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ORIGINAL RESEARCH

Use of Unmanned Aircraft Systems to Delineate Fine-Scale Wetland Vegetation Communities

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Abstract Remote sensing of wetlands has primarily focused on delineating wetlands within a non-wetland matrix. However, within-wetland changes are arguably just as important as loss of wetland area, particularly in a time of accelerated climate change. Remote sensing is a critical source of data for ecological models that explain and predict landscape changes, but data specifications, including spatial and temporal resolution, must be appropriate for applications. Unmanned Aircraft Systems (UASs) can be used to collect fine spatial resolution data with a temporal resolution more tailored to application need, instead of satellite orbital times or flight schedules. We used data collected from an UAS to acquire true color data within a wetland landscape and tested our ability to automatically classify plant communities from fine-resolution data. Classification accuracies were low for certain classes when nine vegetation communities were mapped, but the overall accuracy was on par with other remote sensing analyses. We demonstrate that classification data derived from UAS fine-resolution imagery is reasonably accurate and discuss the benefits and challenges of using UAS for wetland mapping.

Keywords Unmanned aircraft systems · Wetlands · Community ecology · Remote sensing

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Introduction

In the past, remote sensing of wetlands has primarily involved the detection of wetlands within a non-wetland matrix (Ozesmi and Bauer 2002; Xie et al. 2008; Rebelo et al. 2009). However, within-wetland changes are also critical for ecological monitoring and management and may be exacerbated by accelerated climate change (Newton et al. 2009; Houet et al. 2010). Remote sensing is an excellent source of data for contributing to ecological models that attempt to explain and predict landscape changes (Newton et al. 2009; Houet et al. 2010), but until recently data have not been available at the appropriate spatial scale to address many types of within-wetland community alterations. In the past 10 years, there have been significant advancements regarding within-wetland classification using different remote sensing techniques, such as hyperspectral imagery (Jollineau and Howarth 2008; Adam et al. 2010), radar (Bourgeau-Chavez et al. 2005), and LiDAR (Hopkinson et al. 2005; Maxa and Bolstad 2009). However, these data types can be difficult for non-remote sensing experts to understand and analyze (e.g., hyperspectral images often have hundreds of bands). While some types of remotely sensed data are freely available (e.g., Landsat, MODIS, and NAIP), original (non-historic) finer spatial resolution data is often expensive to acquire, which limits its availability and utility (Rango et al. 2006).

It can be difficult to separate within-wetland vegetation types as they are often spectrally similar (Ozesmi and Bauer 2002) or the vegetation patches are small relative to the spatial resolution of the sensor (Ramsey and Laine 1997; Klemas 2013). This is a particular problem with freely available data from medium resolution satellites like Landsat (Landsat 8: 15–100 m resolution). Techniques such as sub-pixel classification and fuzzy classification (Wang 1990; Liu and Wu

Fig. 1 Mosaic of study plot in Water Conservation Area 3A South, Florida USA. Imagery is from an unmanned aircraft system and resolution is 5.0 cm

2005) address this issue, but they require detailed spatial information from a sufficient number of pixels to train the classification model.

Imagery from small Unmanned Aircraft Systems (UAS) are a relatively new source of data that is gaining popularity in ecological applications (Watts et al. 2010; Martin et al. 2012; Anderson and Gaston 2013). UAS can provide imagery with the appropriate resolution (<10 cm) for community level classification (Getzin et al. 2012) and are becoming more financially accessible as technology improves and demand increases (Anderson and Gaston 2013). This high resolution imagery comes with its own challenges, including large data storage needs, technical knowledge needed for processing, and increased spectral variability within patches that can cause a 'salt and pepper effect' that complicates land cover classification (Pu et al. 2011).

The utility of UAS imagery as a source of data for within-wetland plant community classification was tested in the Everglades ridge and slough landscape. The main goal was to differentiate among several types of deep water communities (sloughs), depending on the amount of emergent vegetation versus floating-leafed aquatic plants. It is a subtle difference in remote sensing data, but ecologically important, particularly for an endangered bird species (Zweig and Kitchens 2014). The emergent wet prairies and sloughs are similar in texture and reflectance at medium (30 m) and fine (1 m) resolution data, and UAS imagery provided an excellent opportunity to explore the feasibility of automatically classifying fine-scale communities in challenging systems (Ozesmi and Bauer 2002) and also to explore the unique contribution of UAS to remote sensing of wetlands.

