



**RESEARCH & DEVELOPMENT**

# **Fusing multi-source UAS-derived data to improve project planning and the NCDOT Wetlands Prediction Model**

**Narcisa G. Pricope, PhD – Principal Investigator  
Joanne N. Halls, PhD – Co-Principal Investigator**

**Department of Earth and Ocean Sciences  
University of North Carolina Wilmington**



Title Page for RP2020-04

# **Fusing multi-source UAS-derived data to improve project planning and the NCDOT Wetlands Prediction Model**

**Final project report by Narcisa G. Pricope, Ph.D., Joanne N. Halls, Ph.D., Asami Minei, M.Sc., Elijah Dalton and Carter Eckhardt**

Department of Earth and Ocean Sciences

University of North Carolina Wilmington

601 S College Rd., Wilmington NC 28409

Date of report: January 27<sup>th</sup>, 2022

1. Report No. 2020-04	2. Government Accession No.	3. Recipient's Catalog No.	
4. Title and Subtitle  Fusing multi-source UAS-derived data to improve project planning and the NCDOT Wetlands Prediction Model		5. Report Date January 2021	6. Performing Organization Code
		8. Performing Organization Report No.	
7. Author(s) Narcisa G. Pricope, PhD Joanne N. Halls, PhD		10. Work Unit No. (TRAIS)	
9. Performing Organization Name and Address  University of North Carolina Wilmington 601 S College Rd., Wilmington NC 28409		11. Contract or Grant No. FHWA/NC/2020-04	
		13. Type of Report and Period Covered Final Report  August 1, 2019 – December 31, 2021	
12. Sponsoring Agency Name and Address North Carolina Department of Transportation Research and Development Unit 104 Fayetteville Street Raleigh, North Carolina 27601		14. Sponsoring Agency Code 2020-04	
		Supplementary Notes:	
16. Abstract  Wetlands provide critical ecosystem services across a range of environmental gradients and are at heightened risk of degradation from natural and anthropogenic drivers and continued development, especially in coastal regions. There is a growing need for high resolution, spatially and temporally, accurate habitat identification, and precise delineation of wetlands across a variety of stakeholder groups, including wetlands loss mitigation programs and especially the North Carolina Department of Transportation (NCDOT) Environmental Analysis Unit. Traditional wetland delineations are costly, time-intensive and can physically damage the systems that are being surveyed, while aerial surveys are relatively fast and unobtrusive. With funding from NCDOT, we acquired a DJI Matrice 600 Pro UAS outfitted with a Quanergy M8 LiDAR sensor in March 2020 and have conducted fieldwork at 9 sites in 4 counties in NC to test the performance of LiDAR-derived data in wetland classification. We test the comparative accuracies of a wetland prediction model fitted with UAS and airborne LiDAR terrain and topographic derivatives along with UAS-collected multispectral data at nine coastal sites using machine learning approaches. When mounted on low-flying UASs, LiDAR sensors can measure elevation data even underneath dense canopy cover characteristic of much of the Atlantic Plains forested wetlands. We show that the UAS hyperspatial LiDAR derivatives outperform the airborne LiDAR data in deriving high resolution and high classification accuracy rates, especially when trained with field-collected habitat data and supported by UAS-collected multispectral data. The hyperspatial resolution of LiDAR-derived topography models as well as vertical vegetation structure data (such as canopy height models) can fill wetlands mapping needs and increase accuracy and efficiency of detection and prediction of sensitive wetland ecosystems, thus ensuring more rapid and cost-efficient field assessments.			
17. Key Words Unmanned Aerial Systems, UAS-borne LiDAR technology		18. Distribution Statement	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 93 (not including appendices)	22. Price

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## Acknowledgments

We would like to primarily thank our NCDOT research coordinator, Morgan Weatherford, for his continuous support, excellent leadership and for choosing our team for this research project. We couldn't be more grateful for the opportunity to have conducted this research project and all the student training, publication and field experiences that have resulted from it. A big thank you to John Kirby for his patience along the way and Wesley Cartner for joining us in the field when time allowed. We are especially grateful to the UNCW Department of Earth and Ocean Sciences for providing two Trimble RTK GPS systems available to us at all times for this project and for supporting our computing needs and our students and faculty funded on this project. Yvonne Marsan, the UNCW Department of Earth and Ocean Sciences' Laboratories Manager, provided field and lab support throughout the project. The machine learning classifications would not have been possible without the generosity and support of our colleagues in the UNCW Mathematics and Statistics Department, Dr. Tracy Chen and Dr. Yishi Wang. We would also like to thank our project steering and implementation committee composed of Wendee Smith, Thomas Walls, Lisa Penny, Wesley Carter, Basil Yap, and Leilani Paugh for their time and support throughout the two years of this research project. Last, but not least, this work could not have been possible without the time, dedication, and work conducted by the following undergraduate (U) and graduate students supported by this research project between August 2019 and December 2021: Britton Baxley, James Wu, Eileen Pye, Lauren Whitehouse (U), Kerry Mapes, Asami Minei, James Giddens, Jesse Scopa, Carter Eckhardt, Patrick Connell, and Elijah Dalton (U). Among the students listed, Asami Minei, James Giddens, Carter Eckhardt, Patrick Connell, and Elijah Dalton all completed (or are in the final stages of completion) Master's level theses (Minei and Connell), Master's final projects (Giddens and Eckhardt), and an undergraduate honors thesis in Geography (Dalton) from work conducted under the umbrella of this research project.

## Executive Summary

Wetlands provide critical ecosystem services across a range of environmental gradients and are at heightened risk of degradation from natural and anthropogenic drivers and continued development, especially in coastal regions. There is a growing need for high resolution, spatially and temporally, accurate habitat identification, and precise delineation of wetlands across a variety of stakeholder groups, including wetlands loss mitigation programs and especially the North Carolina Department of Transportation (NCDOT) Environmental Analysis Unit. Traditional wetland delineations are costly, time-intensive and can physically damage the systems that are being surveyed, while aerial surveys are relatively fast and unobtrusive. With funding from NCDOT, we acquired a DJI Matrice 600 Pro UAS outfitted with a Quanergy M8 LiDAR sensor in March 2020 and have conducted fieldwork at 9 sites in 4 coastal counties in NC to test the performance of LiDAR-derived data in wetland classification. We tested the comparative accuracies of a wetland prediction model fitted with UAS and airborne LiDAR terrain and topographic derivatives along with UAS-collected multispectral data at using machine learning approaches. When mounted on low-flying UASs, LiDAR sensors can measure elevation data even underneath dense forest canopy cover characteristic of much of the Atlantic coastal plain forested wetlands. We demonstrated that the UAS hyperspatial LiDAR derivatives outperformed the airborne statewide LiDAR data in deriving high resolution and high classification accuracy rates, especially when trained with field-collected habitat data and supported by UAS-collected multispectral data. The hyperspatial resolution of LiDAR-derived topography models as well as vertical vegetation structure data (such as canopy height models) can fill wetland mapping needs and increase map accuracy and efficiency of wetland detection and prediction of sensitive wetland ecosystems. The main research products generated from this project include a ready-to-fly and operate UAS LiDAR system that has been thoroughly tested and comes with step-by-step operation instructions, fixed-wing UAS multispectral data and derived vegetation indices, *in situ* ground control point (GCP) and ground reference point (GRP) point data, metadata and data dictionaries for all raw and derived datasets, and final machine learning classification products and scripts that can be compared to existing DOT datasets and other potential future delineations.

Given that the goal of this project was to provide NC DOT with detailed approaches to using UAS technologies to derive maps of environmental features (not just wetlands), we worked synergistically with NC DOT so that the products are directly applicable to assisting the Environmental Analysis Unit at DOT in the implementation of project planning and development. Therefore, at all stages of this project, our team has done our best to include one or more NC DOT staff in providing guidance, meet at our regularly scheduled meetings, work in the field when available so that the full UAS flight process and collection of ancillary data were thoroughly understood, review GIS and data products, and participate in technology transfer through a two-day workshop completed before the project ended. The UNCW team feels that we

have been successful if the products from our case studies will have been used in NC DOT project planning.

Finally, in order to ensure adequate technology transfer, not only did we hold a two-day training workshop, but we made every effort for NCDOT staff to be comfortable using the UAV equipment as well as processing data to produce cartographic products and GIS data that can be directly imported into NC DOT enterprise databases during the entire duration of the project, in addition to bi-weekly progress report meetings. At the completion of this project, we are truly grateful for the opportunity to work on this research project and we strongly believe that the correct use of UAS technology can save NC DOT money, long-term, by implementing a strategy that reduces the number of days that surveyors are currently out in the field. However, as our discussion of limitations and modeling section underscore, this technology is not a replacement for surveying, it is a means of utilizing aerial approaches to highlight and map potentially sensitive resources that can then be surveyed and incorporated into the project planning and workflow processes by NCDOT teams across multiple divisions.

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## Introduction

The purpose for research project RP2020-04 was to provide case studies that demonstrate the data collecting workflow (mission planning, flight protocols, ancillary data collection such as GCPs and species-specific spectral curves), image processing techniques and object-based classification algorithms that can provide useful information that can be both directly and indirectly implemented in the Wetland Prediction Model (WPM) tool. Prior to the start of RP2020-04, in PI Pricope's Socio-Environmental Analysis Lab at UNCW, we had been conducting extensive UAS-based research and development centered on: establishing field data collection; sampling and calibration and validation protocols for effective UAS data collection and processing using three different types of drone sensors; implementing processing workflows to create validated, ortho-photogrammetrically and planimetrically correct UAS-derived products (orthomosaics, reflectance maps, indices, 3D digital surface and digital terrain models, 3D models and visualizations, derived metrics such as canopy texture, heights, sizes); and applying and developing geospatial analysis and UAS to satellite imagery fusion techniques, including machine learning vegetation classification algorithms.

In 2018, under RNS-2020-031, the NC DOT requested proposals that guided the implementation of UAS platforms, sensors and imagery into current workflows and the WPM and met the following criteria: review current UAS technologies, are posed to make recommendations for potential acquisition of UAS platforms and sensors by the NC DOT, establish processes and repeatable and transferable protocols for flight planning and create reliable, automated and fast workflows for post processing and algorithms/models for feature classification. Because UASs were seen as a viable solution for identifying important environmental features for planning and project development purposes by improving efficiencies in data capturing and reducing mobilization times and costs, we leveraged our expertise and provided case studies, metrics, models and recommendations to support expressed NC DOT needs, which we detail below.

Effective UAS platform incorporation into WPMs does not only benefit NC DOT compliance by providing them with the ability to quickly capture the most up-to-date UAS data possible, but results from this project also provides guidance on effective workflow integration including machine learning wetland classification techniques. **Our overarching goal for this project was to provide geospatial methods and data that can be used for project planning and implementation with the NC DOT wetland prediction models.** We provided this guidance through our research project by focusing on three main components:

1. **Field and data collection methods:** wetland sampling strategy, Real Time Kinematic (RTK) Global Positioning System (GPS) for collecting Ground Control Points (GCPs) and Ground Reference Points (GRPs), and field spectroradiometer data to derive species spectral curves.
2. **UAS imagery, LiDAR and *in situ* data collection:** flight and mission planning for various sensors, in-field radiometric calibration and GCPs, instrumentation uses in a

variety of coastal wetlands from freshwater to saltwater, photogrammetric image processing workflows to derive planimetric products (RGB, LiDAR, multispectral and thermal).

3. **UAS classification techniques for geospatial modeling:** LiDAR data processing, use of canopy height, LiDAR-derived topographic metrics, comparison with airborne imagery and statewide LiDAR data to improve classification of sensitive habitats, including but not limited to wetlands and make recommendations.

Traditional wetlands delineation methods are not only challenging to complete (especially in areas that are partially or completely inundated or densely vegetated), but can physically degrade the wetland system being surveyed, placing ecosystems that are already both structurally and functionally fragile at further risk (Jeziorska, 2019). To remedy the inefficiencies in both traditional wetlands delineations and nationwide datasets, many researchers now rely on unmanned aerial systems (UASs) as a remote sensing method of choice for wetlands mapping as the miniaturization of both platforms and sensors, increased production, and decreased costs have made them more attainable (Jeziorska, 2019; Kim et al., 2020; Pricope et al., 2020). The utility of UAS sensor technology is further enabled by advances in analytical methods including artificial intelligence and machine learning. In the context of higher population pressures on coastal environments and shifting wetland extents and composition we collaborated with the NC DOT Environmental Analysis Unit to design an effective and automated classification methodology that allows us to leverage freely available aerial imagery and this project-collected UAS-derived data (in situ reference data, UAS LiDAR, and multispectral imagery) collected at sample locations of interest to improve NC DOT's ability to identify environmental features beyond wetlands for early planning purposes for road planning and project delivery.

The following research products have resulted from the completion of our three main objectives, divided into five research tasks (further detailed in the report body):

1. Review of current technologies based on our research, data collection, processing and implementation workflow and final reporting based on the most current, state-of-the-art applications and a recommendation for a powerful and competitive UAS-borne LiDAR sensor acquisition based on our field experimentation and reporting in the peer-reviewed journal *Sensors*;
2. Complete, repeatable and easily-implementable protocols for flight planning, including a design guide and flight planning and implementation protocols for multispectral and LiDAR collection and processing;
3. Complete, repeatable and semi-automated data processing and post processing workflows, including LiDAR step-by-step detailed specifications, including incorporation of in situ data collection using Trimble RTK ground control point (GCP) collection, data transfer and processing in Trimble Business Center;

4. Algorithms and models for feature extraction and classification based on statistical experimentation with several techniques for wetlands classification, having finally settled on pixel-based Random Forest classification that can be computed either in R or Esri's ArcGIS;
5. Training workshop with manuals, data collection and data processing demonstrations conducted on UNCW's campus on November 16-17<sup>th</sup> 2022.

An important secondary and technical objective that emerged post data collection was to quantify metrics derived from UAS-derived light detection and ranging (LiDAR) point clouds in wetlands located along a palustrine to estuarine gradient across nine data collection sites and compared the performance of those metrics in predicting the presence of wetlands. We utilized LiDAR to overcome the challenges of producing accurate surface models from imagery in even sparsely vegetated areas (Rotnicka et al., 2020). We utilized an existing wetlands delineation produced using traditional survey methods from the North Carolina Department of Transportation (NCDOT) and *in situ* ground reference point (GRPs) data as validation in this project.

We addressed two primary research questions:

- 1) Does the inclusion of UAS-derived LiDAR topographic derivatives and canopy height information along with UAS-collected multispectral data accurately classify wetlands using a Random Forest classification model? and
- 2) What are the most important variables for predicting wetland presence?

This report is organized into several sections, following the NCDOT guidance document for final reporting. Specifically, we begin by presenting a literature review that discusses the importance of wetland ecosystems for Coastal Plain human-environment functioning, the need for updated wetland maps and classifications, the emergence of UAS technologies as a mechanism to obtain accessible and on-demand imagery and data, and the emergence of machine learning classification approaches capable of handling large volumes of data such as those generated from UAS data collections. We then proceed to the report body which is organized according to our main project objectives and subdivided into the five major tasks undertaken in this project. We then present the main findings and conclusions organized by each site and discuss some of the challenges, limitations and future directions we envision. Lastly, we provide a set of summative recommendations and our implementation and technology transfer accomplishments. After the references cited section, we have included two appendices: Appendix A contains the R modeling steps for deriving the final wetland classification model, and Appendix B contains the final instruction manual for the project. Student Theses and Final Projects referenced in this report are not included due to length considerations, but can be provided upon request by NCDOT personnel, but for their use only; not to be further distributed until they are officially published or released from embargo from UNCW.



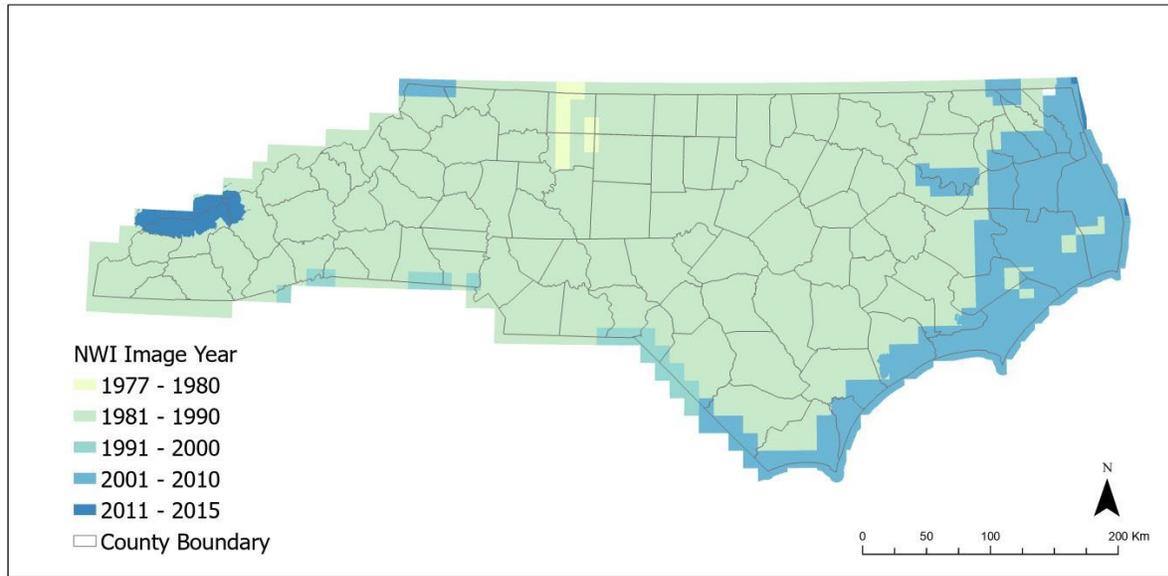
## Literature Review

Wetlands are transitional zones between terrestrial and aquatic ecosystems which experience seasonal or permanent above surface water (Dillabaugh & King, 2008). They are dynamic systems that are subject to an array of changes through river erosion and deposition, vegetation growth, and human impacts (Walker, 2011). Wetlands are considered one of the most productive ecosystems and act as critical habitats for a variety of plants and wildlife (Klema, 2013b; Durgan, Zhang, Duecater et al, 2020). They play crucial roles as carbon sinks due to their extreme ability to sequester carbon (Klema, 2013b). Salt marshes are some of the most productive ecosystems, with productivity reaching as high as 3000 g C/ m<sup>2</sup>/y, exceeding the productivity of some agricultural crops (Campbell, et al., 2000). Not only are they excellent carbon sinks, but they also provide protection from storm runoff, improve water quality, filter agricultural and industrial waste, recharge groundwater stores, and enhance biodiversity (Klema, 2013b). Furthermore, wetlands provide aesthetic, spiritual, and recreational benefits (Luo et al, 2015). Next to tropical rainforests, they are considered one of the most economically important ecosystems, being valued at US \$10,000 per hectare (Kirwan & Megonigal, 2013; Luo, et al., 2015). Despite being critical ecosystems, wetlands are under increasing threat by anthropogenic stressors such as dredge and fill operations, eutrophication, fragmentation, constructed modifications, urban development, and sea level rise (Klema, 2013b; Kirwan & Megonigal 2013). Approximately 25 – 50% of the world’s coastal wetlands have been converted to agricultural or aquaculture uses in the twentieth century with predictions that another 20 – 45% will be lost to sea level rise during this current century (Kirwan & Megonigal, 2013).

Assessing the future ability of wetlands to continue providing ecosystem services requires continuous mapping and this is challenging because of the detailed vertical and horizontal scale of these areas (Kalacska, et al., 2017). Wetlands by nature are periodically flooded, causing access to be limited. This periodic flooding makes conventional surveying more labor intensive and time consuming than it already is. Furthermore, conventional surveying would be extremely harmful to the ecosystem because of the heavy foot traffic that it causes. Forested coastal wetlands are also extremely difficult to map because of their dense canopies (Pricope, et al., 2020). Coastal wetlands pose an even greater challenge due to the constant changing of the tides. During the 1970s and 80s when the National Wetland Inventory (NWI) was first introduced, wetlands were mostly mapped using satellites at relatively coarse spatial resolutions and large temporal revisits (Walker, 2011). This was a significant first step toward creating a system where wetland maps would be stored. However, much of the data that is available today is not as useful as it once was because that data is the original data from the 1980s (Walker, 2011). This data is not useful because there are maps in the inventory that show wetlands that are no longer existent and omit existing wetlands that were missed. North Carolina’s coastal wetlands were last mapped between 2006 and 2015.

The wetlands on the North Carolina and South Carolina border were last mapped between 1986 and 1995 while the rest of the state’s wetlands have not been mapped since the 1980’s. Also, the

limited spatial and temporal resolutions of the satellite imagery make them difficult to classify and define (Pricope, et al., 2020). This has caused the United States to have a very limited database of these wetlands. Accurate and up-to-date Coastal Plain wetland delineation and classification maps and models can contribute to protecting and improving wetland resilience. However, Coastal Plain wetland identification and delineation are labor-intensive, time-consuming, and costly. Traditional wetland delineation and classification are conducted by ground-truthing in the field and these delineations are considered to be the most reliable. Field surveys require specialized knowledge of wetland ecology based on hydric soil and aquatic and emergent vegetation detailed identification. Field surveying in Coastal Plain wetlands is made even more complicated by topography. Most coastal wetlands are dominated by thick forest cover and/or muddy ground unlike grass or non-forested wetlands. When areas of interest have partially or completely inundated ground cover and thick or impenetrable vegetation cover, even locations that are not very remote become difficult to access (Jeziorska, 2019; Pricope et al., 2020). Also, the ecosystems can get damaged in the process of fieldwork. The difficulties of wetland surveying are not only limited to technical complexities but are further complicated by financial and duration considerations. The estimated cost of field-based wetland delineation in east North Carolina ranges from \$ 120 – 180/ per acre and can take several weeks to complete a 2000–3000-acre delineation, according to representatives from North Carolina Department of Transportation (NC DoT) (personal communication, September 1<sup>st</sup>, 2021). Coastal Plain wetlands make up 76.3 % (3,100,703 acres) of wetland areas in North Carolina (Gale, 2021a), and the most recent wetland cover dataset for this area was completed as part of the National Wetlands Inventory (NWI) between 2001-2010 (Figure 1), which wetland cover might have been altered by now. The extensive spatial scale of wetlands in NC will translate to increase cost and manpower conducting these ground surveys, which makes it very difficult to maintain regularly updated wetland maps updated regularly. As such, wetland delineations and classifications based on remotely sensed data are common in filling the gaps between field delineations.



**Figure 1.** NWI source image year map in North Carolina, USA.

There are various wetland systems developed at state, regional, and national levels (LePage, 2011; "Wetlands: Integrating Multidisciplinary Concepts," 2011), and the wetland classes in these classification schemas are developed based on the *Classification of Wetlands and Deepwater Habitats of the United States*, made by Cowardin (Cowardin et al., 1979) and further developed as a second edition in 2013 (Committee, 2013). The Cowardin system was designed to inventory the wetlands and deep-water habitats of the United States. Although deep-water is not considered a wetland ecologically, this classification includes deep-water habitats characterized as “permanently flooded lands lying below the deep-water boundary of wetlands” to have a broader acceptance. The Cowardin hierarchy system is organized as follows: system; subsystem; class; dominance type; and modifiers, and the five main systems are marine, estuarine, riverine, lacustrine, and palustrine (Table 1). The class level system is used to categorize wetland types in this research, however, any areas classified as flooded permanently in the system such as unconsolidated bottom or shore are classified as non-wetland or water in this study.

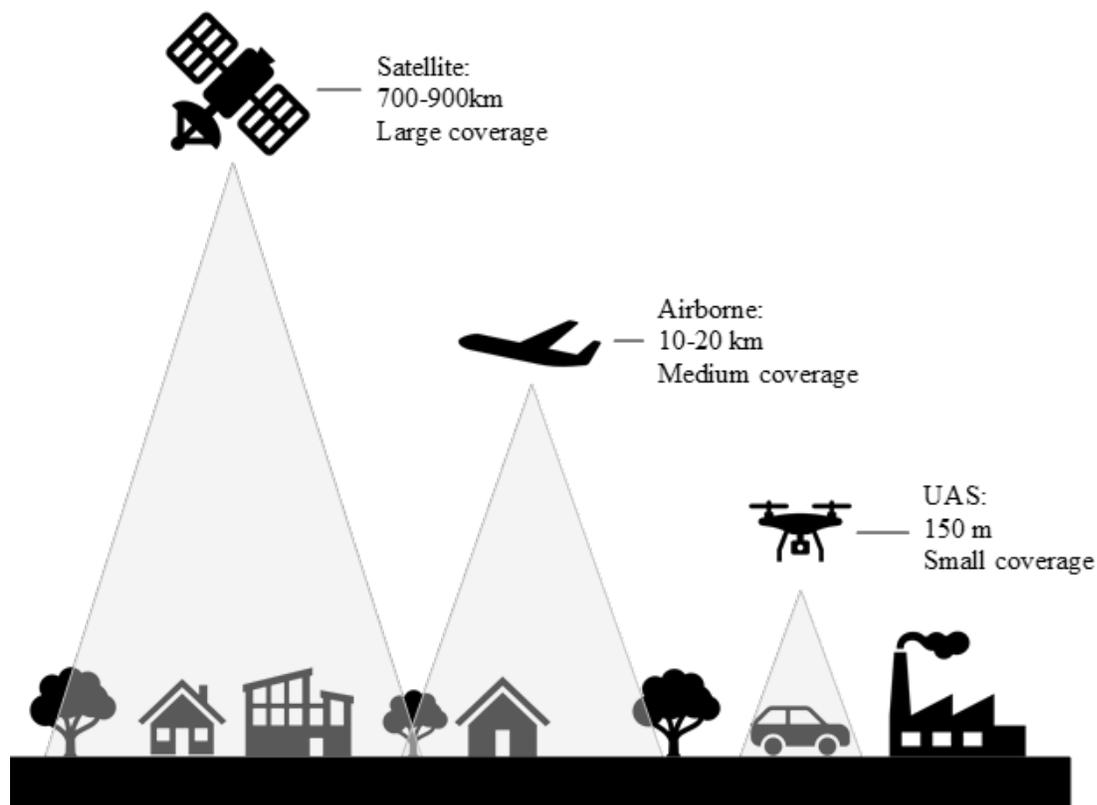
**Table 1.** Description of five wetland systems according to the Cowardin wetland classification system (Cowardin et al., 1979) and also the systems used and referenced in this report classification section.

<b>Wetland System</b>	<b>Description</b>
<b>Marine</b>	The Marine System consists of the open ocean overlying the continental shelf and its associated high-energy coastline. The Marine System consists of the open ocean overlying the continental shelf and its associated high-energy coastline. Marine habitats are exposed to the waves and currents of the open ocean and the Water Regimes are determined primarily by the ebb and flow of oceanic tides.
<b>Estuarine</b>	The Estuarine System consists of deep-water tidal habitats and adjacent tidal wetlands that are usually semi-enclosed by land but have open, partly obstructed, or sporadic access to the open ocean, and in which ocean water is at least occasionally diluted by freshwater runoff from the land.
<b>Riverine</b>	The Riverine System includes all wetlands and deep-water habitats contained within a channel, with two exceptions: (1) wetlands dominated by trees, shrubs, persistent emergents, emergent mosses, or lichens, and (2) habitats with water containing ocean-derived salts of 0.5 ppt or greater.
<b>Palustrine</b>	The Palustrine System includes all nontidal wetlands dominated by trees, shrubs, persistent emergents, emergent mosses, or lichens. It also includes wetlands lacking such vegetation, but with all of the following four characteristics: (1) area less than 8 ha (20 acres); (2) active wave-formed or bedrock shoreline features lacking; (3) water depth in the deepest part of basin less than 2.5 m (8.2ft) at low water; and (4) salinity due to ocean-derived salts less than 0.5 ppt
<b>Lacustrine</b>	The Lacustrine System includes wetlands and deep-water habitats with all of the following characteristics: (1) situated in a topographic depression or a dammed river channel; (2) lacking trees, shrubs, persistent emergents, emergent mosses, or lichens with greater than 30% areal coverage; and (3) total area exceeds 8 ha (20 acres).

Historically, remote sensing technologies have been used as a tool to tackle the issues associated with traditional wetland surveys since the advance of aerial photography in the late 18<sup>th</sup> century (Guo et al., 2017). Remotely sensed data can be used for interpretation and verification, and more often for image classification into distinct vegetation or land cover classes. Image classification refers to a categorization of pixels (reflectance values) in a remotely sensed dataset in order to differentiate among various Earth feature classes such as forest, bare ground, and water. Remote sensing imagery, whether from satellite, airborne sources, or, more recently, unmanned aerial systems (UAS), enables wetland researchers to access data for areas that are physically inaccessible to surveyors and takes significantly less time to collect Earth surface data than field surveys with minimal disturbance to the areas.

Various sensors are used for remote sensing, ranging from optical, visible spectrum data collected by RGB cameras to Light Detection and Ranging (LiDAR), and multispectral (MS) data. Satellite and airborne platforms have been collecting imagery with various spatial, spectral, and temporal resolutions over the past few decades, starting with earth-observing satellites in the 1970s. Satellite and airborne platforms can obtain data for large areas at once, but the common trade-offs are the high cost of imagery access, fixed revisit periods, and large and mixed pixels

that make it difficult to delineate small or medium-sized wetlands or determine wetland cover composition. Although some recent commercial orbital satellites collect imagery with a very high spatial resolution (less than 1 square meter), the imagery costs remain prohibitive for non-commercial purposes.



**Figure 2.** Comparison figure of the three remote sensing platforms in terms of flight altitude and coverage.

Today, wetland mapping is done using digital imagery from aerial remote sensing, such as unmanned aerial systems (UAS) or unmanned aerial vehicles (UAV), in addition to satellite and

airborne-based collections (Table 2). Mapping, delineation, and classification is automated or semi-automated whenever possible. As UAS technology advances, we continue to look for new and improved ways to produce high accuracy outputs. The introduction and relatively widespread adoption of Light Detection and Ranging (LiDAR) technology and the Structure from Motion – Multi View Stereo (SfM – MVS) algorithm based on UAS data have extended our ability to detect and identify wetlands remotely.

**Table 2.** Comparison between the spatial, temporal and spectral resolution of satellite vs. Airborne vs. UAS collections

	Satellite	Airborne	UAS
<b>Field of View</b>	10 – 50 km	2 -5 km	50 – 500 m
<b>Spatial Resolution</b>	1 - 30 m	30 cm -1 m	0.5 – 10 cm
<b>Temporal Resolution</b>	5 - 16 Days	Yearly	On demand
<b>Cost for Data Acquisition</b>	Very high for high resolution imagery	High depending on spatial coverage	Low or relatively low
<b>Data Types</b>	Multispectral	Aerial Photography, LiDAR)	Multispectral and LiDAR

The two main remote sensing sensor types associated with UAS-based wetland analysis, specifically for mapping of wetlands, are multispectral and LiDAR systems. Multispectral sensors collect images within a specific wavelength range across the electromagnetic spectrum. Multispectral measurements have been proven to be highly effective for vegetation classification and evaluating soil moisture content (de Boisvilliers & Selve, 2019). Multispectral imagery is widely used because it is one of the most affordable and available remote sensing systems. While multispectral sensors collect Earth surface reflectance data, an active LiDAR sensor collects a point cloud with elevation and intensity of returns data. A LiDAR sensor emits light energy and receives the returning pulse to calculate the elevation of any objects in the path of the energy beam. The velocity of the light pulse is known; therefore, the topography can be calculated from the time lapse when the pulse was transmitted to when it was reflected (Klemas, 2013a). Over the past decade, many studies have used LiDAR to obtain information about ground elevation and vegetation structure because LiDAR can quickly collect dense elevation data over large areas. LiDAR has been successfully used as an aid for mapping both vegetation and ground elevation in forest ecosystems, such as wetlands (Ritchie, 1996; Lefsky, et al., 2002). LiDAR data can produce high-quality digital terrain models (DTMs) compared to the DEMs that can result from optical imaging sensors or even synthetic aperture radar data. That is because the laser pulse can penetrate through canopy gaps and can collect the ground-level elevation data even underneath the forested area. DEMs are often used to create various topographic

derivatives, including aspect, slope, and curvature. Especially when their spatial resolution is high, both DEMs and their topographic derivatives have been shown to be useful for evaluating hydrologic features in regions of low topography, making them ideal for wetland delineation (Hogg & Todd, 2007; Millard & Richardson, 2013).

The uncertainty in derived elevation products can vary between areas, which is especially problematic in wetlands ecosystems containing dense vegetation. Determining the spatial patterns in vegetation structure and distribution is crucial in delineating wetlands due to their constant change in subtle variations (Fernandez-Nunez, et al., 2017). Wetland vegetation poses further challenges due to their low spectral contrast between species, and their small-scale patterns and distributions (Millard, et al., 2013). Accurate field measurements are crucial to obtain the most accurate vegetation structural parameters (height, vegetation cover, leaf area index, and biomass), while understanding these vegetation structural parameters is important for the accuracy of derived model outputs (Luo, et al., 2015). These derived model outputs include a digital surface model (DSM) representing the ground elevation plus vegetation, a digital elevation model (DEM) representing the area without vegetation, and/or a digital terrain model (DTM) representing only the bare ground. Inaccurately determining the elevation and distribution of wetlands plant species could cause unnecessary errors in these outputs, which then could lead to inaccurate analysis.

Multispectral data collection, especially when conducted from a UAS can further add important information to help improve wetlands classification. Structure from Motion refers to the creation of a 3D product of an area by using a series of 2D images (Kholil, et al., 2021). SfM- MVS creates image derived point clouds and is integrated with a photogrammetric algorithm called Multi – View Stereo (MVS) that increases point cloud density which can be used to create accurate elevation models (Smith, et al., 2016). Point clouds represent 3D shapes or features where each point has its own set of X, Y and Z coordinates. The SfM – MVS algorithm is related to the geometry of structures within a scene from multiple viewpoints on a moving camera, such as a UAV. SfM – MVS is much newer than LiDAR and has been adopted by commercial and open-source software packages designed for non – experts (Berra & Peppas, 2020).

Research shows that the accuracy of land cover classifications improves when combining multispectral and LiDAR data and derivatives, in addition to any field collected data (Rapinel et al., 2015). Fusing or combining multispectral and LiDAR data works because each sensor data can complement each other. While multispectral data can provide spectral reflectance information to classify vegetation, soil, and artificial objects in an image, LiDAR data can offer proxies for hydrology by being able of measuring and detecting subtle changes in elevation or vertical vegetation structural information. However, to the authors' knowledge, the fusion of hyperspatial LiDAR and multispectral data collected via UAS platforms for wetland classification remained unexplored. Hyperspatial resolution is relatively new and enables more precise landscape features to be depicted. Given the low-lying, minimal topography variations of coastal wetlands, typical workflows, and datasets to obtain hydrologic indices and drainage

patterns tend to not work as effectively as they would in areas of more defined terrain. In this paper, building towards the goal of enhanced wetland delineation and classification, we test several wetland prediction models made by image classification and show the relative classification accuracies of two variable-spatial resolution LiDAR sensors mounted on UAS and aircraft platforms in addition to UAS multispectral data (UAS hyperspatial LiDAR + UAS multispectral vs. aircraft non-hyperspatial LiDAR + UAS multispectral).

Because of the detailed and large nature of UAS-collected LiDAR and multispectral datasets commonly used to map wetlands, machine learning (ML) algorithms have emerged as a reasonable approach. Machine learning is defined as computational methods using experiences and examples to improve model performance to make accurate predictions (Mohri et al., 2018), and ML algorithms are trained through either supervised or unsupervised learning. The main distinction between the two approaches is whether the dataset is labeled or not. A supervised learning algorithm uses labeled input and output data while an unsupervised learning algorithm does not. Many studies use supervised ML algorithms to classify wetlands because the input dataset is already labeled (Millard & Richardson, 2013; O'Neil et al., 2018; Tian et al., 2016).

One frequently used ML algorithm for land and vegetation classification is Random Forests (RF) because it produces high classification accuracy, descriptive variable importance, and it is relatively simple to interpret. RF is a supervised classification algorithm that uses an ensemble of decision trees and training data with the bagging method and was developed by Bierman in 2001 (Breiman, 2001). The advantages of RF include the high output classification accuracy, the ability to handle both continuous, categorical data and big/high-dimensional data, and, as such, RF algorithms can contribute to improved wetland delineations and classifications (Tian et al., 2016). Therefore, we built an RF model to classify Coastal Plain wetlands using remote sensing data. The process of RF starts with sampling bootstrapped datasets from a training dataset. A bootstrap resampling technique chooses a random subset from the training dataset with replacement. That means that each time you select a subset of data, you can select the same data more than once. Each decision tree is trained and created independently from the bootstrapped samples in parallel with all other decision trees, which together is called a Random Forest model. Finally, a majority of the predictions are taken to compute the final classification output. Random forest models can generate a variable importance plot which indicate how much each variable is contributing to the classification model, and they are often calculated by the mean decrease accuracy metric (Wei et al., 2015). The Mean Decrease Accuracy plot expresses how much accuracy the model losses by excluding each variable (Martinez-Taboada & Redondo, 2020). Variable importance plots are often used to understand which variables are important in classifying the phenomena of interest which is helpful for this research to understand which independent variables are most important for classifying wetlands.

## Report Body

### PROPOSED TASK BREAKDOWN AND SUMMARY OF PROJECT STAGES

We conducted this research in stages that built on one another during the course of two years, the COVID pandemic notwithstanding. Table 3 shows a summary of the project tasks and the completion timeline. Each of the tasks is then detailed in the sections below and supplemented by two appendices (step-by-step project design, data collection, data pre- and post-processing and model classification and accuracy assessment sections included in a guide).

**Table 3.** RP2020-04 research task breakdown showing % effort of total project hours, timeline for task start and completion and actual task completion date.

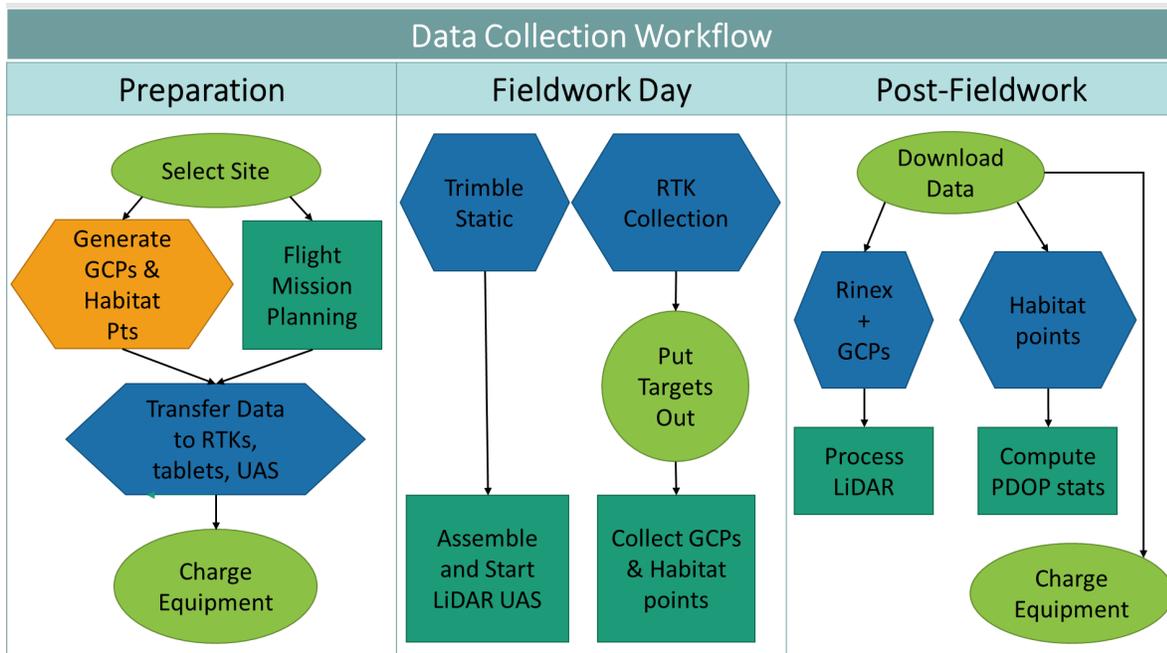
TASK NO.	ABBREVIATED TASK TITLE	TASK AS A PERCENT OF TOTAL PROJECT EFFORT	CUMULATIVE PERCENT OF TASK COMPLETED	SCHEDULED TASK START DATE	ACTUAL OR PLANNED TASK START DATE	SCHEDULED TASK COMPLETION DATE	ACTUAL OR PLANNED TASK COMPLETION DATE
1	Project Design	6.7%	100%	08/19	08/19	12/19	06/30/20
2	Field Work	17.9%	100%	10/19	10/19	12/20	03/31/21
3	Image Processing	32.6%	100%	06/20	10/19	05/21	03/31/21
4	Classification & Accuracy Assessment	35.0%	100%	06/20	03/20	12/21	1/5/22
5	Training & Final Deliverables	7.8%	100%	05/20	05/20	12/21	12/30/21

### Task 1: Design Field Case Studies and Create and Manage Database and Server Configuration

To justify the selection and purchase of a UAS LiDAR sensor selection, two LiDAR sensors, the Quanergy M8 and the Velodyne Puck were demonstrated for our project at NCDOT's Beane Property in New Hanover County by LiDARUSA in March 2020. After a thorough analysis of the two datasets collected on the same day and using the same flight parameters (described in detail in the publication Pricope et al., 2020, published in the leading MDPI journal *Sensors*) and comparison of the specifications and price quotes between the two systems, we determined the Quanergy M8 to be the highest performing and most economical sensor and acquired the Quanergy M8 sensor.

Figure 3 illustrates the three main stages of field work: study design preparation, and implementation in the field, and post field work data processing (see Appendix B for detailed

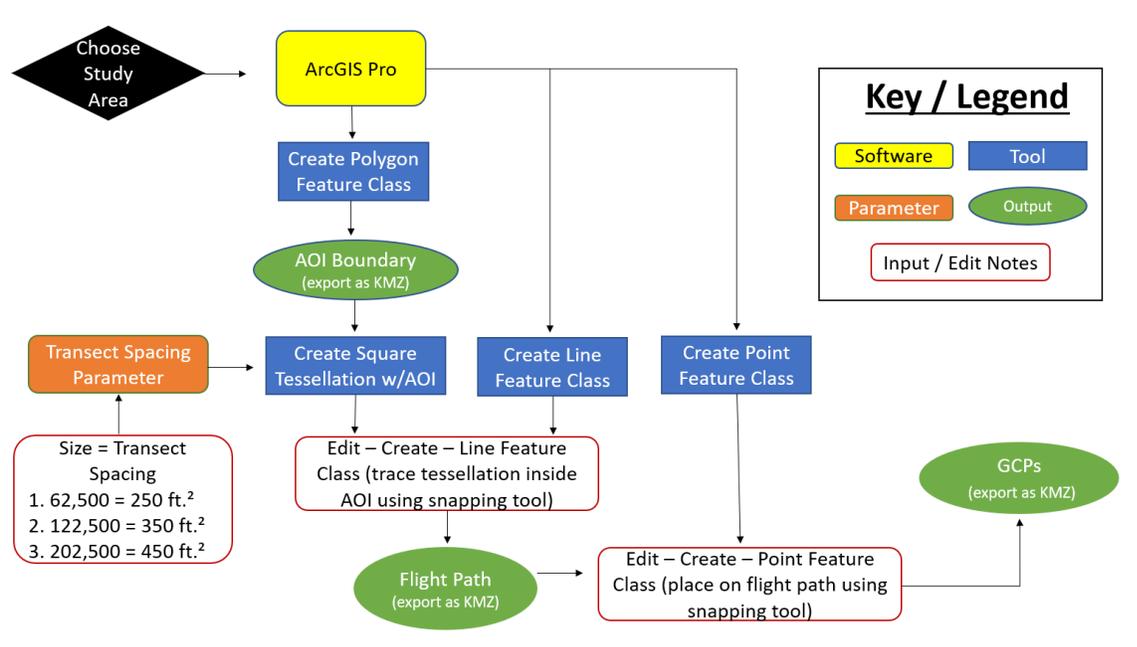
instructions in the “field manual”). In order for collections to achieve their intended goal, several pieces of field equipment must be prepared: 1) the fixed wing and multispectral camera property of Dr. Pricope’s Lab had to be prepared, 2) the LiDAR system needed to be prepared, 3) two Trimble RTKs were charged and loaded with GCP data and habitat sampling points, 4) and ancillary equipment including flight tablet, laptop, radios, also needed to be prepared. The flight mission planning for the LiDAR collection took place in the lab using ArcGIS Pro, while the flight mission planning for the multispectral collections was done using eMotion on a laptop. The photograph below shows us setting up the RTK static collection at Fort Anderson while preparing the other equipment for flight.



**Figure 3.** Data collection workflow showing the three main stages of field preparation, operations on the day of fieldwork and post-fieldwork data download and equipment maintenance.

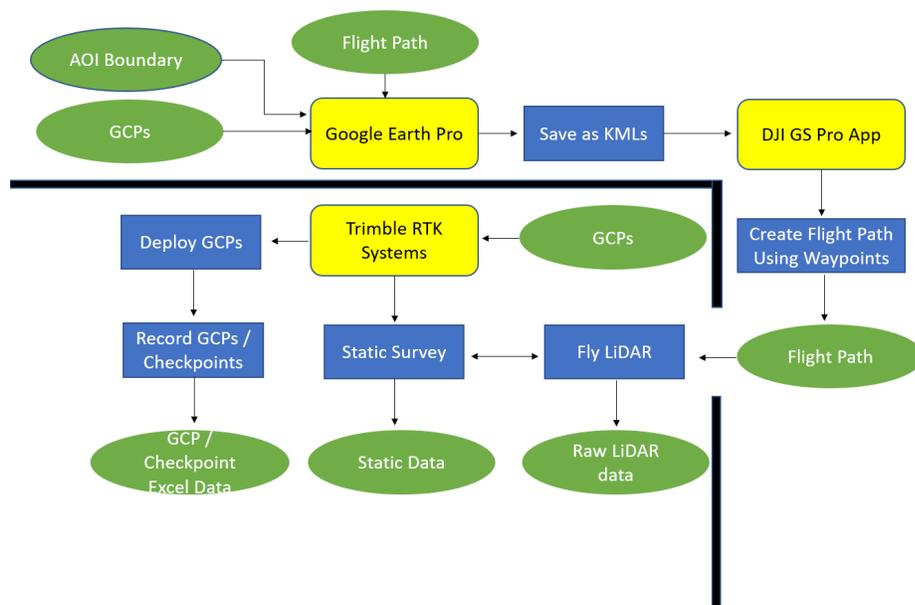


The flight planning for LiDAR collections is the most time-intensive aspect of preparing for a field collection. As detailed in our instructions manual (Appendix B), flight planning begins with a carefully selected study area that then becomes the area of interest (AOI) for all data collected at that respective site (Figure 4). The process of creation of a flight plan to be then uploaded to Ground Station Pro, the software on a typical tablet that is used to fly the Matrice 600 outfitted with the Quanergy M8 LiDAR sensor, is all conducted in ArcGIS Pro. The process outputs not only the flight path exported as a KMZ file, but also the required GCPs that intersect, as much as possible given accessibility and terrain conditions, the actual flight lines.



**Figure 4.** Typical pre-flight workflow for the creation of necessary outputs such as, the AOI boundary, flight path, and GCPs.

In Figure 5 below, we then provide a schematic of how each of the outputs from the flight/mission planning and data collection planning stages translate into implementation components during the actual mission stages for both multispectral and LiDAR collections, along with a visual of an actual mission plan that was implemented at Masonboro Island (Figure 6).



**Figure 5.** Typical implementation of Figure 3 outputs for the collection of data during the photogrammetric and LiDAR flights.



**Figure 6.** An example flight mission map for Masonboro Island showing the area of interest (AOI) for a collection, flight path generated in ArcGIS Pro and uploaded to Ground Station Pro, and the Ground Control Points (GCPs) used for georeferencing.

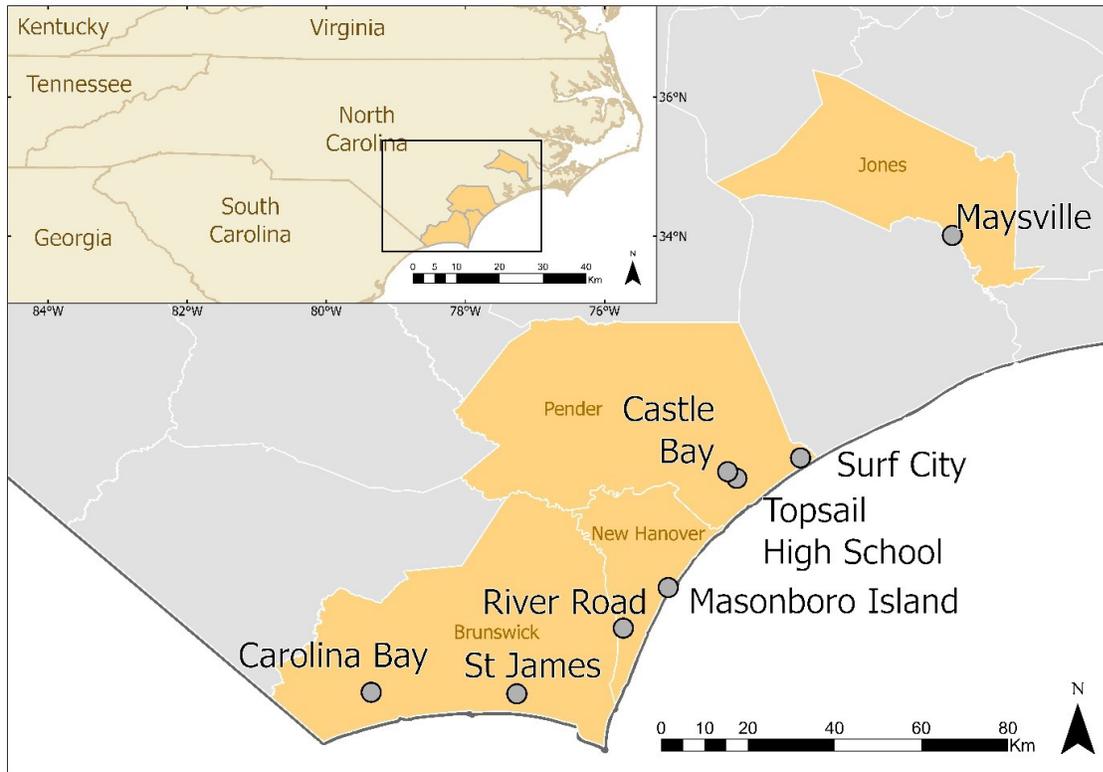
Upon mission completion and return from the field, much care is given to replacing all equipment into proper storage conditions, including recharging or discharging batteries for storage (see Appendix B, instruction manual), curating, downloading, and backing up all newly collected data on the local sever (with nightly backups to avoid any possible data losses) and beginning the organization of all collected data into proper folders and geodatabases. Once all data is properly organized and baked up, we begin creating metadata for each geodatabase indicated in Table 4 below. Metadata for each record was created using an ArcGIS Pro metadata template and each important component (date of acquisition, data type, attributes, who collected the data, etc.) with sufficient detail so that other users can easily understand and use these data. **We recommend conducting proper data management, organization, storage, and backup as well as metadata attribution for any data collected in the field to ensure high data quality standards and data management.**

**Table 4.** Structure of the data dictionaries utilized to organize the field collected data into sub-folders and geodatabases (same folder structure that will be used for transferring all data collected and created from this project to NCDOT).

SUBFOLDER	2ND SUBFOLDER	DESCRIPTION OF CONTENTS
<b>CLASSIFICATION</b>		
<b>FIELDWORK_PREP</b>	mission_planning	Planned drone flight path, AOI, and the target placement information
<b>FINALDATA</b>	classification	Classified dataset that contains the results of RF modeling
	in_situ_vector	GCPs and flight path that are taken on the field. All the data came from LiDAR UAS
	Lidar	Un/constrained lidar data which also came from eGPS (NAD83(2011),US State Plane, NC (3200) in Ft)
	multispectral	Green, nivi, nir, red, and red edge of reflection tif data that are processed in Pix4d (WGS84 /UTMzone 18N(EGM96Geoid))
	thermal	Surface temperature (°C) tif data that are processed in Pix4d (WGS84 /UTMzone 18N).
<b>PRE_PROCESS</b>	Sequoia_Pix4D	Pix4D file to process multispectral data and its associated files
	SODA_Pix4D	Pix4D file to process RGB data and its associated files
	Thermal_Pix4D	Pix4D file to process thermal data and its associated files
<b>RAWDATA</b>	Lidar	All the data here are given by eGPS and the equipment and the process they used were different from ours.
	multispectral	Raw multispectral data that were transferred from a Sequoia memory card
	RGB	Raw RGB data that were transferred from a SODA memory card
	thermal	Raw thermal data that were transferred from a ThermalMap memory card
	in_situ_vector	Some in situ vector data associated with each site
<b>RESULT_VISUALS</b>		LiDAR visuals created from cloudcompare and global mapper

## Task 2: Collect UAS data, conduct in-field calibration and conduct ancillary data collection (GCPs, habitat points, *in situ* multispectral imagery)

In our original proposal to NCDOT, we committed to collecting data at least 9 sites throughout the Atlantic Coastal Plain along a gradient of wetland types representative of the palustrine to riverine to estuarine wetland types on the southeastern NC coast. Figure 7 shows the 9 sites we surveyed (the Masonboro island site was surveyed at two independent times, capturing both low and high tide conditions, hence being counted as two independent collections both in terms of the raw and derived data generated).



**Figure 7.** Study area in southeastern NC showing the nine collection locations across four coastal counties.

The equipment pictured below was utilized throughout the duration of this project to collect all field data: Matrice 600 Pro with the Quanergy LiDAR sensor, two Trimble RTK systems (R8 for static collection and R10 for GCP collection) and an eBee Plus RTK system outfitted with a Parrot Sequia multispectral camera. Table 5 provides a detailed summary of date each site was surveyed and respective dates of data pre-processing for each site.



**Figure 8.** Images of platforms used for data collection. (Left) DJI Matrice 600 Pro with Quanergy M8 LiDAR sensor, (Middle) Trimble RTK R8 and R10, (Right) fixed wing eBee with parrot sequoia multispectral sensor.

### **UAS LiDAR platform and data collection**

The DJI Matrice 600 Pro was used to carry the 800 g Quanergy M8 LiDAR sensor along with a Zenmuse X3 camera to record in flight video for safety monitoring. The M600 Pro is a six – rotor unmanned aerial vehicle with an A3 Pro flight controller and Lightbridge 2 HD transmission system that can reach maximum speeds of 65 km/h. This was equipped with six TB48S batteries for increased flight time as well. The Quanergy M8 is an eight-laser scanner with a range of 150 m at an accuracy of 5 cm. It has a 360-degree horizontal field of view (FOV) and a 20-degree vertical FOV (Pricope, et al., 2020). The Trimble Real – Time Kinematic (RTK) R8 was used to collect static GPS data used for LiDAR processing and the Trimble RTK R10 was used to collect the GCPs.

Once each site was selected, the GCPs for each specific site were selected and generated along with the flight mission plan. Flight mission planning contains creating the flight path for each UAV and selecting where each GCP will be placed based on the flight path. Once these are created, the data was transferred to the Real – Time Kinematics (RTKs), tablets, and UAS. The equipment required was then charged. The day of fieldwork, the LiDAR UAS was flown to gather the raw LiDAR data and a static survey was conducted to gather the static data. Before the

static data could be collected, the GCPs were placed with the RTK systems to record their position.

### **UAS Photogrammetric platform and data collection**

Another instrument used was the 1.3 kg fixed wing eBee plus RTK with a Parrot Sequoia multispectral sensor. The eBee has a wingspan of 116 cm with a ground sampling distance (GSD), at 122 m, of 2.5 cm. It can reach speeds of up to 110 km/h with a maximum flight time of 90 minutes. The parrot sequoia is a 4 - banded multispectral sensor plus RGB camera. The multispectral bands include green (550nm), red (660nm), red edge (735nm), and near infrared (790nm). The Trimble RTK R8 was used to collect static GPS data used for processing and the Trimble RTK R10 was used to collect GCP.

The preparation workflow for photogrammetric data collection is like that of LiDAR in the section above. The flight paths and GCP collection with RTK systems are the same, however, the fixed wing eBee collected multispectral and RGB images instead of raw LiDAR data.

### **Field Collection – Habitat Reference Points**

Habitat ground reference points (GRPs) were used as one of the two reference data (habitat points and NWI data) for training models and testing the wetland classification model accuracies. Habitat reference points were point data with wetland classes and their locational information. To minimize the human bias in selecting the locations of reference data, planned sample locations were generated before the fieldwork. The NWI dataset was used as reference data to map the distribution of wetland classes in study sites. Planned habitat points were generated using the Spatially Balanced Points tool in ArcGIS Pro. We generated 15 GRPs for each wetland class and 50 points for the non-wetland area to ensure that there would be enough data for the random forest classification. Because non-wetland areas include multiple areas of land such as upland grass, artificial objects, and open water, more habitat points were collected in these classes than the wetland classes.

Habitat points were collected in the field (on the same day as the UAS surveys) using a Trimble R10 GNSS RTK System using the Topo points method. Habitat points were collected as close to the planned points as possible, and each point was recorded with a wetland class that was ground-verified. However, many of the planned points were physically impossible to access because of topography, vegetation cover, or inundation level during data collection. Therefore, after field work and back in the lab, the remaining habitat points were created using visual inspections of wetland class using the 2020 National Agriculture Imagery Program (NAIP) imagery for photointerpretation. The NAIP imagery is an open-source data and can be downloaded at the Geospatial Data Gateway of the United States Department of Agriculture (USDA) at [https://datagateway.nrcs.usda.gov/GDGHome\\_DirectDownload.aspx](https://datagateway.nrcs.usda.gov/GDGHome_DirectDownload.aspx). The 2020 true color NAIP imagery was the best option for this project because the LiDAR and habitat points

were collected in the same year or one year later (2020 and 2021). The remaining planned habitat points were overlaid with the true color 2020 NAIP imagery in ArcGIS Pro, and wetland classes were entered to the planned points as much as possible, including a confidence level.

Table 5 provides a list of all sites surveyed, the dates the field work was conducted and the dates all data processing was completed. Table 6 contains all accuracy data for each site such as the vertical (RMSEz) accuracies of the LiDAR point clouds relative to ground control and check points and the horizontal (x,y) RMSE for the collected multispectral imagery, both computed in accordance with the ASPRS photogrammetry and LiDAR processing guidelines shared with our team by Wes Cartner at the DOT. All of the imagery and LiDAR data collected are within the class A accuracies for photogrammetric work as outlined in the ASPRS documentation.

**Table 5.** Field Sites, Dates Surveyed, and Data Collected

Site Name	County	DOT mapped wetlands ?	General Characteristics	Field work date(s)	Lidar UNCONSTRAINED Point Cloud Processed	Lidar CONSTRAINED Cloud Processed	Thermal Processed	Multi-Spectral RGB (Soda) or RGB-NIR-RedEdge (Sequoya) Processed	Number of GCPs Collected	Number of Habitat Points Collected
Beane property	New Hanover	Yes	Managed forest	1-Oct-19	16-Nov-20	16-Nov-20	12/15/2020	11/13/2020	5	N/A
St James	Brunswick	No	Residential development with managed wetlands	5/12/2020	2/15/2021	2/15/2021	N/A	12/19/2020	8	24
Topsail High School	Pender	Yes	Degraded wetlands, dense scrub/shrub	6/2/2020	5-Dec-20	5-Feb-21	3/5/2021	12/10/2020	10	21
Castle Bay GC	Pender	Yes	Mixed managed wetlands, forest and mixed canopy	6/29/2020	2/5/2021	2/9/2021	12/5/2020	12/5/2020	7	34

River Rd	New Hanover	No	Fresh & Salt marsh	10/1/20 - 10/3/20	1/24/2021	5/27/2021	N/A	12/19/2020	11	29
Surf City Bridge	Pender	Yes	Fresh & Salt marsh	11/6/2020	12/14/2020	12/14/2020	N/A	4-Dec-20	15	18
Masonboro - High Tide	New Hanover	No	Barrier island	12/7/2020	12/17/2020	12/31/2020	N/A	N/A	17	43
Masonboro - Low Tide	New Hanover	No	Barrier island	12/11/2020	12/17/2020	No, unconstrained RMSE is good	N/A	5/31/2021	17	43
Maysville Elementary	Jones	Yes	Freshwater managed wetlands, mixed forest	1/22/2021	1/28/2021	1/28/2021	2/25/2021	1/29/2021	9	27
Carolina Bays Parkway	Brunswick	Yes	Freshwater managed wetlands, mixed forest	2/23/2021	2/26/2021	No, unconstrained RMSE is good	N/A	3/9/2021	13	15
Brunswick Town/Ft Anderson	Brunswick	No	Historic site, tidal riverine wetlands	7-May	5/20/2021	No, unconstrained RMSE is good	N/A	5/7/2021	10	N/A
Bald Head Island	Brunswick	No	Barrier island	24-May	In process	In process	N/A	5/28/2021	6	N/A

Once all data were collected, curated, backed up and properly attributed with metadata, we investigated the respective accuracy metrics for both the GCPs collected (Table 6A below for a summary of accuracy metrics for collected GCPs) and for the observed habitat/ground reference data (Table 6B) collected as validation for the wetland classification modeling.

RTK GPS data collection was performed in three modes: static, survey and topographic. “Static” mode is when an RTK GPS is set up near the UAS flight take off/landing and runs throughout the flight operation. This RTK collection is used to add higher ortho accuracy to the collected

UAS data and is incorporated into the UAS data processing workflow (again, please refer to last quarterly report, 3/31/21). GCPs are collected using “survey” mode which requires that the RTK unit remains stationary for at least 3 minutes prior to obtaining a waypoint/coordinate. Lastly, “topo” mode is the fastest data collection method and therefore has lower horizontal accuracy. It is best to use this collection mode when the output does not require GCP accuracy for correcting imagery/UAS data. Therefore, we used “topo” mode to collect the field ground reference points (GRPs) which we have termed “habitat” points since these GRPs will be used in the wetland/habitat classification model.

Trimble RTK GPS units can record several metrics that indicate the level of accuracy (both horizontal and vertical) using Dilutions of Precision (DOP). DOP is the measure of strength of the constellation of satellites at the time a waypoint is recorded where the lower the value the higher the accuracy of the recorded location:

- *PDOP: Position DOP, indicates the strength of the satellite constellation for general position accuracy*
- *HDOP: Horizontal DOP, indicates the strength of the satellite constellation for horizontal position accuracy.*
- *VDOP – Vertical DOP, indicates the strength of the satellite constellation for vertical position accuracy.*
- *TDOP – Time DOP, indicates the strength of the satellite constellation for determining time and the clock offset.*

We have computed the average DOP and precision values for habitat GRPs and GCPs collected at each field site (Tables 6A and B below). As expected, the horizontal positioning is more accurate (lower DOP values) and greater precision than vertical positioning. Gathering more GRPs and GCPs does not lower the DOP values, the average HDOPs are less than 1 which is ideal, but less than 2 is considered excellent, and the standard deviation among the sites is very low which indicates that the DOP differences between sites is small. The average horizontal and vertical precision is also very good. These results are used to assist with developing the final map products because points with higher values can be removed from further processing.

**We recommend utilizing two RTK systems with capabilities to collect centimeter-level accuracy data for both static and GCP data as part of a defensible and accurate (to NC ASPRS standards of vertical and horizontal accuracy) field collection methodology.**

**Table 6A and B.** Field work accuracy for select sites in terms of Ground Control Points (GCPs) in table A and habitat reference points in B.

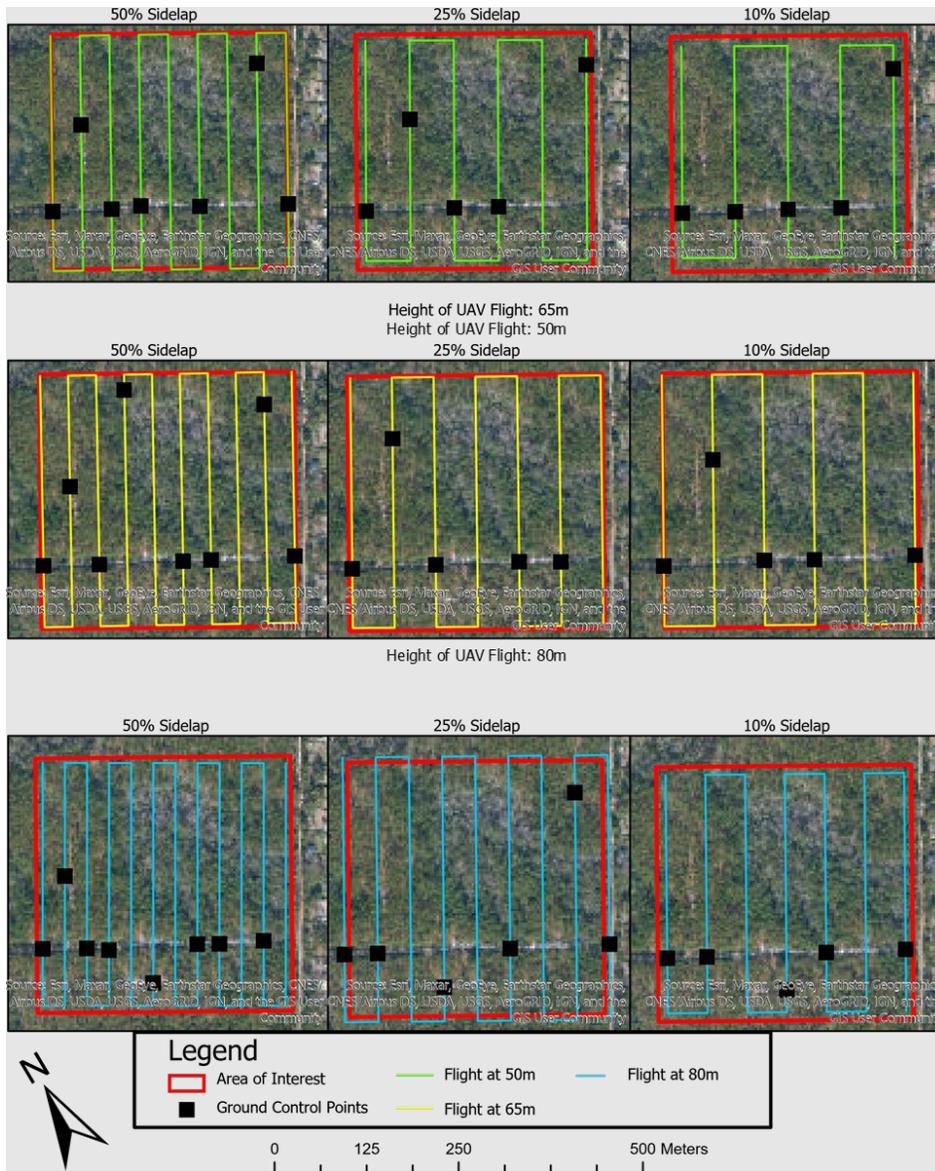
SITE NAME	NUMBER	AVERAGE PDOP	AVERAGE HDOP	AVERAGE VDOP	AVERAGE HORIZONTAL PRECISION	AVERAGE VERTICAL PRECISION
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<b>Topsail High School</b>	10	2.179	0.9924	1.938	0.082	0.015
<b>Castle Bay GC</b>	7	1.418	0.7375	1.212	0.007	0.013
<b>River Rd</b>	11	2.094	1.092	1.778	0.009	0.02
<b>Surf City Bridge</b>	15	1.477	0.7536	1.269	0.007	0.014
<b>Masonboro</b>	17	1.35	0.6762	1.169	0.004	0.008
<b>Maysville Elementary</b>	9	1.451	0.7459	1.244	0.011	0.016
<b>Carolina Bays</b>	13	1.83	0.9497	1.563	0.005	0.008

<b>SITE NAME</b>	<b>NUMBER</b>	<b>AVERAGE PDOP</b>	<b>AVERAGE HDOP</b>	<b>AVERAGE VDOP</b>	<b>AVERAGE HORIZONTAL PRECISION</b>	<b>AVERAGE VERTICAL PRECISION</b>
<b>TOPSAIL HIGH SCHOOL</b>	21	1.357	0.685	1.170	0.015	0.028
<b>CASTLE BAY GC</b>	34	1.881	0.936	1.626	0.013	0.025
<b>RIVER RD</b>	29	1.640	0.908	1.361	0.010	0.014
<b>SURF CITY BRIDGE</b>	18	1.654	0.822	1.433	0.014	0.024
<b>MASONBORO</b>	43	1.397	0.765	1.167	0.009	0.014
<b>MAYSVILLE ELEMENTARY</b>	27	1.359	0.735	1.141	0.012	0.019
<b>CAROLINA BAYS</b>	15	1.677	0.776	1.486	0.007	0.014

Finally, the last component of field data testing, calibration and collection with the LiDAR equipment purchased with NCDOT funding has been to conduct multiple flights over the same area to determine the ideal flight altitude and overlap for future DOT missions. Graduate student Carter Eckhardt completed his MS Geoscience Final Project by testing LiDAR UAS parameters and comparing derived metrics in a 30-acre wooded area in the back of the UNCW campus, dominated with upland forest and forested wetland. Here we planned and collected data over 3 days at three altitudes (50m, 65m, and 80m) and three percentages of sidelap (10%, 25%, and 50%) (Figure 9). Research has shown that low altitude flight increases the spatial resolution of the resulting data, but requires longer flight time because of the greater number of flight lines and covers less area. Therefore, there is a cost to flying at lower altitude (Mesas-Carrascosa et al.

2016), yet altitude has also been determined as the most important flight parameter when collecting UAS Lidar (Sofonia et al. 2019) hence our tests to determine the most appropriate flight parameters for the system acquired through this contract.



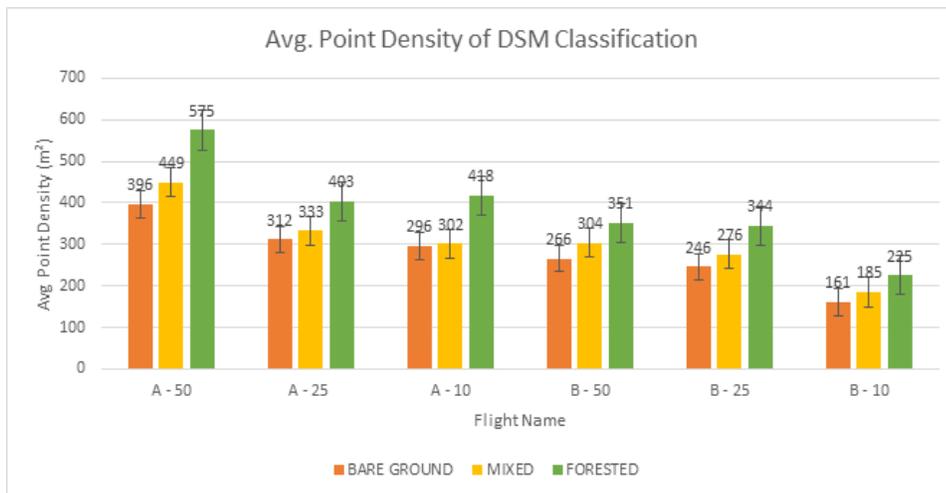
**Figure 9.** Planned flights at a 30 -acre site on the UNCW campus for testing altitude and swath width (percentage sidelap) of the Lidar UAS. Three altitudes (A- 50m, B- 65m and C- 80m) and three percentages of sidelap (10, 25, and 50) were tested for a total of 9 flights.

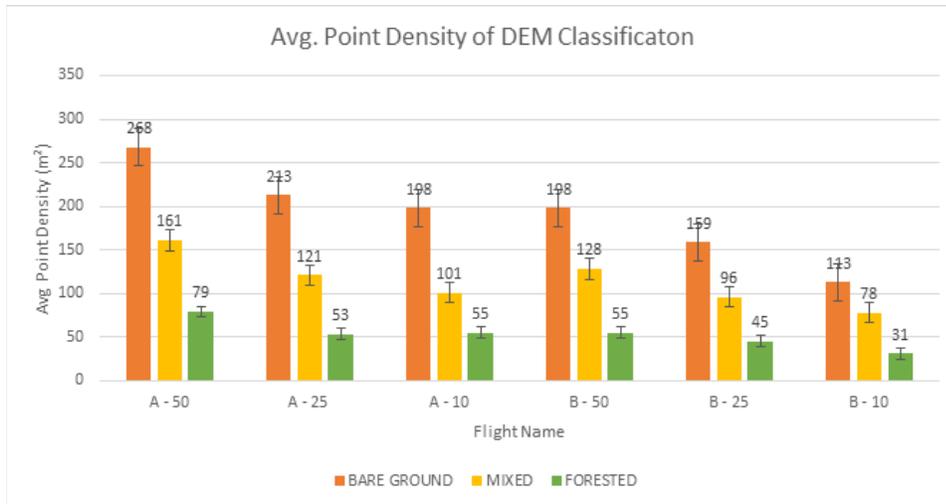
**Table 7.** Post Flight Data from the UAS Matrice 600 based on each flight combination that processed successfully (excludes flight C at 80m altitude).

Flight name	Battery % used	Flight airtime	Battery sets	Flight length (m)
-------------	----------------	----------------	--------------	-------------------

A - 50	51%	14m 15s	1	3,514.04
A - 25	47%	11m 05s	1	2,601.77
A - 10	35%	09m 16s	1	1,920.55
B - 50	56%	15m 35s	1	3,811.80
B - 25	50%	11m 58s	1	2,786.15
B - 50	40%	11m 26s	1	2,455.77

Upon processing all data, the 80m altitude flight data did not process correctly and therefore was excluded; we do not recommend flying the Matrice with the Quanergy that high. The other critical flight parameters for the two other flight altitudes are reported in Table 7. For flights A and B (50m and 65m altitude respectively), graduate student Eckhardt ran geostatistical tools to analyze the resulting point densities and relative vertical information contained in the DEMs and DSMs generated at this site from the resulting point clouds for the dominant land covers in the AOI: forested, bare ground and mixed (Figure 10 A and B).





**Figure 10.** A: Average point density for the DSM based on each fishnet class. B: Average point density for the DEM based on each fishnet class.

Findings showed that, compared to the computer simulated study by Bashar & Remondino (2020), flight overlap percentage does in fact influence point density more than altitude. This can be seen significantly when flight A-10 & B- 50 are compared, flight A-10 has similar point density to B-50 however the percentages of overlap are 10% and 50% respectively. The DSM, which includes the whole point cloud has a higher point density by area than the DEM. This is because the DEM only has the ground points which is the last return included in it and no other returns reducing the number of points by a significant amount. The point density between bare ground, mixed, and forested landcover indicates that the denser the vegetation, the higher the point density. The DSM classification shows a discrepancy between flight A and flight B where we notice a dip at Flight A – 25% compared to Flight A – 50%. The causes of this are unknown. When disregarding the discrepancy, we see a consistent increase from 10% to 50% of point density, however, when taking the flight time into consideration, the 50% overlap is significantly longer and uses more battery life than the 10% due to more transect lines in the flight path. For the DEM classification and point density, we note a constant increase from 10% to 50% overlap for both flight A and B (Figure 10B).

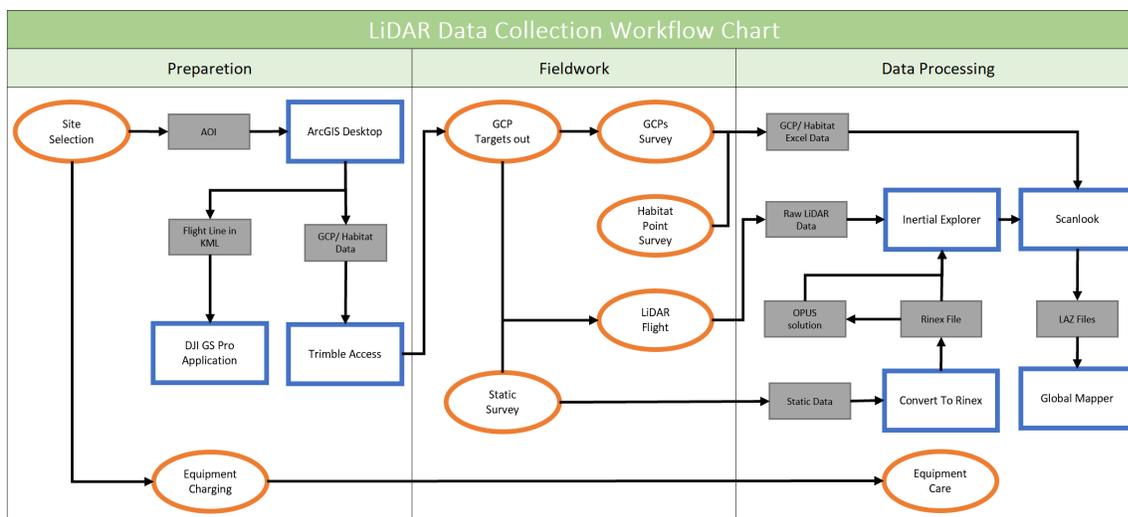
For practical purposes, depending on the size of the area and the ideal point density desired, flight B at 50% has similar statistics to Flight A at 10% however an increase in clearance for the UAS may be needed in some areas making these parameters ideal. The negative impact of flight B at 50% is an increase in flight time and battery percentage used. Researchers have found that 10 to 12 ground control points (GCPs) are recommended per 100 ha study area size (Yu et al. 2020). However, Yu et al. (2020) did not consider the altitude of the UAS or the number of transect lines to be paired with the GCP targets of a certain study area size. Future work would include testing GCP locations based on the classified fishnet to test whether or not placing GCPs in certain areas (i.e., bare ground, mixed, or forest vegetation) would increase vertical RMSE accuracy of the point cloud. Some GCPs & checkpoints were removed due to being outliers or

having to large of a RMSE value to incorporate into the error. This was due to canopy cover and location of the GCPs & checkpoints, as well as fewer satellites and location loss of the Trimble R10 unit.

After further conducting statistical t-tests on these flight combinations, depending on the majority landcover being surveyed, that multiple flight combinations will be suitable for data collection. **We recommend that a forested landcover and mixed landcover should have a UAS flight parameter combination of an attitude at 65m with a swath width overlap percentage of 25%.** This is due to the average point density of the DSM is 276 for mixed and 344 for forested, as well as 96 for the DEM for the mixed & 45 for the forested. **We recommend that for majority bare ground landcovers, the ideal flight parameter combination to be at 50m altitude and an overlap percentage of 25%.** This is due to the point density of the DSM is 312 and the DEM is 213 (all statistically significant findings).

### Task 3: Image and Data Processing: Implement Photogrammetric Structure-From-Motion Processing Workflows on UAS Imagery and LiDAR Data Processing Workflows

Final data deliverables (e.g. point clouds, DTMs, hillshades, orthomosaics, reflectance maps, vegetation indices, topographic indices, canopy heigh models) for all completed field sites: Topsail High School, Castle Bay, St. James, River Road (Wilmington), Surf City construction site, Masonboro island (two campaigns, one at high tide and one at low tide), Maysville elementary and the Carolina Bays parkway were all processed using standardized and repeatable methodologies detailed in the instruction manual (Appendix B). Figure 11 shows a summative flowchart from preparation to collection to initial processing for the LiDAR data, which is the focus of this research project.



