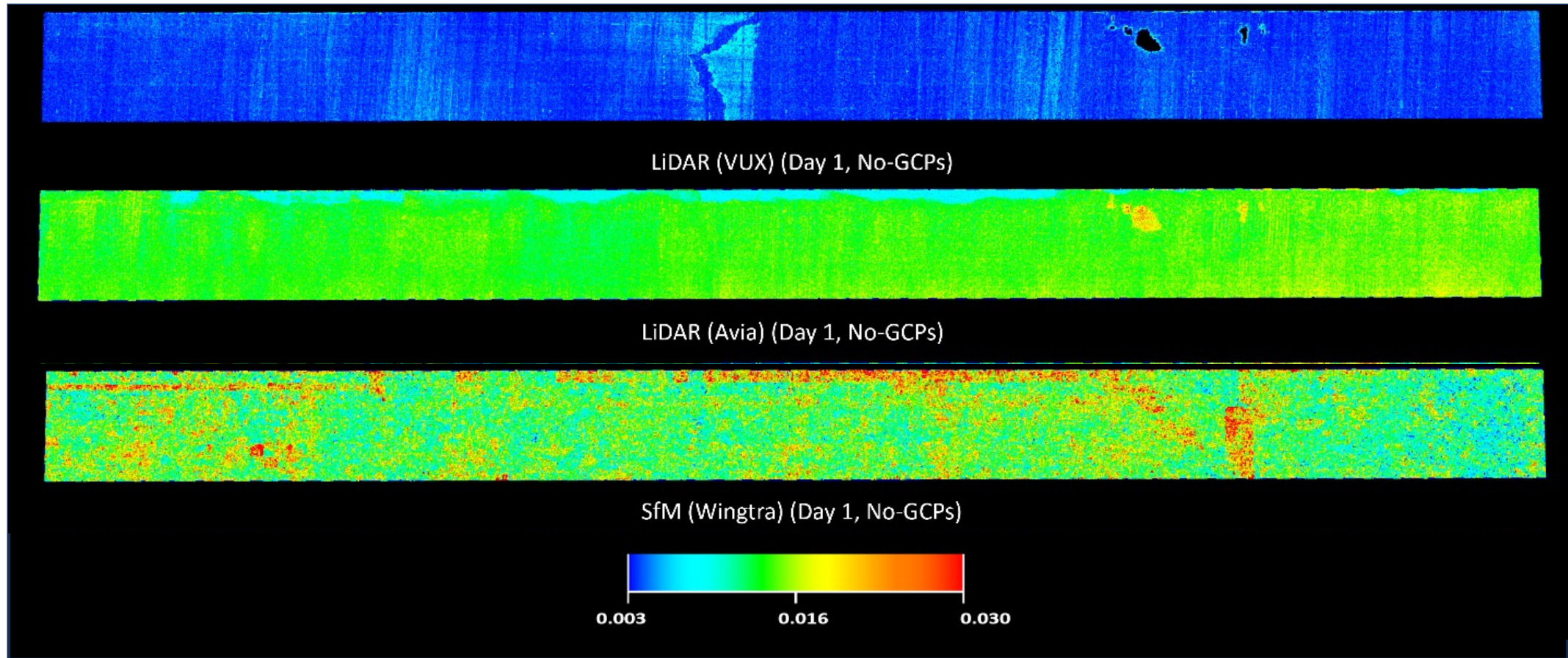
Point Cloud Examples



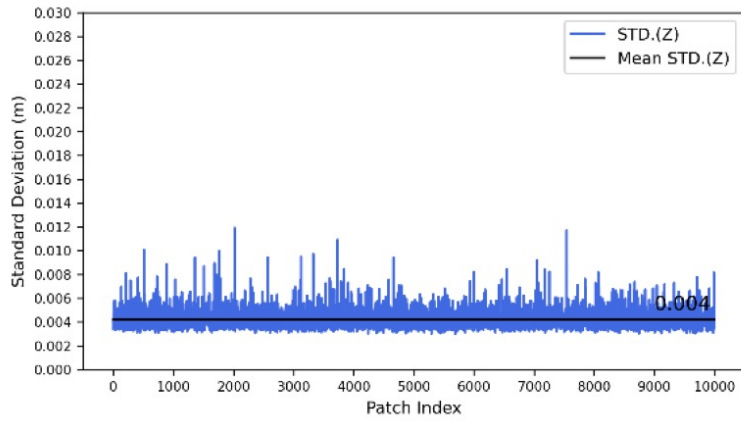
REIGL VUX-1 LR colored by intensity



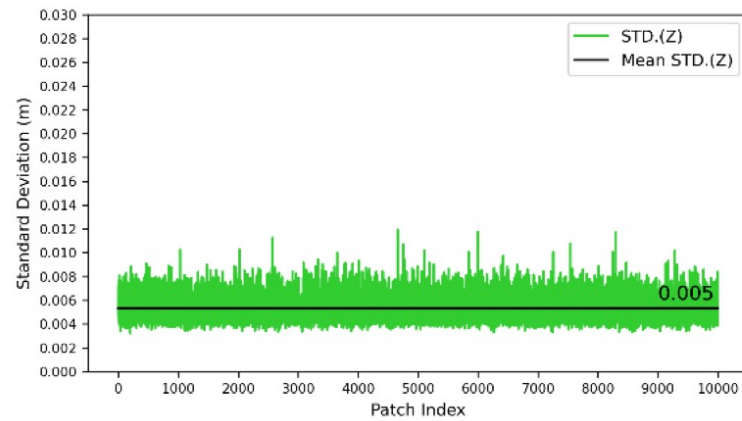
Livox Avia colored by intensity



