EMERGING TECHNOLOGIES IN WETLAND MAPPING AND MONITORING

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Marine Robotics & Remote Sensing

(Director: Dave Johnston)

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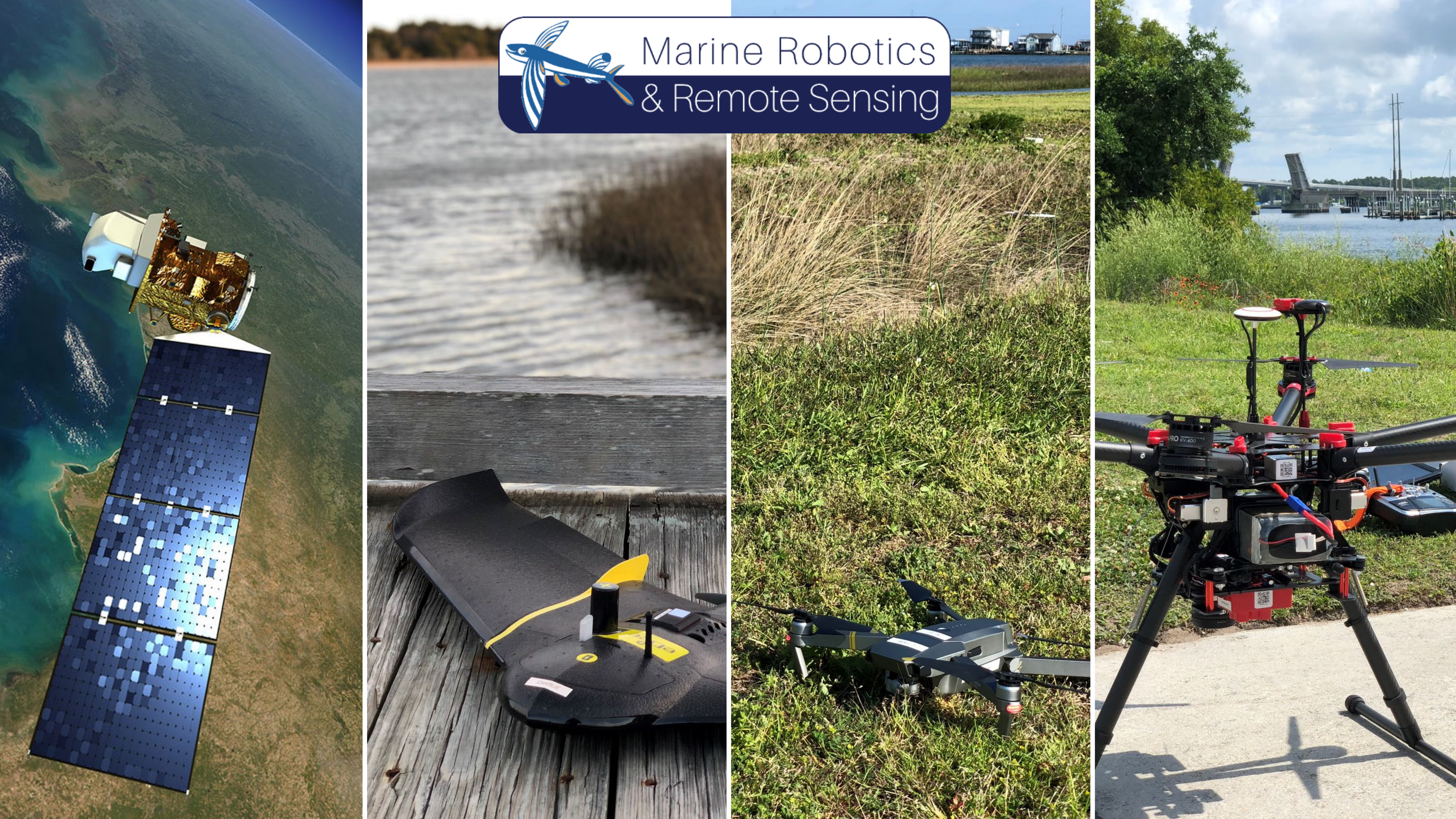

Marine Robotics
& Remote Sensing

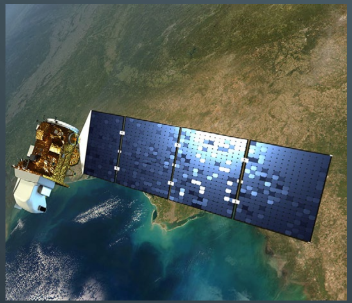
EXPLORING EMERGING TECHNOLOGIES

Examining collaborative efforts in:

- 2D Mapping/3D Modeling of Wetlands with UAS
- Data Fusion of Remote Sensing Products for Wetlands Mapping
- Advances in Imagery Processing (Deep Learning)
- Summary Considerations

REMOTE SENSING WETLANDS

- Currently: lower/moderate resolution satellite data (like Landsat) and aerial imagery/lidar




- Potential to augment current practices with new sources of imagery and ancillary data
- Platform decisions should be objective driven

2D MAPPING/3D MODELING WITH UAS

2D MAPPING

Very high resolution

- 1-3 cm/pixel RGB
- 3-8 cm/pixel Multispectral

Increases:

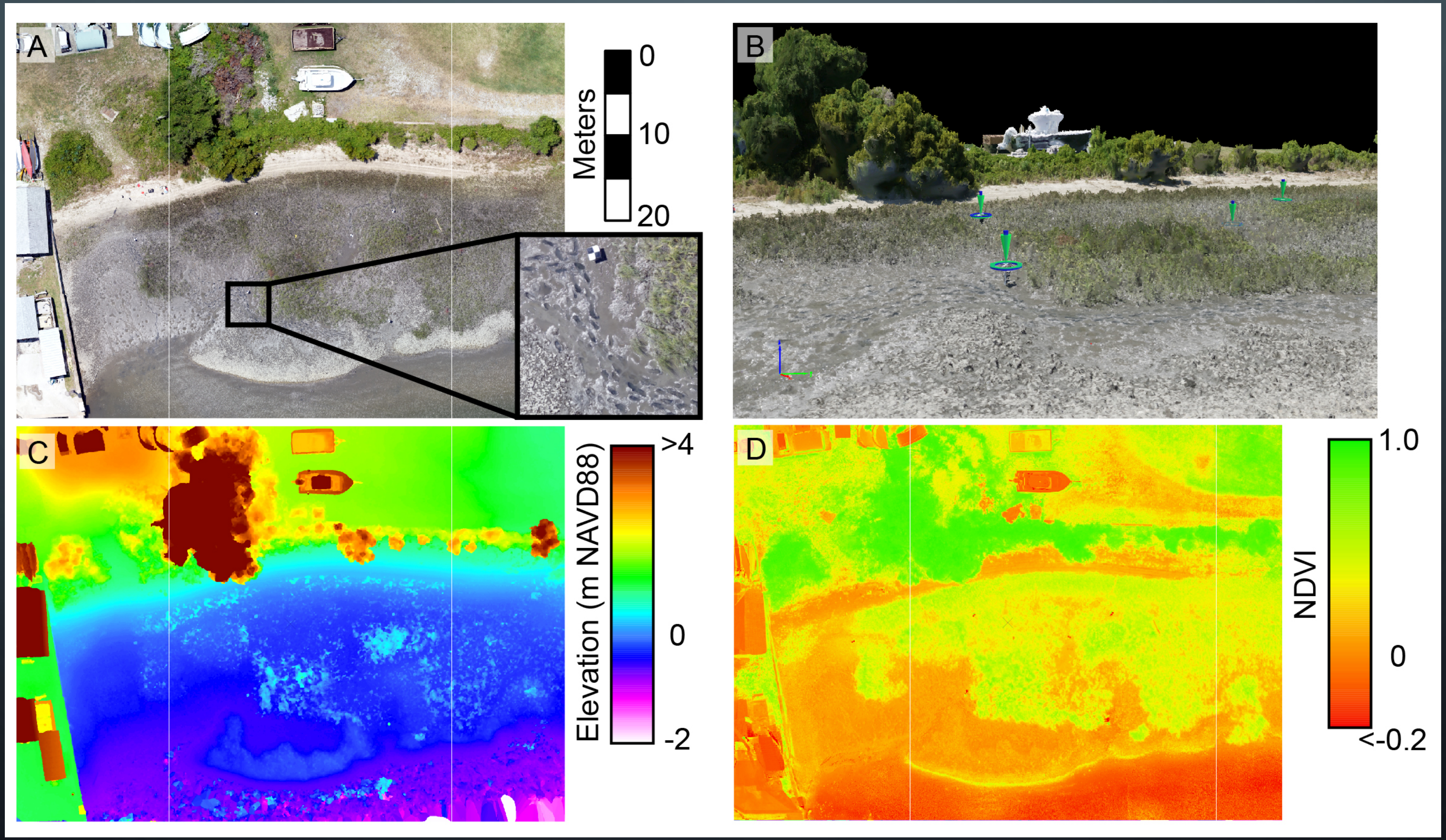
- edge definition
- species differentiation
- temporal resolution

The use of Ground Control Points (GCPs) can achieve cm-scale accuracy if needed – also can be accomplished with RTK-equipped drones

NOAA LIVING SHORELINE (PIVERS ISLAND)

STRUCTURE FROM MOTION (SFM)

UAS PRODUCTS



Ridge and Johnston 2020

STEM HEIGHTS EXAMPLE

In addition to the SfM UAS products, data fusion provides multiple pathways to generate relevant 3D data.

