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Evaluating Drone Truthing as an Alternative to Ground Truthing:
An Example with Wetland Plant Identification

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PURPOSE: Satellite remote sensing of wetlands provides many advantages to traditional monitoring and mapping methods. However, remote sensing often remains reliant on labor- and resource- intensive ground truth data for wetland vegetation identification through image classification training and accuracy assessments. Therefore, this study sought to evaluate the use of unmanned aircraft system (UAS) data as an alternative or supplement to traditional ground truthing techniques in support of remote sensing for identifying and mapping wetland vegetation.

INTRODUCTION: Landscape ecology often involves the identification, quantification, and tracking of system processes (for example, drivers and pressures) and their impacts on feature response and landscape patterns (Elliott et al. 2007, 349). Specific to US Army Corps of Engineers (USACE) missions, civil works project planning, design, and monitoring often requires the identification of habitats and landscape features. Since evaluating ecological processes and patterns requires data from broad spatial extents that cannot easily be collected using field-based methods, researchers are increasingly using remote sensing to provide the data and techniques necessary to classify and detail the distribution, variability, and resiliency of landscape features (Kerr and Ostrovsky 2003; Li et al. 2014).

Remotely sensed imagery and classification approaches can find spectral, textural, shape, and other characteristics unique to individual target types (that is, vegetation type), depending on the spatial and spectral resolution of the imagery used in the analysis. The major steps associated with remote sensing classification to identify wetland vegetation include the following:

1. Image acquisition and preprocessing
2. Selection of training sites and collection of training samples (that is, ground truthing)
3. Selection of an appropriate classifier (that is, algorithm)
4. Feature extraction
5. Post-classification processing
6. Accuracy assessment (German 2014).

Image acquisition and preprocessing involves the collection of remotely sensed data, which must undergo a preparatory preprocessing phase to improve image quality prior to further analysis (Campbell and Wynne 2011, 305). These preparatory steps include radiometric calibration (transformation of digital numbers to physical radiance or reflectance units), atmospheric correction (accounting for atmospheric scattering and absorption), and geometric correction (correcting distortions) (Schott 2007, 57). A suitable classification system is also a prerequisite for a successful classification (Lu and Weng 2007, 824). A classifier should be selected according to the overall needs, image spatial resolution, classifier availability, and time constraints (Lu and Weng 2007, 824). Feature extraction, a technique used to extract the essential elements of an image, removes the noise and errors from the original data and reduces the number of spectral bands required for analysis, thereby reducing computational demands and increasing classification accuracy (Campbell and Wynne 2011, 316). The post-classification processing and accuracy assessments typically consist of qualitative and quantitative assessments of the preliminary classification data. The post-processing techniques usually consist of filtering and manual editing to correct misclassified pixels. Accuracy assessments typically use traditional error matrix methods using validation sites selected from field data (Jollineau and Howarth 2008, 3618).

Although each of these remote sensing classification components can provide its own set of unique challenges, one primary challenge is the collection of training samples, also referred to as ground truthing. In remote sensing, ground truth refers to the traditional on-site gathering of reference data and information that characterize states, conditions, and parameters associated with the Earth's surface (Short 1999, 13-1). These ground truth data represent critical components of wetland classifications because they are necessary for training supervised classification algorithms, validating classified areas, and performing error evaluations (Jensen 2015, 500). Most remote sensing classifiers rely on the statistical distributions of the reflectance values of the target classes as defined by the training (ground truth) data provided for each class (Broussard, Suir, and Visser 2018). However, the traditional collection of ground truth information can be cost and labor limiting, often resulting in insufficient representation of target features and conditions (Schowengerdt 2007; Wich and Koh 2018). This limitation can prove problematic, since classification performance depends strongly on the amount and distribution of representative training samples (Tuia, Persello, and Bruzzone 2016, 41).