30 cm grided surface roughness map (measures std. z-value/precision)

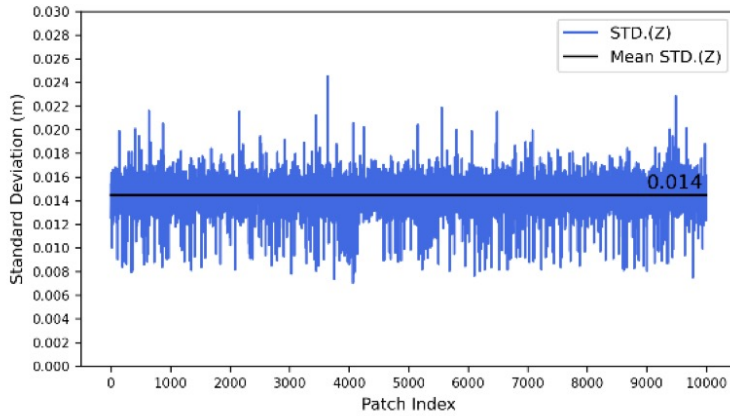


Day 1

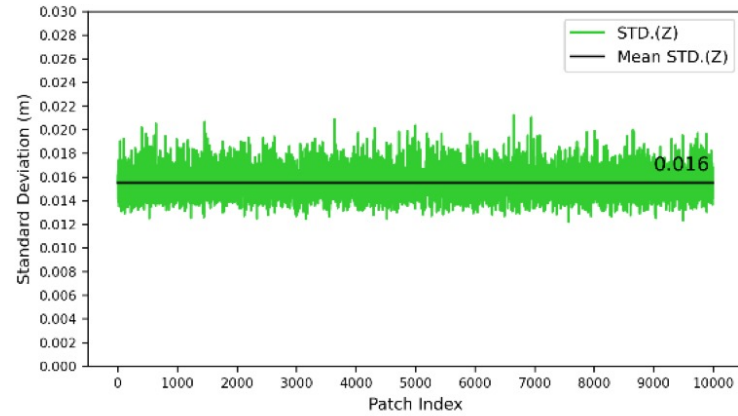


Day 2

Surface Roughness of Runway Surface - VUX LiDAR.



