Quantifying vegetation cover and ecosystem services with hyperspatial UAS imagery in a coastal intermediate marsh



Whitney P. Broussard III Jenneke M. Visser Robert P. Brooks Tom Cousté

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### Outline

- 1. Rationale
- 2. Current state of the science
- 3. Here come the drones
- 4. Remote sensing techniques for vegetation mapping
- 5. Pilot Project in Terrebonne Parish
  - Can UAS hyperspatial, multispectral imagery be used to classify species composition and quantify certain ecosystem service metrics, specifically plant height and NDVI, in a Spartina patens dominated intermediate coastal marsh?
  - This information could be used to develop landscape models of aboveground biomass and carbon sequestration.
- 6. Methods
  - Site location
  - FAA approval, logistics, and flight planning
  - Photogrammetry and Object-Based Image Analysis
- 7. Results
  - RGB and NIR orthomosaics and Digital Surface Models
  - OBIA classifications and accuracy assessment
  - Comparison with CRMS vegetation surveys



# Louisiana's Comprehensive Master Plan for a Sustainable Coast

#### Monitoring Needs for Restoration



Ecosystem services: Which services are important and applicable for coastal marshes in Louisiana?

- Habitat quality: quality and <u>quantity</u> of habitat to support various fish and wildlife (Freeman 1991, Bell 1997).
- Storm Surge/Wave Attenuation: Often based on the <u>location and amount</u> of land, type of vegetation, and land elevation (Costanza et al. 2008).
- Nutrient Uptake: nitrogen removal in sediments and wetlands (Craft 2007, Craft et al. 2009).
- **Carbon Sequestration:** Carbon storage varies with the type of wetland, the <u>acreage</u>, the annual vertical accretion of soil, and aboveground <u>biomass</u> (Mitch and Gosselink 2008, Barbier et al. 2011)

# 2012 Master Plan Model Suite

Stage, Salinity, Water Quality



# Current Wetland Vegetation Information

#### **Coast-wide Surveys**

156 North/South transects spaced 7.5 minutes apart from the Texas state line to the Mississippi state line.

Vegetative data were obtained at predetermined stations spaced 0.5 miles along each transect.

- Species identified
- Five Cover classes (Braun-Blanquet)
  - >**75**%
  - 50-75%
  - 25-50%







#### Local field measurements

#### Landscape spatial analyses

# Brief History of Unmanned Aircraft Systems

- 1898: Tesla teleautomaton First to remotely control a vessel with radio waves
- WWI 1918: Curtiss N-9 floatplane, World's first unmanned aircraft system
- WWII: British "Queen Bee" aircraft designed to be shot down
- Vietnam: UAS reconnaissance
- Desert Storm 1991 & War on Terror: Targeted airstrikes (first wide scale deployment of UAS)
- 2012 Congress mandates UAS integration into NAS (FAA Modernization and Reform Act of 2012)
- 2016 FAA 14 CRF Part 107 issued -licensing of "remote pilot airman certificate with a small UAS rating" and UAS operations in NAS



Inspire 2. www.dji.com



eBee. www.sensefly.com











De Havilland Queen Bee drone, 1941. Copyright Imperial War Museum



Image credit: Qassim Abdullah



1:2.3 1:1333.46 Full mode 2855745.125 user ; 575545.547 user ; 8.000 user / 4.559 user





Image credits: PIX4D

# UAS Technology in Coastal Research

- Late 1970s first use of a fixed wing remotely controlled aircraft in photogrammetry experiments (Przybilla and Wester-Ebbinghaus 1979)
- 1996 monitoring restoration with multispectal video data (Phin et al. 1996)
- 2004 first use of a commercial low-cost UAS to create a high-resolution digital terrain model (Eisenbeiss et al. 2005)
- 2007 High definition video to map local beach erosion (Chong 2007).
- 2007 High resolution imagery to map channel bathymetry and topography (Lejot et al. 2007)
- 2012 UAS Hyperspatial data and OBIA to classify upland swamps (Lechner et al. 2012)
- Several other examples of multispectral and hyperspectral imagery used to map wetlands (Chust et al. 2008, Yang and Argtigas 2010, Klemas 2013).
- UAS are now widely used in a host of environmental applications
  - land use mapping, wetlands mapping, LIDAR bathymetry, flood and wildfire surveillance, tracking oil spills, urban studies, and Arctic ice investigations (Klemas 2015).