The research community is working to understand what method yields the most reliable, accurate information.

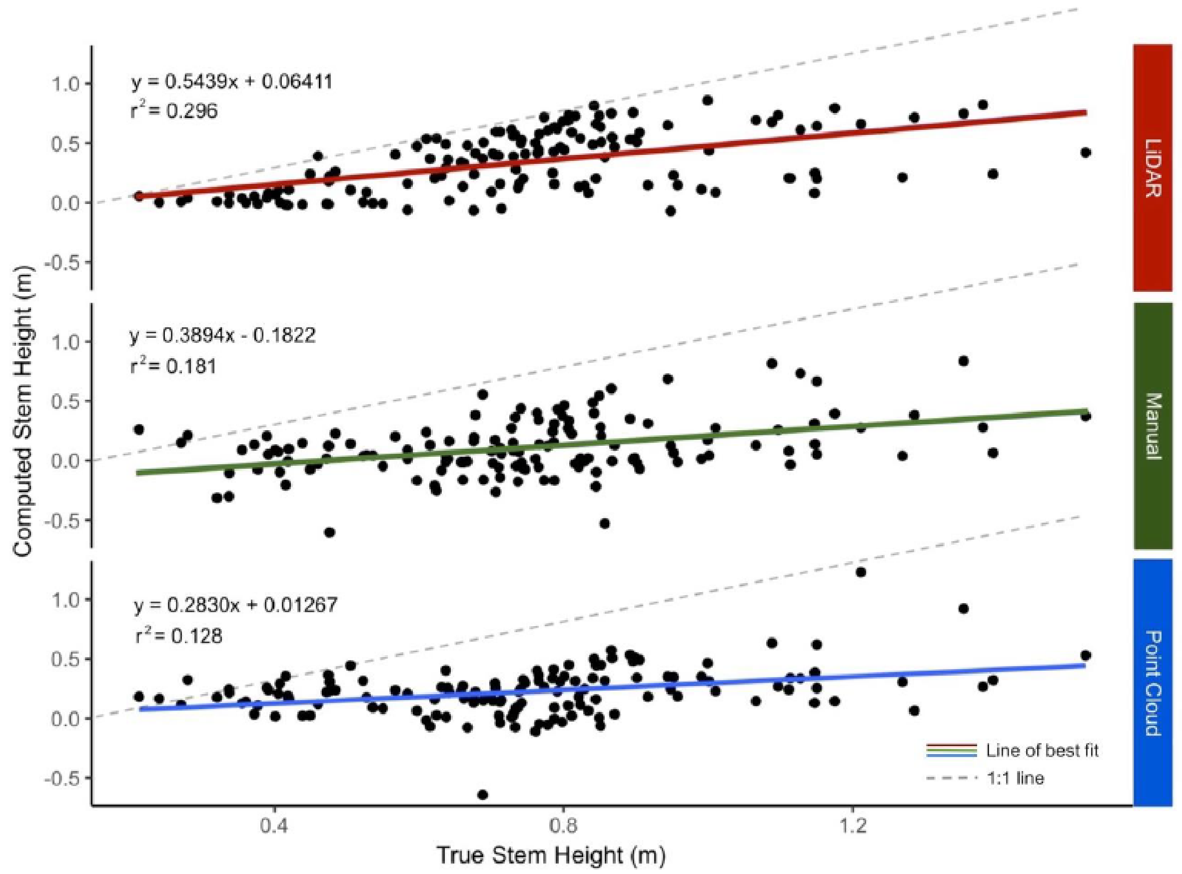


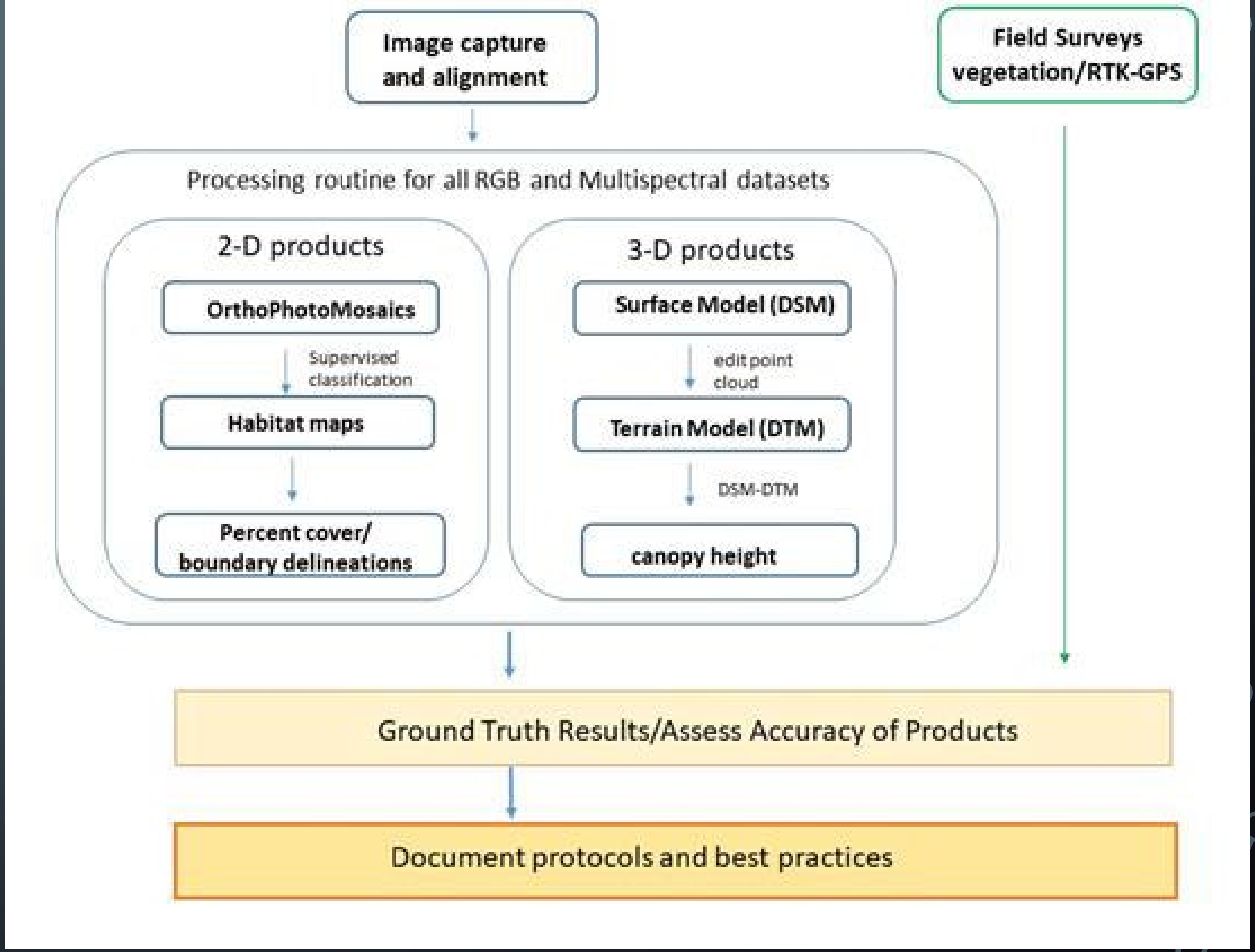
Figure 4. Computed vs. true regression mapped vegetation height derived from UAS imagery to field-measured true stem heights. The 1:1 line, where computed stem height is equal to true stem height, is displayed for reference. Computed vegetation heights are compared across the point cloud, manual, and Light Detection and Ranging (LiDAR)-derived digital terrain models.

DiGiacomo et al. 2020

UPCOMING WORK

Project Leads:

- Jenny Davis (NOAA)
- Brandon Puckett (NCNERR)



