Improving the efficiency and accuracy of evaluating aridland riparian habitat restoration using unmanned aerial vehicles

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Abstract

Unmanned Aerial Vehicles (UAVs) offer new opportunities for accurate, repeatable vegetation assessments, which are needed to adaptively manage restored habitat. We used UAVs, ground surveys, and satellite imagery to evaluate vegetation metrics for three riparian restoration sites along the Colorado River in Mexico and we compared the data accuracy and efficiency (cost and time requirements) between the three methods. We used an off-the-shelf UAV coupled with a multispectral sensor to determine Normalized Difference Vegetation Index (NDVI) and vegetation cover. We were unable to accurately classify vegetation by individual species, but by grouping riparian species of interest (cottonwood-willow, mesquite, shrubs), we achieved high overall model accuracies of 87–96% across sites (Kappa = 0.82–0.95). Producer’s and user’s accuracies were moderate to high for target vegetation classes (69–100%). UAV and ground-survey vegetation percent cover differed due to differences in methodologies (UAVs measure aerial cover; ground surveys measure foliar cover) and sources of error for each method. Correlations between UAV and ground survey vegetation cover were moderate (rs(90) = 0.24–0.58, p < 0.05). UAV NDVI (0.50–0.61) was significantly higher than Landsat NDVI (0.40–0.45) for all sites (p < 0.0001), likely due to presence of shadows with high NDVI values in UAV imagery. UAV NDVI, Landsat NDVI and UAV total vegetation cover were strongly correlated (rs(90) = 0.72–0.85, p < 0.05). UAV surveys were more labor- and cost-intensive than ground surveys in the first year, but were slightly less so in the second year. We conclude that UAVs can provide efficient, accurate assessments of riparian vegetation, which can be used in restoration site management. Due to UAV limitations to assess vegetation in a multi-layered canopy and inability to classify individual riparian species with similar spectral signals, we recommend a combined approach of UAV and ground surveys.

Introduction

Vegetation monitoring metrics such as composition, cover and health are commonly used to evaluate riparian habitat integrity and quality for target conservation species (Elzinga et al., 1998; Michez et al., 2016). These metrics are typically quantified using field survey protocols; however, field surveys of large areas can be time consuming, costly (Merritt et al., 2017; Palmquist et al., 2018) and imprecise due to observer bias (Hope-Simpson, 1940; Scott & Hallam, 2003; Smith, 1994). Recently, Unmanned Aerial Vehicles (UAV) are increasingly being used to acquire fine spatial resolution data for ecological and conservation applications (Anderson & Gaston, 2013; Getzin...
et al., 2012; Jensen et al., 2011; Messinger et al., 2016; Rango et al., 2009). The ability of UAVs to survey long, narrow stretches of habitat at a fine spatial resolution and relatively low cost makes this technique particularly advantageous for assessing riparian habitat (Dufour et al., 2013; Dunford et al., 2009).

Even as UAV-derived ecological data technologies and methodologies evolve, researchers and managers are already using UAVs to assess a variety of ecosystem and habitat metrics. UAV-derived images have been used to monitor rangelands (Rango et al., 2009), arid lands (Sankey et al., 2018), riparian habitat (Cornejo-Denman et al., 2018; Dunford et al., 2009; Michez et al., 2016), and seagrass (Nahirnick et al., 2019) by analyzing vegetation cover, composition, structure, and distribution. UAV-derived images have also been used to monitor the distribution and spread of invasive plants in wetlands (Jensen et al., 2011) and arid lands (Elkind et al., 2019), monitor river processes controlling morphology and habitat (Lejot et al., 2007; Woodget et al., 2017), and assess fish habitat (Jensen et al., 2011; Tammenga et al., 2015).

