High-Resolution Data for Capturing Wetland Vegetation Using Object-Based Classification Methods

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Abstract
The purpose of this study is to use the Unmanned Aerial Systems (UAS) images for mapping wetland vegetation using object-based classification methods and to compare its performance with cropland data layers. The UAS imagery (~0.1-m resolution) and National Agriculture Imagery Program (~0.6-m) data were used to extract wetland vegetation using object-based classification methods in ArcGIS Pro. Spectral indices, such as green chromatic coordinate (GCC) and normalized difference vegetation index (NDVI) coupled with unsupervised classification have been used for vegetation classification. UAS imagery performed slightly better than NAIP for classification yielding 49% vegetation in 2019, while it was 45% in 2018 and 35% in 2016 for NAIP classification. According to cropland data classification, open water land cover class also covered a large portion of the study area. In conclusion, object-based classification using high-resolution imagery has good potential to integrate with ground survey to implement best management practices for restoring wetlands.

Keywords: UAS, wetlands, object- based classification, spectral indices, cropland data

Introduction

Traditional wetland vegetation field survey techniques are labour intensive and often impeded by dense vegetation combined with aquatic or semi-aquatic conditions. Although vegetation sampling is limited to the growing season, managed wetlands need intensive surveys during mowing and flooding seasons to better understand the ecological services provided. Remote sensing data overcomes the sampling limitations and also valuable for assessing spatial and temporal changes of wetlands, such as hydrology (Li et al., 2009), land-use/cover changes (Pande-Chhetri et al., 2017) and carbon footprints (Crichton et al., 2015) to monitor ecological functions.

Unmanned aerial systems (UASs) offer new platforms to collect high spatial/temporal-resolution data at relatively low cost and highly accurate imagery that may be used to distinguish, demarcate and quantify herbaceous species coverage in wetlands as well as assess changes over time (Husson et al., 2014; Kaneko and Nohara, 2014). Several studies have assessed the feasibility and accuracy of UAS derived imagery in distinguishing within-wetland vegetation (e.g., Zweig et al., 2015; Ishihama et al., 2012; Husson et al., 2014; Boon et al., 2016). Species composition was distinguishable in normal color imagery by human interpreters even with a relatively low pixel resolution camera, as long as spatial resolution remained high (Husson et al., 2014). This could in fact favor lower cost UASs as the technology gains popularity in such vegetation surveys.

This study investigates the feasibility of using high-resolution data for the object-based classification method for mapping wetland vegetation. The results compare its performance with pixel-based classification using moderately resolution cropland data layer (CDL).

Methodology

Study area: The study was conducted at a restored wetland of the San Joaquin River National Wildlife Refuge in the Central Valley in California. The study area is located in Stanislaus County in California and the size of the wetland is about 12-ha. The GPS coordinates for the study site is between 37.600345 N -121.209311 E and 37.598870 N -121.207825 E. The San Joaquin River flows through the refuge, which provides mixed habitats for endangered species, such as brush rabbit, amphibians, and migratory birds. Typical wetland management at the refuge involves a combination of summer irrigation, vegetation mowing in late summer or early fall followed by flooding in October in anticipation of migratory waterfowl. The most dominant herbaceous macrophytes in this wetland are *Typha*, *Cyperus*, *Scirpus*, *Juncus*, and *Sagittaria* species (Duffy et al., 2011).

Data acquisition: This study utilized the UAS and Cropland data layer to monitor vegetation changes from 2016 to 2019 periods. The UAS images were acquired on October 25 2019 using a DJI Phantom 4 drone. National Agriculture Imagery Program (NAIP) data was acquired on 14.07.2018 and 21.06.2016 from the Earth Explorer web portal (https://earthexplorer.usgs.gov/). NAIP imagery consists of four multispectral bands at a 0.6-m spatial resolution. USDA-NASS Cropland Data Layer (CDL) had a 30-m spatial resolution and crop-specific land cover data layer was derived from the Landsat 5 TM and Landsat 7 ETM+. We used moderately resolution CDL data during 2016-2019 comparable with high-resolution data to detect vegetation cover.

Vegetation analysis and classification: High-resolution UAS and NAIP imagery were used to detect and classify wetland vegetation from 2016 to 2019 in ArcGIS Pro. Vegetation classification was performed using an integrated method of spectral index, segmentation, and an object-based classification (https://dronecamp.github.io/2020/2020-06-23.html#processing-uav-images-with-arcgis-pro). We computed a spectral index of vegetation greenness from 3-RGB band of UAS imagery (Green Chromatic Coordinate index / GCC) and 4- RGB+NIR band of NAIP imagery (normalized difference vegetation index / NDVI).

$$NDVI = (NIR - RED)/(NIR + RED) \tag{1}$$

$$Green\ Chromatic\ Coordinate\ (GCC) = (Green)/(Red + Green + Blue) \tag{2}$$

Image segmentation was performed and the segment statistics (i.e. mean and standard deviation of spectral indices) was used to detect the vegetated areas. Finally, unsupervised object-based classification was performed to map wetland vegetation (Figure 1).