Day 1



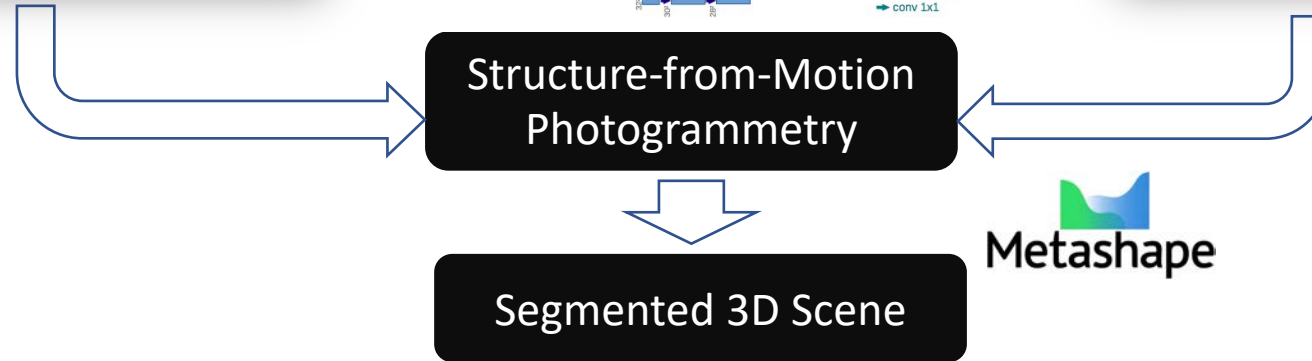
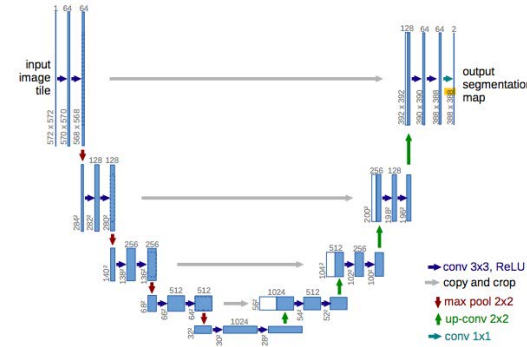
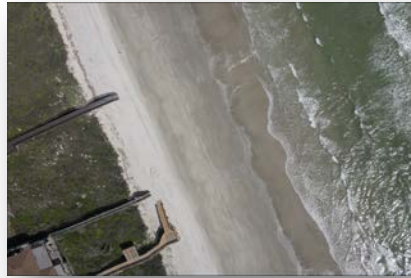
Day 2

Surface Roughness of Runway Surface - Avia LiDAR.