**Figure 11.** Workflow diagram showing the LiDAR collection process from field preparation to implementation and to the initial processing to obtain a point cloud constrained to GCPs.

#### LiDAR data pre – processing

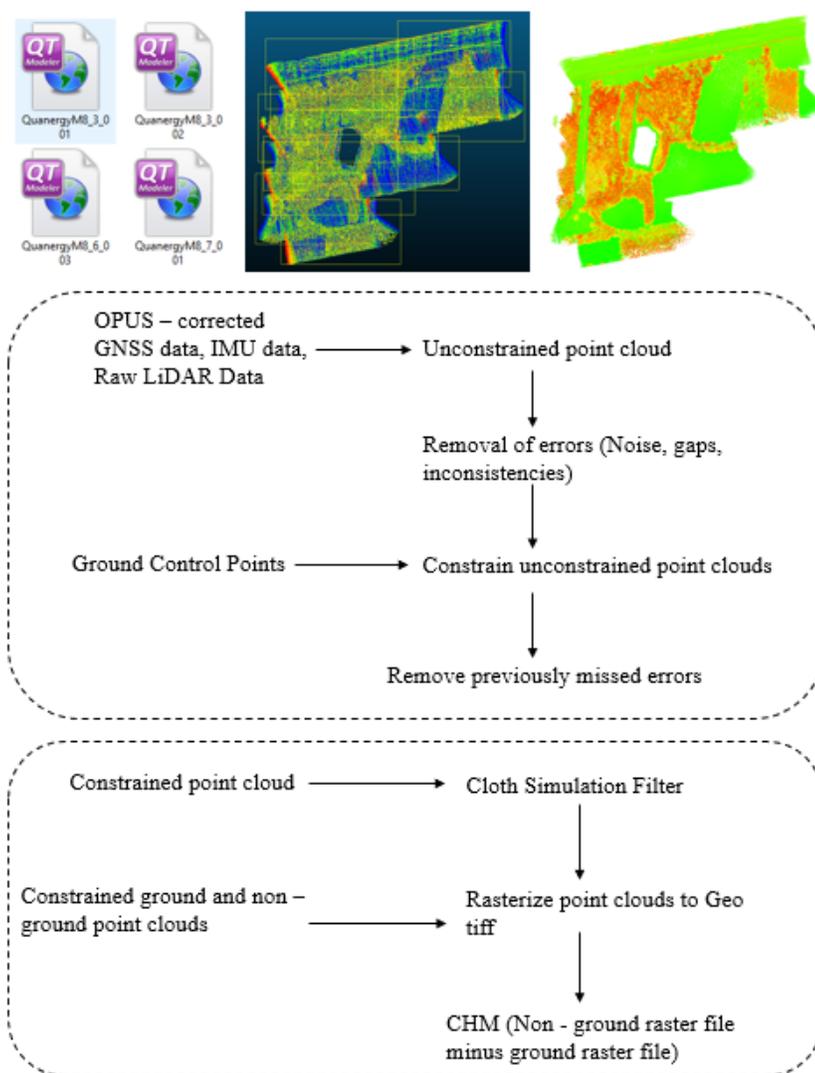
Given that the LiDAR scanner was completely new to our research team, there was a trial-and-error period when we developed our understanding of not only how to properly pre-process, but also collect and manage the LiDAR data streams. Coupled with the COVID pandemic that started immediately after we had received the new equipment there was also a delay receiving it which led to some delay incorporating these new datasets into our project, mapping and the final modeling stages.

The data collected from the LiDAR scanner, the static data from the GPS unit along with data collected from an Inertial Navigation System (INS) and the actual scanner (which includes the Inertial Measurement Unit (IMU)) were used in the LiDAR pre-processing steps. INS is a navigation method where estimations are given by accelerometers and gyroscopes are utilized to follow the position and direction of an object comparative to a known starting stage. The IMU uses drone telemetry to track the position and orientation of a device (Pricope, et al., 2020). The raw Global Navigation Satellite System (GNSS) data is first converted from a T02 file to a RINEX file that is then brought into the Novatel Inertial Explorer. The GNSS data is processed in the Novatel Inertial Explorer where the Online Positioning User Service (OPUS) provides accurate solutions to the data collected from the flight. The OPUS - corrected GNSS data and the data collected from the sensor is then used to create a trajectory to estimate positional accuracy. The OPUS - corrected GNSS data and the data from the sensor is then coupled with the IMU data from the sensor to create a final flight trajectory. This data is then processed in LiDARUSA ScanLook PC to create an unconstrained point cloud (in LAS format) that can be used in other software packages (Pricope, et al., 2020).

The point cloud is then analyzed in the Global Mapper software to locate and remove any errors such as excess noise, data gaps, and/or inconsistencies. The data is then brought back into ScanLook PC to constrain the point cloud to GCPs. A minimum of three ground control points GCPs with XYZ coordinates are required (Smith, et al., 2016). However, the numbers of GCPs depends on the size of the survey and there should be enough to cover the whole area, therefore, a larger number of GCPs might be needed (Javernick et al., 2014; Yu, Kim, Lee, and Son, 2020). One such study by Yu, et al. (2020), showed that the optimal number of GCPs for small and medium (7 and 39 ha) sites is 12 while for large (342 ha) sites it is 18.

The point cloud is then brought back into Global Mapper to locate any more errors previously missed. Once all errors are found, the data are exported to multiple files in LAS format (Pricope, et al., 2020), see Figure 12. Step-by-step instructions for all stages of processing are included in the instructions manual in Appendix B of this report.

## LiDAR Workflow



**Figure 12.** Summative workflow for the raw UAS LiDAR data pre-processing and processing to create digital terrain/elevation and/or digital surface models (DEMs) which can then be used to derive canopy height models for vegetation.

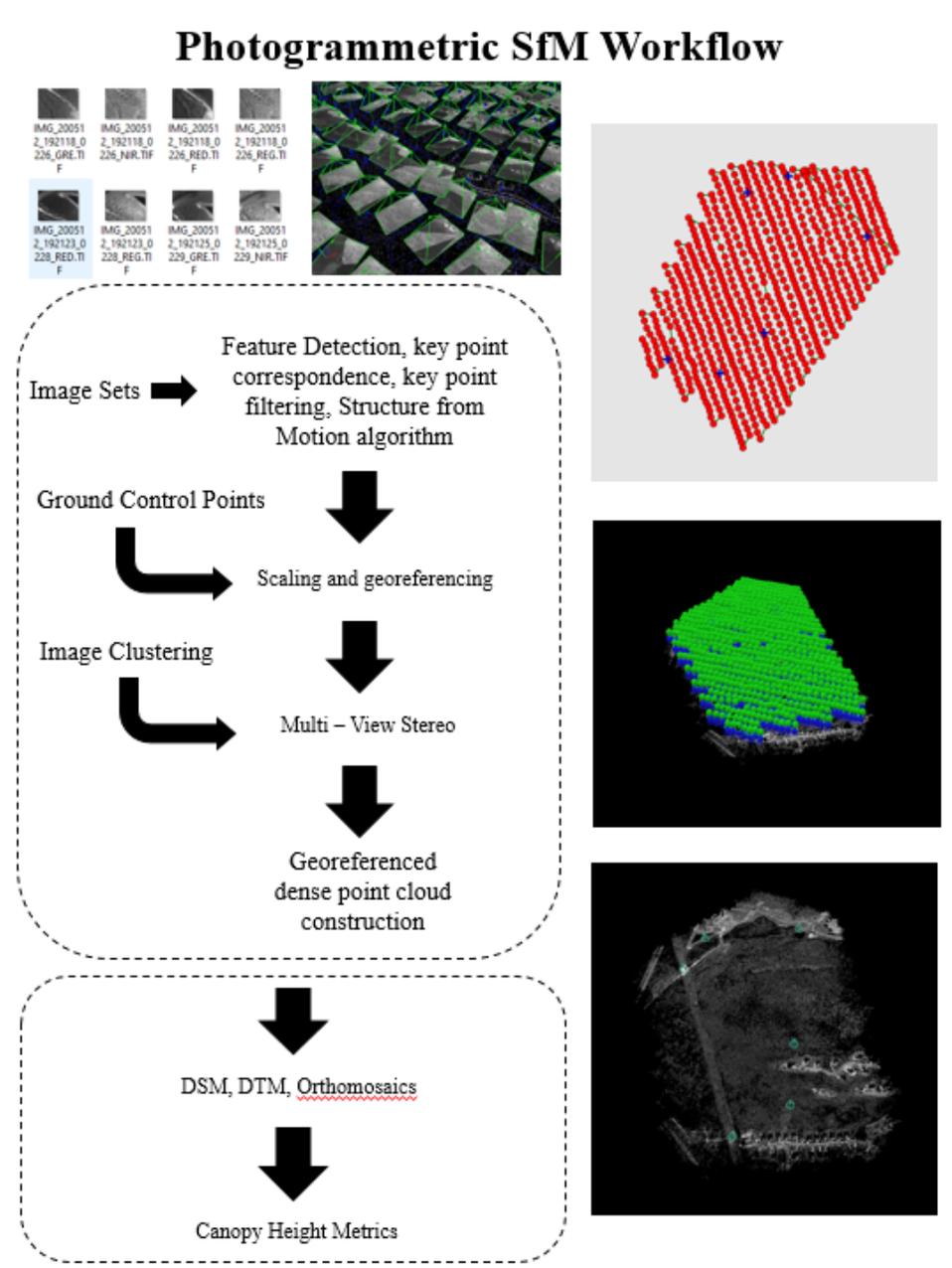
### Photogrammetric data pre – processing for multispectral data

The typical workflow implemented, post fieldwork, using photogrammetric software packages will vary from one to another, but they all follow the standard format of three main phases: sparse point cloud reconstruction, georeferencing, and dense point cloud reconstruction (Berra & Peppas, 2020). This can be further specified into feature detection, key point correspondence, key point filtering, Structure from Motion, scaling and georeferencing, Multi – View Stereo, and georeferenced dense point cloud construction (Smith, et al., 2016).

The workflow being discussed was implemented by using the photogrammetric software Pix4D Mapper. Feature detection takes a set of images from different perspectives to identify key points in each image. This is most useful for SfM – MVS feature detection when images are taken from multiple viewpoints. Feature detection algorithms geometrically normalize regions containing similar features and correct illumination distortions to maintain invariance (Mikolajczyk, et al., 2005). Key point correspondence requires the identification of similarities between features in multiple images. However, representation of these key points is not always guaranteed, therefore, a threshold must be applied.

These thresholds can be complex; therefore, the algorithm will use distance ratios such as the Euclidean distance of the nearest neighbor. The pixel value closest to the predicted x,y coordinate is assigned to the output x,y coordinate. This uses a minimum value which looks to increase the chance of all features being identified. Filters are then applied to identify and remove inaccurate matches. If a feature is beyond the threshold, then it is considered an outlier and not fit for the algorithm. This is repeated until there is 95% certainty that there are no more outliers. Further filters are then applied to remove all outliers (Smith, et al., 2016). Using the corrected feature correspondences, SfM uses a bundle adjustment algorithm to estimate the 3D structure of an area. Smith, et al. (2016, p. 253) define bundle adjustment in two parts: Bundle as, “...the bundles of light rays connecting camera centers to 3D points” and adjustment as, “...the minimization of a non-linear cost function that reflects the measurement error”. The measurement error refers to the possible error created when each image feature is reprojected. The camera’s interior and exterior orientations are determined at the same to further minimize the reprojection error of all overlapping images (Berra & Peppia, 2020).

At this stage the point cloud is sparse and not scaled to real - world units. A minimum of three ground control points (GCPs) with XYZ coordinates are required to fix this (Smith, et al., 2016). However, as discussed above, this depends on the size of the survey area and there should be enough GCPs to cover the whole area (Javernick, et al., 2014; Yu, et al., 2020). The information from the GCPs is then used with the internal constraints as external constraints to readjust the camera’s internal orientations, external orientations, and 3D coordinates to receive the desired coordinate system (Berra & Peppia, 2020). With the addition of external GCPs, the bundle adjustment can be re – run to reoptimize the image alignment and further minimizing the re – projection error. The last step in the SfM – MVS workflow is the use of MVS algorithms to produce dense point clouds. This algorithm usually increases the density of the point cloud by two orders of magnitude (Kholil, et al., 2021). Each pixel is triangulated and back projected to create a 3D surface. This georeferenced point cloud can then be exported to generate a digital surface model (DSM), digital elevation model (DEM), and/or a digital terrain model (DEM). Orthomosaics can be produced as well (Berra & Peppia, 2020), see Figure 13 below.



**Figure 13.** Summative workflow for the photogrammetric data pre-processing on the eBee collected multispectral imagery.

Following the pre-processing methodologies outlined above, the final vertical (unconstrained and constrained to GCPs) RMSEz of UAS LiDAR point clouds and horizontal RMSEs for the multispectral UAS imagery are reported for all sites in Table 8. Beane property final metrics (processed by LiDARUSA) were also reported in detail in Pricope et al., 2020.

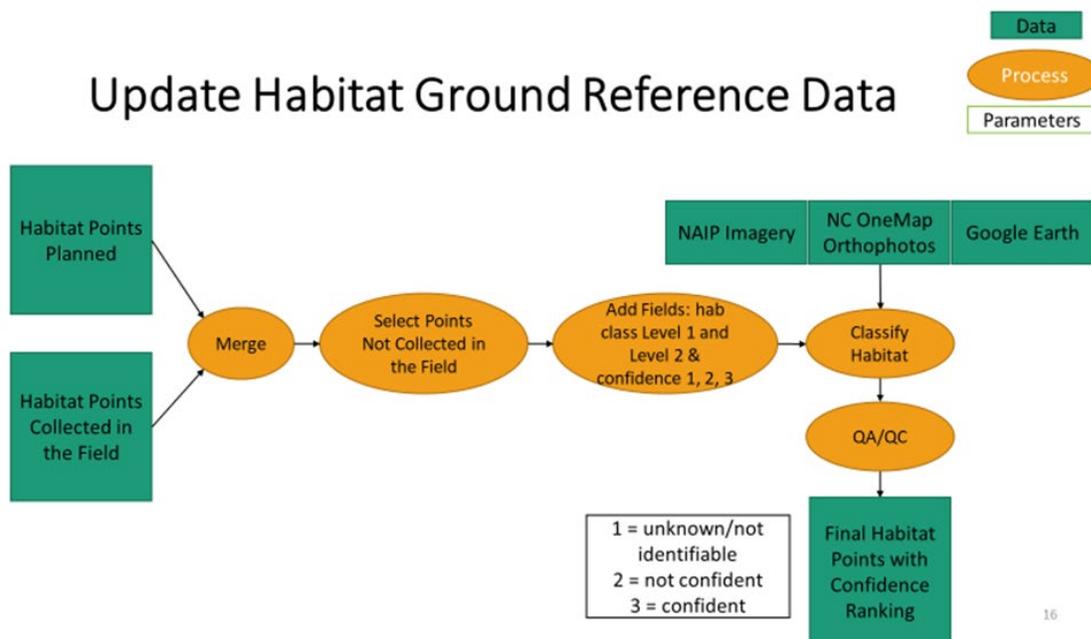
**Table 8.** Field site characteristics, vertical accuracies for both unconstrained and constrained Lidar point clouds, and horizontal accuracies for multispectral imagery.

<i>Site Name</i>	<i>Location</i>	<i>DOT delineated</i>	<i>General Characteristics</i>	<i>Field work date</i>	<i>LiDAR RMSEz (m) Unconstrained</i>	<i>LiDAR RMSEz (m) Constrained</i>	<i>Multispectral RMSE (m) X,Y</i>
<i>Beane property</i>	New Hanover County	Yes	Managed forest	1-Oct-19	n/a	0.03	0.020
<i>St James</i>	Brunswick County	No	Residential with managed wetlands	5/12/2020	0.187	0.34	0.024
<i>Topsail High School</i>	Pender County	Yes	Degraded wetlands, dense scrub/shrub	6/2/2020	0.248	0.038	0.084
<i>Castle Bay GC</i>	Pender County	Yes	Mixed managed wetlands, forested	6/29/2020	0.446	0.169	0.008
<i>River Rd</i>	New Hanover County	No	Fresh & Salt marsh	10/3/2020	1.971	0.049	0.043
<i>Surf City</i>	Pender County	Yes	Fresh & Salt marsh	11/6/2020	0.421	0.078	0.072
<i>Masonboro High Tide</i>	New Hanover County	No	Barrier island	12/7/2020	0.42	0.044	Not flown
<i>Masonboro Low Tide</i>	New Hanover County	No	Barrier island	12/11/2020	0.047	0.047	0.080
<i>Maysville</i>	Onslow County	Yes	Mixed forested wetlands	1/22/2021	0.445	0.051	0.083
<i>Carolina Bays Parkway</i>	Brunswick County	Yes	Mixed forested wetlands with degraded	2/23/2021	0.03	0.03	0.013

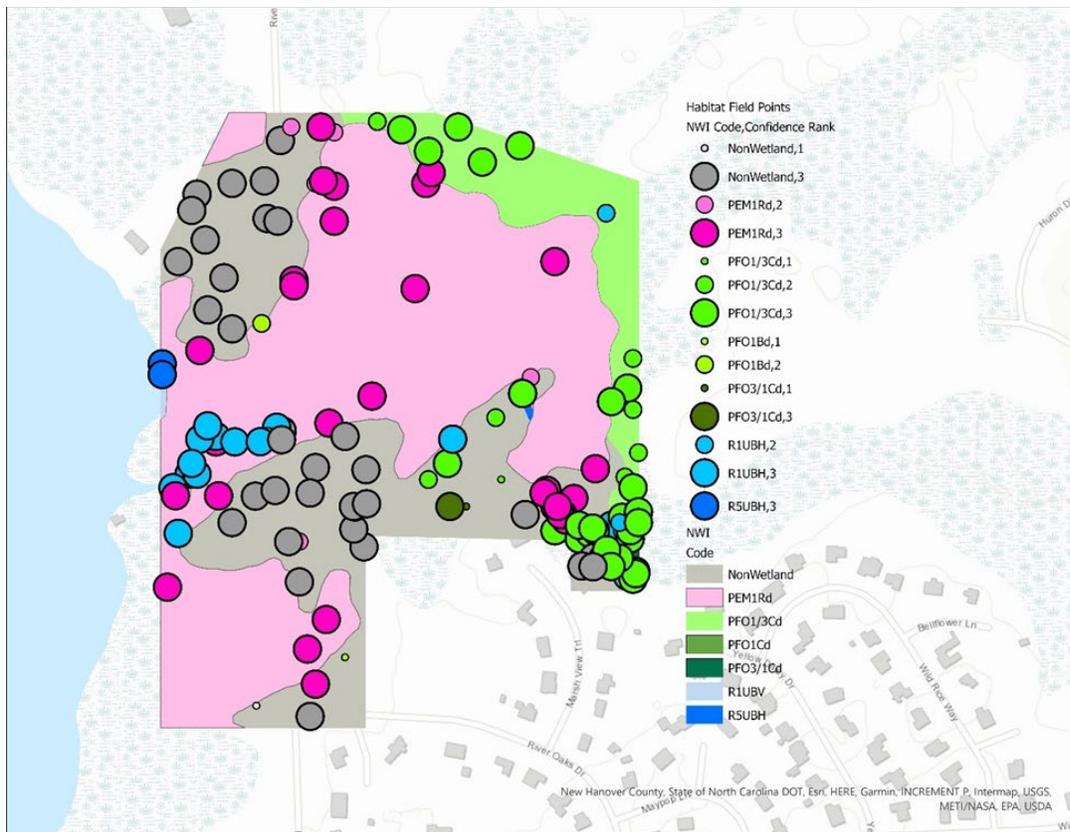
**Habitat Ground Reference Points (GRPs)**

We used two Trimble RTKs to collect Static, Ground Control Points (GCPs), and habitat Ground Reference Points (GRPs). For the habitat GRPs, we used a spatially balanced structured random sampling design (Halls, Frishman, and Hawkes 2018; Theobald et al. 2007) to plan the field collection of GRPs based on the most recent NWI data. Even though the spatially balanced approach enables us to apply an accessibility weight to the random point locations, it was still very difficult to access many of the locations due to the nature of coastal wetlands; however, in total, we collected 225 GRPs at the 8 field sites. Accessibility issues are expected in this ecosystem; and therefore, the next step in the habitat GRP characterization was to use the planned habitat points and compare these with the most recent imagery to assess the planned points. Ultimately, we used these habitat GRPs for a final assessment of the wetland classes derived from the UAS lidar data.

For each site, the planned habitat GRPs, collected habitat points, and imagery from three sources (NAIP, NC OneMap, and Google Earth) were used to update the points to the current habitat type and give an assessment of the confidence we have in these updated attributes. The workflow for this data processing is given in Figure 14, while an example resulting complete GRP dataset, along with the class definition used to create them are included in Figure 15 and Table 9.



**Figure 14.** Data processing workflow to assign habitat classification to each planned Ground Reference Point. Each point was assigned a full NWI code, an abbreviated or generalized NWI code, as well as confidence rankings for both.



**Figure 15.** An example result of classifying the habitat Ground Reference Points (GRPs) using NAIP, Orthophotography and Google Earth to update the planned GRPs and give them a confidence ranking where 1 = unknown, 2 – less confident, and 3 = very confident in the habitat class. As shown in this example, most GRPs have a very high confidence and these points were used later in the project for wetland classification map accuracy assessment.

**Table 9.** The definition of each NWI classes illustrated in the above figure is:

NWI	Definition
<b>PEM1Rd</b>	Palustrine, Emergent, Persistent, Seasonally Flooded-Tidal, Partially Drained/Ditched
<b>PFO1/3Cd</b>	Palustrine, Forested, Broad-Leaved Deciduous, Broad-Leaved Evergreen, Seasonally Flooded, Partially Drained/Ditched
<b>PFO3/1Cd</b>	Palustrine, Forested, Broad-Leaved Evergreen, Broad-Leaved Deciduous, Seasonally Flooded, Partially Drained/Ditched
<b>PFO1Cd</b>	Palustrine, Forested, Broad-Leaved Deciduous, Seasonally Flooded, Partially Drained/Ditched
<b>R1UBV</b>	Riverine, Tidal, Unconsolidated Bottom, Permanently Flooded-Tidal
<b>R5UBH</b>	Riverine, Unknown Perennial (the distinction between lower perennial, upper perennial and tidal cannot be made), Unconsolidated Bottom, Permanently Flooded

**In summary, we recommend following standardized, repeatable and ideally batched data pre-processing workflows for all raw data collections, including for UAS LiDAR, multispectral/RGB/thermal and especially *in situ* reference data (as needed). We especially recommend that great care be taken when selecting the minimum required GCPs (5-10/site, depending on the site characteristics and at least as many check points for validation) to ensure not only intersection with respective flight paths, but also accessibility. Data pre-processing templates and parameter specification sheets are imperative in ensuring standardized data processing across multiple sites.**

#### **Task 4: Classification & Accuracy Assessment: machine learning random forest modeling**

To accomplish the last task of this project, UAS wetland classification, we collected various ancillary GIS and imagery datasets to use in the modeling, prediction, and validation of our wetlands classification (Table 9). As suggested in the literature review above and after testing several other classification approaches (tessellation-based, object-based), we settled on employing a pixel-based k-fold cross-validation random forest machine learning algorithm implemented in RStudio using the *raster* and *h2o* packages under the supervision and with support from Department of Mathematics and Statistics professors Drs. Tracy Chen and Yishi Wang.

**Table 10.** Publicly available data sources assessed for project fit and/or used as ancillary data in different parts of this research project

<b>Data</b>	<b>Purpose</b>	<b>Pros</b>	<b>Cons</b>
NOAA C-CAP	Land cover	Few dates	Low resolution for local analysis
NWI	Wetlands	Detailed attributes	Very outdated
NC CREWS	Wetlands	Similar to NWI, but with emphasis on coastal wetlands	Very outdated
NAIP and other aerial/ortho photography	Interpret Wetlands	High resolution	Usually only B&W or natural color, sometimes NIR
PlanetScope & other satellite Imagery	Can be used to derive wetland map	Very high temporal resolution	Can be expensive, data processing

NC DEM QL-2 Lidar	statewide elevation can derive topography and other geomorphology variables	Decent resolution (2m)	Getting old (2020 QL- 1 is expected soon; 1m)
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To determine the final best approach for modeling, graduate research assistant Asami Minei built a series of pixel-based random forest classifiers to predict wetland presence (binary classification) and wetland types (multi-class classification) using both NWI and habitat GRP data for training and validation. She compared the accuracy of UAS-collected LiDAR to QL2 statewide LiDAR data at four of the total nine sites surveyed as part of this research project. Fourteen scenarios with various combinations of variables from two LiDAR datasets, multispectral, NWI, and habitat sample points were created for comparison (Table 10). For habitat models, only two patterns were tested because we realized that those two showed significant results in the process of constructing the NWI models. Settings for RF were tuned to increase the classification accuracy. Each resulting model was evaluated using overall accuracy, a standard deviation of accuracies, sensitivity, specificity, kappa coefficient, and map visualization. Additionally, a variable importance plot was produced to show each variable’s contribution to the random forest classification.

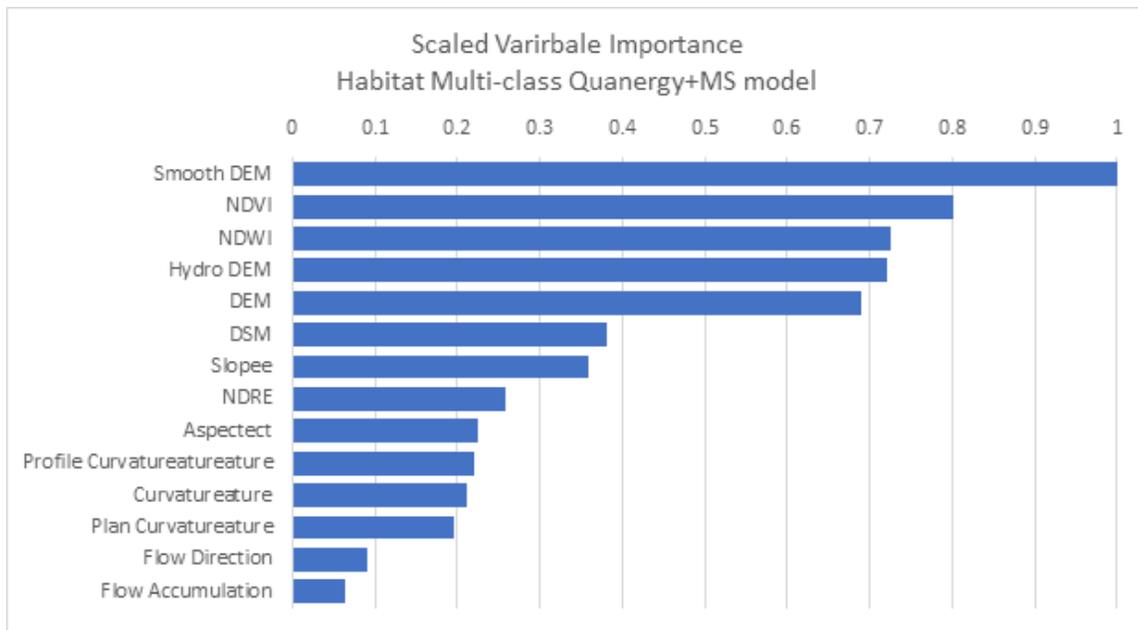
**Table 11.** Random Forest modeling scenarios using both NWI and field-collected habitat data for training and testing purposes. Multispectral includes NDVI, NDRE, and NDWI, and the LiDAR datasets (QL2 and Quanergy) include DEM, DSM, smoothed DEM, Hydro-condition DEM, aspect, slope, curvature, plan curvature, profile curvature, flow direction, and flow accumulation.

#	Response	Predictors
1	NWI Binary	Multispectral
2	NWI Binary	QL2 LiDAR
3	NWI Binary	Quanergy LiDAR
4	NWI Binary	QL2 LiDAR + Multispectral
5	NWI Binary	Quanergy LiDAR + Multispectral
6	NWI Class	Multispectral
7	NWI Class	QL2 LiDAR
8	NWI Class	Quanergy LiDAR
9	NWI Class	QL2 LiDAR + Multispectral
10	NWI Class	Quanergy LiDAR + Multispectral
11	Habitat Binary	QL2 LiDAR + Multispectral
12	Habitat Binary	Quanergy LiDAR + Multispectral
13	Habitat Class	QL2 LiDAR + Multispectral
14	Habitat Class	Quanergy LiDAR + Multispectral

Asami Minei’s Master’s thesis (which can be provided upon request in its entirety) evaluated the potential of UAS LiDAR data integrated with the various field-derived datasets to understand the

extent, location, and type of North Carolina Coastal Plain wetlands. Based on that work, we drew several conclusions that guided the final modeling for this report:

1. Based on the results of model performance scores across the 14 models tested at 4 of the sites (overall accuracies, kappa coefficients, and visual comparisons), the classification models derived from the hyperspatial Quanergy LiDAR data and multispectral datasets showed better performance than the statewide QL2 data. Models trained by field-collected habitat GRPs were more accurate than the models trained by NWI data. **Therefore, the models derived from Quanergy + MS data and habitat reference data performed the best in terms of visual comparison and statistical scores.** However, NWI data used for training can perform better than the habitat points when not enough habitat points were collected or when the landscape being mapped has not changed significantly for a few decades as was the case with Masonboro island. *As such, we used only the Quanergy LiDAR data collected by our team along with the UAS multispectral data trained by GRPs (habitat points) and NCDOT delineated wetlands (where available) for our final modeling in this report.*
2. We show that even with a small number of field-verified point data (GRPs), we can create an accurate wetland map through a random forest algorithm, however, more habitat points would improve the overall accuracies and class-specific sensitivities and specificities.
3. The resulting variable importance plots show that the **elevation variables and vegetation indices are the most important predictors of wetland presence overall (Figure 16).** *As such, given the patterns revealed by this modeling work, we decided against including flow direction and flow accumulation as variables in the final wetland classifications in this report.*



**Figure 16.** Variable importance plot shows the relative contribution to the habitat multi-class model made by the Quanergy and multispectral variables for the River Road site, New Hanover County.

For all sites and results presented in section Findings and Conclusions below, we used the raster and h2o packages in R to construct Random Forest models. R is an open-source programming language developed for statistic computing and graphic, and the h2o package is a machine learning platform developed specifically to tackle computational issues that are common with big datasets. This package was chosen as the machine learning platform because some of the raster stacks had ~5 million pixels within the study area, which caused computational difficulties with other random forest packages in R. A raster stack was imported into R and converted from a raster format to a data frame, which contained all variables as columns and each pixel sample as rows. The number of records (number of pixels within AOI) in the data frame varied based on raster pixel size and the number of reference data. For example, if habitat sample points contained only 58 points, the raster stack only has 58 pixels for training and testing. Two important parameters that are tuned in the model are: the number of decision trees to grow (ntree) and the number of variables randomly sampled as candidates at each tree node (mtry). Ntree was set to a default number of 500 and mtry was set to the same number as the number of the input predictors since there were only fourteen predictors total. We provide the final tuning parameters in Appendix A. The following parameters were included in the raster stacks for each site:

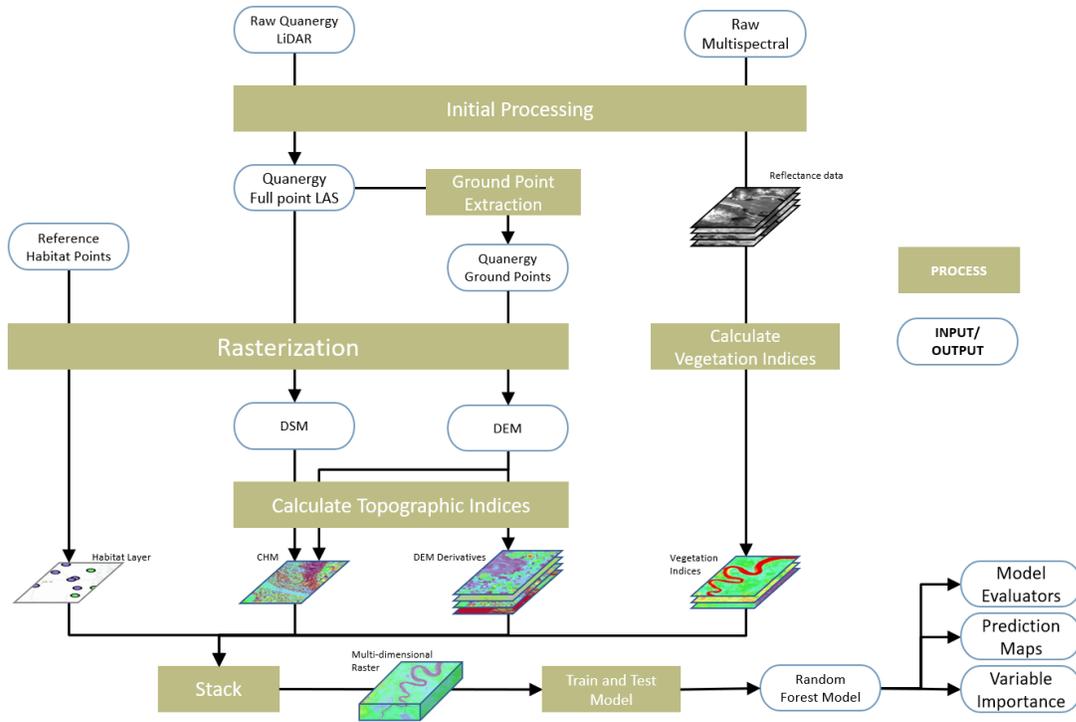
- A. **LiDAR data** (LAS data) is a point cloud of elevation data, was used to create topographic layers and a canopy height model (DSM-DEM).
  - 1) Digital Surface Model (DSM)
  - 2) Digital Elevation Model (DEM)
  - 3) Canopy Height Model (CHM)
  - 4) Smoothed DEM (sDEM)
  - 5) Hydro-condition DEM (hDEM)
  - 6) Aspect
  - 7) Slope
  - 8) Curvature
  - 9) Plan Curvature
  - 10) Profile Curvature
- B. **Multispectral imagery** (green, red, red-edge, and near-infrared) (TIF data) was used to create three vegetation indices.
  - 1) Normalized Difference Vegetation Index (NDVI)
  - 2) Normalized Difference Red Edge Index (NDRE)
  - 3) Normalized Difference Water Index (NDWI)

C. **Habitat point (GRP) data** collected in the field and using ancillary data analysis. In order to use the habitat sampled data as training for our final RF model, the following steps have been undertaken: data consolidation (such as classes UB – unconsolidated bottom - or US –unconsolidated shore – into one water class; conversion of the vector data into a raster dataset (snapped to and matching the resolution of the topographic layers); and finally, inclusion of this training layer based on the field habitat data into the final raster stack dataset containing the 14 layers detailed below using the *composite bands* tool in ArcGIS Pro (Table 11).

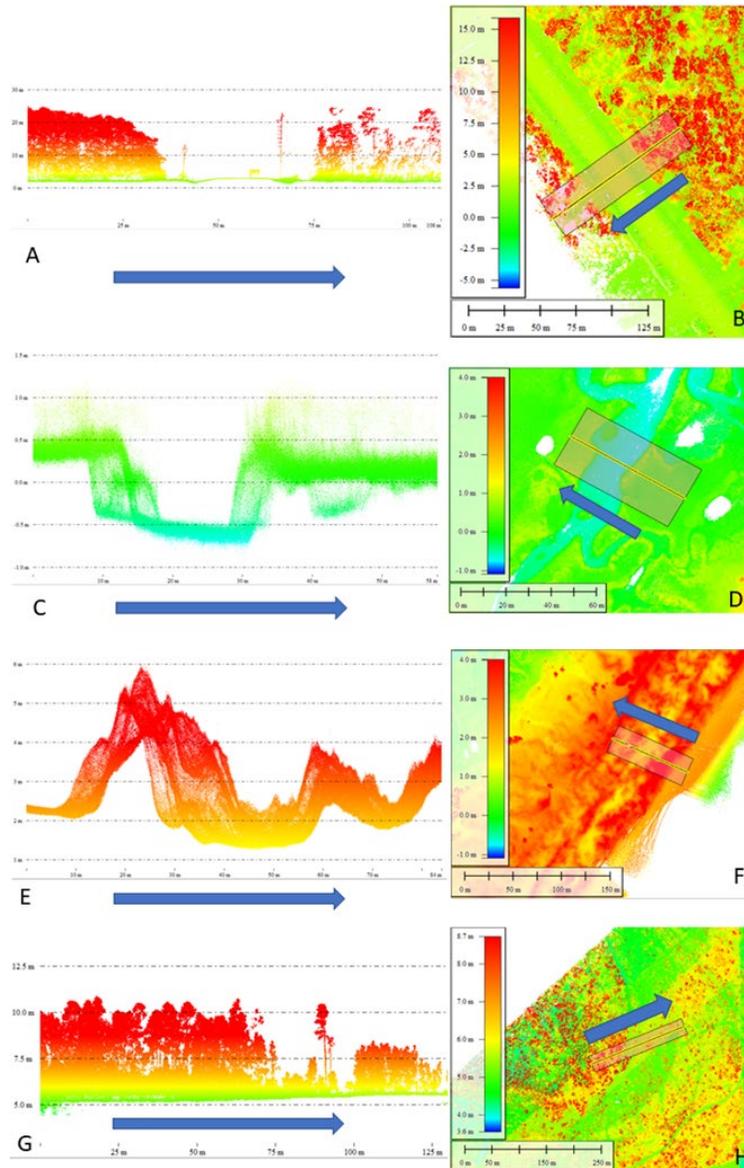
**Table 12.** Final 14 layers included in each raster stack to be imported into R that was used for all final models for all sites with the respective variable names.

1	HABITAT
2	DEM
3	sDEM
4	hDEM
5	DSM
6	CHM
7	Aspect
8	Slope
9	Curvature
10	PlanCurv
11	ProfileCurv
12	NDVI
13	NDRE
14	NDWI

Figure 17 shows the wetland classification workflow beginning with the raw Quanergy and multispectral data and ending with the model evaluation metrics, prediction maps and variable importance plots presented in the next section below. From the overall point clouds, we derived cross-sectional views for all four sites and show the across-site variability and ability of the data to capture both vertical vegetation structure in the tree-dominated sites as well as the underlying topography of swales and ridges of the more estuarine sites dominated by grasses (Figure 18). Unlike prior modeling efforts of coastal wetlands, we created a canopy height model (CHM) to account for wetland vegetation height given the large gradient in vegetation structure existing in our region (Figure 18).



**Figure 17.** Wetland classification workflow based on the Quanergy LiDAR data, multispectral reflectance data and reference habitat points applied to all sites surveyed for this project.



**Figure 18.** Example cross-sections of vertical vegetation structure of wetlands located along a palustrine to estuarine gradient. A-B: Surf City, C-D: Masonboro Low Tide (LT) at back barrier marsh, E-F: Masonboro LT at dunes, G-H: Topsail High School showing the gradient in vegetation structure that could be resolved from our UAS LiDAR data.

After ensuring all the data is snapped properly and within the AOI of each collection site, we used the RStudio (<https://www.rstudio.com/>) programming platform (step-by-step instructions, as well as the code utilized are provided in Appendix A of this final report). Once all the raster stacks were prepared, the K-fold cross-validation (CV) method was used for the random forest algorithm in this study (Figure 19). CV is a widely used resampling method because it assesses the general performance and stability of predictive models and prevents overfitting (Berrar, 2019). In this study, Random Forest classification was conducted using a 5-fold CV. First, the

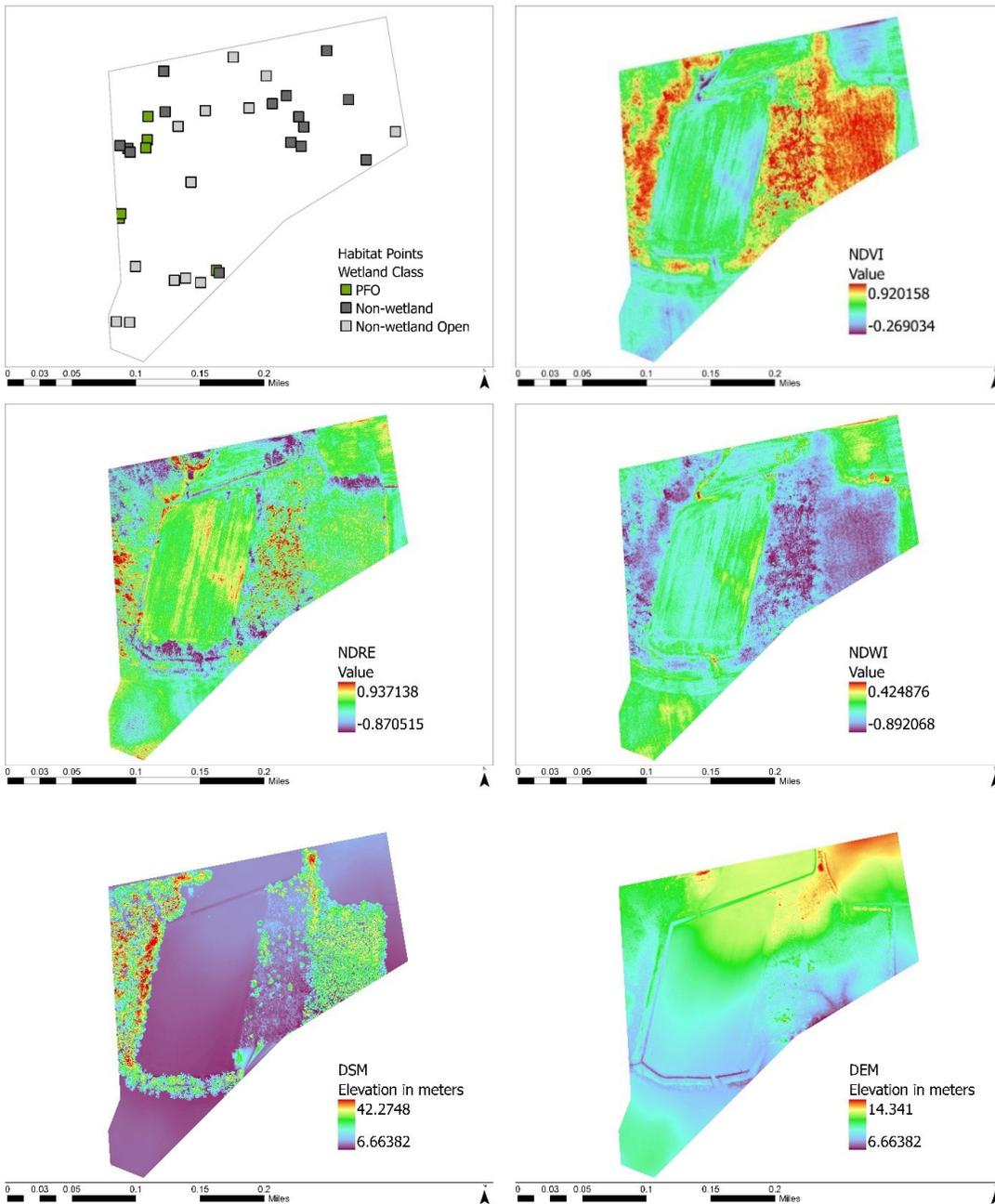
dataset (including training and testing datasets) was randomly shuffled and divided into five folds. For the first run, we removed fold 1 and used the remaining four parts to train a RF model. Then, fold 1 was used to calculate the classification accuracy. This process was repeated four more times with different training and testing set each time. The 5-fold CV method produces five RF models with five classification accuracies, so the average of five accuracies (overall accuracy) and the standard deviation of the five accuracies was calculated as performance metrics. Post-processing consisted of generating performance metrics and prediction maps. There were five model performance metrics that were calculated: averaged overall accuracy, the standard deviation of accuracies, kappa coefficient, sensitivity, and specificity (Table 12; Table 13). Since the overall accuracy was computed by averaging five model accuracies from the 5-fold CV resampling method, the standard deviation of accuracies was calculated to evaluate the model consistency. Additionally, kappa coefficients, sensitivity (true positive rate), and specificity (true negative rate) were calculated from a confusion matrix table. The resulting Random Forest prediction model was made in a raster format and visualized using ArcGIS Pro.

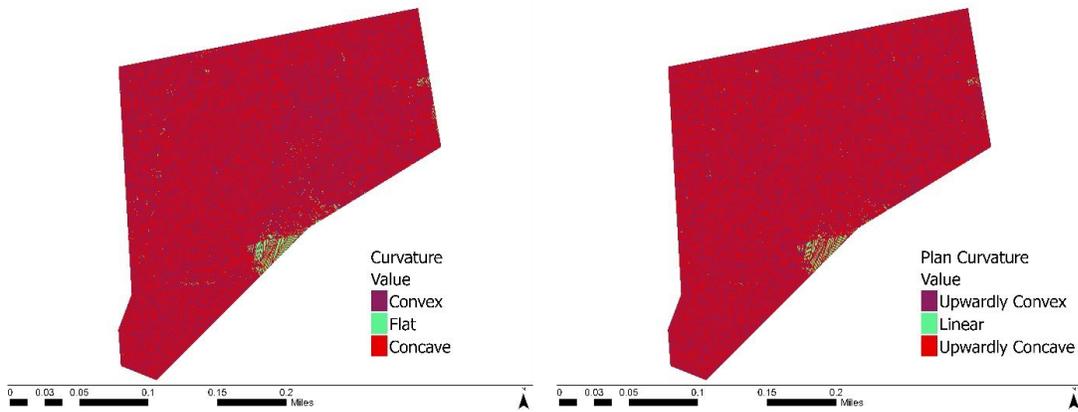
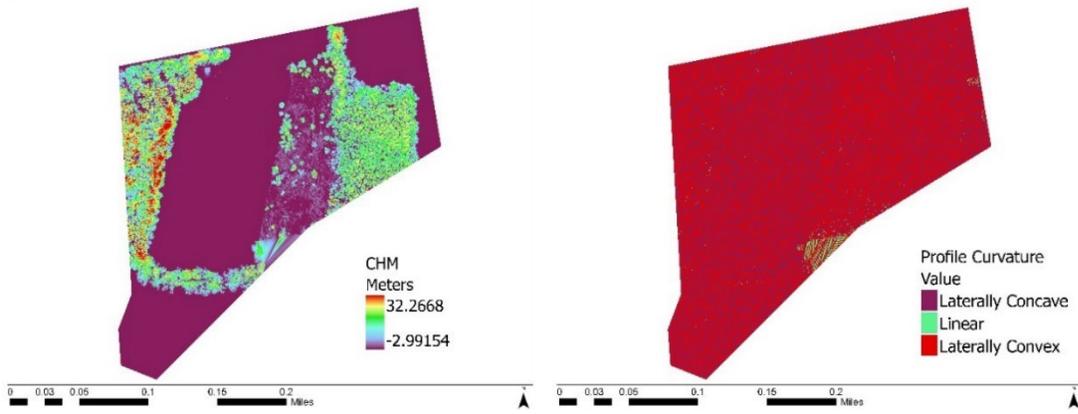
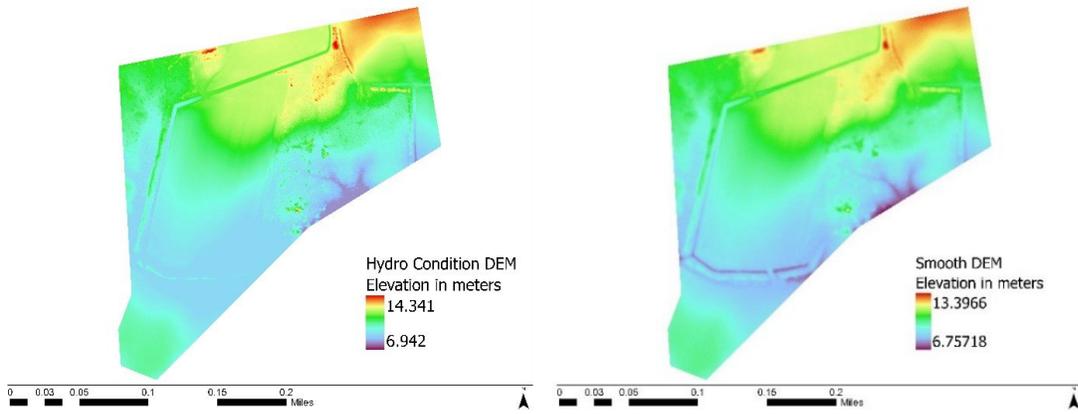
**Table 13.** Description of performance metrics for the random forest modeling used for this study.

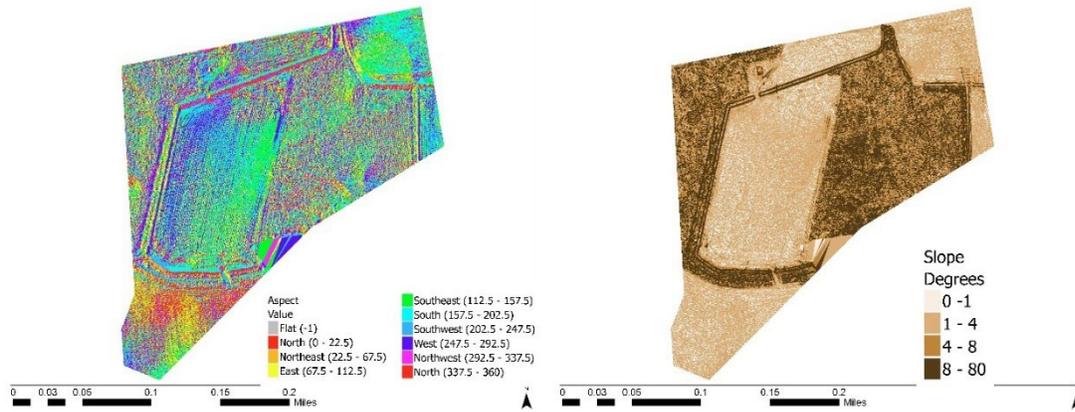
<b>Performance metrics</b>	<b>Description</b>
<b>Averaged Overall Accuracy (AO)</b>	The overall accuracy of each 5-fold cross-validation is calculated by summing the number of correctly classified values and dividing by the total number of values.
<b>Standard Deviation of Accuracies (StD)</b>	The StD of five accuracies is a measure of how dispersed the data is in relation to the mean. Large StD means the data are spread (models are unreliable) and vice versa.
<b>Kappa Coefficient (k)</b>	This index is for assessing agreement between the model and the reference data. It ranges from -1 to 1.
<b>Sensitivity</b>	Sensitivity, true positive rate, measures how often a model correctly generates a positive result for areas that are wetlands (for wetland binary classification).
<b>Specificity</b>	Specificity true negative rate is the proportion of areas that are not wetlands out of all areas (for wetland binary classification).

**Table 14.** Explanation of the Kappa Coefficient values and level of agreement as reported in the next section below.

Value of k	Level of Agreement
-1.0 — 0.0	No agreement
0.01 — 0.20	None to slight
0.21 — 0.40	Fair
0.41 — 0.60	Moderate
0.61 — 0.80	Substantial







**Figure 19.** Example derived input layers that went into each respective raster stack, shown here for the Carolina Bays site.

### **Task 5: Training & Final Deliverables**

The final task of your project was completed in person on the UNCW campus on Nov 16 and 17<sup>th</sup> 2021 and all training materials were handed over to participating DOT personnel. The final version of the training manual has been updated last on January 24<sup>th</sup> 2022 and is included as an appendix (Appendix B) to the final report.

## Findings and Conclusions

### Model performance

We anticipated that the DEM, topographic indices and vertical vegetation structure metrics derived from the UAS-borne LiDAR would substantially improve models of wetlands predictions and delineation in Coastal Plain environments that cover a gradient of wetland types and our results below overall show exactly that. We report the model performance, final classification maps relative to the habitat GRPs and NCDOT-delineated wetlands (where available) and variable importance plots for each site surveyed during the duration of RP2020-04 in the section below, site by site. Overall, we quantitatively compare the model performance metrics (overall accuracies, standard deviation of overall accuracies, kappa coefficients, sensitivities, and specificities) and the model prediction maps that were made by the hyperspatial UAS LiDAR (Quanergy M8) against habitat sample data.

**Overall, the wetland classification models derived from the Quanergy and multispectral data performed the best based on visual comparisons and the performance metrics.**

Standard deviations of overall accuracies provide a measurement of model stability to the overall accuracies. In line with previous research, we detected small improvements in model accuracies when multispectral variables were added to the LiDAR variables, which was the same results by (Rapinel et al., 2015). Although the addition of multispectral variables did not increase the overall accuracies significantly, multispectral data helped stabilize the models.

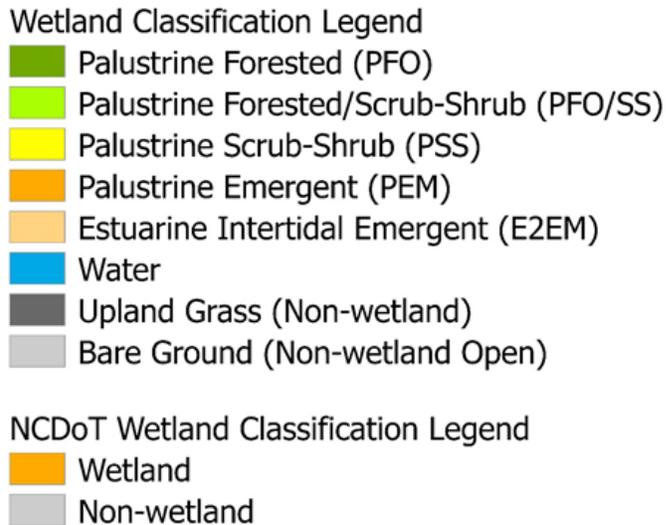
**The class-specific sensitivities and specificities for each site were improved by using habitat points.** However, some of the classes of the habitat models still produced low sensitivities. We hypothesize that the low sensitivities were caused by a small area for the training and testing areas. For example, the area of palustrine scrub/shrub and water were only 0.58% and 1.18% respectively out of the whole study sites. This indicated that it is more difficult to classify small areas than classify larger areas. The details and the quality of the final prediction maps generated depend on the spatial resolution of datasets, response variables, and respective predictors. When compared to the most recent NWI data (see all figures below), the results of our prediction maps showed much more distinct and resolved wetland class patterns because of the very fine spatial resolution of the UAS data utilized.

### Variable Importance

The second research objective for the modeling component of this project was to determine the most important variables (and minimum number of predictor variables) that help classify the Coastal Plain wetlands and that capture the characteristics of the various study areas we surveyed. Variable importance plots show the ranking of variable importance based on the mean decrease accuracy of the models and were created for each model. **Elevation variables (DSM, DEM, smooth DEM, and hydro-condition DEM), canopy height models and vegetation indices (NDVI, NDRE, and NDWI) were always ranked within the top five.** Hydrological variables such as flow direction and flow accumulation were the opposite, resulting in the least

important variables, hence we excluded them from these final model runs. Since the characteristics of the Coastal Plain area are flat areas with aquatic vegetation, those results match the characteristics of this area. The results also showed that the addition of multispectral data largely contributed to the models by vegetation indices being ranked as one of the top variables.

Presented below are classification maps, variable importance plots, and sensitivity/specificity graphs for each site (Figures 20 through 38).

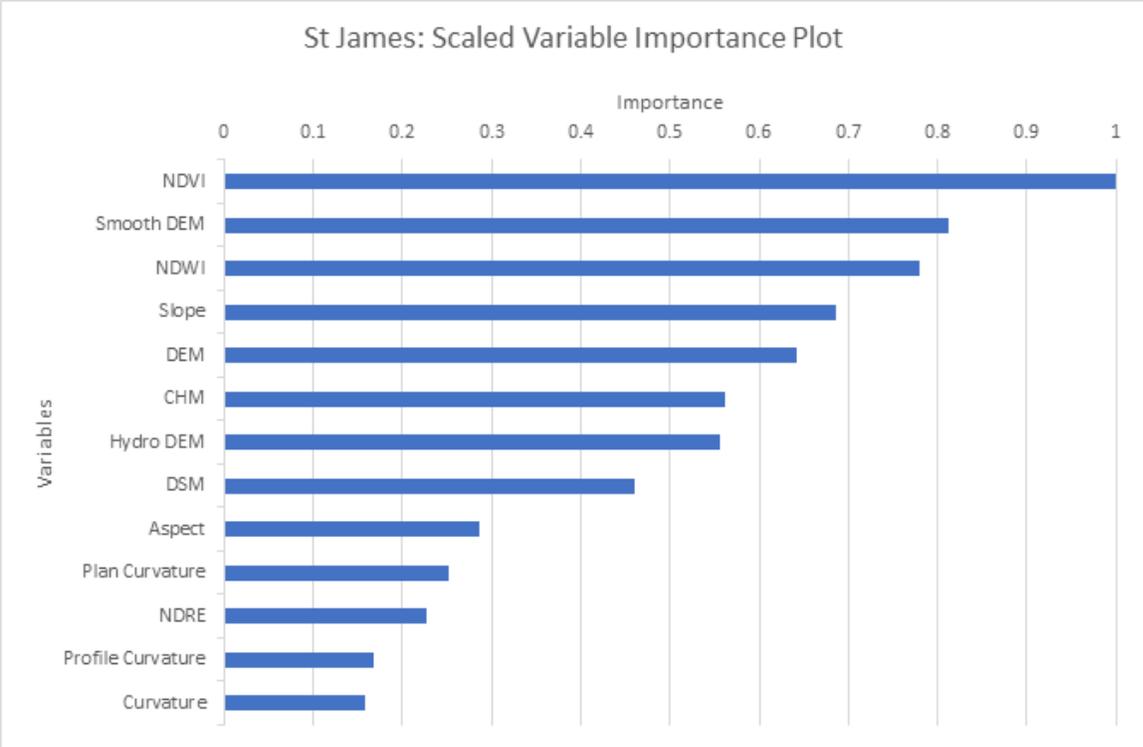


**Figure 20.** The wetland classification breakdown utilized in the final classification maps below.

St James Plantation, Brunswick County, NC (date surveyed May 12<sup>th</sup> 2020)

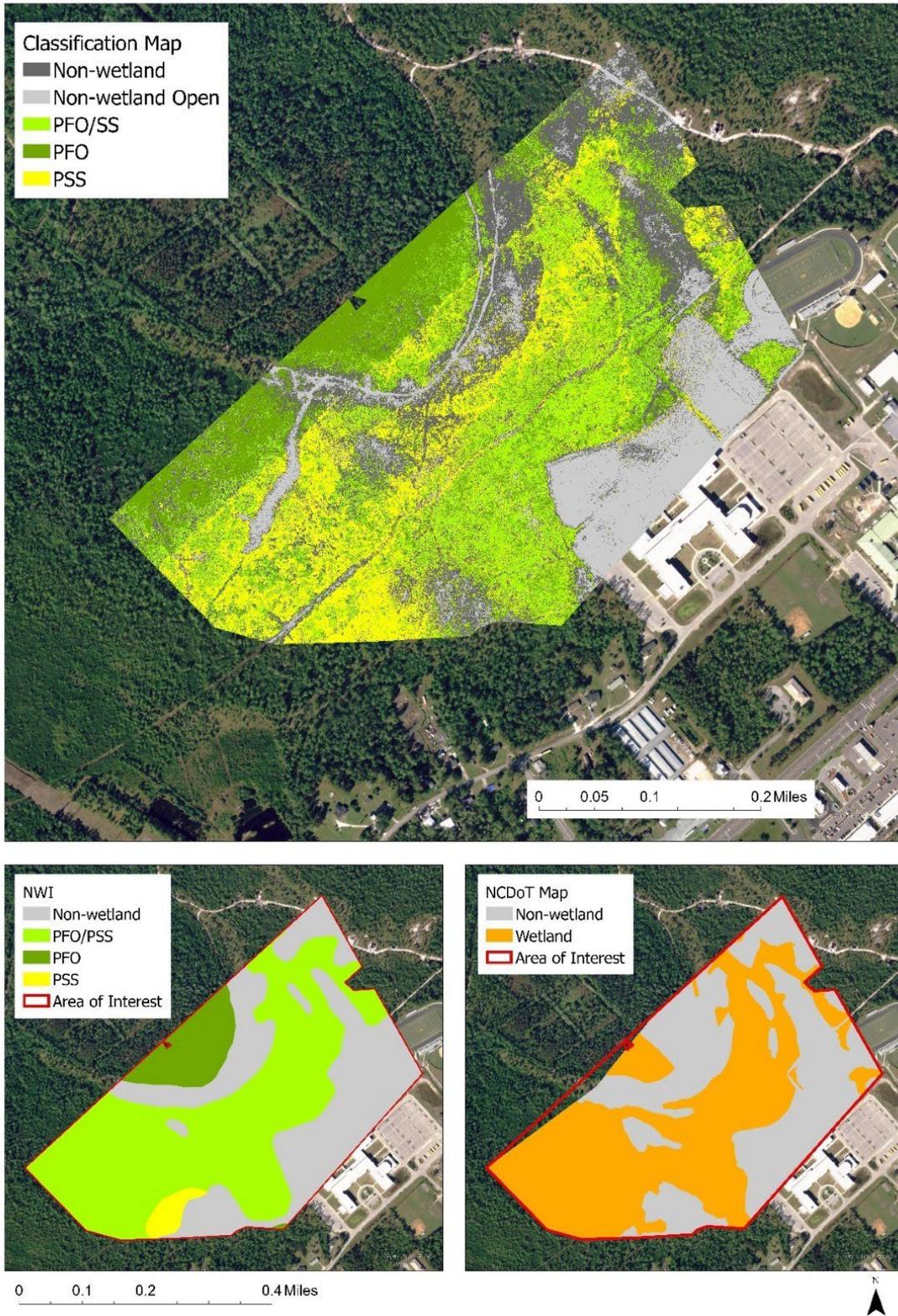


**Figure 21.** Random forest wetland classification map at St James study site.

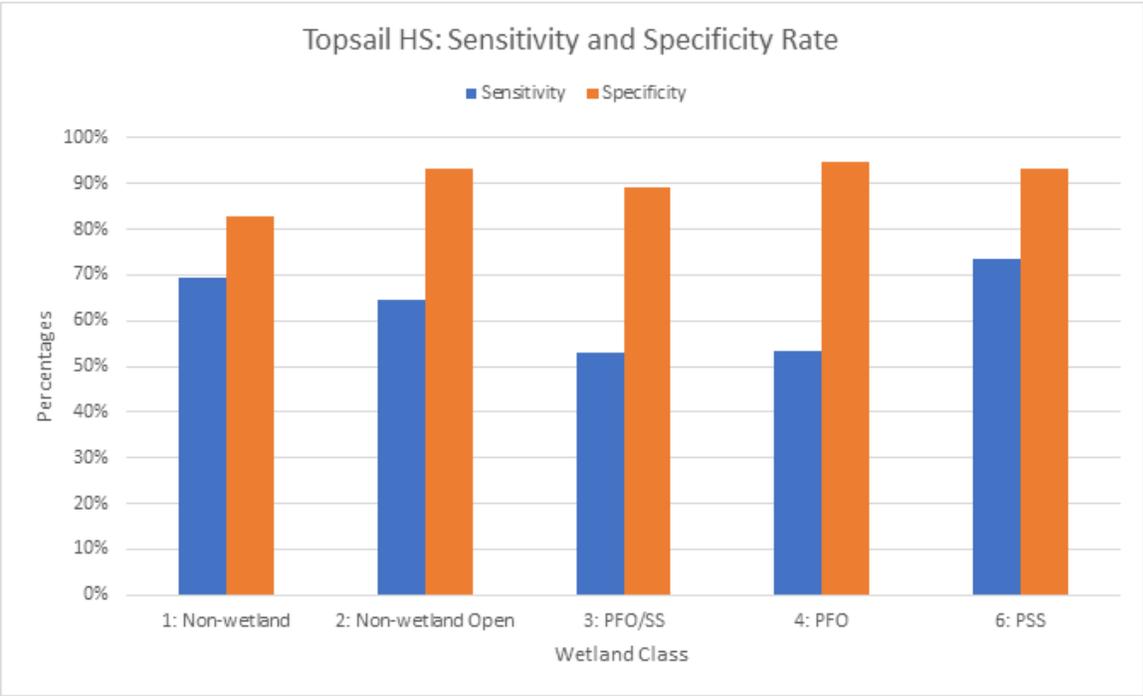
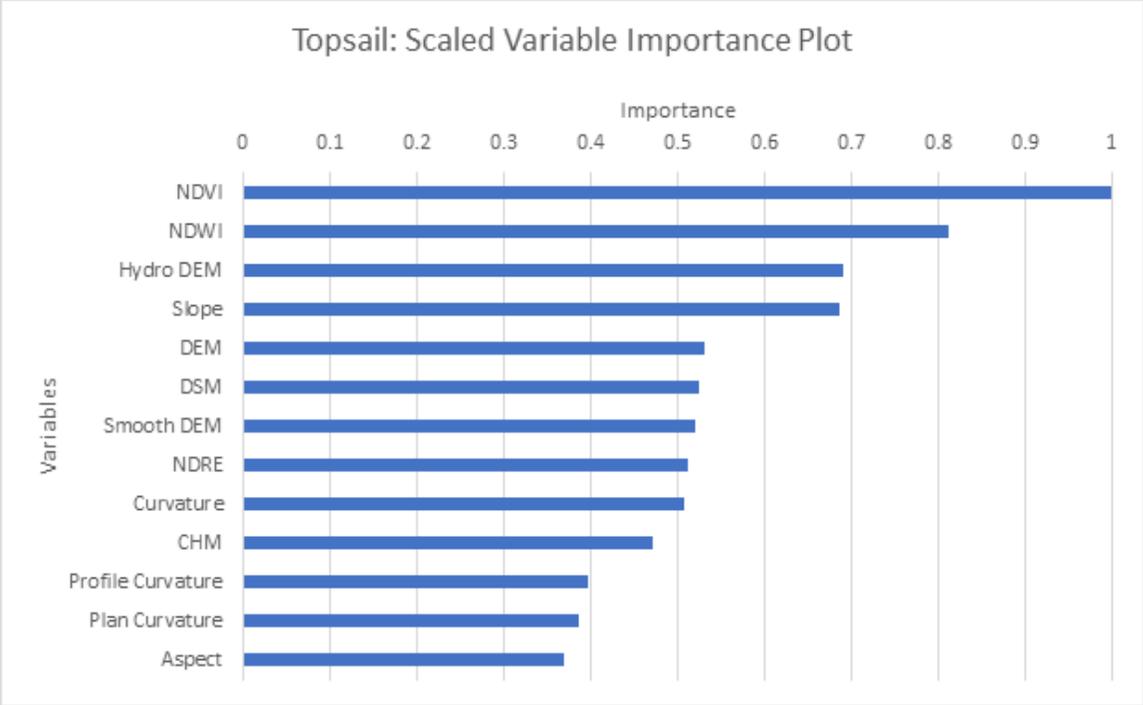


**Figure 22.** The top chart shows the variable importance plot generated for St James, while the bottom chart shows the model sensitivity and specificity for each class.

Topsail High School, Pender County, NC (date surveyed June 2<sup>nd</sup> 2020)



**Figure 23.** Random Forest wetland classification map at Topsail High School study site.



**Figure 24.** The top chart shows the variable importance plot generated for this site, while the bottom chart shows the model sensitivity and specificity for each of the classes represented at this site.

Castle Bay, Pender County, NC (date surveyed June 29<sup>th</sup> 2020)

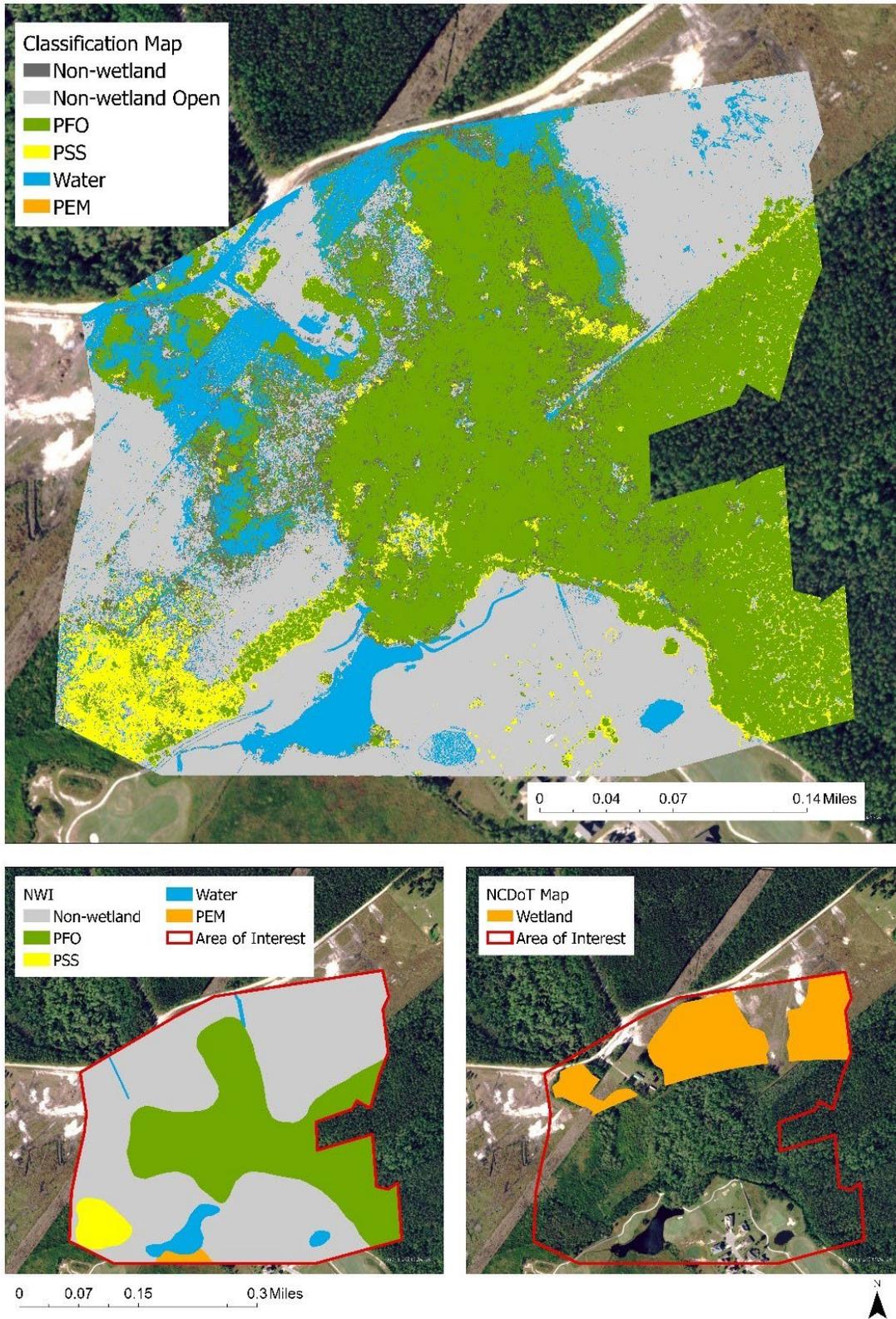
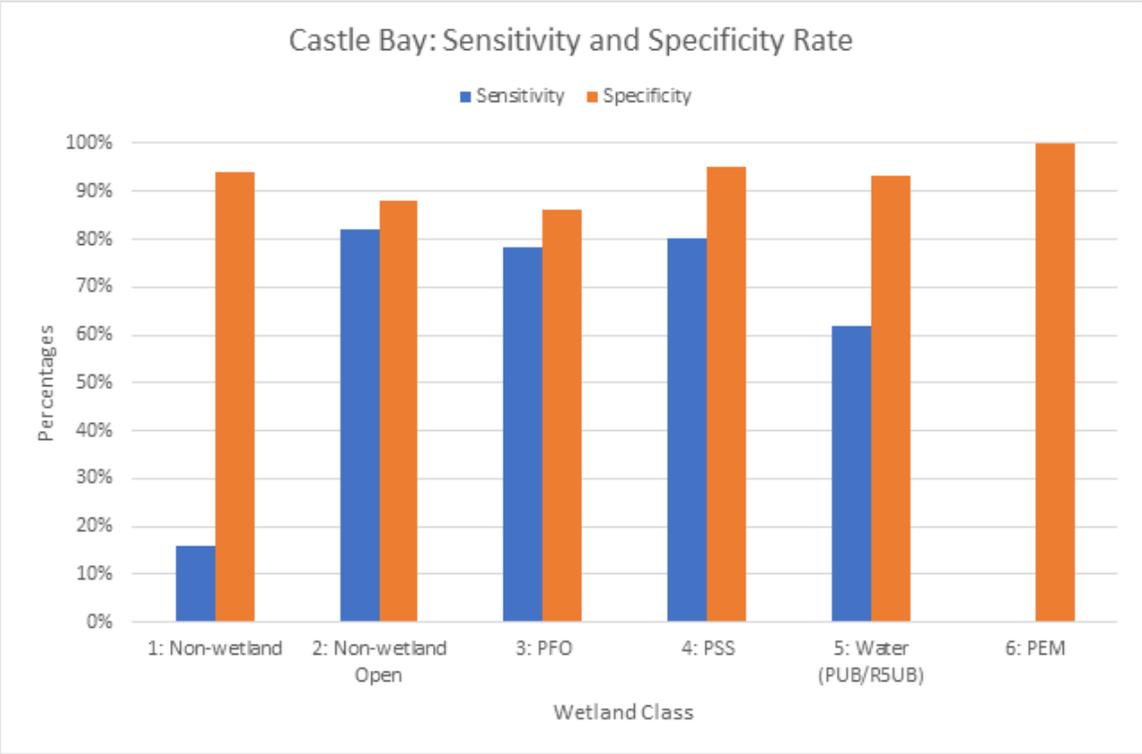
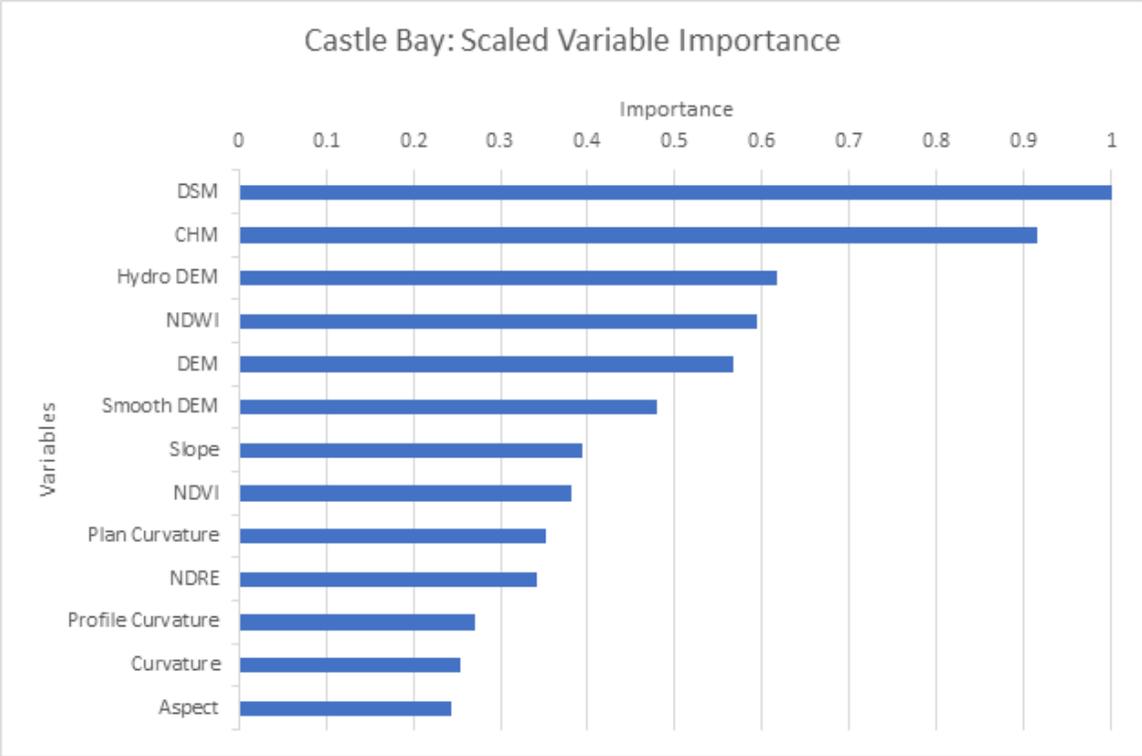
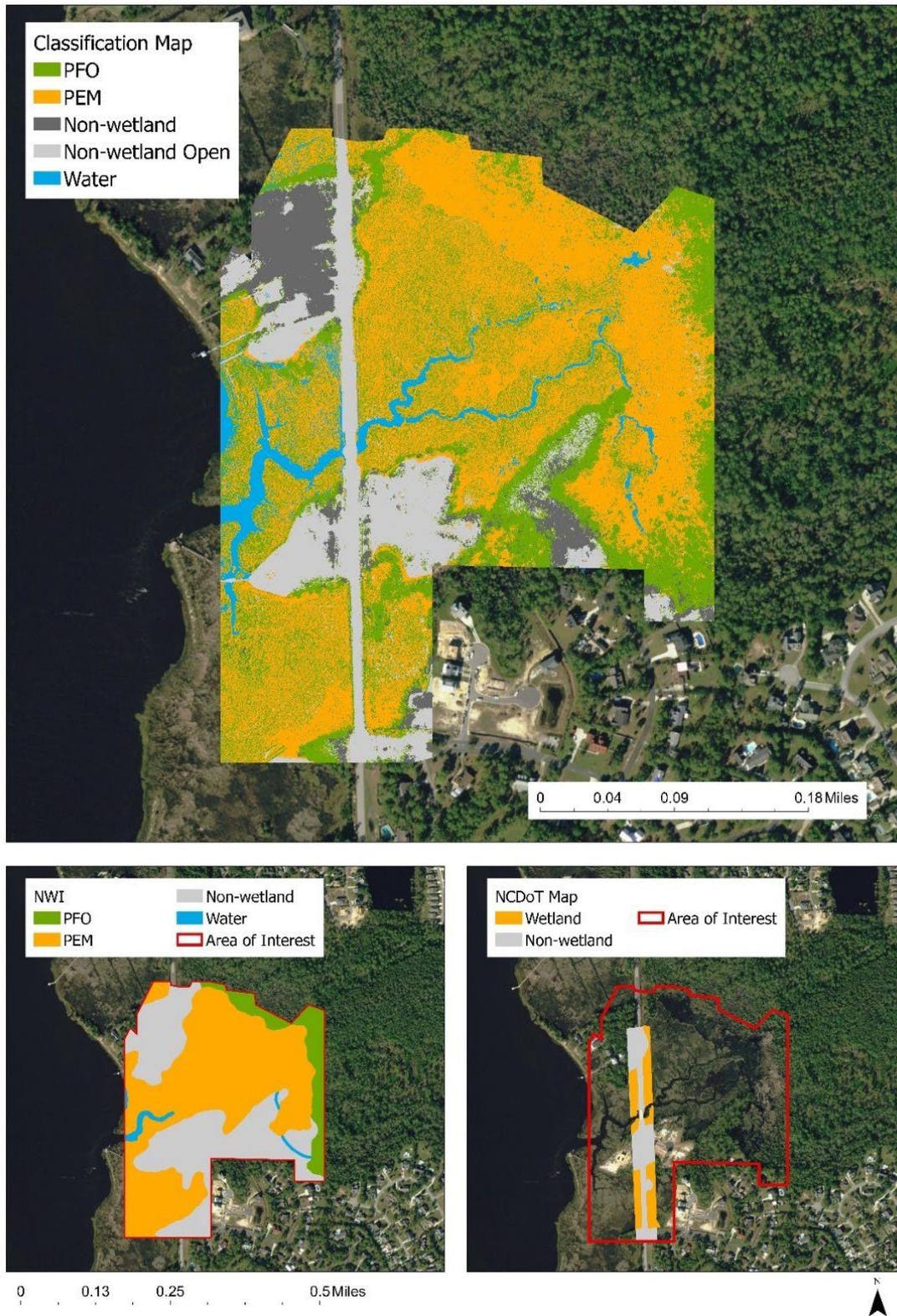


Figure 25. Random Forest wetland classification map at Castle Bay study site.