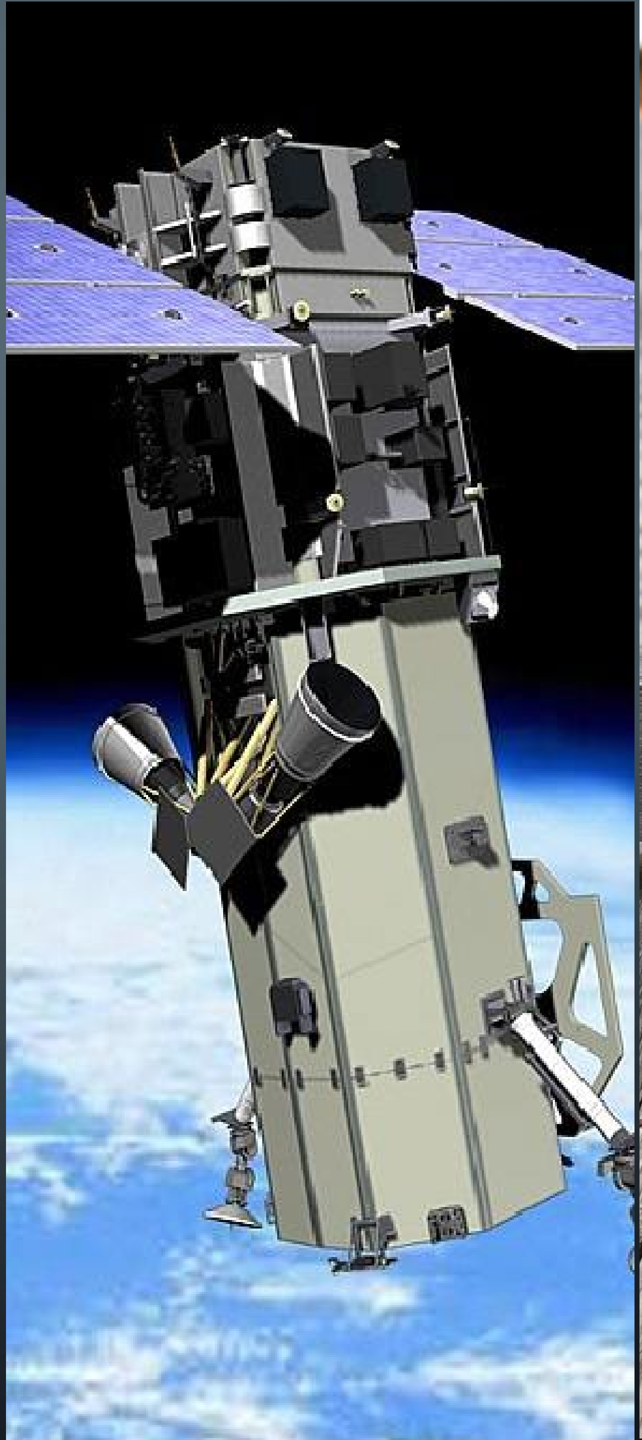
UAS SUMMARY & CONSIDERATIONS

- Benefits
  - Very high resolution look at wetland sites, providing **multiple layers of useful information** (2D & 3D)
  - Research conducted by the NOAA/NERRS/Duke team should provide **explicit guidance** and alleviate the necessity of heavy groundtruthing
- Costs
  - Not feasible for wide scale (all NC coast) application, but could be highly informative at select focus sites throughout the region
  - Not too manpower intensive, but 2-3 trained people would be preferred, especially if needing to capture all site imagery in a narrow window (e.g., peak biomass)
  - Costs to consider: drones, processing software, time

DATA FUSION

DATA FUSION

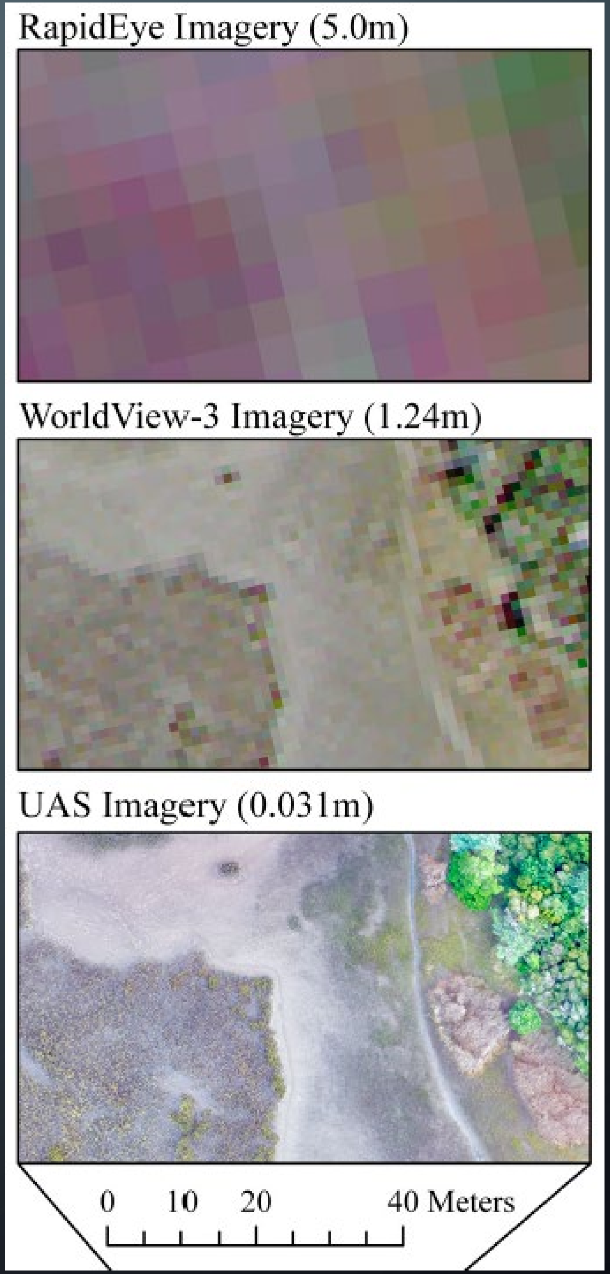
Use very high resolution UAS imagery to feed classifications of satellite imagery




STUDY AREA
Image © 2020 TerraMetrics
Google Earth

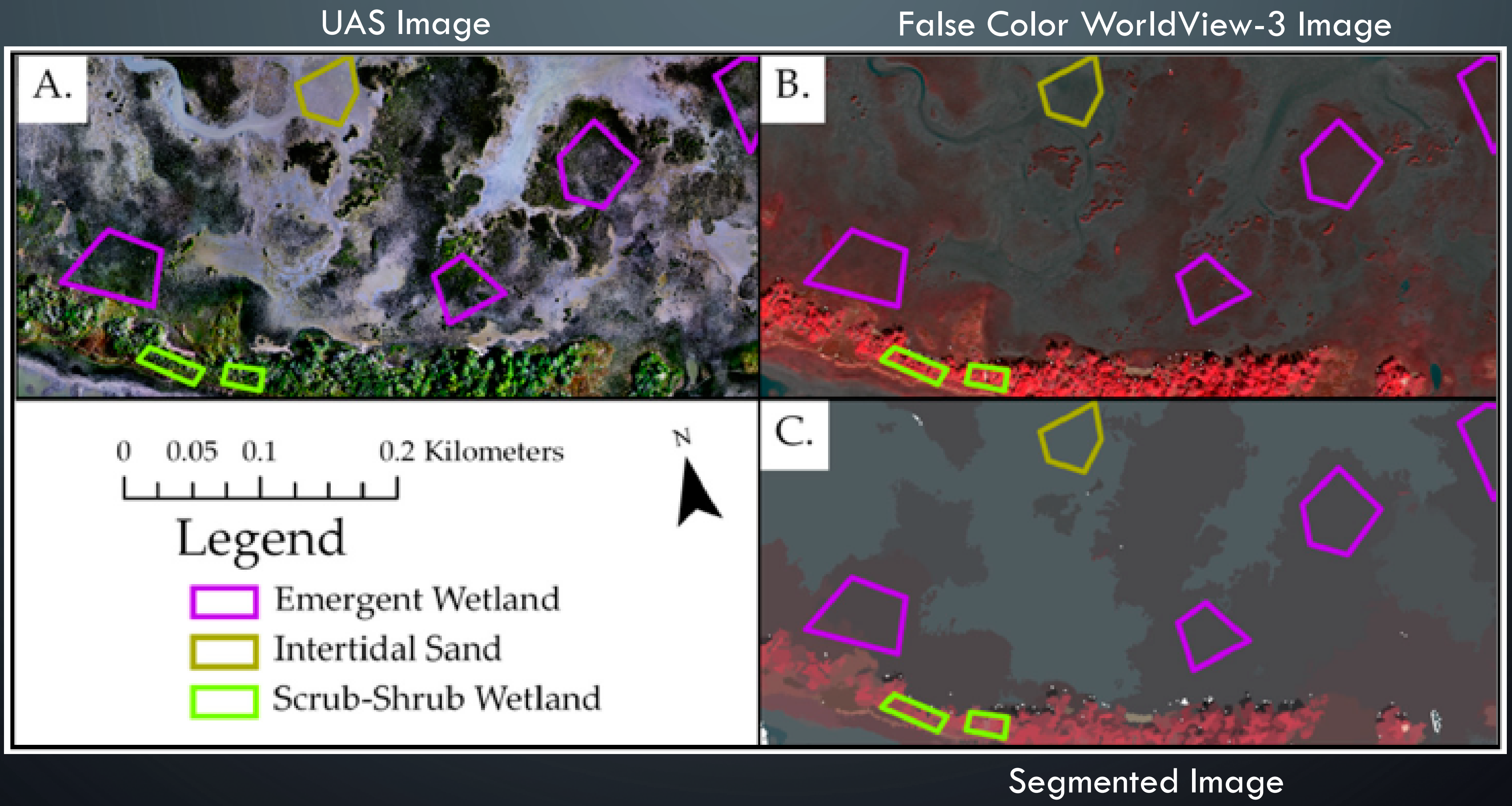
HIGH RES SATELLITE DATA

	WorldView-3	RapidEye
Imagery Details		
Spatial Resolution (m)	1.24	5.0
Radiometric Resolution	11 bit	12 bit
Revisit Rate	4.5 days	5.5 days
Revisit Rate (off-nadir)	Daily	Daily
Date of Acquisition	31 October 2017	20 July 2017
Time of Acquisition	16:14:35 UTC	16:04:21 UTC
Tidal State (m > MLLW)	0.22	-0.07
Bands (nm)		
Coastal Blue	400–450	-
Blue	450–510	440–510
Green	510–580	520–590
Yellow	585–625	-
Red	630–690	630–685
Red Edge	705–745	690–730
NIR 1	770–895	760–850
NIR 2	860–1040	-
Panchromatic	450–800	-