AI for Coastal Mapping

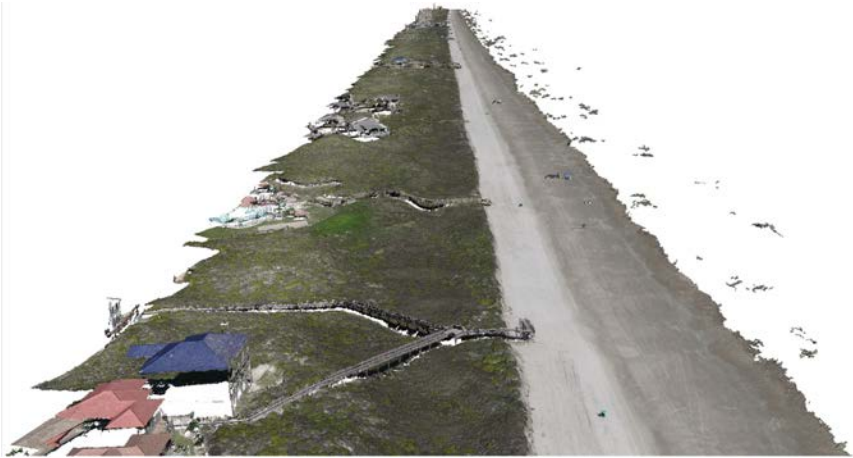
Current Research

AI Image Segmentation within UAS-SfM Workflow

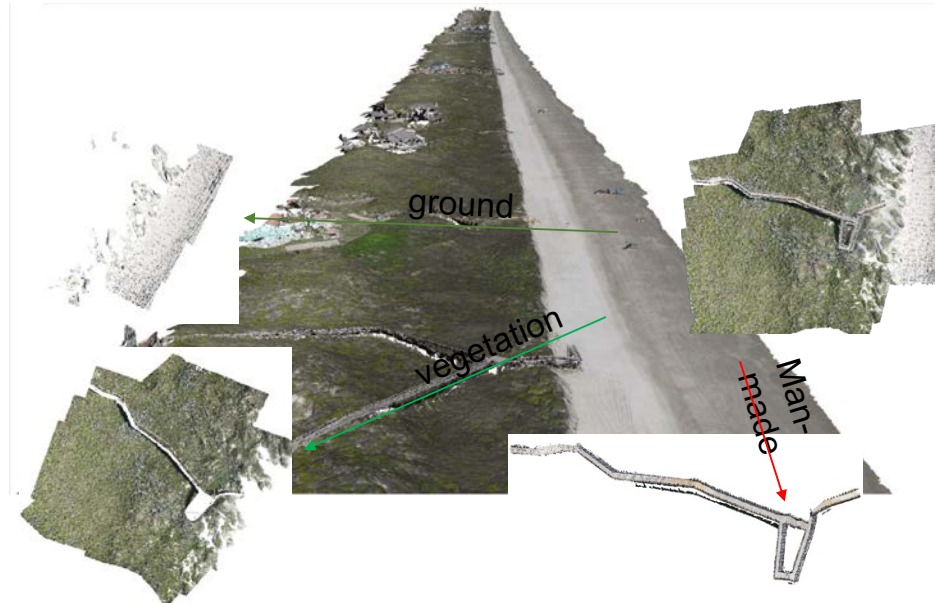


- **Traditional approach** classifies point cloud **after reconstruction**
- **This approach** segments image **before reconstruction**
- reconstruct targets of interest

Before Water Removal

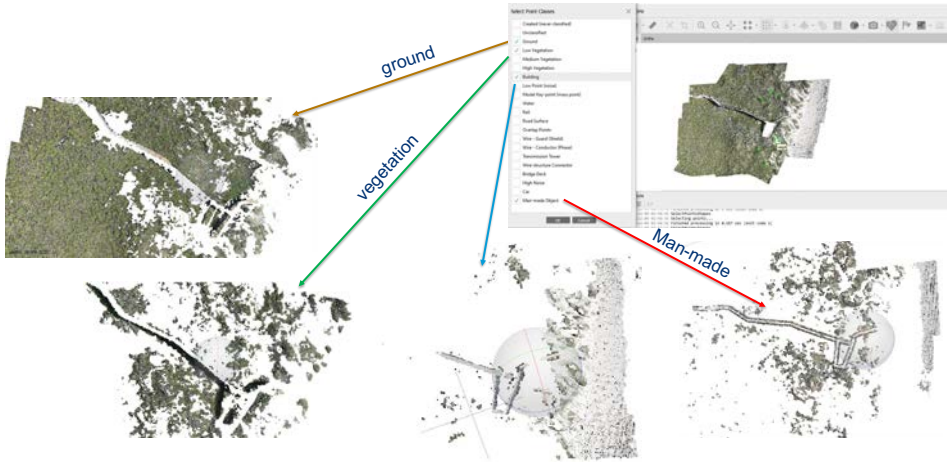


After Water Image Masking



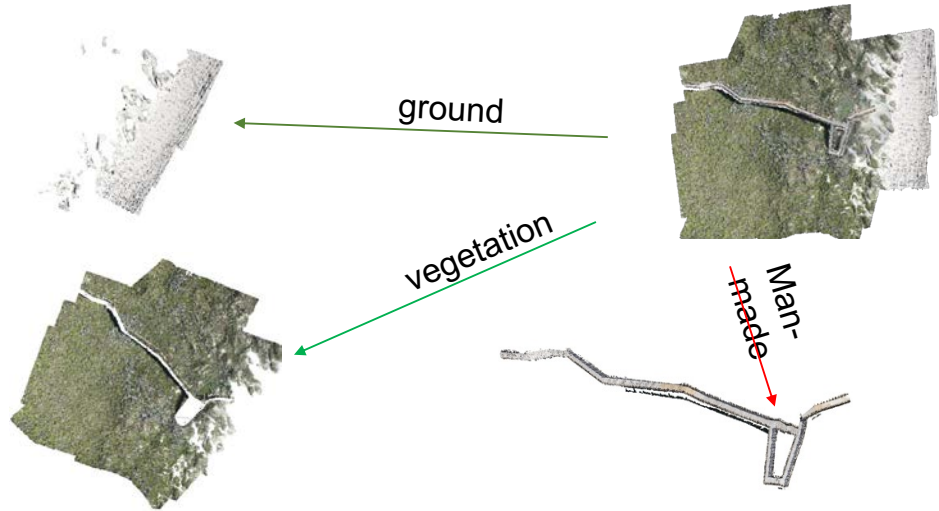
Point Cloud Classification by Software

After Cloud Generation (noisy)