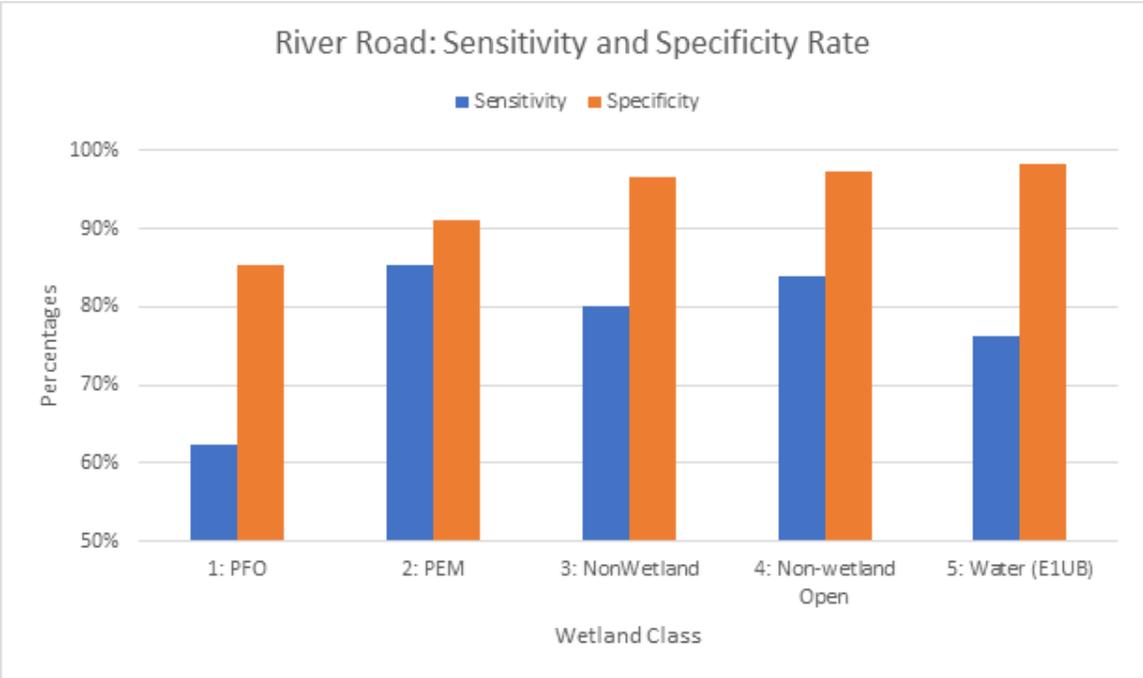
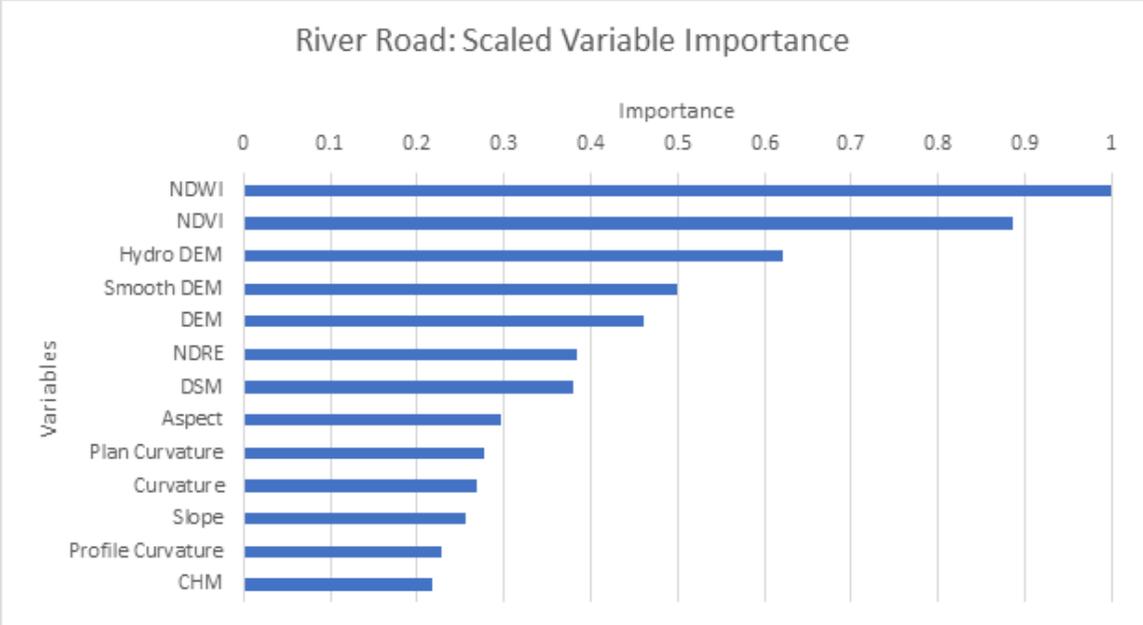


**Figure 26.** The top chart shows the variable importance plot generated for this site, while the bottom chart shows the model sensitivity and specificity for each of the classes represented at this site.

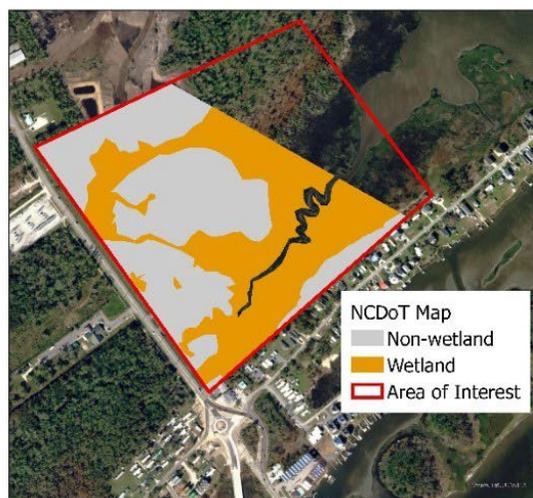
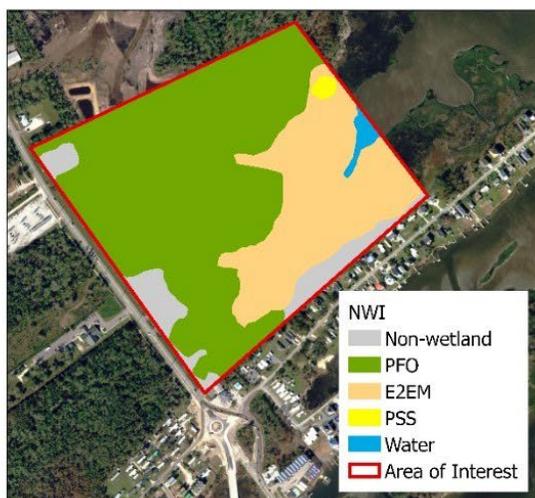
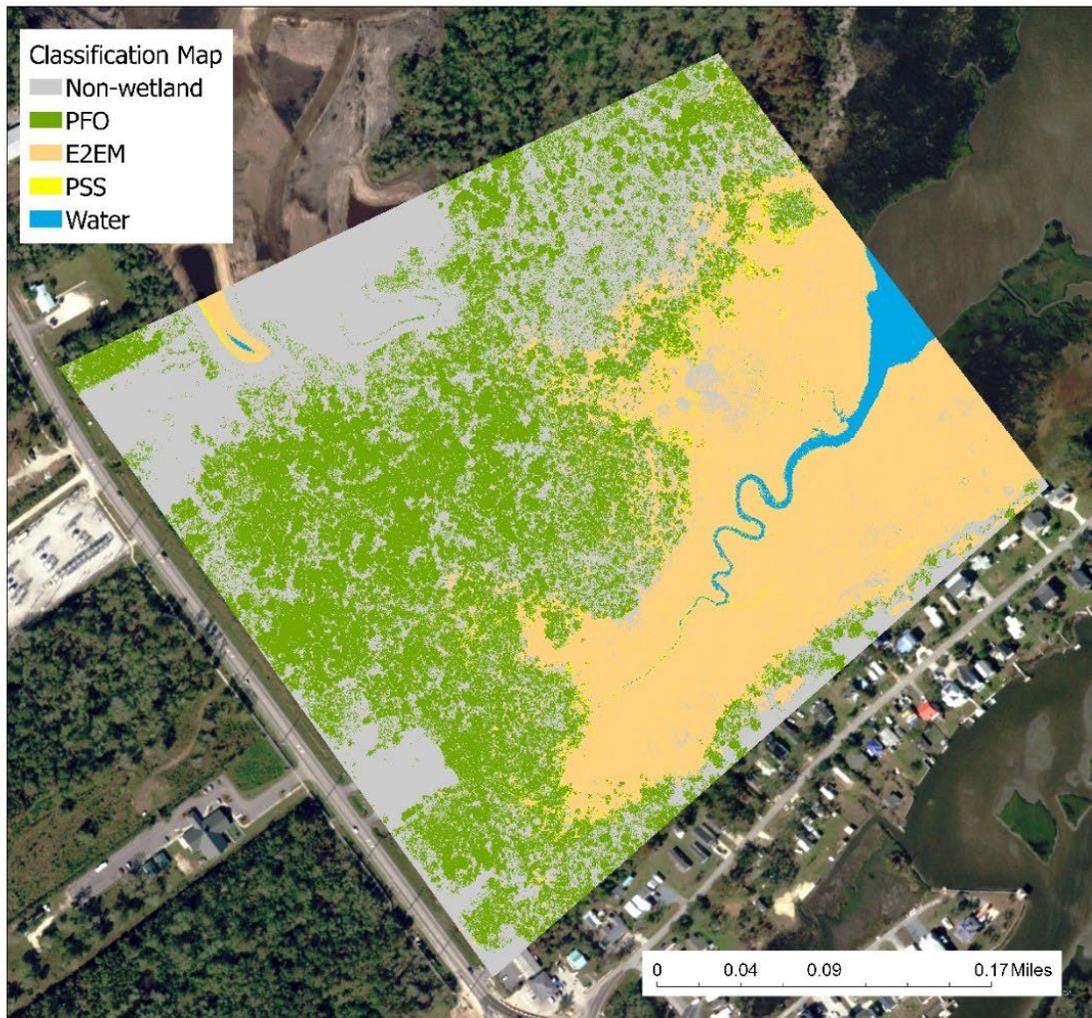
River Road, New Hanover County, NC (date surveyed October 3<sup>rd</sup> 2020)



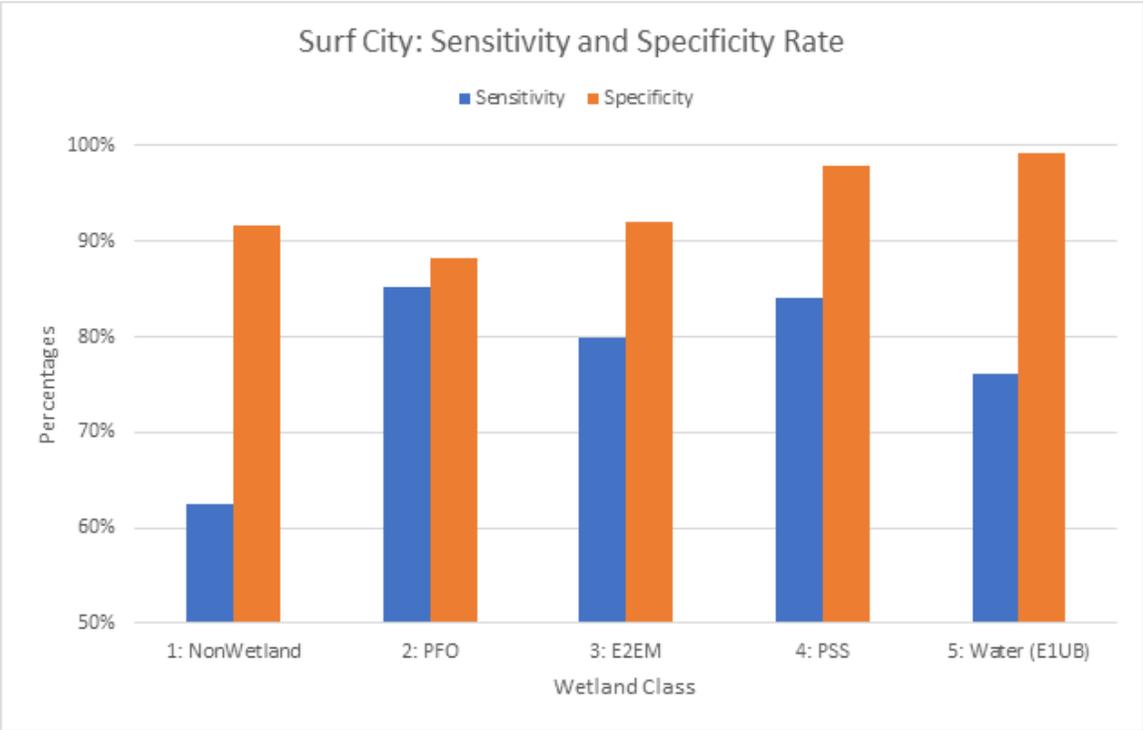
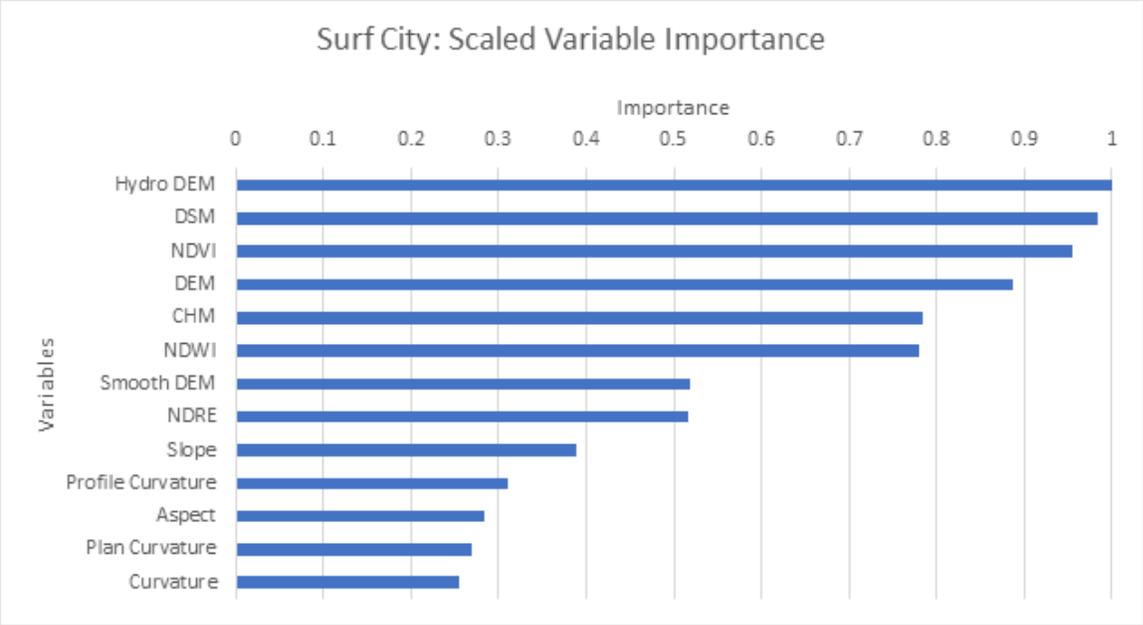
**Figure 27.** Random Forest wetland classification map at River Road study site.



**Figure 28.** The top chart shows the variable importance plot generated for this site, while the bottom chart shows the model sensitivity and specificity for each of the classes represented at this site.



**Figure 29.** Random Forest wetland classification map at Surf City study site.

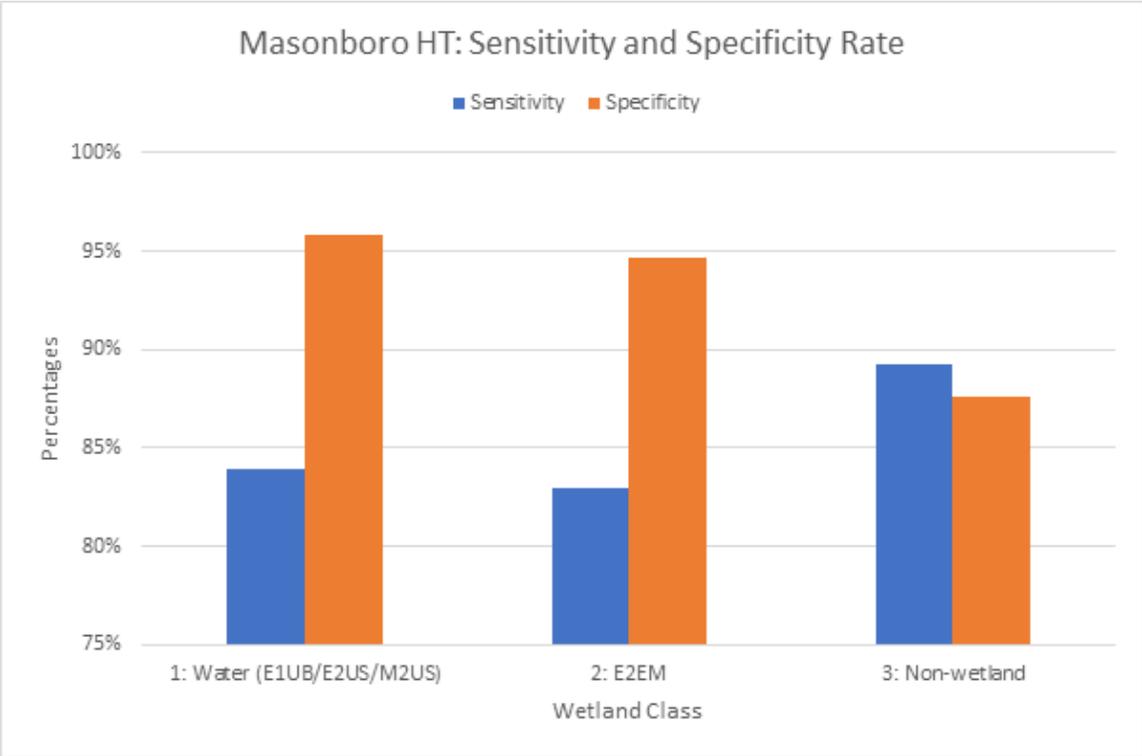
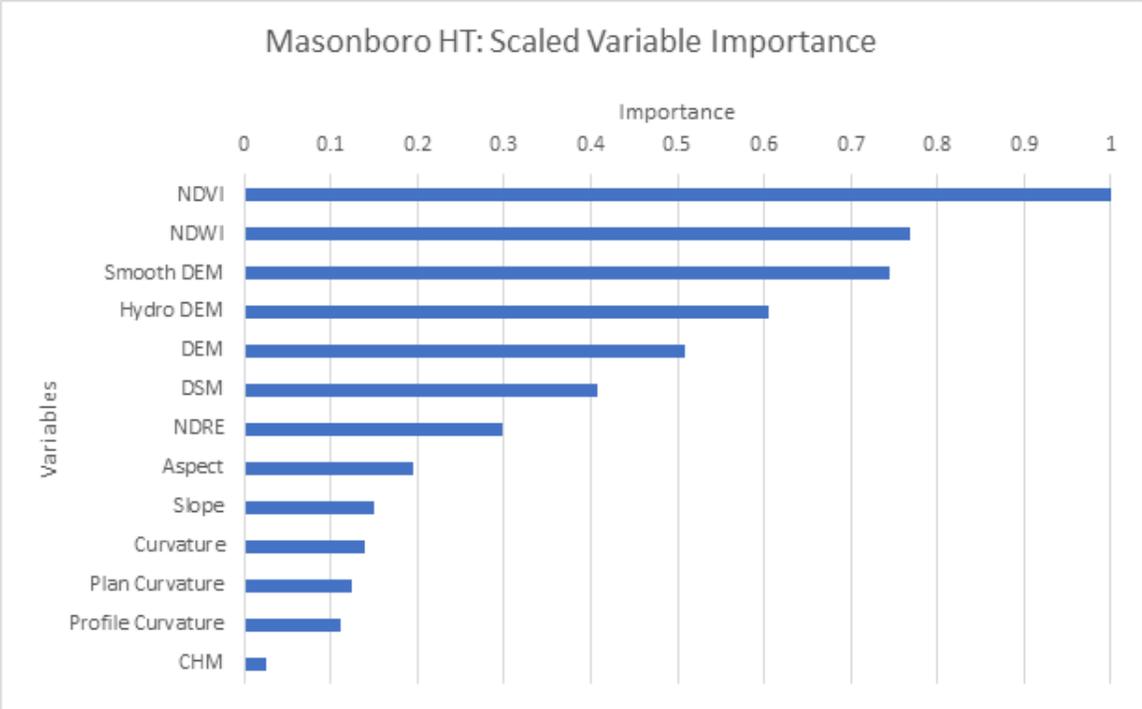


**Figure 30.** The top chart shows the variable importance plot generated for this site, while the bottom chart shows the model sensitivity and specificity for each of the classes represented at this site.

Masonboro High-Tide Survey, New Hanover County, NC (date surveyed December 7<sup>th</sup> 2020)



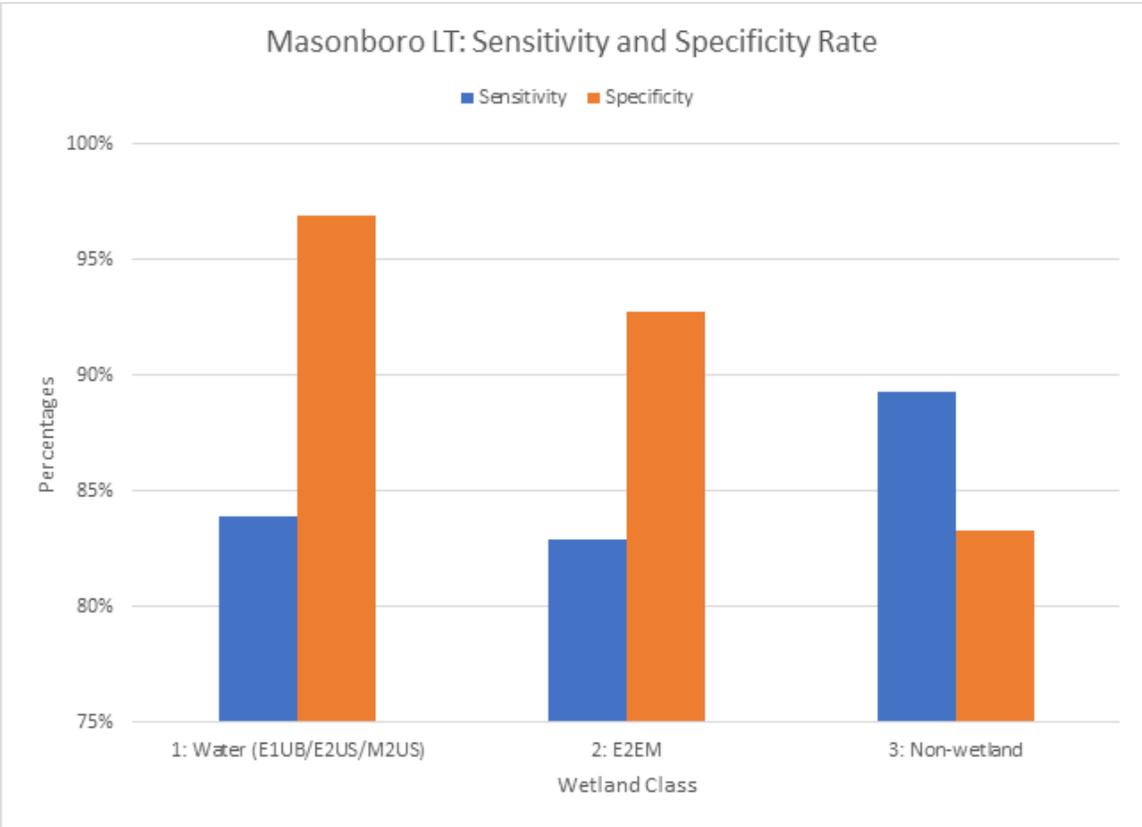
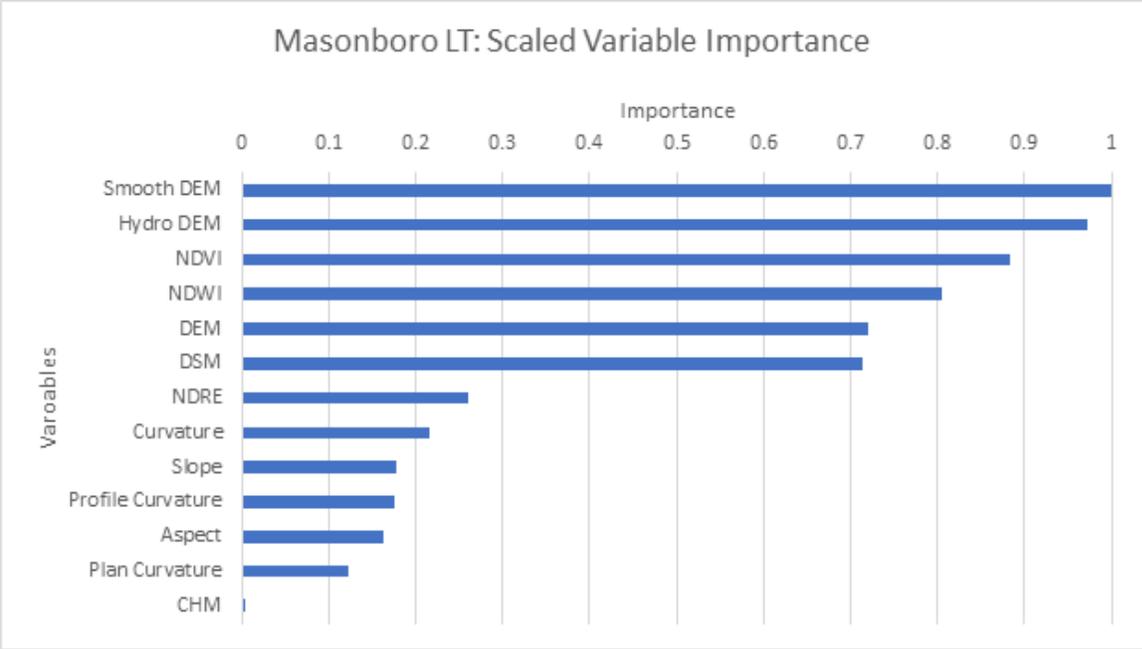
**Figure 31.** Random Forest wetland classification map at Masonboro study site (high tide).



**Figure 32.** The top chart shows the variable importance plot generated for this site, while the bottom chart shows the model sensitivity and specificity for each of the classes represented at this site.



**Figure 33.** Random Forest wetland classification map at Masonboro study site (low tide).



**Figure 34.** The top chart shows the variable importance plot generated for this site, while the bottom chart shows the model sensitivity and specificity for each of the classes represented at this site.

Maysville Elementary, Jones County, NC (date surveyed January 22<sup>nd</sup> 2021)

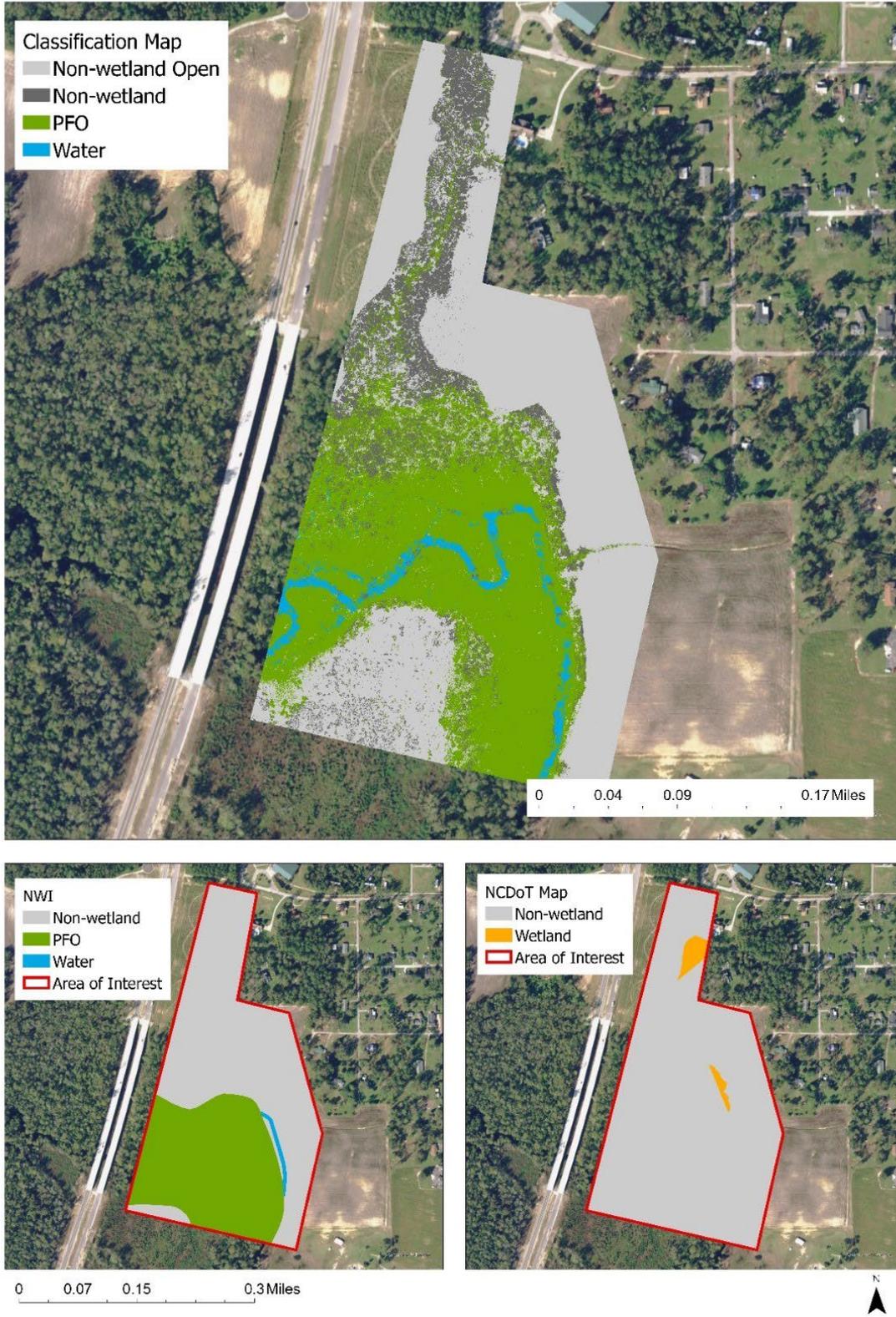
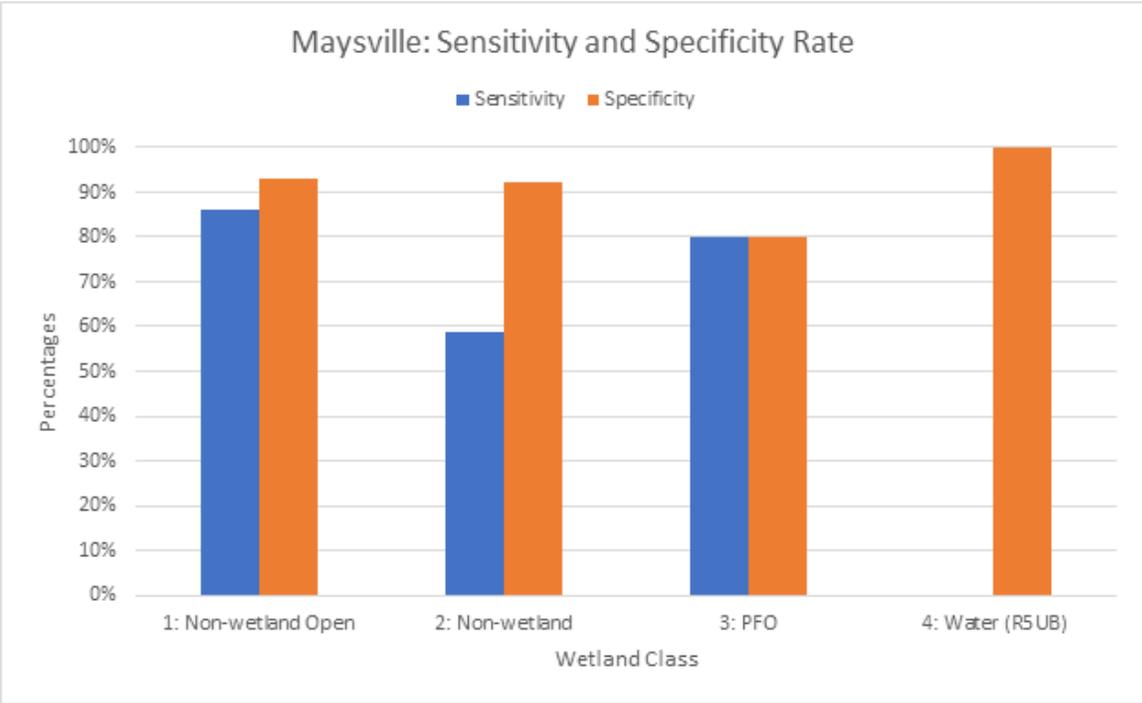
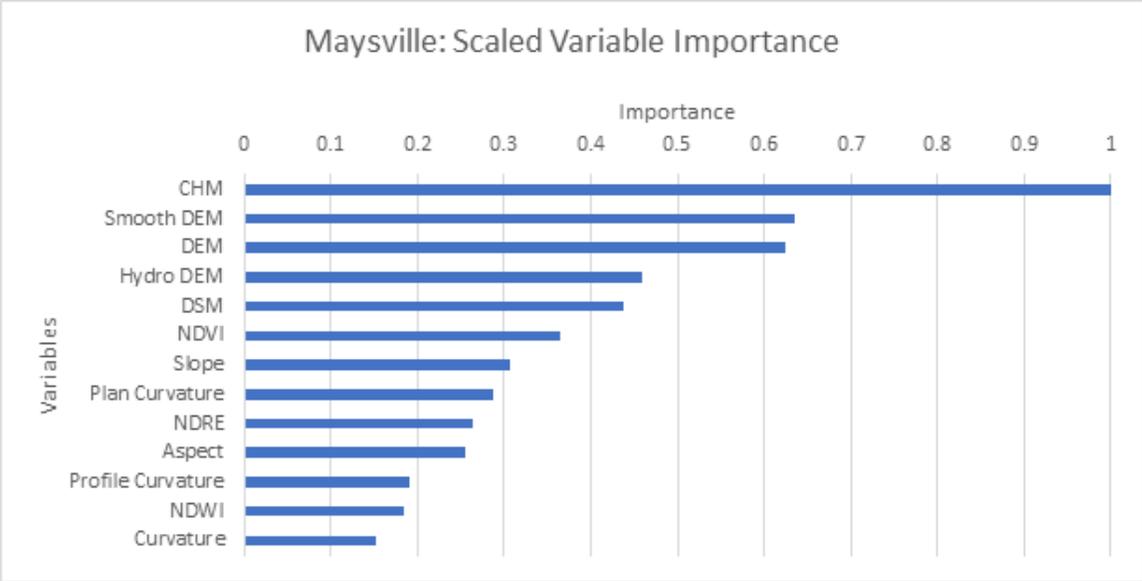


Figure 35. Random Forest wetland classification map at Maysville study site.



**Figure 36.** The top chart shows the variable importance plot generated for this site, while the bottom chart shows the model sensitivity and specificity for each of the classes represented at this site.

Carolina Bays parkway, Brunswick County, NC (date surveyed February 23<sup>rd</sup> 2021)

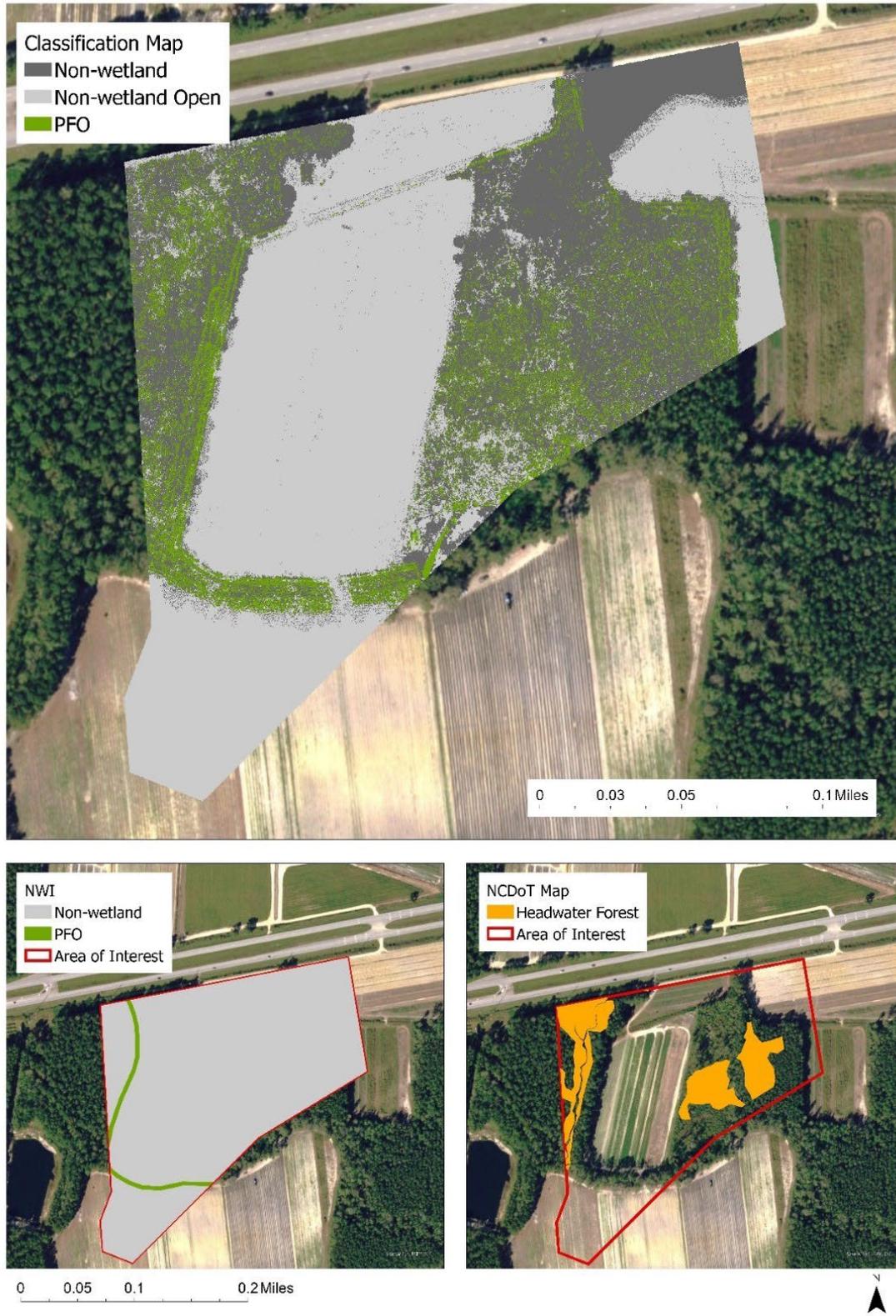
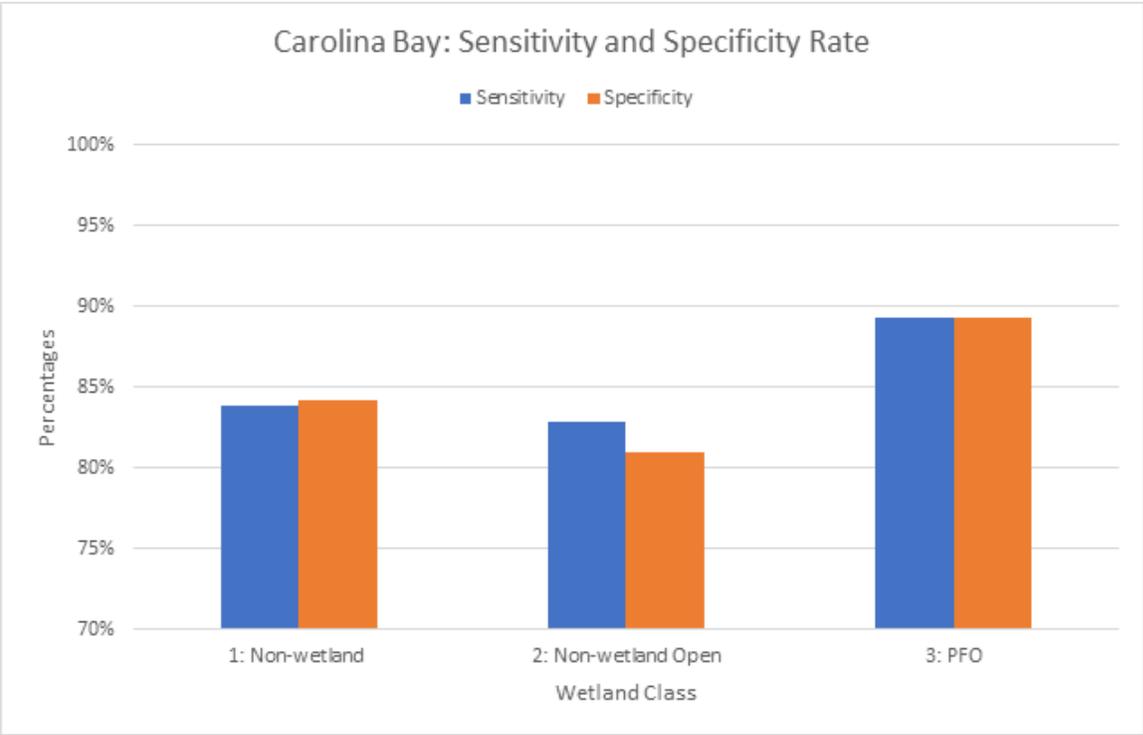
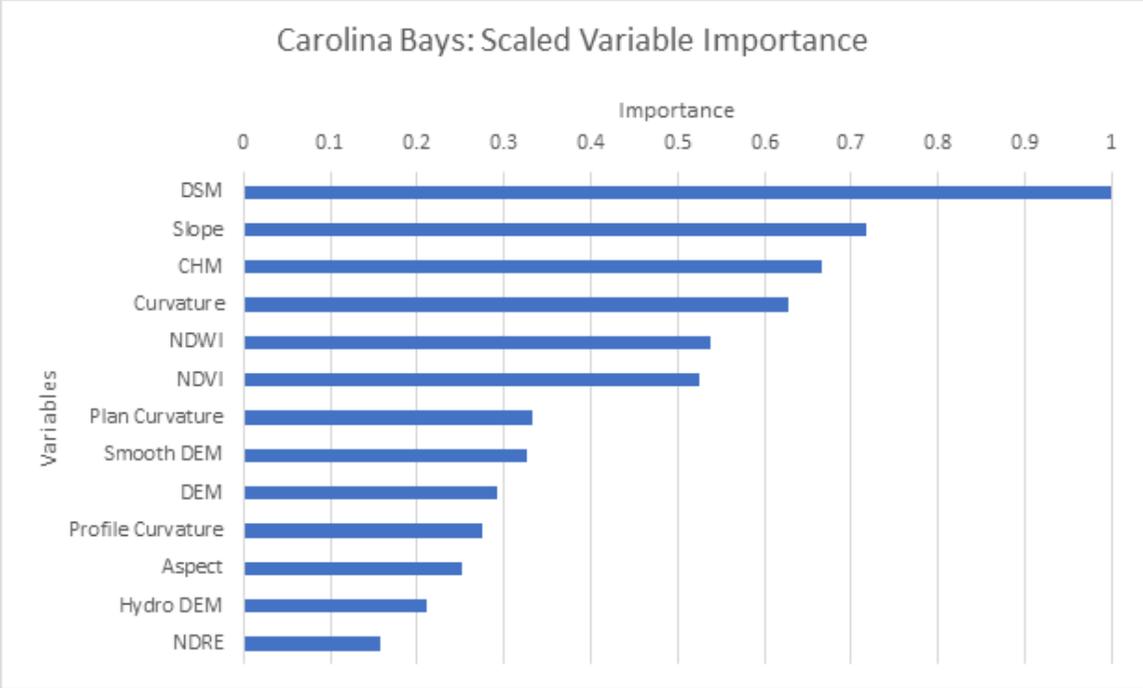


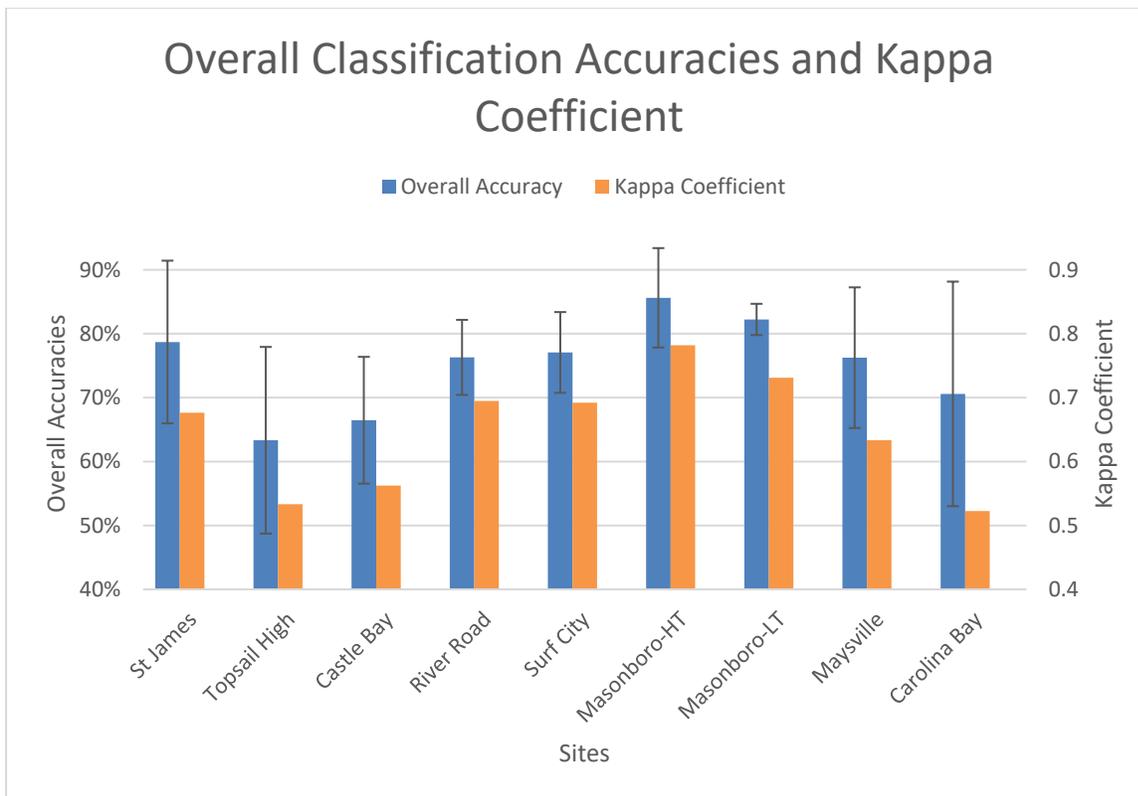
Figure 37. Random Forest wetland classification map at Carolina Bays study site.



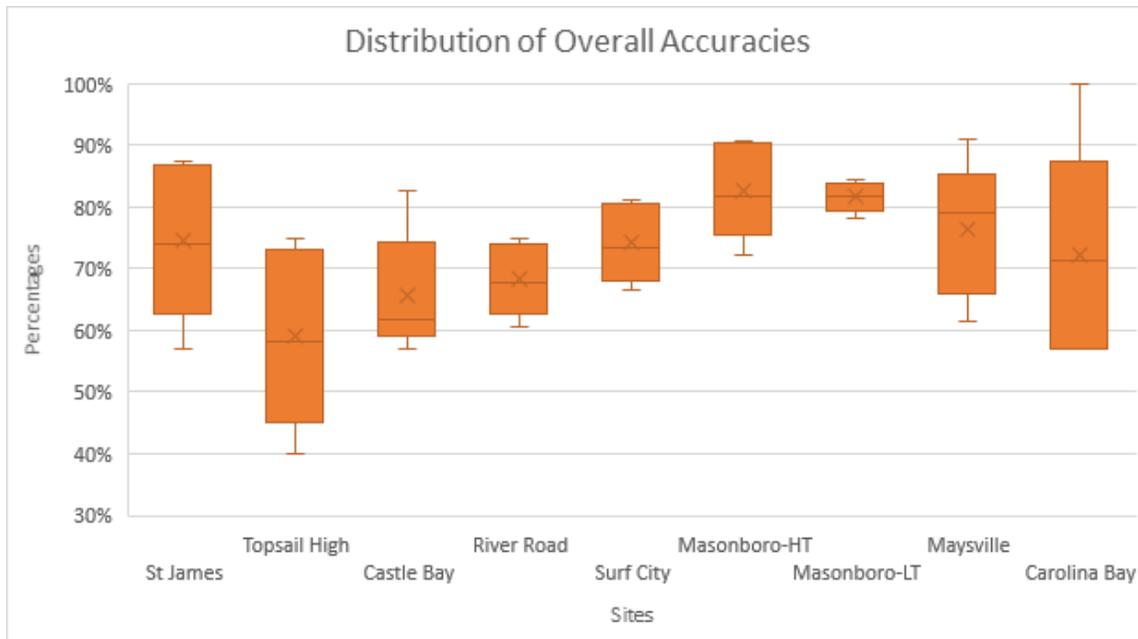
**Figure 38.** The top chart shows the variable importance plot generated for this site, while the bottom chart shows the model sensitivity and specificity for each of the classes represented at this site.

## Overall Study Modeling Statistics

In summary, the Random Forest UAS classification model performed very well and varied across the study area (Figures 39 and 40 and Tables 14 and 15). The estuarine sites (Masonboro and Surf City), with no dense forest canopy, had the highest wetland classification accuracy, but these sites also have the most difficult tidal challenges and as such these results are very good. The two sites with the lowest classification accuracy were Topsail High School which had the lowest number of points we were able to collect in the field and Castle Bay was a mixed forested wetland environment, very challenging to field check, and also included a golf course and therefore the image classification was difficult.



**Figure 39.** Comparison of the overall model classification accuracies and Kappa coefficients for all sites surveyed during this project.



**Figure 40.** The overall distribution of model accuracies by sites with bars indicating the respective standard deviation of each model.

**Table 15.** Summary of overall model accuracy, standard deviation of overall accuracies, Kappa coefficient, and number of total GRPs for each of the nine sites surveyed.

Site Name	Overall Accuracy	StD	Kappa Coefficient	Number of Total GRPs
St James	78.70%	0.13	67.64%	108
Topsail High	63.33%	0.15	53.34%	91
Castle Bay	66.46%	0.10	56.24%	172
River Road	76.30%	0.06	69.48%	137
Surf City	77.07%	0.06	69.21%	157
Masonboro-HT	85.62%	0.08	78.20%	153
Masonboro-LT	82.24%	0.02	73.12%	153
Maysville	76.25%	0.11	63.34%	81
Carolina Bay	70.59%	0.18	52.25%	34

By class, the post classification accuracy assessment is influenced by the number of habitat GRPs there were in each class. Therefore, classes that occupied smaller portions of the study areas, and therefore had far fewer GRPs generally also had lower accuracies. For example, water was only a small portion of several study areas. However, when developing a land cover classification model there is always a point during the process when the goals for deriving the best classification model for the purpose of the project objective exceeds the viable number of accuracy assessment points. In this case, during model development we tested the binary wetland/non-wetland model selection and the accuracy results were excellent. The next step was multiple wetland classes, but the non-wetland areas, which were not in the original plan for the project, were being misclassified in the Random Forest model and as such this necessitated that we return to the habitat GRPs and reclassify the non-wetland habitat GRPs and classify these as “open” if they were located in areas dominated by bare ground. This substantially reduced the number of non-wetland GRPs for these two classes but greatly increased the RF classification model performance.

**Table 16.** Summary table showing the class-level model sensitivity, specificity, user’s, and producer’s accuracy for the nine sites surveyed during this project.

Site Name	Wetland Class	Sensitivity	Specificity	User's Accuracy	Producer's Accuracy	Area Percentages	# Of GRPs
St James	Palustrine Forested	73.81%	84.85%	75.61%	73.81%	30.63%	42
	Non Wetland - Open	85.71%	95.00%	85.71%	85.71%	20.16%	29
	Palustrine Scrub/Shrub	78.95%	87.14%	76.92%	78.95%	49.20%	37
Topsail High	Non Wetland	69.23%	82.81%	62.07%	69.23%	25.82%	27
	Non Wetland - Open	64.71%	93.15%	68.75%	64.71%	16.62%	17
	Palustrine Forested/Scrub/Shrub	52.94%	89.04%	52.94%	52.94%	21.40%	17
	Palustrine Forested	53.33%	94.67%	66.67%	53.33%	17.96%	15
	Palustrine Scrub/Shrub	73.33%	93.33%	12.50%	73.33%	18.18%	15
Castle Bay	Non Wetland	16.00%	94.12%	33.33%	16.00%	6.83%	25
	Non Wetland - Open	82.22%	87.93%	72.55%	82.22%	35.97%	45
	Palustrine Forested	78.26%	86.09%	69.23%	78.26%	40.04%	56
	Palustrine Scrub/Shrub	80.00%	95.21%	63.16%	80.00%	5.58%	15
	Water	62.07%	93.18%	66.67%	62.07%	11.54%	30
	Palustrine Emergent	0.00%	100.00%	0.00%	0.00%	0.05%	1
River Road	Palustrine Forested	62.50%	85.26%	64.10%	62.50%	27.68%	40
	Palustrine Emergent	85.29%	91.09%	76.32%	85.29%	45.53%	34
	Non Wetland	80.00%	96.67%	75.00%	80.00%	6.96%	15

	Non Wetland - Open	84.00%	97.27%	87.50%	84.00%	14.80%	26
	Water	76.19%	98.25%	11.11%	76.19%	5.02%	22
Surf City	Non Wetland	62.50%	91.67%	84.62%	72.13%	34.67%	61
	Palustrine Forested	85.29%	88.24%	67.44%	76.32%	33.22%	38
	Estuarine Intertidal						
	Emergent	80.00%	92.13%	73.68%	93.33%	29.05%	30
	Palustrine						
	Scrub/Shrub	84.00%	97.92%	62.50%	38.46%	1.46%	13
					100.00		
	Water	76.19%	99.30%	0.00%	%	1.60%	15
Masonboro-HT	Water	83.93%	95.88%	92.16%	83.93%	31.95%	56
	Estuarine Intertidal						
	Emergent	82.93%	94.64%	85.00%	82.93%	41.07%	41
	Non Wetland	89.29%	87.63%	80.65%	89.29%	26.97%	56
Masonboro-LT	Water	83.93%	96.91%	93.18%	74.55%	32.22%	56
	Estuarine Intertidal						
	Emergent	82.93%	92.79%	80.95%	82.93%	39.72%	41
	Non Wetland	89.29%	83.33%	75.76%	89.29%	28.06%	56
Maysville	Non Wetland - Open	86.11%	93.18%	91.18%	86.11%	47.50%	36
	Non Wetland	58.82%	92.06%	66.67%	58.82%	13.24%	18
	Palustrine Forested	80.00%	80.00%	64.52%	80.00%	36.71%	25
			100.00				
	Water	0.00%	%	0.00%	0.00%	2.55%	2
Carolina Bay	Non Wetland	83.93%	84.21%	80.00%	80.00%	35.88%	15
	Non Wetland - Open	82.93%	80.95%	73.33%	84.62%	54.21%	13
	Palustrine Forested	89.29%	89.29%	25.00%	16.67%	9.91%	6

## Challenges, Limitations, and Future Directions

It was difficult to establish the overall best methodology for the modeling component of this research. We started out using a tessellation approach to generalize the data into a small area to avoid the computational intensity for random forest models. We switched from a tessellation to a pixel-based approach quickly after finding out that this approach lost a lot of the very high spatial details contained by the Quanergy data. Then, we encountered computational memory and space difficulties using the pixel-based classification, but we figured it out by using a different computer with more memory and an R package that was developed to deal with big data.

One limitation of this research is to create high-quality response variable data given the relative outdatedness of the NWI wetland extent data for North Carolina. Accurate, most-updated Ground Reference Points (GRPs) sample data are needed to create a high-quality and accurate wetland classification. However, the collection of ground-truthing data was difficult because of the topography and general inaccessibility of the sites we surveyed. There were some areas that

we could not access because of the mud cover and some areas could not be validated because of the very dense canopy cover when doing visual inspection using NAIP imagery to create additional training and validation data. Therefore, if the ultimate goal is to increase the accuracy of Coastal Plain wetland prediction models, improvements to the quality of response data will continue to be a high priority for any future mapping and modeling project utilizing UAS technology. Polygon sample data could be used, instead of point data, to encompass the larger area of sample data (Kolarik et al., 2020; Gaughan et al., 2022). Lastly, different machine learning classifications can be tested to compare the model performance, such as different ensemble methods such as gradient boosting would be a great start. However, most advanced machine learning modeling approaches do require a good amount of training data that can be obtained either in the field or using on-screen digitization approaches, both exemplified in this work and final report.

## Recommendations

As discussed in the pages of this report, we make a series of summary recommendations for each task/section. In terms of project design and preparation, we recommend conducting proper data management, organization, storage and backup as well as metadata attribution for any data collected in the field to ensure high data quality standards and data management. For the purpose of mission implementation and data collection, in addition to required FAA and NCDOT legal and operational safety parameters, we recommend utilizing two RTK systems with capabilities to collect centimeter-level accuracy data for both static and GCP data as part of a defensible and accurate (to NC ASPRS standards of vertical and horizontal accuracy) field collection methodology and so that data processing proceeds smoothly. In terms of more specific flight parameters for UAS LiDAR collections, we recommend that in a forested landcover and mixed landcover area you should have a UAS flight parameter combination of an attitude at 65m with a swath width overlap percentage of 25%. Second, we recommend that for majority bare ground landcovers, the ideal flight parameter combination to be at 50m altitude and an overlap percentage of 25%.

For the important components that pertain to data pre-processing, processing, and initial analyses and visualizations of UAS-derived data (LiDAR and imagery based, along with the requisite *in situ* components), we recommend following standardized, repeatable and ideally batched data pre-processing workflows for all raw data collections, including for UAS LiDAR, multispectral/RGB/thermal and especially *in situ* reference data (as needed) and we especially recommend that great care be taken when selecting the **minimum required GCPs** (5-10/site, depending on the site characteristics, as well as the collection of 75-100% as many **check points for validation**) to ensure not only intersection with respective flight paths, but also accessibility to the site locations. Data pre-processing templates and parameter specification sheets are imperative in ensuring standardized data processing across multiple sites.

Finally, for taking the raw data and creating mapping or modeling products, irrespective of the software package to be used, we recommend collecting high spatial resolution data aided by other ancillary datasets, whether UAS-based or not. *As such, we showed that Quanergy LiDAR data collected by our team along with the UAS multispectral data trained by GRPs (habitat points) and NCDOT delineated wetlands (where available) created spatially-accurate wetland delineations when compared to NWI data.* Even though we were able to use random forest algorithms to create these classifications with only a small number of field-verified point data (GRPs), we recommend that more habitat points be collected if overall accuracies and class-specific sensitivities and specificities are required for NCDOT mapping projects at specific sites. Because we used random forest modeling, we were able to create variable importance plots for each type of wetland site surveyed and show that the highly resolved elevation variables, vegetation height and vegetation indices are the most important predictors of wetland presence overall. As such, given the patterns revealed by this modeling work, we decided against including flow direction and flow accumulation as variables in the final wetland classifications given the relative flat topography of the Atlantic Coastal Plains regions; this, however, would be different for sites characterized by more variable topography.

## Implementation and Technology Transfer Plan

The main research products generated from this project include a ready-to-fly and operate UAS LiDAR system that has been thoroughly tested and comes with step-by-step operation instructions, fixed-wing UAS multispectral data and derived vegetation indices, *in situ* GCP and GRP point data, metadata and data dictionaries for all datasets, and final machine learning classification products that can be compared to existing DOT datasets and other potential future delineations.

Given that the goal of this project was to provide NC DOT with detailed approaches to using UAS technologies to derive maps of environmental features (not just wetlands), we worked synergistically with NC DOT so that the products are directly applicable to assisting the Environmental Analysis Unit at DOT in the implementation of project planning and development. Therefore, at all stages of this project, our team has done our best to include one or more NC DOT staff in providing guidance, meet at our regularly scheduled meetings, work in the field when available so that the full UAS flight process and collection of ancillary data were thoroughly understood, review GIS and data products, and participate in technology transfer through a two-day workshop completed before the project ended. The UNCW team feels that we have been successful if the products from our case studies will have been used in NC DOT project planning.

Second, to ensure adequate technology transfer, not only did we hold a two-day training workshop, but we made every effort for NCDOT staff to be comfortable using the UAV equipment as well as processing data to produce cartographic products and GIS data that can be

directly imported into NC DOT enterprise databases during the entire duration of the project, in addition to bi-weekly progress report meetings. At the completion of this project, we are truly grateful for the opportunity to work on this project and we strongly believe that the correct use of UAS technology can save NC DOT money, long-term, by implementing a strategy that reduces the number of days that surveyors are currently out in the field. However, as our discussion of limitations and modeling section above underscore, this technology is not a replacement for surveying, it is a means of utilizing aerial approaches to highlight and map potentially sensitive resources that can then be surveyed and incorporated into the project planning and workflow processes by NCDOT teams across multiple divisions.

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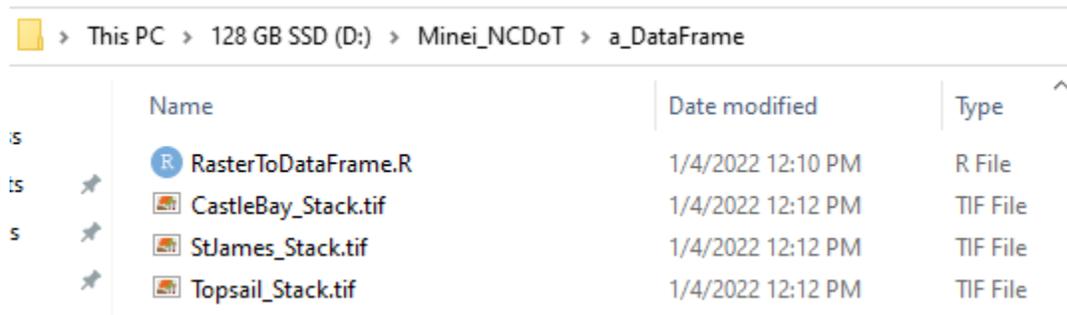
## Appendices

### APPENDIX A: RANDOM FOREST ANALYSIS SCRIPT AND STEP-BY-STEP INSTRUCTIONS

We will use the R language to run random forest analysis. RStudio (<https://www.rstudio.com/>), programming platform, is used throughout this guide.

#### RASTER TO DATA FRAME

1. Create a file for this step and put “RasterToDataFrame.R” and stack tifs.



2. We are going to convert the raster layers into data frame, which is the most common dataset format used in R. Open the “RasterToDataFrame.R” file in RStudio.
3. Run the “**1. setting environment**” section. Make sure you change the work path before you run it.

```
5- # 1. setting environment -----
6 ## install packages
7 # Only run once to download packages in your computer
8 install.packages("rgdal")
9 install.packages("yaImpute")
10 install.packages("raster")
11 install.packages("dplyr")
12 install.packages("sf")
13 install.packages("ggplot2")
14 install.packages("rpart")
15
16 # Run this every time you open
17 library(rgdal)
18 library(yaImpute)
19 library(raster)
20 library(dplyr)
21 library(sf)
22 library(ggplot2)
23 library(rpart)
24
25 ## Set working path
26 ## CHANGE THE PATH ###
27 setwd("D:/Minei_NCDot/a_DataFrame")
```

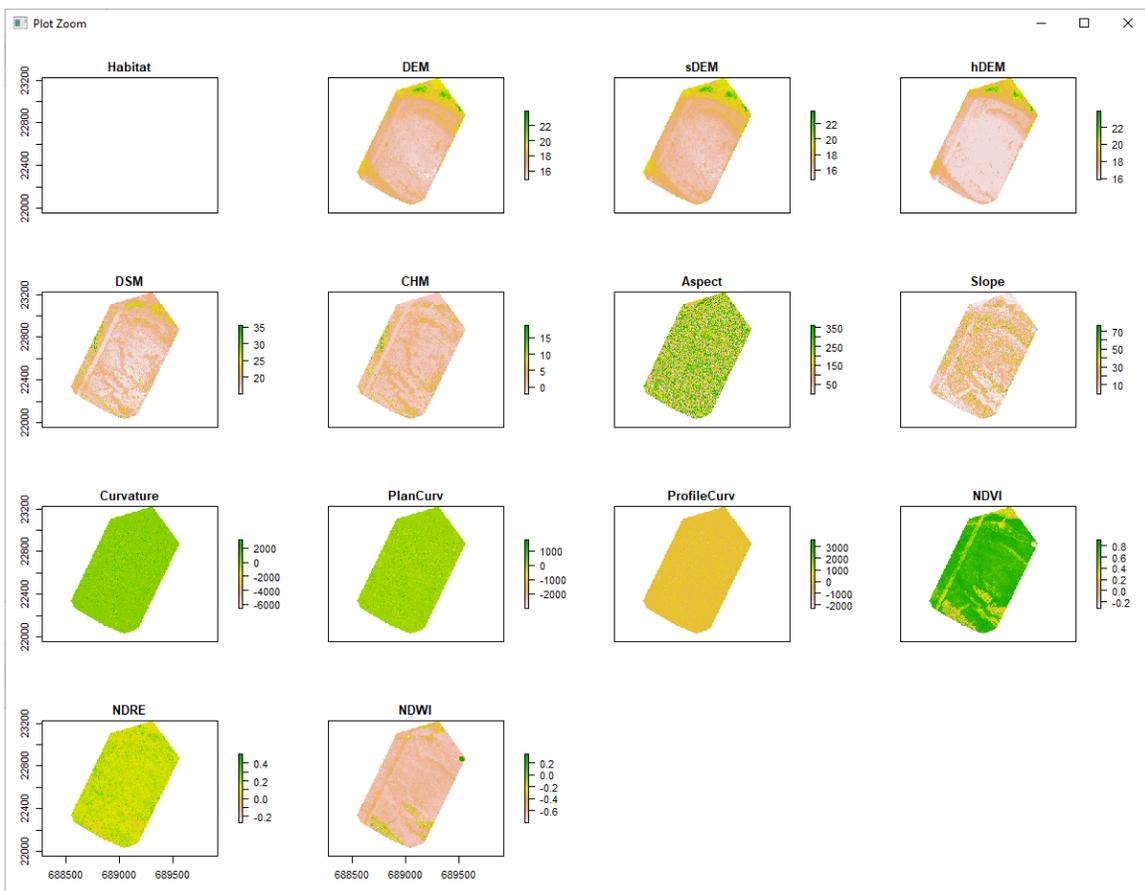
4. Run the “2. Load and name” section. Make sure you change the name of the tif file exactly as you named it.

```

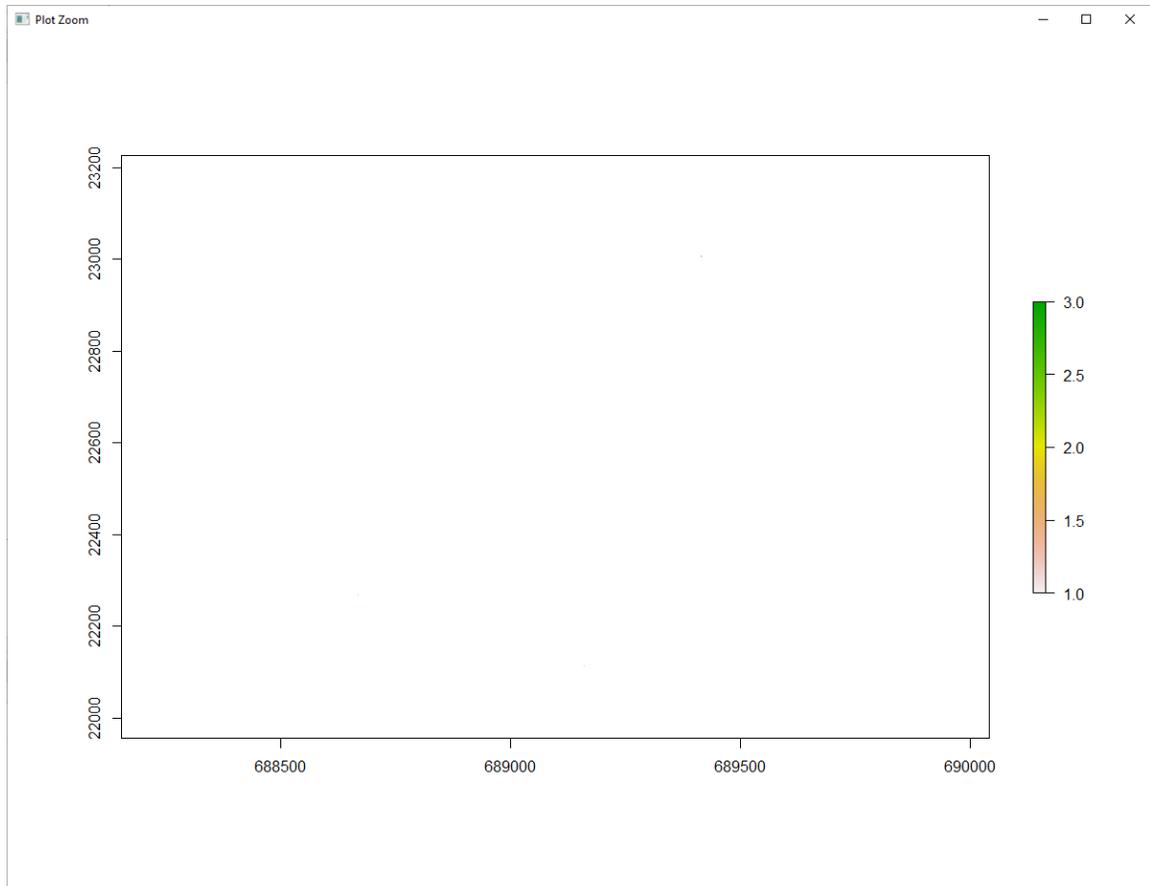
30 # 2. Load and name -----
31 # Load full stack of a raster layer
32 # if this fails, try updating your R system
33 ## CHANGE TIF FILE ###
34 st <- stack("StJames_Stack.tif")
35
36 names(st) <- c("Habitat",      "DEM",      "sDEM",      "hDEM",
37               "DSM",         "CHM",     "Aspect",   "Slope",
38               "Curvature",  "PlanCurv","ProfileCurv",
39               "NDVI",        "NDRE",    "NDWI")
40
41 # plot each raster lyers
42 plot(st)

```

When you run line 42, all the raster layers were plotted in the plot window.



This is the zoomed in the Habitat layer. Since the pixels were too small, you cannot see anything. But you can see that there are three classes stored in this data based on the scale bar.



5. Run the “3. Convert the raster into DataFrame” section.

```
45 # 3. convert the raster into DataFrame -----
46 # Create two dataframe: all dataset and dataset with all the null dataset removed
47 # na.rm = T -> removes all the null data
48 df_hab <- as.data.frame(st, xy = TRUE, na.rm = T)
49
50 st$Habitat[is.na(st$Habitat)] <- 0
51 df_all <- as.data.frame(st, xy = TRUE, na.rm = T)
```

6. Save the dataframe as RDS dataset.

```
60 # 4. save data -----
61 saveRDS(df_hab, file = "StJames_hab.rds")
62 saveRDS(df_all, file = "StJames_all.rds")
```

## RANDOM FOREST CLASSIFICATION USING H2O

1. Create a folder and put those files like shown below.
  - Wetland\_RF\_H2O.R
  - SiteName\_all.rds
  - SiteName\_hab.rds
  - SiteName\_Stack.tif

Name	Type
 Wetland_RF_H2O.R	R File
 StJames_all.rds	RDS File
 StJames_hab.rds	RDS File
 StJames_Stack.tif	TIF File

2. Open the “**Wetland\_RF\_H2O.R**” and run the “1. Setting environment” section. You only install packages once in your computer but run library every time you run.

```
5- ## 1.Setting environment =====
6 #install.packages('readr');install.packages('h2o');install.packages('caret');
7 library(readr)
8 library('h2o')
9 library(e1071)
10 library(caret)
```

3. Run the “2. Load RDS data” section. Make sure to change the path to the folder (**fb <- folder path**) and change the name of the RDS file.

```
13- ## 2.load RDS data =====
14 fn<-"D:/Minei_NCDOT/b_StJames"
15 setwd(fn)
16 df.rds<-readRDS("StJames_hab.rds"); names(df.rds); attach(df.rds)
```

- In like 21, select only variables (remove the x and y coordinate). Here we use H2O package to run random forest analysis. Make sure to run line 25 – 27 every time when you are out of memory.

```
19- ## 3.Random Forest Model =====
20 df.rds$Habitat<-factor(df.rds$Habitat)
21 vari <- df.rds[ ,1:14]
22 dim(vari)
23
24 ## using H2o;
25 h2o.shutdown(prompt = FALSE)
26 localH2O <- h2o.init(nthreads = -1,max_mem_size = '4g')
27 h2o.init()
28
29 ## empty vari
30 y.dep <- 1;
31 x.indep <- c(2:14)
32
33 ## record processing time
34 start.time <- Sys.time()
35
36 ## RF for accuracy with CV (k=5)
37 train.h2o <- as.h2o(vari);
38 rforest.model<- h2o.randomForest(y=y.dep,
39                                 x=x.indep,
40                                 training_frame = train.h2o,
41                                 nfold=5,
42                                 mtries=4,
43                                 max_depth=14,
44                                 ntrees = 500,
45                                 seed = 1122,
46                                 keep_cross_validation_predictions=TRUE,
47                                 keep_cross_validation_fold_assignment = TRUE)
48
49 rforest.model
```

When you run rforest.model, this is what you get:

*Model Details:*

=====

*H2OMultinomialModel: drf*

*Model ID: DRF\_model\_R\_1641325516784\_1 .....*

- Run the “4. Save model as file” section. Change line 68, 69 as accordingly. When you save the model, it will be saved as the model ID in the folder. For line 72 and 73, you can see the variable importance.

```

52- ## 4.save the model =====
53 # store the path to the model and reload the model
54 path <- h2o.saveModel(rforest.model, path=fn, force=TRUE )
55 rf.load <- h2o.loadModel(path)
56
57 # take out the cross validation prediction results
58 cv <- h2o.getFrame(rf.load@model[["cross_validation_holdout_predictions_frame_id"]][["name"]])
59 cv.vec <- as.vector(cv[,1])
60
61 # create dataset of x,y,and prediction results
62 pre <- data.frame(X =as.numeric(x),
63                 Y =as.numeric(y),
64                 PREDICT = as.numeric(cv.vec))
65 attach(pre); contrasts(factor(PREDICT)); summary(factor(PREDICT))
66
67 # Save the dataset as RDS abd restore it
68 saverDS(pre, file = "StJames_XY_prediction.rds")
69 pre <- readRDS(file = "StJames_XY_prediction.rds")
70
71 # plot variable importance
72 h2o.varimp(rf.load)
73 h2o.varimp_plot(rf.load)

```

Name	Date modified	Type	Size
 .RData	1/4/2022 2:44 PM	R Workspace	11 KB
 .Rhistory	1/4/2022 2:44 PM	RHISTORY File	1 KB
 DRF_model_R_1641325516784_1	1/4/2022 2:46 PM	File	2,677 KB

- Next step is to use the random forest model that was created in the previous section, predict wetland classification with all the areas. Make sure to change the line 80 accordingly. Also, line 89-91 can tell you how long the model took to train and predict.

```

73- ## 5.Predicting wetland with all data =====
74 #install.packages('ggplot2'); install.packages('raster'); install.packages('sp');
75 library(ggplot2)
76 library(sp)
77 library(raster)
78
79 # import the data to be trained
80 df.all <-readRDS("StJames_all.rds")
81 allpre <- df.all[ ,2:14]
82 dim(allpre)
83
84 # if those two does not work, go back and rerun line 25-27
85 train.h2o <- as.h2o(allpre);
86 pre.all <- h2o.predict(rf.load, newdata = train.h2o)
87
88 ## Stop recording time and calculate processing time
89 end.time <- sys.time()
90 time.taken_rf <- end.time - start.time
91 time.taken_rf

```

7. Run the section 5 to save the x, y, and prediction results for the training data. Make sure you change the line 99 and 100 as you like.

```
94 - ## 5. Save an object to a file and restore it =====
95 pre2 <- data.frame(X =as.numeric(df.all$x),
96                   Y =as.numeric(df.all$y),
97                   PREDICT = as.numeric(as.vector(pre.all$predict)))
98 attach(pre2)
99 saveRDS(predict, file = "stJames_Final_prediction.rds")
100 pre <- readRDS(file = "stJames_Final_prediction.rds"); attach(pre)
```

8. S

```
103 - ## 6. Create prediction map in raster =====
104 # Reference: https://www.youtube.com/watch?v=LwCEe9o0vac
105 st <- stack("stJames_Stack.tif")
106 names(st) <- c("Habitat", "DEM", "sDEM", "hDEM",
107              "DSM", "CHM", "Aspect", "Slope",
108              "Curvature", "PlanCurv", "ProfileCurv",
109              "NDVI", "NDRE", "NDWI")
110
111 # finding out the extent, coordinate system, # of row and columns
112 ex <- extent(st); n.row<-dim(st$Habitat)[1];n.col <-dim(st$Habitat)[2];
113 ncell(st$Habitat); my.crs <- crs(st$Habitat)
114
115 #create a empty raster and bring the prediction results and plot it
116 r <- raster(ex, ncol=n.col, nrow=n.row, crs= my.crs)
117 r_new <- rasterize(pre2[,1:2], r, pre2[,3], fun=mean)
118 plot(r_new)
119
120 #save prediction raster in tif
121 writeRaster(r_new, filename = 'stJames_PreMap.tif',options=c('TFW=YES'))
```



---

# DATA COLLECTION, PROCESSING AND MODELING GUIDE FOR LIDAR UAS AND IN SITU FIELD DATA IN SUPPORT OF RESEARCH PROJECT 2020-04

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Final version submitted to the North Carolina Department of  
Transportation



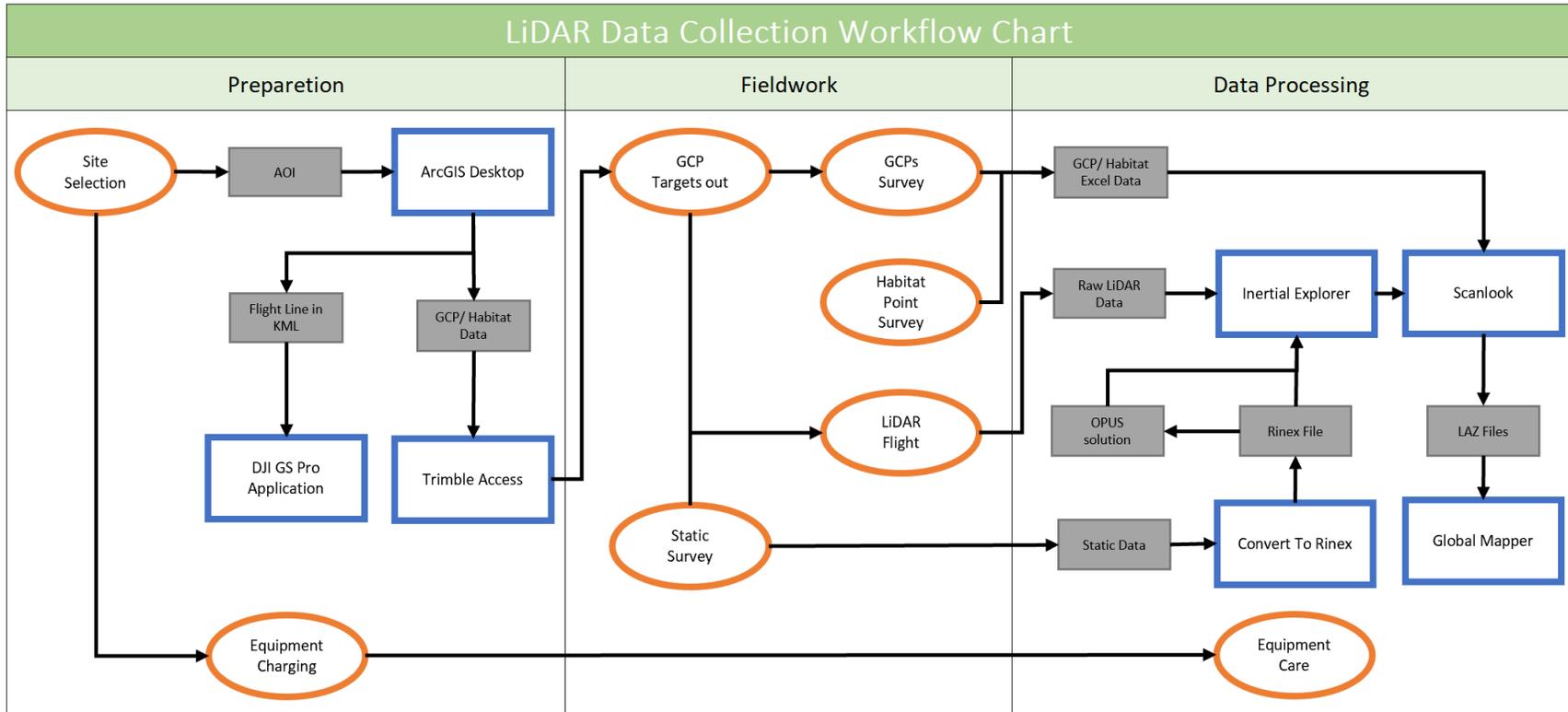
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# OVERARCHING WORKFLOW CHART



## Section 1: SITE SELECTION

The first step is to design a study area that will be surveyed with a LiDAR sensor mounted on a DJI Matrice 600 Pro. Here are some tips on how to create an Area of Interest (AOI) in ArcGIS Desktop.