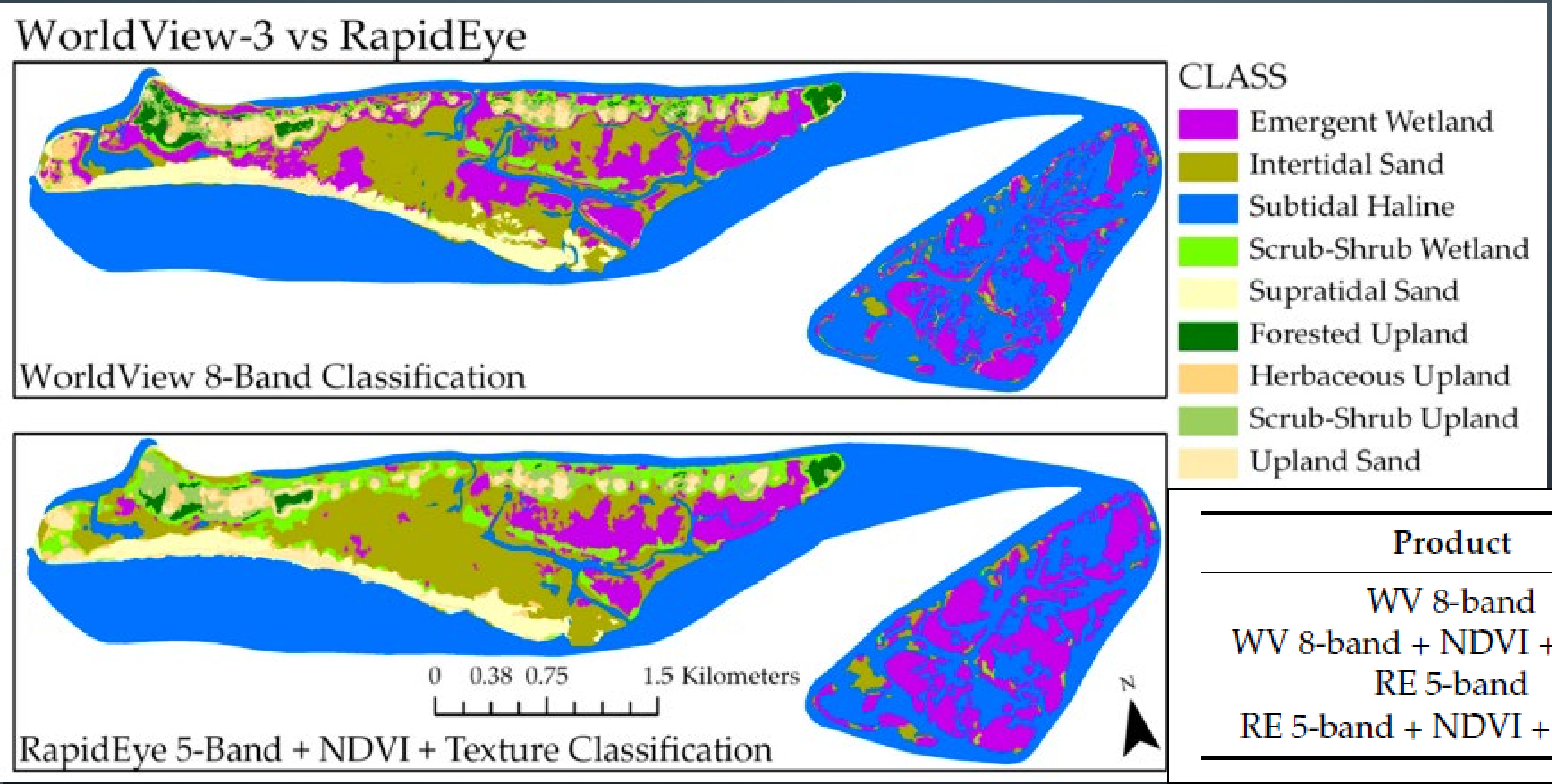
Gray et al. 2018

TRAINING WITH UAS



Gray et al. 2018

FINAL ACCURACY



Product	Field	UAS
WV 8-band	93%	93%
WV 8-band + NDVI + texture	79%	83%
RE 5-band	86%	90%
RE 5-band + NDVI + texture	87%	92%

Gray et al. 2018

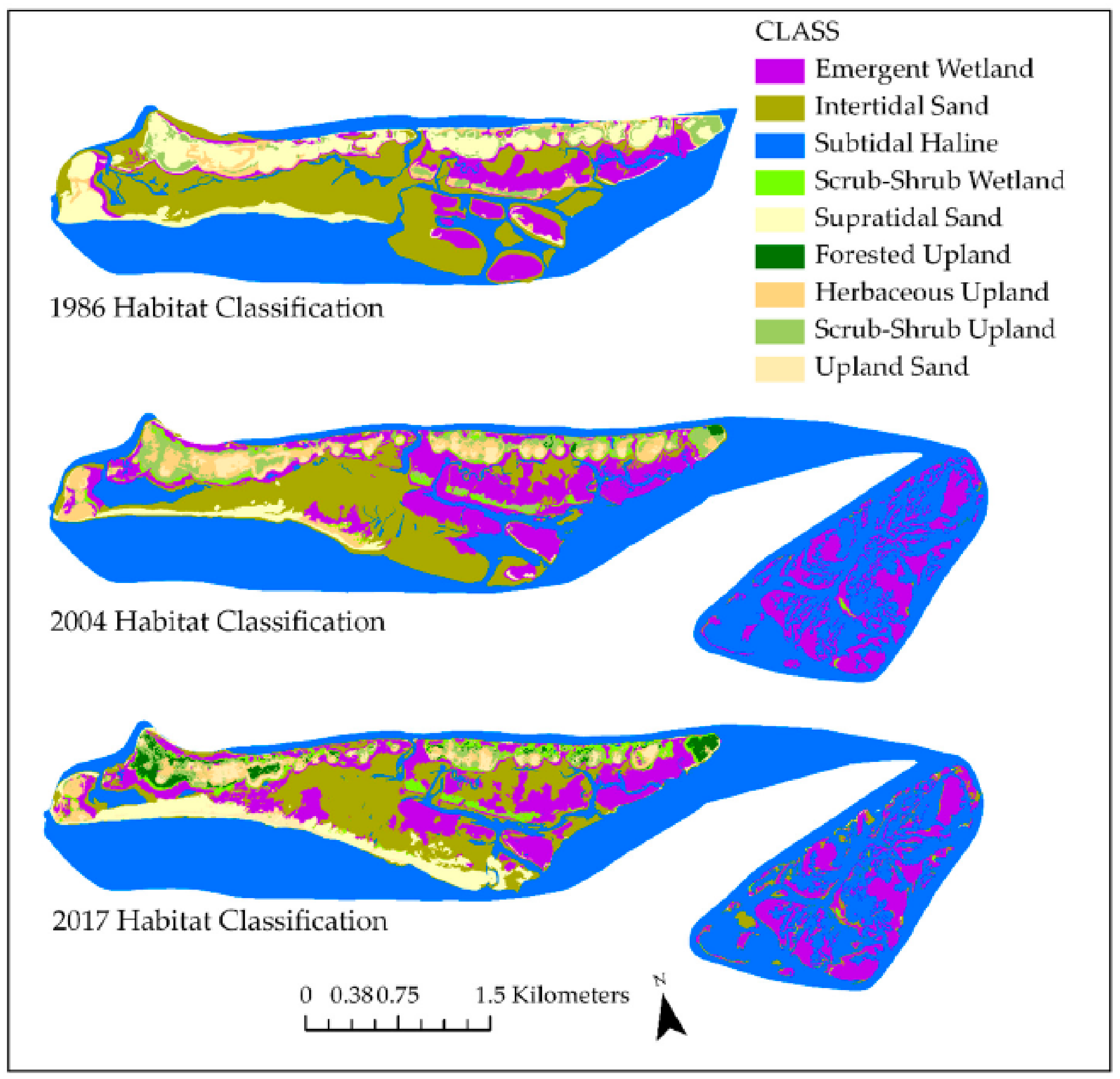
DATA FUSION SUMMARY AND CONSIDERATIONS

Benefits

- Provides the opportunity to scale up mapping and monitoring of potential UAS focus sites (previous section), providing increased accuracy of satellite imagery classification

Costs

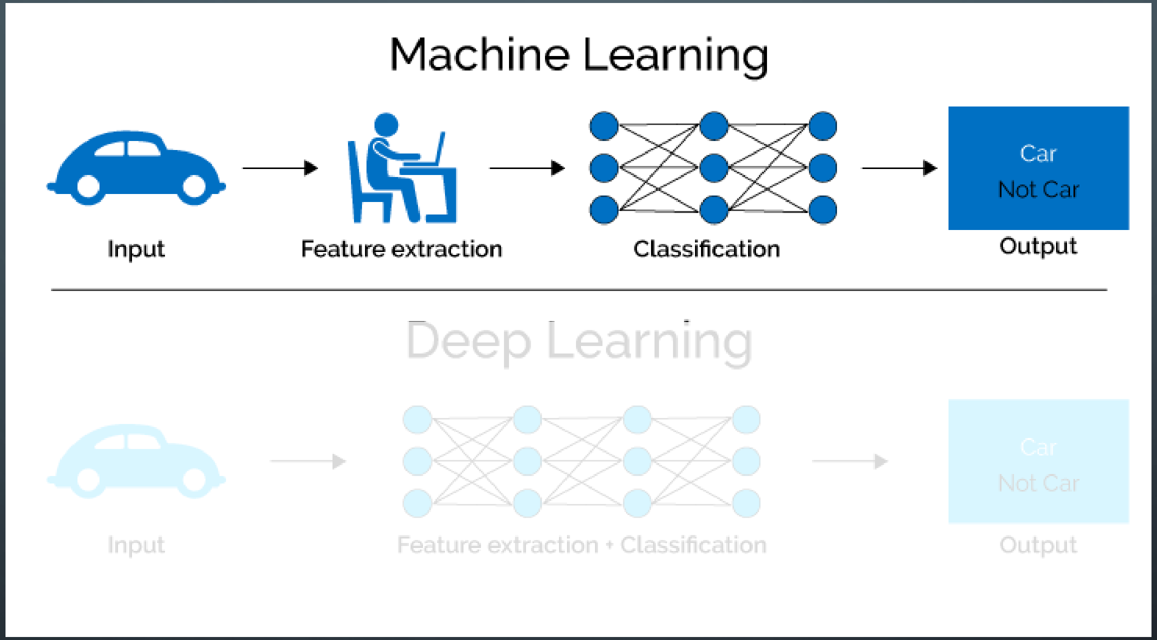
- Generally includes the costs from the UAS section
- Higher resolution satellite data if desired (e.g., WorldView-3), but could potentially still yield good results with other freely available datasets (e.g., Landsat, Sentinel)
- Some groundtruthing would likely be needed, but can be augmented with UAS