Direct Reconstruction of Target of Interest

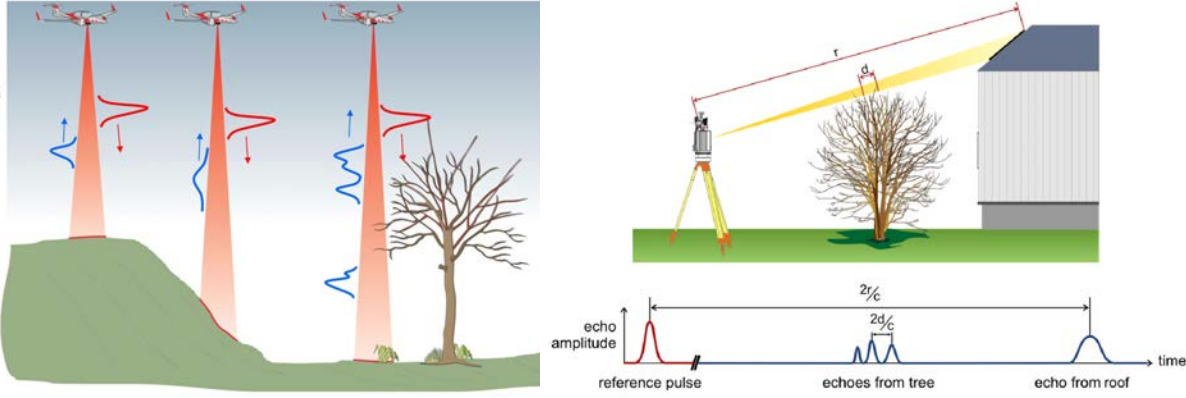
Based on AI image segmentation (less noisy)



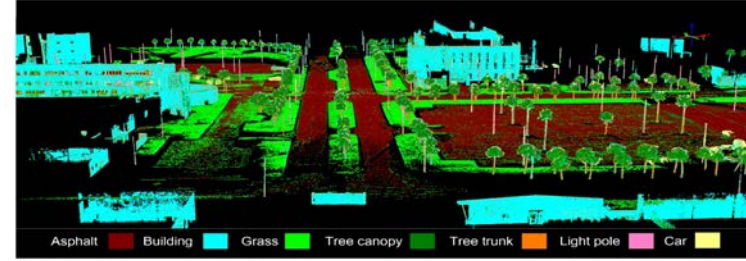
Current Research

Deep Learning for Direct Classification of FW LiDAR

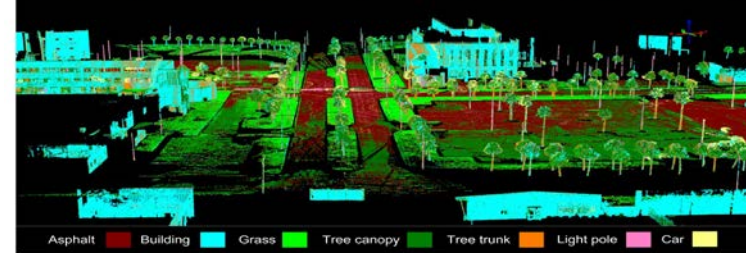
Full Waveform (FW) Lidar



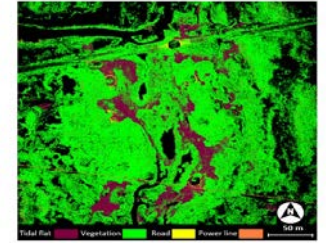
Source: Riegli



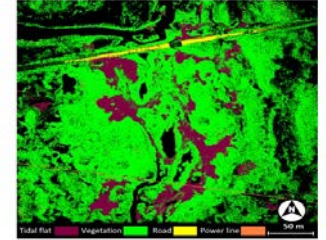
a) Classification result on feature vectors containing the calibrated waveform attributes