Several alternatives to traditional field-based ground truthing methods have been used successfully. These alternatives include using existing maps or data to find representative areas for each target class (for example, land cover or National Wetlands Inventory data), using aerial photographs to identify target features (for example, delineating coastline from high-resolution imagery), and using manned aircrafts to observe and record details related to critical landscape features (for example, performing visual vegetation survey from a hovering helicopter) (Alesheikh, Ghorbanali, and Nouri 2007; Neldner and Clarkson 1995; Sasser et al. 2008; Schowengerdt 2007). A novel and relatively untested surrogate for ground truth data is the use of UAS-captured imagery to identify targets or class training samples (Szantoi et al. 2017, 2). UAS-collected data provide many advantages over in situ and other air- and space-borne collections. These advantages include the ability to survey larger and more difficult to access areas, better spatial resolution imagery and video, and the potential for more frequent collections. This application, recently termed drone truthing, could conceptually provide drone-derived training data with increased quantity and distribution for classifying and evaluating other air- and space-borne imagery (Smith 2010; Wich and Koh 2018).

This study sought to evaluate UAS-based drone truth data as a surrogate to traditional ground truth methods. Specifically, the study compared drone-based vegetation identification to traditional field-collected data in coastal Louisiana wetlands, then assessed the accuracy and feasibility of using drone truth training data in conjunction with other air- and space-borne imagery for future landscape and species level classifications.

METHODS

Study Area. This study was conducted in the Sabine National Wildlife Refuge (SNWR) and the Mississippi River Delta (MRD) (Figure 1). The SNWR primarily consists of brackish wetlands located west of the Calcasieu Ship Channel near Hackberry, Louisiana. This area experienced significant conversion from wetlands to open water between 1956 and 1978 because of hurricane impacts and altered hydrologic and salinity regimes (Miller 2014, 1). A shift from intermediate- and fresh-dominated marsh species to more brackish species also occurred, between 1968 and 1988 (Miller 2014, 1). Since 2002, wetland restoration measures (Calcasieu/Sabine-28 (CS-28) construction from 2002 to 2015) were implemented "as part of the Coastal Wetland Planning, Protection, and Restoration Act (CWPPRA) to provide direct and indirect structural and functional benefits within the [SNWR] and surrounding wetlands" (Suir, Sasser, and Harris 2020, 2644). The CS-28 project consisted of separate creation (cycles) and reference areas ranging in size from 51 ha[1] to 93 ha within an open-water area of approximately 1,153 ha (Figure 1).

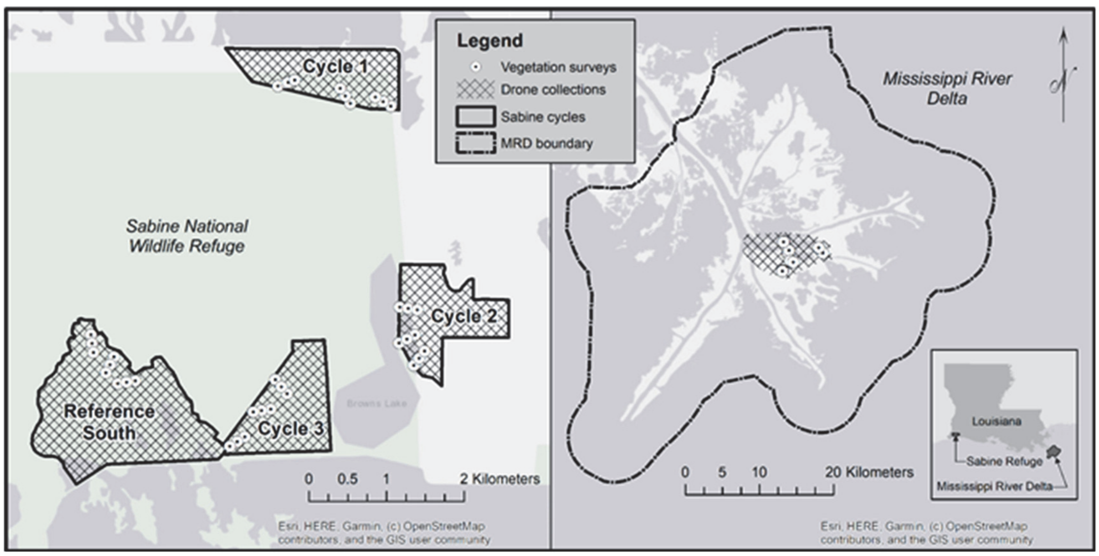

Figure 1. Location map of paired vegetation survey and unmanned aircraft system (UAS) collection points within the Sabine National Wildlife Refuge (SNWR) and the Mississippi River Delta (MRD) study areas.