Gray et al. 2018

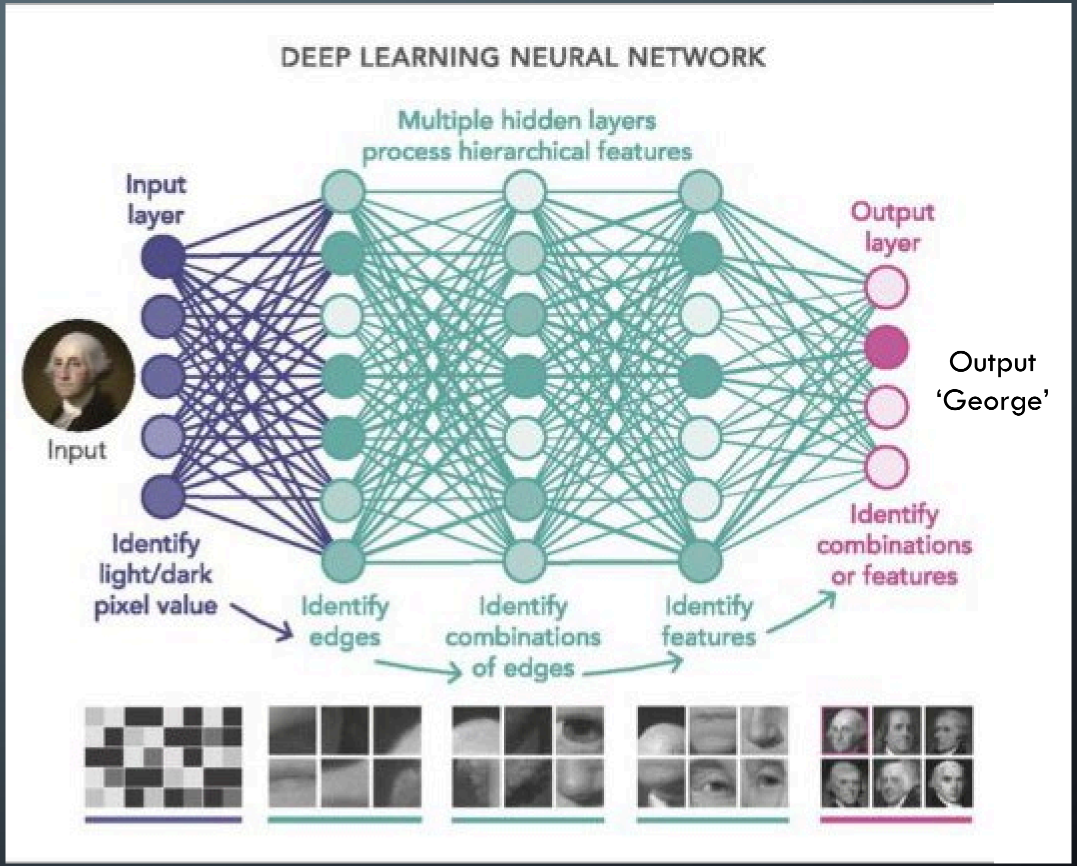
DEEP LEARNING

WHAT IS DEEP LEARNING?



Semiengineering.com

WHAT IS DEEP LEARNING?



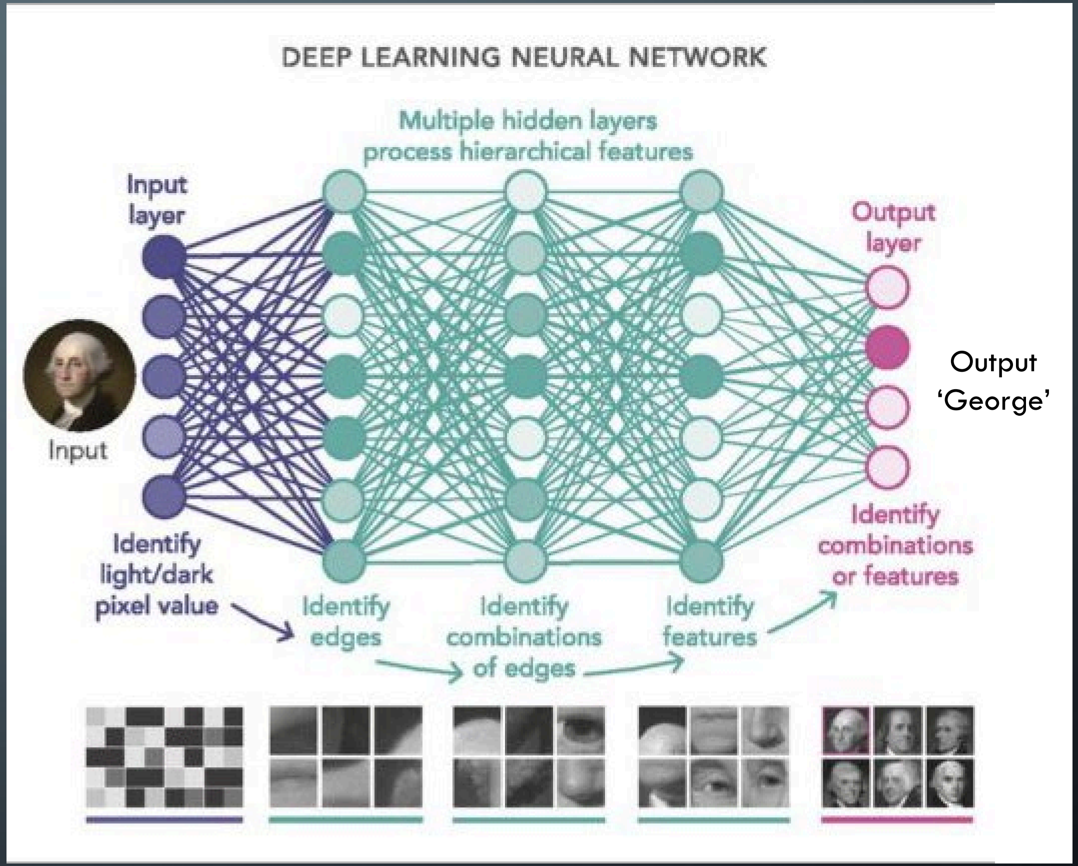
Nextbigfuture.com

BUILDING A NEW WORKFLOW

A **Recurrent Convolutional Neural Network (RCNN)** is being tested to see if we can decrease the amount of effort required to produce land cover maps.

This method should

- reduce post-processing burden
- increase generalizability
- increase speed of map creation