Methods

The study area was a 1-km^2 plot in Water Conservation Area 3A South in the Florida Everglades (Fig. 1). This area has been monitored since 2002 for vegetation community change with field biomass and density data (Zweig and Kitchens 2008). We wanted to classify the following communities within the plot: trees/shrub, emergent vegetation (no water visible between plants, no water lily), open slough (no emergents visible between water lilies), sparse emergent slough (some emergent with water lily, less water visible between lilies), emergent slough (emergent with water lily, least water visible between lilies), periphyton slough (lilies with tan/brown periphyton layer visible), degraded sawgrass (sawgrass in clumps with water visible between), shrubby sawgrass (sawgrass with interspersed dark green clumps), and continuous sawgrass (no dark green clumps or water visible).

The Nova 2.1 is a UAS that was designed and developed for the U.S. Corps of Engineers—Jacksonville District (COE) by the University of Florida Unmanned Aircraft Systems Research Program (UFUASRP). The Nova line was specifically developed by the UFUASRP for natural resources applications (Watts et al. 2010; Martin et al. 2012). The completely electric-powered, hand-launched, 2.7 m wingspan aircraft can weigh up to 6.4 kg fully loaded, is capable of terrestrial or amphibious landings, and has an average flight time of approximately 40 min. The Nova 2.1 has autonomous flight control, and is capable of maintaining predefined flight lines keeping the optical payload nadir (oriented vertically downward) over the target area. For this project, the Nova 2.1 collected true color (RGB, 380–750 nm) images at 150 m above ground level and at an airspeed of 16 m/s.

Through a Certificate of Airworthiness issued by the Department of the Army (Redstone Arsenal, Huntsville, Alabama), and a Memorandum of Agreement between the Department of Defense and the Federal Aviation Administration (FAA), the COE was granted permission to fly the Nova 2.1 UAS for low-altitude aerial photography surveys over the study area in Water Conservation Area 3A South. A COE three-person flight crew trained and experienced with the Nova 2.1 UAS executed the flights on 14–16 August 2012. The weather conditions varied over the 3 days of flights, from clear to partly cloudy with low winds and little haze.

The onboard imaging sensor was an off-the-shelf 10-megapixel Olympus® E-420™ digital single-lens reflex (dSLR) camera with a fixed focal length 25 mm Olympus® Zuiko Digital™ pancake lens. Camera settings for these flights were: aperture priority exposure mode (aperture of f/2.8, with max aperture of 2.97265625), exposure time automatically selected by the camera (ranged from 1/400 s to 1/4, 000 s), ISO 100, manual white balance, normal saturation, no flash, autofocus, and pattern metering mode. The images were saved in JPEG format type with 314 dpi horizontal and vertical resolution. The camera captured images with an approximate ground resolution of 5 cm per pixel at a 150 m flight altitude, and a shutter open frequency of approximately one image every 3 s. This equates to a single image covering roughly 77×102 m on the ground, or 0.78 ha per image. Photogrammetric lens corrections and camera calibration parameters were estimated using Agisoft LLC® Lens© (Agisoft LLC, St. Petersburg, Russia) software. The software estimated the full camera calibration matrix including non-linear distortion coefficients (focal length in pixels: f_x,f_y; principal point coordinates: c_x,c_y; skew coefficient between the x and y axis; and radial as well as tangential distortion coefficients using Brown's distortion model: k_1,k_2,k_3,k_4,p_1, and p_2).

Only one electronic component of the entire payload was not commercially available off-the-shelf; a custom sensor timing synchronizer board which integrated Global Positioning System (GPS) positional data and Inertial Navigation System (INS) attitude data with the camera shutter exposure data. It was essential for the camera to have an integrated GPS/INS unit of greater accuracy than is provided by a recreational-grade GPS in order to acquire data appropriate for orthophoto mosaic generation and further analyses. The optical payload GPS/INS sensor was independent of the GPS/INS unit used for the operation of the aircraft autopilot system.

The photos were mosaicked using Agisoft LLC® PhotoScan© Professional Edition software. The software was designed to create 3D models from overlapping 2D still images using automated reconstruction algorithms. Generating orthophoto mosaics is a workflow of five steps: 1) imagery and metadata input; 2) photographic alignment and generation of a sparse point cloud through tie point matching; 3) reconstruction of the scene geometry via creation of a 3D polygon mesh and photo optimization; 4) texture atlas production of the 3D polygon mesh into an orthophoto mapping projection; and 5) exportation of the orthophoto mosaic and its world file metadata. It is not apparent that Agisoft LLC® PhotoScan© Professional Edition uses any radiometric correction or histogram matching. Perhaps because the images were all acquired within hours of each other, radiometric correction appeared to be less critical than when satellite images or aerial photos taken days or months apart are mosaicked. The mosaic was further georectified to U.S. Geological Survey digital orthophoto quarter quads until the total root mean square error was less than 1.0 m, or 20 pixels. This was to account for warping and other issues in the mosaicking process.