National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL), which originally derived from classified LandSat ETM+ was used to classify major land-use/cover types within the study area. The CDL data comprises crops and land-use/cover data (https://nassgeodata.gmu.edu/CropScape/). Therefore, minor CDL classes were then collapsed into four major categories such as open water, wetlands, fallow/idle cropland, and crops.

Results

The extent of the study area is estimated as 11.65-ha. Vegetation mapping showed a great extension of plant communities coverage in 2019 followed by 2018 and 2016 (Figure 2 and Table 1). The high-resolution UAS imagery (~0.10-m) performed well with object-based classification resulting in better image segmentation, and aggregation of segments into meaningful objects. Vegetation coverage in 2018 is less compared to 2019 and aerial coverage of open water is increased. The vegetation extent in 2016 is comparatively less could be a result of mowing vegetation for creating habitats for water birds.

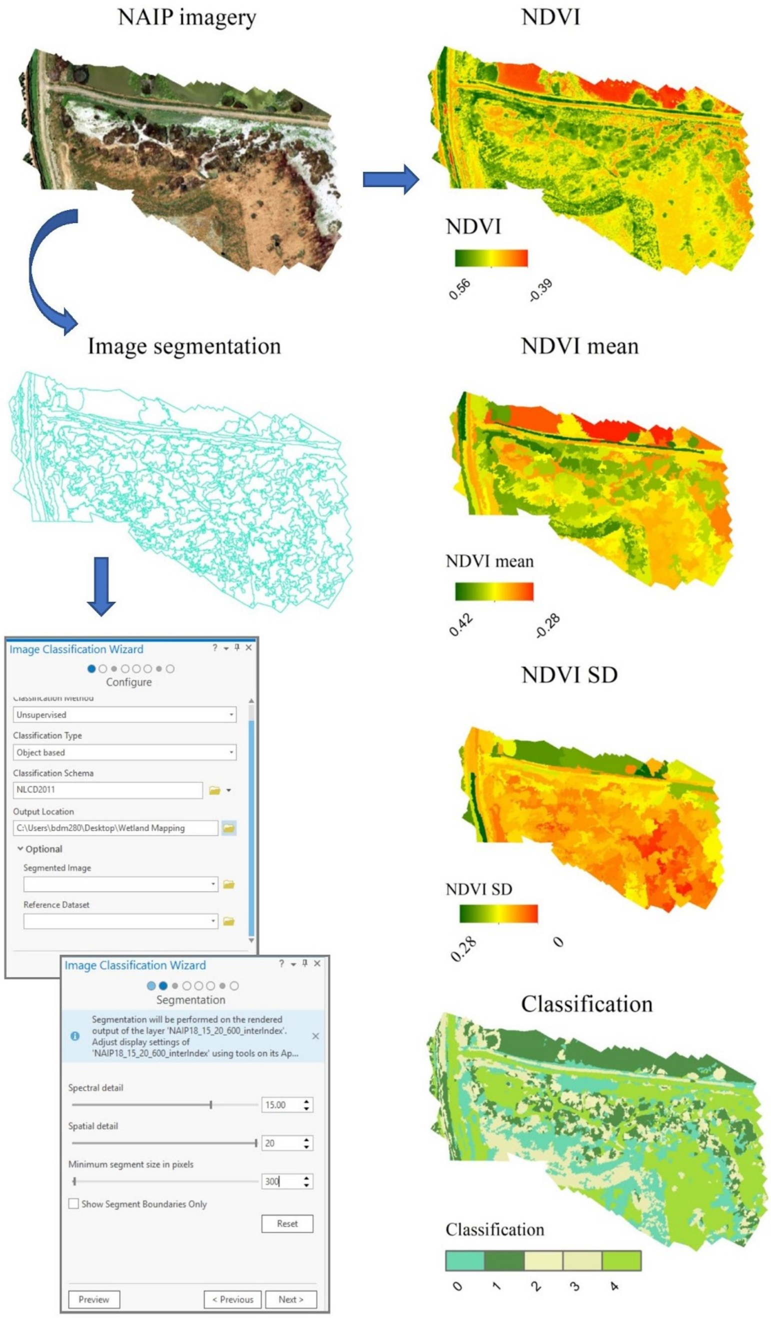

Figure 1:. Flowchart shows the major steps for object-based image classification. The procedure shows an integrated method of classification steps: NDVI and its derivatives, NDVI mean and standard deviation (SD), segmentation, and an object-based classification.