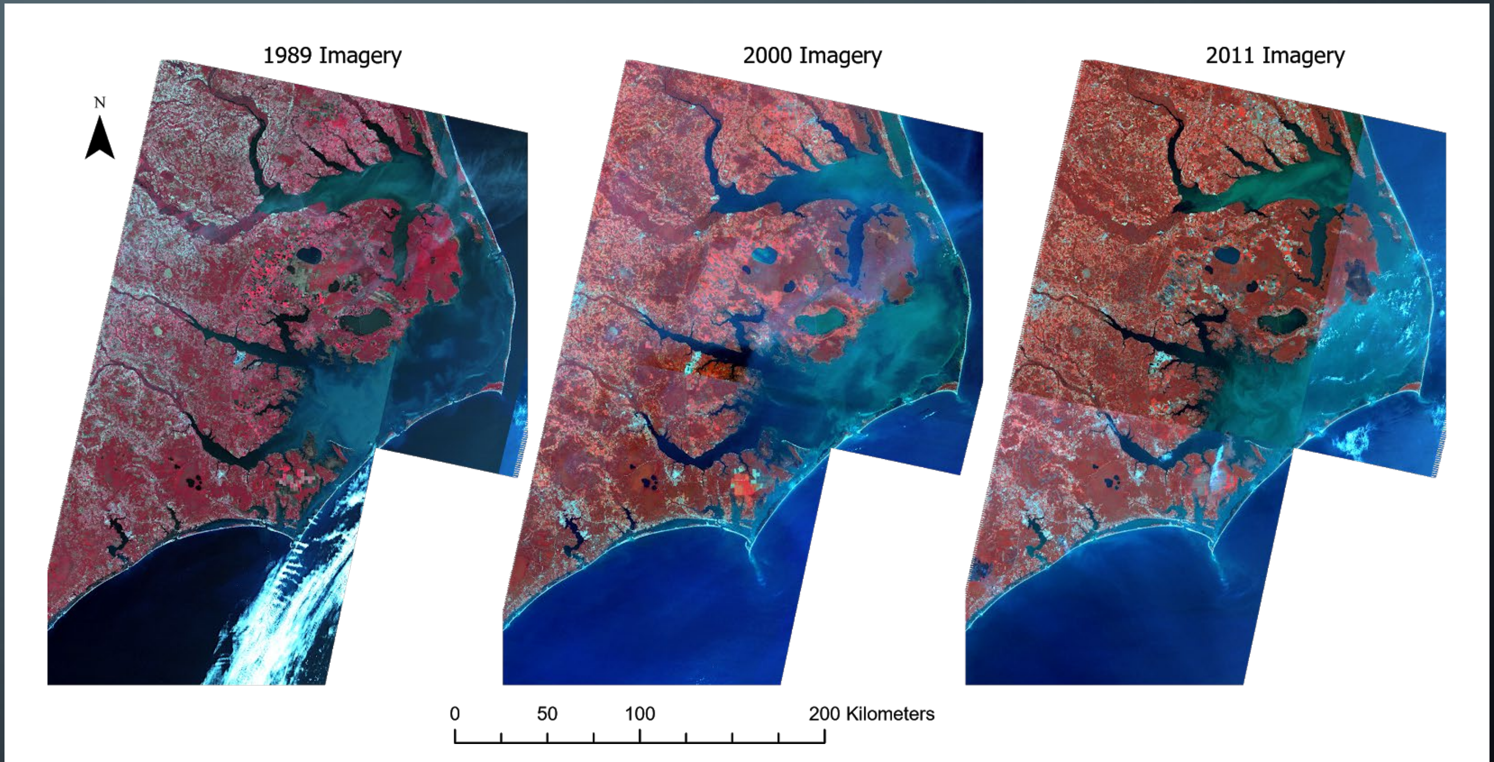
Nextbigfuture.com

ENC THROUGH TIME

Study area includes the Albemarle-Pamlico region of Eastern North Carolina

Recurrent (in RCNN) is referring to the time series

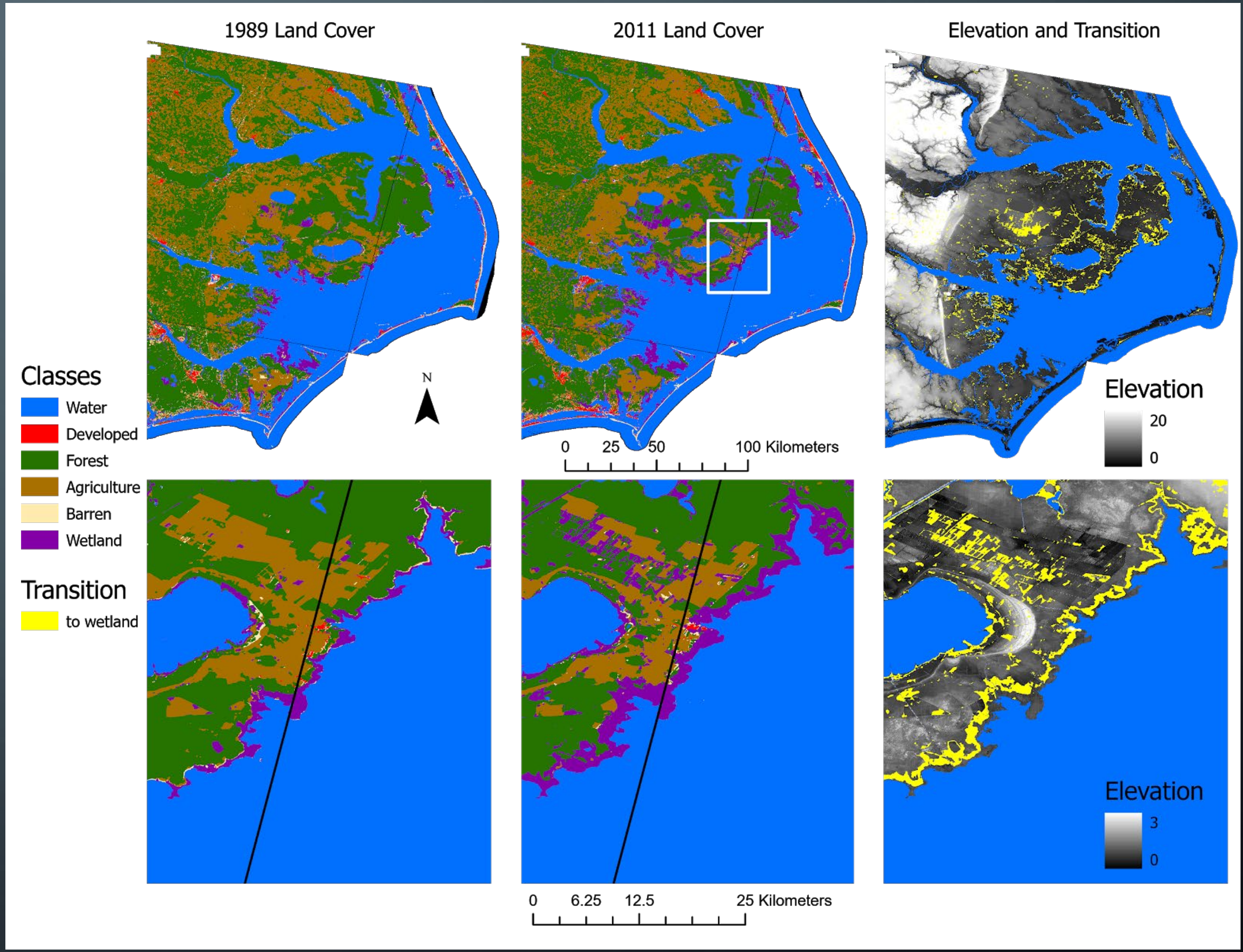
Landsat 5 imagery from **3 years** each with **5 time steps** (winter, spring, summer, early fall, late fall)



Gray et al. (in prep)

LAND COVER CHANGE

Identifying areas of major transition within the Albemarle-Pamlico region



Gray et al. (in prep)

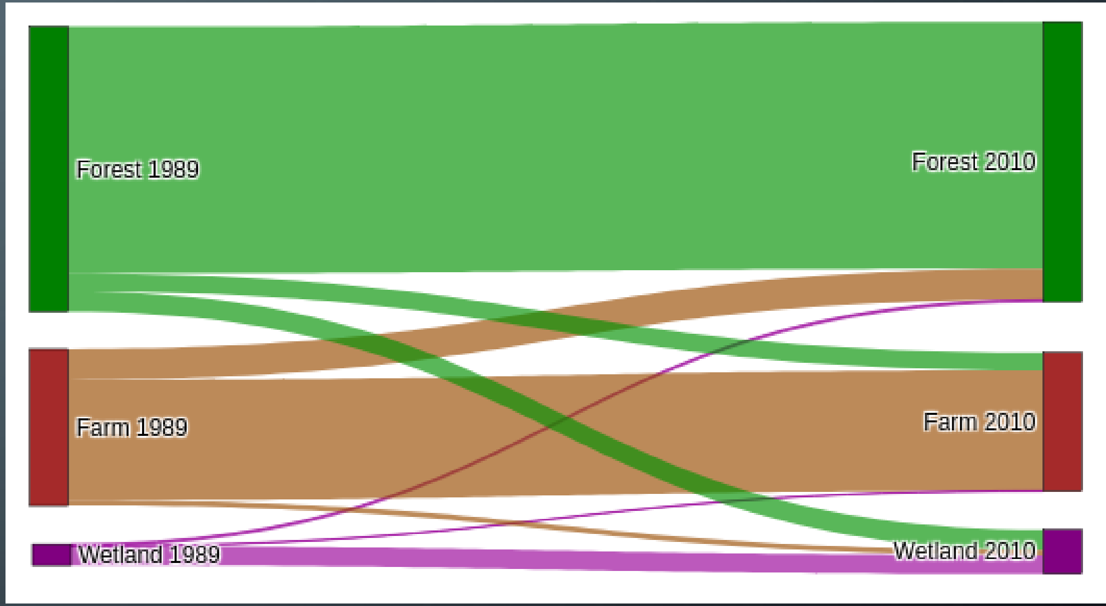
DEEP LEARNING SUMMARY AND CONSIDERATIONS

Benefits

- At full maturity, the RCNN should be able to ingest a new set of Landsat tiles (~4 for all of ENC) and output the classifications within **1 day of cloud processing**. This could provide automated area calculations/changes of wetland areas at almost any desired timescale (but also consider that Landsat resolution is 30m)

Costs

- A data analyst would need to be familiar with using jupyter notebooks, cloud computing (~$50-100/day) or be set up for local processing (processing time scales to hardware), and should conduct an accuracy check after a run (verifying randomly selected tiles)
- A series of groundtruth points throughout would be highly useful but could potentially be collected opportunistically, since high-precision GPS isn't needed
- The model could be retrained on higher resolution data, but that would require someone's time (likely on the order of 2-3 months)



Gray et al. (in prep)

NEWER SATELLITES

OTHER DATASETS (E.G., SAR, HYPERSPECTRAL)

SENTINEL-2

DECIDING ON THE PLATFORM

Objective driven	Sat (Low Res)	Sat (High Res)	Drone
Large scale rough classification	X		
Large-moderate scale finer classification – 'macro view'	X	X	X (training)
Examining shorter term changes (< decade)		X	X
Examining fine scale changes (< m) – 'micro view'			X
3D modeling			X