The Feature Analyst (Overwatch Systems, Austin, Texas, USA) extension for ArcGIS 10.1 (ESRI, Redlands, California, USA) was used to classify the image. Feature Analyst is an ArcGIS add-on that uses machine learning algorithms (neural networks and genetic algorithms) along with texture and spectral characteristics to classify user-defined categories of land cover. It integrates manual and task-specific automated approaches through an iterative cycle of automated modeling and correction by the user (Blundell and Opitz 2006). For each class (Table 1), an expert on vegetation communities in this area created 20+ training samples from the 5 cm resolution imagery using their knowledge of the area and field data obtained on the date the imagery was acquired. To account for glare on the water surface, extra classes were included in the initial model that represented the main classes but with significant glare, e.g.,: Open Slough with glare or Emergent Slough with glare. These extra classes were combined with the corresponding main classes in the final classification. Feature Analyst allows an initial training and then subsequent re-training, where the accuracy of each class (indicating which polygons are correct and which are incorrect) can be assessed

Table 1 Class descriptions and producer and user's accuracy for classification of high resolution imagery (0.5 m) from Water Conservation Area 3A South, Florida, USA

Class	Class description	Producer's	User's
Sparse emergent slough	Water lily-dominated with emergent vegetation	33 %	26 %
Open slough	Water lily-dominated with open water	46 %	92 %
Emergent slough	Water lily and emergent vegetation co-dominate	81 %	43 %
Deteriorated sawgrass	Sawgrass with open water areas	69 %	27 %
Emergent	Emergent vegetation dominant with few water lilies	85 %	57 %
Tree/Shrub	Tree or shrub islands	98 %	98 %
Shrubby sawgrass	Sawgrass with shrubs interspersed	50 %	93 %
Continuous sawgrass	Unbroken sawgrass patch	64 %	47 %
Periphyton slough	Open or sparse emergent slough dominated by periphyton on the water surface	93 %	100 %

and re-classified, refining the current model. The accuracy of each class was visually assessed and each land cover type was re-classified at least two times until there was no visible improvement.

The resolution of the native images (5 cm) was too high for the scale of our community analysis. Because the texture of plant communities at the study site did not occur at that scale, the analyses resulted in a 'salt and pepper' classification. The data were resampled to 0.5 m and classified using the training samples from the 5 cm resolution image. These training samples were adequate for classification at both resolutions.

The nine classes were also combined into three (slough, emergent, sawgrass) that were not as fine-scale, but still ecologically important—ridge-like, emergent aquatic, and aquatic vegetation. This was to determine if accuracy could be improved while still separating the image into classes that may be difficult to classify using coarser-resolution imagery. The combination of degraded sawgrass, shrubby sawgrass, and continuous sawgrass became the sawgrass class. Emergent slough, sparse emergent slough, and periphyton slough were combined into one slough class, and emergent vegetation remained a separate class. Trees/shrubs were ignored for this analysis.

Accuracy was assessed with 30 random points for each class, and used to calculate a confusion matrix, producer's and user's accuracy, and the Kappa statistic. Producer's accuracy represents the probability of a reference pixel being classified correctly, and user's accuracy is the probability that a pixel classified on the map accurately represents the current vegetation configuration. The Kappa statistic describes agreement between the derived classification and reference data (Jensen 2005), with 0 representing agreement expected by chance and 1 indicating perfect agreement. The Kappa statistic of different classifications can be directly compared and they can be used to test hypotheses (Congalton and Green 2008).

Results

Classification of imagery with a resolution finer than 0.5 m resulted in unsatisfactory classifications with high rates of error obvious from preliminary visual observations (0.1 m and 0.3 m were also tested). There was also a substantial amount of confusion between sawgrass communities and periphyton slough which were very similar in color, perhaps due to the rough surface of the periphyton that gave it a similar texture to sawgrass. This confusion was corrected in the final classification by changing all sawgrass communities within the boundaries of sloughs to periphyton slough. This was done manually, but could potentially be automated with a slough/sawgrass boundary GIS layer.