The MRD (also known as the Plaquemines-Balize Delta) consists of all land and shallow estuarine areas between the two northernmost passes of the Mississippi River and the Gulf of Mexico (Louisiana Coastal Wetlands Conservation and Restoration Task Force 1993, 12) (Figure 1). The MRD, which consists of approximately 300 km2 of wetlands (Couvillion et al. 2017, 5), provides critical ecosystem services, ranging from regulating (that is, storm, flood, and drought), supporting (that is, soil formation and nutrient cycling), to provisioning services (that is, food and freshwater) (Mendelssohn et al. 2012, 562; Suir 2018, 106). The MRD has experienced dramatic loss of wetlands and significant reductions in ecosystem goods and services over the last half century

[1] For a full list of the spelled-out forms of the units of measure used in this document, please refer to *US Government Publishing Office Style Manual*, 31st ed. (Washington, DC: US Government Publishing Office, 2016), 248–52, https://www.govinfo.gov/content/pkg/GPO-STYLEMANUAL-2016/pdf/GPO-STYLEMANUAL-2016.pdf.

(Day et al. 2000; Couvillion et al. 2011; Suir et al. 2014) and has recently suffered marked die-offs of critical and stabilizing Phragmites australis (Knight et al. 2018; Suir, Saltus, and Reif 2018).

Field collections of vegetation data. Most remote sensing classifiers rely on the statistical distributions of the reflectance values of the target classes as defined by the training (on-the-ground) data provided for each class (Carle 2013, 17). This study used an onscreen ocular identification of plant species using UAS-collected video and imagery and compared the results of that exercise to ground truth vegetation survey data. The field collections of vegetation data consisted of existing CWPPRA, Coastwide Reference Monitoring System (CRMS), and Louisiana Coastwide Vegetation Survey data as well as newly collected data from Louisiana State University (LSU) and University of Louisiana–Lafayette (UL-L) researchers (Table 1).

Table 1. Specifications of ground-collected data in the SNWR and MRD study areas. (LSU: Louisiana State University; UL-L: University of Louisiana–Lafayette)

Data	System	Sensor	Source	Date	Location
Vegetation Composition	Braun-Blanquet scale	Ocular	UL-L	June–July 2019	SNWR
Vegetation Composition	Composition	Ocular	LSU	2017 to 2019	MRD
Vegetation Composition	Braun-Blanquet scale	Ocular	CRMS	Annual since 2006	MRD/SNWR
Vegetation Composition	Braun-Blanquet scale	Ocular	CWPPRA	Annual	MRD/SNWR
Vegetation Composition	Braun-Blanquet scale	Ocular	Coastal Vegetation Survey	2013	MRD/SNWR

The monitoring components of CRMS and CWPPRA consist of a network of monitoring sites in coastal Louisiana used to collect, process, and analyze pedologic (i.e., surface elevation), spatial (i.e., land cover), hydrologic (i.e., salinity), and vegetative (i.e., species cover) data for characterizing coastal wetland landscapes inside and outside of CWPPRA projects (Louisiana Coastal Wetlands Planning Protection and Restoration News, 2018, 3). These programs collect vegetation species composition, relative abundance, and aboveground biomass data (Steyer and Stewart 1992). The Louisiana Coastwide Vegetation Surveys consist of standardized vegetation surveys that document species composition, abundance, and corresponding marsh type (that is, fresh, intermediate, brackish, or saline) (Visser et al. 1998). These surveys use transects oriented in a north-south direction (3 km spacing), with sampling sites located at 0.8 km spacing along each transect (Sasser et al. 2014). For new data collections, vegetation species composition and percent cover were collected from within 2×2 m quadrats at each project sample site during periods of peak biomass (Figures 1 and 2C). A team of researchers from the LSU Department of Entomology collected species composition data for monoculture stands in the MRD project site from 2017 to 2019. Likewise, researchers from the UL-L Department of Biology performed vegetation surveys within the SNWR project sites in 2019.