Additionally, infrared sensors mounted on UAVs provide remotely sensed vegetation indices (VIs) with high spatial resolution—another powerful tool for vegetation assessments. VIs such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) can detect changes in greenness (a proxy for vegetation health) by assessing vegetation density and plant productivity changes over time (Bao et al., 2017; Glenn et al., 2008; Jarchow et al., 2017; Jones et al., 2008). While satellite-based NDVI and EVI have been used to evaluate the vegetation response to restoration treatments by quantifying changes in greenness (Hausner et al., 2018; Norman et al., 2014; Shanafeld et al., 2017; Wilson & Norman, 2018), the scale is often too coarse (typically 15–30 meter resolution) for site- and/or species-specific applications (Rango et al., 2009). UAV-based VIs are widely used in precision agriculture to improve crop management, including detecting vegetation stress and invasive species (Dash et al., 2017; Fang et al., 2016; Zaman et al., 2011). Similarly, although less common, UAV-based VIs have been applied to track natural vegetation phenology changes over time (Van Iersel et al., 2016) and to manage invasive plants (Lishawa et al., 2017).

The application of UAV-based vegetation assessments to ecological restoration is novel, and has the potential to significantly improve restoration outcomes through adaptive management. Just as UAVs are used to improve agricultural management, UAV-based monitoring of restoration sites could inform the timing and spatial extent of needed management actions, such as treating invasive plant species, applying water to mitigate plant stress, and planting or replanting native species to promote habitat connectivity. Over the longer term, annual repeat UAV surveys could accurately and objectively quantify the achievement of restoration goals via metrics of vegetation cover, composition, structure and health.

Both short- and long-term monitoring of restoration sites are critical to assess implementation success and habitat quality over time. However, many restoration projects fail to meet monitoring needs due to budget and time constraints (González et al., 2015; Suding, 2011). UAV-based vegetation surveys could provide managers with a cost-efficient way to assess restoration site vegetation. We tested the hypothesis that UAV-based surveys are more time- and cost-efficient than ground surveys for quantifying vegetation cover by species group in restored riparian habitat in the Colorado River Delta in Mexico.

To evaluate UAV-based vegetation surveys of restored riparian habitat in arid lands, we comprehensively compared costs, labor, and data accuracy between UAV and ground surveys. Specifically, we implemented an automated land cover classification method for UAV images and compared UAV-based to ground-surveyed vegetation cover and composition. We also compared UAV-derived to satellite-derived NDVI data.

**Materials and Methods**

**Study area**

We conducted the study in three riparian restoration sites located along the Colorado River in the Colorado River Delta (Delta) in Baja California and Sonora, Mexico (Figure 1). The Delta is a hot, arid region with a mean annual precipitation of 50 mm and temperatures exceeding 46°C in the summer (Martínez-Gutiérrez & Mayer, 2004). Historically, the Colorado River delivered 16.7 billion cubic meters of water annually (Stahle et al., 2003) to its delta, supporting 800,000 ha of wetland habitat and cottonwood-willow gallery forest several kilometers wide (MacDougal, 1904). Following the construction of large-scale dams on the river in the mid-1900s, Colorado River flows became > 100% allocated to agriculture, cities, and industry, ceasing flow at the river’s mouth. In just a few decades, the Colorado River Delta transformed into a desiccated landscape dominated by invasive saltcedar (*Tamarix* spp.) with small, disconnected patches of remnant riparian habitat (Glenn et al., 2001).

To revive portions of the Delta’s wetlands, landmark binational water management agreements Minute 319 (2013–2017) and Minute 323 (2018–2026) provided environmental flows and funding for native riparian habitat restoration along the Colorado River in Mexico (International Boundary and Water Commission, 2012, 2017).
Environmental organizations mechanically cleared restoration sites of undesirable shrubs, primarily saltcedar and arrowweed (*Pluchea sericea*), and subsequently revegetated with native plants, including cottonwood (*Populus fremontii*), willow (*Salix gooddingii* and *S. exigua*), mesquite (*Prosopis glandulosa*), and baccharis (*Baccharis salicina* and *B. salicifolia*).

