QUANTIFYING WETLAND TYPE AND ECOSYSTEM SERVICES WITH HYPERSPATIAL UAS IMAGERY

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Tom Cousté



Louisiana is Experiencing a Coastal Crisis

Predicted Land Change over the Next 50 Years



- 18% of US oil and 24% of US gas production totaling \$16B USD per year
- 1st in the nation in total shipping tonnage 20% of the nation's waterborne commerce
- \$2.8B USD fisheries industry in Louisiana 16% of US fisheries come from Louisiana coast



Louisiana's Comprehensive Master Plan for a Sustainable Coast

committed to our coast



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
 - >75%
 - 50-75%
 - 25-50%
 - 5-25%
 - <5%



Photos: Greg Linscombe and Jenneke Visser



Coastwide Reference Monitoring System





TYPICAL CRMS SITE SAMPLING & DATA COLLECTION

Aspects of ecosystem structure and function are measured at each site including marsh elevation, vegetative assemblage, and hydrologic parameters



What about Unmanned Aircraft Systems (UAS)?

- i. Late 1970s first use of a fixed wing remotely controlled aircraft in photogrammetry experiments (Przybilla and Wester-Ebbinghaus 1979)
- ii. 2004 first use of a commercial low-cost model helicopter with semiautomated navigation to create a high-resolution digital terrain model (Eisenbeiss et al. 2005).
- iii. Chong (2007) used high definition video to map local beach erosion.
- iv. Lejot et al. (2007) used very high spatial resolution imagery to map channel bathymetry and topography.
- v. Lechner et al. (2012) utilized hyperspatial data provided by a UAS and object-based image analysis (OBIA) methods to classify upland swamp communities.
- vi. Multispectral and hyperspectral imagery used to map wetlands (Phinn et al. 1996, Chust et al. 2008, Yang and Argtigas 2010, Klemas 2013).
- vii. UAS are now widely used in a host of environmental applications, such as 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

- i. UAS technology allows flexible deployments high-temporal and hyperspatial resolution (<1dm) data (Niethammer et al. 2012).
- ii. Rocchini (2007) demonstrated that higher resolution datasets from Quickbird satellite imagery showed highly significant correlations with species richness as opposed to coarser resolution datasets from Aster and Landsat imagery, which were not highly correlated.
- iii. In Coastal Louisiana, UAS have the ability to fly the current helicopter transects and to collect hyperspatial aerial images at higher frequencies. Multispecral reflectance will help automate species richness and cover estimates. Photogrammetry can provide elevation estimates and Digital Surface Models (DSM).

Landsat derived DEM - 30m GSD



Landsat derived DEM - 30m GSD



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 project will design a pilot study to collect hyperspatial/multispectral aerial imagery from a UAS in a brackish marsh environment in coastal Louisiana.
- The objective is to collect 2.5cm
 GSD RGB and NIR imagery of a 1 km² area.
- Create raster datasets that are georeferenced and ready for object-based image analysis



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.

PROJECT GOALS AND OBJECTIVES

- **Object-Based** Image Analysis
 - Species composition and ecosystem service metrics
 - Land-water interface (edge habitat and fragmentation)
 - Species composition
 - Plant height
 - Aboveground biomass
 - Carbon Sequestration
 - 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





HARDWARE

Туре	Fixed wing
Weight	
Wingspan	
Wing area	
Dimensions 100 cm x 65	cm X 10.5 cm (39.37 in x 25.59 in x 4.13 in)
Material EPP foam;	Carbon frame structure; Composite elements
Propulsion Ele	ctric pusher propeller; brushless 700 W motor

OPERATION

Endurance ¹	. 50 minutes
Range ¹ 60	km (37.28 mi)
Cruise speed	cmh (50 mph)
Maximum ceiling ²	m (16,404 ft)

ACQUISITION PERFORMANCE

AREA COVERAGE TABLE

Height	GSD	Coverage/flight [km ²] (1)		Coverage/day [km ²] (2)			
		70%	80%	90%	70%	80%	90%
75 m	2.0 cm	1.1 km ²	0.8 km ²	0.4 km ²	6.85 km ²	4.5 km ²	2.3 km ²
(246 ft)	(0.79 in)	(0.43 mi ²)	(0.31 mi ²)	(0.15 mi ²)	(2.63 mi ²)	(7.74 mi ²)	(0.88 mi ²)
100 m	2.6 cm	1.8 km ²	1.2 km ²	0.6 km ²	10.8 km ²	7.2 km ²	3.6 km ²
(328 ft)	(1.02 in)	(0.7 mi ²)	(0.64 mi ²)	(0.23 mi ²)	(4.17 mi ²)	(2.78 mi ²)	1.39 mi ²)
150 m	3.9 cm	3.1 km ²	2.1 km ²	1.0 km ²	18.7 km ²	12.5 km ²	6.2 km ²
(492 ft)	(1.54 in)	(1.2 mi ²)	(0.81 mi ²)	(0.39 mi ²)	(7.22 mi ²)	(4.83 mi ²)	(2.39 mi ²)

Sony NEX-5R camera and Voigtländer lens used in the Trimble UX5 Aerial Imaging Rover

Flight Plan

Take off and landing located north of the project area.