UAS-based imagery and video collections. UAS data in the MRD were collected on multiple dates (August 2015 and June 2016, Louisiana Department of Wildlife and Fisheries

[LDWF]; February 2018, LSU), using different UAS airframes and sensors (Table 2). The LDWF UAS collections, which consisted of oblique photographs and video, were conducted in the Pass-a-Loutre Wildlife Management Area in preparation for a 30-year commemorative event related to crevasses created in 1986. The flights were conducted using a multirotor quadcopter (DJI Phantom 3 Advanced) designed for commercial purposes related to aerial video. The flights were conducted June 16–17, 2016, in various areas of the refuge. Typical flight times ranged from 20–25 min, never exceeding a height of 122 m. The airframe was equipped with a Sony-made 12-megapixel 1/2.3-inch Complementary Metal-Oxide Semiconductor sensor behind a f2.8 20 mm lens (35mm equivalent), creating a 94° field of view. Video was captured primarily at 1080p (1920×1080) at 30 frames per second. The flights were conducted at various heights, and no specific flight plans or transects were in place. The purposes of the flights were cinematic and to highlight the vegetative growth and sediment dispersal that occurred over the last 30 years.

LSU collected UAS imagery within the MRD using a DJI Phantom drone equipped with a low-cost Sentera Single Sensor capable of capturing images in the 575 nm to 1050 nm wavelengths (for example, green to near-infrared [NIR]) of the electromagnetic spectrum. AgVault data management software was used for autonomous flight control, image acquisition, and mosaicking of acquired images. Images of the study area were acquired on cloudless days at a flight altitude of 90 m with 80% image overlap (frontlap and sidelap) (Sartain, Fleming, and Mudge 2019, 18).

UL-L conducted UAS collections in the SNWR study area using a multirotor platform (Yuneec H520). The flights, which coincided with the SNWR vegetation surveys, occurred in June and July of 2019. The flight area, time, altitude, and duration were configured using the internal autopilot flight planning software DataPilot. The internal GPS module geotagged all images with an initial accuracy of 5 m horizontal and 8 m vertical. The hover accuracy of the aircraft was 1.5 m horizontal and 0.5 m vertical. The typical flight times ranged 15–23 min. The airframe was equipped with a Yuneec E90 RGB camera with a 23 mm lens and a diagonal field of view of 91°. Photo resolution was 3:2 (5472 × 3648), and effective pixels were 20 megapixels. All flights were conducted at 68 m altitude above ground level using consecutive transects to cover the survey areas with an image overlap of 80% (frontlap and sidelap). This altitude was chosen to maximize field of view while achieving <2.5 cm ground sample distance (GSD) or pixel resolution in the final maps for a precise analysis of vegetation classes and to minimize possible blurred portions (Broussard, Suir, and Visser 2018).

Table 2. Specifications of UAS collected data in the SNWR and MRD study areas.

Data	System	Sensor	Source	Date	Flight time (min)	Altitude (m)	Resolution (cm)	Location
Orthomosaic Images	DJI Phantom	Sentera NIR	LSU	Feb 2018	10–15	90	4	MRD
Oblique Images	DJI Phantom	Sony Camera	LDWF	Aug 2015 & Jun 2016	20–25	≤122	—	MRD
Oblique Video	DJI Phantom	Sony Camera	LDWF	Aug 2015 & Jun 2016	20–25	≤122	1080p	MRD
Orthomosaic Images	Yuneec H520	Yuneec E90	UL-L	June–July 2019	15–23	68	2.5	Sabine

Image interpretation of vegetation. *Image interpretation* is the process of visually examining an aerial photograph or digital remote sensing image or video and manually identifying target features within the image (Aber et al. 2019, 163; The Landscape Toolbox 2020). The interpretation process is based on inherent elements within an image, along with prior knowledge—such as vegetation zone, seasonality, and anthropogenic activities or impacts—to differentiate landscape features (Zhao et al. 2014, 4800). These knowledge elements (for example, plant height and color variations) and image attributes (that is, size, shape, tone, texture, shadow, association, and pattern) are especially important for interpretation of wetland vegetation (Aber et al. 2019, 163; Suir et al. 2014, 6; Zhao et al. 2014, 4800).