We surveyed three restoration sites—Herradura (27 ha surveyed), Cori Rombo (18 ha), and CILA (80 ha) (Figure 1) in Fall 2018. During sampling, trees in the restoration sites generally ranged from 2 to 8 years in age, with a maximum height of 15–20 meters (m). The CILA and Herradura sites are predominantly restored with cottonwood and willow, while Cori Rombo is predominantly restored with mesquite, conforming to groundwater depth and soil characteristics of each site.

**Ground surveys**

In accordance with Minutes 319 and 323, a monitoring program assesses the impacts of water deliveries and restoration on vegetation and wildlife in the Delta (International Boundary and Water Commission, 2018). Vegetation monitoring plots of 5x15 m were randomly established in restoration sites with more than two years of growth. We sampled vegetation from September 14 to October 17, 2018 (end of plant growing season) at a density of 0.70–0.78 sampling plots/ha (19 plots in Herradura, 14 in Cori Rombo, and 57 in CILA). In each plot, we estimated foliar cover, or the estimated leaf area of combined layers of vegetation (Daubenmire, 1959; Floyd & Anderson, 1987), for trees and shrubs by species, for all shrubs combined, for all trees combined, and in total.
(combined trees and shrubs). Percent cover was categorized as 0%; < 1%; 1–5%; 5–25%; 25–50%; 50–75%; or 75–100%. Because birds are the primary conservation target for restored species, the ground survey methods focus on woody species (trees and shrubs) rather than ground cover or herbaceous species.

**UAV surveys**

**UAV data acquisition**

We conducted UAV flights from October 15 to November 8, 2018 using a DJI Phantom 4 quadcopter equipped with a Global Positioning System (GPS) and Global Navigation Satellite System (Glonass). We mounted (using Sky Flight Robotics Inc. kit) a MicaSense RedEdge-M (MicaSense, Seattle, WA, USA) multispectral sensor with blue, green, red, red edge, and near-infrared narrow bands. We used a DroneDeploy Desktop Flight Planning application to generate flight plans for each restoration site plus a 20-m buffer. Flight altitude was 70 m from the home waypoint with 80–85% front lap overlap, 75% side overlap, and 15 m/s maximum flight speed. We set up the multispectral sensor using the WiFi access point, selecting overlap auto-capture. We captured multispectral images in 16-bit Tagged Image File Format (TIFF). We photographed a calibration panel before and after each flight to apply a radiometric calibration. The weight of the mounted sensor limited the drone’s battery life, and several flights were required to cover each site’s flight path (Table 1). To minimize shadows, we conducted flights near solar noon. Before each flight, we established a minimum of four control points per site with visible markers that we later surveyed with a Real-Time Kinematic system (GEOMAX ZENITH 25 GNSS) to ensure geometric accuracy.

**UAV image processing**

We used Agisoft PhotoScan Professional (Version 4.3 Software 2018) to process the multispectral images, following a workflow developed by the USGS National Unmanned Aircraft Systems Project Office (USGS, 2017). We applied a MicaSense radiometric calibration function and then created a low-density point-cloud model with calibrated images. Next, we used a photogrammetric least-squares bundle adjustment to optimize photo alignment. We reduced model error by removing inaccurate points through the following iterative steps: (1) poor geometry was corrected using a reconstruction uncertainty function, (2) pixel matching errors were corrected using a projection accuracy function, and (3) pixel residual errors were adjusted using a reprojection error function. We strived for projection accuracy between 2 and 3 pixels and pixel error below 0.4 (USGS, 2017). By tightening tie point accuracy to 0.3–0.5 (within the recommended range under our flight conditions; USGS, 2017), we achieved a reprojection error of 0.3–0.35 pixels. Lastly, we built Digital Elevation Models (DEM) and orthomosaics (16-bit TIFF) for each site.