### 1.1: Things You Need to Start

Software: ArcGIS ArcMap 10.7.1

Polygon Data: NWI (National Wetland Inventory-2010)

Polygon Data: NC WAM and NCDOT Wetland Delineation Data (if available)

Polygon Data: NC Parcel Data

Coordinate System: "NAD\_1983\_StatePlane\_North\_Carolina\_FIPS\_3200" in meters

### 1.2: Tips for Selection

Based on existing wetland delineations (NWI and/or NCWAM data), we want to select places where they are the variety of wetland types and its unique patterns.

Here are more things to consider:

Take-off/ landing area

Enough area for drones to take off and land in plus areas for Trimble and other necessary equipment.

Flight area

Around 80-100 acres will be adequate. One set of a drone battery (DJI Matrice 600 Pro) can be flown over about 40 acres. Consider the fieldwork schedule and drone battery.

Obstacles

Check for potential objects that might obstruct drone flight such as buildings, power line, and tall trees.

Surveyors must keep a visual line of the sight on the drone.

Permission

Contact landowners for permission to fly and putting out targets. Check the parcel data to see the names of them. Be sure to check if there are any gates preventing us to drive.

Access to Ground Control Points (GCPs)

Check for the accessibility where you want to put targets.

Proximity

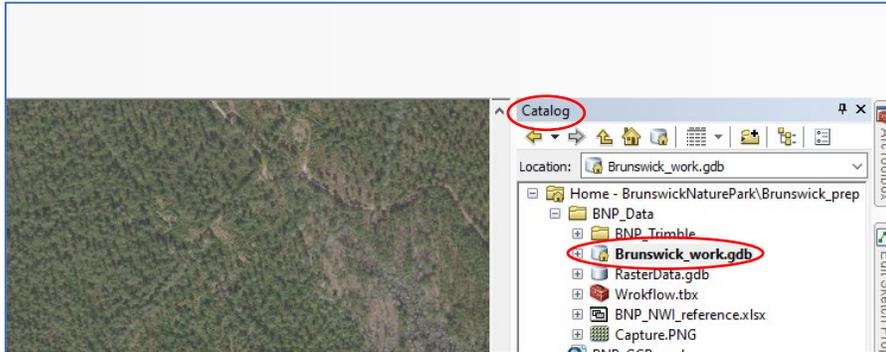
Check for the safe flight zone: <https://www.dji.com/flysafe/geo-map>.

### 1.3: Creating AOI in .shp and .kml

Following to the site selection, you are going to create a flight area in polygon and .kml files. Shape file for further analysis and kml file will be uploaded to a DJI GS Pro application for automatic drone flight. Here, we will create those in ArcGIS ArcMap.

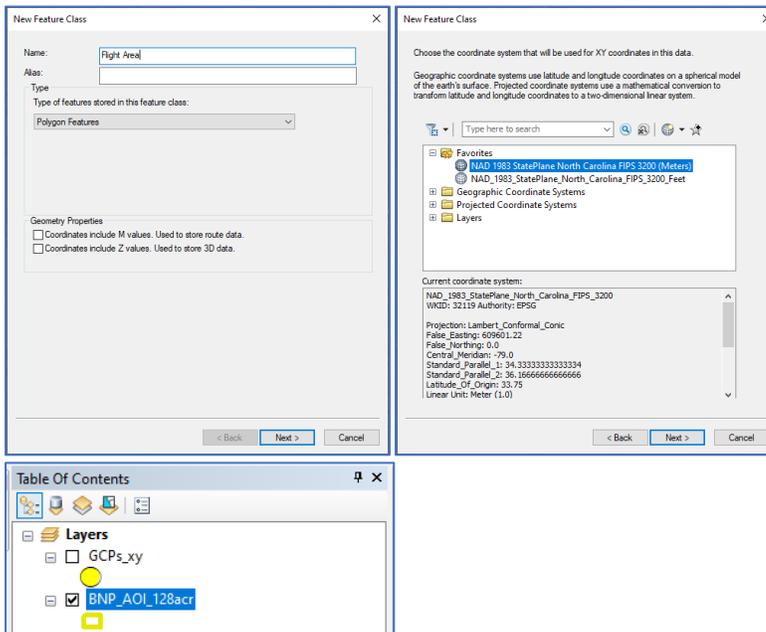
#### 1. Creating Polygon Layer in ArcMap

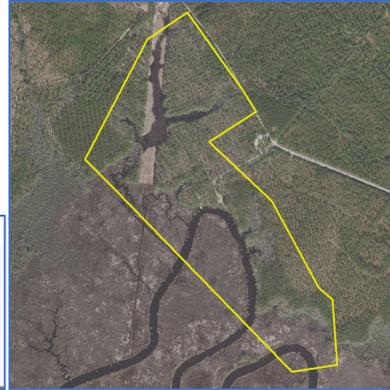
Here is one of the ways to create a study area in polygon data. Start with a new map in ArcMap. Go to **Catalog** and right click on **Geodatabase** (create one if you don't have yet). **"New"** -> **"Feature Class"**, then a **"New Feature Class"** window pops up.



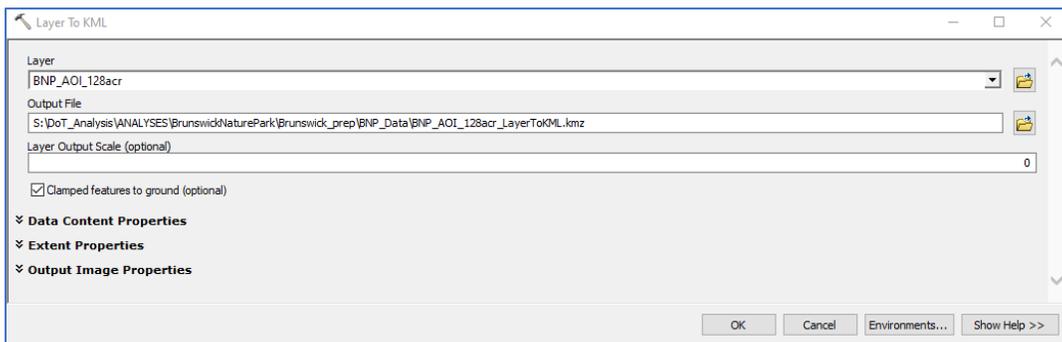
#### 2. Edit Polygon

In the process of **"New Feature Class"**, make sure to put the right coordinate system you want. After creating the feature class, right click on the polygon in the **"Table of Contents"** you just created and then, go to **"Edit Features"** -> **"Start Edit"** to draw a polygon. When done editing, click **"Editor"** -> **"Save Edits"** and **"Stop Editing"**.



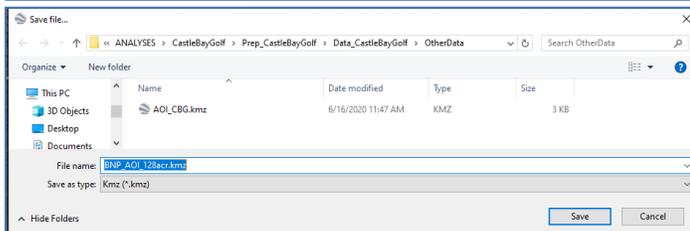
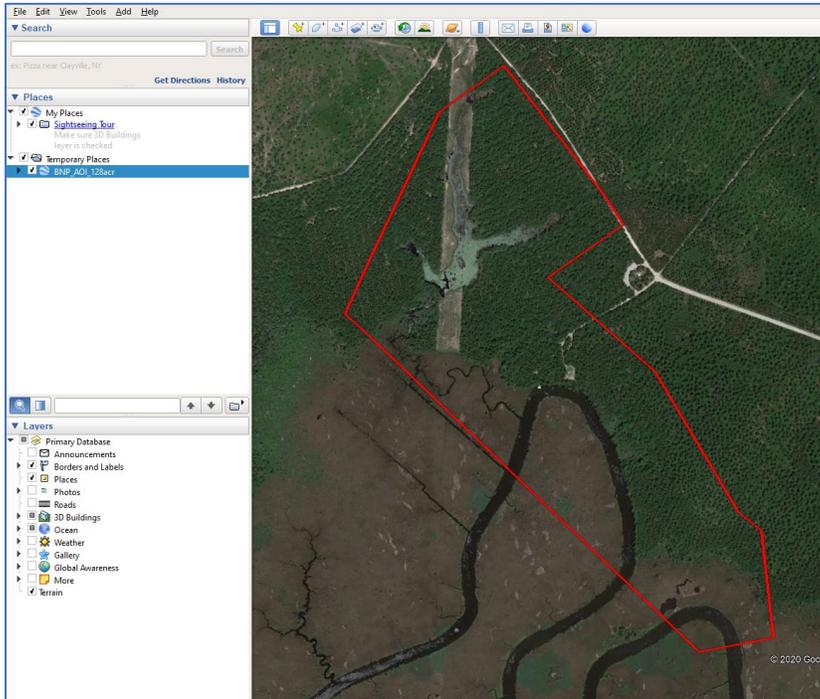


Use “**Layer To KML**” tool to export the data into .kmz format (save it outside of a geodatabase). This tool converts a feature or raster layer into a KML file containing a translation of Esri geometries and symbology. This file is compressed using ZIP compression, has a .kmz extension, and can be read by any KML client including ArcGIS Explorer, ArcGlobe, and Google Earth. Converting into .kml allows us to upload the AOI in DJI GS Pro application to create automatic UAV flight.



#### 4. Open KMZ data in Google Earth Pro

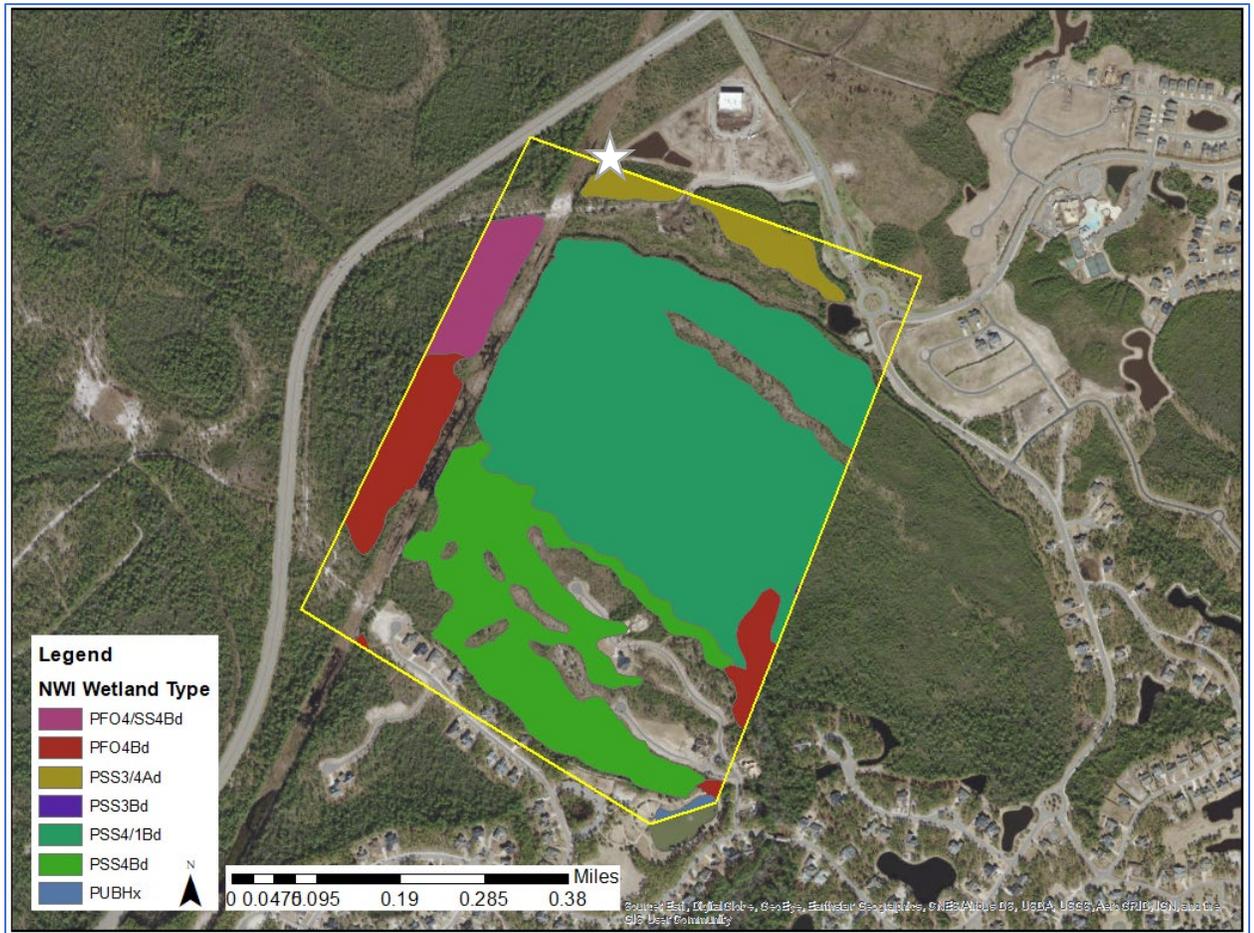
When the export process is done, open the File Explorer and click **.kmz** file to open in Google Earth Pro. In Google Earth Pro, go to **“File” -> “Save” -> “Save Place As”**. Then, save the polygon data as **.kml**. Make sure to save it with the background no fill.



## 1.4: AOI Examples

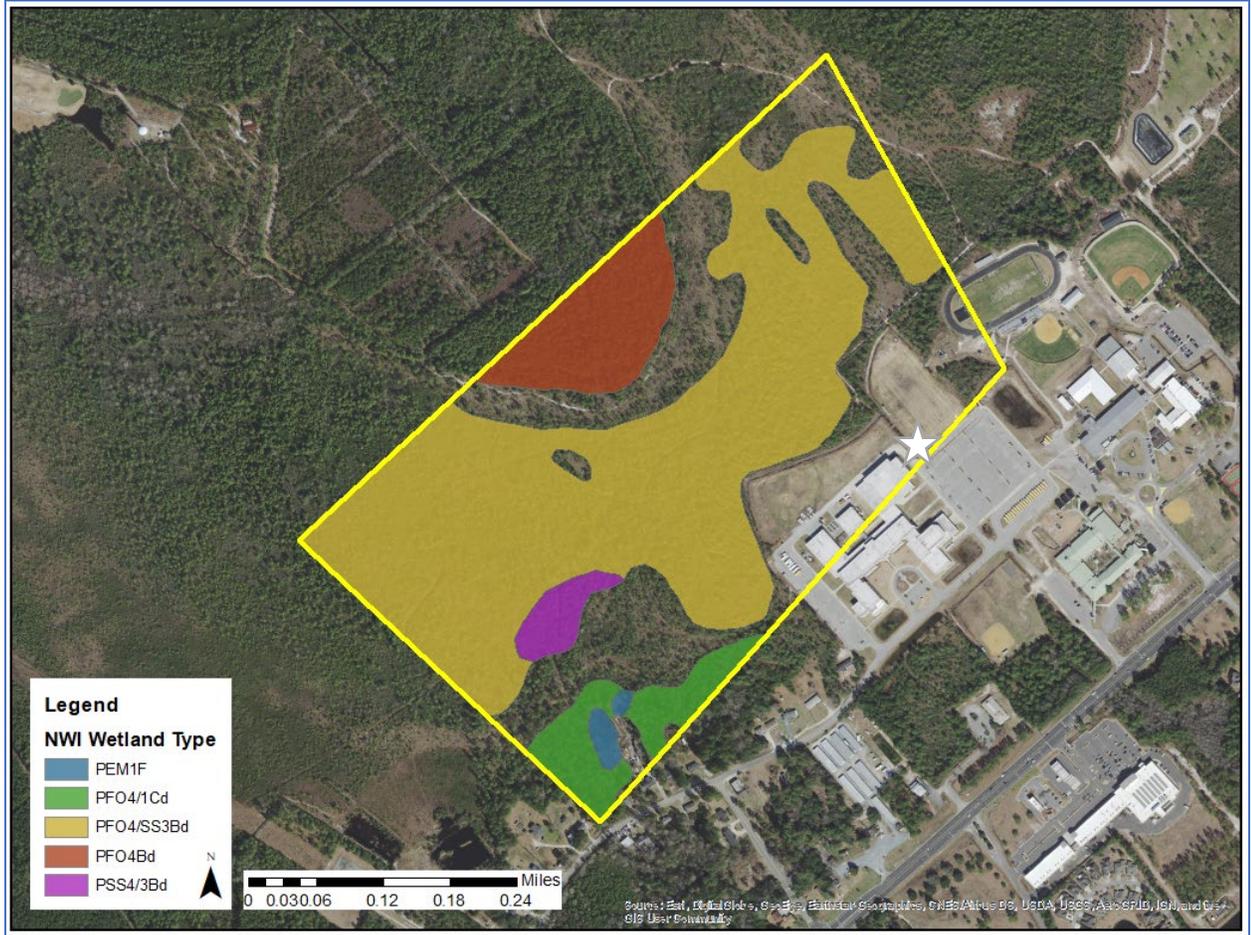
### 1. St. James

- Date: 5/12/2020
- Area: 202 acres
- Take off base: 
- 7 kinds of wetland
- Residential areas within flight area – hard to get permission for flight/ GCPs



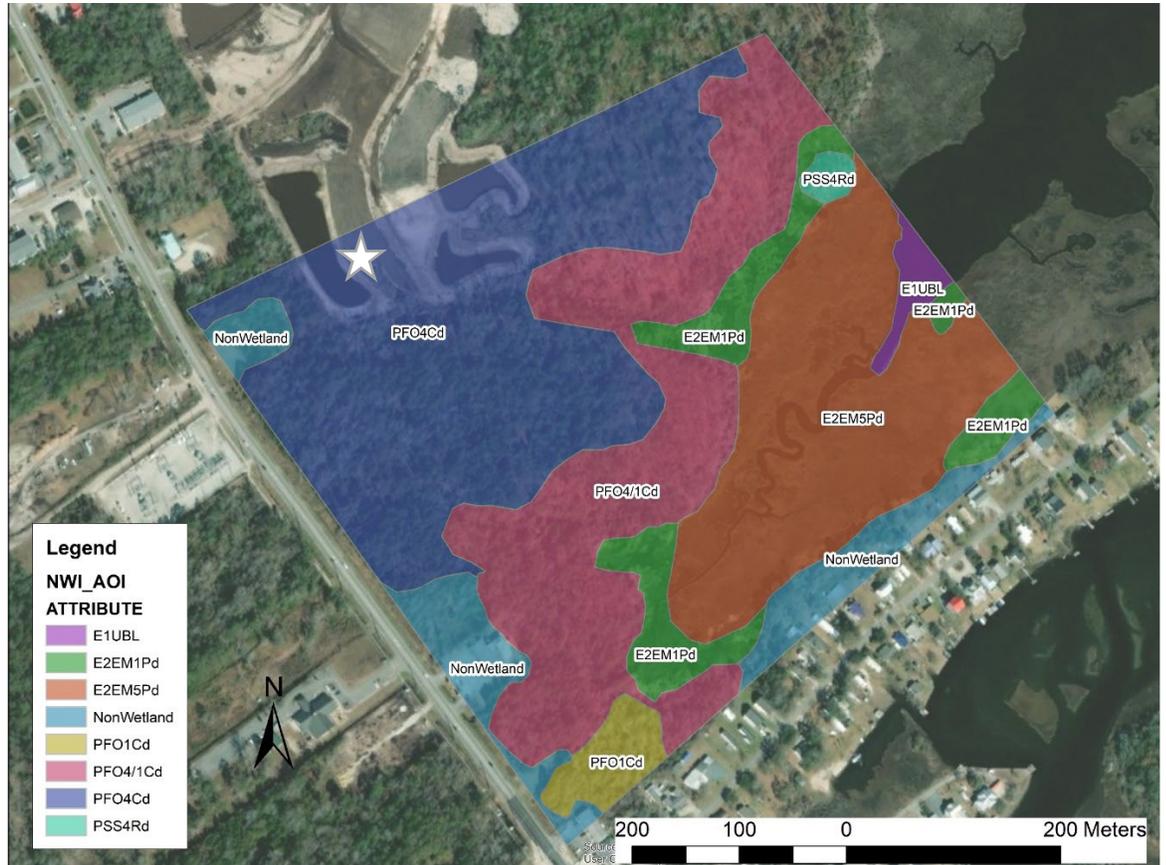
2. Topsail High School

- Date: 6/2/2020
- Area: 128.45 acres
- Takeoff landing area: ☆
- 5 different wetlands



### 3. Surf City

- Date: 11/6/2020
- Take off base: ☆
- 7 wetland types



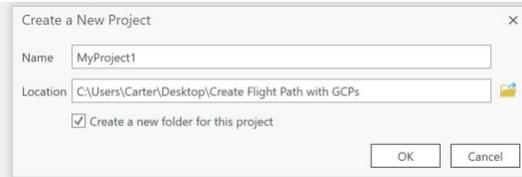
## Section 2: FLIGHT MISSION PLANNING

This step is for creating a flight path of kml in arcmap using a tessellation approach, then uploading it to the DJI GS Pro app to create an automated UAV flight. Along with the flight path, in the next step we will plan on where to place the Ground Control Points (GCPs).

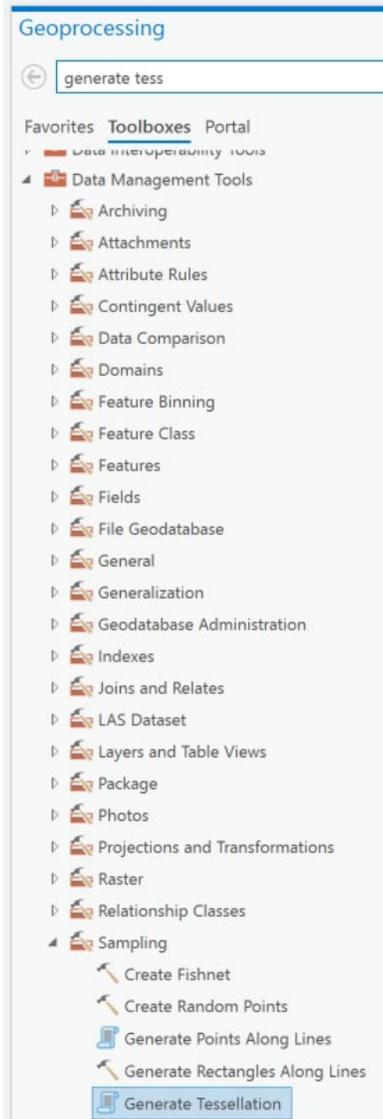
### 2.1: Creating and adding AOI, flight path and GCPs in ArcPro

Open ArcGIS Pro  - click “Map” (under Blank Templates) - 

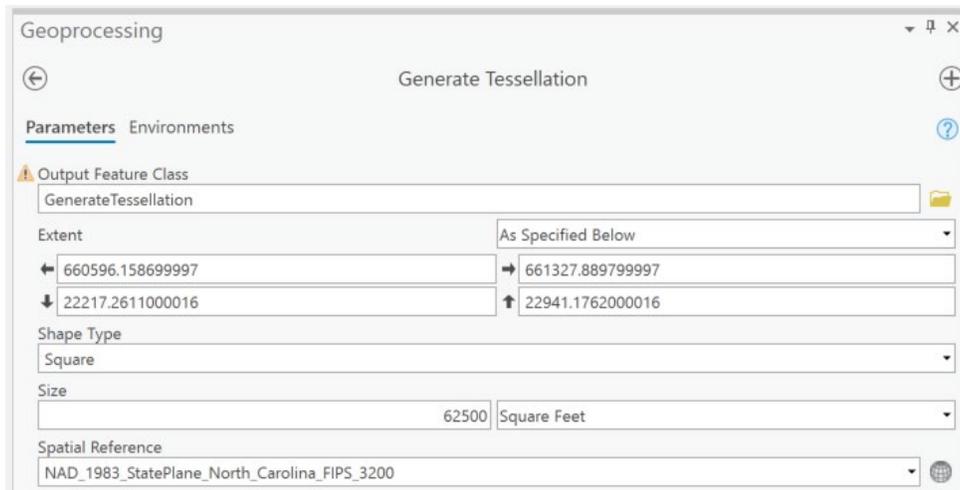
#### a. Name and Save Project to Location of your choice



## **Step 2: Generate Tessellation:**



- Under Parameters: Click on the \*Extent drop down and chose your AOI layer (this will change to “As Specified Below”. Shape type = Square. Size = 62,500 Square Feet\*\*

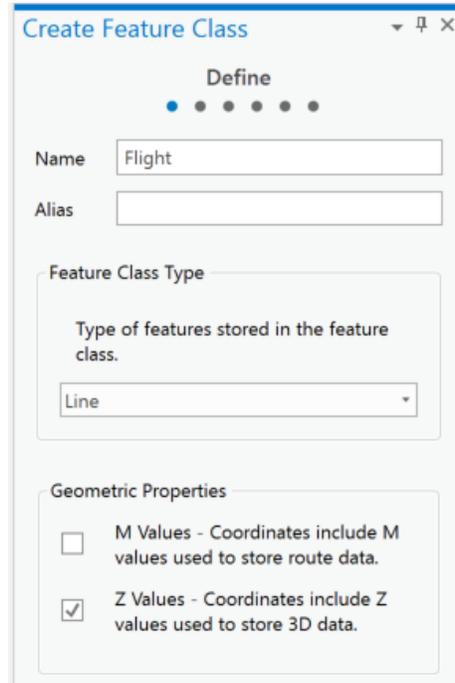


- Hit the  button and it will automatically align over your AOI on the map.



### **Step 3: Create Flight Path:**

- Go to “View” (at the top) – Click on  - Folders - Project Name – Right click on .gdb (File GeoDatabase) – New – Feature Class



**Create Feature Class**

Define

Name: Flight

Alias:

Feature Class Type

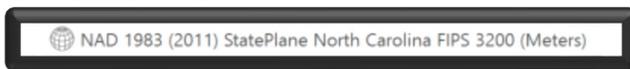
Type of features stored in the feature class.

Line

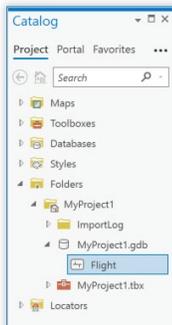
Geometric Properties

M Values - Coordinates include M values used to store route data.

Z Values - Coordinates include Z values used to store 3D data.

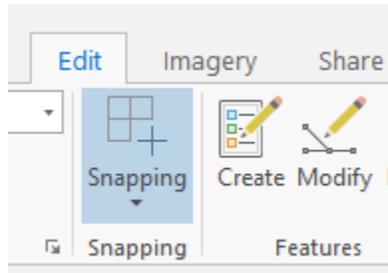


Click “**Finish**”



\*To upload new feature class right click and click “add to current map”

- To create a Flight Path for the drone click Edit – Create – Choose the Flight Path layer under Create Features



- Make sure snapping is on and place flight path on the tessellation inside the AOI that you've created making sure not to skip a line
- To make this easier upload a road imagery map to make sure not to place over open traffic and roads.

\*The take-off location for the drone does not matter until the DJI App portion



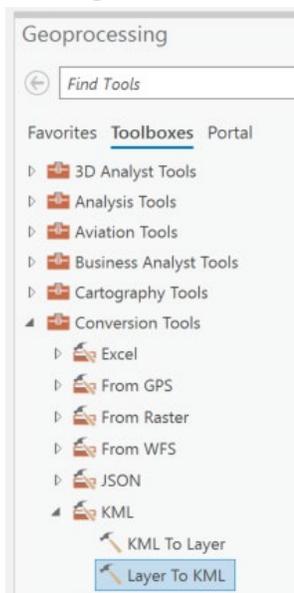
- Use the Edit tab – Create – Click GCPs

**\*Make sure Snapping is on and you lay GCPs along the flight path layer in accessible areas\***

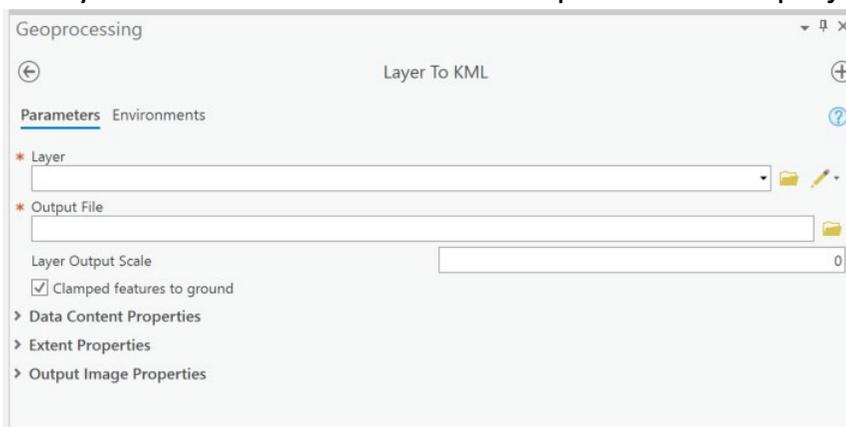
- See Section 4 & 5 below for GCP Creation and Trimble Upload.

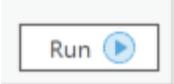
## 2.2: Converting Layers to KML through Google Earth Pro

- Convert the GCP layer, Flight Path layer, and AOI layer in tools through conversion tools – KML – Layer to KML



- Use the drop-down arrow under \*Layer to convert each individual layer – Select the file icon in \*Output File to the project file to save.



- Do this for each layer and hit  after each is uploaded to send them to the file of the project.

\*There should be a green complete icon after each conversion\*

- Once uploaded zoom in to make sure all layers line up nicely to your study area and it is exactly what you want, this includes:
  - GCPs are in a suitable location to be recorded in the field after flight
  - Flight Path does not cross over or intersect open traffic or major roads
  - AOI is around the correct study area you hope to survey
    - \*Note: This AOI can touch major roads because it is not what the drone will trace but is what the drone will overlap and collect.

If you are satisfied: Right click each KMZ file and click “Save as” to the same file of your KMZ files but change KMZ to KML file at the bottom of save menu.

### 2.3: Uploading KMZ files to DJI Ground Station Pro (GSP) App through Email



- Click on the KML files that you have added to your project folder and drag them into an email that you can send to your mobile/tablet device.

- Click on each file individually and select the  "upload" icon so it can be sent to the GSP App.
  - \*This will show up in "files" in the GSP app\*
- Open DJI GS Pro App on tablet or phone that will control the drone during flight in the field – click on "My Missions" (bottom right of home screen) – Under the middle tab click materials – files – swipe right to uploaded new files brought in from email.
- Once missions are on the right table called "Map" - Click on the "Map" – Click on each file - Swipe left on the drop down tab – Click "Pin" on each one of them so they show up on the map.
- Under the flight layer click the "Create Mission" button – The Map by waypoint button should be the only one to appear. Click the icon below:



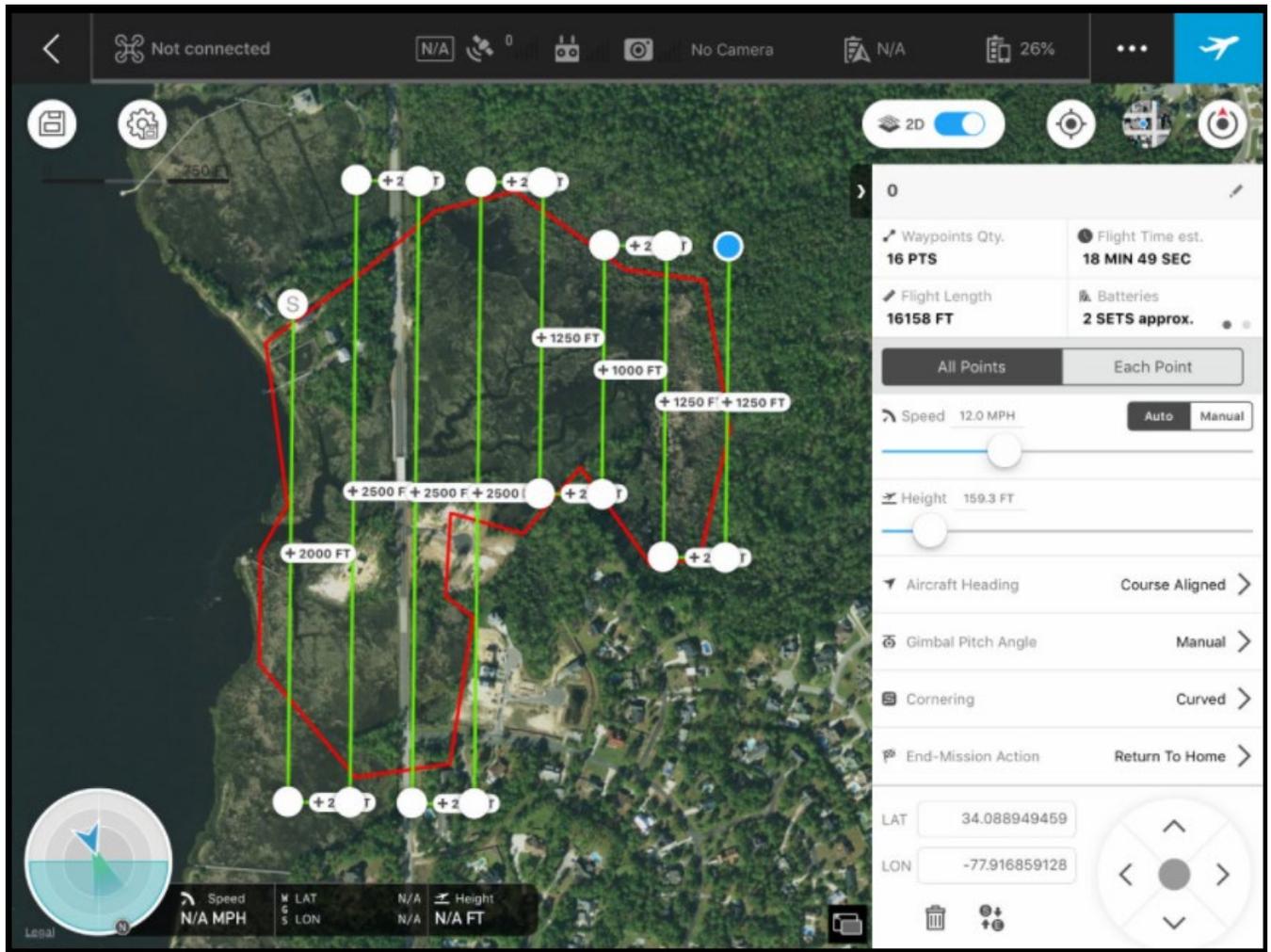
- Now the flight plan you designed in ArcGIS Pro should be under the Mission tab with the name "0". Rename the mission to the area you are mapping and modify the mission by clicking on the name and hitting "EDIT" at the bottom right next to Fly.

\*This allows the drone to turn at each corner and more of a gentle turn rather than a jagged 90.00 corner, thus creating potential errors in data collection\*

- Once Flight is complete and you have checked that all parameters are correct including:
  - Speed

- Height
- Mission Start & Stop

Click Save icon on the top left of app.



## Section 3: GCP and CHECK POINTS GENERATION

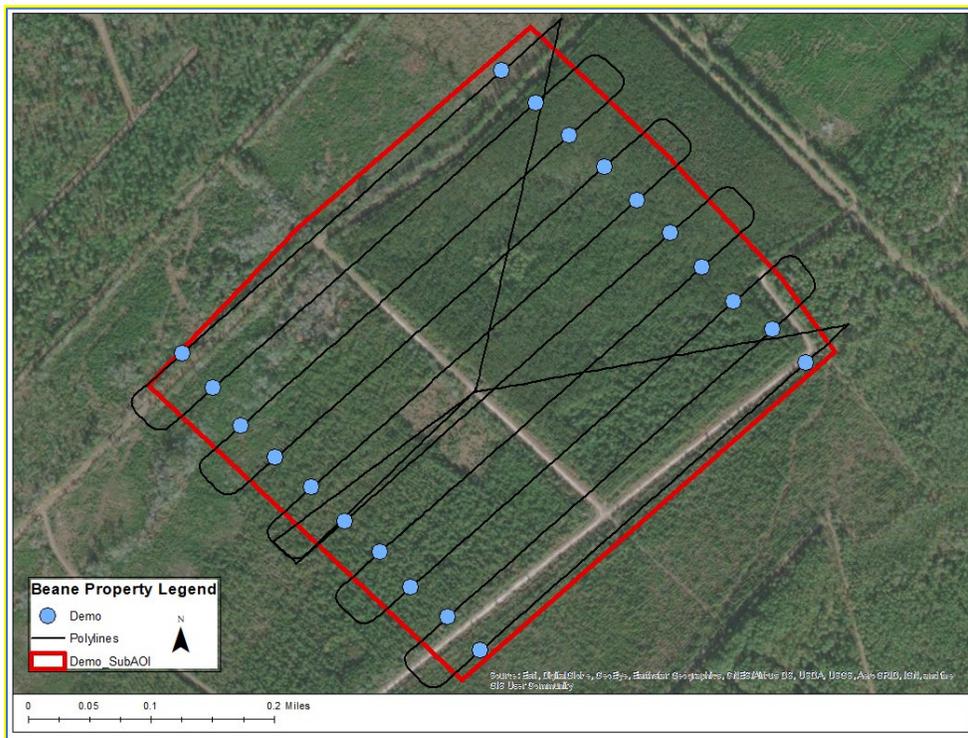
Ground Control Points (GCPs) are used to align collected UAS data to known GNSS locations to improve the accuracy of the data in post-processing. Cardboard targets will be placed to measure GCPs in a RTK system. In terms of acquiring LiDAR data, it is recommended to place GCP targets right below the flight path to get the best end results.

### 3.1: Tips for Layout

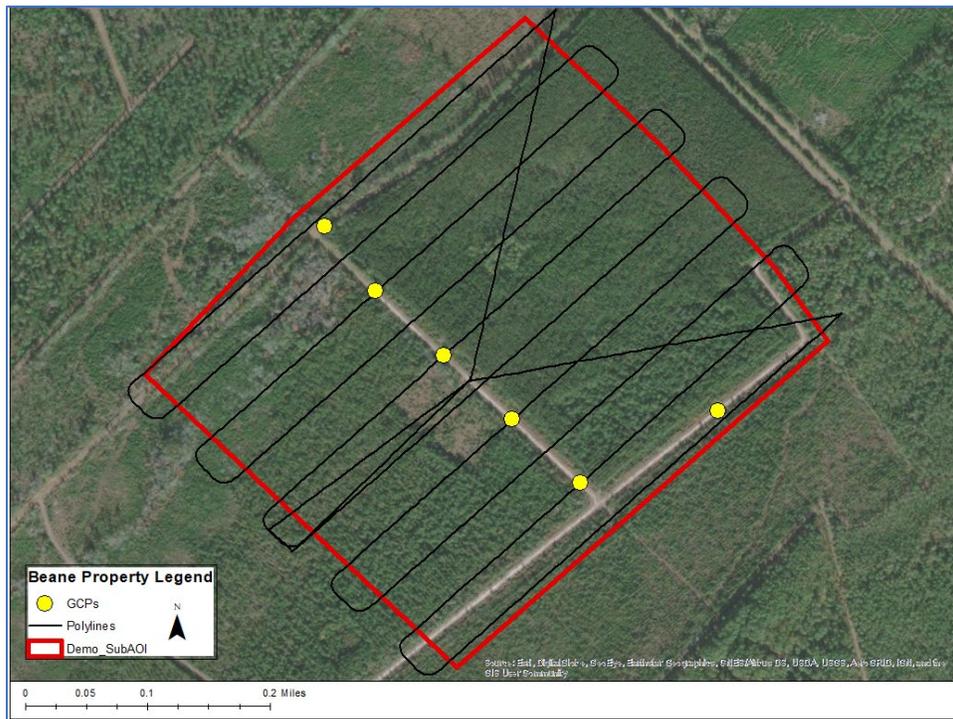
- Ideally GCPs on each end of the flight path
- Minimum of 5-7 points
- Check out for the accessibility and the owners
- Spread out evenly within the AOI

### 3.2: Target Location

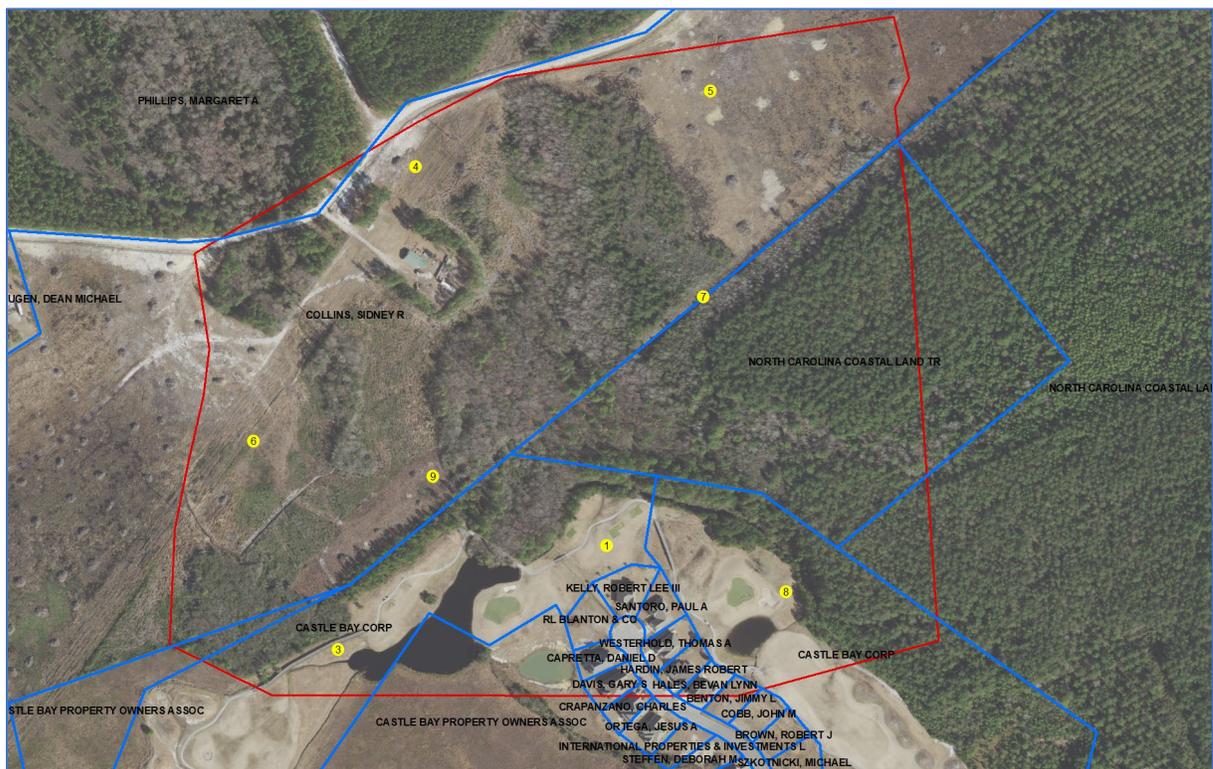
Target location should be directly below the flight path of drone to have the least error when processing the LiDAR data. As described above, the targets should be placed as much as possible on flight paths as shown in the image below.



If not possible due to the accessibility, you can use less targets like the image below.



Once the location of target is decided, add XY coordinate system and export it into a csv file to import into a Trimble unit. Also, you may want to check with property owners to get permission for your target to put down.



### 3.3: Things You Need to Start

Line Data: Flight path of UVA

Polygon Data: Area of Interest (AOI)

Coordinate System: "NAD\_1983\_StatePlane\_North\_Carolina\_FIPS\_3200" in meters

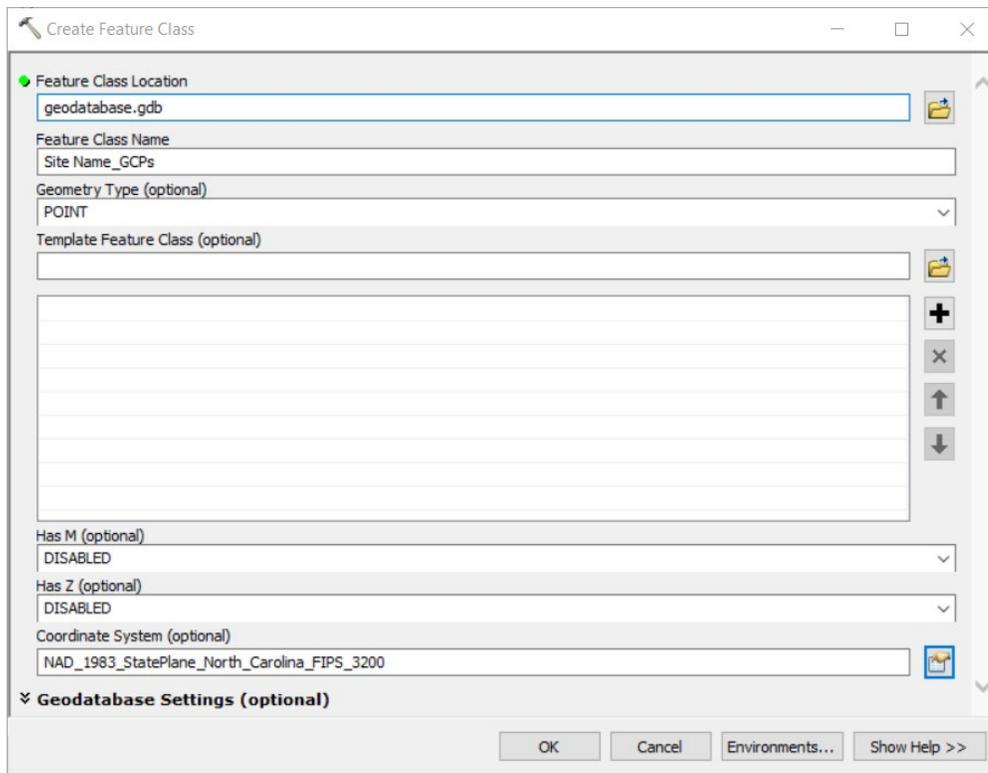
### 3.4: Generation of checkpoints

#### 1. Open ArcMap and Add Data

Open ArcMap and add AOI and flight path data.

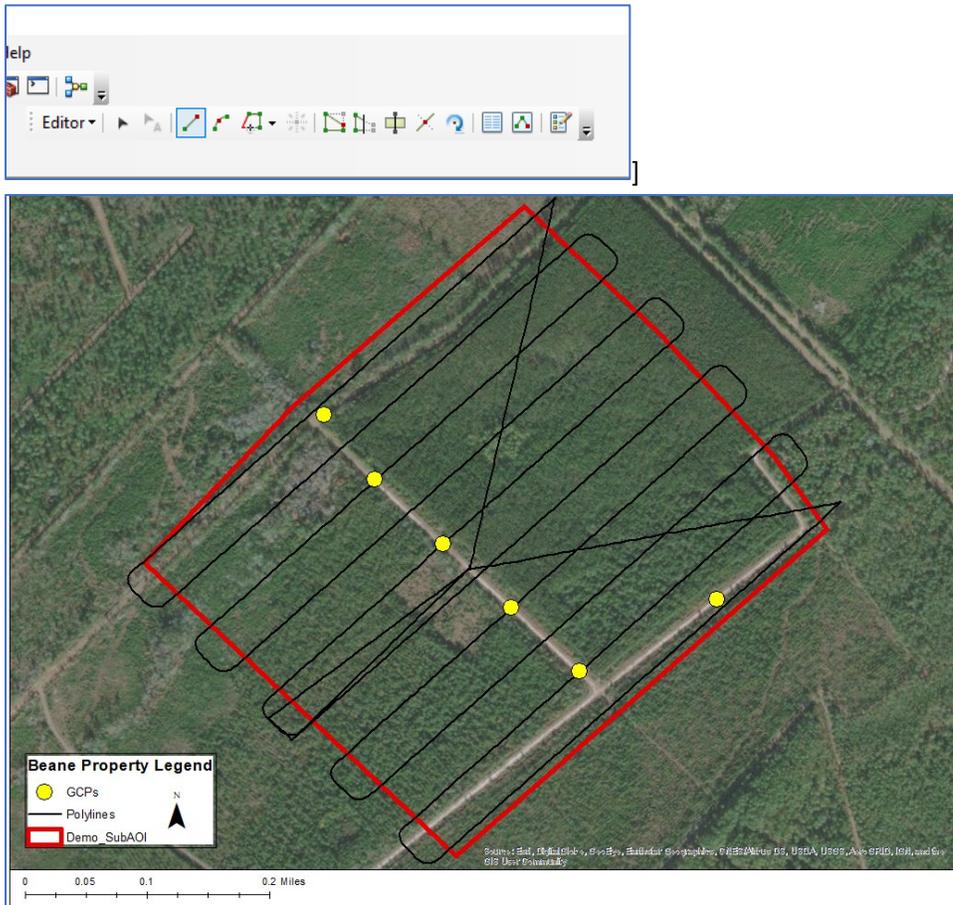
#### 2. Create point feature

Using a **"Create Feature Class"** to create an empty point data



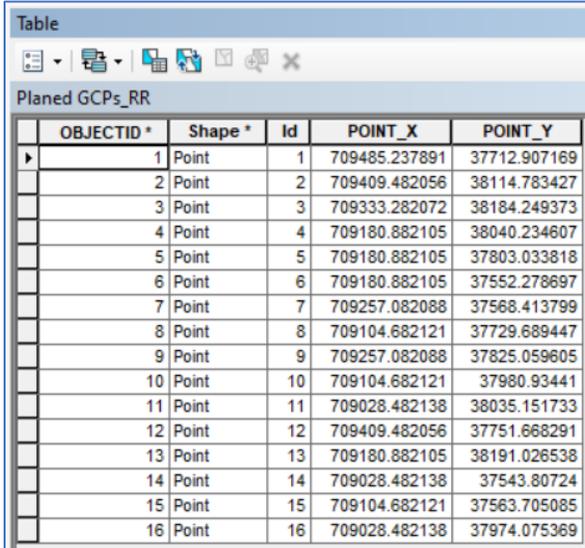
### 3. Edit Point Feature

Go to “**Edit Features**” -> “**Start Edit**” to start placing points where you plant to place targets.  
When done editing, click “**Editor**” -> “**Save Edits**” and “**Stop Editing**”.



4. Add XY Coordinate

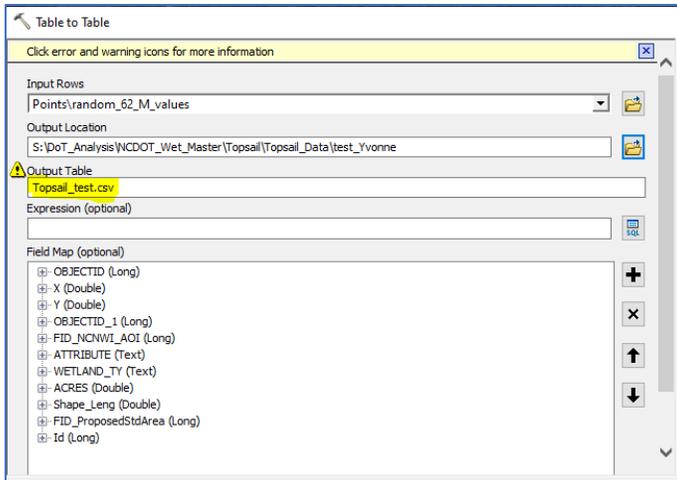
Use “**Add XY Coordinates**” to add XY coordinates. Make sure the points have the correct coordinate system: “NAD\_1983\_StatePlane\_North\_Carolina\_FIPS\_3200” in meters.



The screenshot shows a table window titled "Table" with a toolbar at the top. Below the toolbar, the table name "Planed GCPs\_RR" is displayed. The table contains 16 rows of data, each representing a point. The columns are labeled as follows: OBJECTID\*, Shape\*, Id, POINT\_X, and POINT\_Y. The data is as follows:

OBJECTID*	Shape*	Id	POINT_X	POINT_Y
1	Point	1	709485.237891	37712.907169
2	Point	2	709409.482056	38114.783427
3	Point	3	709333.282072	38184.249373
4	Point	4	709180.882105	38040.234607
5	Point	5	709180.882105	37803.033818
6	Point	6	709180.882105	37552.278697
7	Point	7	709257.082088	37568.413799
8	Point	8	709104.682121	37729.689447
9	Point	9	709257.082088	37825.059605
10	Point	10	709104.682121	37980.93441
11	Point	11	709028.482138	38035.151733
12	Point	12	709409.482056	37751.668291
13	Point	13	709180.882105	38191.026538
14	Point	14	709028.482138	37543.80724
15	Point	15	709104.682121	37563.705085
16	Point	16	709028.482138	37974.075369

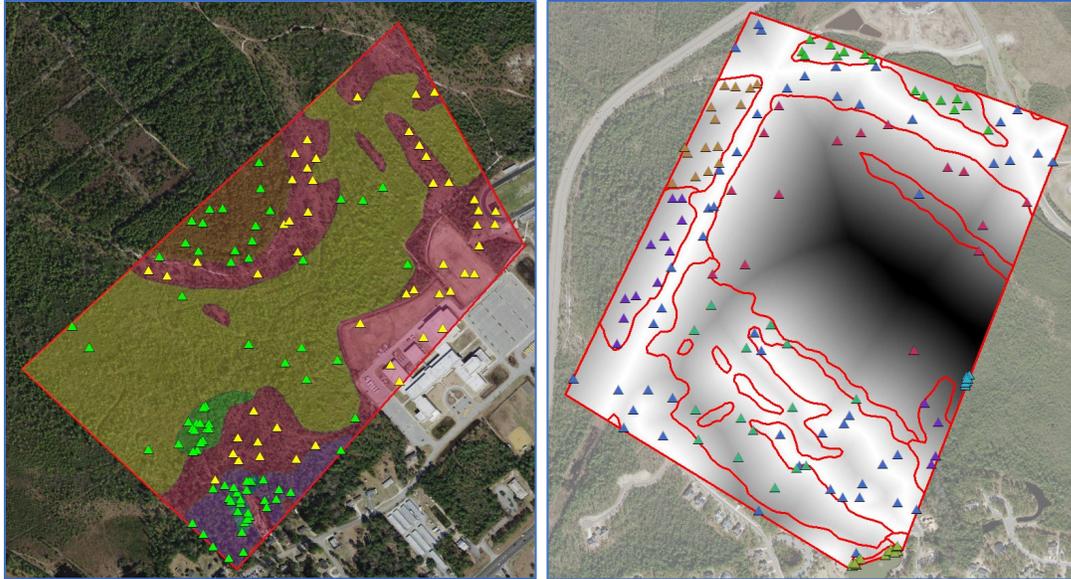
Use “**Table to Table**” to make this attribute table into CSV file. Make sure the data contains the object ID, XY coordinate system, and reference habitat type (ATTRIBUTE) at least. Save this outside of GDB as “---.csv”. These reference points are for Trimble to recognize. The column order has to be: **X – Y – Object ID – Code**



	A	B	C	D
1	709485.2	37712.91	1	GCP1
2	709409.5	38114.78	2	GCP2
3	709333.3	38184.25	3	GCP3
4	709180.9	38040.23	4	GCP4
5	709180.9	37803.03	5	GCP5
6	709180.9	37552.28	6	GCP6
7	709257.1	37568.41	7	GCP7
8	709104.7	37729.69	8	GCP8
9	709257.1	37825.06	9	GCP9
10	709104.7	37980.93	10	GCP10
11	709028.5	38035.15	11	GCP11
12	709409.5	37751.67	12	GCP12
13	709180.9	38191.03	13	GCP13
14	709028.5	37543.81	14	GCP14
15	709104.7	37563.71	15	GCP15
16	709028.5	37974.08	16	GCP16

## Section 4: GENERATION OF HABITAT POINTS (optional)

Here is one of the ways of how you can create habitat reference points in ArcGIS. Habitat points can be collected in order to help with final data classifications. We are going to show two different methods to create 15 random points (+ 50 points for only non-wetland area) for each habitat class based on NWI. Read "Create Random Points" and "Create Spatially Balanced Points" tools in Arc Help for more information.



Polygon Data: Area of Interest (AOI)

Polygon Data: NWI (National Wetland Inventory-2010)

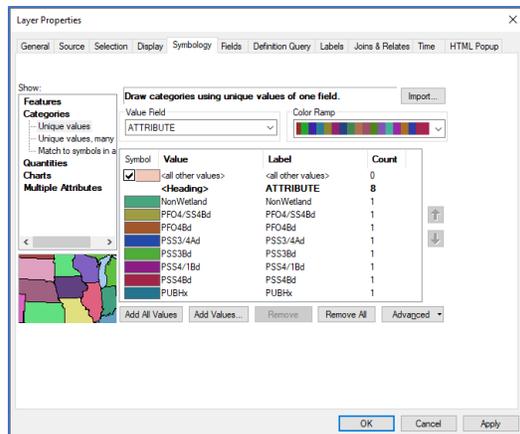
Polygon Data: NC WAM and Wet Master (if available)

Coordinate System: "NAD\_1983\_StatePlane\_North\_Carolina\_FIPS\_3200" in meters

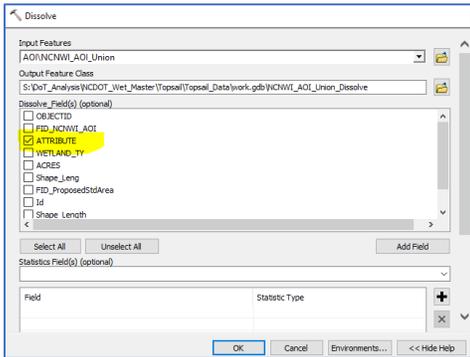
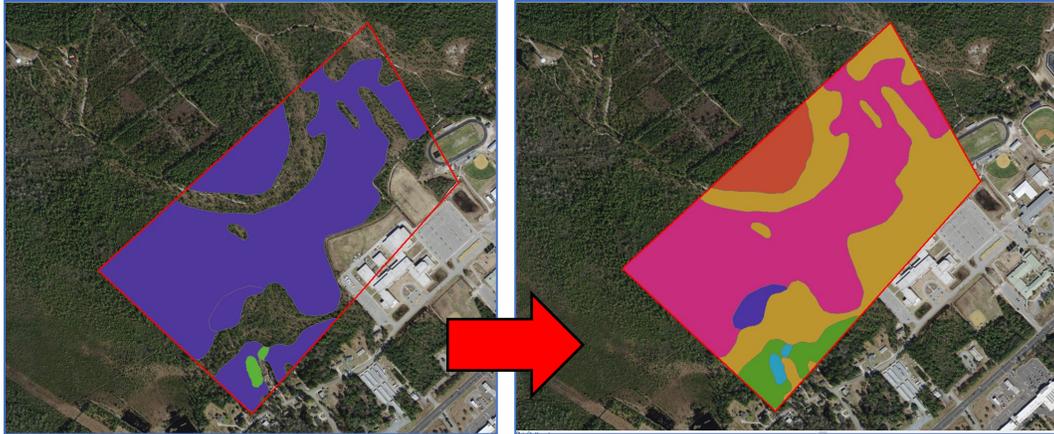
## 4.2: Generation of Habitat Points

### 6. Open ArcMap and Add Data

Open ArcMap and add AOI and NWI data. Change the symbology of NWI by going to Layer Properties. Click Symbology -> Categories -> ATTRIBUTE -> Add All Values. Always check the coordinate system as “NAD\_1983\_StatePlane\_North\_Carolina\_FIPS\_3200” in meters. If it’s not the right coordinate system, use “**Project**” tool to convert.



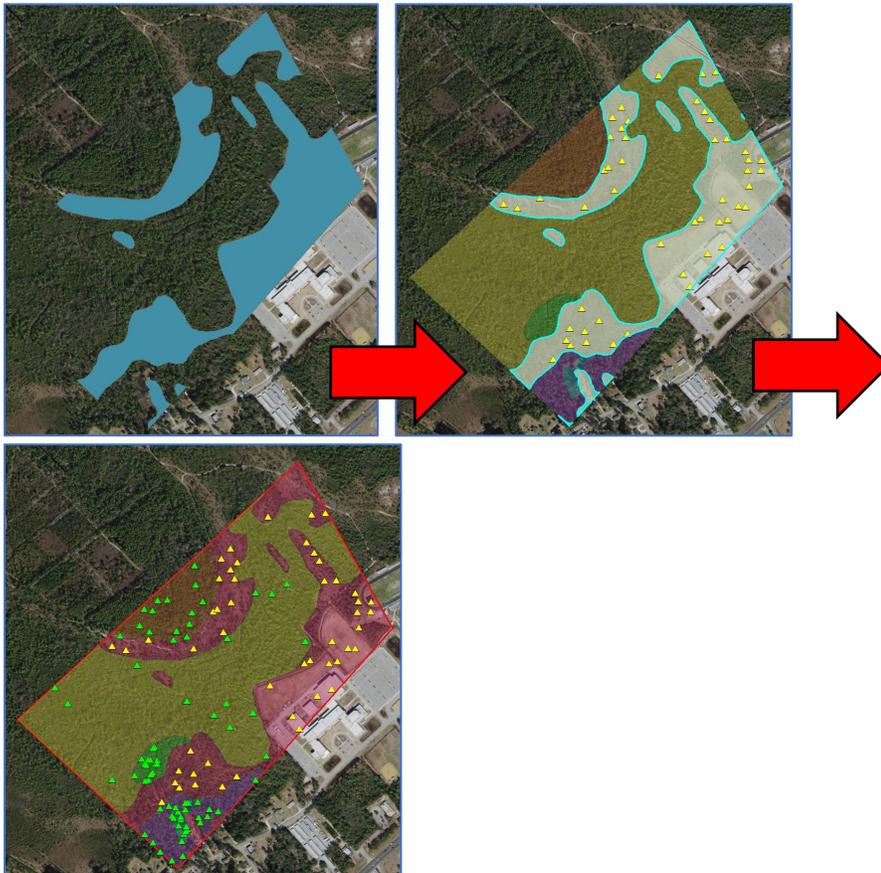
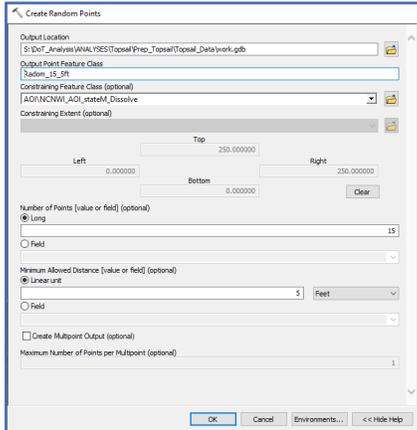
Use “**Clip**” (Analysis) to extract the NWI polygon that overlay the AOI. Use “**Union**” to union the NWI and study area polygon to fill in the non-wetland area. “**Dissolve**” the polygon by attribute. Open the attribute table and type “NonWetland” for the black column in ATTRIBUTE.



FID *	Shape *	ATTRIBUTE	Shape_Length
1	Polygon	NonWetland	9492.746394
2	Polygon	PFO4/SS4Bd	759.035656
3	Polygon	PFO4Bd	1803.015497
4	Polygon	PSS3/4Ad	1217.449954
5	Polygon	PSS3Bd	73.913066
6	Polygon	PSS4/1Bd	3460.375647
7	Polygon	PSS4Bd	4276.062979
8	Polygon	PUBHx	279.794501

## 8. Create Random Points (CRP)

As it was mentioned above, for non-wetland area 50 random points are going to be generated as this area includes more than one landcover class (built, upland grass, upland shrub, upland forest, open water, and other). Select only NonWetland polygon and run **“Create Random Points”** tool to generate 50 points. Then, select all wetland polygons to create 15 points for each of the class. Change the Linear unit accordingly.



## 9. Assess the Results

Look at the results along with the most recent imagery/map of the site and figure out if you can walk to the points. (Although if it is in dense forest, you would not collect the point data because the tree cover prevents the satellite network to come in) If so, skip to 6. If not, go to step 5 for the Spatially Balanced Points approach.

For example, you would not get to collect all points in the yellow area, so it is worth trying the Spatially Balanced Points approach.

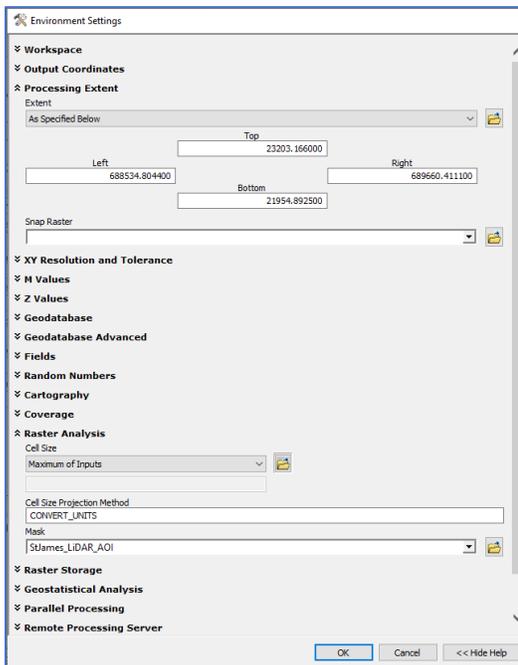
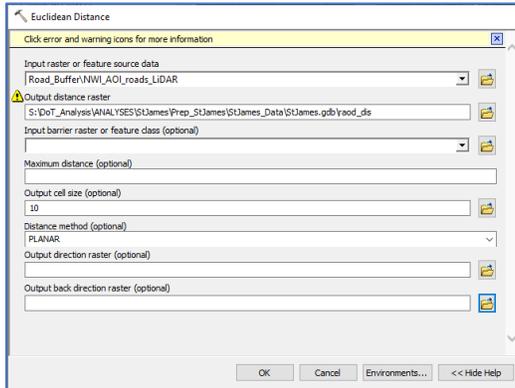


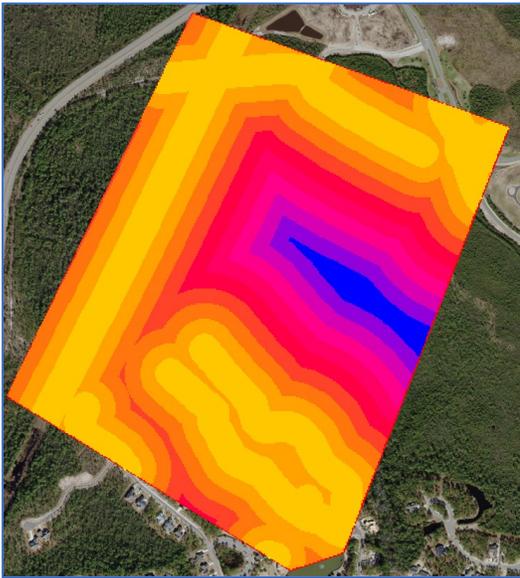
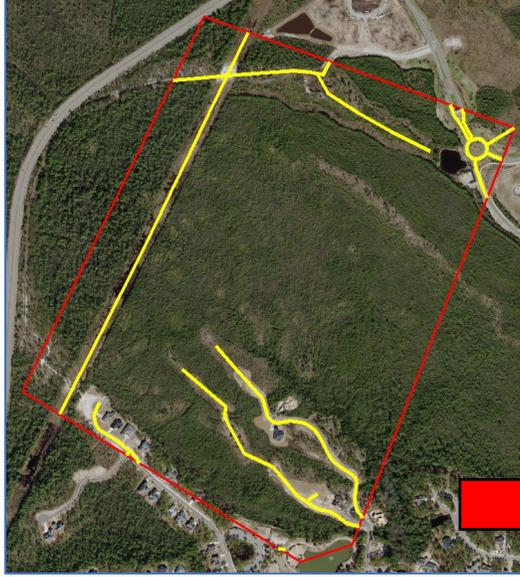
## 10. Spatially Balanced Points Approach

Here, we are starting over and create a weighted random sample using the Spatially Balanced Points approach where you increase the weight on access areas.

### a. Create a “Euclidean Distance” Raster based on a Line

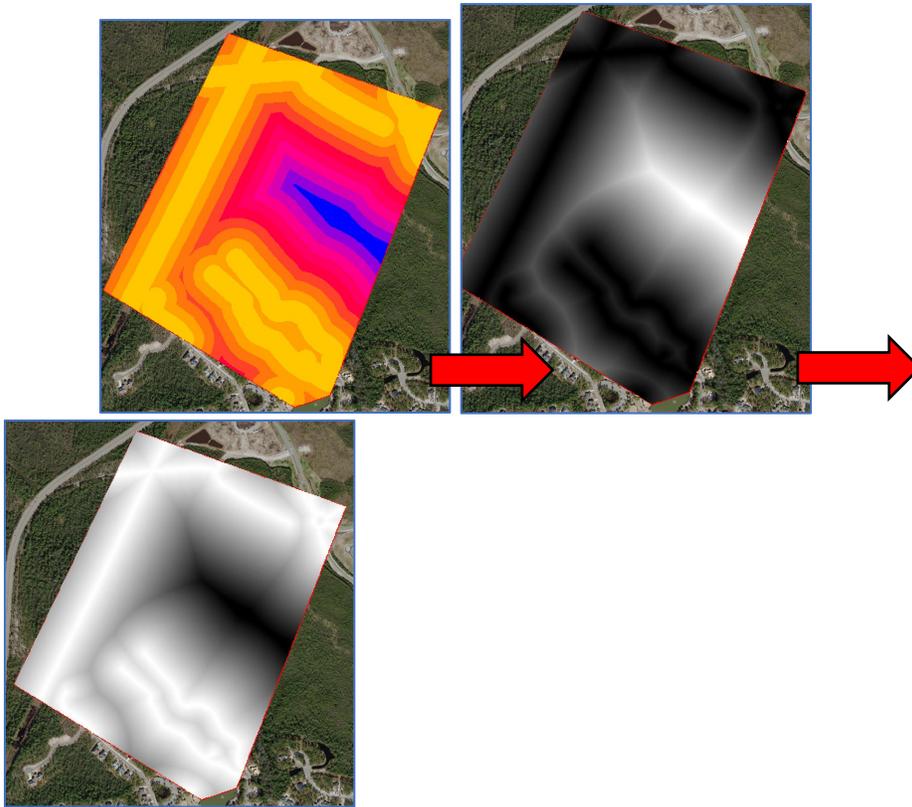
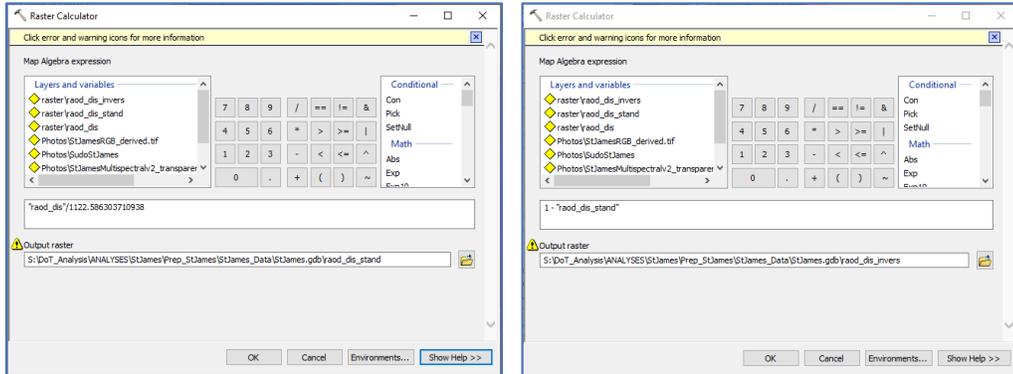
Create a line feature where it covers road and accessible areas and run a “**Euclidean Distance**” tool to create raster. In Environment settings, define the processing extent and raster analysis as study area (10 feet or 3 meters).





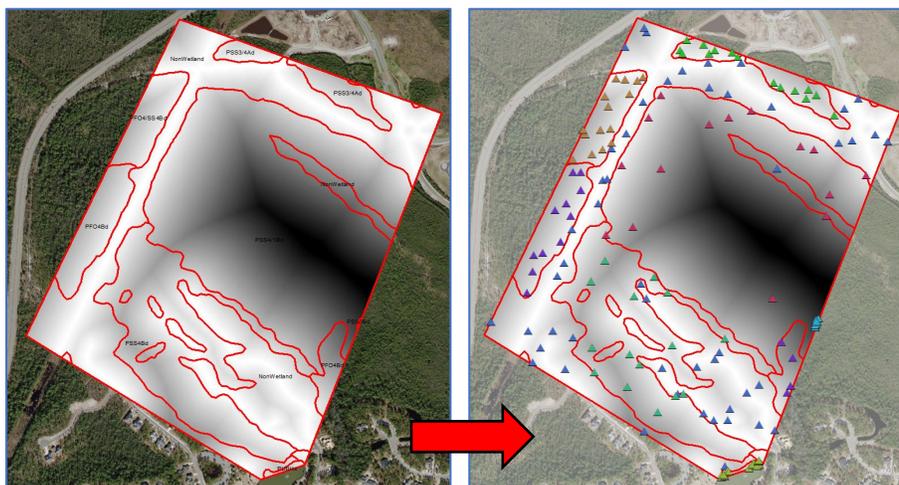
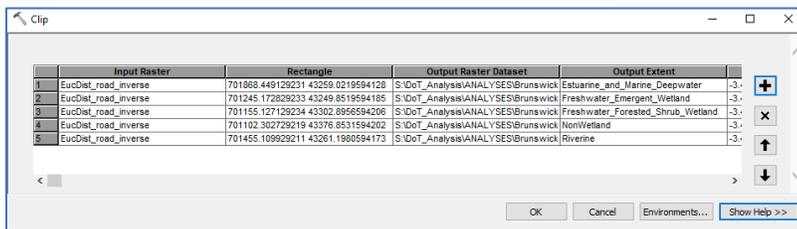
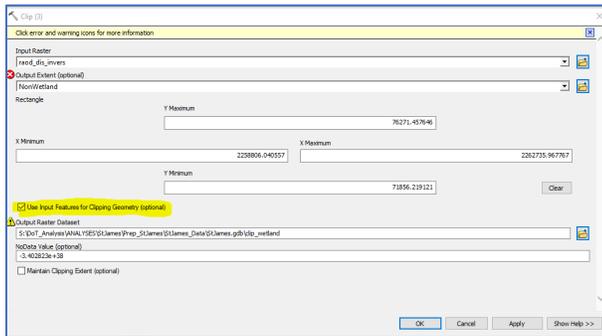
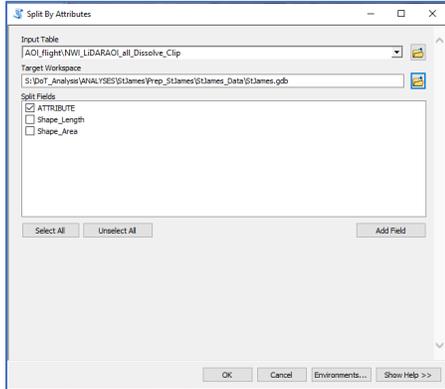
## b. Raster Calculator

Use “Raster calculator” tool to make the range from 0 – 1 (raster / max value). Use “Raster Calculator” tool again to inverse the value. E.g. 1 -> 0, 0 -> 1



c. Clip and Create Spatial Balanced Point (SBP)

Clip each of habitat types and run a “create spatially balanced point” for each of them. You can use this “Separate by Attribute” tool to break up the habitat polygon into each. Using batch would be a great way to save time.