This study consisted of a blind experiment using field-based survey collections and drone-based image interpretations to identify dominant plant species at matching sample sites but without knowledge from the other method. The image interpretation method used a heads-up, on-screen identification of dominant wetland plants at designated survey locations (2×2 m quadrats) within UAS-collected video (MRD) and derived orthomosaic areas (MRD and SNWR sites). A wetland plant expert performed image interpretations of dominant plants at each collection site. These interpretations were performed without knowledge of the ground truth survey results. The 2×2 meter quadrats (for example, red square in figure 2, panel C), established for and during the ground truth vegetation surveys, were used as bounding areas for the heads-up onscreen interpretations.

Statistical analysis. Traditionally, remote sensing accuracy assessments consist of statistical analyses to evaluate the accuracy of a classified image using ground truth verification data. However, for this study the statistical assessments instead evaluated the accuracy of the drone-based vegetation identifications as compared to the standard ground truth data. To accomplish this task, the ArcGIS Desktop v10.7.1 Confusion Matrix tool computed user and producer accuracies, derived a Cohen's Kappa statistic for measuring agreement, and generated an overall accuracy score. For this study, the *producer's accuracy* assessed the probability (individual class accuracies) that real features on the ground were correctly identified using the drone truth techniques. The *user's accuracy*, or reliability, assessed the probability (individual class accuracies) that features identified using the drone-based image interpretation were present on the ground (per ground truth data). The Cohen Kappa measured the interrater agreement for categorical scales (Boslaugh 2012, 11). The Kappa value ranges from −1 to 1, and although there are no absolute standards for judging Kappa values, Landis and Koch (1977, 372) provide accepted guidelines: <0 poor; 0–0.20 slight; 0.21–0.40 fair; 0.41–0.60 moderate; 0.61–0.81 substantial; 0.81–1.0 almost perfect. The *overall accuracy*, expressed as a percentage, evaluated the proportion of all ground truth classes that were correctly classified using the drone truth interpretations.

RESULTS AND DISCUSSION: This study used a total of 52 paired collection stations: 37 in the SNWR study area and 15 in the MRD. There were seven dominant plant species identified: *Distichlis spicata*, *Phragmites australis*, *Sagittaria lancifolia*, *Schoenoplectus robustus*, *Spartina alterniflora*, *Spartina patens*, and *Zizaniopsis miliacea* (Table 3). Although water features were not included in the assessments, bare ground was, and provides the eighth and final class. The dominant feature percent cover ranged from 20% (bare ground, with larger percentage of water) for a collection site in SNWR Cycle 2 to 99% (*Distichlis spicata*) for a site in SNWR Cycle 1. The average cover value for dominant feature for all sites was 62.3%.

Figure 2 shows examples of UAS-collected video and orthophotos from the MRD (panels A and B) and SNWR sites (panel C). Panels A and B are video captures that illustrate the differences in image attributes (that is, size, shape, tone, texture, shadow, association, and pattern) between various dominant plants in the MRD. In panels A and B, there are discernable differences in the texture, tone, and pattern associated with *Phragmites australis* and nearby floating aquatic and woody vegetation. Similarly, in panel C (SNWR Cycle 3 orthophoto mosaic; 28 June 2019, 2.5 cm, UL-L) there are discernable differences between the wind-blown or lodged feathery and lighter-toned *Spartina patens* (central and southern portions of panel C) and the darker and more rigid texture of the *Spartina alterniflora* (northern periphery of panel C).