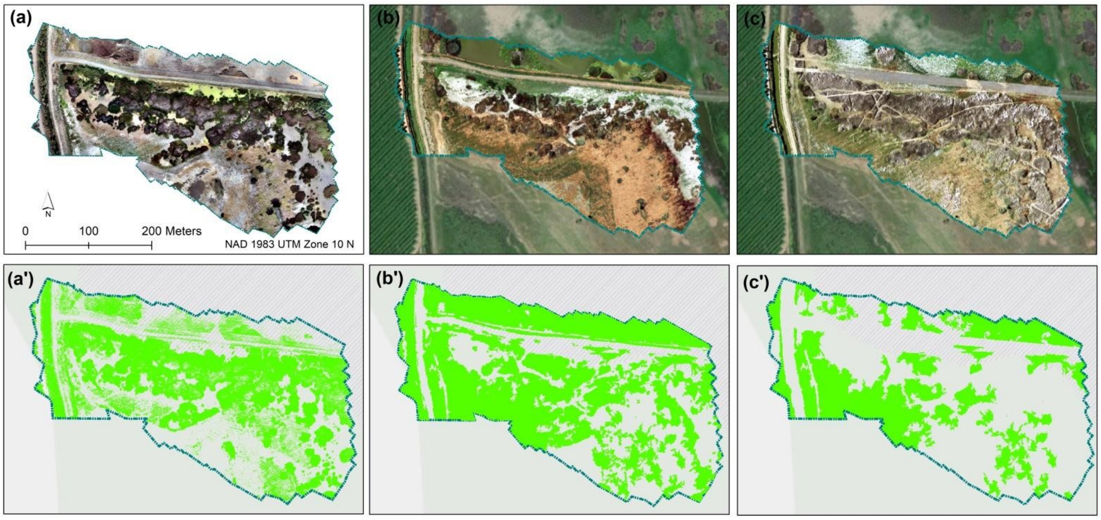

Figure 2: Vegetation Analysis & Classification using the UAS and NAIP imagery at the San Joaquin River National Wildlife Refuge wetland. (a) UAS imagery acquired on 2019.10.25 (0.1-m resolution), (b) NAIP imagery acquired on 2018.07.14 (0.6-m resolution), (c) NAIP imagery acquired on 2016.06.21 (0.6-m resolution). The classified vegetation is shown in green color from a'-c'.

Table 1 compares vegetation changes of San Joaquin River National Wildlife Refuge wetland from 2016 to 2019 using high resolution UAS/NAIP data and moderately resolution CDL data. According to the CDL classification, wetlands acreage is comparable in 2019 and 2016, while it is low (0.81) in 2018 resulting in increased open water extent (7.12-ha). We compare vegetation cover using both high- and moderately resolution data, and results are more or less similar in 2019 and 2018, while vegetation cover in 2016 is nearly double for CDL data. The reasons for such vegetation change could be the difference of image acquisition dates, sensors, and management practices (i.e. mowing of emergent vegetation) of the constructed wetland.

Table 1. Compare vegetation classification results of the high-resolution imagery and moderately resolution cropland data.

High- resolution UAS/NAIP	Year	2019	2018	2016
	Imagery	UAS	NAIP	NAIP
	Vegetation extent (ha)	9.33	5.24	4.05
	% Vegetation cover	48.82	45.04	34.82
Moderaely resolution CDL data	Extent (ha) ↓ Year ⟶	2019	2018	2016
	Open Water	4.78	7.12	4.13
	Wetlands	3.68	0.81	3.84
	Fallow/Idle Cropland	0.08	1.46	0.28
	Crops	3.04	1.98	3.40
	% Vegetation cover	58.74	37.37	64.58

Discussion

Spatially delineating herbaceous vegetation from heterogeneous wetland habitats is challenging and we introduced an object-based approach and spectral indices together for partitioning vegetation as an effective method. We choose spatial value (20) somewhat higher than spectral value (15), set minimum segment size to 300, and GCC threshold to >0.34 to improve object-based classification for delineating vegetation boundaries (Figure 1). This study can further improve classifying plant communities using ground trothing data as showcased in recent studies (Pande-Chhetri et al., 2017; Madurapperuma et al., 2020). Most restored wetlands in the Central Valley are heavily dependent on artificial hydrology and are often managed to provide habitat for waterfowl and water birds (Kahara et al., 2016). Therefore, monitoring vegetation health of restored wetland using high-resolution imagery is useful for applying best conservation practices especially for providing refuge for aquatic birds and amphibians.

Conclusion

High-resolution UAS imagery performed well with object-based classification for mapping wetland vegetation that overcomes the problem of salt-and-pepper effects resulting from traditional pixel-based classification methods. UAS imagery limits the spectral resolution, however we were able to capture vegetation health or greenness of vegetation through Green Chromatic Coordinate index. The wetland is managed by mowing and flooding temporarily to facilitate habitats for aquatic birds and therefore monitoring the vegetation growth seasonally is useful to evaluate ecological processes.

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