## 11. Merge and Spatial Join

Merge all the generated points (by **SBP** or **CRP**). Use spatial join to extract attribute values to each point so that each point has a wetland code.

Join Data

Join lets you append additional data to this layer's attribute table so you can, for example, symbolize the layer's features using this data.

What do you want to join to this layer?

Join data from another layer based on spatial location

1. Choose the layer to join to this layer, or load spatial data from disk:

NCNW/AOI\_stateM\_Dissolve

2. You are joining: Polygons to Points

Select a join feature class above. You will be given different options based on geometry types of the source feature class and the join feature class.

Each point will be given all the attributes of the polygon that:

it falls inside.

If a point falls inside more than one polygon (for example, because the layer being joined contains overlapping polygons) the attributes of the first polygon found will be joined.

is closest to it.

A distance field is added showing how close the polygon is (in the units of the target layer). A polygon that the point falls inside is treated as being closest to the point (i.e. a distance of 0).

3. The result of the join will be saved into a new layer.

Specify output shapefile or feature class for this new layer:

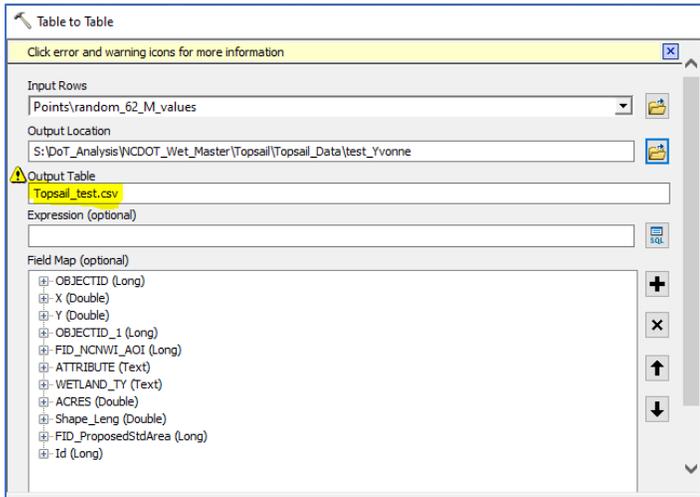
S:\DoT\_Analysis\ANALYSES\Topsail\Prep\_Topsail\Topsail\_J

[About joining data](#)

OBJECTID_1 *	Shape *	CID	ATTRIBUTE
58	Point	2	PEM1F
59	Point	2	PEM1F
60	Point	2	PEM1F
61	Point	2	PEM1F
62	Point	2	PEM1F
63	Point	2	PEM1F
64	Point	2	PEM1F
65	Point	2	PEM1F
66	Point	3	PFO4/1Cd
67	Point	3	PFO4/1Cd
68	Point	3	PFO4/1Cd
69	Point	3	PFO4/1Cd
70	Point	3	PFO4/1Cd
71	Point	3	PFO4/1Cd
72	Point	3	PFO4/1Cd
73	Point	3	PFO4/1Cd
74	Point	3	PFO4/1Cd
75	Point	3	PFO4/1Cd
76	Point	3	PFO4/1Cd

12. Add XY Coordinate and Convert to CSV file

Use “**Add XY Coordinates**” to add XY coordinates. Make sure the points have the correct coordinate system: “NAD\_1983\_StatePlane\_North\_Carolina\_FIPS\_3200” in meters. Use “**Table to Table**” to make this attribute table into CSV file. Make sure the data contains the object ID, XY coordinate system, and reference habitat type (ATTRIBUTE) at least. Save this outside of GDB as “----.csv”. These reference points are for Trimble to recognize.



Edit the CSV file. Make sure to get rid of the headers and other unnecessary data. Order has to be: X – Y – Object ID – Habitat type

	A	B	C	D	E
1	688871.6	22962.26	1	PFO4/SS4Bd	
2	688850.3	22898.25	2	PFO4/SS4Bd	
3	688966.1	23041.51	3	PFO4/SS4Bd	
4	688917.3	23035.41	4	PFO4/SS4Bd	
5	688777.1	22819	5	PFO4/SS4Bd	
6	688877.7	22901.3	6	PFO4/SS4Bd	
7	688856.4	22846.43	7	PFO4/SS4Bd	
8	688892.9	23038.46	8	PFO4/SS4Bd	
9	688810.6	22886.06	9	PFO4/SS4Bd	
10	688950.9	23032.36	10	PFO4/SS4Bd	
11	688862.5	22989.69	11	PFO4/SS4Bd	
12	688804.6	22898.25	12	PFO4/SS4Bd	
13	688929.5	22995.79	13	PFO4/SS4Bd	
14	688880.8	22864.72	14	PFO4/SS4Bd	
15	688828.9	22834.24	15	PFO4/SS4Bd	
16	688777.1	22785.47	16	PFO4Bd	
17	689356.2	22188.06	17	PFO4Bd	
18	689371.5	22282.55	18	PFO4Bd	
19	688652.2	22459.34	19	PFO4Bd	
20	688694.8	22566.02	20	PFO4Bd	
21	688798.5	22785.47	21	PFO4Bd	
22	688728.4	22681.84	22	PFO4Bd	
23	688758.8	22700.13	23	PFO4Bd	
24	688743.6	22596.5	24	PFO4Bd	
25	689365.4	22206.35	25	PFO4Bd	

## Section 5: IMPORT DATA to TRIMBLE ACCESS

Here is to show how to import data to Trimble unit. The Trimble data controller uses a single shapefile (.shp) as a background image. Bringing in .shp files will make fieldwork much easier. Here, we will use R10 unit as an example. Depending on the unit, the appearance might look different. To find out more information, go to the additional files and read “TrimbleAccess\_Projects\_and\_Jobs”.

### 5.1: Things You Need to Start

Trimble Units for GCPs and Habitat Points

(We have 2 units R8 – TSC3, and R10 – TSC7)

In USB Drive

[CSV File: GCPs Data](#)

[CSV File: Habitat Data](#)

Point Shape File: Habitat data

Point Shape File: GCPs Data

Point Line: Flight Path

Polygon Shape File: NWI of AOI

Shape File: NC County Boundary

\*Shape files can be obtained when you save the layer in ArcMap outside of geodatabase

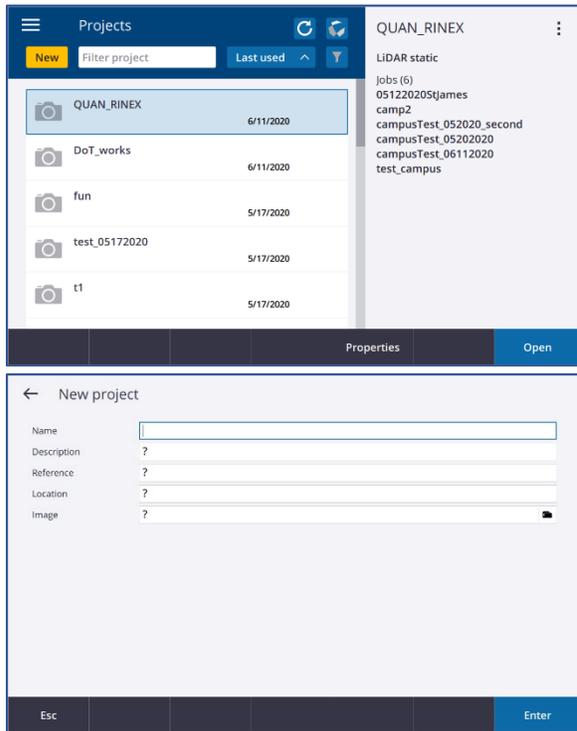


 BNP_GCPs.csv	Microsoft Excel C...
 BNP_habitat.csv	Microsoft Excel C...
 BNP_GCPs_7.shp	SHP File
 BNP_NWI.shp	SHP File
 BNP_trails.shp	SHP File
 nc_county_spm.shp	SHP File
 SBP_BNP_habitat_110.shp	SHP File

## 5.2: Data Import (R10)

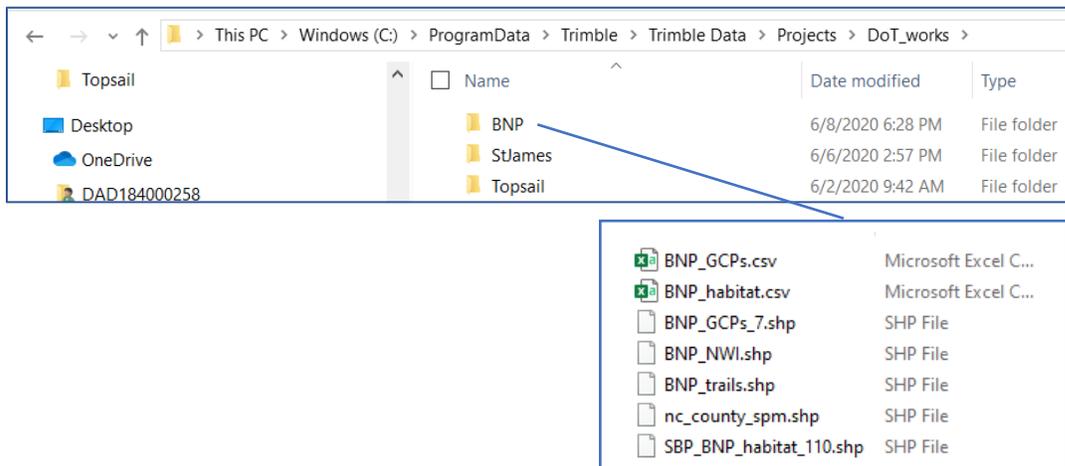
### 1. Open Trimble Access App

Turn on the Trimble unit and open **Trimble Access**. Then, this window (this might be different depending on the version) should pop up. Click **“New”** to create a project, which is a folder for grouping Trimble Access jobs and the files used by those jobs. Here, I already have created project named **“DoT\_works”**.



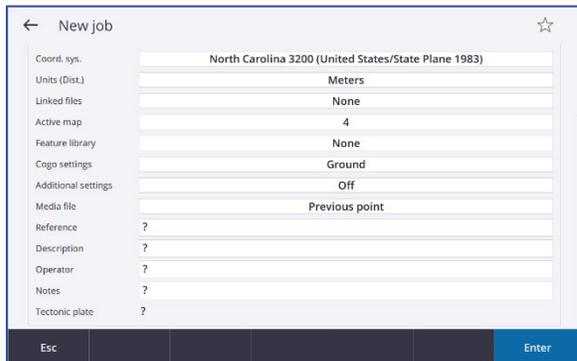
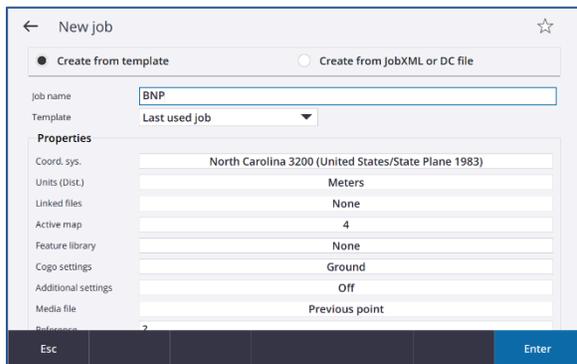
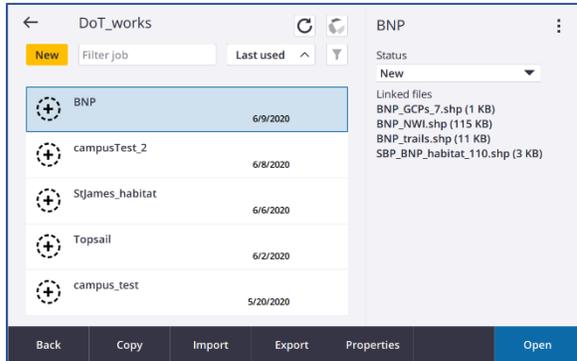
After creating a project, the **“DoT\_works”** file should be created under here:

**“C:\ProgramData\Trimble\Trimble Data\Projects”**. In **“DoT\_works”**, create a site name folder like **“BNP”**. Inside this, paste all the necessary data that you have created for fieldwork.



### 3. Create a job

Come back and open the “DoT\_work” project in Trimble Access and hit “New” to create a **job**. Fill out in a “New job” window. Select “Last used job” for template if you wish to inherit the properties from previously used project.



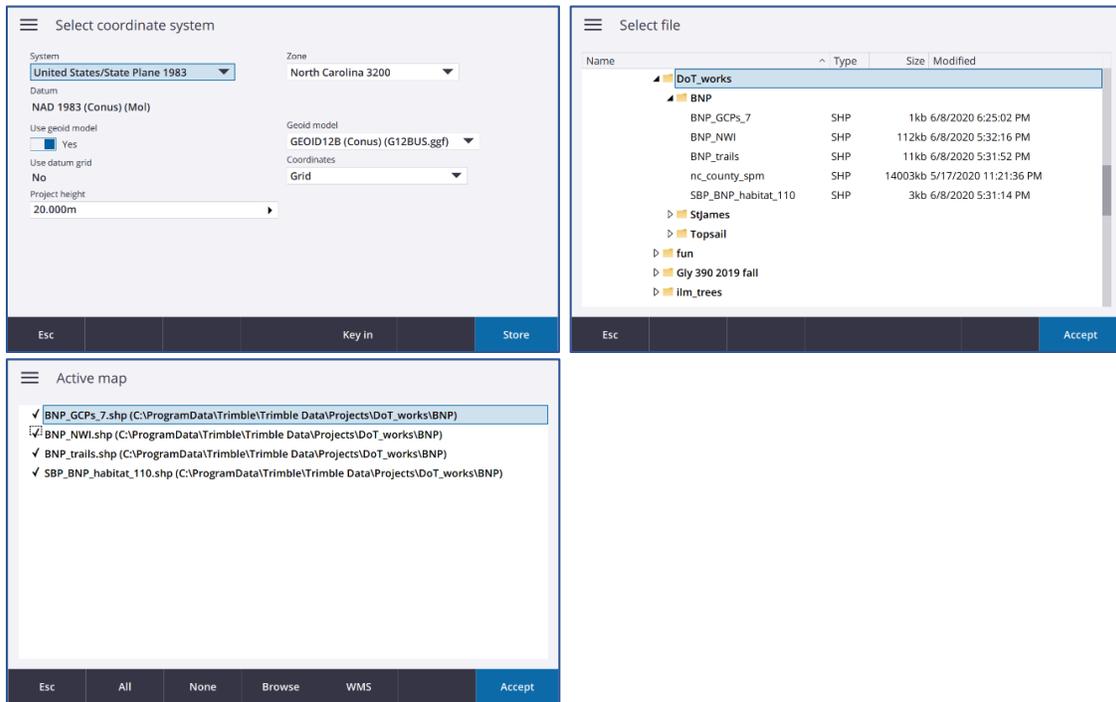
Then we hit the import button.

#### 4. Job Setting

Clicking “**coordinate system**” under “**Properties**” will lead you to a “**Select coordinate system**” window. Here, the coordinate system should be the same as that of .shp files you imported.

Start entering “**Active map**” where you connect to the .shp files. In “Active map” window, hit “Browse” to select .shp files you wish to bring in. Once you bring all the data to Active map, make sure to check the boxes right next to the names.

When all the setting is done, choose “**Accept**” and the map with features will be created.



## 5. Import CSV Files

From the job page – select **Import**. For “File name”, use the folder icon to navigate to your project file location and select the .csv file (GCPs and habitat point csv files). Click “**Accept**” to process with the import. You should receive a Transfer Complete message. The imported points can be reviewed using the point properties. Open job -> Select Job data -> select Point Manager.

That is all for importing data. The interactive map with features should be projected.

The image displays three screenshots of a mobile application interface, likely for field data collection or management.

**Top Screenshot: Job List**  
The interface shows a list of jobs under the heading "DoT\_works". The jobs listed are:

- BNP (6/9/2020)
- campusTest\_2 (6/8/2020)
- StJames\_habitat (6/6/2020)
- Topsail (6/2/2020)
- campus\_test (5/20/2020)

On the right, the "BNP" job is selected, showing its status as "New" and a list of linked files:

- BNP\_GCPs\_7.shp (1 KB)
- BNP\_NWL.shp (115 KB)
- BNP\_trails.shp (11 KB)
- SBP\_BNP\_habitat\_110.shp (3 KB)

At the bottom, there are navigation buttons: Back, Copy, Import, Export, Properties, and Open.

**Middle Screenshot: Import Settings**  
The "Import" screen allows configuration of file import settings:

- File format: Comma Delimited (\*.CSV, \*.TXT)
- Point name: Field3
- Northing: Field2
- Elevation: Unused
- Duplicate point action: Overwrite
- File name: ?
- Point code: Field4
- Easting: Field1
- Null elevation: ?

An "Esc" button is visible at the bottom left.

**Bottom Screenshot: Map View**  
The map view shows a geographic area with numerous points plotted. The points are labeled with numbers and codes, such as "GCP\_3", "G2", and "Base\_parking". A scale bar indicates 500m. The interface includes a toolbar on the left with various map interaction tools and a "Measure" button at the bottom right.

## Section 6: EQUIPMENT CHARGE AND CARE

Here is how to take care of equipment UNCW Research Team uses for the LiDAR data collection. This includes charging/ discharging, and field work checklist.

### 6.1: Charging List

LiDAR System

DJI Matrice Battery (18) and  
Controller



iPad



Quanergy sensor LiPo Battery  
(4)



eBee System

Charge/discharge LiPo  
batteries (4)

Full (100%) – before flight

Storage (70%) – when stored

Computer



### Trimble System

MiFi (2)



Rover Battery

(2 sets \* n Trimbles)



Tablets (\* n Trimbles)



### Additional Tech

Walkie-talkies (2)



## 6.2: Charge DJI Matrice Batteries and Controller

### 1. Battery and Controller

Take out a battery box from the bottom of DJI, controller, and battery codes.

### 2. Charge Equipment

Set it up like the photo below to start charging. When charging, the batteries' lights will flash. When fully charged, they stop flashing. Push the button to see all four bars flash to make sure it is all charged. It will take about 2 hours for 6 batteries to be 100% charged.



### 6.3: Charge Quanergy Sensor Battery

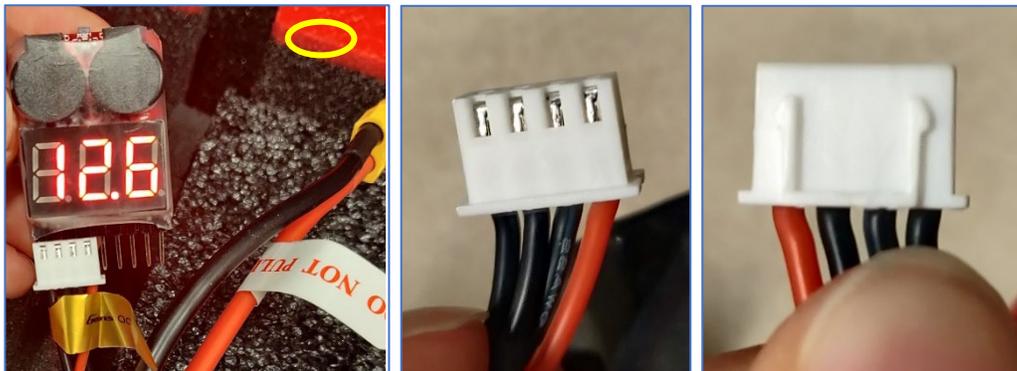
#### 1. Lipo Battery

There are 2 sets of 2 LiPo batteries (4 total). They should be always in storage charged (70%) except before the flight in fully charged (100%). For more info about lipo battery (<https://www.instructables.com/Lithium-Polymer-Etiquette/>)



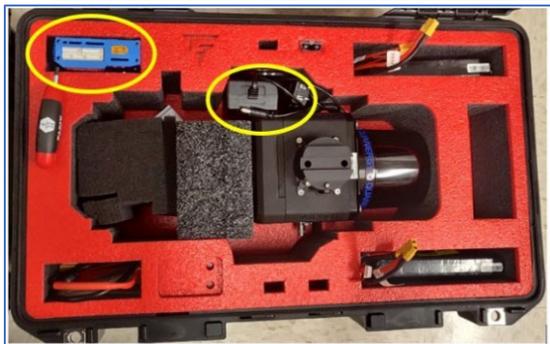
#### 2. Measure Voltage

Before charging, measure the voltage with this small device. Use the balancing cable (white one) with the arrows facing down. When it shows **12.6**, it is fully charged. Make sure you put it on the left side with the correct face up.



#### 3. Equipment

Use this blue charger and code to charge the LiPo batteries.



4. Plug in Balancing Cable

Plug in the white balancing cable **first** and the yellow power cable next. Put the balancing cable in with arrows facing up in a **3 cells space**.



5. Start charging

Hold a start button to check the battery and press start again to confirm charging. It beeps when fully charged. This is what it looks like when fully charged. Push the stop button twice

to get back to the main menu. Unplug the **yellow cable first**, then the white cable next.



## 6.4: Charge eBee Lipo Battery

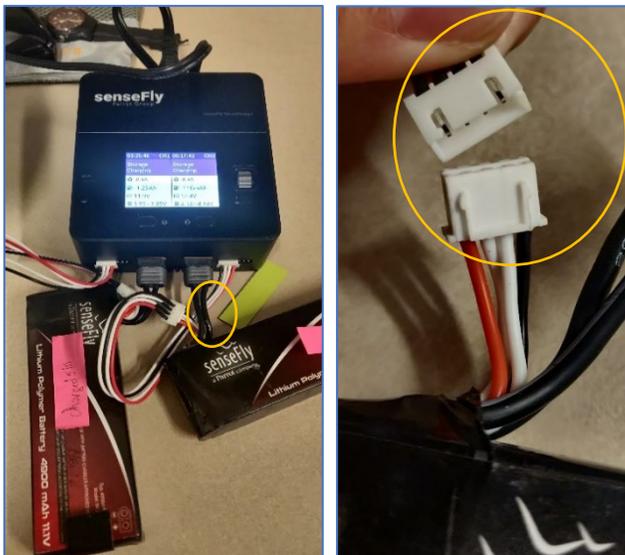
### 1. Charge Types

There are a few different types of charge for eBee charger. Know when the next flight will be and decide which to use.

- a) **Full (100%)**: fully charge before a flight
- b) **Storage (70%)**: set it storage charge when you do not plan to fly for a while

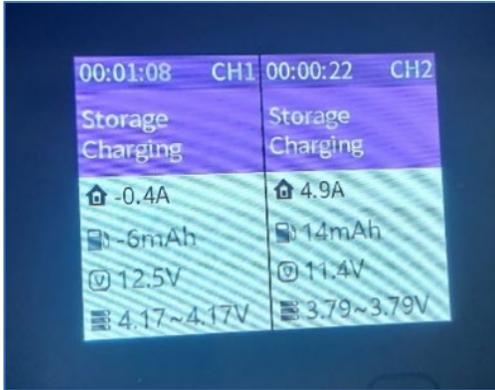
### 2. Plug in

After plug in, connect the balancing cable to the female with the correct way first, and the black powering cable next.



### 3. Setting Up

Click down on the wheel to select: **eBee Plus > full or storage charge**. Discharging takes much more time than charging. One thing to know is the voltage. When it is fully charged, it should be close to 12 V. They will beep once fully charged.



## 6.5: Charge Trimble System

### 1. Charge MiFi

Charge like a normal phone.



### 2. Rover Batteries

Depending on the version of Trimble, the battery may look different. The way to charge them is the same.



## 6.6: Equipment Checklist (EXAMPLE)

Pilot-in-command: _____	Check-out ( _ / _ / _ )	Check-in ( _ / _ / _ )
<b>senseFly eBee Plus</b>		
eBee drone		
cameras: SODA, Sequoia, ThermoMap, Zenmuse		
batteries (4)		
smart charger		
regular charger		
radio modem		
extra skid plate		
extra wings		
repair kit (includes extra props, rubber bands, & tape etc)		
registration + GCPs + CHECK POINTS		
<b>Mavic Pro drones</b>		
Mavic Pro Platinum drone		
Mavic Pro Platinum controller & cords		
Mavic Pro drone (oldest)		
Mavic Pro controller & cords		
batteries (5)		
charger		
extra props		
registration		
<b>Mavic Pro drones</b>		
Mavic 2 Pro drone (orange)		
Mavic 2 Pro controller & cords (orange)		
batteries (3) (orange)		
Mavic 2 Pro drone (purple)		
Mavic 2 Pro controller & cords (purple)		
batteries (3) (purple)		
Smart charger for Mavic 2 Pros		
extra props		
registration		
<b>DJI Matrice 600 Pro &amp; Quanergy LiDAR: 3 BOXES TOTAL</b>		
Matrice hexacopter drone (big box)		
Matrice controller & cords + Mini iPad! + charger (big box)		
Box of 3 sets of 6 batteries: 18 total (heavy, small box)		
Quanergy M8 LiDAR (second small box)		
Quanergy M8 battery charger and 2 sets of Lipo batteries (4 total)		
Extra props		
registration		
<b>Additional tech &amp; equipment</b>		
walkie-talkies (2)		
walkie-talkie charger		
LAPTOP, charger, and mouse		
memory cards (one for each drone plus one extra)		
mini SD card converter		
SD-USB adaptor		
power inverter		
phone chargers for field		

<b>Documents</b> FAA Pilot cards flight plans, maps, etc RTK SYSTEM AND ADDTL GPS		

## Section 7: TRIMBLE – HOW TO CREATE AND BEGIN A STATIC SURVEY

A static survey collects GNSS (Global Navigation Satellite System) to improve the LiDAR data in the post-processing.

### Components

Trimble Set (quick release adopter, mount, connection cable,  
Trimble Unit  
Tripods

#### 7.1: Select a Base Station

For good performance, place the GNSS receivers in a protected and secure location. Do not set up the base station directly beneath or close to overhead power lines or electrical generation facilities. The electromagnetic fields associated with these utilities can interfere with GNSS receiver operation. For more information, visit here: [R10 GNSS - User Guide](#) (pg. 36 - )

#### 7.2: Trimble Setup

One of the common ways to set up the base station is to use a tripod.



1. Attach Adaptor/ Rover to Pole

Mount the quick release adapter onto the height extension pole with measurement lever.  
Attach the GNSS receiver to the quick release adapter.



2. Attach the Tripod Leg

Attach the tripod legs onto the pole, and level the bubble onto the center.

3. Attach Mount

Attach the mount to the pole.



#### 4. Connect Epoch Cable

For static survey, you want to connect GNSS via a cable. Connect the epoch cable to the rover and the tablet. Make sure to connect the cable to the rover matching with the red marks.



### 7.3 How to create a static survey using a Trimble RTK system – R8 & R10

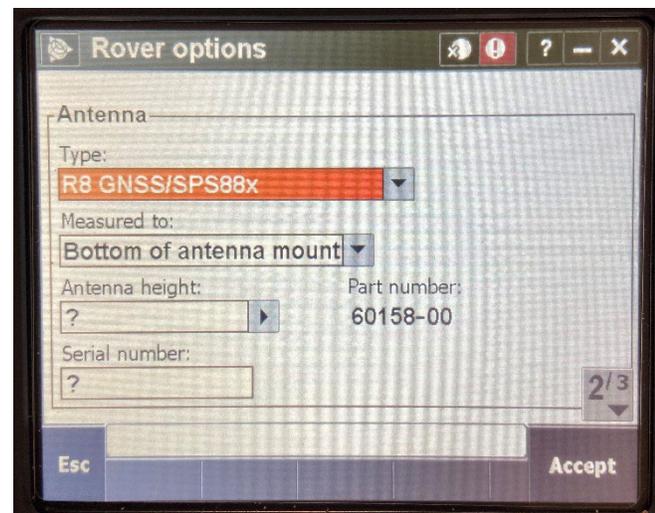
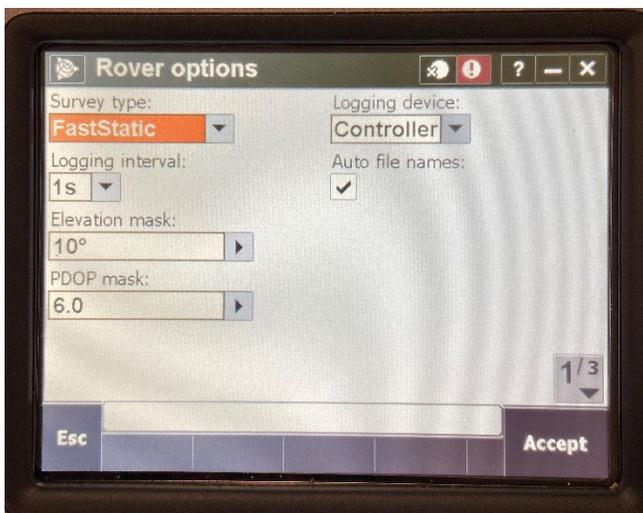
#### R8 instructions

Creating a new static survey on the TSC3 handheld model for R8 Trimble requires a new project folder to be created in the static style.

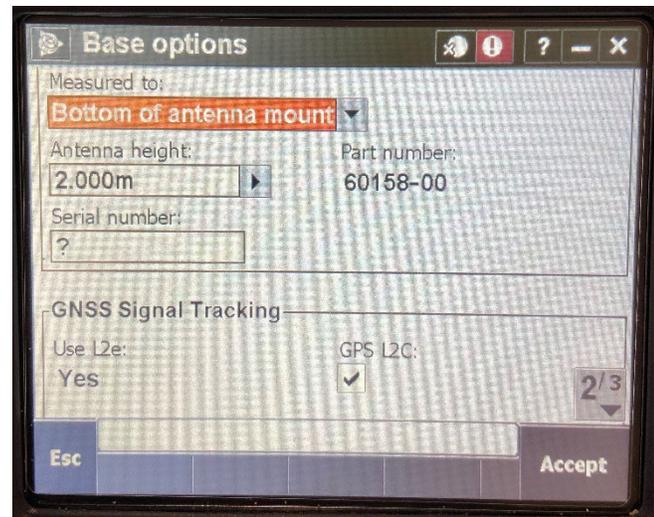
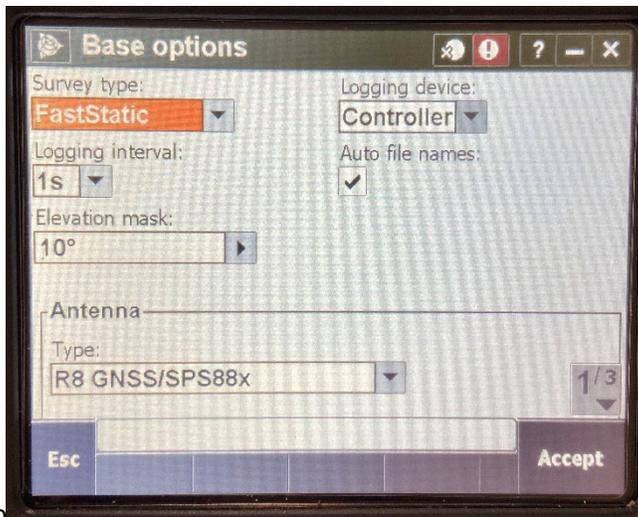
1. **Open Trimble Access Menu → Click Settings → Survey Styles → Create New (Add Name and Style Type- GNSS) → Accept**

For the next steps, “Rover options” and “Base options” parameters will need to be defined for survey style to function.

2. **Rover options → Define Parameters → Accept**



3. **Base Options → Define Parameters → Accept → Store**



R10 instructions

Creating a new static survey on the TSC7 handheld model for R10 Trimble requires a new project folder to be created. In the new project folder, jobs can be created with outlined parameters to start a static survey. The general workflow to create a project folder is as follows:

1. Open Trimble Access and navigate to projects menu
2. Tap “New” on the top left under the three horizontal bar menu button  
**Add in project folder details → Create New Job → Tap Coordinate System → Fill in associated parameters (example below) → Job created and ready to use in static survey**

#### 7.4: How to Start Static Survey – R8

To get the best accuracy of GNSS data, it is recommended to run the static survey at least for 20 minutes before you start your UAV flight.

1. Open Trimble Access  
Open “Trimble Access” in your tablet. Select: **General survey -> open job -> Quan\_Rinex -> select measure -> drone static -> measure points**

## 2. Setups for Drone Statics

You will be required to fill in the survey settings here:

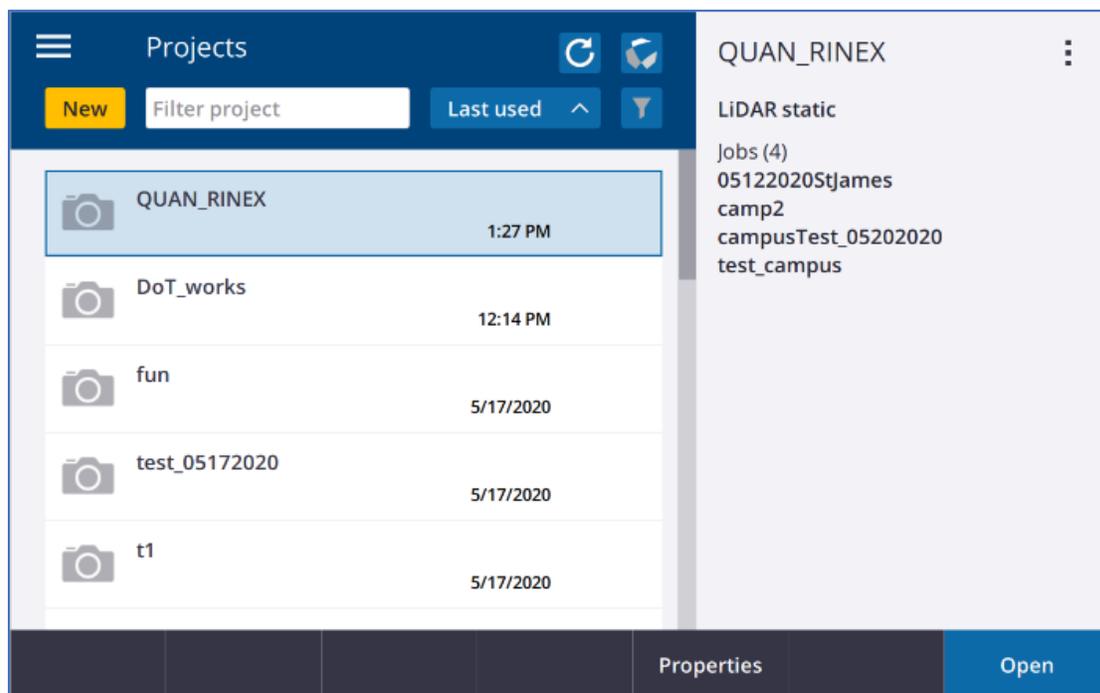
- a. Point name: "Topsail"
- b. Method: FastStatic point
- c. Antenna height: 2 m
- d. Measured to: bottom of antenna mount

Then, hit to measure.

## 7.5: How to Start Static Survey – R10

### 1. Open Trimble Access

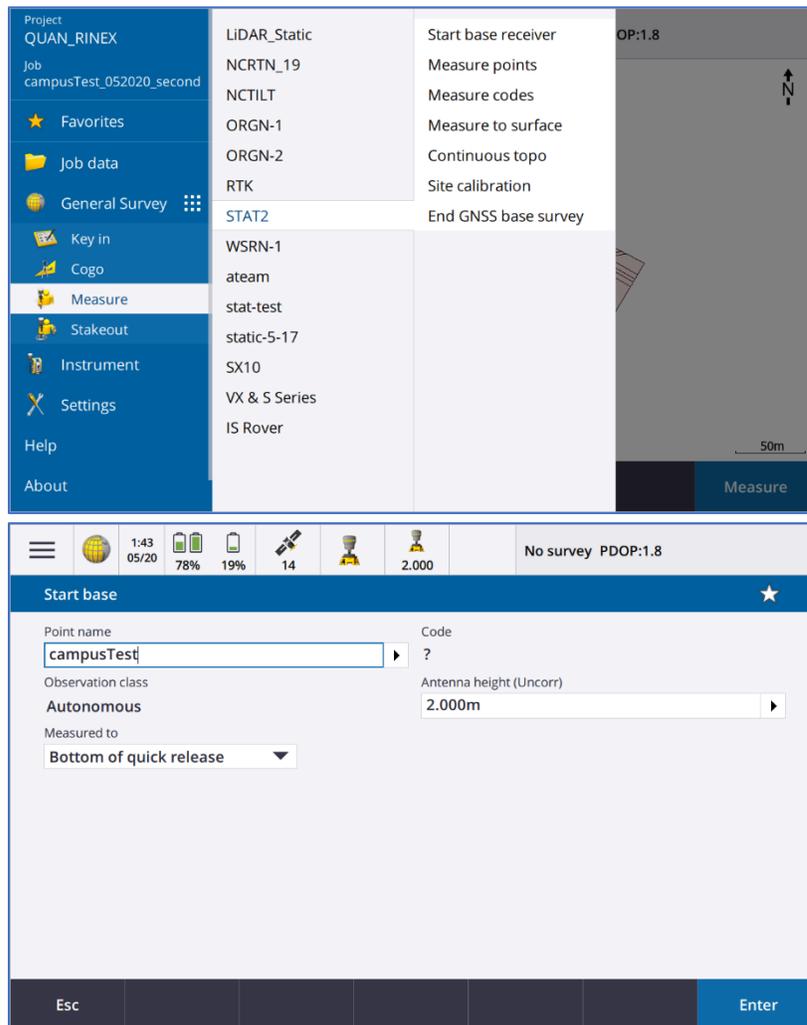
Open "Trimble Access" in your tablet. Open "QUAN\_RINEX" project. Create a new job by clicking the "New" tab.





### 3. Start Your Survey

Once you have created your job, it is ready to start your static survey. Navigate to: “Measure” -> “STAT2” -> “Start Base Receiver”. “Start Base” window will pop up.



For “Start Base”,

- a. Point name: “CampusTest”
- b. Measured to: Bottom of quick release
- c. Antenna height: 2 m

Press enter. You can ignore the warning sign, then start.

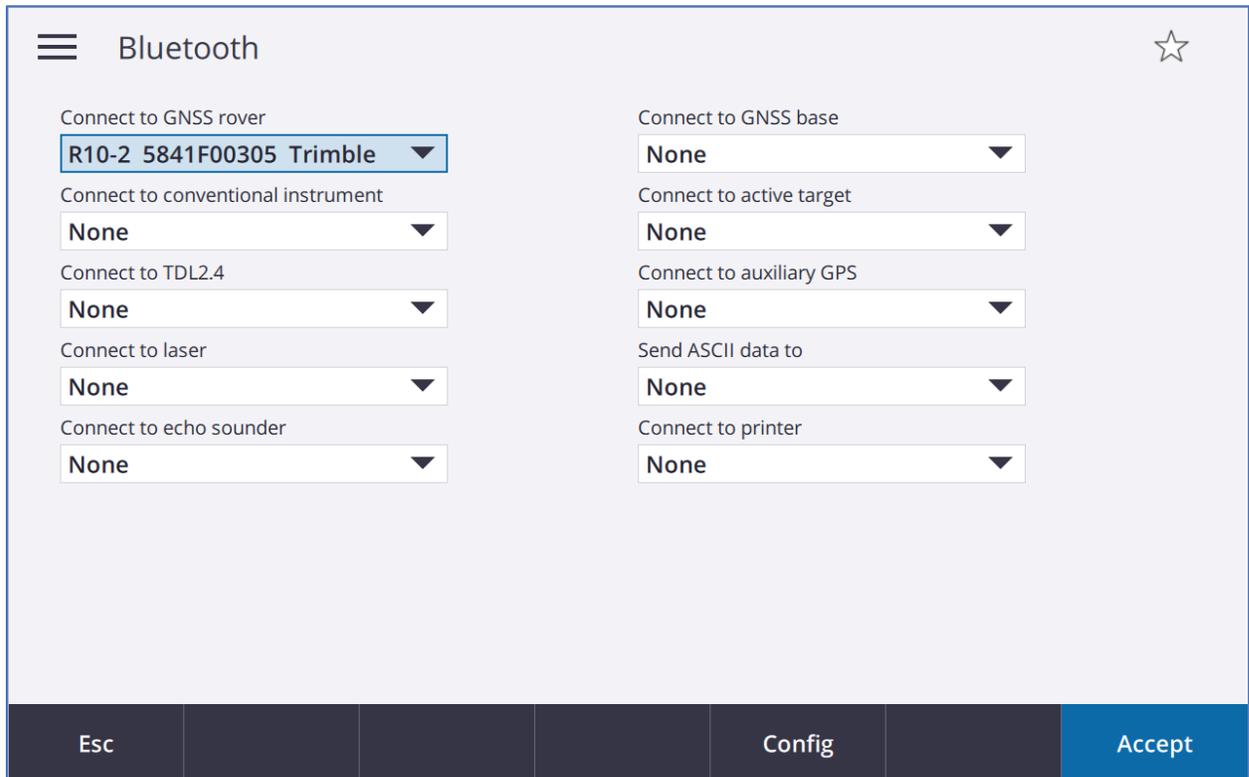
## 7.5: Troubleshooting

### Error: Trying to connect via Cable

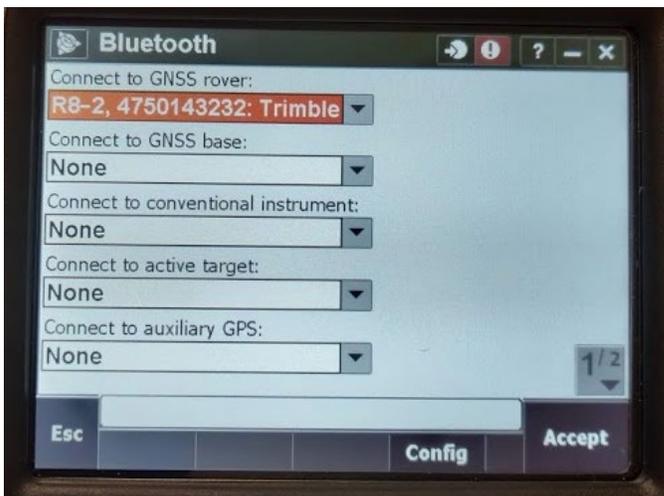
For static survey, Trimble units should connect to GNSS via cable not Bluetooth. If this error pops up, you need to go to a Bluetooth setting to change your settings.

R10 (Settings -> Connect -> Bluetooth)

Connect to GNSS -> Cable



R8 (Settings -> Connect -> Bluetooth)



## Section 8: THE QUANERGY M8 LiDAR SYSTEM

Here is how to set up the Quanergy System on the field after the LiDAR drone assembly.

### Before the System Setup

- Assemble a drone
- Have started Trimble static over 20 mins

### 8.1: Quanergy System Setup

#### 1. Power System

Connect the two red/black power cables to the LiDAR system. They all go in one way. Press the button on the side of Quanergy to start up the LiDAR system. It will take 45-60 seconds to Hot Spot to be ready.





## 2. Hot Spot

In the tablet, exit all the applications and switch from WiFi to HotSpot.

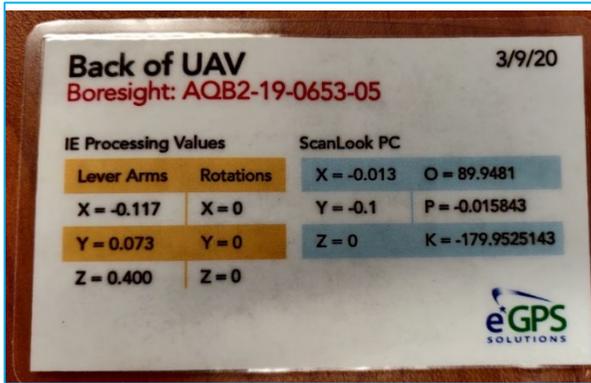
Hotspot name: **AQB2-19**

PWD: **scanlook**

Go to your browser in your iPad and type in the IP address "**192.168.0.1**". Add to your favorites. It will take you to a setting page.

### 3. System Settings

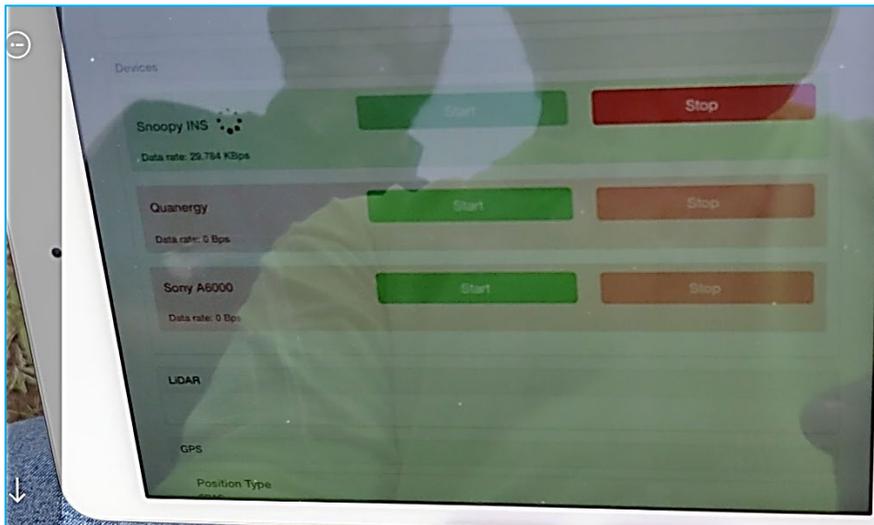
Go to the settings to make sure all the measurements are correct.



Make sure that INS script on the bottom of the page is set for “back of UAV snoopy 2-IL”. Set for Antenna-A-Lever Arms as the same as the above, then hit save.

Go to Snoopy tab to change the project name – no space!! (ex. Test1)

Then we are ready to start! Hit Snoopy INS start. Wait till it turns green about 30 seconds. What they are doing is the drone is tracking satellite signals such as GPS or GLONASS and getting IMU data



Press start on Quanergy to begin scanning. When it turns green, all the Lidar system set up is done and the mission for data collection can begin.

### 4. Shutting-down the system

When the flight is done, the system needs to be carefully shutdown. Go back to the webpage, you start stopping from the bottom (Quanergy -> Snoopy INS). Wait for it to turn it to pink, and then stop the IMU. Then, go to the top of the page to hit “shutdown”. When the website is shutdown, the hot spot is also going to disappear.

## Section 9: TRIMBLE – POINT SURVEY

Point survey will be used to measure the coordinate systems of GCP targets and habitat points. Those points will be used for georeferencing, accuracy assessment, and classification analysis.

### 9.1: Things You Need to Start

Trimble Box (rover etc.)

Trimble Unit (R10, R8)

- CSV File: Habitat Data
- CSV File: GCPs Data
- Point Shape File: Habitat data
- Point Shape File: GCPs Data
- Line Data: Lines of accessible areas (if needed)
- Polygon Shape File: NWI of AOI
- Shape File: NC County Boundary

Tripod (only for GCP collection)

MiFi

### 9.2: Trimble Setup

The setup is very similar to the static survey except for not using a cable.

#### 1. Attach Adapter/ Rover to Pole

Mount the quick release adapter onto the height extension pole with measurement lever. Attach the GNSS receiver to the quick release adapter. No need to use tripod necessarily unless you do a GCP collection.



## 2. Attach Mount and Legs

Attach the mount and legs to the pole.



### 9.3: How to Start a Point Survey – R8

#### 1. Turn on MiFi

Turn on your MiFi (pocket WiFi) to enable the Trimble unit to connect to rover via Bluetooth

#### 2. Connect Tablet to MiFi

Open your Trimble tablet and navigate to Setting -> WiFi Connection to make sure the unit is connected to your MiFi

#### 3. Open Trimble Access

Open "Trimble Access" in your tablet. Open your point collection job you have already created. Select DoT\_work -> your job.

#### 4. Setups for Topo

To start your survey, select Measure, then:

- a. Measure: RTN2015
- b. GNSS contacts: MiFi
- c. Select data source: VRS\_CM Rx
- d. Method
  1. Habitat points: Topo point (3sec)
  2. GCPs: Observed control point (3mins)

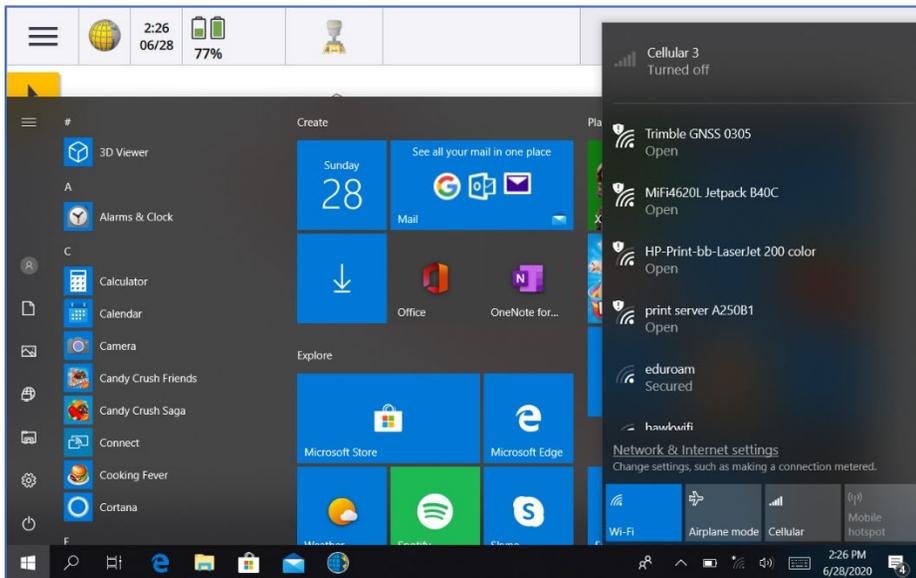
## 9.4: How to Start a Point Survey – R10

### 1. Turn on MiFi

Turn on your MiFi (pocket WiFi) to enable the Trimble unit to connect with rover via Bluetooth

### 2. Connect Tablet to MiFi

Open your Trimble tablet and connect your MiFi to this tablet.



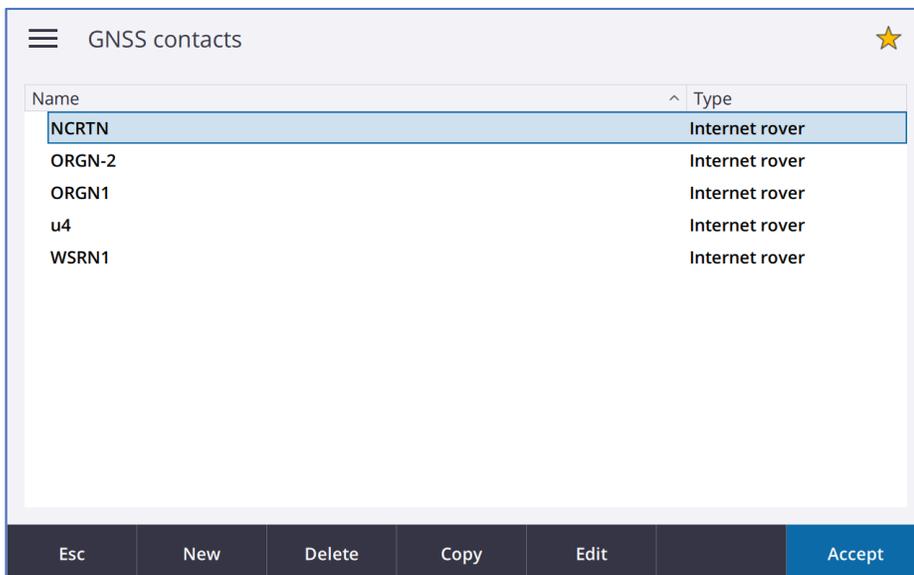
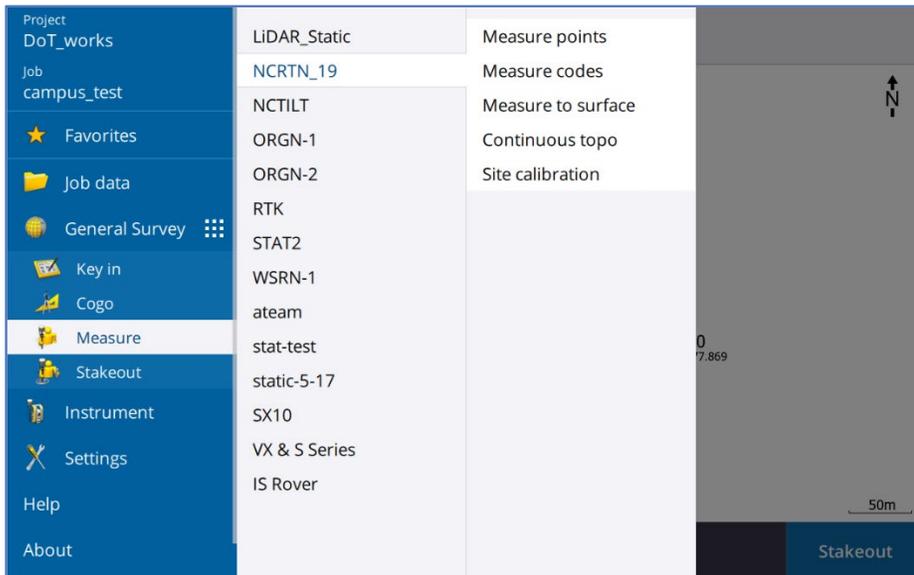
### 3. Turn on Rover



#### 4. Open Trimble Access

Open “Trimble Access” in your tablet. Open your point collection job you have already created. Select DoT\_work -> your job. Then, go to Measure -> NCRTN\_19 -> Measure Points. Then, select:

- a. Select survey style: NCRTN\_19
- b. GNSS contacts: NCRTN
- c. Select Data source: VRS\_CMRx
- d. Method
  - a. Habitat points: **Topo point (3sec)**
  - b. GCPs and check points: **Observed control point (3mins)**



☰ 🌐 2:28 06/28 🔋 76% 🔋 89% 📶 15 🔦 ? No survey PDOP:1.6

Select data source

Mount point	Identifier	Distance ^	Format	Format details	Carrier
VRS_CMRp	VRS_CMRp	-	CMR+	Obs(1),Info(10... L2	
VRS_CMRx	VRS_CMRx	-	CMRx	Obs(1),Info(10... L2	

Esc All Refresh Accept

☰ 🌐 2:28 06/28 🔋 76% 🔋 89% 📶 15 🔦 2.000 📍 RTK H:0.008m V:0.015m ✓

Measure points ★

Point name

Code

Method

Antenna height (Uncorr)

Measured to

Esc Options Measure

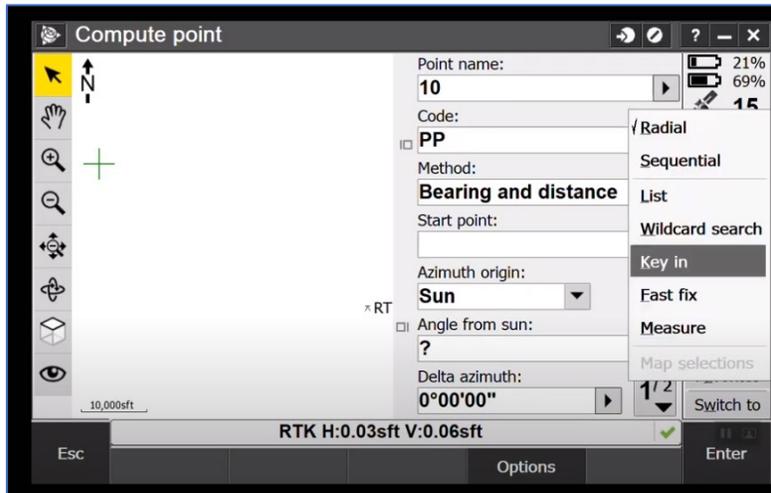
## 9.5: Tips for Point Collection

### Off-Set Collection

Reference video: [Tuesday Tip - GPS offsets with Trimble Access](#). During your collection, sometimes topo points can be in the deep forest where access is limited. An off-set tool will enable you to collect a point remotely.

During your survey, the first thing you will do to do off-set is to go to Cogo. Cogo -> Compute Point

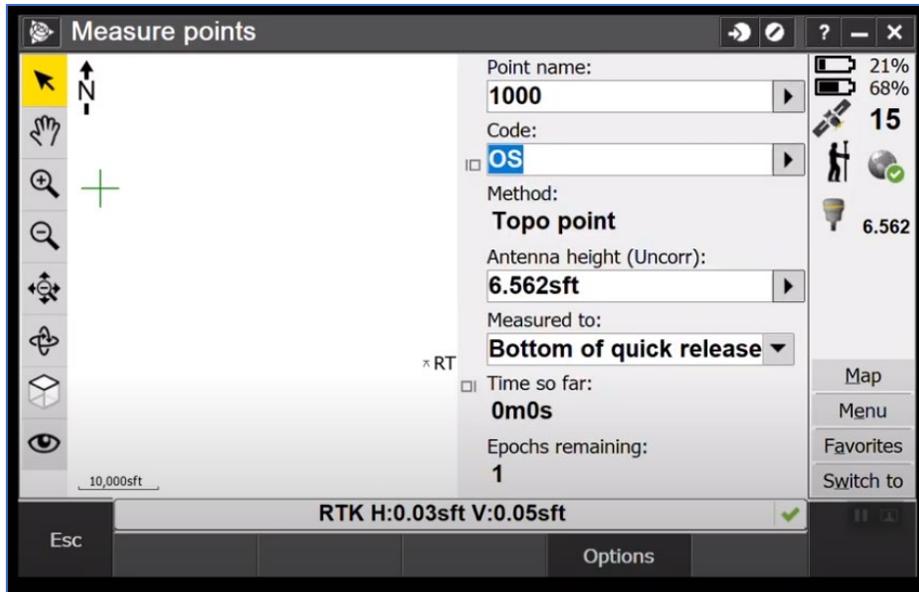
In the compute point window:



- Point name: name the point of where you want to collect remotely
- Code: PP – power pole (for example)
- Method: Bearing and distance
- Start Point: Measure

Measure points

- Point name: where you are
- Code: OS (Off-set)
- Method: Topo
- Height: 2m
- Measure to: Bottom of quick release



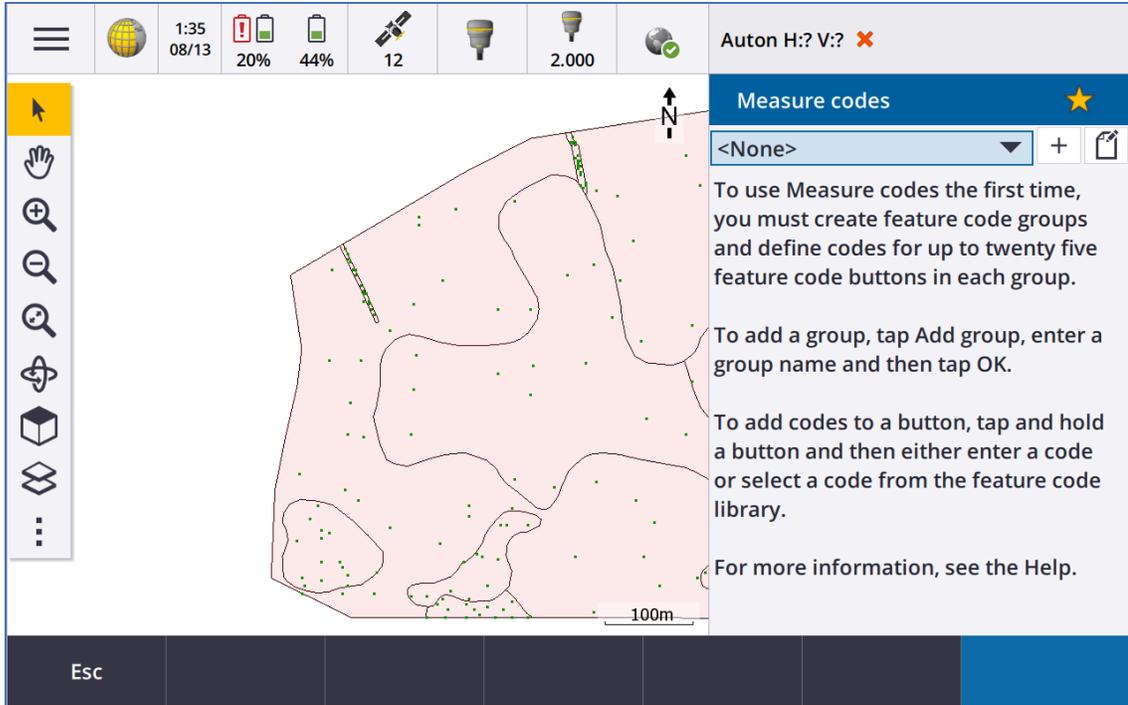
## Measure Codes

If you have set up the measure codes, it will make your survey easier and quick. It is possible to survey by picking from a defined selection of codes as shown below instead of picking codes from a list or manually entering them, as in the Measure Points screen. Defined codes can be no more than 25. This method is particularly useful if you are only using a small number of codes on a regular basis, measuring string features, or need to constrain the number of codes used on a series of cross sections for example.

### 1. Open Job

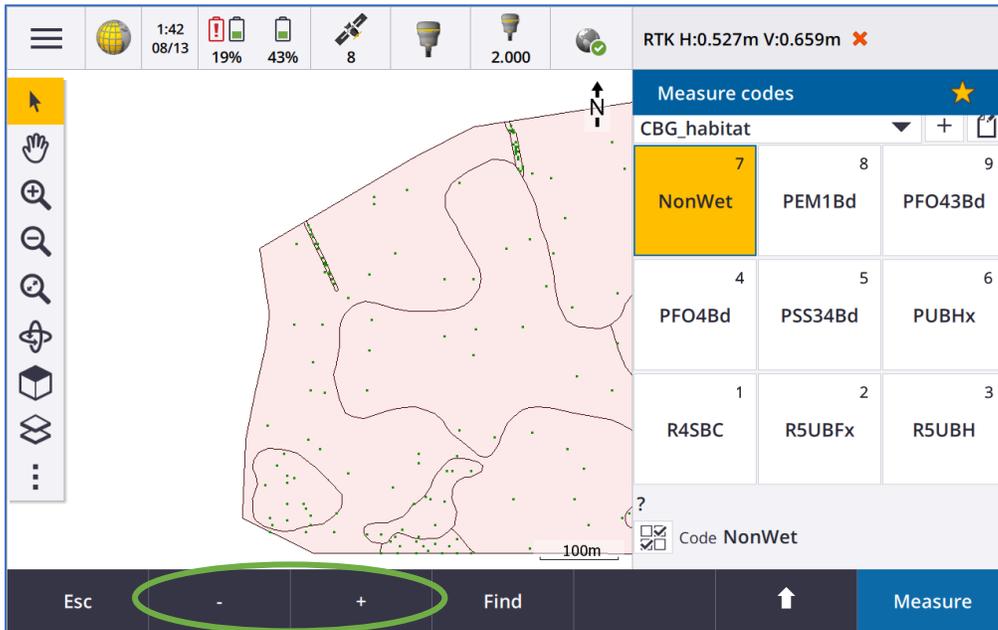
Have MiFi and R10 Rover ready and go outside. Open the job. Go to Menu -> Measure -> NCRTN\_19 -> **Measure codes** -> GNSS contacts: **NCRTN** -> Select Data source: **VRS\_CM Rx**

The first time this screen is used you will need to press the Add group button (+) to create a screen of blank buttons.



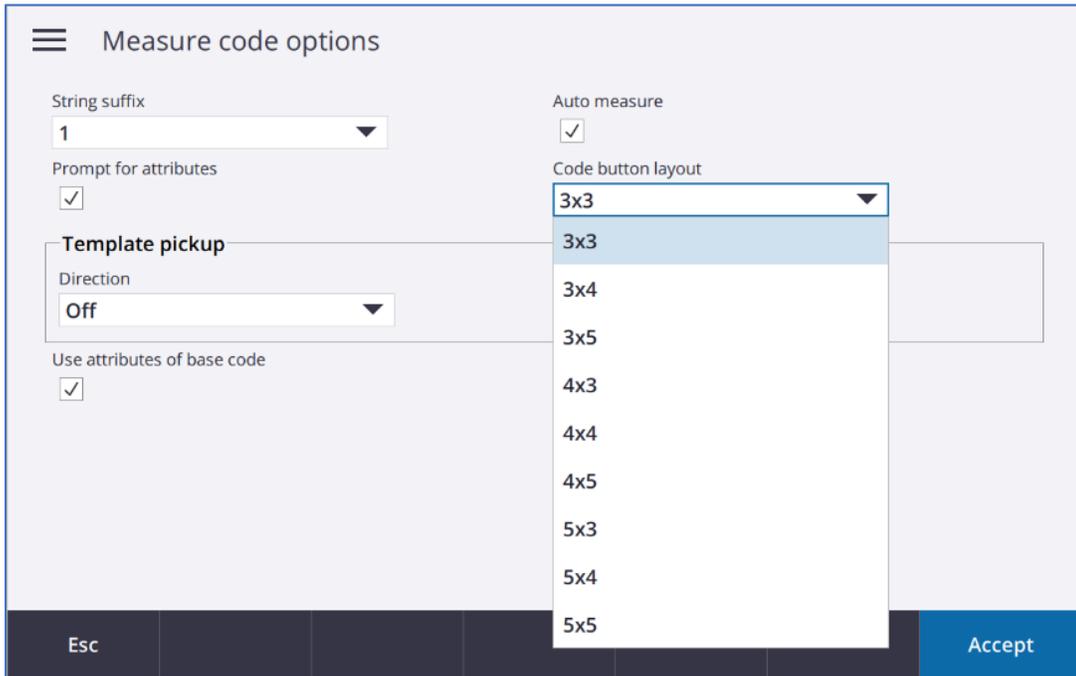
## 2. Assign Code

The default setting has 9 (3\*3) code layout. To assign a code to a button, **tap and hold** on a button and then release. Enter the code required. String numbers can be attached to codes by highlighting the button required and using the – and + keys at the base of the screen.



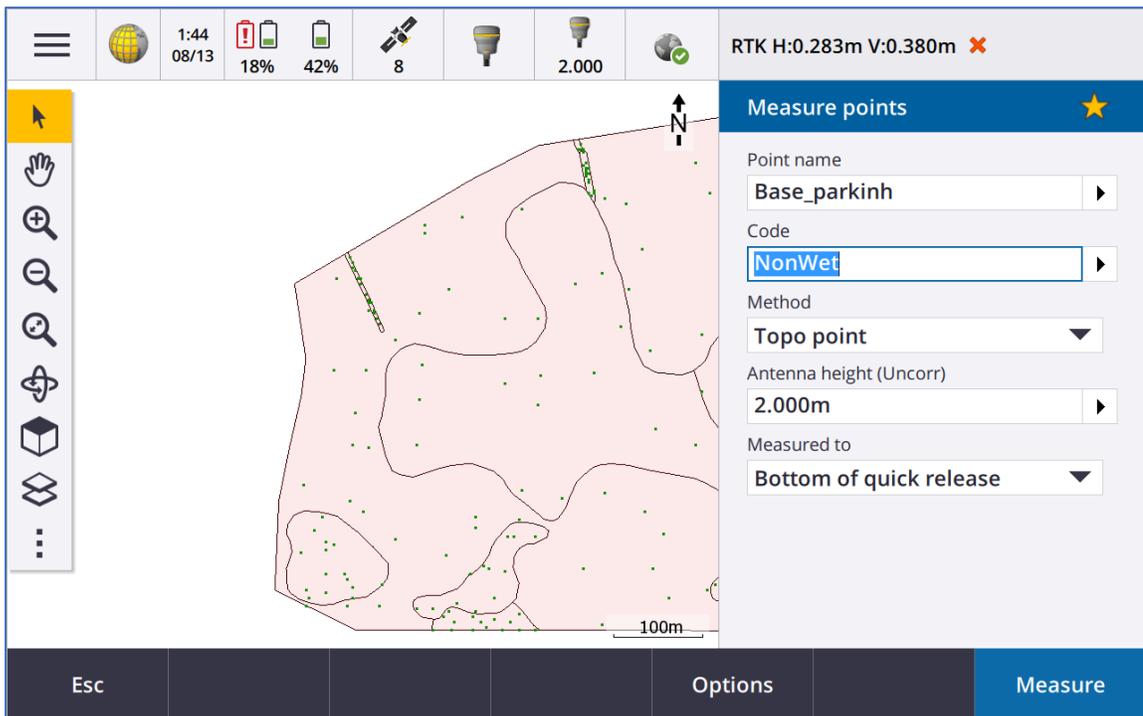
## 3. Change Code Layer

If you wish to change the code button layout on the screen, go to “Measure code options”. Here you can play with those settings if you want.



#### 4. Measure Point

To measure a code point, just tap the button required. After tapping it, this measure points window will show-up.



## Section 10: Download FIELDWORK DATA

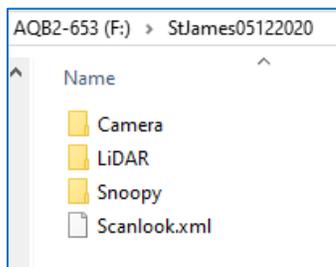
The first thing you do following field work data collection is to take off the data and save it to your local drive somewhere you can pre-process.

### 10.1: DJI Matrice 600 Pro– Quanergy M8 LiDAR sensor and Zenmuse X5 RGB camera (flown concurrently)

Following your fieldwork, download the LiDAR data from the Matrice with the USB stick (AQB2-19-0635-05) and Zenmuse with a micro SD

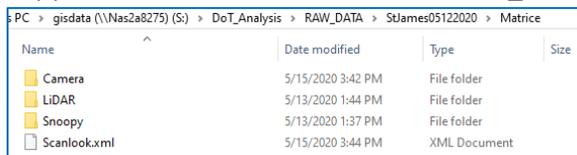
#### 1. Download Quanergy Data

Open the UBS and open your project: F:\StJames05122020



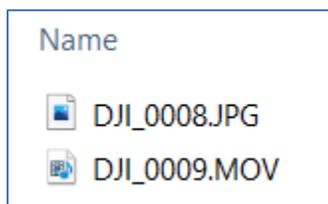
#### 2. Copy and Paste

Copy all the files to the DoT Server: S:\DoT\_Analysis\RAW\_DATA\StJames05122020\Matrice



#### 3. Download Zenmuse Data

Zenmuse has a micro SD card inserted on its side.



## 10.2: eBee – sequoia (Multispectral), SODA (RGB), thermal map (Thermal)

If you fly eBee with multispectral, RGB, and thermal, there will be a memory card for each sensor. A SD card reader will be stored in an eBee box. Download the data of the correct data to the server:

From: F:\DICM\EP- EP-01-22439\_0128

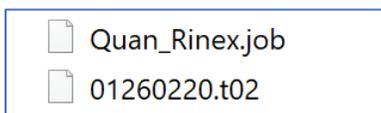
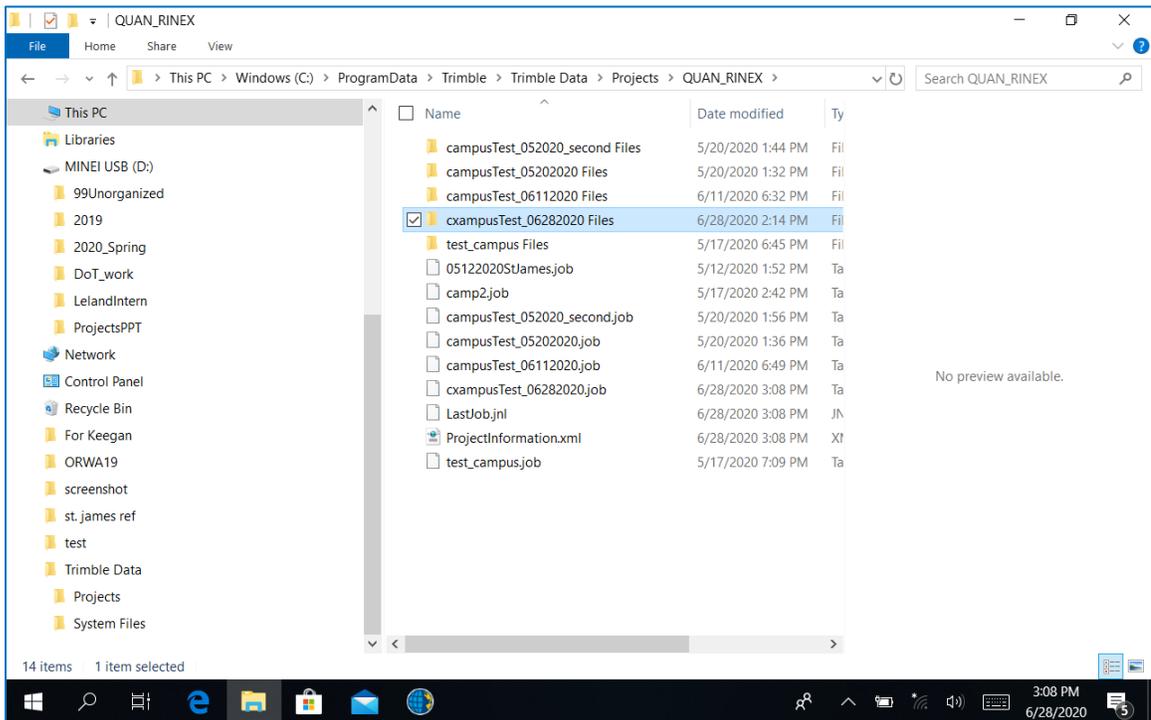
To: S:\DoT\_Analysis\RAW\_DATA\StJames05122020\eBee\EP-01-22439\_0128

A multispectral sensor has 5 lenses for red, green, red edge, infrared, and RGB, and it takes 5 shots of photo at a time. So, there is going to be a series of 5 photos for each shot.

## 10.3: Exporting Trimble Data– R8, R10

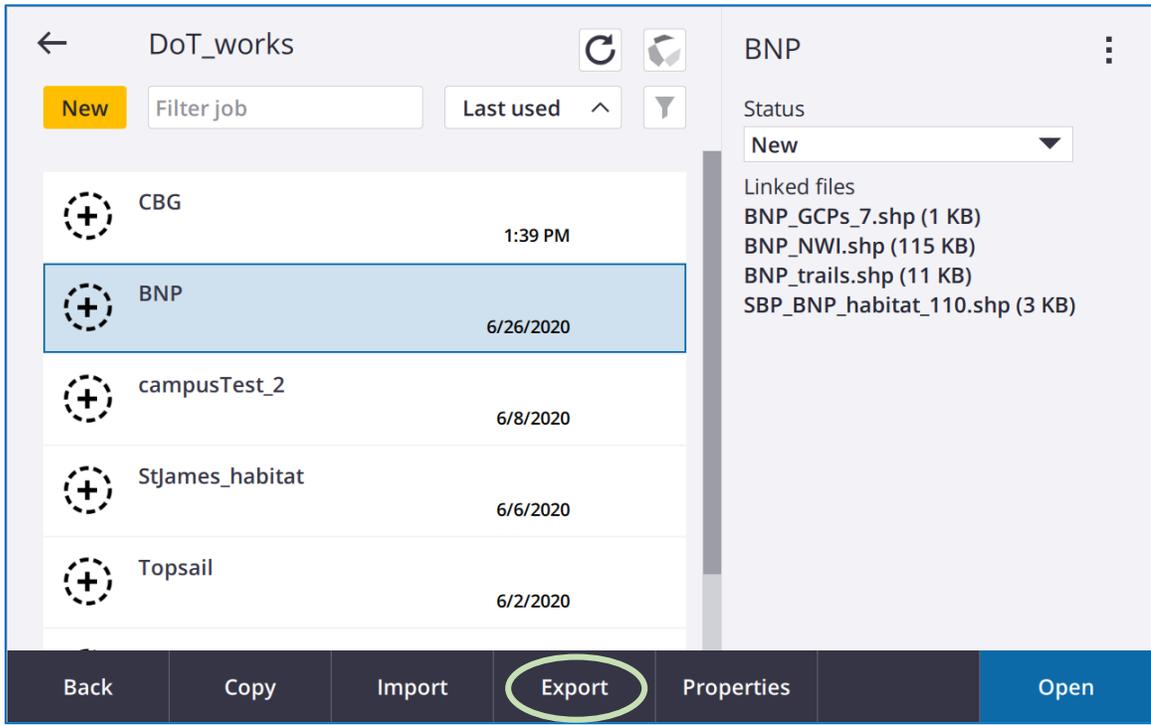
### 1. Static Data

Turn on a Trimble unit and find a static data in file explore. The data is stored in a “QUAN\_RINEX” folder. Copy a job and .t02 file over to the server.