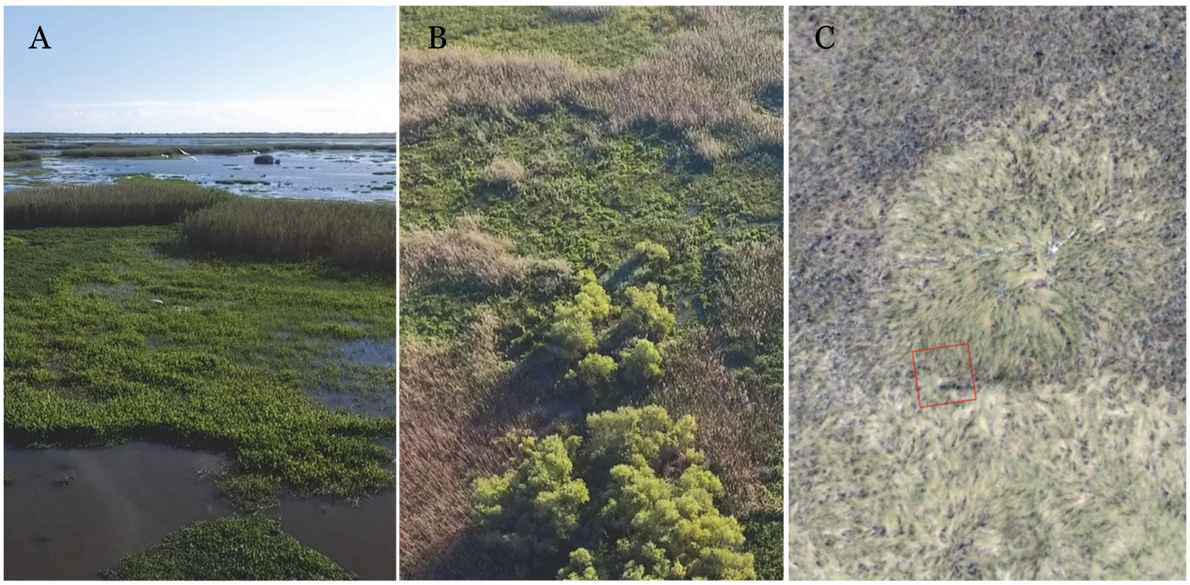

Figure 2. Examples of wetland features and plant species that are discernable using UAS-collected video (panels A and B, MRD) and orthophotos (panel C, Sabine).

To evaluate the accuracy of the UAS collections and interpretations, a confusion matrix was constructed to compare the ground and drone truth results. Table 3 shows the confusion matrix containing each of the eight classes, with Kappa and overall accuracy of the drone truth results. The user accuracies ranged from 50% (bare ground) to 100% (*Distichlis spicata*, *Phragmites australis*, and *Zizaniopsis miliacea*), while the producer accuracies ranged from 0% (*Schoenoplectus robustus*) to 100% (bare ground, *Spartina patens*, *Zizaniopsis miliacea*).

These sites consisted largely of three dominant plant species, *Phragmites australis*, *Spartina alterniflora*, and *Spartina patens*, which combined accounted for 85% of the species present at all survey stations. The user and producer accuracies of those three species ranged from 87.5% (user accuracy for *Spartina patens*) to 100% (user and producer accuracy for *Phragmites australis* and *Spartina patens*, respectively). Other plant species had a limited number of samples, which can affect accuracies. This limitation was observed for *Schoenoplectus robustus*, which was dominant at only one survey site, but the image interpretation returned a bare ground classification for that quadrat. This discrepancy is potentially due to the high reflectivity of *Schoenoplectus robustus* in the imagery, giving it similar image attributes to bare ground. Regardless of sample size, when compared to the traditional ground truth method, the drone truth method had an overall accuracy of 90.39% and a Kappa score of 0.873. The Kappa score falls in the Landis and Koch (1977, 371) established almost perfect range of 0.81–1.0.

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Table 3. Confusion matrix comparing ground truth to drone truth dominant plant species in the SNWR and MRD study areas.

Class value	Bare ground	*Distichlis spicata*	*Phragmites australis*	*Sagittaria lancifolia*	*Schoenoplectus robustus*	*Spartina alterniflora*	*Spartina patens*	*Zizaniopsis miliacea*	Classification overall	Producer accuracy (precision)	Overall accuracy (OA)	Kappa
Bare ground	**1**	0	0	0	0	0	0	0	1	100%	—	—
Distichlis spicata	0	**4**	0	0	0	1	0	0	6	66.67%	—	—
Phragmites australis	0	0	**13**	1	0	0	0	0	14	92.86%	—	—
Sagittaria lancifolia	0	0	0	**0**	0	0	0	0	0	—	—	—
Schoenoplectus robustus	1	0	0	0	**0**	0	0	0	1	0%	—	—
Spartina alterniflora	0	0	0	0	0	**14**	1	0	15	93.33%	—	—
Spartina	0	0	0	0	0	0	**14**	0	14	100%	—	—
Zizaniopsis miliacea	0	0	0	0	0	0	0	**1**	1	100%	—	—
Truth overall	2	4	13	1	0	15	16	1	**52**	-	—	—
User accuracy (recall)	50%	100%	100%	0%	—	93.33%	87.50%	100%	—	—	—	—
Overall accuracy (OA)	—	—	—	—	—	—	—	—	—	—	**90.39%**	—
Kappa	—	—	—	—	—	—	—	—	—	—	—	**0.873**