We created final rasters using the ArcGIS Pro 2.2 mosaic function. To reduce processing time for the largest site, CILA, we used a resampling function that lowered the original resolution by a factor of 5 (20-cm pixel size). We maintained the original resolution for Herradura and Cori Rombo sites (4-cm pixel size). We reprojected final rasters to World Geodetic System 1984 (WGS84) Universal Transverse Mercator (UTM) Zone 11N.

**UAV NDVI and image classification**

We calculated NDVI using the ArcGIS Pro 2.2 raster function by applying the formula:

$$\text{NDVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}},$$

where NIR is the near infrared band (Band 5) and R is the red band (Band 3) in the multispectral sensor.

We attempted to classify vegetation cover by species from UAV images, but were unable to do so with acceptable accuracy. Therefore, we grouped cover types into the following classes: 1) cottonwood and willow, 2) mesquite, 3) shrubs, 4) herbaceous species (only in Cori Rombo), 5) bare ground, 6) water, and 7) shadow. We classified images using supervised classification methods (both object- and pixel-based) and Supportive Vector Machine (SVM) classifier in ArcGIS Pro 2.2. As classification variables, we used the five bands plus the NDVI layer for the Cori Rombo and CILA sites, and just the five bands for the Herradura.

We trained the classification by selecting samples from the segmented image using approximately 1% of the image pixels for training and 1% for validation. The training sample classes were defined based on expert experience.
knowledge of the cover types in the sites. To evaluate classification accuracy, we used a stratified random sampling strategy to produce a confusion matrix of producer’s, user’s, and overall classification accuracy. Producer’s accuracy is the proportion of correctly classified pixels. User’s accuracy is the number of correct predictions relative to the total number of times a class was predicted. We used the Kappa coefficient to assess overall agreement of the confusion matrix, which removes pixels that may have been classified correctly by chance (Wegmann et al., 2016). Kappa coefficient values close to 1 indicate high model accuracy (Cohen, 1960).

**Landsat NDVI**

Collaborating with the University of Arizona Vegetation Index and Phenology Lab, we acquired and processed Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) Collection 1 Level 2 satellite data (https://eathexplorer.ugsg.gov/), including NDVI, surface reflectance, and pixel quality. Cloudy pixels were filtered out using Quality Assessment band pixel-level validity flags. We created rasters in ArcGIS Pro 2.2 using images collected on dates that closely matched the UAV survey dates.

**Statistical analyses**

To assess method performance, we compared UAV- to ground survey-derived vegetation cover at plot and site scales for each site. For plot-scale ground survey vegetation cover, we used percent cover of each cover class (total vegetation cover, cottonwood-willow, mesquite, and shrubs) in vegetation plots (75 m²) to calculate the mean value for each site. For plot-scale UAV cover, we used ArcGIS Pro 2.2 zonal statistics computation tool to extract mean percent UAV cover by class from circular polygons (15-m diameter) encompassing each ground survey vegetation plot center. For site-scale UAV cover, we calculated the area of each cover class and the percent cover for each vegetation type.

We also compared UAV- to Landsat-derived NDVI at plot and site scales. For plot-scale Landsat NDVI, we calculated weighted mean NDVI of each 15 m-diameter polygon, and for UAV NDVI, we extracted mean NDVI from the 15-m polygons. To compare site-scale UAV and Landsat NDVI, we calculated mean UAV NDVI for the same area occupied by the 30-m Landsat pixels and averaged the values of the 30-m areas for each site.

For all vegetation percent cover and NDVI data, we tested data normality using a Shapiro test. We used a paired t-test and Sign test in R version 3.3.1 (R Core Team, 2016) BSDA package (Arnholt & Evans, 2017) to detect significant differences between plot-scale UAV and ground-surveyed percent cover and between UAV and Landsat NDVI at plot and site scales.