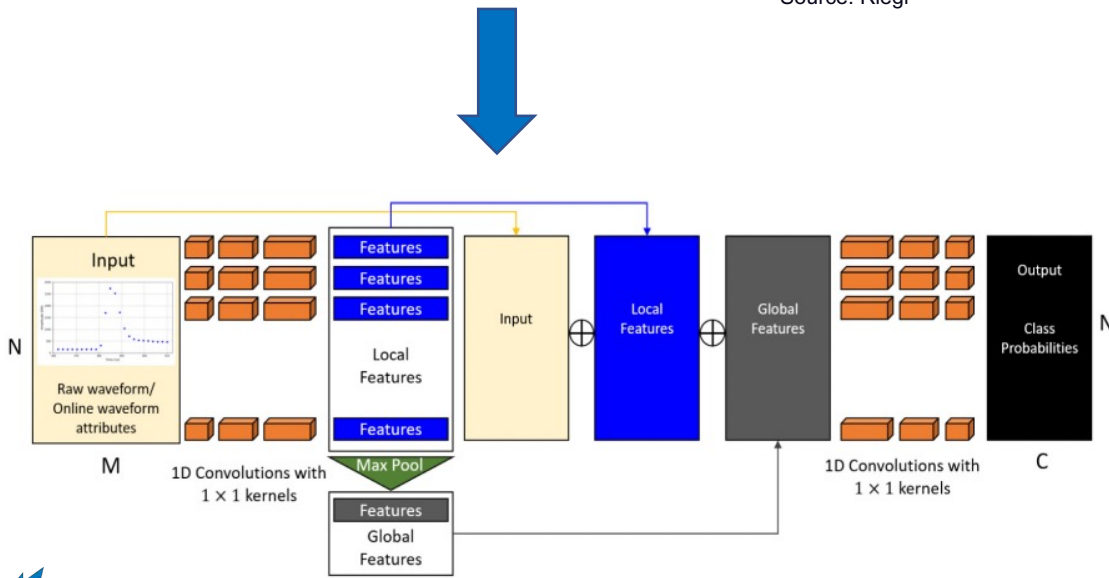
b) Classification result on feature vectors containing samples of digitized echo waveform.



(a)



(b)



IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 60, 2022

Terrestrial Lidar Data Classification Based on Raw Waveform Samples Versus Online Waveform Attributes

Mohammad Pashaei¹, Member, IEEE, Michael J. Stueck¹, Member, IEEE, and Jacob Berrhill¹

Abstract—In this study, the potential of raw samples of digitized echo waveforms collected by full-waveform (FW) terrestrial laser scanning (TLS) for point cloud classification is investigated. Two different TLS systems are employed, both equipped with a waveform digitizer for access to the raw waveforms and online waveform processing which assigns individual waveform attributes to each point measurement. Point cloud classification based on samples of the raw single-pulse echo waveforms is compared with point cloud classification based on the calibrated waveform attributes. A deep convolutional neural network (DCNN) is designed for the supervised classification. Feature importance is used as a technique to evaluate feature importance and natural variability of the raw waveforms. Results show that the performance of the point cloud classification is improved when the raw waveforms are used as input. This is due to the fact that the raw waveforms contain more information about the target than the calibrated waveform attributes. The results also show that the performance of the point cloud classification based on the raw waveforms attributes at both study sites. Results also show that the contribution of the range, on the one hand, and the waveform attributes on the other hand, significantly improve the classification performance. Finally, the performance of the DCNN for detecting ground points to generate a digital terrain model (DTM) based on the samples of the raw waveform samples is assessed and compared to a DTM generated from a progressive morphological filter and a real-time kinematic (RTK) GNSS survey data.

Index Terms—Deep learning, full-waveform analysis (FWA), light detection and ranging (lidar), machine learning, point cloud classification, remote sensing (RS).

I. INTRODUCTION

CONVENTIONAL terrestrial and airborne laser scanning (ALS) systems based on the Time-of-Flight (ToF) principle measure the distance to a target by emitting a laser pulse and measuring the time it takes to return to the scanner. The returned waveform, such as the number of relevant peaks and parameters describing the shape of each detected echo in the waveform signal is a challenging task in signal processing [1]. Moreover, the echo pulse attributes used to be discriminative enough to be exploited as relevant features in the feature vector of the target for efficient classification. Depending on the employed FW lidar system for collecting waveforms data, and the required accuracy to extract waveform attributes, different techniques have been developed for waveform decomposition and modeling [4], [7]. By carrying out a radiometric calibration procedure on waveform data, most relevant features can also be introduced to the feature vector of the target to improve the accuracy of the classification task [3], [5].