COST/BENEFIT

Drone Platform	Costs	Pros	Cons
Quadcopter	1.5k – 7k	Less launch/recovery requirements Oblique imagery possible	Smaller flight areas
Fixed-wing	17k	Larger flight areas (>1km^2/flight)	Restricted recovery locations
Both	+3-4k for RTK +5k for multispectral	Increased accuracy and precision **Radiometric calibration**	

Satellite Platform	Costs	Pros	Cons
Landsat	Free	Large archive	Longer revisit time (~8-16 days)
Sentinel-2	Free	Good resolution (10-20 m) Shorter revisit (~ 3-4 days)	More data
WorldView-3	\$15-20/km^2 (archive) \$30/km^2 (tasking)*	High resolution (1.24 m) Revisit (~4.5 days)	Very data rich

Funding through:

North Carolina Marine Fisheries

NC Coastal Reserve & National Estuarine Research Reserve

Sea Grant North Carolina

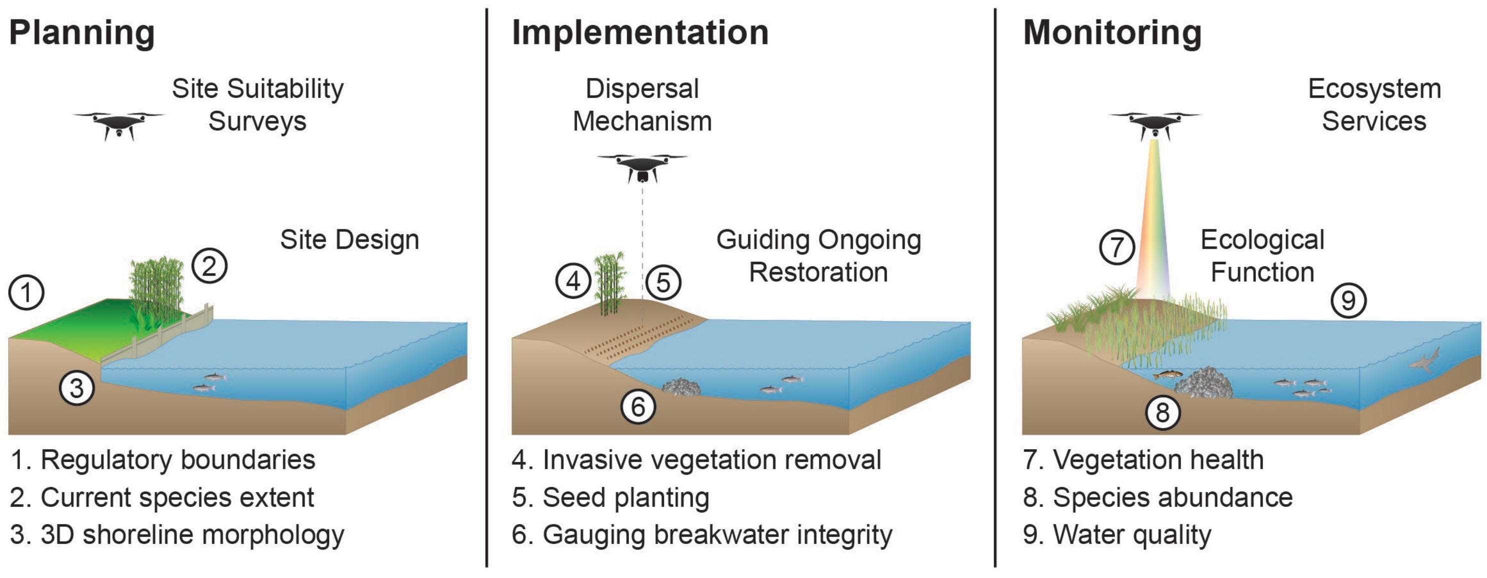
North Carolina space grant

ESTCP

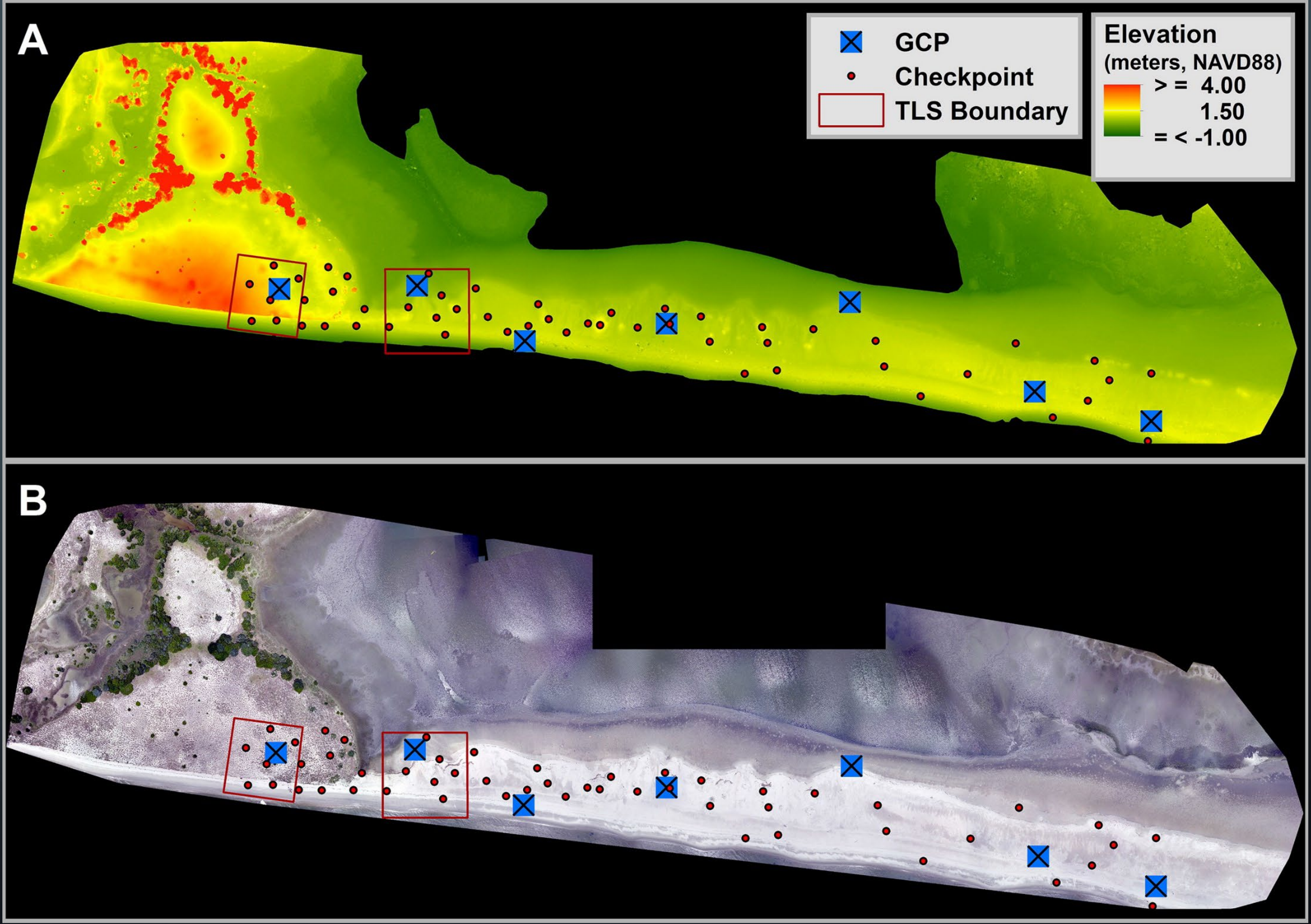
Duke University | Bass Connections

QUESTIONS?