We performed a correlation analysis using combined restoration site data to assess the relationships between UAV-based metrics (NDVI, total vegetation cover, and vegetation cover by species group), ground-based metrics (combined shrubs and trees, and vegetation cover by species group), and Landsat NDVI. We conducted a Spearman’s Rank Order correlation, as our data did not meet normality assumptions, and tested correlation significance at the 0.05 level using R version 3.3.1 (R Core Team, 2016), packages Hmisc and Corrplot. We developed correlograms, which are graphical representations of a correlation matrix, to show Spearman’s coefficient values and the statistical significance of each relationship analyzed.

**Comparison of efficiency**

Efficiency was assessed by comparing the time spent to complete project tasks and the overall cost of UAV versus ground surveys. We report the percent difference in time spent and costs by site, rather than per unit area, because ground surveys sample a significantly smaller area than drone surveys, thus making them inherently more expensive per unit area. Because our objective is to characterize vegetation at the site scale, percent difference is appropriate.

\[
\% \text{ difference cost of task n} = \frac{\text{UAV survey cost for task n (100)}}{\text{Ground survey cost for task n}},
\]

\[
\% \text{ difference time spent of task n} = \frac{\text{UAV survey hours for task n (100)}}{\text{Ground survey hours for task n}}.
\]

**Results**

**UAV cover classification accuracy**

Overall accuracies of UAV-derived land cover classifications (Figures 2–4) were high, ranging from 87% for CILA (kappa = 0.82) to 96% for Herradura (kappa = 0.94) and Cori Rombo (kappa = 0.95) (Tables 2–4). Producer’s and user’s accuracy were very high (94–100%) for the non-vegetation classes (bare ground, water, and shadow) in all sites, except for low user’s accuracy of shadow cover (40%) in CILA, where shadows within shrub canopies were classified as shrubs, and CILA bare ground cover (80%), where shrubs were classified as bare ground.

Producer’s and user’s accuracies were relatively high for the target vegetation classes (69–100%), except for herbaceous cover in Cori Rombo (58% producer’s accuracy, 50% user’s accuracy). Shrub and herbaceous cover mixed with cottonwood-willow and mesquite trees were
misidentified during the sample training process and misclassified at all sites. On average across sites, mesquite cover class had the highest producer’s accuracy, while shrub cover class had the highest user’s accuracy but the lowest producer’s accuracy. In other words, although the UAV method accurately mapped shrubs when they were present, it also tended to map other cover types as shrubs.

**UAV, ground survey, and Landsat comparisons**

Agreement between UAV- and ground-survey vegetation cover estimates varied by cover class and by site (Figure 5). Across nearly all sites and all cover classes, site-scale UAV cover estimates were less than plot-scale UAV- and ground-based cover (Figure 5).
UAV NDVI was significantly higher than Landsat NDVI for all sites (Figure 6). UAV NDVI followed a similar pattern across sites as UAV plot-scale total vegetation cover and shrub cover (Figure 5).

**UAV, Landsat, and ground survey correlations**

UAV NDVI and Landsat NDVI were strongly correlated ($r_s(90) = 0.77$, $p < 0.05$). UAV total vegetation cover was positively correlated with both UAV NDVI and Landsat NDVI ($r_s(90) = 0.85$, $p < 0.05$; $r_s(90) = 0.72$, $p < 0.05$, respectively) (Figure 7). UAV-based vegetation cover classes (cottonwood-willow, mesquite, and shrubs) were significantly correlated with UAV and Landsat NDVI ($r_s(90) = 0.23–0.63$, $p < 0.05$), with UAV cottonwood-willow having the strongest correlation to NDVI.

Correlations between UAV and ground survey vegetation cover were moderate in most cases, with significant positive correlations between all UAV cover estimates and their corresponding ground-based estimates ($r_s(90) = 0.24–0.58$, $p < 0.05$) (Figure 6). Additionally, UAV cottonwood-
willow was positively correlated with ground-based combined tree and shrub cover \((r_s(90) = 0.43, p < 0.05)\).