Sectional Aeronautical Raster Chart with project boundaries shown in red.



FAA Part 107 compliant operations (DO NOT UNDERESTIMATE!)



Flight Plan: Manual Calculations

Compute the Ground Coverage of Each Image

 $\begin{array}{l} \textit{Ground Coverage} \ = (6000 \ \textit{pixels} * 1 \textit{in}) \times (4000 \ \textit{pixels} * 1 \textit{in}) \\ = 6000 \textit{in} \times 4000 \textit{in} \\ = 500 \ \textit{ft} \times 333.3 \ \textit{ft} \end{array}$

Compute the Number of Flight Lines

Line Spacing (SP) = Image coverage (w) * ((100 - Sidelap)/100) = 500ft * (100 - 60/100)= 200ft

Number of Flight Lines (NFL) = (Width of Project/SP) + 1 = (3,281ft/200ft) + 1= 17.4

NFL rounds up to 18.

Flying Altitude



Number of Images to be Acquired

Airbase (B) = Images Coverage (H)×((100 - Endlap)/100)= 333.3 ×((100 - 80)/100)= 66.6

Number of Images (NIM) = (Length/B) + 1+4= (3,281ft/66.6ft) + 1 + 4= 54.3 NIM rounds up to 55.

 $Total Number of Images = NFL \times NIM = 18 \times 55$

= 990

Time Between Images

Time (t) = Airbase (B)/Aircraft speed (v) $= 66.6ft/80 km hr^{-1}$ $= 66.6ft/262467.2 ft hr^{-1}$ = .000254 hr= 0.9 sec CRMS_GEP_103

CRMS_GCP_303

 \diamond

CRMS_GCP_201

CRMS_GCP_301

¢ CRMS_GCP_105

CRMS_GCP_304

CRMS_GCP_101



Ground Control Points







Take Off



Chase home

Belly land

Control Station





Post-Processing: Trimble UAS Master

X

Basic GCP/Manual Tie Point Editor

GCP/Manual Tie Point Table (NAD83 / Alabama East)

	Label	Туре	X [m]	Y [m]	Z [m]	Accuracy Horz [m]	Accuracy Vert [m]
0	PTO	3D GCP	126274.845	475152.214	237.188	0.020	0.020
)	PT1	3D GCP	126349.601	475111.065	237.163	0.020	0.020
)	PT4	3D GCP	126466.869	475248.735	239.754	0.020	0.020
	PT5	3D GCP	126417.080	475294.835	240.122	0.020	0.020
7	PT7	3D GCP	126260.102	475357.215	240.109	0.020	0.020
0	WCC1	3D GCP	126255.220	475279.270	238.740	0.020	0.020
	20000	3D GCP	126341.382	475184.369	239.617	0.020	0.020
ć	20001	3D GCP	126451.077	475211.185	239.906	0.020	0.020

Images Preview 5. L 신 예 2 DSC01165_geotag.JPG 8 X D ~ DSC01269_geotag.JPG \otimes DSC01205_geotag.JPG DSC01227_geotag.JPG Q DSC01166_geotag.JPG DSC01268_geotag.JPG DSC01146_geotag.JPG DSC01228_geotag.JPG DSC01204_geotag.JPG DSC01167_geotag.JPG DSC01145_geotag.JPG Ð. DSC01267_geotag.JPG DSC01108_geotag.JPG DSC01203_geotag.JPG * DSC01168_geotag.JPG v 4 🌾 🗳 📕 🦉 w XI ۷ Mp

A screenshot of the Basic Editor and the GCP/Manual Tie Point Table showing the location of a ground control point 20000 in image DSC01165_geotag.JPG.

Post-Processing: Trimble UAS Master

Summary

Project	Wiregrass_Broussard	
Processed	2016-04-07 23:19:42	
Average Ground Sampling Distance (GSD)	1.84 cm / 0.72 in	
Area Covered	0.0684 km ² / 6.8379 ha / 0.0264 sq. mi. / 16.9055 acres	
Time for Initial Processing (without report)	11m:07s	

Quality Check

Images	median of 33179 keypoints per image	0
Oataset	89 out of 89 images calibrated (100%), all images enabled	0
② Camera Optimization	1.29% relative difference between initial and optimized internal camera parameters	0
Matching	median of 14466.8 matches per calibrated image	0
3 Georeferencing	yes, 8 GCPs (8 3D), mean RMS error = 0.024 m	0

A screenshot of the processing quality report showing the summary and quality check information.

	Error X (m)	Error Y (m)	Error Z (m)
Mean (m)	⊦0.007065	-0.000724	0.015766
Sigma (m)	0.031913	0.018155	0.024366
RMS Error (m)	0.032686	0.018169	0.029022

Localization accuracy per GCP and mean errors in the three coordinate directions.