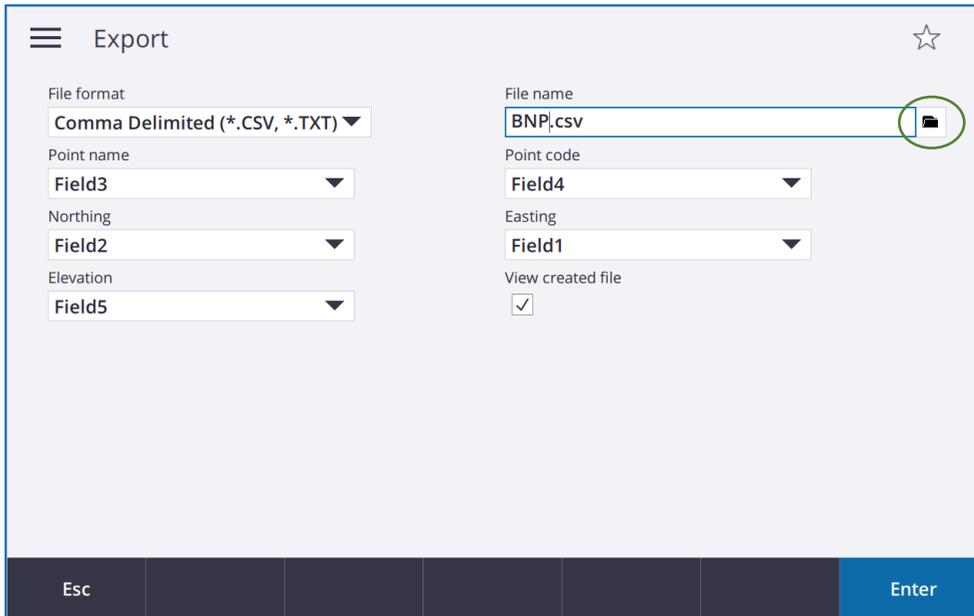


## 2. RTK Data (GCPs and Habitat Pts)

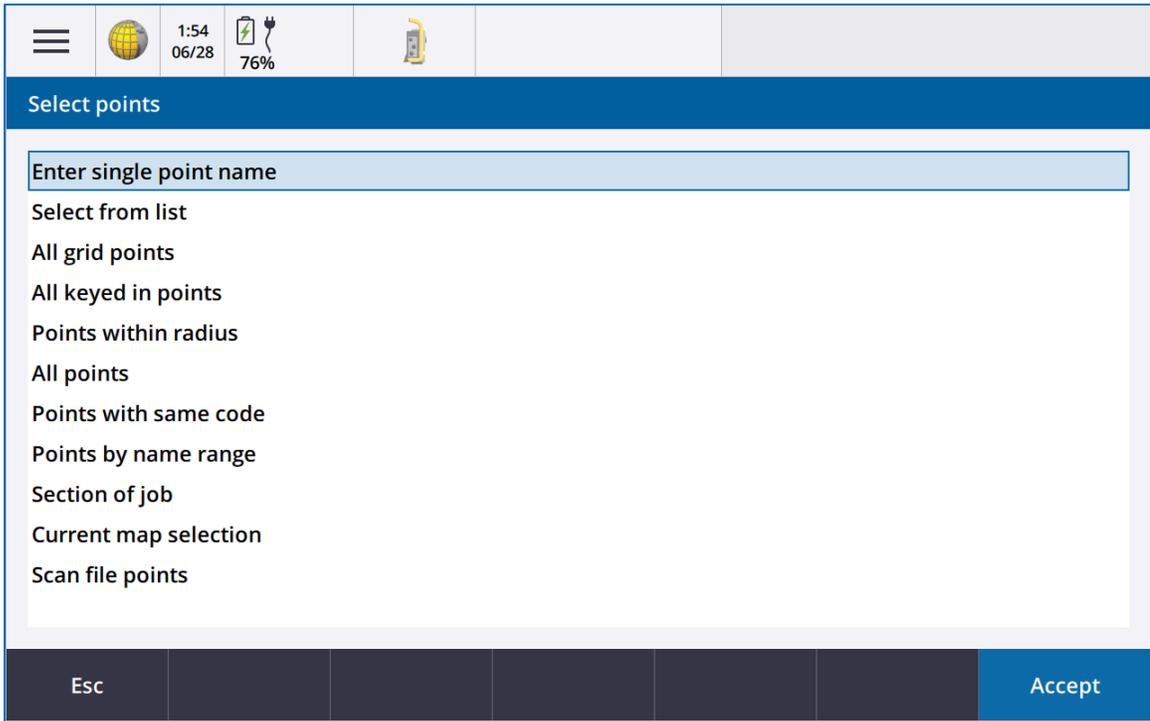
To export point data in excel file from Trimble, the first step is to select DoT\_works -> BNP (your job). Tap Export.



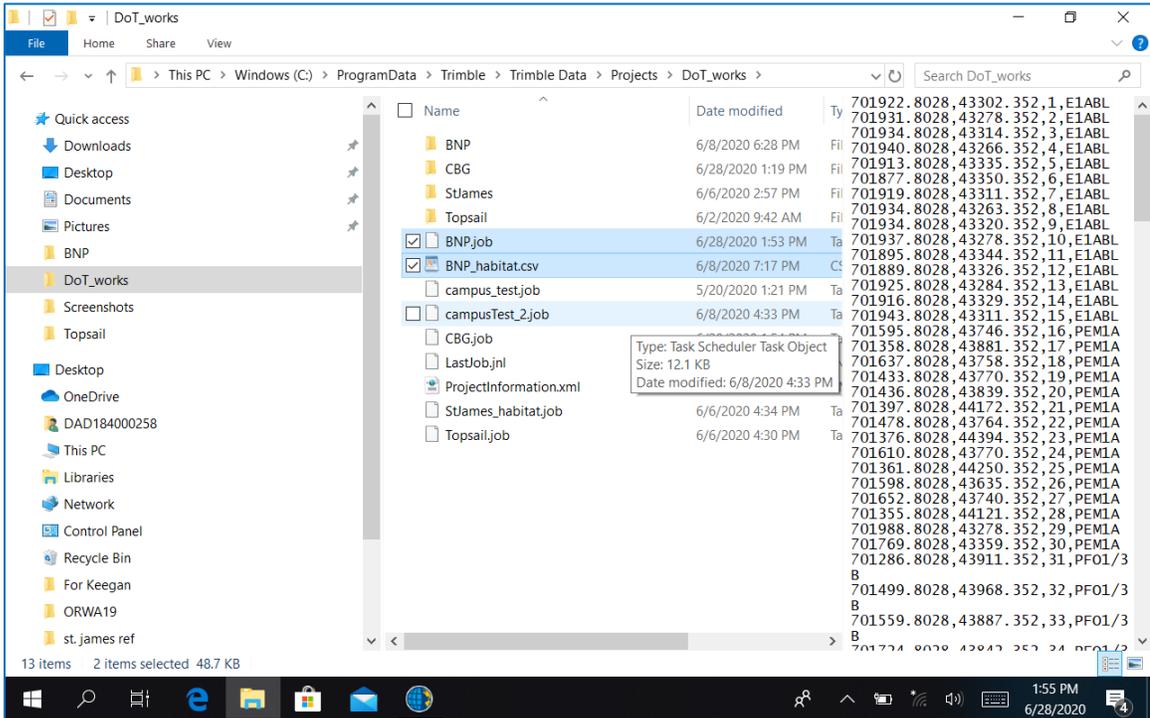
Select the file format and click on the file mart next to File name to select where you will save this data (in a USB stick).



Select your point format. "All points" is recommended.

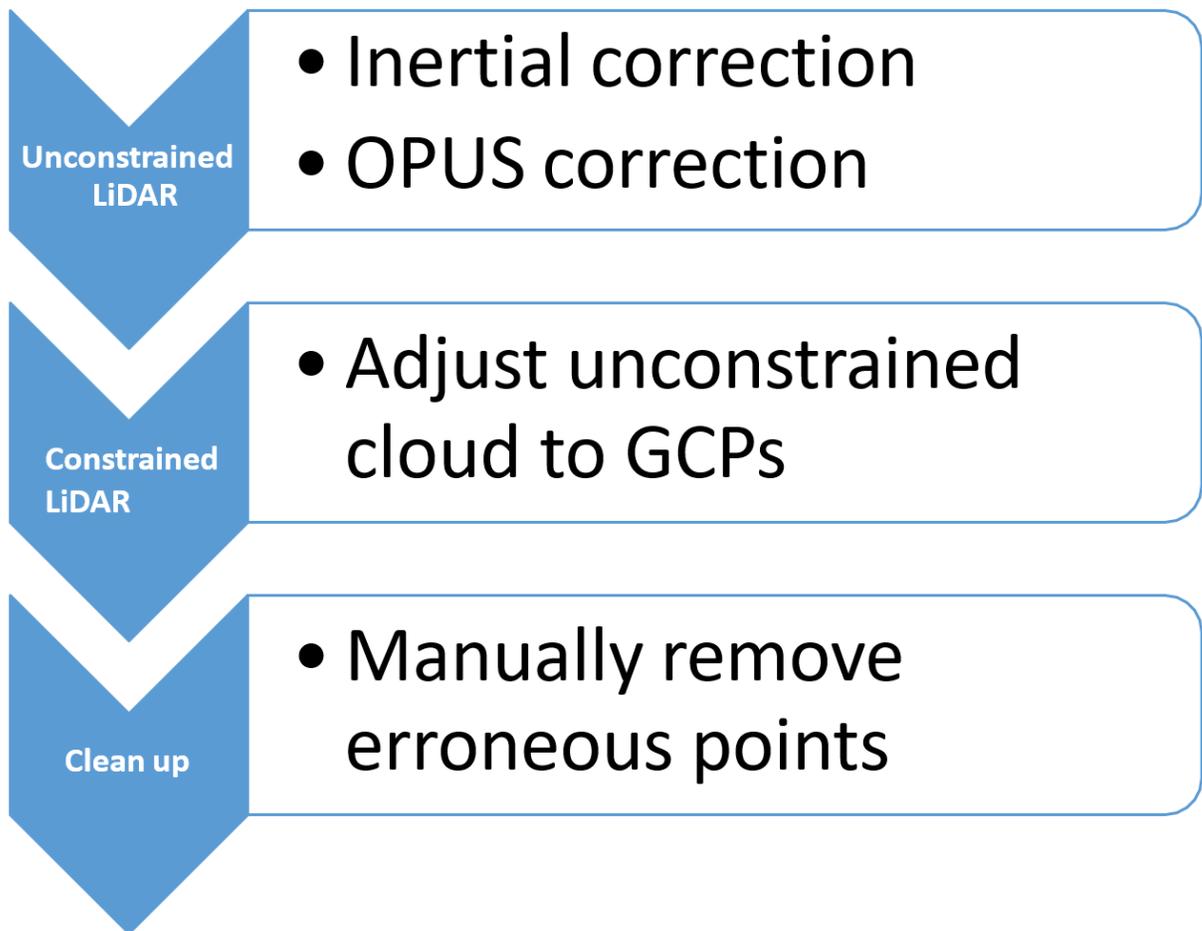


Also to be exported is a .job data. This data contains all info about the survey, such as time stamps and coordinate systems. Go to DoT\_works and copy and paste "BNP.job" to DoT server.



## Section 11: LiDAR PROCESSING PREP

Pre-processing LiDAR is a complex, multi-step process. The software programs required include: Inertial Explorer, Scanlook PC, Cloud Compare and Global Mapper, however there are few things to do before the actual processing the data. The process is very briefly outlined below and discussed sequentially below.



### 11.1: File Organization

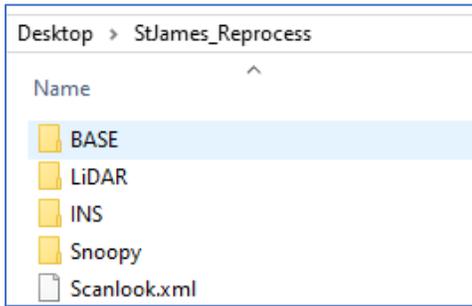
#### 1. Create Folders

In local drive (like Desktop), **create a folder** "SiteName". Copy "LiDAR", "Snoopy" and Scanlook.xml and paste them in the new folder "SiteName".

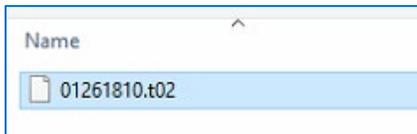
Name	Date modified	Type	Size
Camera	10/6/2020 12:16 AM	File folder	
LiDAR	10/5/2020 2:17 PM	File folder	
Snoopy	10/5/2020 2:05 PM	File folder	
Scanlook.xml	10/6/2020 12:17 AM	XML Document	

2. Create Empty Folders

In "SiteName", create empty folder named "INS" and "BASE" folders.

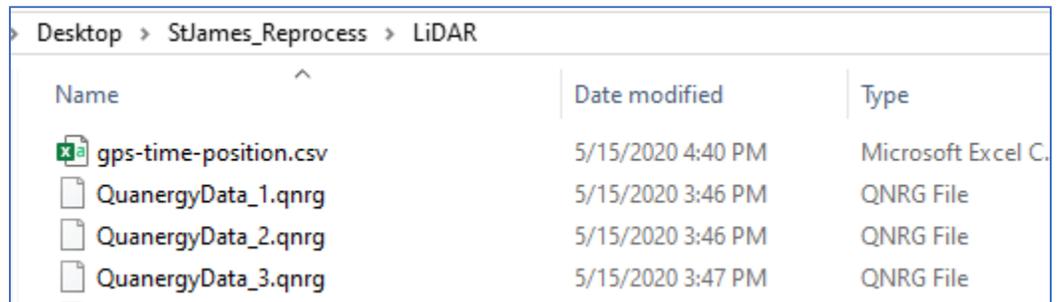


3. In BASE: Bring the Static Data (...t02) from the "TRIMBLES"-> "StaticData" file.

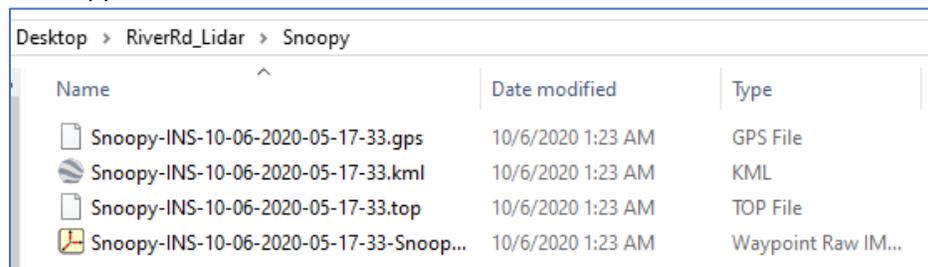


4. Let's look inside **INS**, **LiDAR**, and **Snoopy** files.

- a. In INS: empty now
- b. In LiDAR:



- c. In Snoopy:



## 11.2: AirData Flight Path Generation

This is the website where you can upload your flight log to see the detailed flight information. There information will be helpful when generating a point cloud in Scanlook PC.

AIRDATRA: <https://airdata.com/>

Username: [am3303@uncw.edu](mailto:am3303@uncw.edu)

Password: [am3303@uncw.edu](mailto:am3303@uncw.edu)

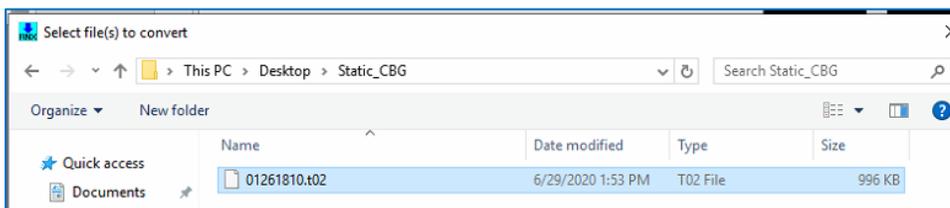
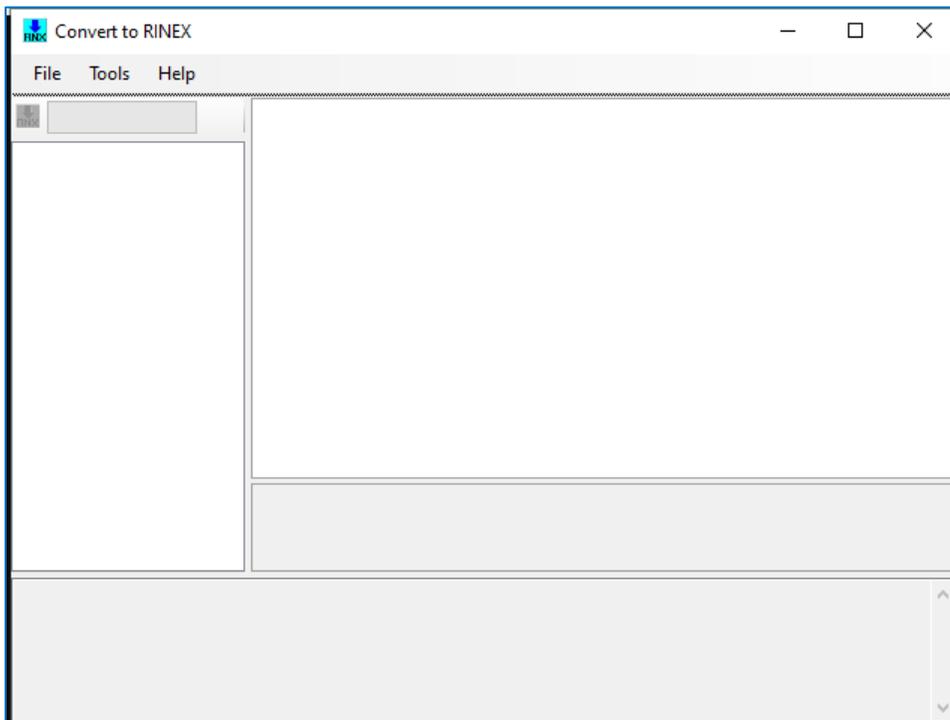
Airdata: How to upload flight logs: <https://app.airdata.com/dji-gs-pro#:~:text=Once%20your%20flight%20logs%20are,to%20flights%22%20to%20view%20them.>

### 11.3: Rinex Conversion

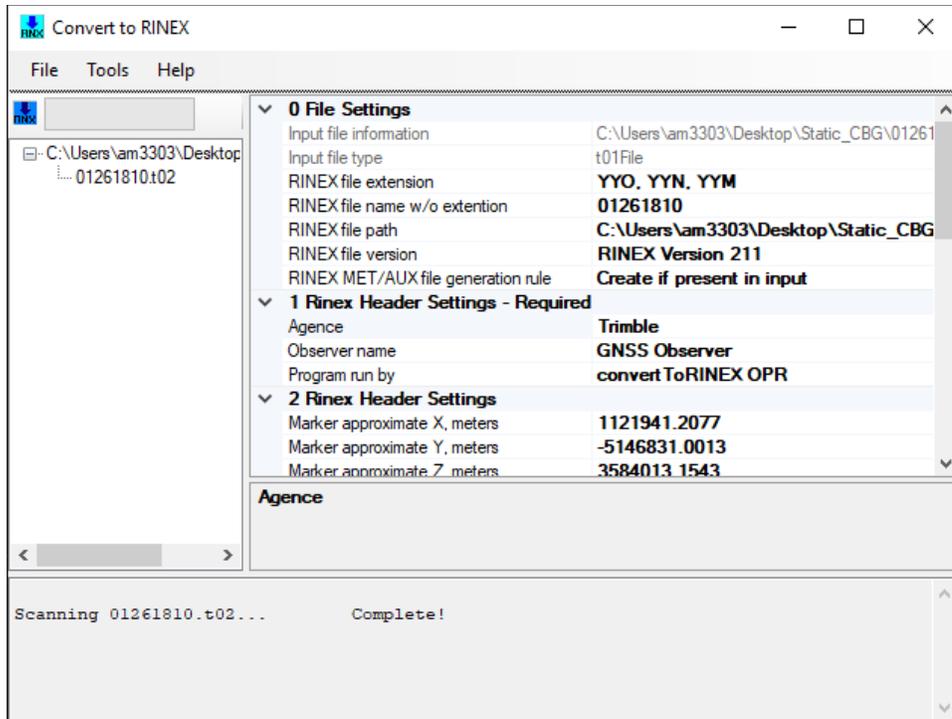
After downloading static data as a T02 file from Trimble, you need to convert the file to Rinex format. The RINEX converter is a free software

#### 1. Start **Convert to Rinex**

(Go to here for more info: [https://www.trimble.com/support\\_trl.aspx?Nav=Collection-40773&pt=Trimble%20RINEX](https://www.trimble.com/support_trl.aspx?Nav=Collection-40773&pt=Trimble%20RINEX)). Go to **File** -> **Open**. Then **select .t02** file.



Then, software scan starts.



## 2. Convert to Rinex

When scanning is completed, go to **File -> Convert Files**. Then Rinex file(.o,n,g) is created from a .t02 file.

- \*\*.o files: observation data files, contain **satellites position** data.
- \*\*.n files: navigation data files, contain **GPS** ephemeris data.
- \*\*.g files: navigation data files, contain **GLONASS** (Russian) ephemeris data.

01261810.20g	8/16/2020 5:51 PM	20G File
01261810.20n	8/16/2020 5:51 PM	20N File
01261810.20o	8/16/2020 5:51 PM	20O File
01261810.t02	6/29/2020 1:53 PM	T02 File

## 11.4: OPUS SOLUTION

OPUS (NOAA's Online Positioning User Service) provides free access to high-accuracy National Spatial Reference System (NSRS) coordinates. OPUS uses software which computes coordinates using the NOAA CORS Network (NCN). The OPUS result will be used in the LiDAR processing.

### 1. Go to OPUS websites

To use OPUS, simply upload a GPS data file (collected with a survey-grade GPS receiver) to the OPUS upload page. Your computed NSRS position will be emailed to you. If you choose, your position can also be shared publicly on the NGS website.

OPUS: <https://geodesy.noaa.gov/OPUS/>

Data file: .20o (converted from Trimble)

Antenna: "TRMR8\_GNSS NONE" or your Static Trimble Unit

Antenna Height: 2 meters

Email: Type your email and

Either "Upload to Rapid Static" or "Upload Static" depending on the survey time

**Upload your data file.**  
Solve your GPS position & tie it to the National Spatial Reference System.  
[What is OPUS?](#) [FAQs](#)

01263110.20o  
\* data file of dual-frequency GPS observations. [sample](#)

INTEGRATED GPS L1/L2+L2C/L5 GLO L1/L2 TRIMBLE R8 GNSS ANTENNA  
**antenna** - choosing wrong may degrade your accuracy.

meters above your mark.  
**antenna height** of your antenna's reference point.

\* email address - your solution will be sent here. [Privacy Act Statement](#)

to customize your solution.

for data 15 min. - 2 hrs.     for data 2 hrs. - 48 hrs.



**Upload successful!**

You will receive an email when processing is complete.

uploaded:		Solving with:	
data file	01260220_modified.21o	solution format	Standard
converted to	0126022p.21o (RINEX format)	base sta. used	--
antenna	TRMR8_GNSS NONE	base sta. excluded	--
antenna height	2.000 meters	state plane zone	--
email address	am3303@uncw.edu		
processor	Rapid-Static	project ID	--

## 2. OPUS Results in Email

You will get an OPUS result by Email. Copy and paste it to a text file to keep it as a record.

```
OPUS.txt - Notepad
File Edit Format View Help
OPUS solution : 01261331.200 OP1596662956525
opus <opus@ngs.noaa.gov>
Wed 8/5/2020 5:30 PM
FILE: 01261331.200 OP1596662956525

          NGS OPUS SOLUTION REPORT
          =====

All computed coordinate accuracies are listed as peak-to-peak values.
For additional information: https://nam05.safelinks.protection.outlook.com/?url=https%3A2F3A

USER: am3303@uncw.edu          DATE: August 05, 2020
RINEX FILE: 0126133p.200      TIME: 21:30:22 UTC

SOFTWARE: page5 1801.18 master52.pl 160321  START: 2020/05/12 15:12:00
EPHEMERIS: igs21052.eph [precise]          STOP: 2020/05/12 17:47:00
NAV FILE: brdc1330.20n                    OBS USED: 6844 / 7239 : 95%
ANT NAME: TRMR8_GNSS NONE                 # FIXED AMB: 43 / 46 : 93%
ARP HEIGHT: 2.000                         OVERALL RMS: 0.015(m)

REF FRAME: NAD_83(2011)(EPOCH:2010.0000)   ITRF2014 (EPOCH:2020.3625)

X: 1088592.781(m) 0.003(m) 1088591.906(m) 0.003(m)
Y: -5182910.027(m) 0.002(m) -5182908.526(m) 0.002(m)
Z: 3542351.090(m) 0.001(m) 3542350.988(m) 0.001(m)

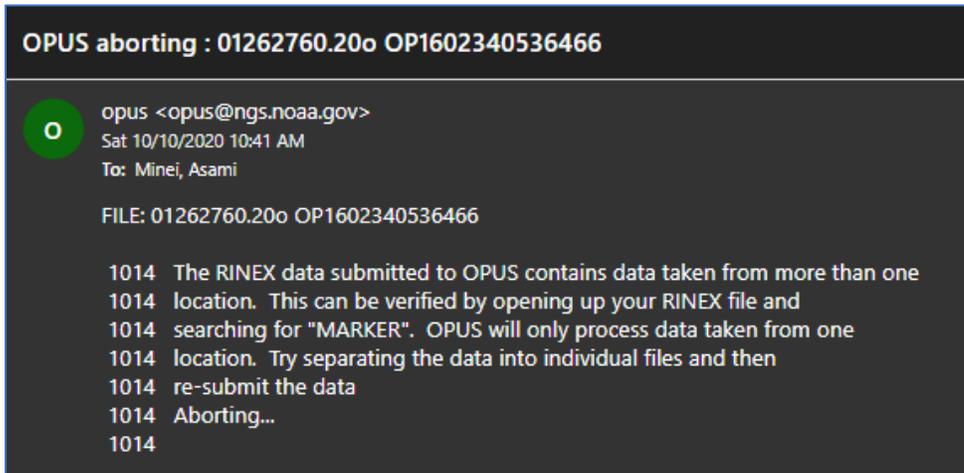
LAT: 33 57 20.08998 0.001(m) 33 57 20.11712 0.001(m)
E LON: 281 51 42.12954 0.003(m) 281 51 42.10823 0.003(m)
W LON: 78 8 17.87046 0.003(m) 78 8 17.89177 0.003(m)
EL HGT: -17.295(m) 0.003(m) -18.720(m) 0.003(m)
ORTHO HGT: 19.412(m) 0.057(m) [NAVD88 (Computed using GEOID18)]

          UTM COORDINATES          STATE PLANE COORDINATES
          UTM (Zone 17)          SPC (3200 NC)
Northing (Y) [meters] 3760921.447 23152.510
Easting (X) [meters] 764451.184 689259.883
Convergence [degrees] 1.59933056 0.49735000
Point Scale 1.00046220 1.00012599
Combined Factor 1.00046492 1.00012871

<----->
Ln 57, Col 33 100% Windows (CRLF) UTF-8
```

### 3. Error

Sometimes the OPUS email comes back with error message like the image below.



**It failed** because there were two static surveys recorded in the same name. In River Road, the wind knocked down Trimble during the first static survey. We started it over in a stable place but in the different place from the first survey. That is why the email says, "*data taken from more than one location*".

Go back to 20o file to fix this problem. Open that rinex file up in notepad and scroll down, probably two pages, and follow those directions that OPUS is giving you and **remove the data** between the bottom of the "big" header/notes and where you actually cranked it up with the DC which should, depending on how long you let it sit there, be a page or two, maybe three. Delete that area and resubmit. <https://rplstoday.com/community/software-cad-mapping/rinex-file-question/>).

4. Delete the blue area and re-submit it to the OPUS to see if this wo

```

01260220.21o - Notepad
File Edit Format View Help
2.11 OBSERVATION DATA Mixed(MIXED) RINEX VERSION / TYPE
cnvtToRINEX 3.13.0 convertToRINEX OPR 28-Jan-21 06:15 UTC PGM / RUN BY / DATE
-----
maysville MARKER NAME
aysville MARKER NUMBER
GNSS Observer Trimble OBSERVER / AGENCY
4750143232 TRIMBLE R8 GNSS 4.63 REC # / TYPE / VERS
TRM60158.00 ANT # / TYPE
1156707.7940 -5107145.5082 3629140.4718 APPROX POSITION XYZ
2.0000 0.0000 0.0000 ANTENNA: DELTA H/E/N
1 1 0 WAVELENGTH FACT L1/2
5 C1 C2 L1 L2 P2 # / TYPES OF OBSERV
2021 1 22 15 48 37.0000000 GPS TIME OF FIRST OBS
2021 1 22 17 29 0.0000000 GPS TIME OF LAST OBS
0 RCV CLOCK OFFS APPL
18 LEAP SECONDS
19 # OF SATELLITES
G01 1886 1886 1886 3772 1886 PRN / # OF OBS
G03 4053 3891 3954 7519 3628 PRN / # OF OBS
G04 1582 1477 1531 2390 913 PRN / # OF OBS
G10 2576 2542 2559 4997 2455 PRN / # OF OBS
G16 4722 0 4722 4722 4722 PRN / # OF OBS
G21 777 0 777 777 777 PRN / # OF OBS
G22 5964 0 5964 5964 5964 PRN / # OF OBS
G25 4198 3965 4119 7950 3985 PRN / # OF OBS
G26 5964 5964 5964 11928 5964 PRN / # OF OBS
G29 2792 2385 2662 4790 2405 PRN / # OF OBS
G31 5964 5964 5964 11928 5964 PRN / # OF OBS
G32 5941 5936 5941 11871 5935 PRN / # OF OBS
R01 5964 0 5964 5964 5964 PRN / # OF OBS
R02 5837 0 5834 5800 5805 PRN / # OF OBS
R03 261 0 258 176 212 PRN / # OF OBS
R08 3234 0 3227 2997 3047 PRN / # OF OBS
R10 117 0 110 0 0 PRN / # OF OBS
R12 5964 0 5964 5964 5964 PRN / # OF OBS
R13 2907 0 2904 2904 2904 PRN / # OF OBS
CARRIER PHASE MEASUREMENTS: PHASE SHIFTS REMOVED COMMENT
END OF HEADER

2 1
*** Start of Kinematic Data *** COMMENT
21 1 22 15 48 37.000000 0 13G01G10G21G22G25G26G31G32R01R02R08R10
R12
24136397.344 4 24136403.461 9 126837838.631 4 98834532.620 9 24136403.12946
22786444.828 6 22786450.176 9 119743521.195 6 93306712.304 9 22786450.77347
24873017.422 5 130708744.360 5 101850851.28446 24873019.51646
23148568.406 2 121646482.628 2 94789507.47546 23148566.67646
21832170.375 6 21832176.285 9 114728861.730 6 89399112.888 9 21832175.48449
22667102.688 6 22667109.996 9 119116500.641 6 92818034.967 9 22667109.62147
20373989.156 7 20373991.695 9 107066035.816 7 83428119.487 9 20373991.55149
20976485.453 7 20976490.020 9 110232172.618 7 85895216.735 9 20976489.78948
19414285.117 7 103780411.757 7 80718170.433 9 19414291.340 9
22078886.438 3 117817134.291 3 91635591.771 6 22078888.043 6
21405553.039 7 114625597.076 7 89153355.565 8 21405555.043 8
23037453.305 2 122802794.444 2
20489076.281 8 109448822.968 8 85127140.827 9 20489081.301 9

3 5
*** Start of Occupation *** COMMENT
maysville MARKER NAME
aysville MARKER NUMBER
1156707.7940 -5107145.5082 3629140.4718 APPROX POSITION XYZ
2.0000 0.0000 0.0000 ANTENNA: DELTA H/E/N
21 1 22 15 48 38.000000 0 13G01G10G21G22G25G26G31G32R01R02R08R10
R12
24136627.641 4 24136634.523 9 126839052.743 4 98835478.683 9 24136634.21146
22787104.078 6 22787109.473 9 119746983.062 6 93309409.859 9 22787109.58247
24873280.523 6 130710124.891 6 101851927.01246 24873282.19946
23148136.109 2 121644210.077 2 94787736.64646 23148134.43446
21832487.805 6 21832493.664 9 114730530.872 6 89400413.516 9 21832492.78549
22666446.758 6 22666453.742 9 119113053.076 6 92815348.557 9 22666453.29347
20373962.805 7 20373965.219 9 107065897.846 7 83428011.982 9 20373965.04749

```

## Section 12: LiDAR PROCESSING STEP 1 – INERTIAL EXPLORER

This guide will provide you with step-by-step instructions on how to create a trajectory for your specific dataset using Inertial Explore.

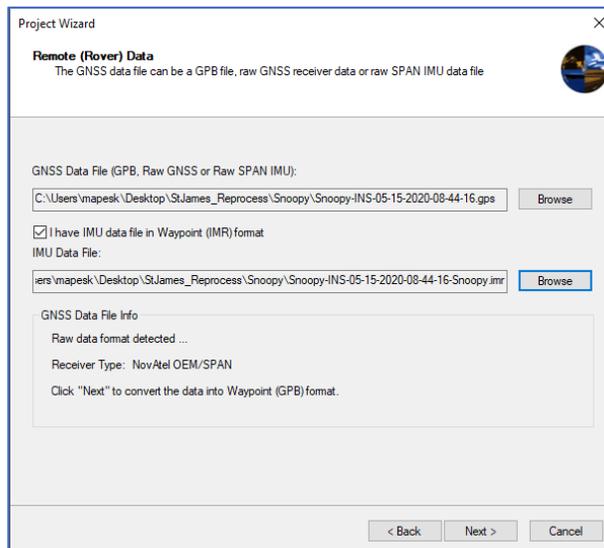
### 12.1: Inertial Explore: Project Setting

Open Inertial Explorer -> File -> New Project -> Project Wizard -> Next.

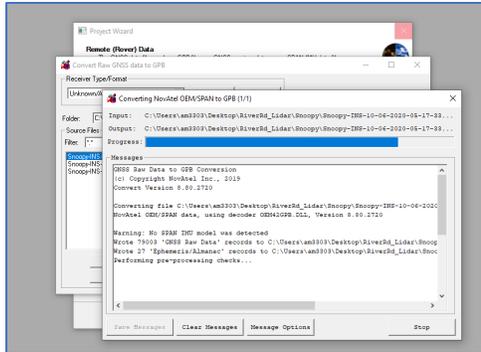
1. Under “INS”, name your project. Click Next.



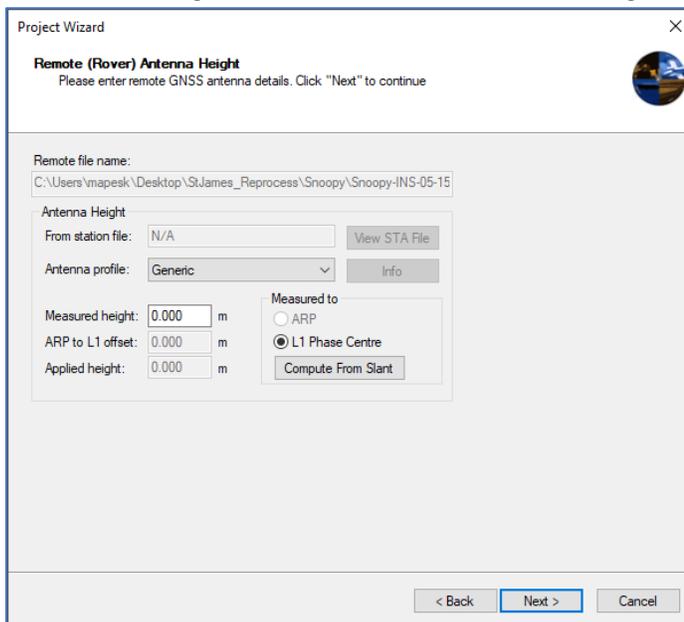
2. For GNSS: Snoopy -> .gps file  
For IMU Data: Snoopy -> .imr file (if you have)



Click **Next** (\*A processing window will pop up for about 15 seconds)



3. On the "Remote (Rover) Antenna Height" window, **do not alter** any of the settings as the antenna height offsets were accounted for during the flight



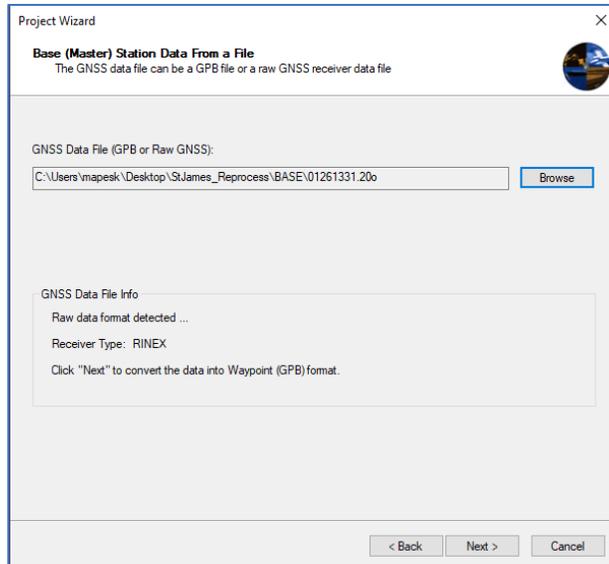
4. Choose **“I would like to add base station data”**  
Under **“Precise Files”** choose the **“Download precise files”** option

The screenshot shows the 'Project Wizard' dialog box with the title 'Base (Master) Station Option'. The text inside reads: 'You can choose whether or not to include base station data in your project. Please select a source for the precise files if you plan to perform PPP processing.' There are two radio buttons: the first is selected and labeled 'I would like to add base station data', and the second is labeled 'I would like to do PPP processing (requires precise files; no base station will be added)'. Below these is a 'Precise Files' section with three radio buttons: 'Download precise files' (selected), 'Add existing precise files from disk', and 'Do not add precise files'. At the bottom, there are buttons for '< Back', 'Next >', and 'Cancel'. A note at the bottom left says 'Click "Next" to continue'.

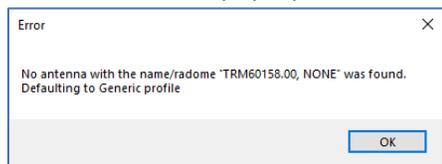
5. On the **“Base (Master) Station”** window, **click** on the **“Add Station from File”**, and then **click next**.

The screenshot shows the 'Project Wizard' dialog box with the title 'Base (Master) Station'. The text inside reads: 'You can add a base station to your project'. On the left, under 'Action to Perform:', there is a list of options: 'Add Station from File' (highlighted in blue), 'Add Station from Download', 'Edit Station', 'Remove Station', and 'Finish'. On the right, under 'Base Stations Currently in Project:', there is an empty table with two columns: 'Name' and 'File'. Below the table is a 'Description' field containing the text 'Add base station from GNSS data file'. At the bottom, there is a note: 'Select "Finish" when you are done adding base station data'. At the bottom right, there are buttons for '< Back', 'Next >', and 'Cancel'.

6. On the **“Base (Master) Station Data From a File”**, select **Browser** and navigate to the **BASE** folder and choose the **20o** file. This file will be translated to be **gpb** file.



7. Error window will pop-up. Click OK.



8. For "Base (Master) Station Information"

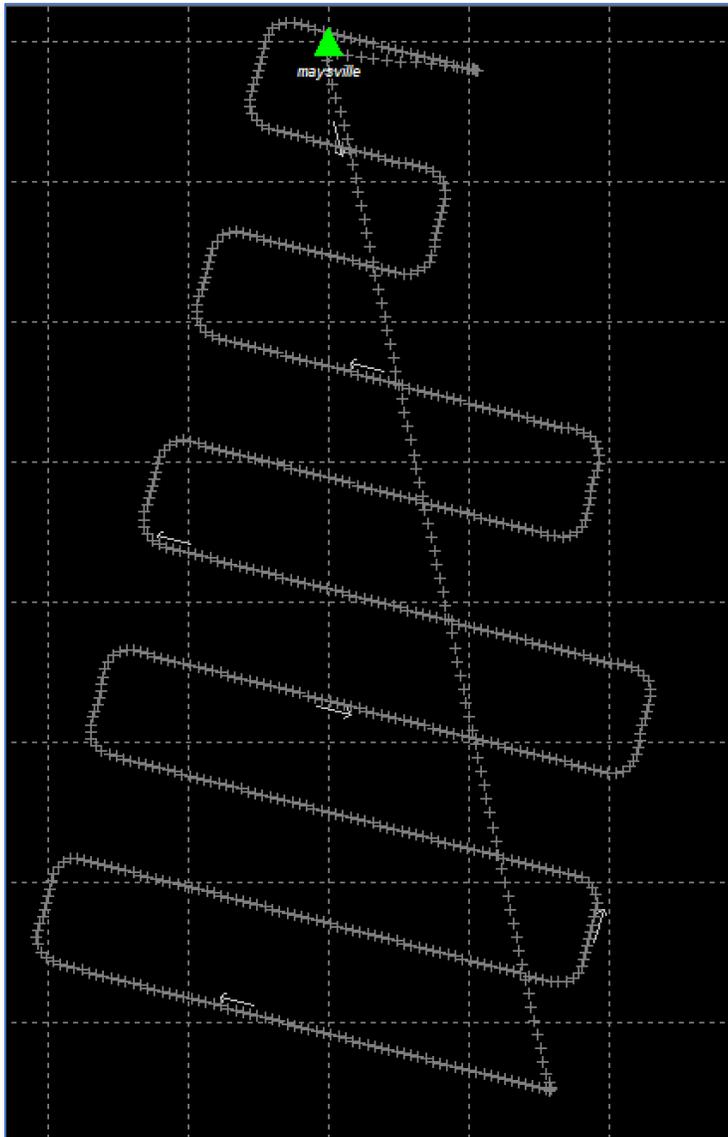
- Coordinate: correct the small decimals, change datum, Elip height, epoch. Go look at the OPUS text to find out.
- Antenna profile: select "TRMR8\_GNSS"
- Measured to: ARP (Antenna Reference Point)



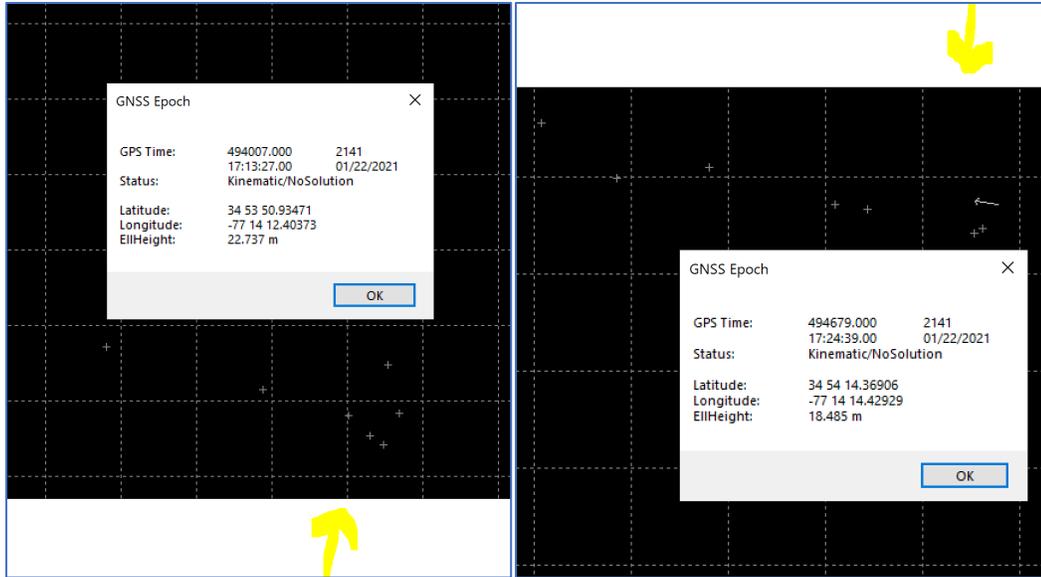
## 12.2: Process GNSS

The trajectory is now created. The line shows the flight path.

1. Click Process -> Process GNSS



If you like to clip off some flight path by time, make sure to have the start and end time by clicking on the point.

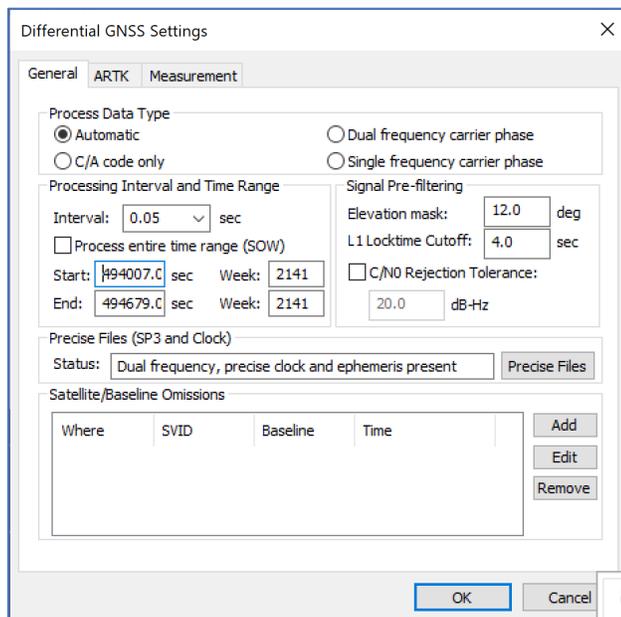
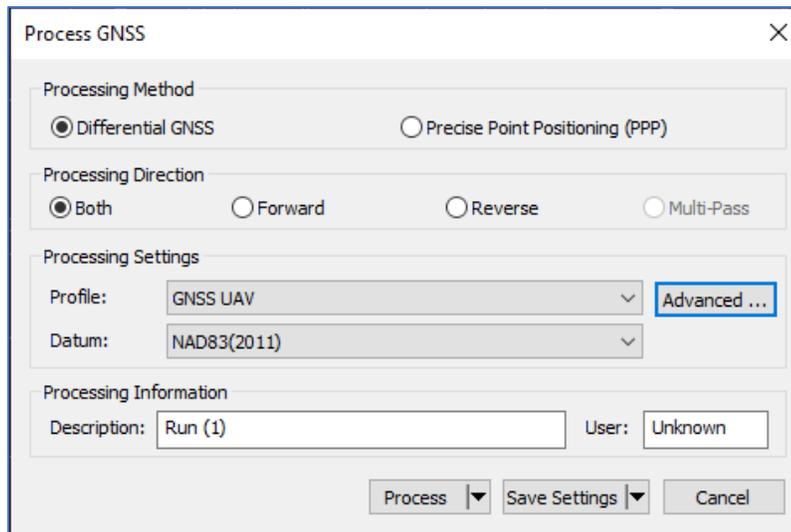


Start: 494007.000 – 17:13:27

End: 494679.000 – 17:24:39

2. Click on the “Process” -> “Process GNSS”
  - Processing Method: Differential GNSS
  - Processing Direction: Both
  - Profile: GNSS UAV
  - Datum: NAD83(2011)

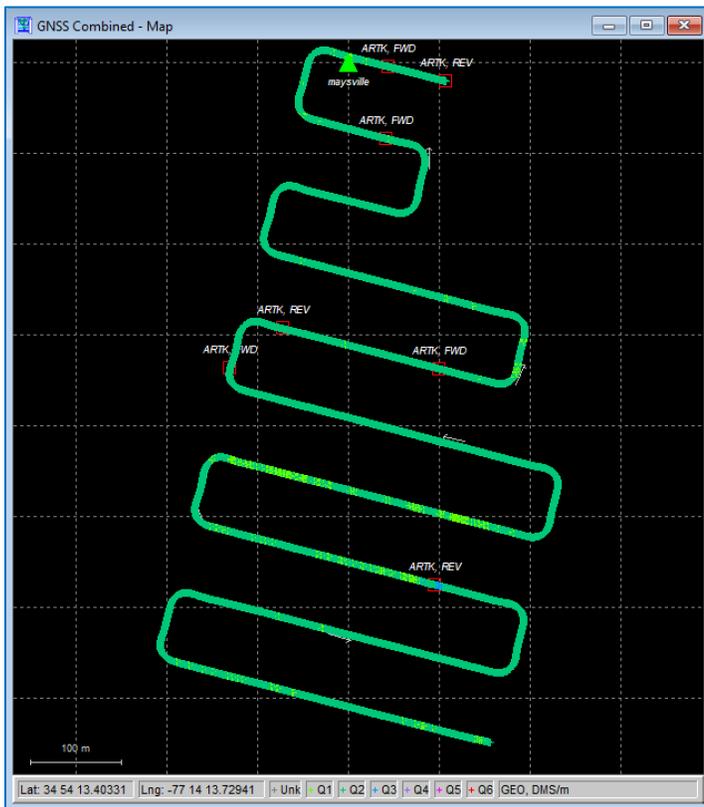
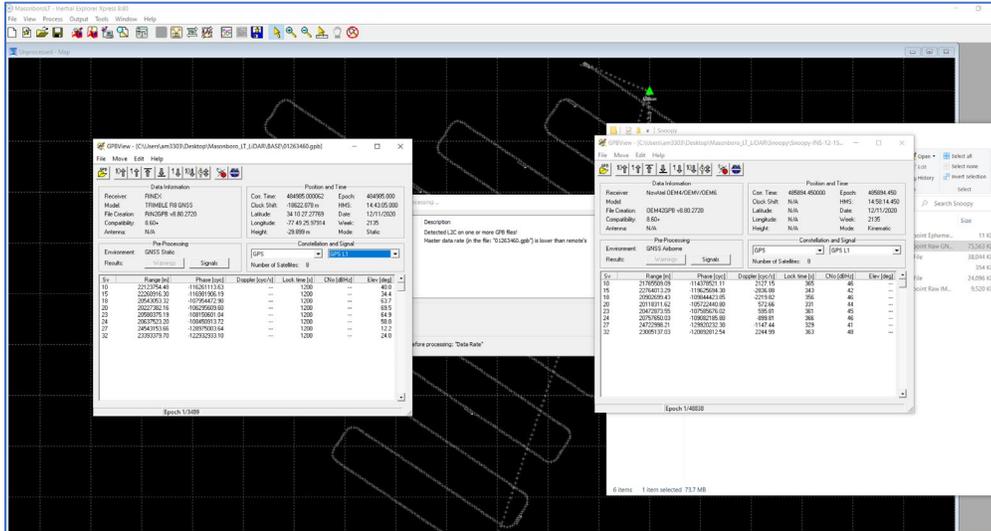
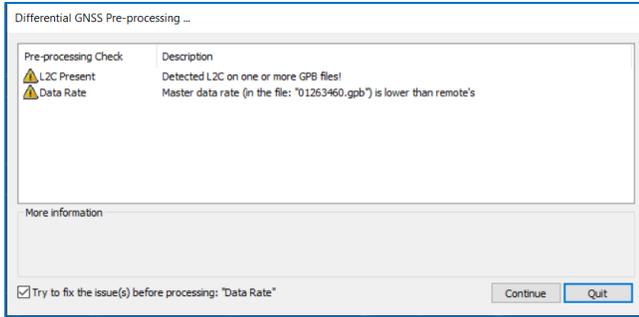
Select the datum in which you need your trajectory to be in. Advanced for selecting certain time frame.



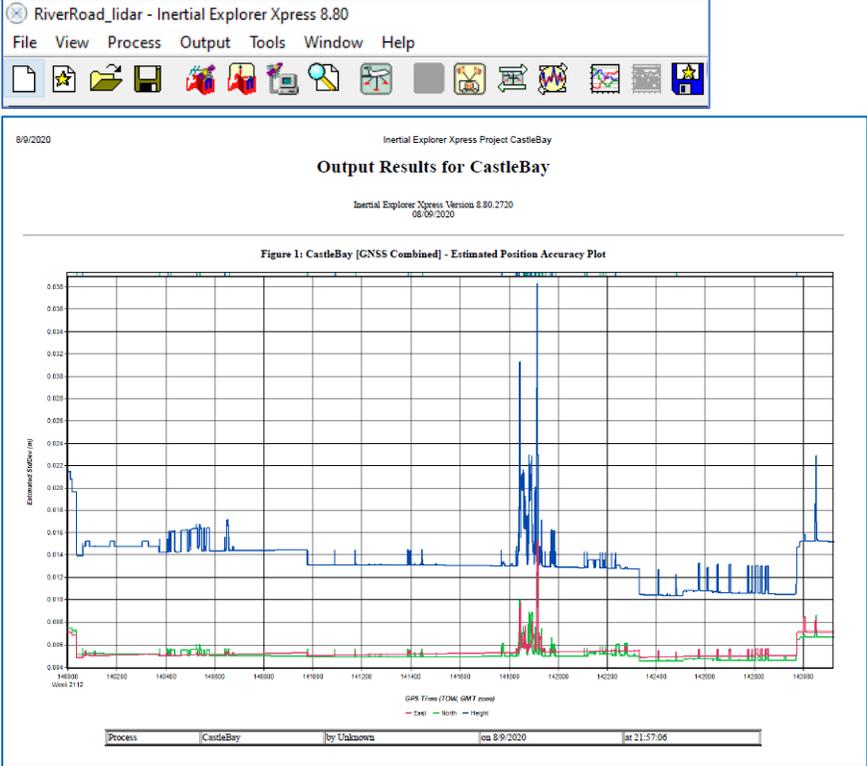
Start: 494007.000 – 17:13:27

End: 494679.000 – 17:24:39

The warning might come up, but you can hit continue.



3. Check the accuracy by selecting Plot Results -> Estimated Position Accuracy



### 12.3: Process Tightly Coupled

1. Click on the “Process” -> “Tightly Coupled”
  - Click Process -> Tightly Coupled.
  - Profile: SPAN UAV (STIM300)
  - Datum: NAD83(2011)

Process Tightly Coupled

Processing Method  
 Differential GNSS  Precise Point Positioning (PPP)

Processing Direction  
 Both  Forward  Reverse  Multi-pass

Processing Settings  
Profile: SPAN UAV (STIM300)  Filter Profiles   
Datum: NAD83(2011)

IMU Installation  
 No lever arm info in IMR file

Lever Arm Offset (IMU to GNSS antenna)  
X: 0.000 m Y: 0.000 m Z: 0.000 m  Z to ARP  Z to Phase Centre

Body to IMU Rotation (order: Z, X, Y)  
X: 0.000 deg Y: 0.000 deg Z: 0.000 deg

GNSS Heading Offset  
0.000 deg

Processing Information  
Description: TC (1) User: Unknown

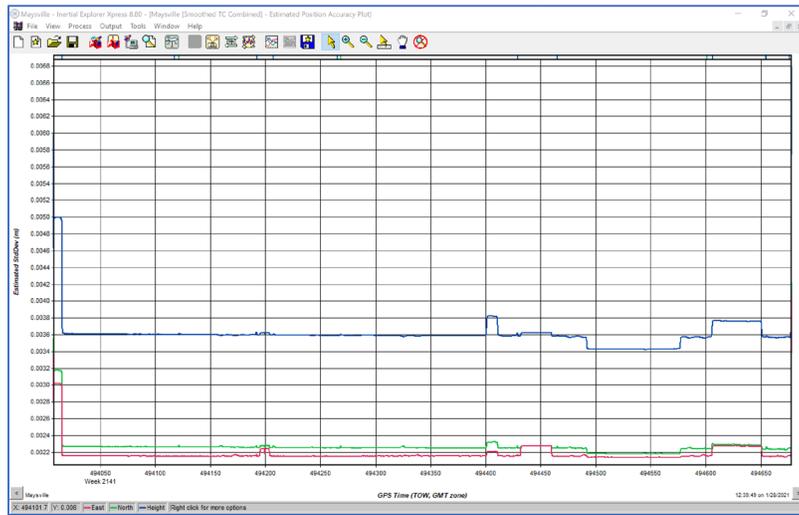
The GNSS trajectory is first processed and the resulting time-stamped position and velocity updates are passed to the loosely coupled processor. In this two-stage mode, users can extensively QC their processed GNSS-trajectory prior to LC processing.

Process (Tightly Coupled) - In this mode, GNSS and INS data are processed simultaneously. This mode is generally favored in challenging GNSS conditions as it maximizes GNSS availability, as phase updates (which form the distance and direction traveled between epochs) can be applied where as few as two satellites are available. This serves to significantly limit inertial error growth in the absence of a full GNSS position update.

This might take a while. Now trajectory has been processed. Now trajectory has been processed.

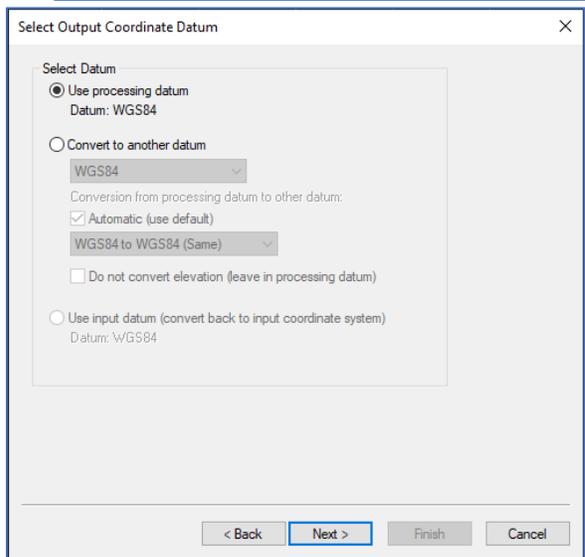
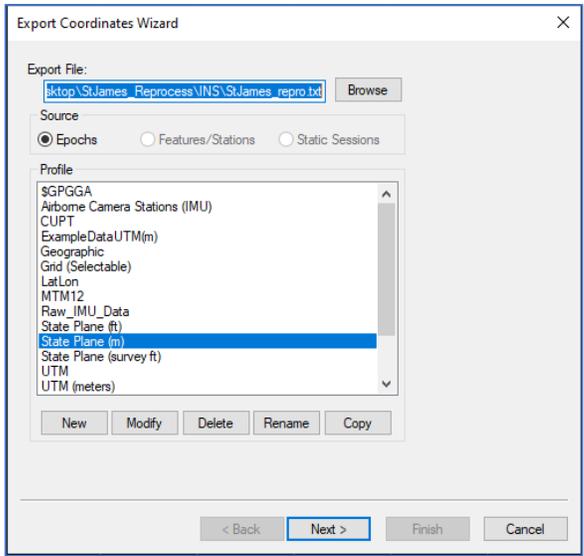


2. Run the estimated accuracy assessment again to see how this process improved.



## 12.4: Export Trajectory

Next step is to export the project. Go to Output -> Export Wizard



Select Grid System and Settings

Select Grid to use for Transformation

Grid: US State Plane

Datum: WGS84

Enter Zone Number

Zone:

Select State Plane Zone

Zone: NC (3200)

Enter Grid Coordinates

Easting (X):

Northing (Y):  Metres

Height (Z):

< Back Next > Finish Cancel

Geoid Correction

Geoid

Geoid file name:

Geoid datum: NAD83(2011) [NAVD88]; Output datum: WGS84

< Back Next > Finish Cancel

**IMU Epoch Settings** [X]

Limit Exported Time Range

Range #	Start Time (seconds)	End Time (seconds)

Add  
Remove

Export Interval Options

Binary trajectory interval:  (s)

Time Interval:  (s)

Distance Interval:  (m)

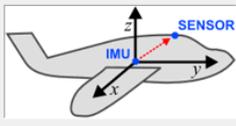
Transfer IMU Coordinates

Apply lever arm (IMU to Sensor)

X:  (m)

Y:  (m)

Z:  (m)



< Back   Next >   Finish   Cancel

**W-P-K Conversion** [X]

Axes Definition

System:  Geodetic    Grid: US State Plane, NC (3200)

Order:  [v]

Axes:  [v]

User angles: TX:  (deg)

TY:  (deg) (order IMU->Sensor)

TZ:  (deg)

Boresight Angles

Correct for boresight angles (IMU->Sensor orientation difference)

BX:  (deg)  

BY:  (deg)

BZ:  (deg) (order BX-BY-BZ applied)

< Back   Next >   Finish   Cancel

Sequence Number Options

Start sequence number value:

Increment sequence number by this value:

Reset to Start when sequence number larger than this value:

Continue incrementing if epoch/feature not written

Finish

< Back   Next >   Finish   Cancel

Export Definition Complete

Information  
 File: C:\Users\mapesk\Desktop\StJames\_Reprocess\INS\StJames\_rep...  
 Source: GNSS/INS Epochs

Export Fields  
 Sequence Number  
 GPS Time [Seconds of the Week]  
 GPS Week Number [GPS Weeks]  
 State Plane-East [Metres]  
 State Plane-North [Metres]  
 Orthometric Height [Metres]  
 Omega Angle [Decimal Degrees (signed)]  
 Phi Angle [Decimal Degrees (signed)]  
 Kappa Angle [Decimal Degrees (signed)]

View ASCII output file on completion   Preview

< Back   Next >   Finish   Cancel

Done!

```

C:\Users\mapesk\Desktop\CastleBayGolf\INS\CastleBay2.txt
Project:      CastleBay2
Program:     Inertial Explorer Version 8.80.2720
Profile:     State Plane (n)
Source:      GNSS/INS Epochs(Smoothed TC Combined)
SolFile:     C:\Users\mapesk\Desktop\CastleBayGolf\INS\CastleBay2.cts
ProcessInfo: CastleBay2 by Unknown on 8/13/2020 at 12:50:31

Datum:       VGS84
Master 1:   Name 0126, Status ENABLED
            Antenna height 2.000 m, to ARP [TRMR8_GNSS(NONE)]
            Lat, Lon, El Hgt 34 24 34.75375, -77 42 09.55195, -21.576 m [NAD83(2011), 2010.000]
Remote:     Antenna height 0.000 m, to L1PC [Generic(NONE)]
IMU to GNSS Antenna Lever Arms:
            x=0.000, y=0.000, z=0.000 m (x-right, y-fwd, z-up)
Body to Sensor Rotations:
            xRot=0.000, yRot=0.000, zRot=0.000 degrees (Rotate IMU into Vehicle Frame)
Geoid:      GE01D18(CONUS).wpg [NAVD88] (Absolute correction)

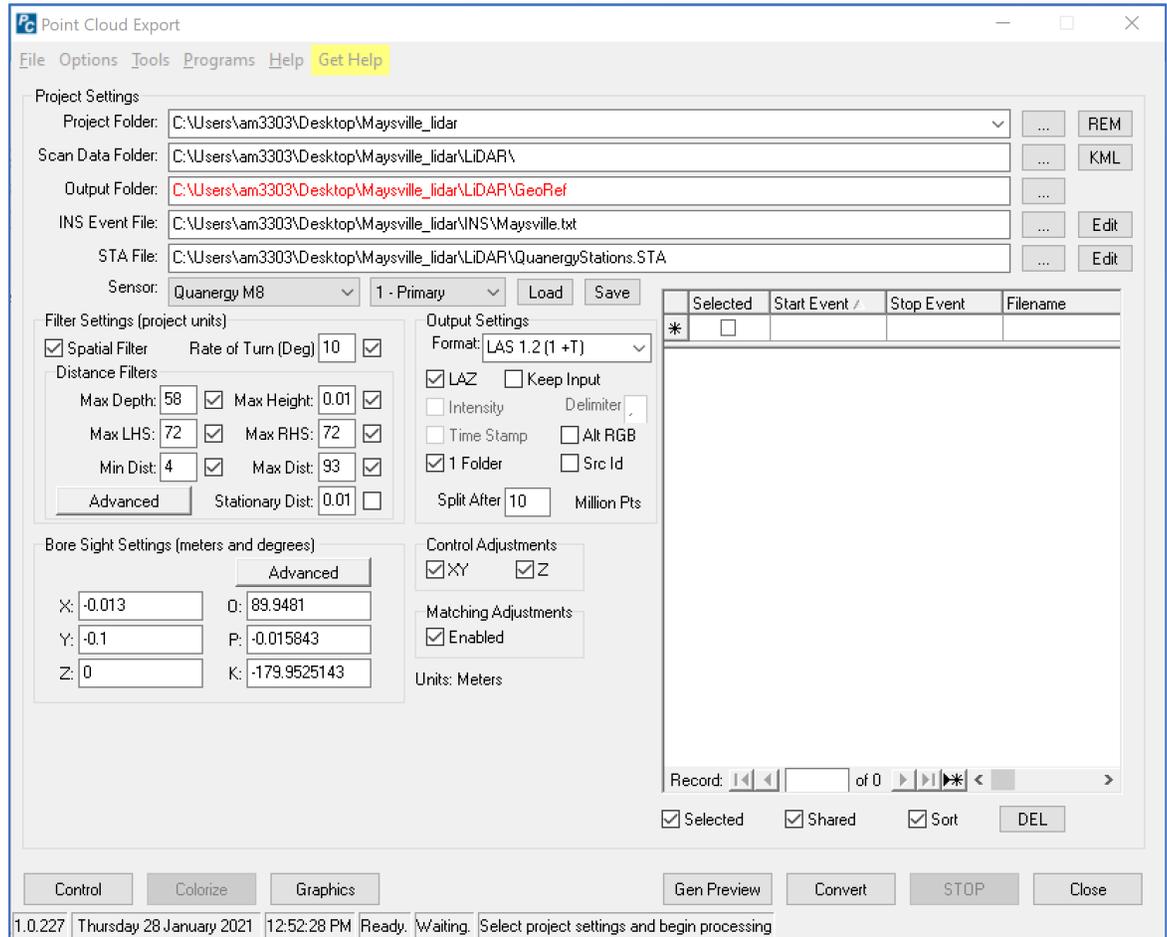
Map projection Info:
  Defined grid: US State Plane, NC (3200)
  U.S. State Plane for NC (3200)
W-P-K Settings:
  System:   Map (US State Plane, NC (3200))
  Order:    W primary, P secondary, K-tertiary
  Axes:     x-right, y-forward, z-up
  Boresight: Off
  
```

## Section 13: LiDAR PROCESSING STEP 2 – Scanlook PC

This guide will provide you with step-by-step instructions on operating ScanLook PC which is needed for point cloud generation. Once successfully completed, you will be able to output point clouds viewed and manipulated in third party software.

### 13.1: Project Setting

1. Search and open “scanlook pc point cloud creation”.



2. Project Settings

For the “**Project Folder**”, place the data path of the LiDAR main folder (should be “SiteName\_LiDAR” in the local drive).

In this example, select “C:\Users\mapesk\Desktop\CastleBayGolf”, which file has all the “Inertial Explorer” data. After you selected that main project folder, then the rest of folders should ALL AUTOMATICALLY FILE IN from your main project folder. **THE GEOREF folder needs to be red as it needs to be created.** You can edit the folder connections if they did not automatically file in.

Sensor: Quanergy M8, 1 – Primary

Project Settings

Project Folder:	C:\Users\mapesk\Desktop\CastleBayGolf	...	REM
Scan Data Folder:	C:\Users\mapesk\Desktop\CastleBayGolf\LiDAR\	...	KML
Output Folder:	C:\Users\mapesk\Desktop\CastleBayGolf\LiDAR\GeoRef	...	
INS Event File:	C:\Users\mapesk\Desktop\CastleBayGolf\INS\CastleBay2.txt	...	Edit
STA File:	C:\Users\mapesk\Desktop\CastleBayGolf\LiDAR\Quanergy\Stations.STA	...	Edit
Sensor:	Quanergy M8	1 - Primary	Load Save

Selected Start Event / Stop Event Filename

3. Filter Settings (Units Meters)/ Distance Filters  
 Check: Spatial Filter and Rate of Turn (Deg) as 10

Filter Settings (project units)

Spatial Filter    Rate of Turn (Deg)

Distance Filters

Max Depth:      Max Height:

Max LHS:      Max RHS:

Min Dist:      Max Dist:

   Stationary Dist:

Air Data for more info about flight mission

Here are the explanation of each parameters and its example numbers if you fly at

175ft.

- Max Depth: 175ft (53.3m)
  - Discards all points more than the entered value below the scanner. It is not an absolute depth, but it is relative to the scanner itself.
  - If we fly at 150ft, the max depth needs to be bigger, but not too big.
- Max Height: 0.01ft (0.01m)
  - It won't process above this height. So, in this case, it won't take any point at more than 0.01 ft above the sensor.
- Max LHS / RHS (Right Hand Side): 150 ft (45.7m)
  - These filters discard all points beyond the range set
  - This is to match the distance between the flight lines.
- Min Distance: 12 ft (3.66m)
  - Set filters to discard all points within the Min Distance
- Max Distance: 250 ft (76.2m)
  - Set filters to discard all points outside the Max Dist.
  - think hypotenuse resolving the distance between flight lines and sensor
- Stationary Distance: No Select unless mobile mapping

- Sets the minimum distance the vehicle must travel between revolutions of the selected sensor to be included in the output data. If the vehicle does not travel enough then those points in that revolution of the scanner are discarded.

#### 4. Output Settings

- Format: LAS 1.2  
Select the output format in which you want to generate depending on which 3rd party point cloud post-processing program you use you may need to generate one.
- Check: LAZ and 1 Folder

Output Settings

Format: LAS 1.2 (1 +T)

LAZ     Keep Input

Intensity    Delimiter: ,

Time Stamp     Alt RGB

1 Folder     Src Id

Split After: 10 Million Pts

#### 5. Bore Sight Settings

Enter in the Bore Sight Values that will be given to you provided from LidarUSA.

Back of UAV    3/9/20  
Boresight: AQB2-19-0653-05

IE Processing Values		ScanLook PC	
Lever Arms	Rotations	X	O
X = -0.117	X = 0	X = -0.013	O = 89.9481
Y = 0.073	Y = 0	Y = -0.1	P = -0.015843
Z = 0.400	Z = 0	Z = 0	K = -179.9525143

eGPS SOLUTIONS

Bore Sight Settings (meters and degrees)

Advanced

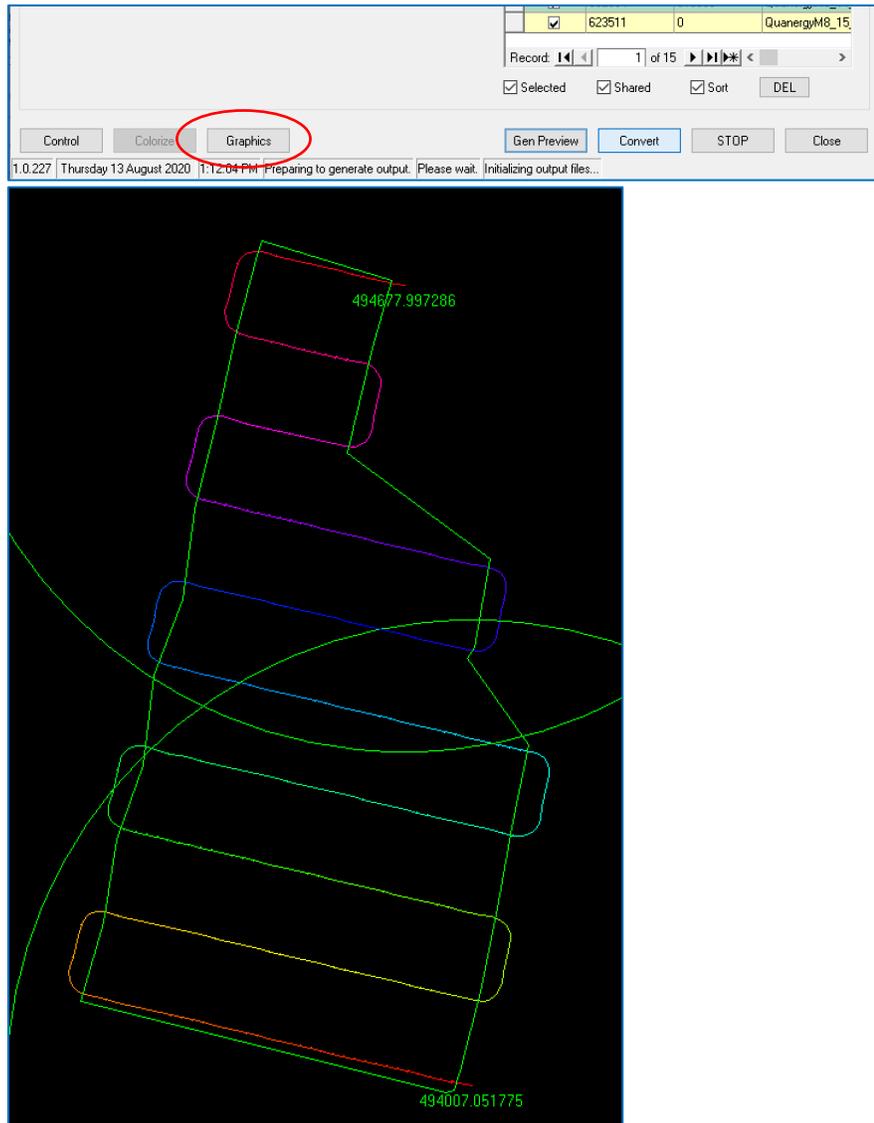
X: -0.013    O: 89.9481

Y: -0.1    P: -0.015843

Z: 0    K: -179.9525143

## 13.2: Graphics

1. The **“Graphics”** button on the bottom of the window, will show you the trajectory. In this menu you can select the parts which you would like to see a gridded display. Right click your mouse then in this menu go down to **“Boundary”** then click, **“Start Boundary”**. You might want to cut out the corner turns to reduce errors. Exit the graphic window when done.



Now, data selected in the previous step will show up in the selected menu.

Selected	Start Event /	Stop Event	Filename
* <input type="checkbox"/>			
<input checked="" type="checkbox"/>	97010	125756	QuanergyM8_1_
<input checked="" type="checkbox"/>	132662	162221	QuanergyM8_2_
<input checked="" type="checkbox"/>	167592	198092	QuanergyM8_3_
<input checked="" type="checkbox"/>	205233	236042	QuanergyM8_4_
<input checked="" type="checkbox"/>	243314	274910	QuanergyM8_5_
<input checked="" type="checkbox"/>	303992	320787	QuanergyM8_6_
<input checked="" type="checkbox"/>	429035	460179	QuanergyM8_7_
<input checked="" type="checkbox"/>	467839	499795	QuanergyM8_8_
<input checked="" type="checkbox"/>	506919	539271	QuanergyM8_9_
<input checked="" type="checkbox"/>	545794	578956	QuanergyM8_10_

### 13.3: Convert

1. If you click, “**Convert**” the selected data (or the entire project) depending on what you want to convert for your project will be the file format you selected. To find these generated files, click in the “**Lidar**” folder of your project, then click in the “**GeoRef** folder”.

The screenshot shows a software interface with several panels. On the left, there are 'Bore Sight Settings (meters and degrees)' and 'Control Adjustments' (with checkboxes for X, Y, Z and Matching Adjustments). On the right, there is a table of data with columns for 'Selected', 'Start Event /', 'Stop Event', and 'Filename'. The 'Convert' button at the bottom is circled in red. Below the table, there are navigation controls and checkboxes for 'Selected', 'Shared', 'Sort', and 'DEL'.

C > Desktop > Topsail\_LiDAR > LiDAR

Name	Date modified	Type
GeoRef	7/9/2020 5:31 PM	File folder
gps-time-position.csv	6/5/2020 5:22 PM	Microsoft Excel C...
gps-time-position2.csv	7/9/2020 2:30 PM	Microsoft Excel C...
QuanergyData_1.qnrg	6/5/2020 3:44 PM	QNRG File
QuanergyData_2.qnrg	6/5/2020 3:45 PM	QNRG File

> Desktop > Topsail\_LiDAR > LiDAR > GeoRef

Name	Date modified	Type
output	7/9/2020 5:31 PM	File folder
QuanergyM8_001.laz	7/9/2020 4:19 PM	LAZ Laser Point File
QuanergyM8_002.laz	7/9/2020 4:21 PM	LAZ Laser Point File
QuanergyM8_003.laz	7/9/2020 4:23 PM	LAZ Laser Point File
QuanergyM8_004.laz	7/9/2020 4:24 PM	LAZ Laser Point File
QuanergyM8_005.laz	7/9/2020 4:26 PM	LAZ Laser Point File
QuanergyM8_006.laz	7/9/2020 4:27 PM	LAZ Laser Point File

## Section 14: DATA PROCESSING IN GLOBAL MAPPER –ACCURACY ASSESSMENT

This guide will provide you with step-by-step instructions on operating Global Mapper which is needed to assess vertical accuracy. Once successfully completed, you will be able to see the total RMSE.

### 14.1: Check Points

On the field, you will collect two kinds of points: **check points and control points**. Control points measured on each target will be used to georeference the LiDAR data. Check points could be measured on the target or random place with high accuracy and will be used to assess the vertical accuracy of the unconstrained point clouds here.

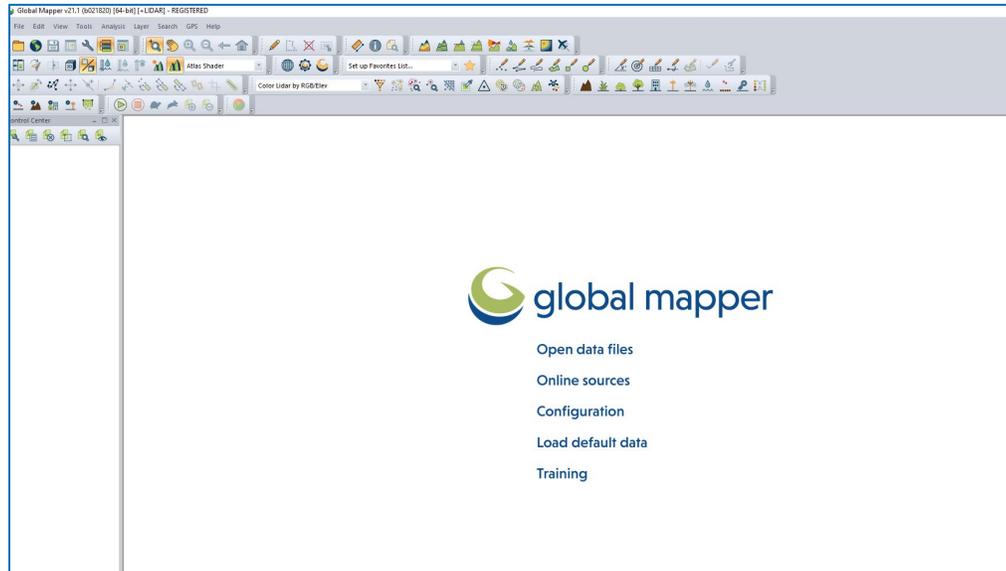
Creating a check point **csv** file out of the Trimble data. Format like the images below.