These sites consisted largely of three dominant plant species, *Phragmites australis*, *Spartina alterniflora*, and *Spartina patens*, which combined accounted for 85% of the species present at all survey stations. The user and producer accuracies of those three species ranged from 87.5% (user accuracy for *Spartina patens*) to 100% (user and producer accuracy for *Phragmites australis* and *Spartina patens*, respectively). Other plant species had a limited number of samples, which can affect accuracies. This limitation was observed for *Schoenoplectus robustus*, which was dominant at only one survey site, but the image interpretation returned a bare ground classification for that quadrat. This discrepancy is potentially due to the high reflectivity of *Schoenoplectus robustus* in the imagery, giving it similar image attributes to bare ground. Regardless of sample size, when compared to the traditional ground truth method, the drone truth method had an overall accuracy of 90.39% and a Kappa score of 0.873. The Kappa score falls in the Landis and Koch (1977, 371) established almost perfect range of 0.81–1.0.

CONCLUSIONS: This technical note describes a proof of concept for using UAS collections as an alternative to traditional field-based ground truth data. While drone truthing techniques incur time and costs for UAS data collection, processing, and interpretation, the amount of potential return in terms of number, diversity, and distribution of samples is where drone truthing could provide significant improvements to site assessment and characterization. We assume field-based surveys are the “truth,” but the limited number of field sites, access constraints, and sampling design means that, while the discrete samples are assumed to be the highest level of accuracy, the extrapolation of those data across a larger area may not form a comprehensive or accurate representation of a project area. Thus, the increased quantity and extent provided by drone truthing means we have the ability to more accurately identify the plant species, target features, and landscape types across larger areas. This increased capability is important, since “a sufficient number of training samples and their representativeness are critical” for accurate image classifications (Lu and Weng 2007, 825).

The use of drone truthing to establish training data for supervised classification of wetlands and other critical vegetation communities could be of significant importance to USACE Civil Works restoration and monitoring efforts. The ability to collect a higher volume and distribution of diverse samples could result in more efficient and accurate monitoring and quantification of wetland ecosystem structure and function. An example of potential drone-truthing applications is in remote areas, like the *Phragmites australis* research conducted in the MRD (Suir, Saltus, and Reif 2018), which presents limited access and requires high labor because of dense vegetation in expansive wetlands. Another study that could have benefited from drone-truthing applications is the recent use of hyperspectral airborne imagery to classify wetland zones in 24 extensive wetlands along coastal Lake Ontario (Suir, Wilcox, and Reif accepted June 2021). Like many studies involving image classification of vegetation, this study used vegetation survey data from an established monitoring program; however, those data were limited to predetermined transects that did not fully represent the composition and distribution of plants within the study sites.

This proof of concept used existing and ongoing data collections to evaluate drone truthing as an alternative to traditional ground truthing methods in relatively simple monoculture stands of wetland vegetation. Future research should consider study designs and data collections for the exclusive purpose of comparing ground- and drone-truthed methods. These focused studies could further evaluate the potential advantages that drone truth data have over traditional ground-based collections. These studies should also evaluate drone truth methods and results in more complex wetland landscapes. For example, in fresher systems with a more moderate mix of plant species (Johnson, Sasser, and Gosselink 1985; Suir and Sasser 2017). Additionally, future research should compare image-based classification accuracies using ground truth versus drone truth data. These advancements will help researchers better understand the level of impact that drone truthing data can have on remote sensing analysis methods. They could also help shift to machine learning algorithms and more automated processes that require a lot of training samples (which many remote sensing projects cannot accommodate because of the limited number of ground samples) (Khan and Al-Mulla 2019, 51). This further research could also potentially help overcome the issues associated with limited samples for rare or underrepresented plant species, as observed with this study's *Schoenoplectus robustus*–dominated site. Ultimately, drone truthing has the potential to overcome some of the major limitations related to on-the-ground, field-collected training data.

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