Orthomosaic and the corresponding sparse Digital Surface Model (DSM) before densification

Object Based Image Analysis

- i. Hyperspatial sub-decimeter imagery acquired using UAV platforms is commonly analyzed using OBIA classification methods (e.g. Laliberte and Rango 2009, Laliberte and Rango 2011).
- ii. For medium and low spatial resolution imagery acquired by satellites, such as Landsat or MODIS, the target is usually smaller than the pixel size. Pixelbased remote sensing classification schemes, like maximum likelihood classifiers that use spectral information, are often unsuitable for classifying hyperspatial data resulting in a lower overall classification accuracy (Blaschke 2010).
- iii. As spatial resolution increases, variance in observed spectral values within target classes increases, making spectral separation between the classes more difficult to specify and classify (Marceau and Hay 1999, Blaschke 2010).
- iv. OBIA methods address these scaling issues by segmenting the finer pixels into image objects that are made up of multiple neighboring pixels sharing similar spectral values (Blaschke, 2009)



Classified Map





NDVI





Products and Timeline

i. The purpose of this project is to investigate the efficacy of using UAS technology to monitor wetland vegetation species composition and to quantify ecosystem services. The final deliverable will be a published paper that reports on the methods developed and lessons learned.

ii. Timeline:

- Post-Processing UAS imagery
- OBIA and Derived Products
- Draft of Methods and Results
- Final Report for Publication
- Submit for Publication

December-January 2016 January-February 2017 End of February 2017 March 2017 April 2017

References

- Blaschke, T. (2010). Object based image analysis for remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing, 65(1), 2–16.
- Chong, A.K. (2007) HD aerial video for coastal zone ecological mapping. The 19th Annual Colloquium of the Spatial Information Research Centre.
- Chust, G., et al. (2008). Coastal and estuarine habitat mapping, using LIDAR height and intensity and multi-spectral imagery. Estuarine, Coastal and Shelf Science, 78(4), 633–643.
- Eisenbeiss, H., Lambers, K., & Sauerbier, M. (2005). Photogrammetric recording of the archaeological site of Pinchango Alto (Palpa, Peru) using a mini helicopter (UAV). Annual Conference on Computer Applications and Quantitative Methods in Archaeology CAA, (March 2005), 21–24.

Klemas, V. (2013). Airborne Remote Sensing of Coastal Features and Processes: An Overview. Journal of Coastal Research, 29(2), 239-255.

- Klemas, V. (2015). Coastal and Environmental Remote Sensing from Unmanned Aerial Vehicles: An Overview. *Journal of Coastal Research*, 315(5), 1260–1267.
- Laliberte, A. S., & Rango, A. (2009). Texture and scale in object-based analysis of subdecimeter resolution unmanned aerial vehicle (UAV) imagery. *IEEE Transactions on Geoscience and Remote Sensing*, 47(3), 1–10.
- Laliberte, A. S., & Rango, A. (2011). Image Processing and Classification Procedures for Analysis of Sub-decimeter Imagery Acquired with an Unmanned Aircraft over Arid Rangelands. *GIScience & Remote Sensing*, 48(1), 4–23.
- Laliberte, A. S., et al.. (2011). Multispectral remote sensing from unmanned aircraft: Image processing workflows and applications for rangeland environments. *Remote Sensing*, 3(11), 2529–2551.
- Lechner, A. M., et al. (2012). Characterising Upland Swamps Using Object-Based Classification Methods and Hyper-Spatial Resolution Imagery Derived From an Unmanned Aerial Vehicle. ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences, I-4(September), 101–106.
- Marceau, D., and Hay, G. J (1999). Contributions of remote sensing to the scale issue. Canadian Journal of Remote Sensing, 25(4), 357–366.

Niethammer, U., et al. (2012). UAV-based remote sensing of the Super-Sauze landslide: Evaluation and results. Engineering Geology, 128, 2–11.

- Phinn, S. R., et al. (1996). Monitoring Wetland Habitat Restoration in Southern California Using Airborne Multi spectral Video Data. *Restoration Ecology*, 4(4), 412–422.
- Przybilla, H.-J., & Wester-Ebbinghaus, W. (1979). Bildflug mit ferngelenktem Kleinflug- zeug. Bildmessung Und Luftbildwesen Zeitschrift Fuer Photogrammetrie Ferner- Kundung, 47(5), 137–142.
- Rocchini, D. (2007). Effects of spatial and spectral resolution in estimating ecosystem diversity by satellite imagery. *Remote Sensing of Environment*, 111(4), 423–434.
- Yang J., Artigas F. J., (2010) Mapping salt marsh vegetation by integrating hyperspectral and LiDAR remote sensing. In: Wang, J. (ed.). Remote Sensing of Coastal Environments. Boca Raton, FL: CRC, pp. 173–190.

THANK YOU!

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