In some laser systems, especially terrestrial laser scanning (TLS) systems, the system response model is usually unknown or too complex for modeling and decomposing the waveforms using typical parametric functions [2]. To take the advantage of the capability of FW TLS systems as

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Classification of Terrestrial Lidar Data Directly From Digitized Echo Waveforms

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Abstract—Information derived from full-waveform (FW) light detection and ranging (lidar) data has already been shown to be relevant for point cloud analysis tasks. Relevant waveform attributes to populate the corresponding point feature vector are typically provided through a post-processing FW analysis (FWA) technique based on fitting the echo waveforms with a parametric function describing the shape and location of the echo pulse in the waveform. However, for some FW lidar scanning systems, describing the complete system response model using a simple parametric function seems challenging or impractical. Earlier studies have shown the potential of a waveform's digital samples as relevant features for point cloud classification. The main goal of this study is to extend earlier experiments on direct exploitation of raw waveform signals collected by a FW terrestrial laser scanning (TLS) system to multiclass waveform analysis for point cloud classification in both urban and natural environments. Calibrated waveform attributes, derived from a waveform processing algorithm, are evaluated by the proposed FW data classification technique via deep learning. Classification performance derived through the proposed technique demonstrates high information content of raw digitized waveform samples. Results show that the proposed technique of digitized echoes carry more information about the physical properties of the target than those containing calibrated waveform attributes.

Index Terms—Deep learning, full-waveform (FW) analysis (FWA), lidar, point cloud classification, terrestrial laser scanning (TLS).

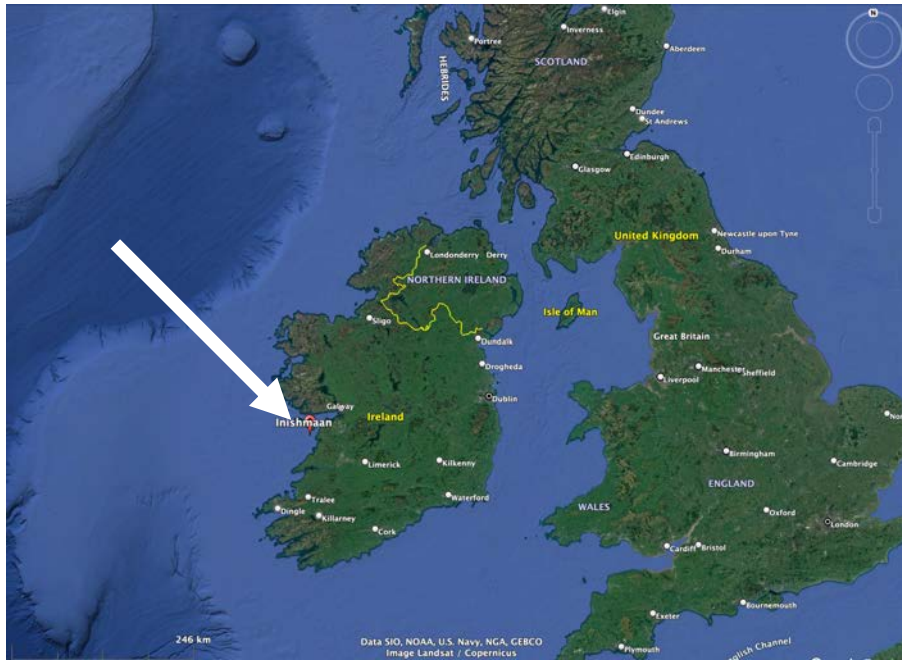
I. INTRODUCTION

TERRESTRIAL laser scanning (TLS) systems are increasingly being used for topographic and land cover mapping [1], [2]. There are two distinct techniques used in both techniques: (1) Time-of-Flight (ToF) and (2) Phase Shift Keying (PSK). The ToF technique is the most common and is based on measuring the time it takes for a laser pulse to return to the scanner. The returned waveform, such as the number of relevant peaks and parameters describing the shape of each detected echo in the waveform signal is a challenging task in signal processing [1]. Moreover, the echo pulse attributes used to be discriminative enough to be exploited as relevant features in the feature vector of the target for efficient classification. Depending on the employed FW lidar system for collecting waveforms data, and the required accuracy to extract waveform attributes, different techniques have been developed for waveform decomposition and modeling [4], [7]. By carrying out a radiometric calibration procedure on waveform data, most relevant features can also be introduced to the feature vector of the target to improve the accuracy of the classification task [3], [5].