	A	B	C	D	E	F
1	Point ID	Easting	Northing	Elevation	Code	
2	gcp-1	688658.7	22361.12	17.693	LiDAR Target	
3	gcp-2	688757.9	22546.59	16.171	LiDAR Target	
4	gcp-3	688892.6	22304.06	16.066	LiDAR Target	
5	gcp-4	689087.3	22478.44	15.455	LiDAR Target	
6	gcp-5	689540	22894.81	19.255	LiDAR Target	
7	gcp-6	689006.3	23078.65	18.524	LiDAR Target	
8	gcp-7	689274.1	22999.84	18.323	LiDAR Target	
9	gcp-8	689188.6	23149.93	19.479	LiDAR Target	
10						

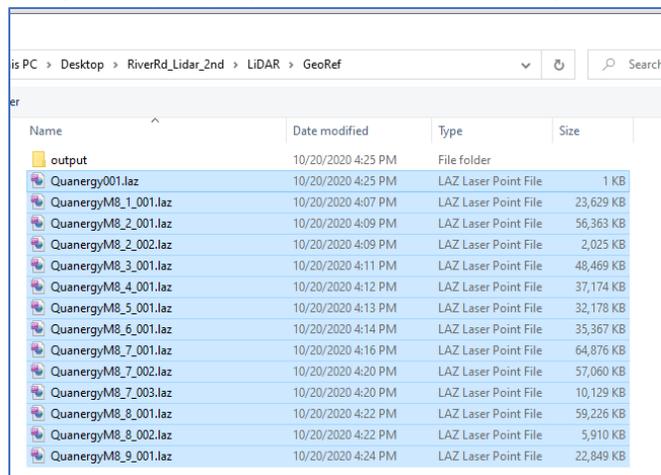
Name	x	y	z	Habitat	Check/ Control
gcp_0	770582.512	129466.932	9.994	woody field	Control
gcp_1	770546.498	129398.302	10	Woody field	Control
gcp_2	770549.528	129319.607	10.33	Woody field	Control
gcp_3	770506.234	129254.739	10.758	Woody field	Control
gcp_6	770721.455	129042.01	11.181	Woody field	Control
gcp_7	770741.664	128958.522	9.969	woody field	Control
gcp_8	770732.892	128883.926	10.918	woody field	Control
gcp_9	770726.727	128806.342	8.599	woody field	Control
gcp_10	770706.664	128731.741	4.733	woody field	Control
hab_13	770483.336	129120.095	9.792	forest by stream	Error
hab_23	770502.861	129236.441	10.883	forest edge	Check
hab_38	770729.599	128758.12	6.503	woody field	Check
hab_37	770767.545	128937.03	10.415	woddy	Check
hab_91	770726.818	128930.189	11.389	RU	Check

## 14.2: Load Data

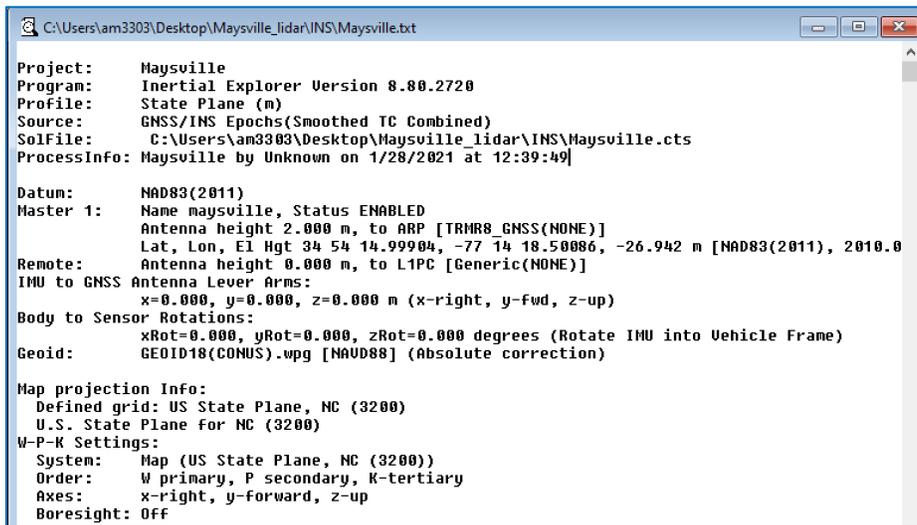
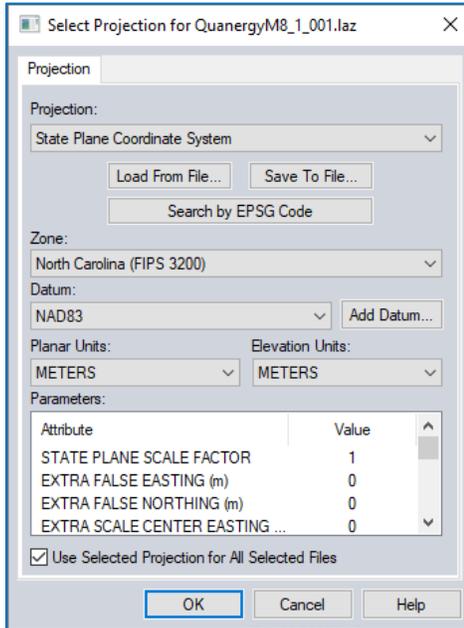
### 1. Open global mapper and select **Open data files**



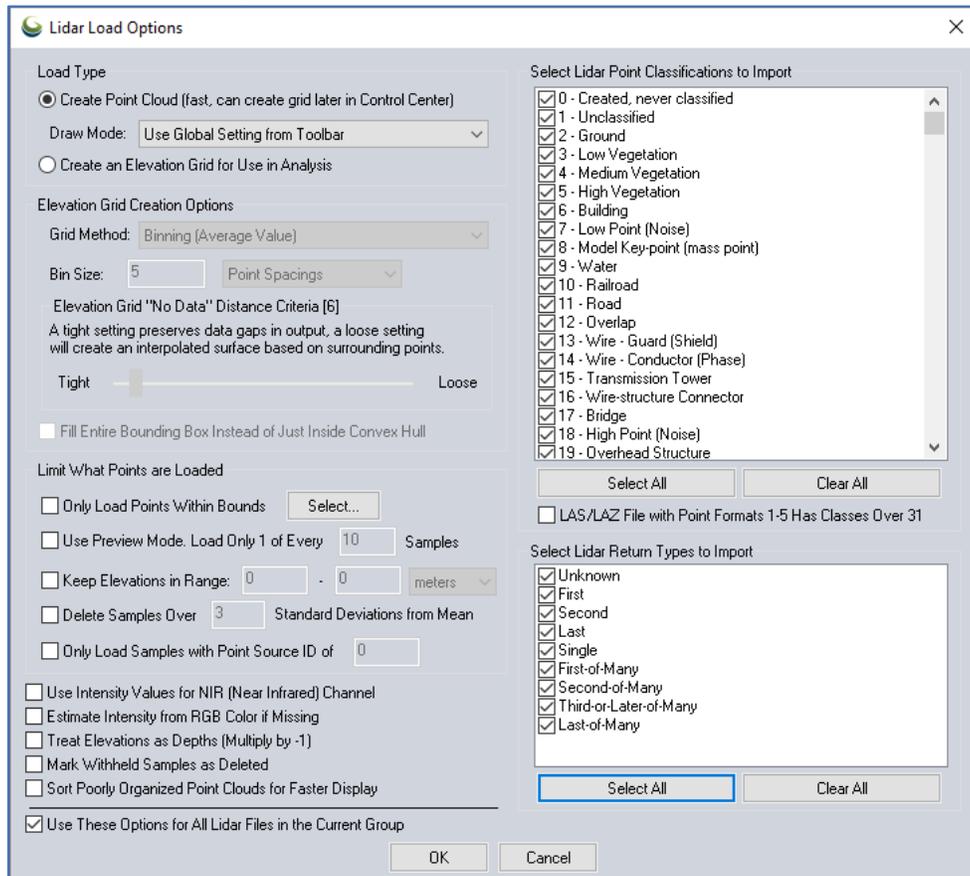
### 2. Navigate to your project folder and **select the point cloud file**



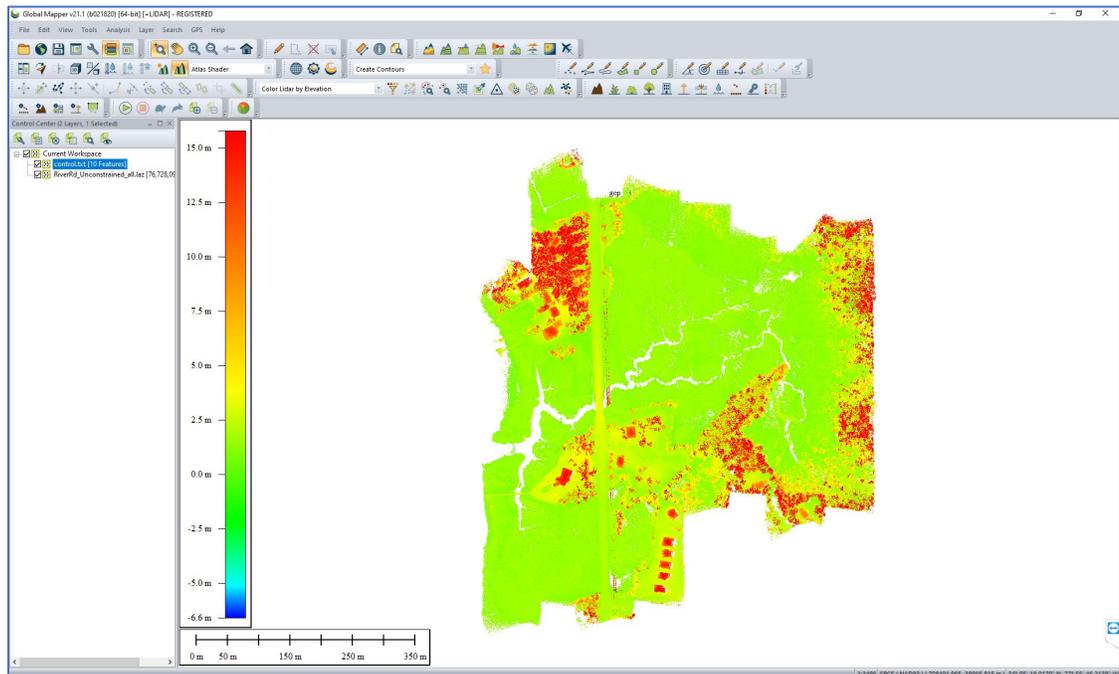
3. Select Projection for LAZ data. **State Plane NC 3200, NAD 83**, and all in **meters**. Check for “Use Selected Projection for All Selected Files” If you are unsure about the coordinate system, you can find that information by opening the **SiteName.text** file from the Inertial Xplore.



#### 4. Use a default setting



#### 5. Now you have loaded all Laz files



#### 6. Load the control.csv file: File -> Open data files -> control.csv

Easting	Northing	Elevation	ID
709496.333	37703.268	1.55	gcp_1
709180.963	38040.27	1.113	gcp_4
709180.83	37803.035	2.275	gcp_5
709184.563	37556.371	1.512	gcp_6
709252.875	37567.695	2.179	gcp_7
709117.575	37792.911	1.689	gcp_8
709257.194	37825.141	2.605	gcp_9
709104.741	37980.972	2.371	gcp_10
709419.341	37746.617	2.467	gcp_12
709181.157	38191.025	0.748	gcp_13
709028.38	37974.078	1.749	gcp_16

7. Generic ASCII Text File Import Options. Change coordinate layout depending on how your control.csv is formatted out. The first row in the file has the column titles. In this case, you would want to **skip at start of file: 1**.

Generic ASCII Text File Import Options (control.txt)

Import Type

- Point Only (All Features are Points)
- Point, Line, and Area Features
- Area Only (All Features are Polygons / TINs)
- Elevation Grid from 3D Point Data
- Lidar Point Cloud (3D Points + Optional Intensity/Color)

Coordinate Order: X / Easting / Longitude Coordinate First

Coordinate Format: Default (Decimal or Separated)

Coordinate Layout

Fields to Skip at Start of Line: 0

Rows to Skip at Start of File: 1

Coordinate Pairs Per Line: 1

Coordinate Line Prefix

- None. Coordinates appear immediately at the start of any lines in the text file that they appear in.
- All coordinate lines begin with the text string specified below.

For example, some ASCII formats may begin a coordinate line with XY.

Select Coordinate Offset/Scale...

Use Selected Options for All ASCII Files

Coordinate Delimiter

Select the characters that are used to separate the coordinates in a coordinate line from the file. Select the Auto-Detect option if you are not sure.

- Auto-Detect
- Space or tab
- Tab
- Comma
- Semi-colon

Feature Classification

Assign Loaded Area Features the Classification: Unknown Area Type

Assign Loaded Line Features the Classification: Unclassified Line Feature

Assign Loaded Point Features the Classification: Unknown Point Feature

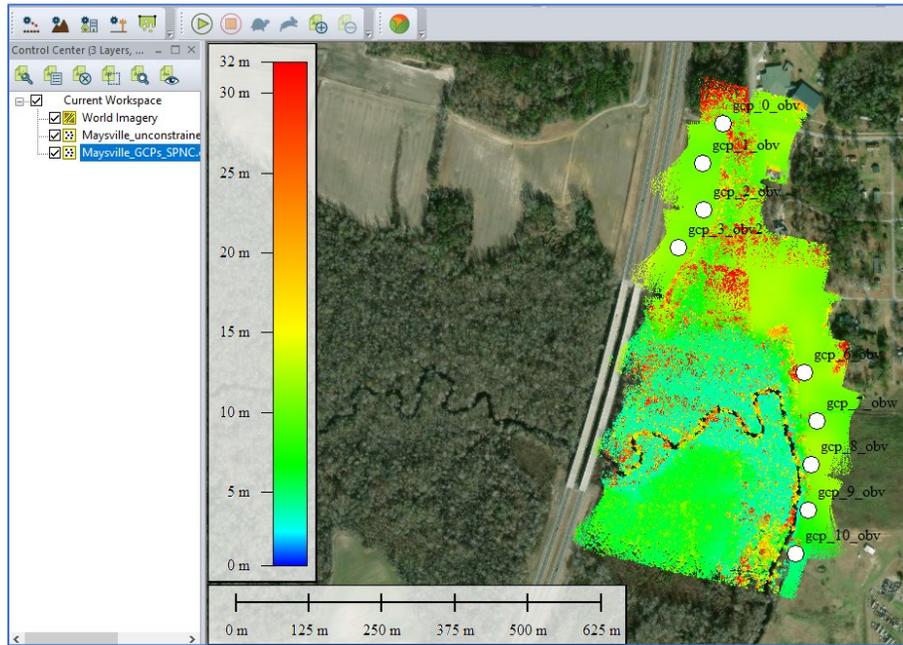
Assign Loaded Lidar Samples the Classification: 0 - Created, never classified

- Include attributes from lines with coordinate data
- Column headers in first row of file (points/WKT only)
- Treat 3rd coordinate value as elevation. No Data = -999999
- Treat coordinate values 4-8 as fly-through path data
- Break Line/Area Features on Change in Field 3
  - Break Field is Pen Up/Down (0/1)
- Create Areas from Closed Lines

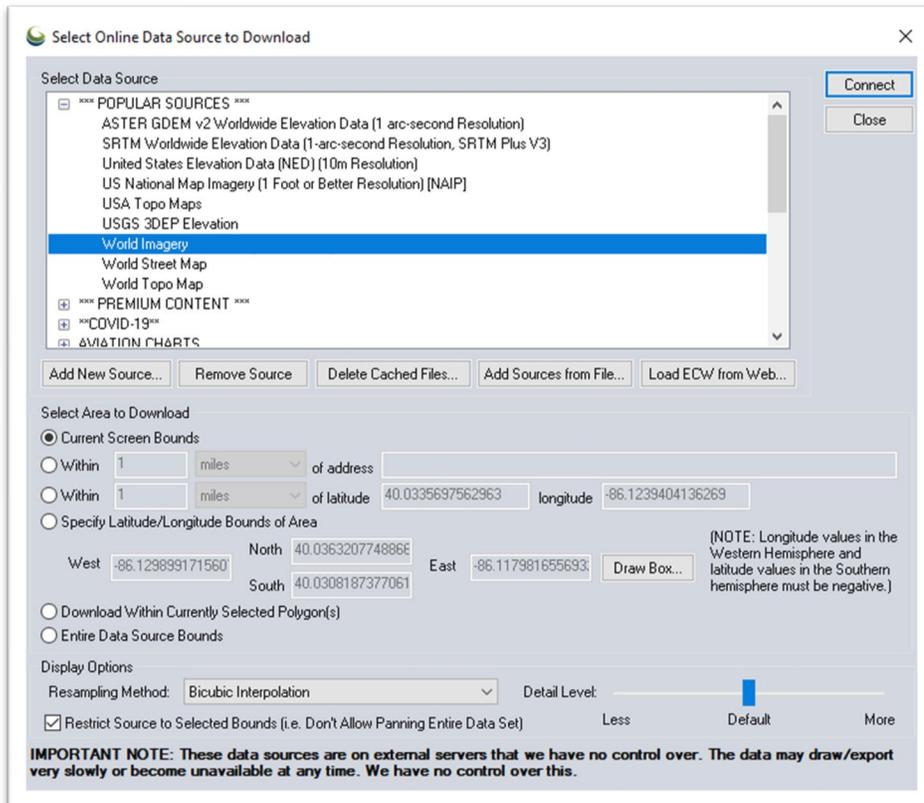
OK Cancel Help

8. Assign the same coordinate system as LiDAR data.

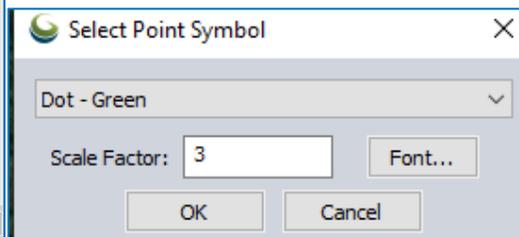
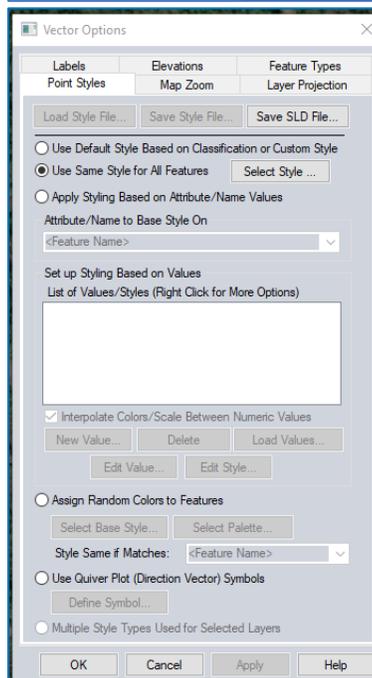
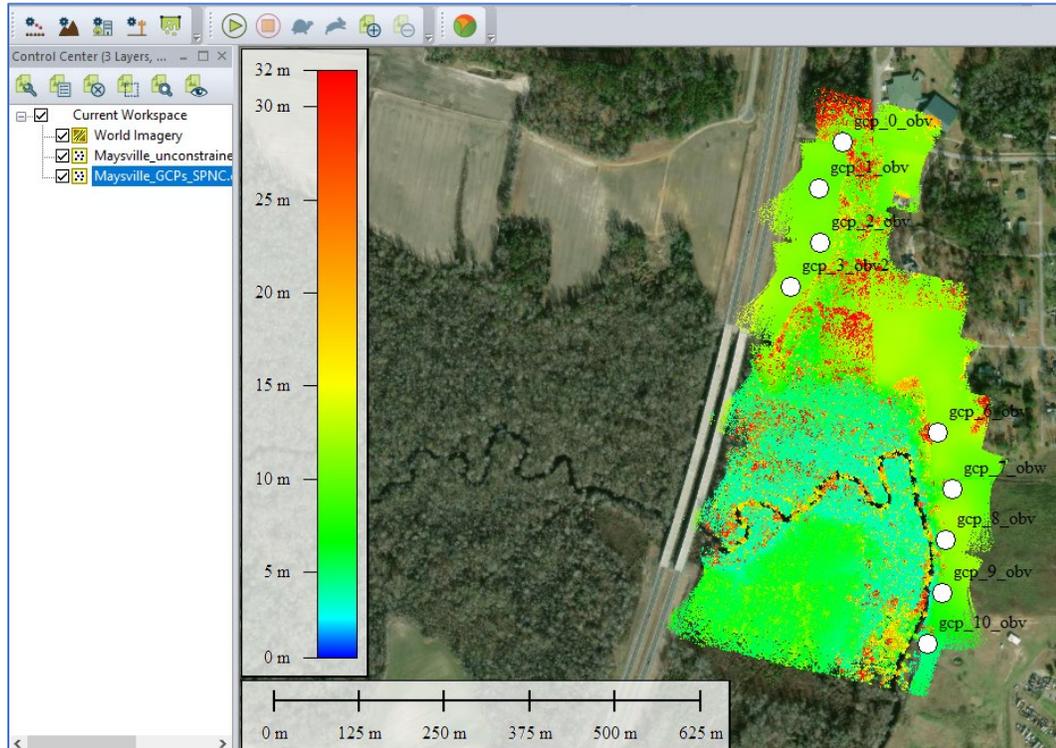
- Now you have loaded the point clouds and GCP data. But how do we know they are in the correct place? Let's add a base-map.



- Go to **File > Download Online Imagery/Topo/Terrain Maps**. Select **World Imagery**.

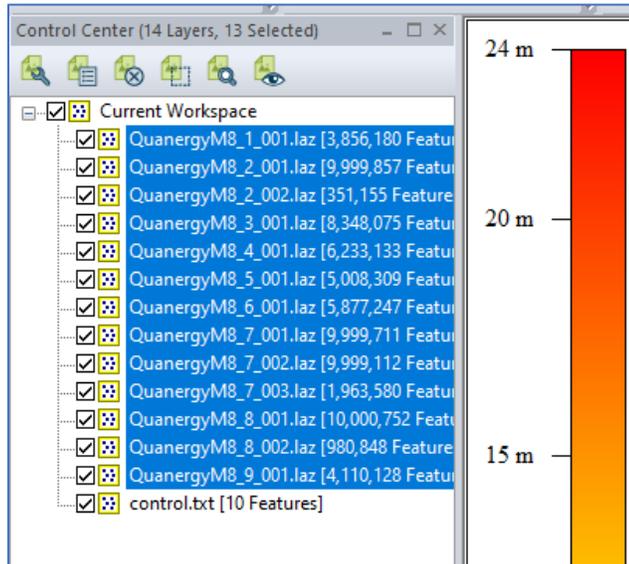


11. Now we can assess if our data and GCPs are showing up in the located where we conducted our survey. But, our GCPs are very difficult to see, so let's change their symbology so they are more visible. Double click on the GCP layer in the table of contents. Under the **Point Style** tab, click the radio button for **Use Same Style for all Features**, then click the **Select Style** button next to that. Choose a **color** that stands out from the drop-down and increase the **scaling factor** slightly. Click Ok then Apply then Ok again.

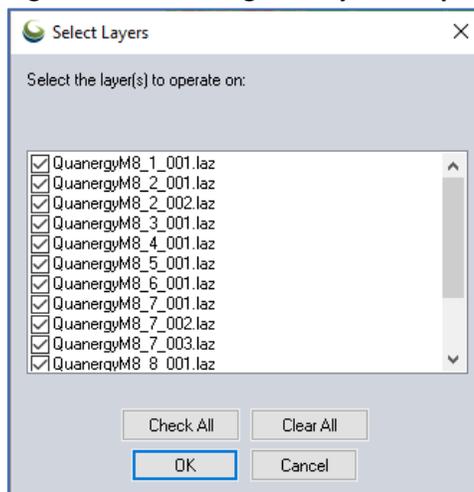


### 14.3: Merge LASs

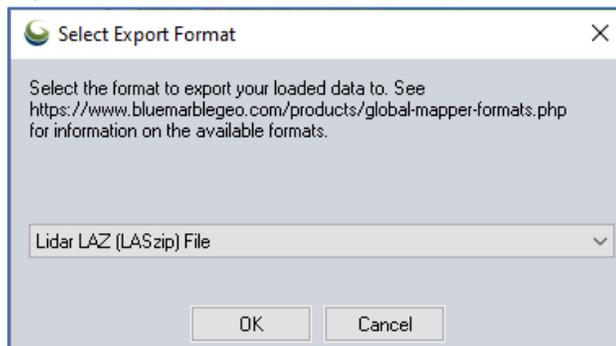
1. Merge all Laz files to create one point-cloud las. Select all in Control Center.



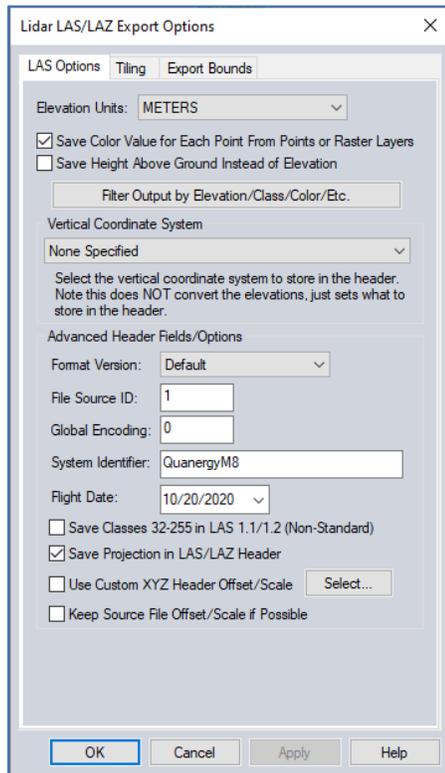
2. Right click on it and go to **Layer -> Export**. Hit Ok.



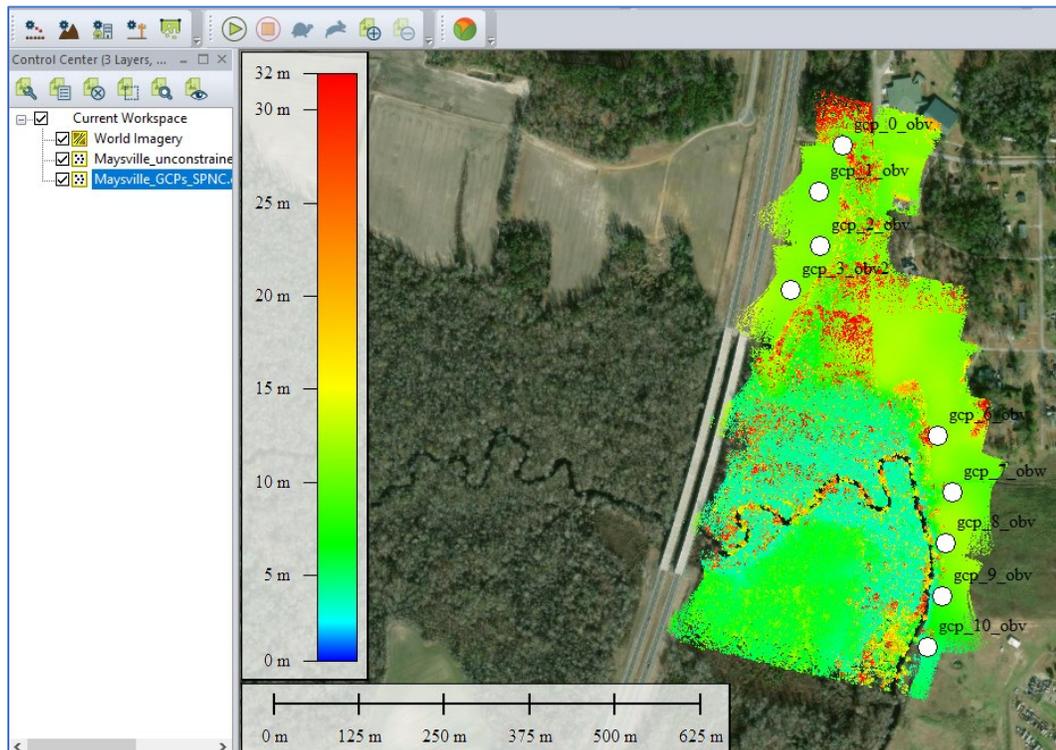
3. Export in LAZ file



- Keep the default setting and hit OK.

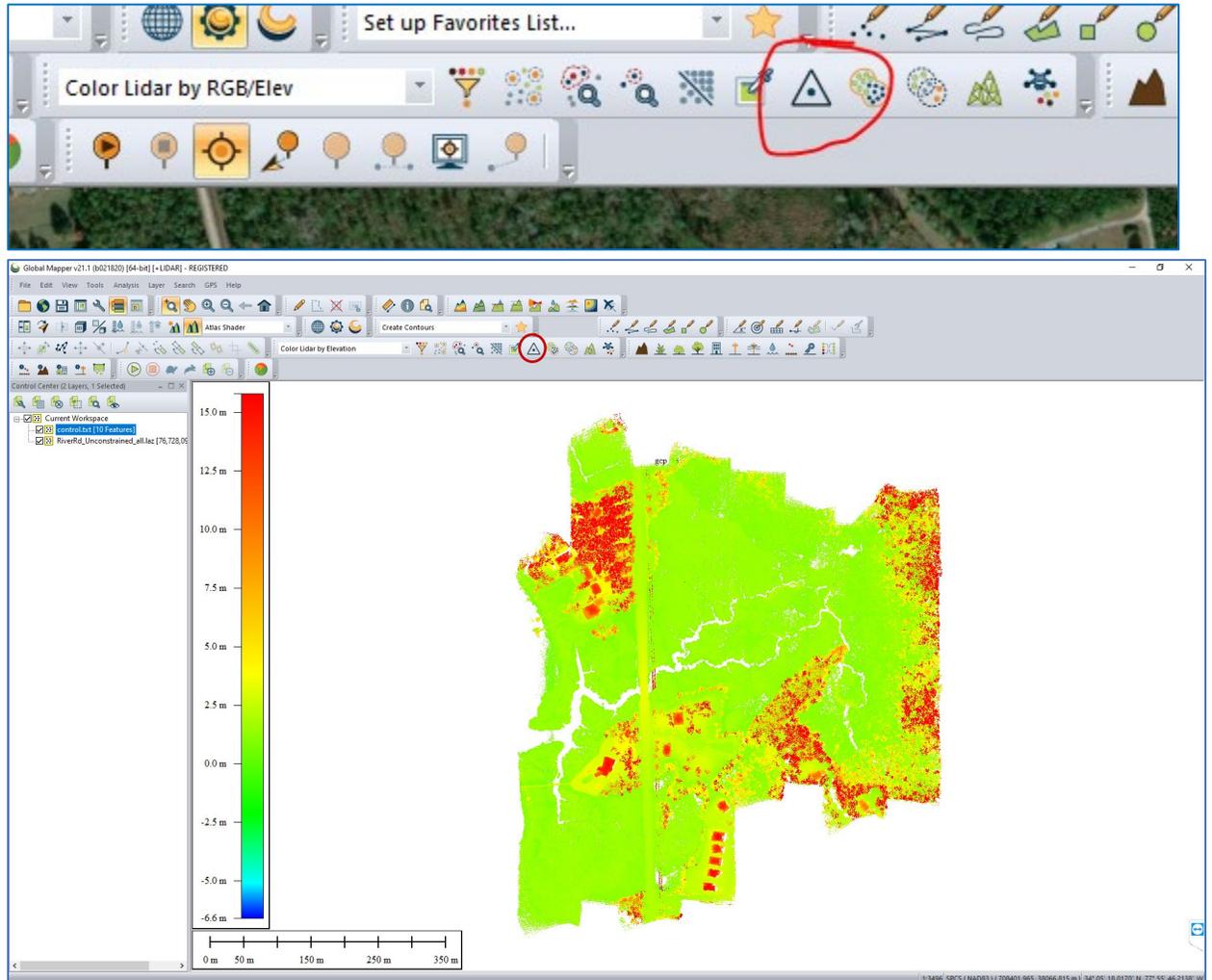


- Then, name it as you like.
- Load the new Las into Global Mapper

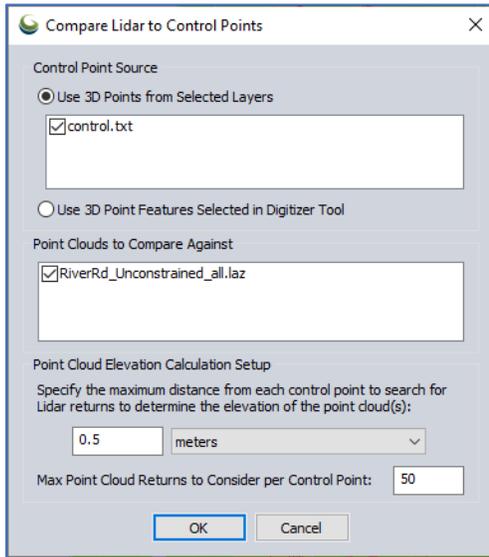


## 14.4: Accuracy Assessment

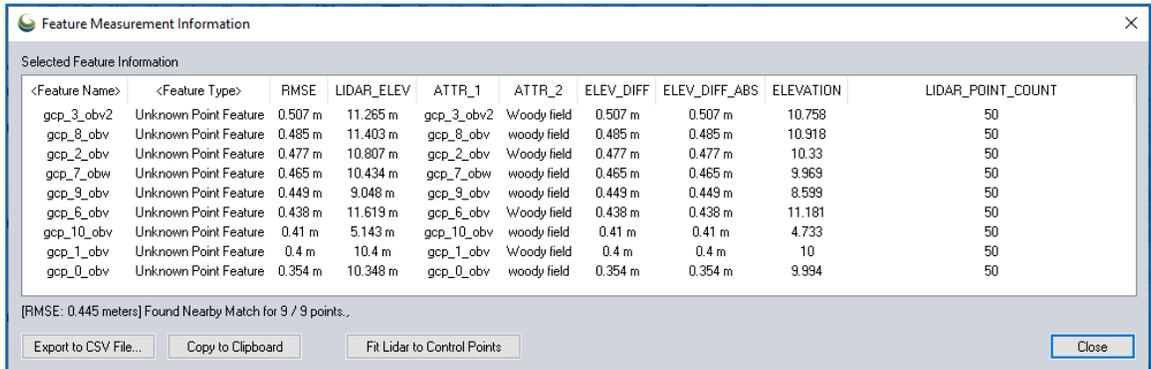
1. Click on LiDAR QC.



- Set **0.5 meter** for point cloud elevation calculation setup, and **50** as max pint cloud returns to consider per control point.



- Finally, you will get a result table. Export to CSV. The total RMSE for your unconstrained data is 0.445 m.



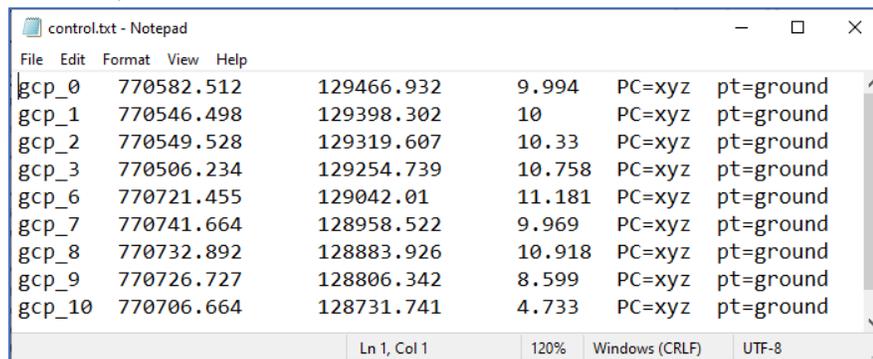
- You will repeat the tool for the constrained data later.

## Section15: LIDAR PROCESSING STEP 3 – Scanlook PC LIDAR POINT CLOUD CONSTRAINING

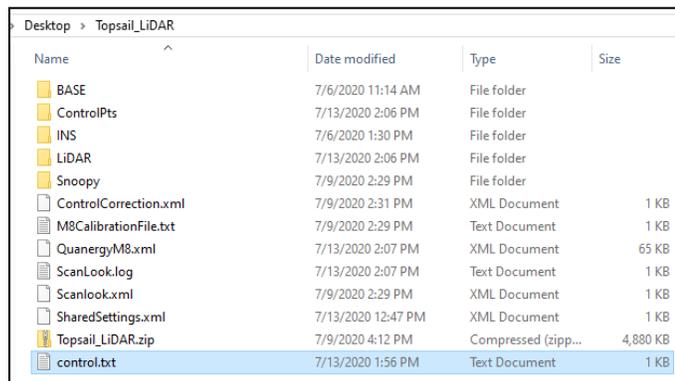
We are back on Scanlook again; this step be optional and is only required is the desired vertical accuracy of the point cloud is above 4cm. This guide will provide you with step-by-step instructions on constrain the point clouds with the GCPs to improve the total RMSE.

### 15.1: Control.txt

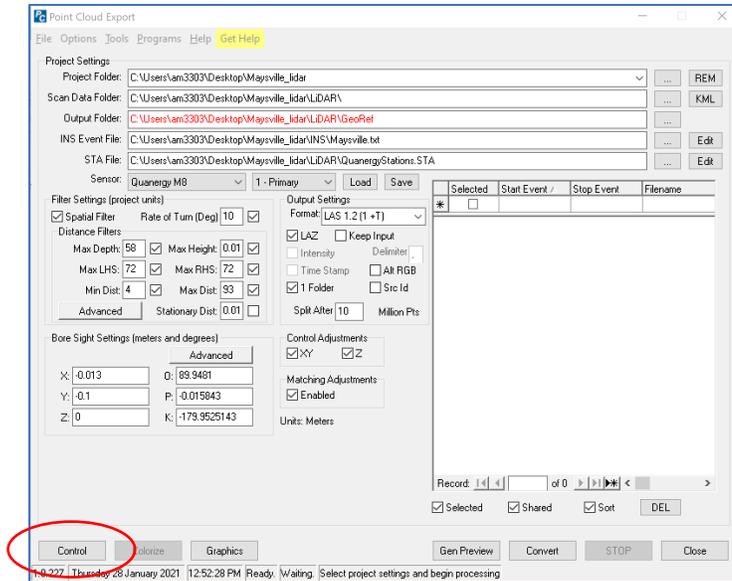
1. From your GCP points data, create a Text File of the point data. Go to your project folder and save this as a “**control.txt**” file. The picture below is an example of the format you will use. Save this in **the main folder**. Set this coordinate system as NCSPM3200 (meter). Save as Text (Tab Delimited).



```
control.txt - Notepad
File Edit Format View Help
gcp_0 770582.512 129466.932 9.994 PC=xyz pt=ground
gcp_1 770546.498 129398.302 10 PC=xyz pt=ground
gcp_2 770549.528 129319.607 10.33 PC=xyz pt=ground
gcp_3 770506.234 129254.739 10.758 PC=xyz pt=ground
gcp_6 770721.455 129042.01 11.181 PC=xyz pt=ground
gcp_7 770741.664 128958.522 9.969 PC=xyz pt=ground
gcp_8 770732.892 128883.926 10.918 PC=xyz pt=ground
gcp_9 770726.727 128806.342 8.599 PC=xyz pt=ground
gcp_10 770706.664 128731.741 4.733 PC=xyz pt=ground
Ln 1, Col 1 120% Windows (CRLF) UTF-8
```

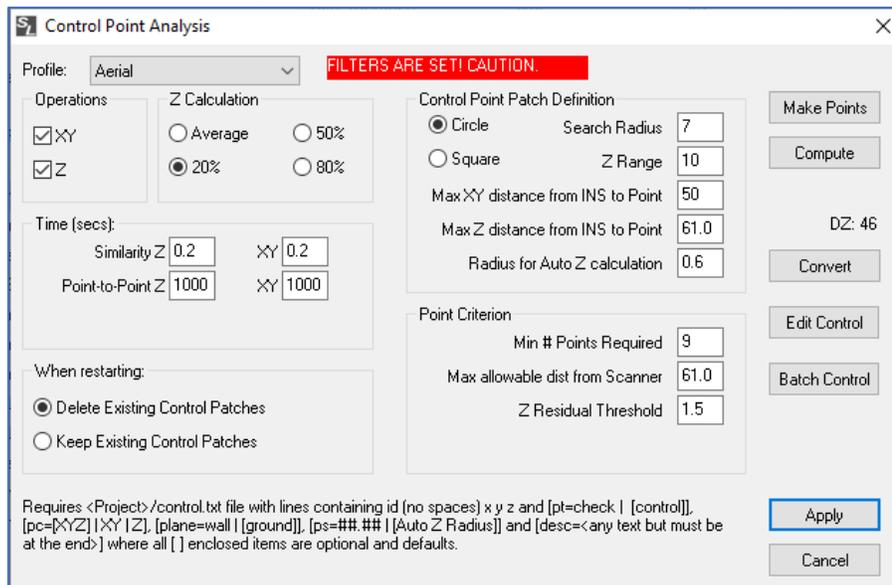


2. Reload in your project in Point Cloud Export and click, “**Control**”. Then the “Control Point Analysis” screen will appear.



## 15.2: Control Point Analysis

1. Set numbers like the image below. Click, "Make Points". The process might take several minutes. These numbers are simply suggestions and may need to be modified to narrow or widen the search area for control point definition.



2. The picture (Example) below will appear on your screen "Measure and Edit Control Points". You are to find a target for each of point ID. Why do we have multiple gcp-4s? Because the lidar sensor detected the target twice on the way and back depending on where the target is located in a relationship with the lidar. Statu "use" means it is used for the correction, but you can manually correct it too. Your goal here is to have as low of Residual X, Y as possible.

Point Id	Measure	IsCheck	Type	Status	As Typ	Survey X	Survey Y	Survey Z	Measured X	Measured Y	Measured Z	Residual X	Residual Y	Residual Z	Corr X	Corr Y	Corr Z
gcp_1	→	No	XYZ	use	Z	709496.333	37703.268	1.550	709496.379	37703.278	1.895	0.046	0.010	0.345			-0.3
gcp_12	→	No	XYZ	use	Z	709419.341	37746.617	2.467	709419.331	37746.536	2.843	-0.010	-0.081	0.376			-0.3
gcp_4	→	No	XYZ	use	Z	709180.963	38040.270	1.113	709181.019	38040.264	1.400	0.056	-0.006	0.287			-0.2
gcp_4	→	No	XYZ	force	XYZ	709180.963	38040.270	1.113	709180.930	38040.270	1.507	-0.033	0.000	0.394	0.033	0.000	-0.3
gcp_4	→	No	XYZ	use	Z	709180.963	38040.270	1.113	709180.951	38040.275	1.501	-0.012	0.005	0.388			-0.3
gcp_5	→	No	XYZ	use	Z	709180.830	37803.035	2.275	709180.826	37803.015	2.605	-0.004	-0.020	0.330			-0.3
gcp_5	→	No	XYZ	use	Z	709180.830	37803.035	2.275	709180.831	37803.036	2.566	0.001	0.001	0.291			-0.2
gcp_6	→	No	XYZ	use	Z	709184.563	37556.371	1.512	709184.549	37556.390	1.867	-0.014	0.019	0.355			-0.3
gcp_8	→	No	XYZ	use	Z	709117.575	37792.911	1.689	709117.571	37792.962	2.020	-0.004	0.051	0.331			-0.3

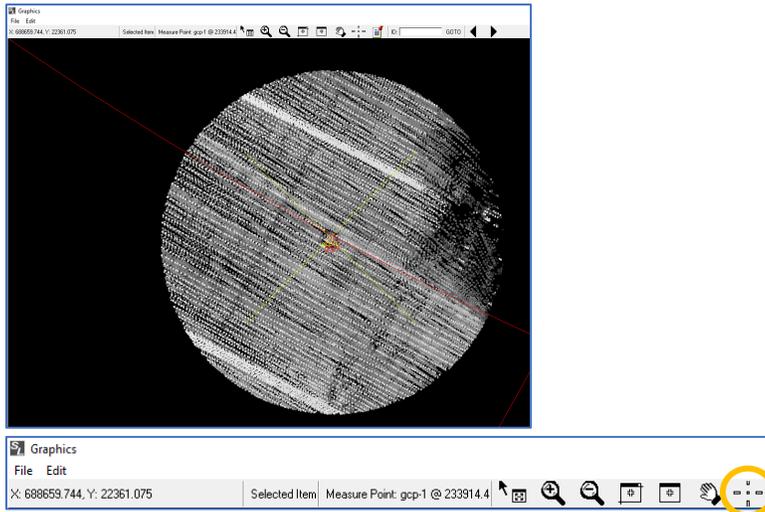
Double click to measure the point.

This example has the status of “failed” in red background which mean the algorithm with the parameters in the Control Point Analysis window could not find the GCPs. Go back to the window and change the parameters in the Control Point Analysis window to find targets.

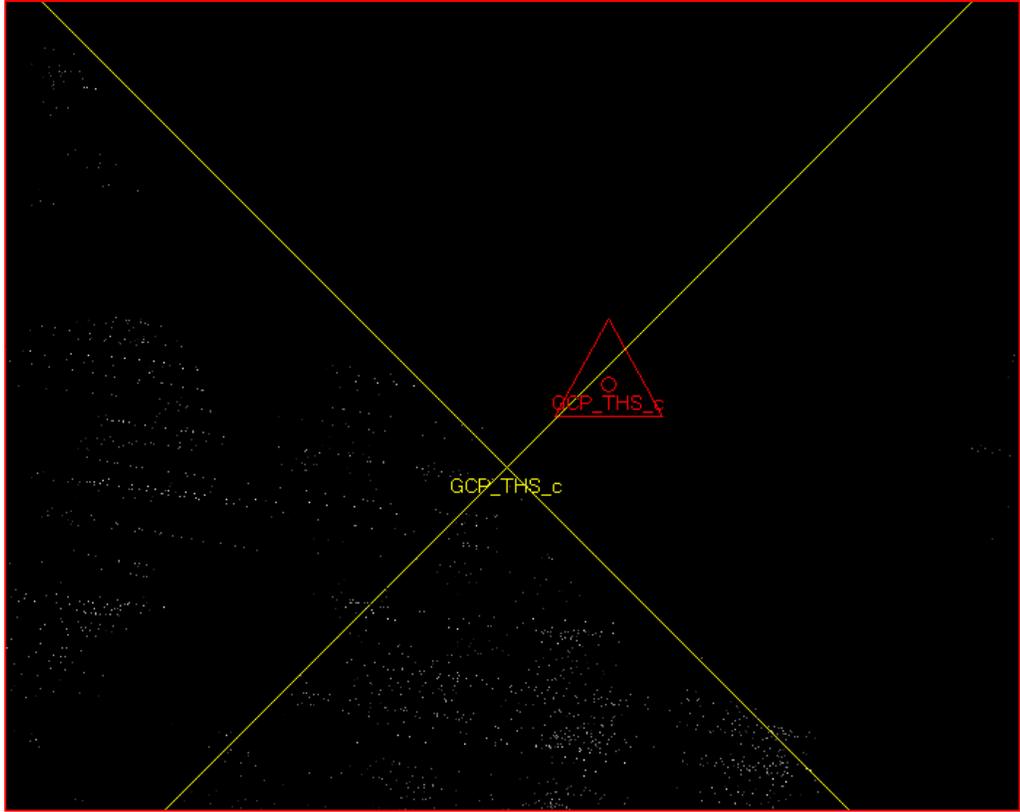
Point Id	Measure	IsCheck	Type	Status	As Typ	Survey X	Survey Y	Survey Z	Measured X	Measured Y	Measured Z
gcp-1	→	No	XYZ	failed	Z	688558.664	22361.117	17.633	688658.704	22361.102	17.918
gcp-1	→	No	XYZ	failed	Z	688558.664	22361.117	17.633	688658.750	22360.974	18.008
gcp-1	→	No	XYZ	failed	Z	688558.664	22361.117	17.633	688658.693	22361.203	18.028
gcp-2	→	No	XYZ	use	Z	688757.898	22546.592	16.171	688757.931	22546.579	16.373
gcp-3	→	No	XYZ	use	Z	688892.640	22304.056	16.066	688892.643	22304.034	16.124
gcp-3	→	No	XYZ	use	Z	688892.640	22304.056	16.066	688892.645	22304.042	16.197
gcp-3	→	No	XYZ	failed	Z	688892.640	22304.056	16.066	688892.627	22304.109	16.374
gcp-4	→	No	XYZ	use	Z	688987.324	22478.439	15.455	689087.312	22478.398	15.536
gcp-4	→	No	XYZ	failed	Z	688987.324	22478.439	15.455	689087.077	22478.574	15.825

Double click to measure the point.  Sort Force Use Skip All AsZ Print Reset Layout Reset Compute Apply OK Close

- Click on the “Green Arrow” this will open up the “Graphics” page and will allow you to view and correct your control points. Use the “measure” button when you wish to drop a red dot where you think it is the measured point. Or you can draw an X to mark. You can click, capital “L” on your keyboard then click and drag over the point that you are trying to measure, in the example below you can see the green lines that are drawn to make a correction to the control point measured.



THIS IS AN EXAMPLE OF A POINT THAT WE CANNOT SEE IN THE CLOUD THEREFORE WE CANNOT USE IT.



- The correction will show up, under Corr X Y.

Measure and Edit Control Points

Point Id	IsCheck	Type	Status	As Typ	Survey X	Survey Y	Survey Z	Measured X	Measured Y	Measured Z	Residual X	Residual Y	Residual Z	Corr X	Corr Y	Corr Z	Dist
g-1	No	XYZ	skip	Z	743055.984	77423.870	1.521	743056.038	77423.848	1.939	0.054	-0.022	0.418	0.005	0.007	-0.384	70
g-10	No	XYZ	force	XYZ	742295.906	77479.642	2.184	742295.938	77479.682	2.964	0.033	0.040	0.380	-0.033	-0.040	-0.380	57
g-12	No	XYZ	force	XYZ	742435.082	77622.053	3.084	742435.119	77622.076	3.414	0.037	0.023	0.330	-0.037	-0.023	-0.330	54
g-12	No	XYZ	force	XYZ	742435.082	77622.053	3.084	742435.074	77622.071	3.406	-0.008	0.018	0.322	0.008	-0.018	-0.322	55
g-12	No	XYZ	skip	Z	742435.082	77622.053	3.084	742435.063	77622.043	3.401	-0.019	-0.010	0.317	-0.020	-0.019	-0.325	67
g-12	No	XYZ	force	XYZ	742435.082	77622.053	3.084	742435.102	77622.072	3.409	0.020	0.019	0.325	-0.020	-0.019	-0.325	54
g-15	No	XYZ	force	XYZ	742319.410	77521.945	1.774	742319.404	77521.991	2.162	-0.006	0.046	0.388	0.006	-0.046	-0.388	57
g-3	No	XYZ	force	XYZ	742934.932	77318.876	1.785	742934.933	77318.874	2.152	0.001	-0.002	0.367	-0.001	0.002	-0.367	58
g-5_redo	No	XYZ	force	XYZ	742814.808	77212.345	1.836	742814.813	77212.335	2.228	0.005	-0.010	0.392	-0.005	0.010	-0.392	55
g-8	No	XYZ	force	XYZ	742561.308	77056.626	1.712	742561.278	77056.589	2.176	-0.030	-0.037	0.464	0.030	0.037	-0.464	58
g-9	No	XYZ	force	Z	742476.605	77172.106	1.283	742476.616	77172.091	1.655	0.011	-0.015	0.372	-0.011	0.015	-0.372	56

Double click to measure the point.  Sort Force Use Skip All AsZ Print Reset Layout Reset Compute **Apply** OK Close

- You can increase the size of the point by going to Edit -> Options. Change the "Lidar Point Size".

Graphic Opti...

Scale Control:

Max Segment Length:

Lidar Point Size [1]:

Draw Labels

Draw Measured X

Close

- After the corrections have been made, click **Compute** and **Apply**. Then, exit this window.

Measure and Edit Control Points

Point Id	IsCheck	Type	Status	As Typ	Survey X	Survey Y	Survey Z	Measured X	Measured Y	Measured Z	Residual X	Residual Y	Residual Z	Corr X	Corr Y	Corr Z	Dist
g-1	No	XYZ	skip	Z	743055.984	77423.870	1.521	743056.038	77423.848	1.939	0.054	-0.022	0.418	0.005	0.007	-0.384	70
g-10	No	XYZ	force	XYZ	742295.906	77479.642	2.184	742295.938	77479.682	2.964	0.033	0.040	0.380	-0.033	-0.040	-0.380	57
g-12	No	XYZ	force	XYZ	742435.082	77622.053	3.084	742435.119	77622.076	3.414	0.037	0.023	0.330	-0.037	-0.023	-0.330	54
g-12	No	XYZ	force	XYZ	742435.082	77622.053	3.084	742435.074	77622.071	3.406	-0.008	0.018	0.322	0.008	-0.018	-0.322	55
g-12	No	XYZ	skip	Z	742435.082	77622.053	3.084	742435.063	77622.043	3.401	-0.019	-0.010	0.317	-0.020	-0.019	-0.325	67
g-12	No	XYZ	force	XYZ	742435.082	77622.053	3.084	742435.102	77622.072	3.409	0.020	0.019	0.325	-0.020	-0.019	-0.325	54
g-15	No	XYZ	force	XYZ	742319.410	77521.945	1.774	742319.404	77521.991	2.162	-0.006	0.046	0.388	0.006	-0.046	-0.388	57
g-3	No	XYZ	force	XYZ	742934.932	77318.876	1.785	742934.933	77318.874	2.152	0.001	-0.002	0.367	-0.001	0.002	-0.367	58
g-5_redo	No	XYZ	force	XYZ	742814.808	77212.345	1.836	742814.813	77212.335	2.228	0.005	-0.010	0.392	-0.005	0.010	-0.392	55
g-8	No	XYZ	force	XYZ	742561.308	77056.626	1.712	742561.278	77056.589	2.176	-0.030	-0.037	0.464	0.030	0.037	-0.464	58
g-9	No	XYZ	force	Z	742476.605	77172.106	1.283	742476.616	77172.091	1.655	0.011	-0.015	0.372	-0.011	0.015	-0.372	56

Double click to measure the point.  Sort Force Use Skip All AsZ Print Reset Layout **Compute** **Apply** OK Close

7. In the Control Point Analysis, make sure the check marks “XY” and “Z” are checked. Hit “Apply” then exit the window.

Control Point Analysis

Profile: Aerial FILTERS ARE SET! CAUTION.

**Operations**

XY  
 Z

**Z Calculation**

Average  50%  
 20%  80%

**Time (secs):**

Similarity Z  XY   
Point-to-Point Z  XY

**When restarting:**

Delete Existing Control Patches  
 Keep Existing Control Patches

**Control Point Patch Definition**

Circle Search Radius   
 Square Z Range   
Max XY distance from INS to Point   
Max Z distance from INS to Point   
Radius for Auto Z calculation

**Point Criterion**

Min # Points Required   
Max allowable dist from Scanner   
Z Residual Threshold

DZ: 46

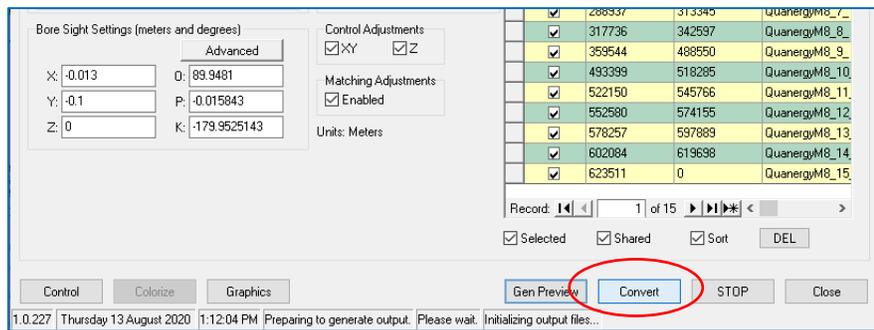
Make Points  
Compute  
Convert  
Edit Control  
Batch Control

Requires <Project>/control.txt file with lines containing id (no spaces) x y z and [pt=check | [control]].  
[pc=[XYZ] | XY | Z], [plane=wall | [ground]], [ps=##.## | [Auto Z Radius]] and [desc=<any text but must be at the end>] where all [ ] enclosed items are optional and defaults.

Apply  
Cancel

### 15.3: Covert

1. Come back to the main window and click **“Convert”** to generate the constrained LiDAR. Your constrained LAZs will be created in a file.



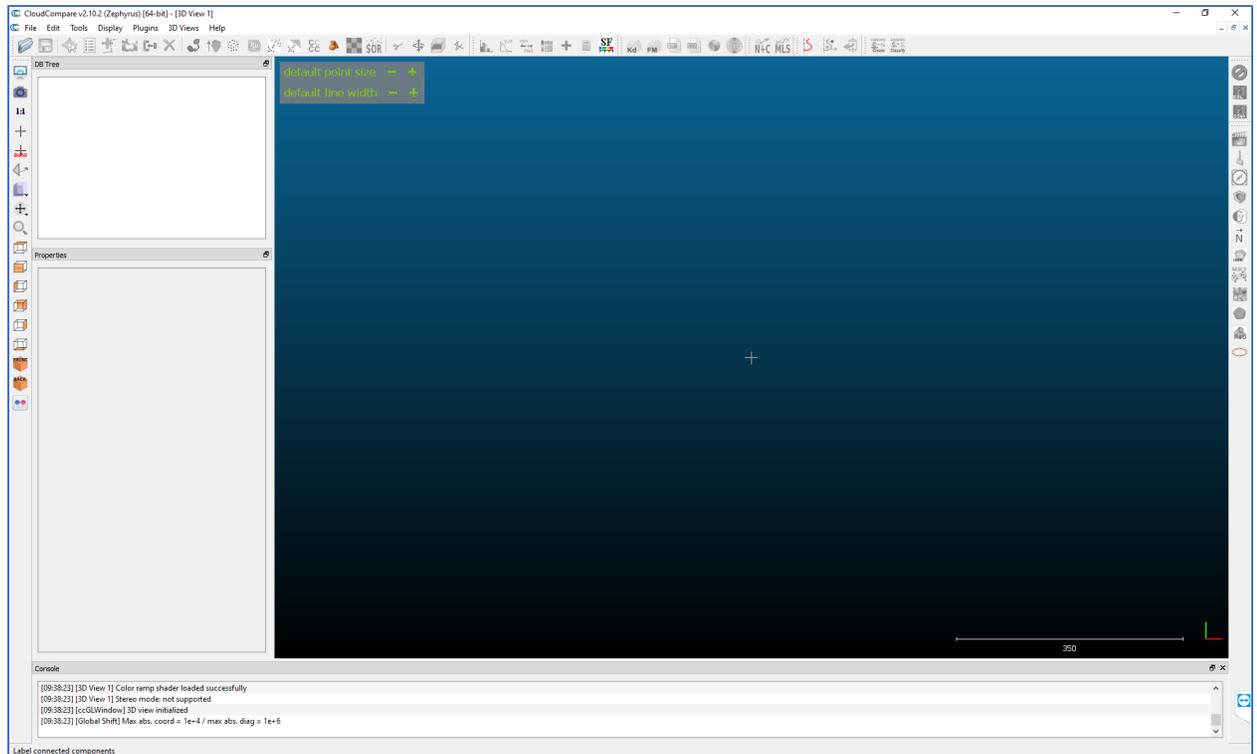
2. Now you will go back to **Section 15: Global Mapper** to conduct the accuracy assessment again with check points.

## Section 16: PROCESSING IN CloudCompare – LIDAR POINT CLOUD CLEANUP

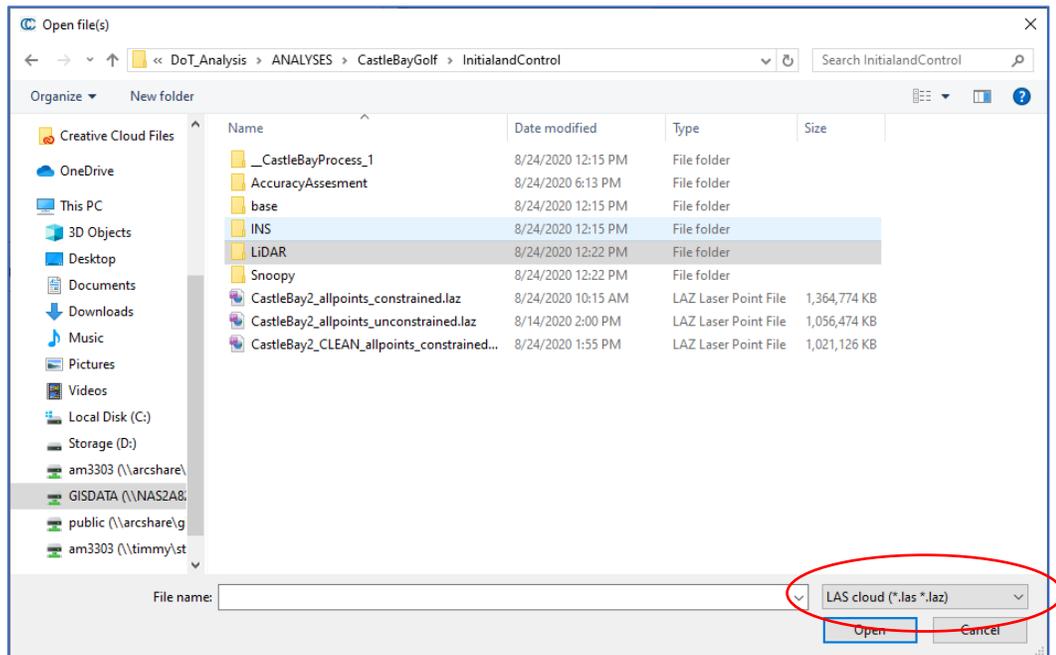
This guide will provide you with step-by-step instructions on operating CloudCompare which is a 3D point cloud processing software. Once successfully completed, you will be able to clean up the erroneous points and create some visuals.

### 16.1: Load Data

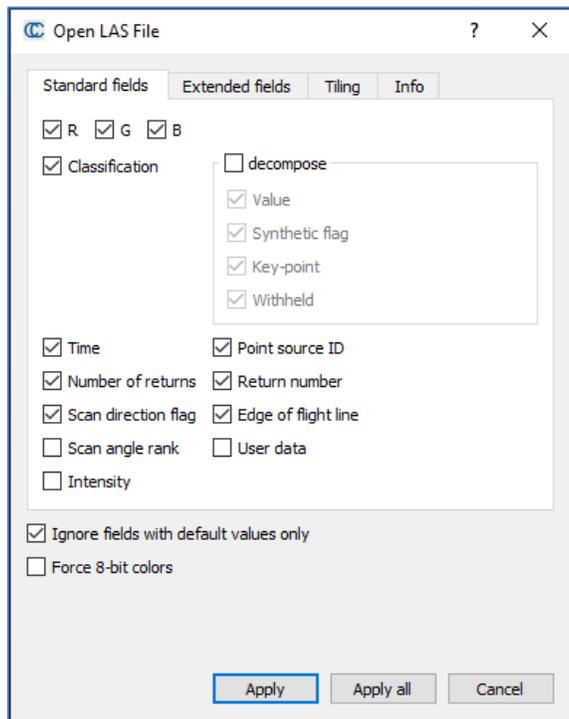
#### 1. Open CloudCompare.

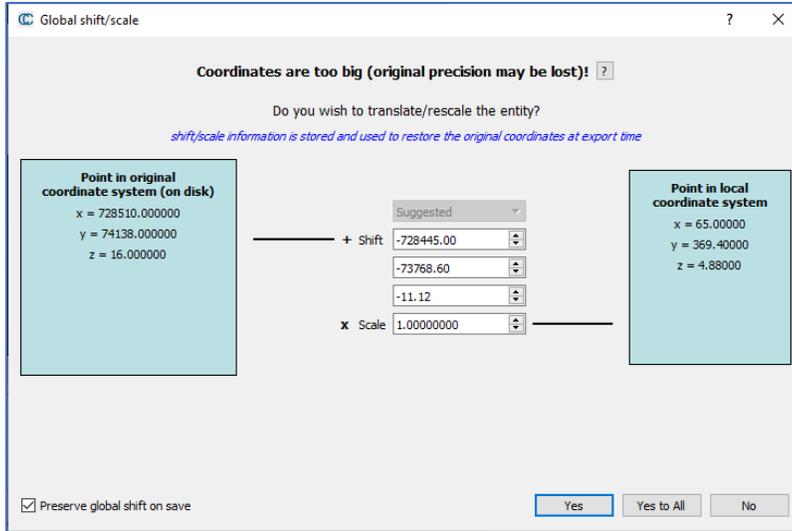


2. Go to **File** -> **Open** to select the LiDAR file(.LAS/ LAZ). Make sure you will be able to see LAS cloud data.

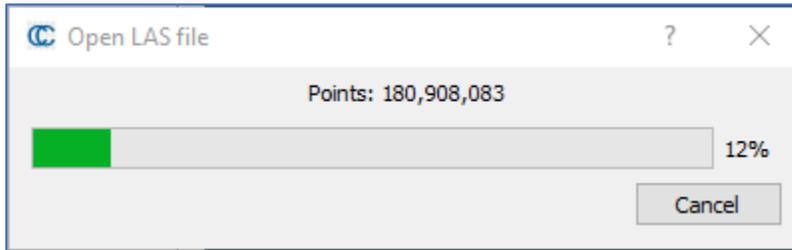


3. You can unselect some boxes for faster process

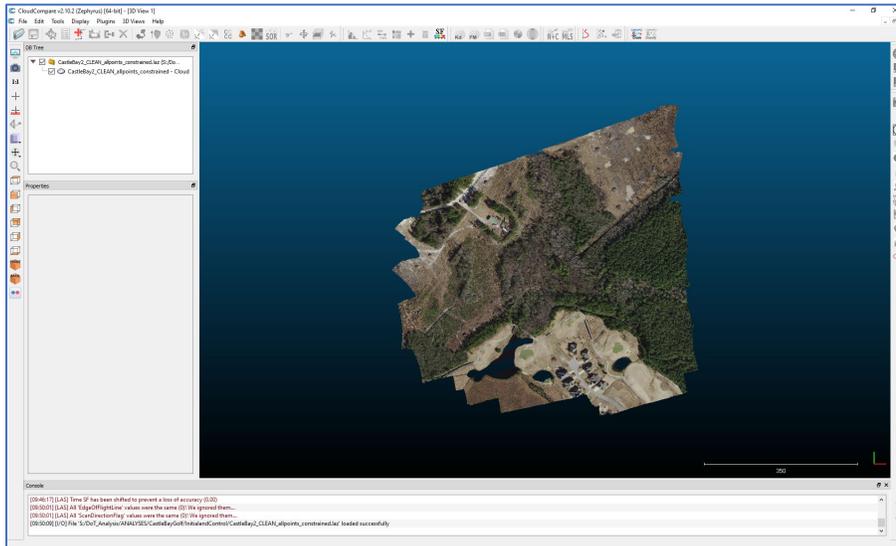




4. Loading takes a few moments as it is a huge data

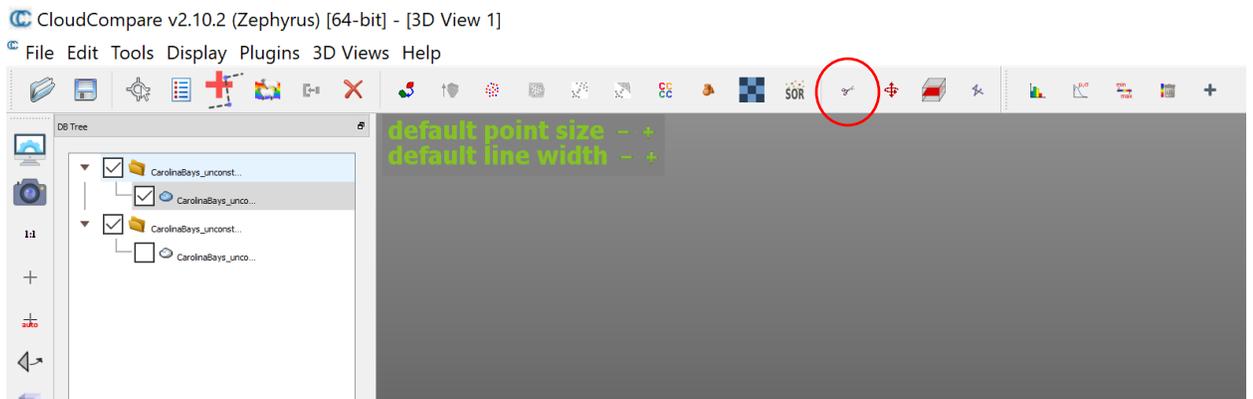
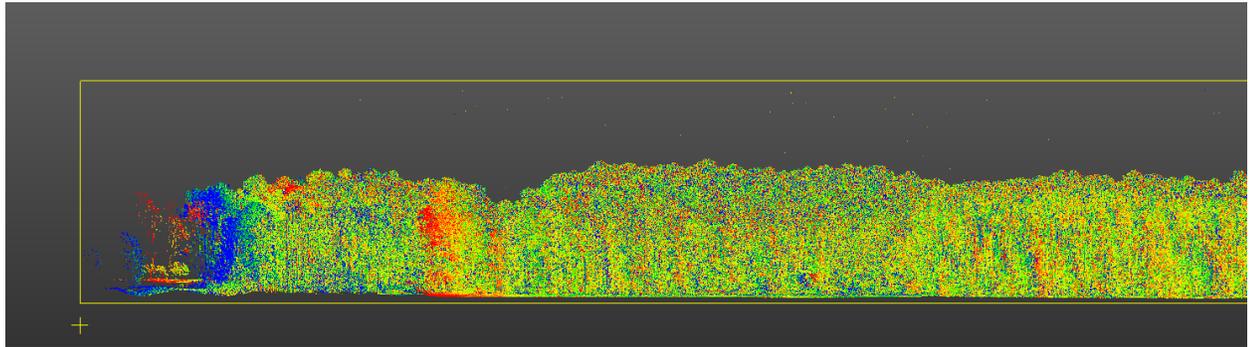


5. Data might be colored by the safelight imagery.

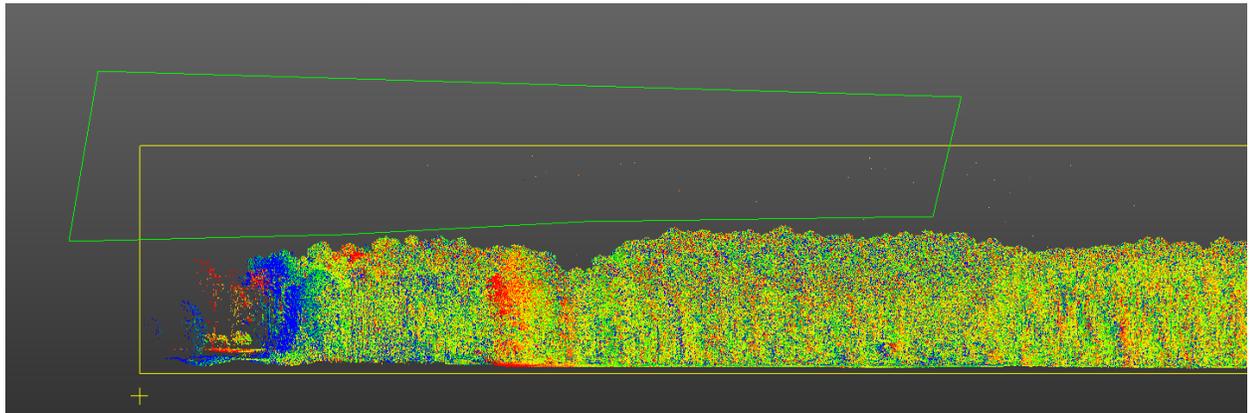


## 16.2: Clean Points

1. Change the angle of the point data so that you can see some erroneous points. Click on the **Segment** tool to segment them out.



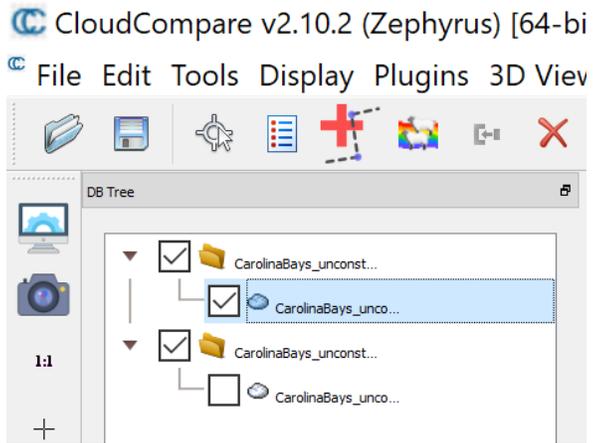
2. Zoom in and select erroneous point and **segment out**.



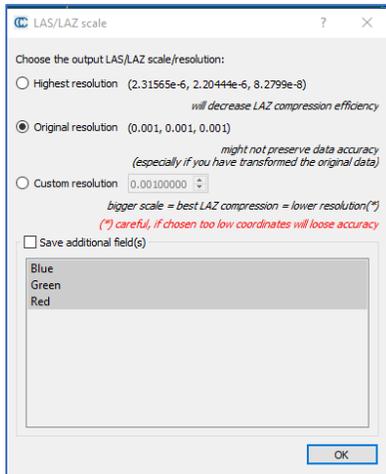
3. Using a small segment tool window, you can segment out, stop or restart.



4. When you are done removing them, lets save it. Now highlight the layer and save it as LAS data. **File -> save**.

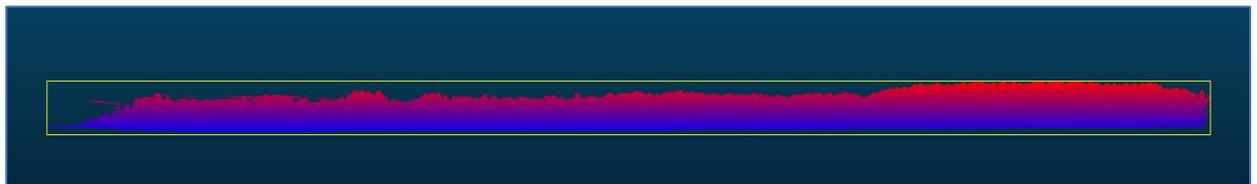
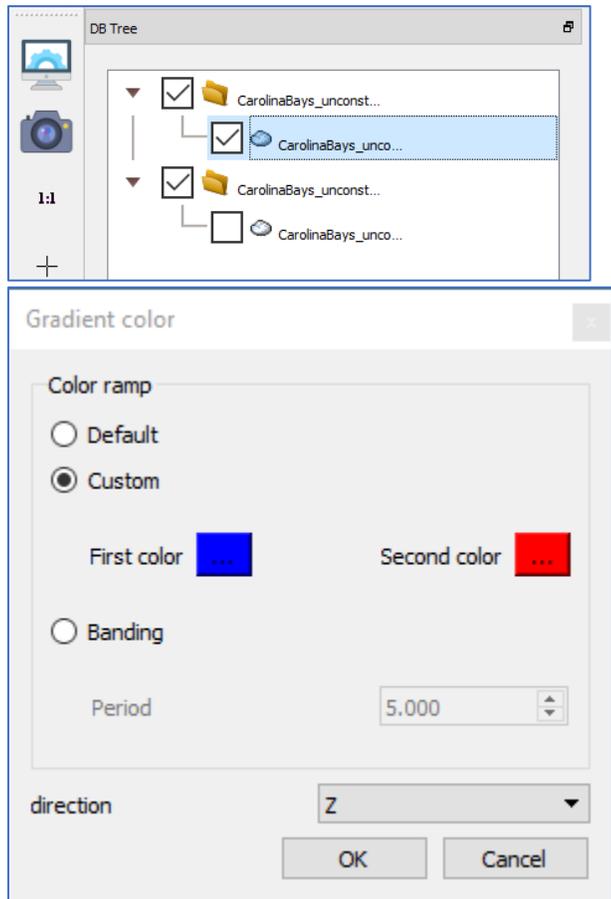


5. Select 'Original resolution' then 'OK.'

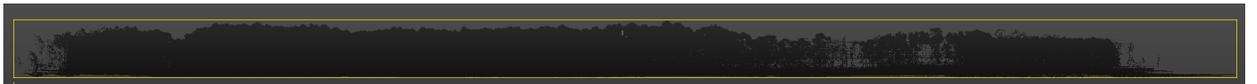


### 16.3: Visuals

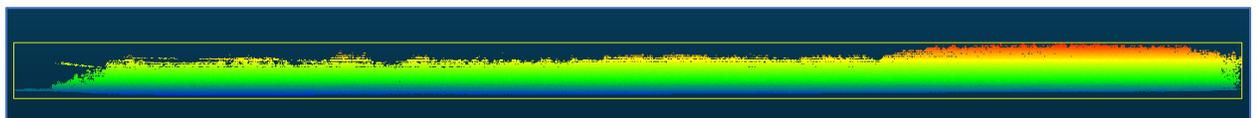
1. Highlight the layer you would like to change colors. **Edit -> Colors -> Height Ramp** for changing color by elevation (z). Select blue for the first color and red for the second.



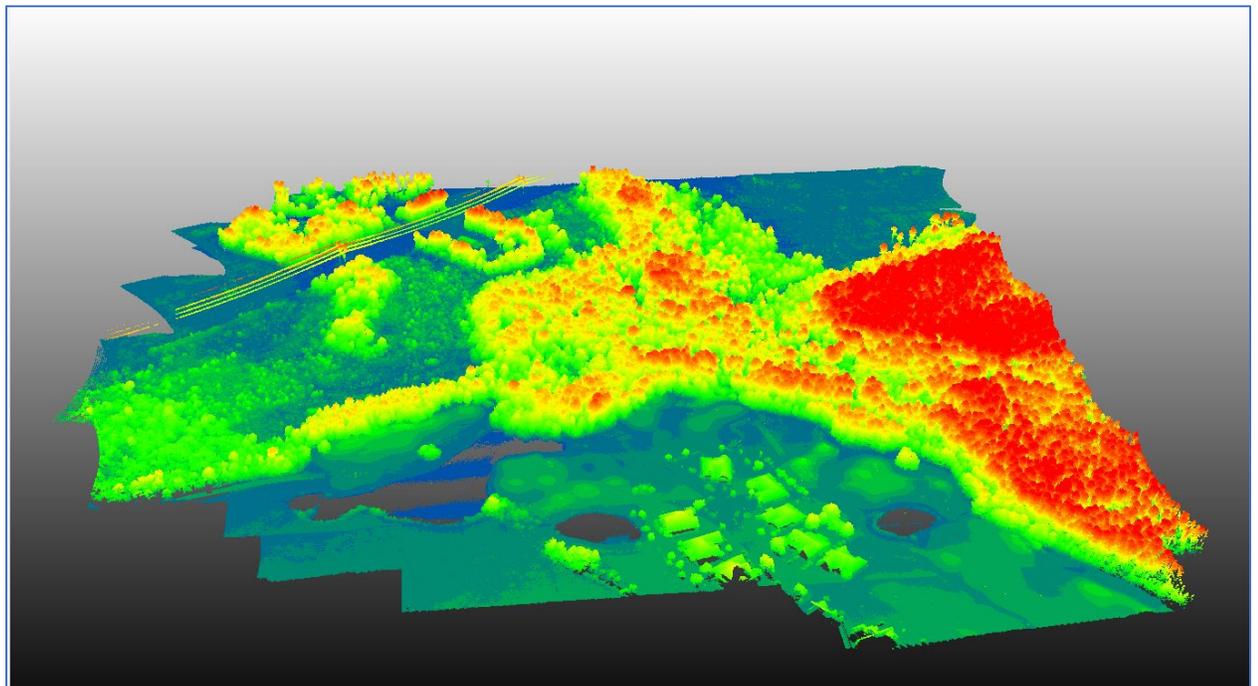
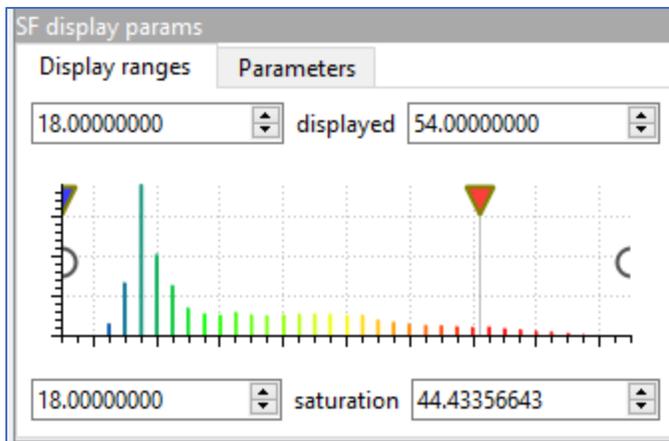
2. **Edit -> Colors -> Convert to Gray Scale**



3. **Edit -> Colors -> Convert to Color Scale**



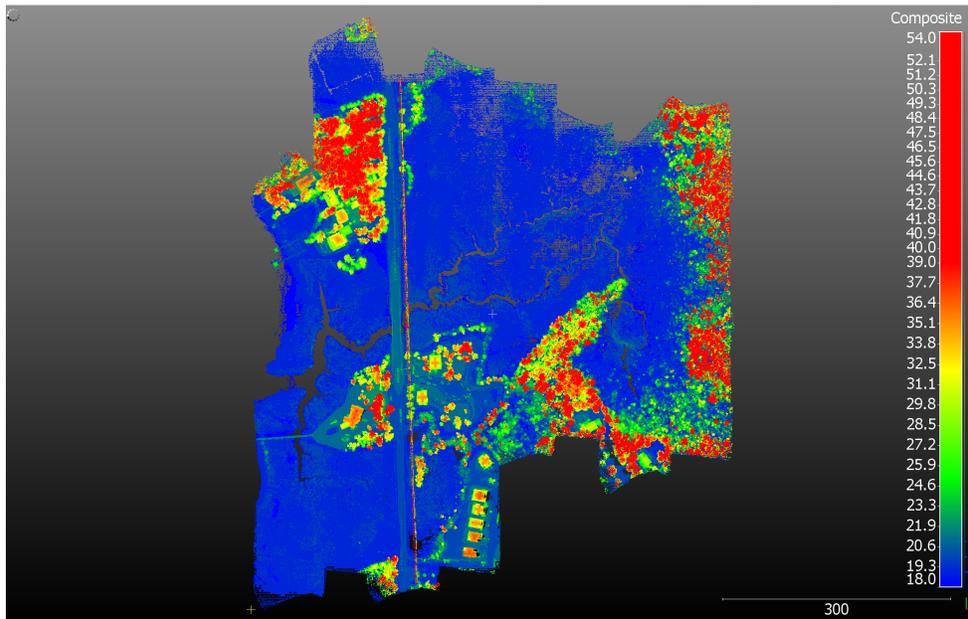
4. Change the display parameters to make it look good



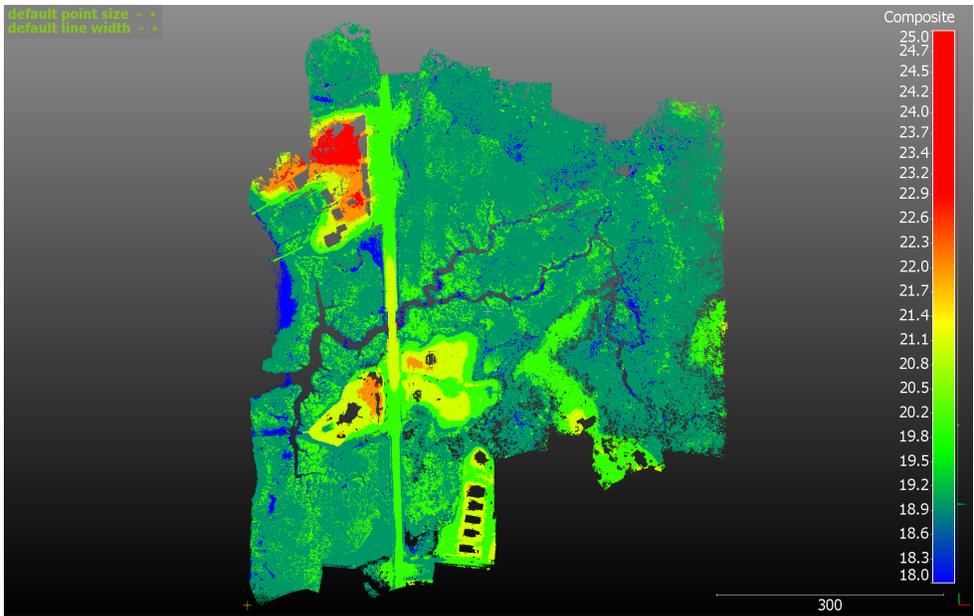
## Section 17: HOW TO MAKE DEMs & DSMs FROM LIDAR POINT CLOUDS

DEM and DSM are in a raster format (2D not 3D) and they are used for many GIS applications. DEM, Digital Elevation Models, represent the bare-Earth surface, removing all natural and built features while DSM, Digital Surface Models, captures both the natural and built/artificial features of the environment. We made a full point cloud was created in the last section. Here we explain how to extract a ground level point cloud from the full point cloud and convert those clouds into a raster format.