# Comparisons between satellite data, traditional aerial photography, and UAS imagery

- Flexible deployments high-temporal and hyperspatial resolution (<1dm) data (Niethammer et al. 2012)
- High resolution, multispectral reflectance will improve vegetation cover estimates and correlations with species richness (Rocchini 2007).
- Photogrammetry techniques can produce point cloud models and provide elevation estimates (for bare earth) and Digital Surface Models (DSM) for vegetation, buildings, towers, and other hard structures.
- Lidar sensors can produce point cloud models, allow for elevation estimates in covered sites, and improve elevation accuracies.

### Landsat derived DEM - 30m GSD



Aerial Imagery: Landsat DEM

### Landsat derived DEM - 30m GSD



Aerial Imagery: Landsat DEM

# Aerial Photography - 1m GSD



Aerial Imagery: Coastal Wetlands Planning, Protection and Restoration Act (CWPPRA), 2008

# Aerial Photography - 1m GSD



Aerial Imagery: Coastal Wetlands Planning, Protection and Restoration Act (CWPPRA), 2008

# UAS Aerial Photography - 2.5cm GSD



# UAS Aerial Photography - 2.5cm GSD



Individual

## UAS Aerial Photography - 2.5cm GSD



Leaf shape/area

### PROJECT GOALS AND OBJECTIVES

This pilot study collected hyperspatial/multispectral aerial imagery from a UAS in a intermediate marsh environment in coastal Louisiana to determine the feasibility of the technology for vegetation mapping and landscape analyses of ecosystem service metrics.

- 1. Collect 2 cm GSD RGB and NIR imagery of a 1  $km^2$  area.
- 2. Create georeferenced orthomosaic and DSM raster datasets
- 3. Object-Based Image Analysis
  - Species composition and ecosystem service metrics
    - Land-water interface
    - Dominant species classification
    - Plant height
    - Productivity (NDVI)



Aerial Imagery: Coastal Wetlands Planning, Protection and Restoration Act (CWPPRA), 2008

Project location in Terrebonne Parish, Louisiana. Coastwide Reference Monitoring System (CRMS) site in Cyan, Flight Blocks in yellow, GCPs are white crosses.

# Fieldwork Trimble UX5 Aerial Imaging Rover





Sony  $1\alpha$ -5100 with RGB sensor



Sony NEX-5r with NIR sensor

Туре	 . Fixed wing
Weight	 kg (5.51 lb)
Wingspan	 1 m (3.28 ft)
Wing area	 34 dm

#### **OPERATION**

Endurance <sup>1</sup>	minutes
Range <sup>1</sup>	7.28 mi)
Cruise speed	50 mph)
Maximum ceiling <sup>2</sup>	5,404 ft)

Image credits: Trimble Navigation Limited



### Flight Plan Software



29.45586° N, 90.66253° W



Aerial Imagery: Coastal Wetlands Planning, Protection and Restoration Act (CWPPRA), 2008

Ground Control Points











#### Take Off

#### **Control Station**



#### Chase home





#### Belly land

### Post-Processing: Trimble UAS Master

🚸 UAS ApplicationsMaster - [D:\GIS-UAS\_Data\....\Setup\CRMS\_BIk2NIR\_Setup.prj]

- 0 ×



A screenshot of the Photogrammetry software Trimble UAS Master showing the wireframes of the raw NIR imagery, Ground Control Points, and orthomosaic overview. Over 1000 images per flight!

### Post-Processing: Trimble UAS Master

🛃 UAS Measurement - [D:\GIS-UAS\_Data\....\Setup\CRMS\_BIk3\_Setup.prj]

– 0 ×



MEASURE 1:1 1:175.64 3494850.262 user ; 348009.387 user ; -46.163 user 🖰

A screenshot of the Georeferencing Editor and the GCP/Manual Tie Point Table showing the location of a ground control point 301 in image 7112.

Each GCP is measured (located) within each available picture to orientate the orthomosaics and georeference them to a datum.

# Post-Processing: Trimble UAS Master

#### Ground Control Point Accuracy

ID	X [cm]	Y [cm]	Z [cm]	Total [cm]
102	1.04	-0.15	-3.61	3.76
103	-1.15	0.71	-0.08	1.35
201	-3.33	-2.49	-1.48	4.41
202	3.90	0.16	-3.73	5.40
203	-0.45	1.82	-0.24	1.89
Maximum	3.90	-2.49	-3.73	
Mean	0.00	0.01	-1.83	
Std. Dev.	2.69	1.58	1.76	
RMSE (x,y,z)	2.40	1.42	2.42	
RMSEr	2.79	SQR ]	T(RMSE RMSEy2	Ex2 + )
ACCr (95% Confidence Level)	4.83	RMSEr * 1.7308		
ACCz (95% Confidence Level)	4.74	RMSEz * 1.9600		600



Point found in (0-2) images.

Point found in (3-4) images.

Point found in (5-10) images.

: Point found in (>10) images.