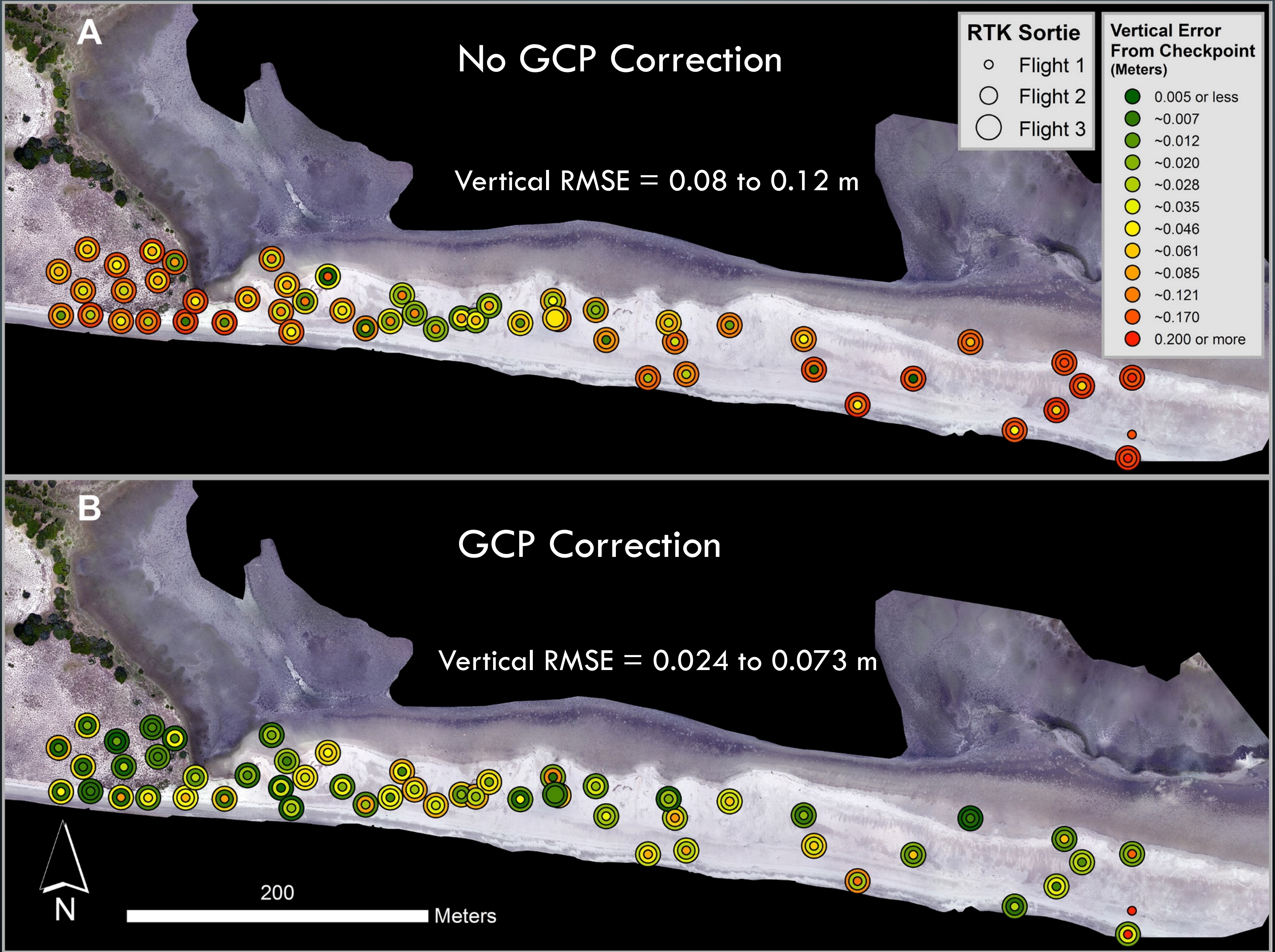
SUPPLEMENTAL SLIDES



Ridge and Johnston 2020



Seymour et al. 2018, *Journal of Coastal Research*



A
No GCP Correction
Vertical RMSE = 0.08 to 0.12 m
RTK Sortie
Flight 1
Flight 2
Flight 3
Vertical Error
From Checkpoint
(Meters)
0.005 or less
~0.007
~0.012
~0.020
~0.028
~0.035
~0.046
~0.061
~0.085
~0.121
~0.170
0.200 or more
B
GCP Correction
Vertical RMSE = 0.024 to 0.073 m
N
200
Meters

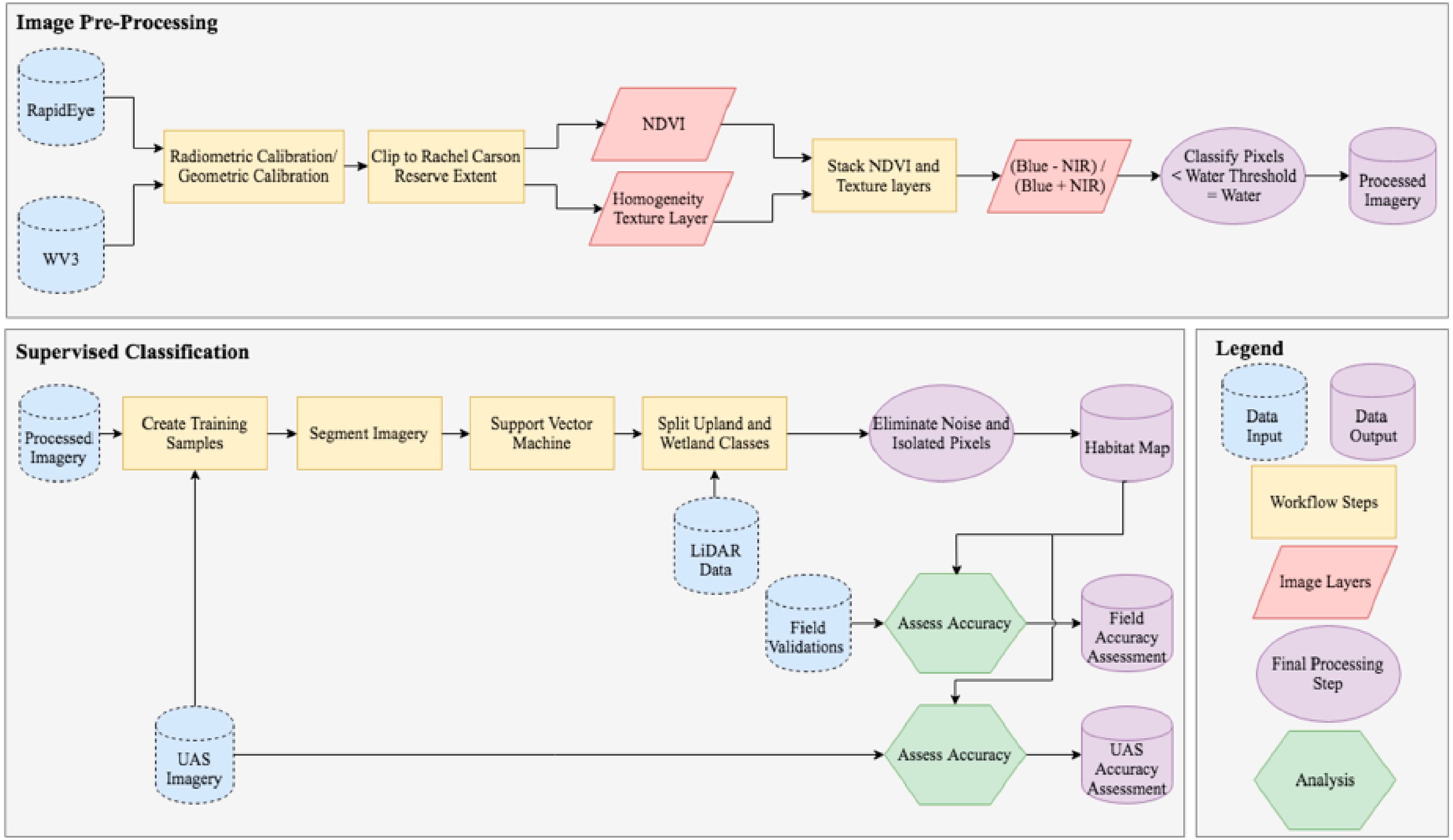
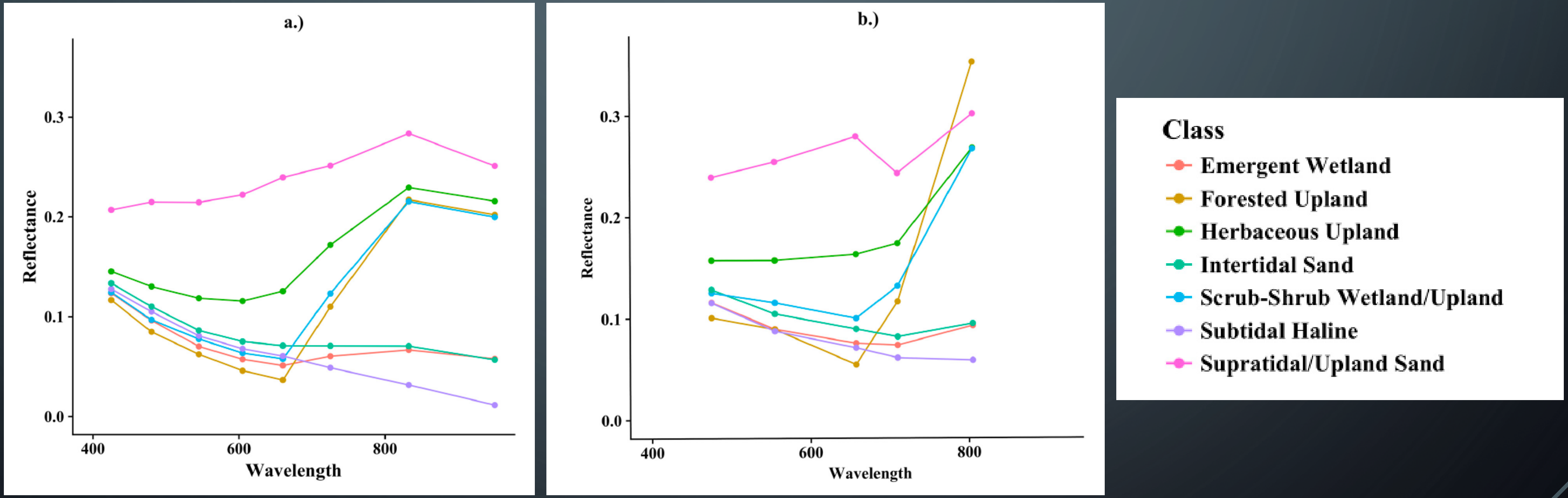


Figure 2. Image processing included calibration, creation of additional image layers to test impact on final accuracy, and thresholding to eliminate complex water pixels. The classification workflow included creation of training samples using unoccupied aircraft system (UAS) imagery, segmentation of RE and WV-3 imagery, classification using a support vector machine, and filtering the classification output by elevation using LiDAR data.

Gray et al. 2018

SPECTRAL CHARACTERISTICS



Gray et al. 2018