DSM:



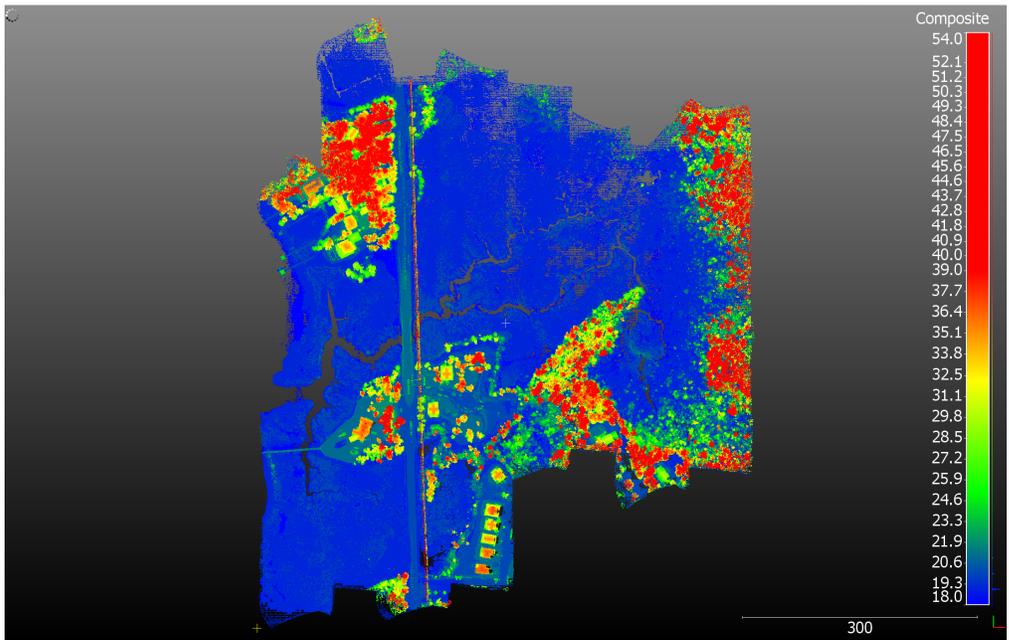
DEM:



## 17.1: DSM Generation in CloudCompare

### 1. Load data

Open CloudCompare and load the full point cloud (las) that you previously created.



### 2. Cloth Simulation Filter

The loaded data file will be filtered for ground points using the Cloth Simulation Filter (CSF) plugin here. The CSF extracts ground points from discrete return LiDAR point clouds and produces results with accuracies comparable to most state-of-the-art filtering algorithms.

The separation of ground and non-ground points is essential to the creation of an

accurate digital surface model (DSM). Select **plugin** -> **CSF**. For more information:  
[https://www.cloudcompare.org/doc/wiki/index.php?title=CSF\\_\(plugin\)](https://www.cloudcompare.org/doc/wiki/index.php?title=CSF_(plugin))

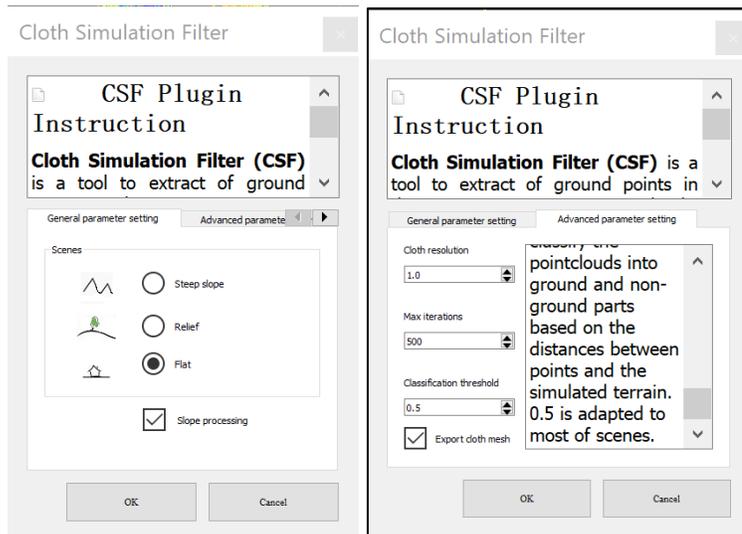
### 3. Parameters

**Two parameters:** General parameter and Advanced parameter. The general parameter means that it must be set each time the program runs. The advanced parameter means that it can be set according to the users need.

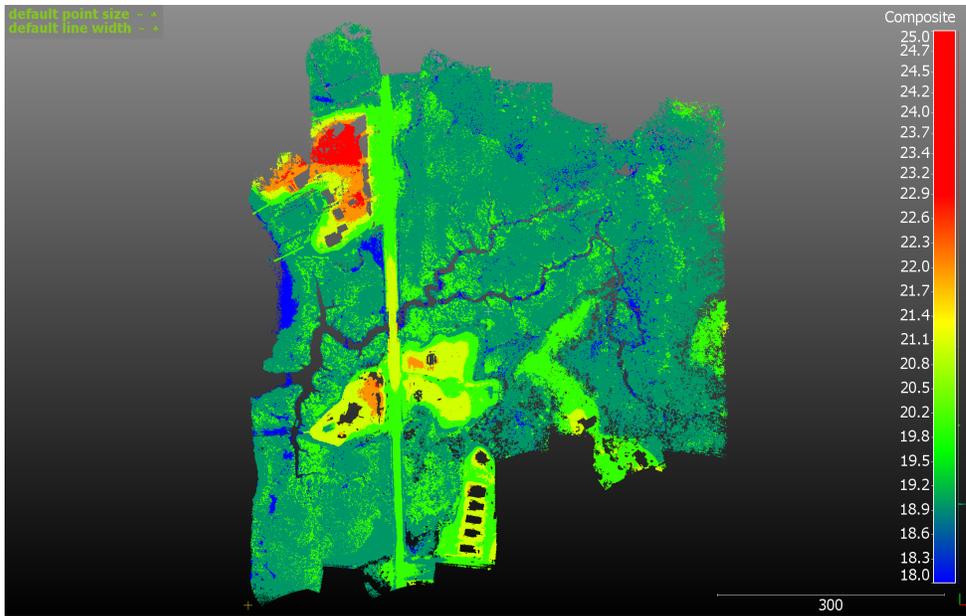
General parameters- select one of the scenes (steep slope, relief, or flat) and uncheck the slope post processing for no steep slope

Advanced parameters – 1m DEM, 500 iteration, 0.5 classification threshold (those numbers are suggestions-).

Cloth resolution refers to the grid size (the unit is same as the unit of point clouds(m)) of cloth which is used to cover the terrain. The bigger cloth resolution you have set, the coarser DTM you will get.



4. Save your DEM as las. Select the name of the layer and select file -> save. Make sure to save as LAS not LAZ if you wish to process LiDAR data in ArcGIS later.



## 17.2: Load and Find Pixel Size

Here you will use ArcGIS Pro to convert the LiDAR data (3D) to raster format (2D).

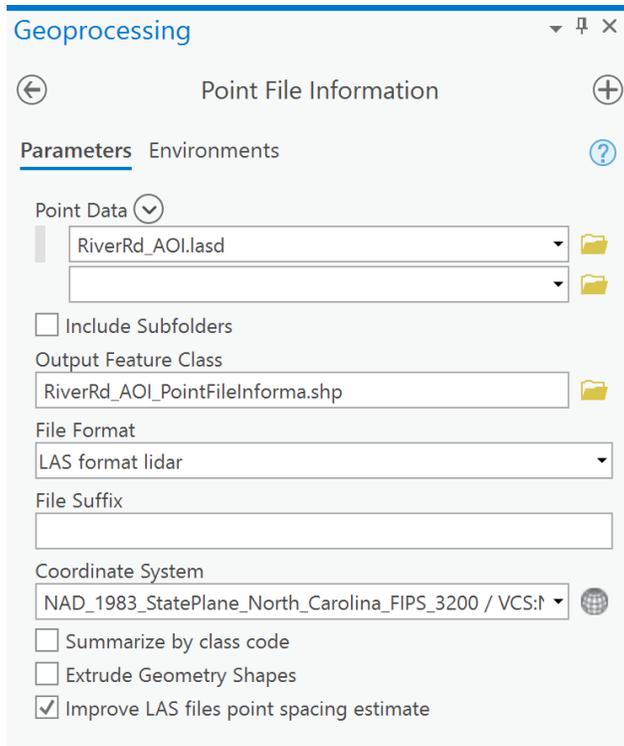
### 1. Open ArcGIS Pro and Load

Open your ArcGIS Pro project and load your DEM and DSM las.

### 2. Calculate cell size for output raster data

The level of detail (features/phenomena) represented by a raster is often dependent on the cell (pixel) size, or spatial resolution, of the raster. The cell must be small enough to capture the required detail, but large enough so computer storage and analysis can be performed efficiently. For more info: <https://desktop.arcgis.com/en/arcmap/10.3/manage-data/raster-and-images/cell-size-of-raster-data.htm>

**Point File Information tool** –This tool calculates the average of point spacing. This point spacing number will be used to calculate the appropriate the spatial resolution of raster output.



Load your DEM.las data to find out the point spacing. Make sure to check the checkbox next to “Improve LAS files point spacing estimate.” A shapefile will be created as an output. Open the output table to find the point spacing. You might think the average point spacing is a good cell size for the output raster, but this typically results in too many empty, or NoData, cells because lidar points are not evenly spaced. A reasonable size is four times the point spacing. For more information about rasterization cell size:

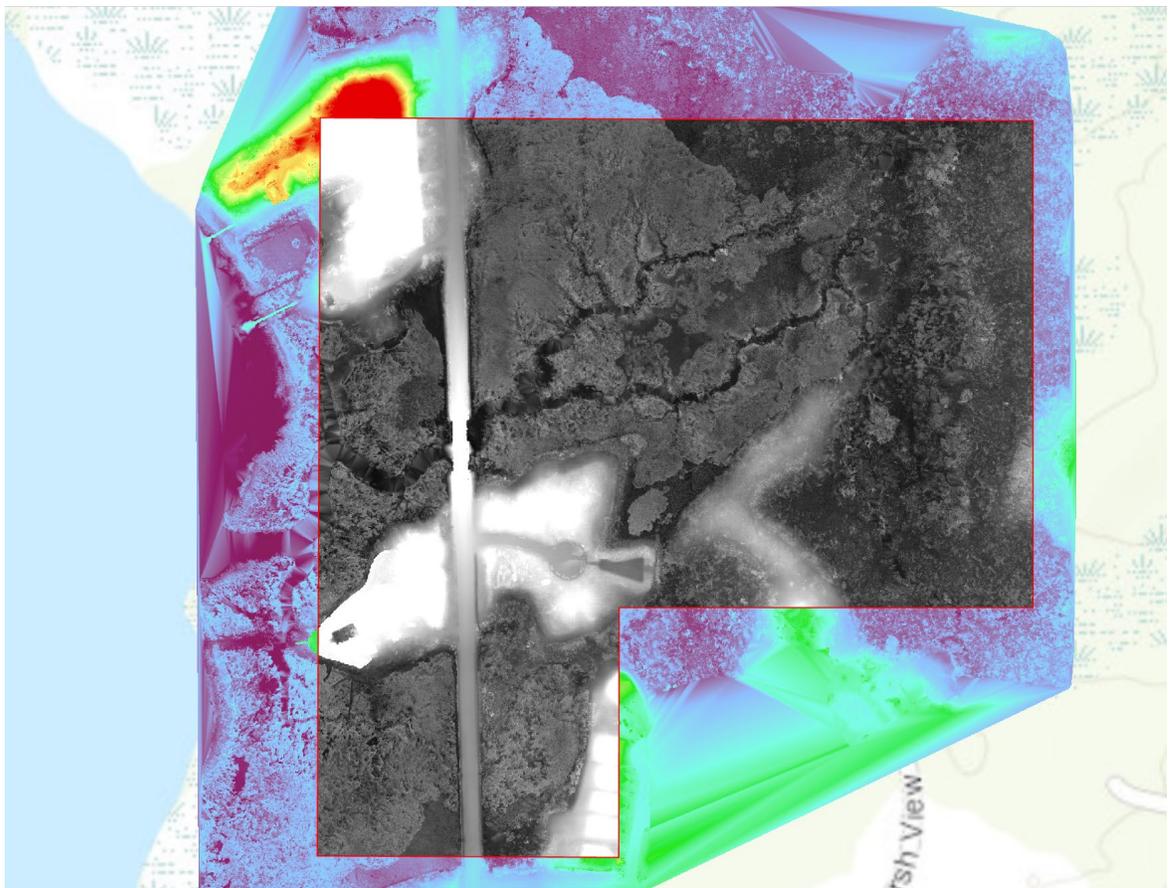
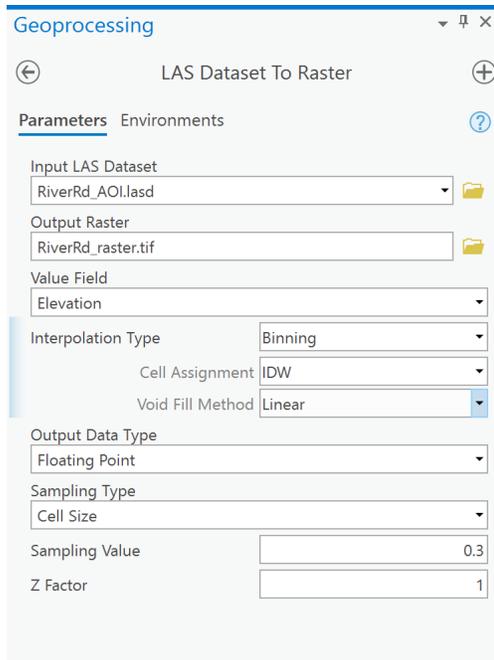
<https://desktop.arcgis.com/en/arcmap/10.3/manage-data/las-dataset/lidar-solutions-assessing-lidar-coverage-and-sample-density.htm>

For example:

Pt spacing: 0.07287134 m  
 Raster resolution: 0.3 m<sup>2</sup> (0.07287134x 4)

### 3. LAS Dataset to Raster

Use a “LAS Dataset To Raster” tool. Load your DEM.las data and put the calculated raster resolution for cell size sampling values. You can save the TIF file in a regular folder not the geodatabase.



Repeat the same steps for full point cloud. Make this with the same spatial resolution since we are doing pixel-based classification.

## Section 18: HOW TO PREPARE VARIABLES FOR CLASSIFICATION MODELS

To make a wetland classification map, we will create a classification model through machine learning algorithms. In machine learning, classification refers to a predictive modeling problem where a class label (wetland class here) is predicted for a given example of input data. Therefore, the machine learns how to classify based on the sample dataset given. In this manual, the classification models are made from LiDAR, multispectral, and habitat data through random forest classification. Here we explain the predictor variables. The response variable (wetland class data) is the cause. Its value is independent of other variables in your study. The predictor variable (UAS data) is the effect. Its value depends on changes in the independent variable.

Learn more about RF here: ([https://www.youtube.com/watch?v=J4Wdy0Wc\\_xQ&t=187s](https://www.youtube.com/watch?v=J4Wdy0Wc_xQ&t=187s)).

**Predictors:** LiDAR data (LAS data) is a point cloud of elevation data, which will be used to create ten topographic layers:-:

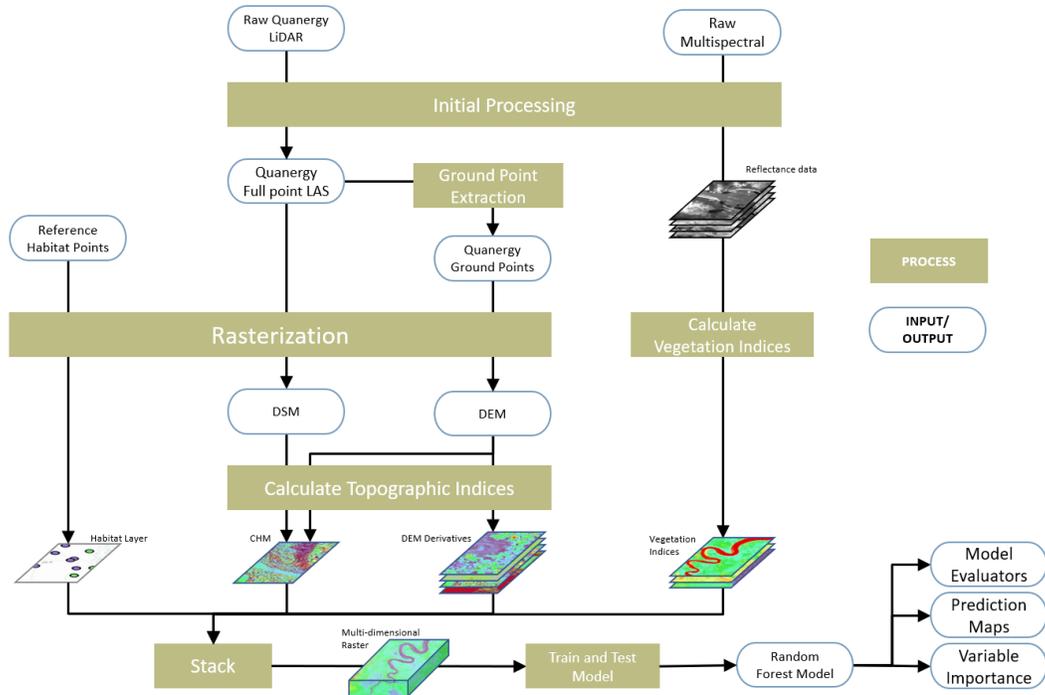
1. Digital Surface Model (DSM)
2. Digital Elevation Model (DEM)
3. Canopy Height Model (CHM)
4. Smoothed DEM (sDEM)
5. Hydro-condition DEM (hDEM)
6. Aspect
7. Slope
8. Curvature
9. Plan Curvature
10. Profile Curvature

**Predictors:** Multispectral imagery (green, red, red-edge, and near-infrared) (TIF data) is collected in the field. Three vegetation indices are created from this dataset.

1. Normalized Difference Vegetation Index (NDVI)
2. Normalized Difference Red Edge Index (NDRE)
3. Normalized Difference Water Index (NDWI)

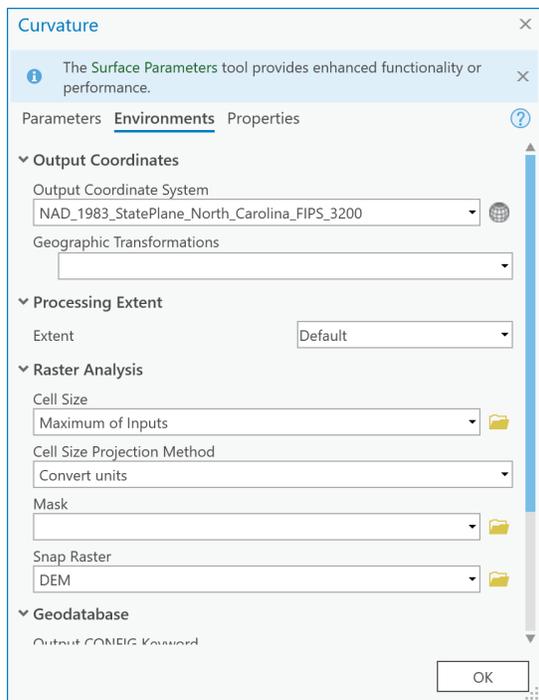
**Response:** Habitat sample data that were collected in the field using on screen analysis are used to train and verify the wetland model, which is called a response variable. The figure below indicates the workflow of data processing.

The workflow below shows the overall steps of how to create a wetland classification model.



## 18.1: Variables made by LiDAR Data

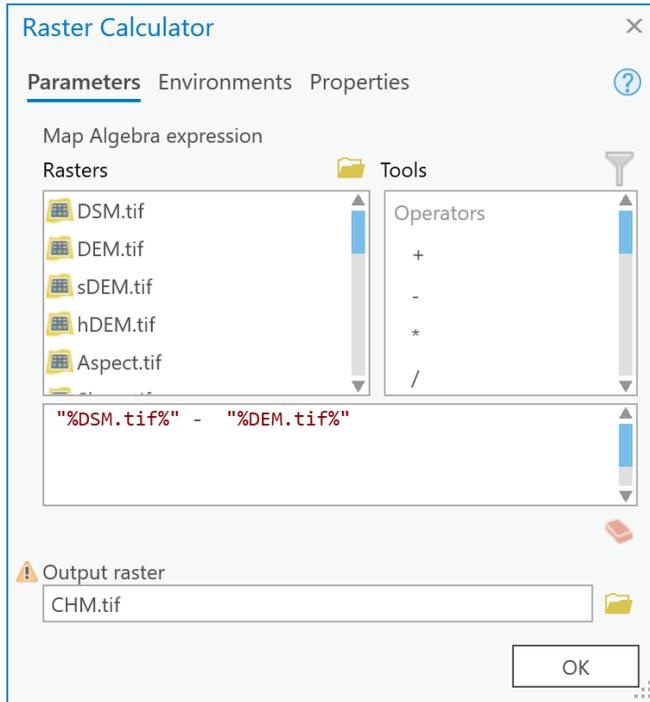
In the previous section, we have already made raster DEM and DSM. Here additional eight raster layers will be generated from the DEM using ArcGIS Pro. Make sure to set up the tool in the environments tab so that the output raster is snapped to either DEM or DSM.



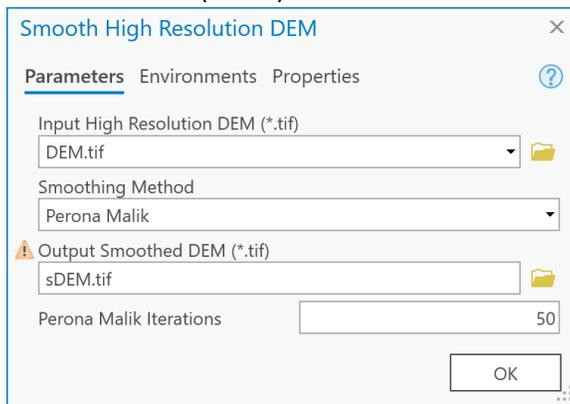
1. Digital Surface Model (DSM)
2. Digital Elevation Model (DEM)

### 3. Canopy Height Model (CHM)

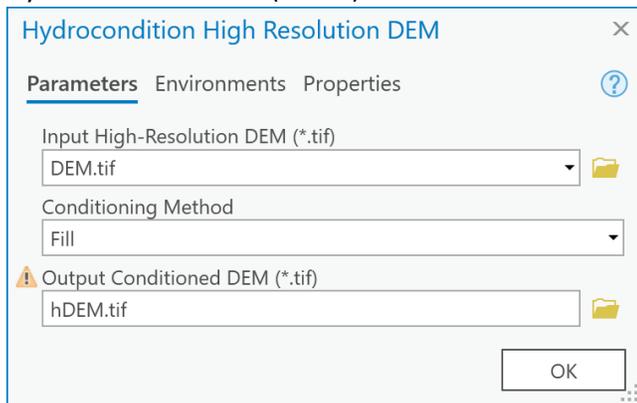
DSM - DEM



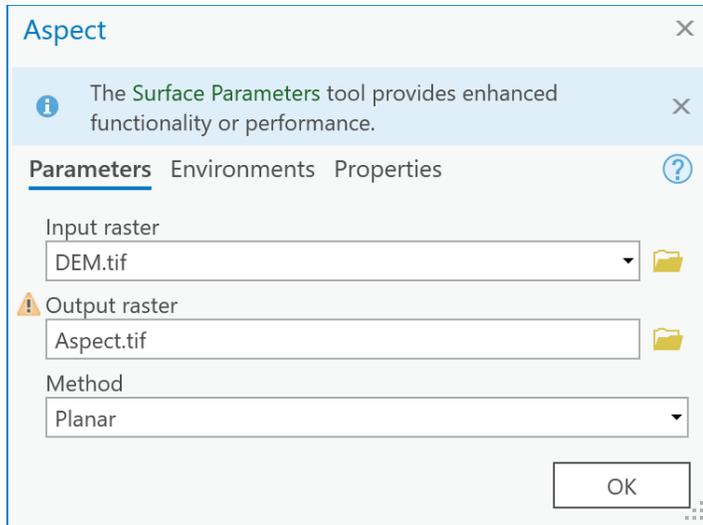
### 4. Smoothed DEM (sDEM)



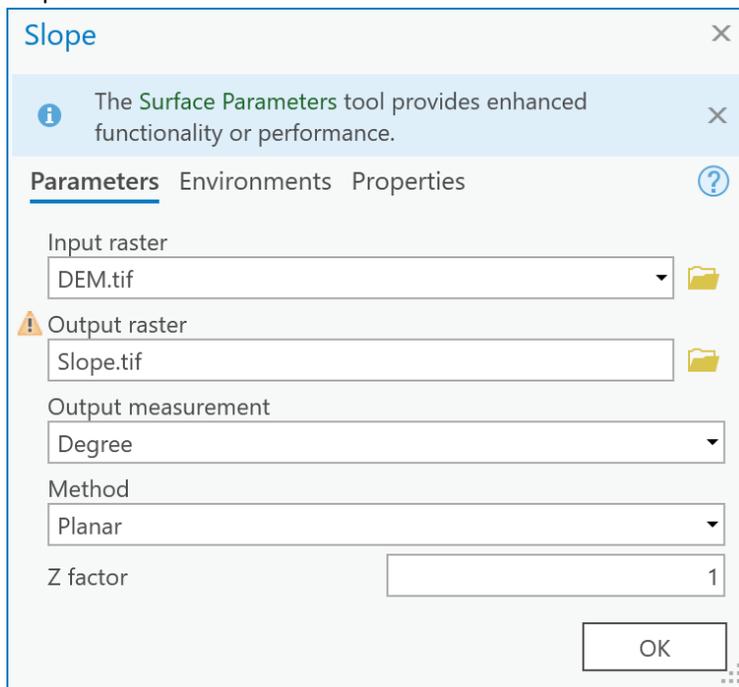
### 5. Hydro-condition DEM (hDEM)



### 6. Aspect



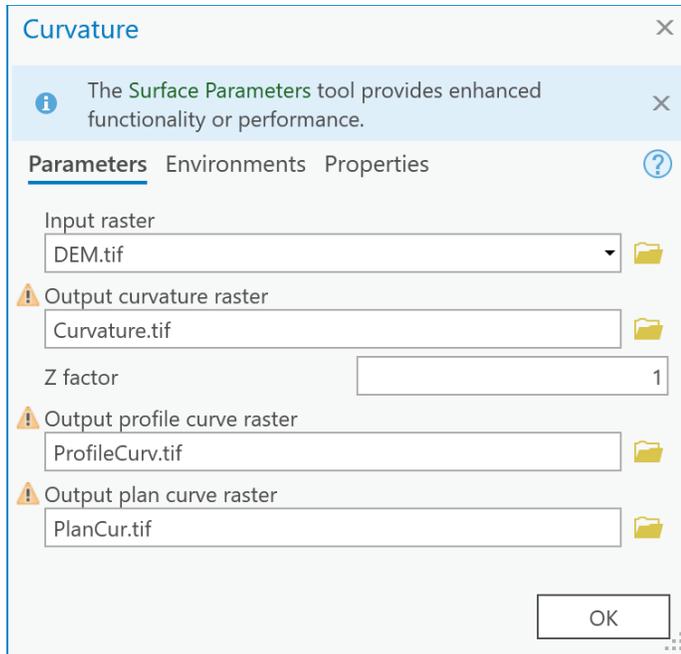
7. Slope



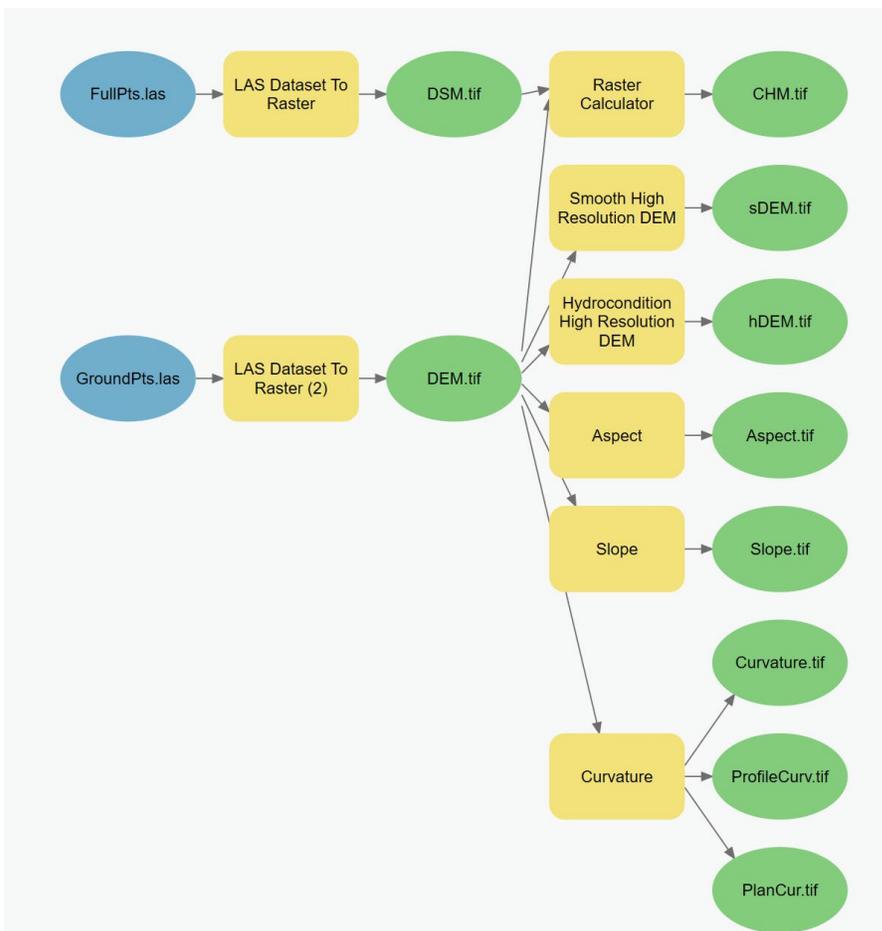
8. Curvature

9. Plan Curvature

10. Profile Curvature



Model builder in ArcGIS Pro is a very useful way to keep all the settings and everything organized.



## 18.2: Variables made by Multispectral Data

~~These~~ The vegetation indices can be calculated using multispectral layers and it can be done in ArcGIS or any other software that you may have.

1. Normalized Difference Vegetation Index (NDVI)

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

2. Normalized Difference Red Edge Index (NDRE)

$$NDRE = \frac{(NIR - Red\ Edge)}{(NIR + Red\ Edge)}$$

3. Normalized Difference Water Index (NDWI)

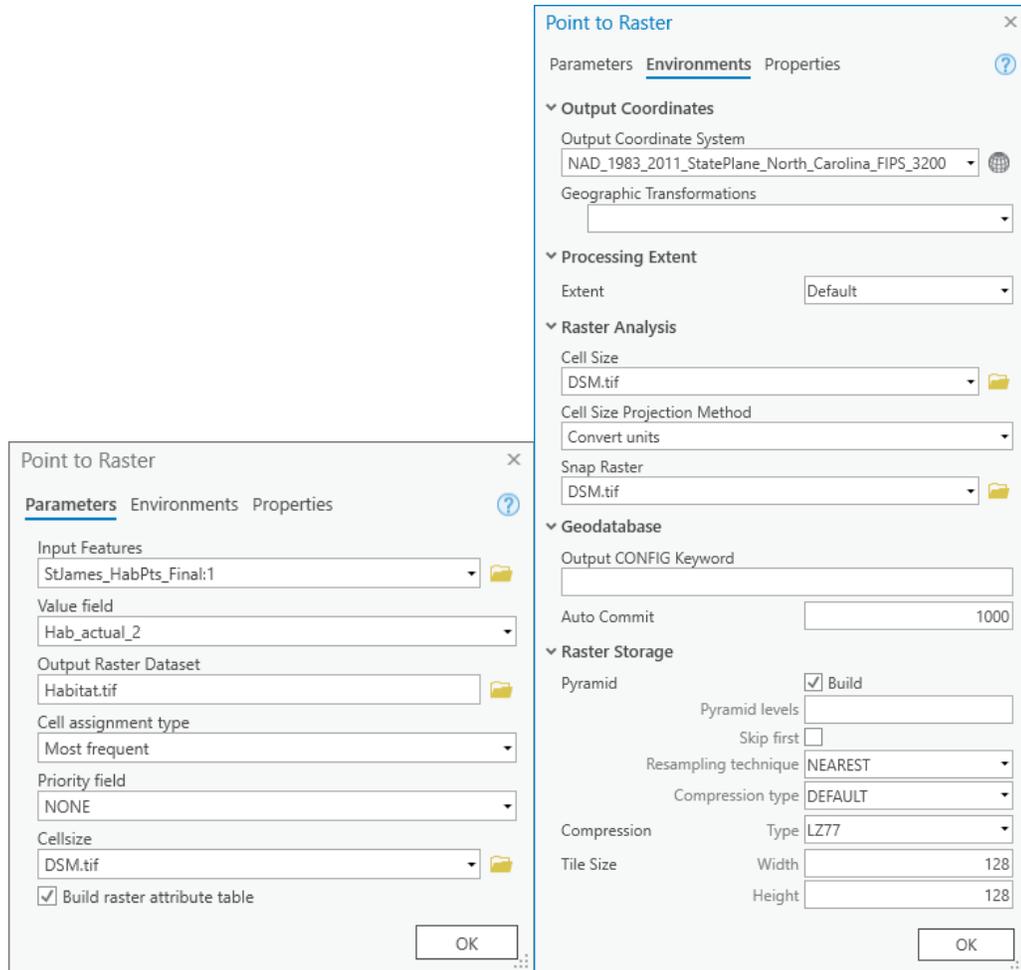
$$NDWI = \frac{(Green - NIR)}{(Green + NIR)}$$

## 18.3: Variables made by Habitat Data

1. Open the habitat point data in ArcGIS. If the class name contains ~~---~~UB (unconsolidated bottom) or ~~---~~US (unconsolidated shore), the classes are not wetland but water. If you see more than one of them, make sure to combine those US/UB classes together into one class and name it as water.

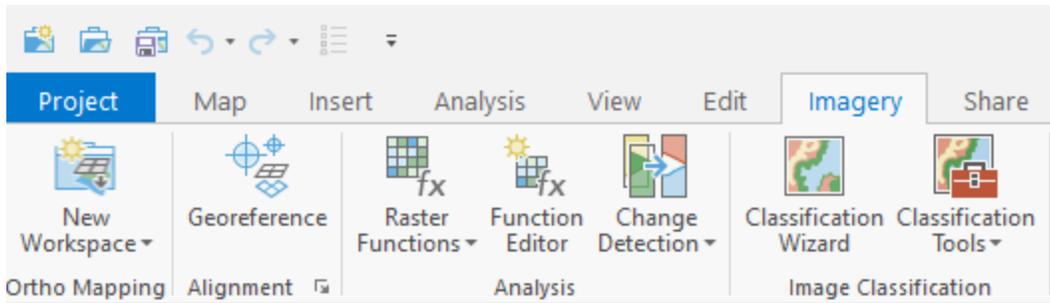


- Since the habitat data is still in vector format, you will need to convert it into a raster format by using a “**Point to Raster**” tool. Make sure to set the cell size and snap the aster to one of the topo raster layers that you have made in the previous section. Save the data as tif file.

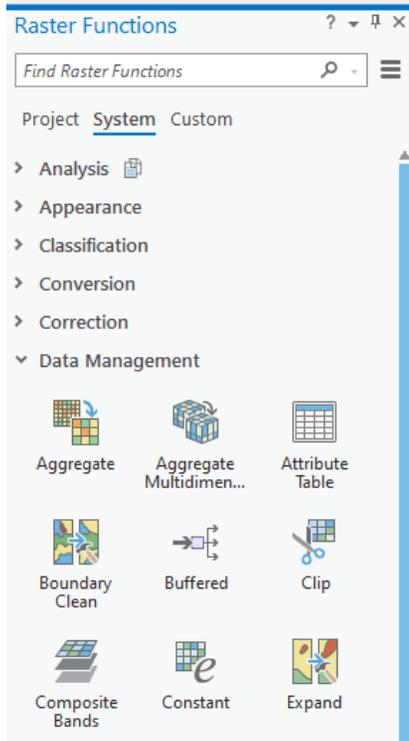


#### 18.4: Making a Raster Stack

- Now you have prepared all the layers. Topo layers (10) + vegetation index (3) + Habitat data (1) = 14. Here you are going to stack all the raster layers into one single tif file, which is ~~also~~ called multi-dimensional raster.
- Go to Imagery -> Raster Functions. Then, a Raster Functions window will pop up.

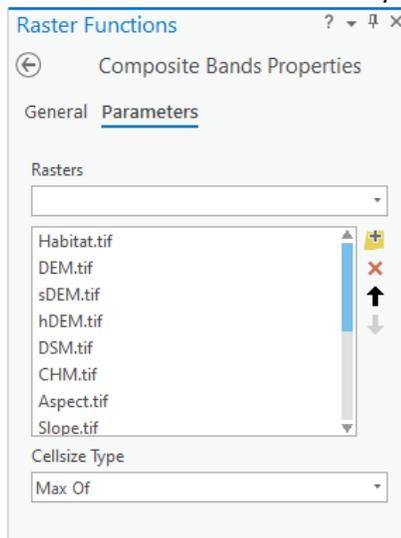


3. Search and click on "Composite Bands."

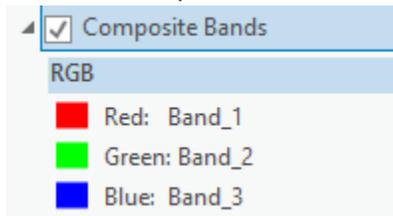


4. Select all the tif layers. Once you combine them, you will not be able to see the band names anymore. Therefore, make sure to remember the order of layers you input.

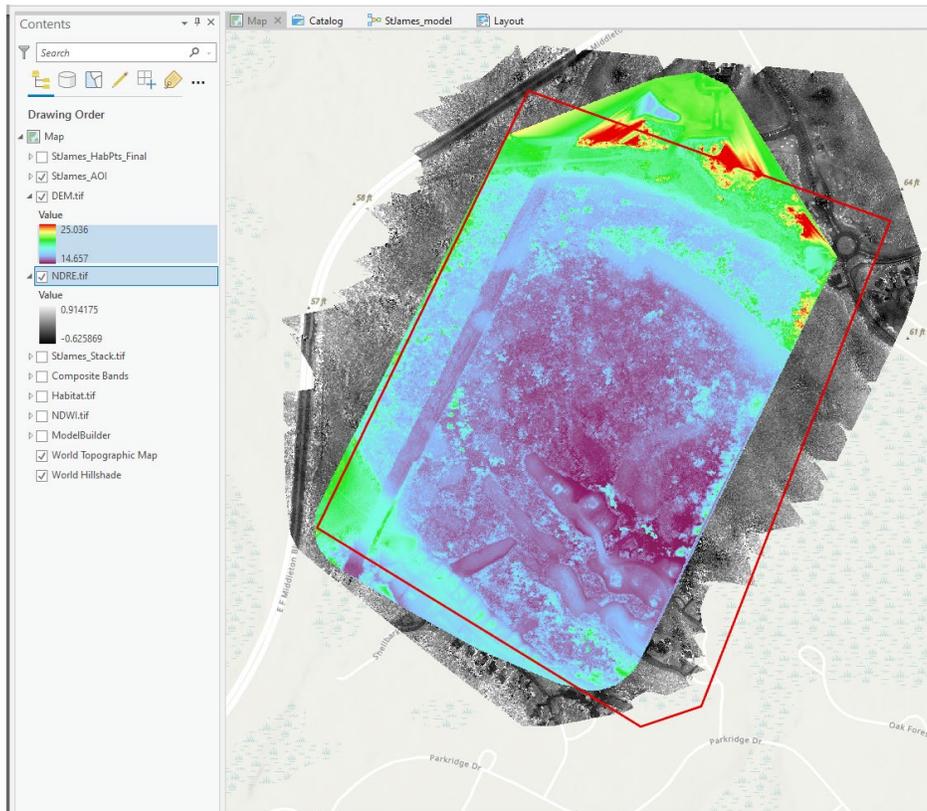
1	Habitat
2	DEM
3	sDEM
4	hDEM
5	DSM
6	CHM
7	Aspect
8	Slope
9	Curvature
10	PlanCurv
11	ProfileCurv
12	NDVI
13	NDRE
14	NDWI

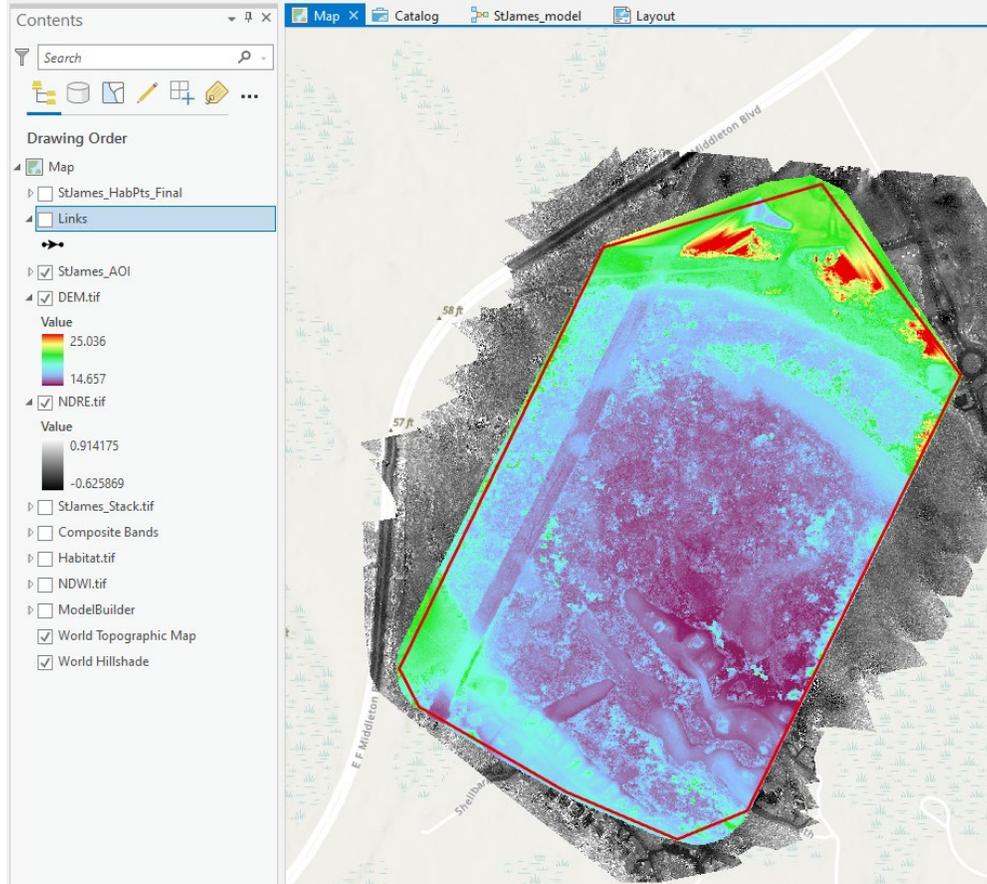


- Then, the composite Bands will be created.



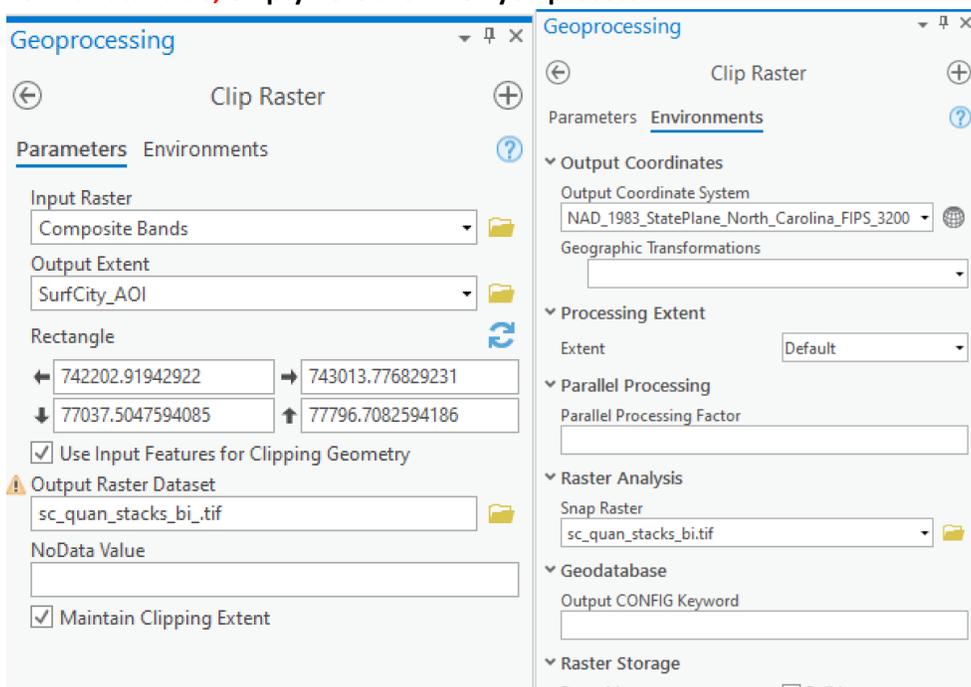
- Check if the AOI is within all the raster layers. If not, adjust the AOI to fit it. For example, the AOI (red rectangle) below is too big to fit both topo and vegetation index layers, so you can make it a little smaller.



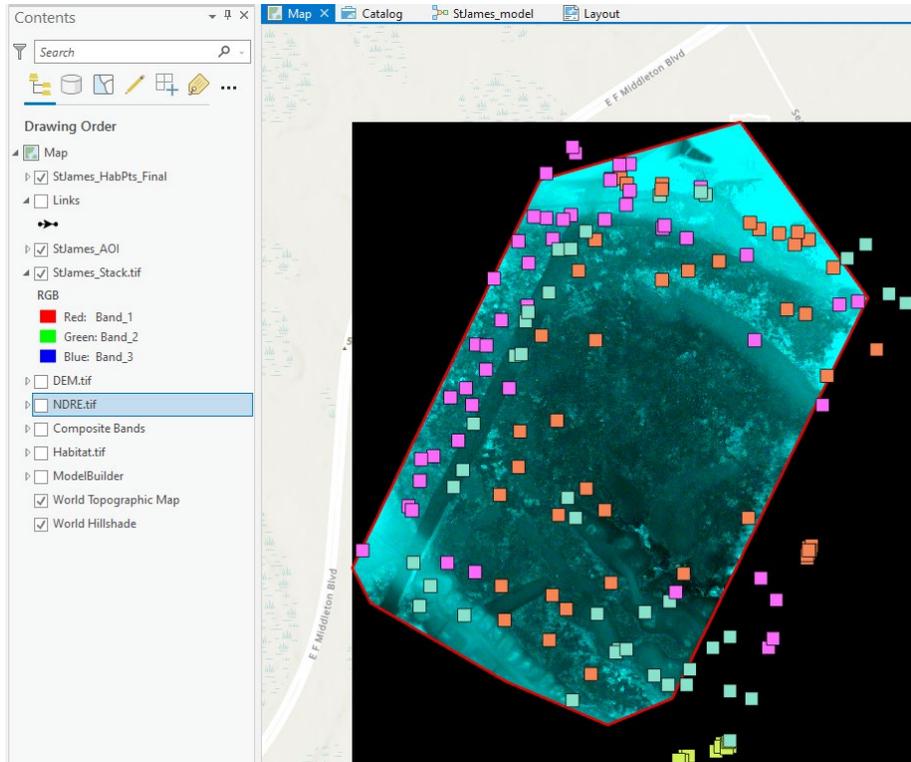


7. Now clip this Composite Band with the AOI to remove unnecessary areas.

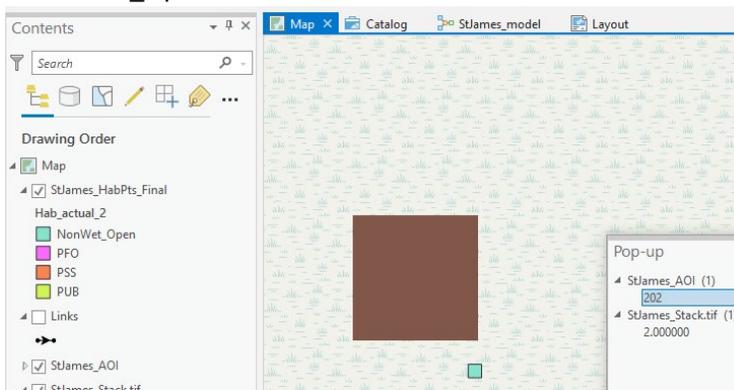
**For NoDataValue, empty here ~~the~~ when you process.**



8. Stack raster clipped to AOI is created. Now turn on and show the habitat points and stack raster on the map. The stack raster has habitat data, but the wetland classes of the habitat data is stored in numbers instead of text. Comparing the habitat points with the stack raster's habitat data and find which number coincides with which habitat name.



For example, if you click on the brown raster pixel of stack raster, that shows as 2, which is NonWet\_Open.



## Section 19: RANDOM FOREST ANALYSIS

With a stack raster is created, from here, we are going to use R programming language to run a random forest classification. RStudio (<https://www.rstudio.com/>), a programming platform, is used throughout this guide.

### 19.1: Raster to Data frame

We are going to convert the raster layers into data frame, which is the most common dataset format used in R. Open the “RasterToDataFrame.R” file in RStudio.

1. Create an empty file and bring the “RasterToDataFrame.R” and the raster stack that you prepared in the previous section.

is PC > 128 GB SSD (D:) > Minei\_NCDOT > a\_DataFrame

Name	Date modified	Type
 RasterToDataFrame.R	1/4/2022 12:10 PM	R File
 CastleBay_Stack.tif	1/4/2022 12:12 PM	TIF File
 StJames_Stack.tif	1/4/2022 12:12 PM	TIF File
 Topsail_Stack.tif	1/4/2022 12:12 PM	TIF File

2. Open the RasterToDataFrame.R in RStudio and run the “**1. setting environment**” section first. Make sure you change the work directory at line 27 (setwd) to the folder you just made before you run it.

```
5 # 1. setting environment -----
6 ## install packages
7 # Only run once to download packages in your computer
8 install.packages("rgdal")
9 install.packages("yaImpute")
10 install.packages("raster")
11 install.packages("dplyr")
12 install.packages("sf")
13 install.packages("ggplot2")
14 install.packages("rpart")
15
16 # Run this every time you open
17 library(rgdal)
18 library(yaImpute)
19 library(raster)
20 library(dplyr)
21 library(sf)
22 library(ggplot2)
23 library(rpart)
24
25 ## Set working path
26 ## CHANGE THE PATH ###
27 setwd("D:/Minei_NCDOT/a_DataFrame")
```

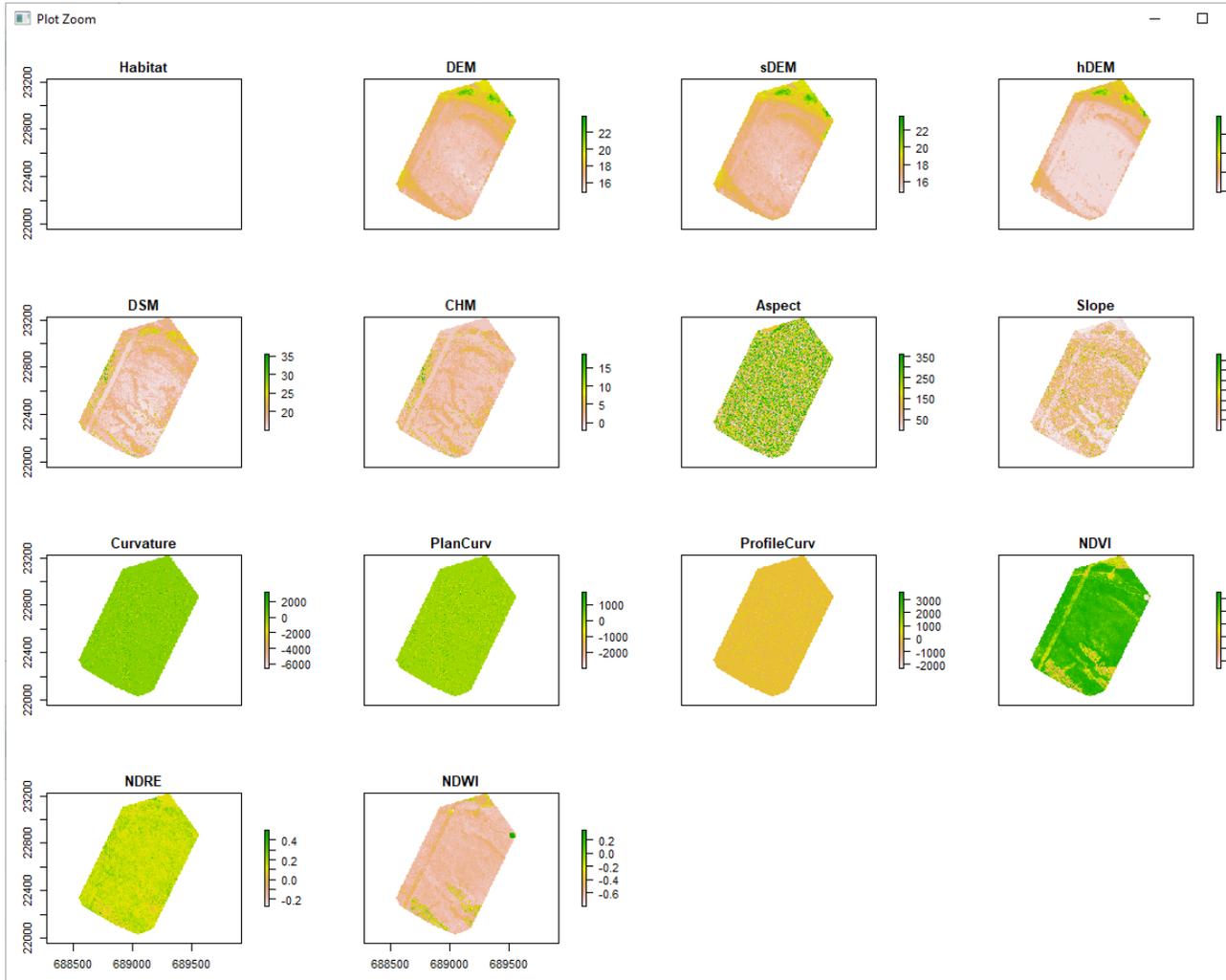
- Run the "2. Load and name" section. Make sure you change the name of the tif file (line 34) exactly as it is saved.

```

30 - # 2. Load and name -----
31 # Load full stack of a raster layer
32 # if this fails, try updating your R system
33 ## CHANGE TIF FILE ###
34 st <- stack("StJames_Stack.tif")
35
36 names(st) <- c("Habitat",      "DEM",      "sDEM",      "hDEM",
37               "DSM",          "CHM",      "Aspect",    "Slope",
38               "Curvature",    "PlanCurv", "ProfileCurv",
39               "NDVI",         "NDRE",     "NDWI")
40
41 # plot each raster lyers
42 plot(st)

```

When you run the line 42, all the raster layers will be plotted in the plot window.



- Run the “3. Convert the raster into DataFrame” section.  
For this site, about ninety habitat points were **created from made-out-of-all** the areas of pixel. `df_hab` is the dataset that only covers the areas of pixels where habitat points were collected. **because-**When you train a model you don't need a dataset that does not have response data.

`df_all` is a dataset including all the areas of data, which will be used to predict wetland classes based on the predictors.

```
45 - # 3. convert the raster into DataFrame -----
46 # Create two dataframe: all dataset and dataset with all the null dataset removed
47 # na.rm = T -> removes all the null data
48 df_hab <- as.data.frame(st, xy = TRUE, na.rm = T)
49
50 st$Habitat[is.na(st$Habitat)] <- 0
51 df_all <- as.data.frame(st, xy = TRUE, na.rm = T)
--
```

- Save the dataframe as RDS dataset.

```
60 - # 4. save data -----
61 saveRDS(df_hab, file = "StJames_hab.rds")
62 saveRDS(df_all, file = "StJames_all.rds")
--
```

## 19.2: Random Forest Classification using H2O package

- Create a folder and put those files below.

- Wetland\_RF\_H2O.R
- SiteName\_all.rds
- SiteName\_hab.rds
- SiteName\_Stack.tif

Name	Type
 Wetland_RF_H2O.R	R File
 StJames_all.rds	RDS File
 StJames_hab.rds	RDS File
 StJames_Stack.tif	TIF File

- Open the “Wetland\_RF\_H2O.R” and run the “1. Setting environment” section. You only install packages once in your computer but run `library` every time you run.

```
5 - ## 1. Setting environment =====
6 #install.packages('readr');install.packages('h2o');install.packages('caret)
7 library(readr)
8 library('h2o')
9 library(e1071)
10 library(caret)
```

- Run the “2. Load RDS data” section. Make sure to change the path to the folder (**fn <- folder path**) and change the name of the RDS file.

```
13 - ## 2.load RDS data =====
14   fn<-"D:/Minei_NCDOT/b_StJames"
15   setwd(fn)
16   df.rds<-readRDS("StJames_hab.rds"); names(df.rds); attach(df.rds)
```

4. Here we use H2O package to run random forest analysis. Here I would recommend running by each block to make sure it runs correctly. Make sure to run line 25 – 27 every time when you get an error of running out of computer memory.

```

19 ## 3.Random Forest Model =====
20 df.rds$Habitat<-factor(df.rds$Habitat)
21 vari <- df.rds[ ,1:14]
22 dim(vari)
23
24 ## using H2o;
25 h2o.shutdown(prompt = FALSE)
26 localH2O <- h2o.init(nthreads = -1,max_mem_size = '4g')
27 h2o.init()
28
29 ## empty vari
30 y.dep <- 1;
31 x.indep <- c(2:14)
32
33 ## record processing time
34 start.time <- Sys.time()
35
36 ## RF for accuracy with CV (k=5)
37 train.h2o <- as.h2o(vari);
38 rforest.model<- h2o.randomForest(y=y.dep,
39                                 x=x.indep,
40                                 training_frame = train.h2o,
41                                 nfold=5,
42                                 mtries=4,
43                                 max_depth=14,
44                                 ntrees = 500,
45                                 seed = 1122,
46                                 keep_cross_validation_predictions=TRUE,
47                                 keep_cross_validation_fold_assignment = TRUE)
48
49 rforest.model

```

When you run `rforest.model` at line 49 (copy and paste the results as it will be used for post analysis). Below is an example of results: ~~this is what you get for example:~~

*Model Details:*

=====

*H2OMultinomialModel: drf*

*Model ID: DRF\_model\_R\_1641325516784\_1 .....*

- Run the “4. Save model as file” section. Change the names of the files (line 68 and 69) as accordingly. When you save the model, it will be saved as the model ID in the folder. In this example, the model is saved as “DRF\_model\_R\_1641325516784\_1”  
When you run **line 72 and 73** (copy and paste the results if you want to make the variable importance plot later), you can see the variable importance.

```

52 - ## 4.save the model =====
53 # store the path to the model and reload the model
54 path <- h2o.saveModel(rforest.model, path=fn, force=TRUE )
55 rf.load <- h2o.loadModel(path)
56
57 # take out the cross validation prediction results
58 cv <- h2o.getFrame(rf.load@model[["cross_validation_holdout_predictions_frame_1_ame"]])
59 cv.vec <- as.vector(cv[,1])
60
61 # create dataset of x,y,and prediction results
62 pre <- data.frame(X =as.numeric(x),
63                  Y =as.numeric(y),
64                  PREDICT = as.numeric(cv.vec))
65 attach(pre); contrasts(factor(PREDICT)); summary(factor(PREDICT))
66
67 # Save the dataset as RDS abd restore it
68 saveRDS(pre, file = "StJames_XY_prediction.rds")
69 pre <- readRDS(file = "StJames_XY_prediction.rds")
70
71 # plot variable importance
72 h2o.varimp(rf.load)
73 h2o.varimp_plot(rf.load)

```

Name	Date modified	Type	Size
 .RData	1/4/2022 2:44 PM	R Workspace	11 KB
 .Rhistory	1/4/2022 2:44 PM	RHISTORY File	1 KB
 DRF_model_R_1641325516784_1	1/4/2022 2:46 PM	File	2,677 KB

- Next step is to use the random forest model that was created in the previous section, **and** predict wetland classification for the whole area. Make sure to change the name of the file (line 80) accordingly. Also, line 89-91 can tell you how long the model took to train and predict.

```
73 - ## 5.Predicting wetland with all data =====
74 #install.packages('ggplot2'); install.packages('raster'); install.packages('randomForest')
75 library(ggplot2)
76 library(sp)
77 library(raster)
78
79 # import the data to be trained
80 df.all <- readRDS("StJames_all.rds")
81 allpre <- df.all[,2:14]
82 dim(allpre)
83
84 # if those two does not work, go back and rerun line 25-27
85 train.h2o <- as.h2o(allpre);
86 pre.all <- h2o.predict(rf.load, newdata = train.h2o)
87
88 ## Stop recording time and calculate processing time
89 end.time <- Sys.time()
90 time.taken_rf <- end.time - start.time
91 time.taken_rf
```

- Run the section 5 to save the x, y, and prediction results for the model result data. Make sure you change the names of the file you will save (line 99 and 100) as you like.

```
94 - ## 5.Save an object to a file and restore it =====
95 pre2 <- data.frame(X =as.numeric(df.all$x),
96                   Y =as.numeric(df.all$y),
97                   PREDICT = as.numeric(as.vector(pre.all$predict)))
98 attach(pre2)
99 saveRDS(pre2, file = "StJames_Final_prediction.rds")
100 pre <- readRDS(file = "StJames_Final_prediction.rds"); attach(pre)
```

### 19.3: Export Results as Raster

1. Section 6 is to create the raster data that shows the model prediction of wetland class and export it.

```
103 ## 6.Create prediction map in raster =====
104 # Reference: https://www.youtube.com/watch?v=LwCEe9o0vac
105 st <- stack("StJames_Stack.tif")
106 names(st) <- c("Habitat", "DEM", "sDEM", "hDEM",
107 "DSM", "CHM", "Aspect", "Slope",
108 "Curvature", "PlanCurv", "ProfileCurv",
109 "NDVI", "NDRE", "NDWI")
110
111 # finding out the extent, coordinate system, # of row and columns
112 ex <- extent(st); n.row<-dim(st$Habitat)[1];n.col <-dim(st$Habitat)[2];
113 ncell(st$Habitat); my.crc <- crs(st$Habitat)
114
115 #create a empty raster and bring the prediction results and plot it
116 r <- raster(ex, ncol=n.col, nrow=n.row, crs= my.crc)
117 r_new <- rasterize(pre2[,1:2], r, pre2[,3], fun=mean)
118 plot(r_new)
119
120 #save prediction raster in tif
121 writeRaster(r_new, filename = 'StJames_PreMap.tif',options=c('TFW=YES'))
```

## Section 20: DATA POST ANALYSIS

This section explains how to do the post processing, which consists of the calculation of model performance matrices, making prediction maps, and making variable importance plots.

### 20.1: Calculating Model Performance Matrices

Assume you have copied and pasted the model result (line 49) and there you can find a classification matrix, and this is what it looks like. Here we show how to calculate the overall accuracies, producer and user's accuracy, sensitivity, specificity, and finally kappa coefficient.

		Classification Model		
		1: PFO	2: NonWet	3: PSS
Reference	1: PFO	31	3	8
	2: NonWet_Open	3	24	1
	3: PSS	7	1	30

- Overall accuracies

$$(31 + 24 + 30) / 108 = 0.7870$$

$$\hat{=} 78.7\%$$

		Classification Model			total
		1: PFO	2: NonWet	3: PSS	
Reference	1: PFO	31	3	8	42
	2: NonWet_Open	3	24	1	28
	3: PSS	7	1	30	38
Total		41	28	39	108

- Producer's accuracy (1: PFO) = sensitivity

$$31 \div 42 = 0.738$$

$$\hat{=} 74\%$$

		Classification Model			total	Producers
		1: PFO	2: NonWet	3: PSS		
Reference	1: PFO	31	3	8	42	0.74
	2: NonWet_Open	3	24	1	28	0.86
	3: PSS	7	1	30	38	0.79

- User's accuracy (1: PFO)

$$31 \div 42 = 0.738$$

$$\hat{=} 76\%$$

		Classification Model			total	Producers
		1: PFO	2: NonWet	3: PSS		
Reference	1: PFO	31	3	8	42	0.74
	2: NonWet_Open	3	24	1	28	0.86
	3: PSS	7	1	30	38	0.79
Total		41	28	39	108	
Users Accuracy		0.756	0.857	0.769		

- Sensitivity = producer's accuracy

5. Specificity (1: PFO)

$$(24 + 1 + 1 + 30) \div (24 + 1 + 1 + 30 + 3 + 7) = 56 \div 66$$

$$= 0.84848$$

$$\approx 84.85 \%$$

		Classification Model			total	Producers	sensitivity	specificity
		1: PFO	2: NonWet	3: PSS				
Reference	1: PFO	31	3	8	42	0.7381	0.7381	0.8485
	2: NonWet_Open	3	24	1	28	0.8571	0.8571	0.9500
	3: PSS	7	1	30	38	0.7895	0.7895	0.8714
	Total	41	28	39	108			
Users Accuracy		0.756	0.857	0.769				

6. Kappa coefficient

$$\text{Pr}(a) = (31 + 24 + 30) \div 108$$

$$= 0.7870$$

$$\text{Pr}(e) = (0.38 \cdot 0.39) + (0.25 \cdot 0.25) + (0.36 \cdot 0.35)$$

$$= 0.14782 + 0.067081 + 0.127072$$

$$= 0.341973$$

$$K = (\text{pr}(a) - \text{Pr}(e)) / (1 - \text{Pr}(e))$$

$$= (0.7870 - 0.341973) \div (1 - 0.341973)$$

$$= 0.445027 \div 0.658027$$

$$= 0.6763$$

$$\approx 67.63 \%$$

		Classification Model			total	Producers	sensitivity	specificity	true/total
		1: PFO	2: NonWet	3: PSS					
Reference	1: PFO	31	3	8	42	0.7381	0.7381	0.8485	0.389
	2: NonWet_Open	3	24	1	28	0.8571	0.8571	0.9500	0.259
	3: PSS	7	1	30	38	0.7895	0.7895	0.8714	0.352
	Total	41	28	39	108				
Users Accuracy		0.756	0.857	0.769					
true/total		0.380	0.259	0.361					

k=(pr(a) - Pr(e)) / (1-Pr(e))	
Pr(a)	0.787037
Pr(e)	0.34
k	0.676394

Pr(a) = (true+true)/total
Pr(e) = (0.38*0.39)+(0.29*0.25)+(0.36*0.35)

		Classification Model							
		1: PFO	2: NonWet	3: PSS	total	true/total	Producers	sensitivity	specificity
Reference	1: PFO	31	3	8	42	0.39	73.81%	0.738095	0.848485
	2: NonWet_Open	3	24	1	28	0.26	85.71%	0.857143	0.95
	3: PSS	7	1	30	38	0.35	78.95%	0.789474	0.871429
	Total	41	28	39	108				
	true/total	0.380	0.259	0.361					
	Users Accuracy	75.61%	85.71%	76.92%			accuracy	0.787037	

$k = (Pr(a) - Pr(e)) / (1 - Pr(e))$	
Pr(a)	0.787037
Pr(e)	0.34
k	0.676394

$Pr(a) = (true + true) / total$
$Pr(e) = (0.31 * 0.35) + (0.68 * 0.64)$

## 20.2: Making Prediction Map

Now that you have created and exported the final result map in raster format, you can visualize this in ArcGIS Pro. Simply load the TIF file and classify the map by wetland class.

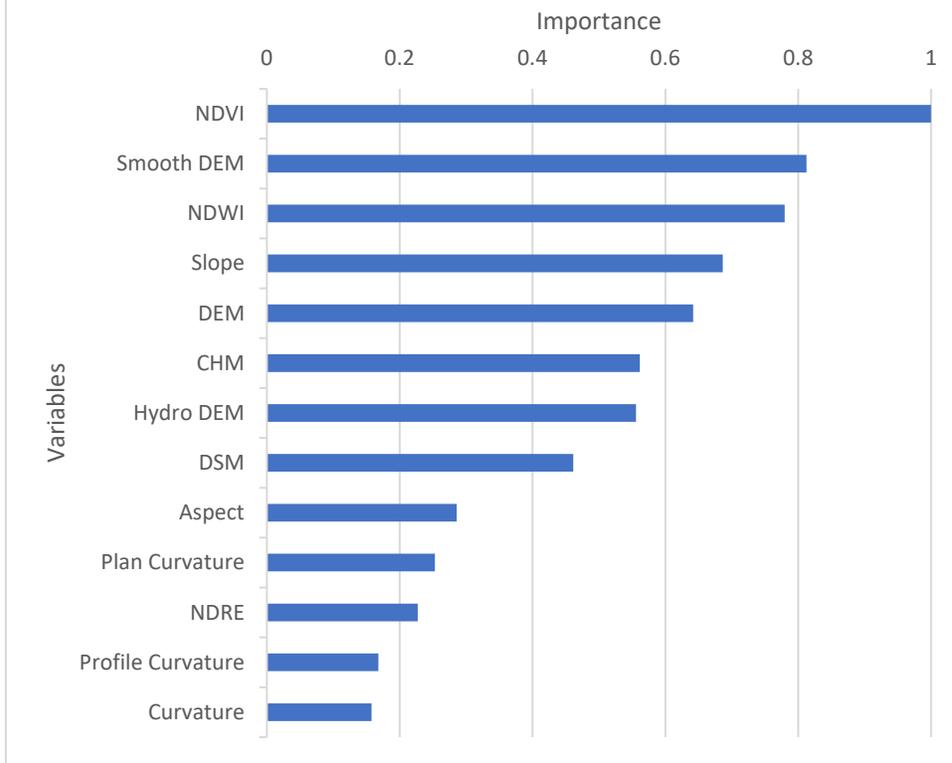


### 20.3: Making Variable Importance Plots

When you run line 72, you will get a result table of variable importance plot. You can make this into a bar plot graph using Excel for example.

Variable	Importances:			
	variable	relative_importance	scaled_importance	percentage
1	NDVI	3934.388672	1	0.151746
2	Smooth DEM	3196.75708	0.812517	0.123297
3	NDWI	3067.769531	0.779732	0.118322
4	Slope	2700.459229	0.686373	0.104155
5	DEM	2525.5	0.641904	0.097407
6	CHM	2208.754883	0.561397	0.08519
7	Hydro DEM	2186.508545	0.555743	0.084332
8	DSM	1814.694214	0.461239	0.069991
9	Aspect	1124.103271	0.285712	0.043356
10	Plan Curvature	994.933533	0.252881	0.038374
11	NDRE	893.176453	0.227018	0.034449
12	Profile Curvature	660.776001	0.167949	0.025486
13	Curvature	619.562866	0.157474	0.023896

### St James: Scaled Variable Importance Plot



## APPENDIX C: EXAMPLE METADATA TABLE

In creating metadata, each final feature class for each respective study area was given detailed metadata based on how the data was acquired and what purpose each layer served in the project before being copied into the final geodatabases. These feature classes consisted of layers involved in mission planning, field work, and post-fieldwork lab methods. Each feature class metadata report contained a title, purpose, abstract, credits, use limitations (if applicable), extent, and scale range. A template was created to fill metadata for each feature class in each site. Each study site's NWI, County NAIP, and County CREWS layers had existing original metadata, which was kept as it was found. Metadata files were created for all the other layers across each study site. A description of each feature class and a list of component fields for the Carolina Bays study area is shown in table below, for illustrative purposes.

**Table AC 1.** Table displaying metadata for the Carolina Bays study area. The field mission was conducted on February 23rd, 2021.

Feature Class	Description	Fields
Carolina_Bays_AOI	Area of interest polygon created for the Carolina Bays study site. Field operations and data collection are conducted within this area of interest. AOIs are selected from locations containing multiple National Wetland Inventory (NWI) wetland types.	OBJECTID, Shape, SHAPE_Leng, Area, Shape_Length, Shape_Area
Carolina_Bays_FP_Plan	Planned flight path created for drone flights and imagery collection over the Carolina Bays study site.	OBJECTID, Shape, Id, Shape_Length
Carolina_Bays_FP_Collected	Flight path taken and recorded by drone flights over the Carolina Bays study site for imagery collection.	OID, Shape, Name, FolderPath, SymbolID, AltMode, Base, Clamped, Extruded, Snippet,

		Popupinfo, ShapeLength
Carolina_Bays_GCP_Plan	Ground control points created and placed as evenly as possible across the area of interest and intended to be beneath the flight path of the drones as they collect imagery of the study area. Ground control points will be used to constrain the imagery collected.	OBJECTID, Shape, Id, POINT_X, POINT_Y
Carolina_Bays_GCP_Collected	The locations of all ground control points created and placed around the area of interest were recorded during the field mission. Ground control points will be used to constrain the imagery collected.	OBJECTID, PointName, x, y, z, habitat, trimble, observed_topo, Shape, LiDAR_Use
Carolina_Bays_Habpts_Plan	Randomly generated 15 habitat points created using a spatially balanced approach for accessibility for each NWI wetland type and 50 habitat points placed in non-wetland areas across the study site.	OBJECTID_12_13, Shape, ATTRIBUTE, POINT_X, POINT_Y
Carolina_Bays_Habpts_Final	Habitat points collected in the field in addition to the planned habitat points placed across the Carolina Bays study site. Each point was examined using imagery from various sources, including Google Earth, Google Maps, North Carolina OneMap, and the National Agriculture Imagery Program (NAIP) to determine whether the point matched its previous NWI habitat type designation, and to update the point if it did not match its previously given habitat type. Confidence levels were then assigned to each point's full NWI habitat code as well as to each point's NWI habitat code shortened to contain the habitat's main system, subsystem, and class levels.	OBJECTID_12_13, Shape, OBJECTID_12, ATTRIBUTE, POINT_X, POINT_Y, Hab_actual, Confidence, Hab_actual_2, Confidence_2
Carolina_Bays_NWI	This data set represents the extent, approximate location and type of wetlands and deepwater habitats in the United States and its Territories. These	FID, Shape, ATTRIBUTE, AreaHEC, AreaAcres, AreaM,

	<p>data delineate the areal extent of wetlands and surface waters as defined by Cowardin et al. (1979) to provide current geospatially referenced information on the status, extent, characteristics and functions of wetlands, riparian, deepwater and related aquatic habitats.</p>	<p>Shape_Length, Shape_Area</p>
Brun_naip	<p>This data set contains imagery from the National Agriculture Imagery Program (NAIP). The NAIP acquires digital ortho imagery during the agricultural growing seasons in the continental U.S. This file was generated by compressing NAIP imagery that cover the county extent. The NAIP imagery is generally acquired in projects covering full states in cooperation with state government and other federal agencies who use the imagery for a variety of purposes including land use planning and natural resource assessment. The NAIP is also used for disaster response often providing the most current pre-event imagery.</p>	<p>OBJECTID, Shape, IDATE, SDATE, EDATE, BCON, CAM_TYPE, CAM_MAN, HARD_FIRM, SENSNUM, AC_TYPE, ACTAILNUM, RED_RNGE, GREEN_RNGE, BLUE_RNGE, NIR_RNGE, Shape_Length, Shape_Area</p>
Brun_crews	<p>The North Carolina Coastal Region Evaluation of Wetland Significance or NC-CREWS. NC-CREWS functions in a hierarchical manner, analyzing three primary wetland functions (Hydrology, Water Quality and Wildlife Habitat), seven wetland subfunctions and 39 landscape and wetland parameters. Wetlands are assigned ratings of Beneficial Significance, Substantial Significance or Exceptional Significance, depending on how well they perform the various wetland functions.</p>	<p>OBJECTID, Shape, AREA, PERIMETER, BRUN_WETS_, BRUN_WETS1, W_TYPE, HGM, WET_NAME, Shape_Length, Shape_Area</p>

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**01/2022**