**Efficiency comparisons**

First-year UAV-based vegetation survey costs greatly exceeded ground-based vegetation survey costs. In year 1, UAV surveys cost 104% more and required 46% more time than ground surveys (Table 5). In year 2, after equipment had been obtained and methods learned, UAV surveys became slightly more cost- and time-efficient than ground surveys.

**Discussion**

**Evaluation of UAV-based vegetation assessment methods**

Combining object-based and pixel-based classification methods, we classified riparian restoration site vegetation cover by species groups of interest (cottonwood-willow and mesquite), achieving high overall accuracies (> 85%) for most vegetation cover classes and sites.

Variation in site producer’s and user’s accuracies are related to site composition and structure. For example, mixed canopies of tall cottonwood-willow with shrub understories led to errors of omission (producer’s accuracy) and commission (user’s accuracy) at Herradura and CILA, where it was difficult to separate the spectral signatures of these species. In contrast, as the youngest and mesquite-dominated site, Cori Rombo, has a less stratified vertical canopy and fewer vegetation classification errors (with the exception of the herbaceous class, which includes diverse grass and herbaceous species). At CILA shrubs were misclassified as bare ground or shadows. This is likely due to errors introduced during the reflectance calibration process which created image irregularities within spectral properties.

We were unable to accurately classify the UAV spectral images by individual riparian species of interest. Similarly, Dunford et al., (2009) had difficulty distinguishing...
between poplar and willow species and individual pine species in Mediterranean riparian forest using UAV orthomosaic image classification. Our cottonwood-willow class producer’s (82–97%) and user’s accuracies (75–88%) were higher than Dunford et al., (2009) (producer’s accuracies of 46–70% depending on the classification method used; user’s accuracies of 37–86%), likely due to our combined species approach. Misclassification in Dunford et al., (2009) study also resulted from changes in radiometric conditions across the landscape due to variable light conditions during acquisition. Even though we calibrated the images before processing, it is difficult to assess the extent to which our classification error results from conducting flights over the course of several days, with inevitable differences in light conditions.

Michez et al., (2016) distinguished between individual species in Belgium riparian forest (alder, ash, sycamore maple, pine, and willow species) with relatively high accuracies (producer’s accuracies > 75%, user’s accuracies > 77%). However, their study focused on species composition and identification of diseased trees, not on percent cover. By sampling late in the year, they used phenological differences to distinguish between evergreen pine trees and deciduous riparian trees that had lost foliage, but this would not work well to estimate foliar cover, as was the purpose of this study.
Sankey et al., (2018) classified semi-arid vegetation using a custom-integrated UAV octocopter with survey-grade GPS, Light Detection and Ranging (lidar) scanner, and hyperspectral nano-sensor, achieving producer’s accuracies of 82–100% and user’s accuracies of 55–91% for individual shrub and grass species. In their study, classification error primarily resulted from similar spectral signatures of species. As previously noted, we encountered similar spectral signatures between cottonwood-willow and mesquite classes and to a lesser degree with shrubs (see supplemental information). Cottonwood and willow species’ NDVI ranges overlap with those of arrowweed and nonnative saltcedar (0.4–0.8 and 0.1–0.8 respectively; Nagler et al., 2001, 2004), which are common understory species in all of our restoration sites. This in part explains the difficulties in accurately classifying native riparian target species. Morphological similarity between species can also complicate classification at the species level (Mishra et al., 2018).