In some laser systems, especially terrestrial laser scanning (TLS) systems, the system response model is usually unknown or too complex for modeling and decomposing the waveforms using typical parametric functions [2]. To take the advantage of the capability of FW TLS systems as



Ocean Wave Energy Study



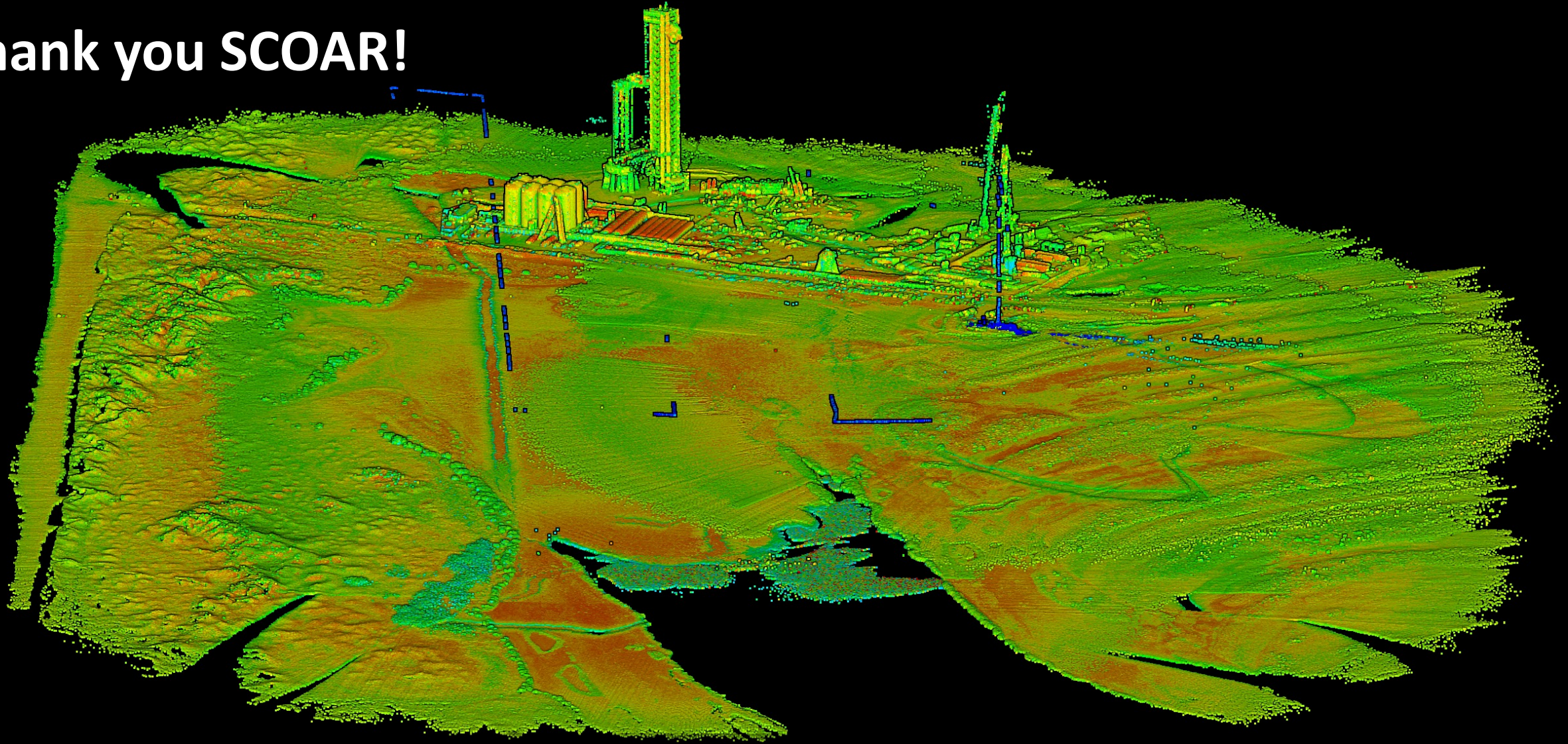
- **UAS surveys** conducted in September 2023, of Inishmaan and Tory Island, Ireland.
- Map boulder sizes and locations relative to sea level to examine energy transport of massive ocean waves







Thank you SCOAR!



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