The overall classification accuracy of the 0.5 m imagery (Fig. 2) for the nine classes was 69 % and the Kappa statistic was 0.65. User's accuracy—the probability that the

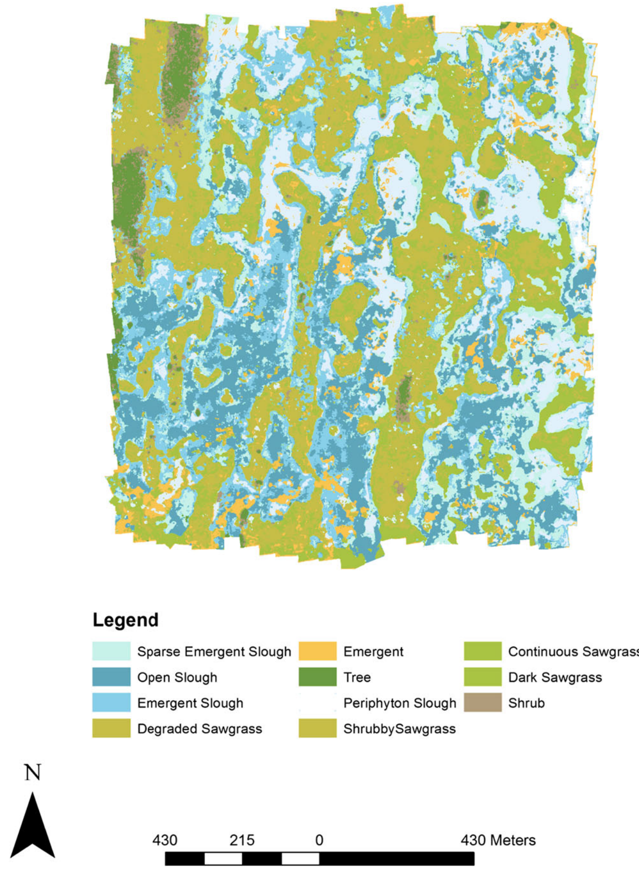

Fig. 2 Automatic classification of Water Conservation Area 3A South, Florida USA

classification correctly represents reality (Table 1)—was very low for sparse emergent slough (27 %) and deteriorated sawgrass (27 %). They were most often misclassified as open slough and shrubby sawgrass, respectively (Table 2). User's accuracy was high for open slough (92 %), tree/shrub (98 %), periphyton slough (100 %), and shrubby sawgrass (93 %). The other classes were accurate approximately 50 % of the time: emergent slough (43 %), emergent (57 %), and continuous sawgrass (47 %). They were most often misclassified as sparse emergent slough, shrubby sawgrass/open slough, and shrubby sawgrass, respectively.

The overall accuracy of three classes was 91 % with a Kappa statistic of 0.84. The user's accuracy was high for sawgrass (90 %) and slough (100 %) and moderate for emergent (57 %). Emergent was almost equally misclassified as slough and sawgrass, six and seven times, respectively.

Discussion

The primary goals were to test the feasibility of UAS data for fine spatial scale wetland vegetation classification using computer-assisted procedures and to explore the unique contribution of UAS to wetland remote sensing. Classification of

Table 2 Confusion matrix for classification of high resolution imagery from Water Conservation Area 3A South, Florida, USA

	Sparse emergent slough	Open slough	Emergent slough	Deteriorated sawgrass	Emer-gent	Tree/Shrub	Peri-phyton slough	Shrubby saw-grass	Continuous sawgrass	Row total
Sparse emergent slough	8	22	1							31
Open slough	1	22	1							24
Emergent slough	15		13			1	1			30
Deteriorated sawgrass				9	3			14	7	33
Emergent		4		1	17		2	6		30
Tree/Shrub			1			55				56
Periphyton slough							39			39
Shrubby sawgrass								28	1	29
Continuous sawgrass				3				8	14	25
Column total	24	48	16	13	20	56	42	56	22	

UAS imagery with resolution higher than 0.5 m resulted in unsatisfactory error rates. This is likely a matter of scale—the resolution of the imagery did not match the resolution of community texture or the texture of a training patch. It is also possible that such high resolution allowed for unimportant details within vegetation patches, such as shadows or increased texture, to confuse the classification. At 0.5 m resolution, when split into nine vegetation communities, the classification accuracies achieved in this analysis were low, particularly for certain classes, but the overall accuracy was on