#### Horizontal accuracy (95% Confidence) 4.83cm

Vertical accuracy (95% Confidence) 4.74cm













# Object Based Image Analysis

- High resolution datasets spectral variance increases within target classes
- Spectral separation between the classes is more difficult to specify and classify (Marceau and Hay 1999, Blaschke 2010).
- Similar to human interpretation, OBIA methods address these scaling issues by segmenting or grouping the finer pixels into image objects that are made up of multiple neighboring pixels sharing similar attributes such as spectral signature, texture, shape, and context to other objects(Blaschke, 2009)
- This makes classification easier because we're now working with average values by object (100's to 1000's of pixels) rather than individual 2-3cm pixels
- UAS imagery is commonly analyzed using OBIA classification methods (e.g. Laliberte and Rango 2009, Laliberte and Rango 2011).



### Object Based Image Analysis (multispectral segmentation)



5214, 12302) = (3492556.70, 348450.78) Zoom:50% Dist: 1542.87 Feet (survey)

### Object Based Image Analysis (multispectral segmentation)



5262, 12320) = (3492561.42, 348452.55) Zoom:50% Dist: 1538.97 Feet (survey)

12,223 Objects



### Object Based Image Analysis (multispectral segmentation)



Level 1/1



# Accuracy Assessment

Stratified Random Sampling by predicted class

50 Water 50 Grass 20 Other 10 Reed



# **Error Matrix**

	1) Water	2) Grass	3) Other	4) Reed	Count	Producer's Accuracy
1) Water	<b>49</b>	0	0	0	49	100%
2) Grass	7	35	6	0	48	73%
3) Other	2	2	16	0	20	80%
4) Reed	0	0	2	8	10	80%
Count	58	37	24	8	127	
User's Accuracy	84%	95%	67%	100%		

#### **Reference Class**

Overall Accuracy: 85% Kappa Coefficient: 0.78

**Predicted Class** 

# Challenges with land-water interface and high resolution imagery



OBIA classified this point as land, but high res imagery shows vegetation extending over water

Comparisons with CRMS Data















#### CRMS0392 - 1985 through 2010



**Data Source:** Coastal Protection and Restoration Authority (CPRA) of Louisiana. 2017. Coastwide Reference Monitoring System-Wetlands Monitoring Data. Retrieved from Coastal Information Management System (CIMS) database. http://cims.coastal.louisiana.gov. Accessed 24 April 2017.







# Comparison with 2012 CRMS Vegetation Survey



# Comparison with 2012 CRMS Vegetation Survey

	Marsh Elevation			
	CRMS	CRMS Predicted		
Vo3	0.229	0.52		
Vo9	0.229	0.77		
V61	0.229	0.55		

	Maximum Plant Height (ft)				
	CRMS Predicted (diff. <b>model</b> marsh elev.		Predicted f. <b>modeled</b> Fit arsh elev.)		Fit
Vo3	4.84	3.97	82%	4.26	88%
Vo9	3.91	0.86	22%	1.406	36%
V61	1.6	1.19	74%	1.504	94%



# Comparison with 2012 CRMS Vegetation Survey

	% Land		
	CRMS	Predicted	Fit
Vo3	5%	94%	+89%
Vo9	1%	8%	+7%
V61	100%	94%	-6%

	Vegetat	tion Classi	Notor		
	CRMS	Predicted	Fit	Notes	
Vo3	Grass	Grass	100%	Amaranthus, Patens, Cyperus mix	
Vo9	Grass	Grass	100%	Patens clump	
V61	Other	Other	100%	Bacopa, Eleocharis, Pluchea mix	







# Expected UAS Challenges

- Flight time Battery life
- Beyond Line of Site operations
- Privacy Issues and permissions
- Take Off Landing Zones
- Standardizing segmentation algorithms
- Radiometric concerns for large scale
  assessments



# **Expected UAS Benefits**

- Save time and money
- Increased efficiency for vegetation and elevation surveys
- Fewer personnel requirements and ability to overcome site accessibility issues
- More frequent monitoring events
- Develop high resolution 3D structural models, multispectral orthomosaic images of entire projects, surface elevation models, and volumetric measurements
- Multiple habitat types
- Project operations (marsh creation compaction)and long-term monitoring (settling along shorelines barriers and vegetation expansion)
- high resolution maps of the land-water interface, land loss, and habitat fragmentation metrics
- Ability to scale up from the 200 m site (really 10, 4m<sup>2</sup> plots) to a 1km2 to capture site variability (easy to do in one day).
- Another method to link on-the-ground field measurements with landscape-level remotely sensed data.



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# THANK YOU!

For more information wbroussard@louisiana.edu