Table 3 Regulatory rules, technical, and other considerations for use of UAS

Rule	Type
Must obtain Certificate of Airworthiness for every geographic area	Regulatory
Autopilot must be kept secure from foreign nationals	Regulatory
Flight crew must consist of three people: a licensed, manned aircraft pilot, one spotter, and one ground control person	Regulatory
All flight crew must have Federal Aviation Administration Class 2 medical clearance	Regulatory
Flights are limited to one nautical mile line-of-sight radius from the ground control station	Regulatory
Flight altitudes are limited	Regulatory
Flights cannot be within 30 miles of major airports (Class B airspace) without difficult-to-obtain permissions	Regulatory
Notice to Airmen must be filed with the FAA 72–48 h before flight	Regulatory
Local FAA towers must be notified 24 h prior to flying, again before the first flight, and a final time when flights are completed	Regulatory
Certain electronic components or the data obtained by these components, may have export control regulations associated with them. U.S. State Department, U.S. Customs, and Border Security must be contacted to determine if transport of those items out of the U.S. is permitted and if those items are permitted to enter certain countries	Regulatory
Determine UAS configuration by your scientific question. It affects your choice of:	
Type of airframe (weight, payload volume, launching/landing requirements, runtime, portability, resilience, and transect vs. hover-and-stare capacity)	Technical
Type of payload (optical sensor, physical dimensions, weight, power consumption, heat production, resolution, availability, resilience)	Technical
Post-processing requirements (turning photos into data)	Technical
Statistics to analyze spatial data	Technical
Budget	Other

par with other ecological remote sensing analyses, 35–90 % (Ozesmi and Bauer 2002; Johansen et al. 2007; Newton et al. 2009). In comparison to another Everglades study using SPOT data (Rutchey and Vilchek 1999), the accuracy of the nine plant community classification was not substantially lower, 80.9 % vs. 69 %. 80 % accuracy was considered the best that might be expected from an automated satellite imagery analysis in such a heterogeneous landscape (Rutchey and Vilchek 1999).

The three community classification performed better than the nine (overall accuracy=91 %, Kappa=0.84) and still separated important fine-scale differences in vegetation structure (wet prairie versus slough). Wet prairies, a shallow emergent aquatic community, are habitat for many Everglades species (Loftus and Eklund 1994) including the endangered Everglade Snail Kite (Zweig and Kitchens 2014). Being able to quantify the amount of wet prairie would be very important for future Everglades restoration activities. It was more accurate than the nine community classification and a manual aerial photo classification of other Everglades vegetation (Rutchey et al. 2008). The automatic classifications can be considered particularly successful, even with lower accuracy values, due to the complexity of the landscape. Communities *within* a wetland are being defined, not by different species, but by the density of species within the community (Zweig and Kitchens 2008). This is unique, particularly when using computer classification algorithms and not delineating communities by hand. It important to note that expert knowledge was critical to producing our classification, both in terms of on the ground and remote sensing knowledge.

This analysis is one of the first to use UAS imagery not as a photo or map, but as data for fine-scale, ecological community classification, and its success highlights possible uses for UAS data in the future. There are many benefits to using UAS to collect remote sensing data for ecology (Anderson and Gaston 2013). It decreases the risk to human life from traditional low-level flights (Sasse 2003), can provide data on cloudy days, has flexible mission planning, lower cost, and can provide different resolution data from a single flight on the same day if better resolution is needed after an initial assessment (Rango et al. 2006; Martin et al. 2012). However, because it is still an emerging technology, there are obstacles to successfully acquiring data (Martin et al. 2012), both regulatory and technical. These problems are rarely discussed (Anderson and Gaston 2013) in UAS literature, so we provide a detailed overview for future UAS users (Table 3).

An important consideration when using this new data source is to let the scientific question define the data specifications and not let the technology define the scientific question. Technology that can provide finer resolution data but these data may not always be beneficial. In the case of the current analysis, the resolution acquired by the UAS was too fine for the communities of interest, and if this had not been a research flight, would have been a large expense for the wrong data. Much like ecological field data taken without a solid study and statistical design (Eberhardt and Thomas 1991), without proper pre-flight data collection methodology (location, flight altitude, resolution, sensor type, etc.), UAS data could have limited scientific value at a high cost.

Despite the challenges associated with starting an ecologically focused UAS program, the ability to collect fine spatial resolution data should be valuable for wetland ecology. For example, UAS data could be used to link field based information to reflectance from medium resolution satellites and thus guide the extrapolation of the field data (Ozesmi and Bauer 2002). They are also more flexible with flight requirements than fine spatial resolution multispectral sensors that have similar resolutions to the resampled UAS imagery used in this study. With advancing technologies and regulatory issues currently being addressed by the FAA, challenges associated with UAS use should significantly decrease in the near future and open this source of data to a wider audience.

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