Lidar technology combined with high-resolution spectral imagery has been used to classify riparian vegetation by species in other studies; however, this approach is very

Table 5. Efficiency comparisons between UAV monitoring and ground survey monitoring.

| Tasks                        | Time spent (% difference) | Year 1 | Year 2 |
|------------------------------|---------------------------|--------|--------|
| Training/Research/Testing    | 361%                      | –83%   |        |
| Data Collection              | –56%                      | –56%   |        |
| Data Processing/Analysis     | 248%                      | 148%   |        |
| Reporting                    | 13%                       | 13%    |        |
| Project Management           | –12%                      | –12%   |        |
| Total                        | 46%                       | –14%   |        |

Cost (% difference)

| Item            | Year 1 | Year 2 |
|-----------------|--------|--------|
| Labor           | 57%    | –7%    |
| Travel          | –22%   | –60%   |
| Equipment       | 972%   | 124%   |
| Total           | 104%   | –4%    |

Positive numbers indicate that UAV cost or time exceeded that of ground surveying.

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Lidar technology combined with high-resolution spectral imagery has been used to classify riparian vegetation by species in other studies; however, this approach is very
expensive and thus can limit its application (Huylenbroeck et al., 2020). While Sankey et al., (2018) use of UAV lidar and hyperspectral imagery classified species fairly accurately, the cost of their specialized and custom-integrated equipment is prohibitive for most routine applications.

**Comparison of UAV and ground survey methods**

Differences in percent vegetation cover estimated by UAV and ground surveys are due to differences between methods as well as sources of error associated with each method. UAV surveys quantify aerial vegetation cover, whereas ground surveys quantify foliar cover of all vertically overlapping species. Without lidar, UAV surveys cannot accurately quantify understory species cover. This was evident for the Herradura site, where UAV surveys did not quantify willow species cover beneath taller cottonwoods, leading to a significant difference between ground-based and UAV-based cover estimates.

In sites where the upper tree canopy layer is sparse, UAV surveys can quantitatively herbaceous and grass species cover. At Cori Rombo, where mesquite trees sparsely cover an understory of grass, herbaceous, and shrub species, vegetation cover estimates by UAV greatly exceeded estimates from ground surveys, which did not include grass and herbaceous species. In contrast, UAV and ground survey estimates were statistically similar at the CILA and Herradura sites, where the upper tree canopy is dense.

Site-scale UAV percent cover estimates tended to be lower than both UAV and ground survey plot-scale estimates. This makes sense because site-scale surveys include roads, firebreaks, and surface water, which are not included in ground surveys and UAV plot-scale analyses because plots are located only in areas that were planted with native vegetation.

Errors in the UAV-based approach due to the classification process and presence of shadows also contributed to differences in cover estimates. For example, UAV classification of cottonwood-willow in Cori Rombo may have included seepwillow (*Baccharis salicifolia*), whereas ground surveys do not. Seepwillow has a spectral signature for NDVI that overlaps with willow and cottonwood species (0.1–0.7; Nguyen et al., 2019). On the other hand, ground survey errors likely result from more subjective human visual estimates of cover classes, introducing bias. This bias can be minimized through training and calibration.

Rango et al., (2009) analyzed the relationship between UAV and ground survey-derived rangeland vegetation cover, achieving higher correlation ($R^2 = 0.86–0.98$) than in our study ($R^2 = 0.24–0.58$). In our study, combining data from three restoration sites likely weakened correlations between UAV and ground surveys because the sites differ in dominant species and vegetation structure. Also, riparian habitat is more structurally diverse than ranges, with layered canopies that present additional challenges for classification.

**UAV NDVI and Landsat NDVI**

In theory, satellite and UAV platforms should produce comparable NDVI results at different scales, despite the different radiometric behaviors of their respective sensors (Khaliq et al., 2019). As expected, NDVI from both sensors was correlated in our study; however, UAV NDVI was significantly higher than Landsat NDVI in all sites, contrary to other comparative studies (Zabala, 2017). Our higher UAV NDVI is likely due to differences in the radiometric resolution and bidirectional reflectance distribution function (BRDF), a result of angular variation in reflectance (Ramussen et al., 2016). Landsat has a wider range in the red band than the multispectral sensor used in this study (636–673 nanometers (nm) vs. 664–673, respectively), but a narrower range in the near-infrared band (851–879 nm vs. 820–860 nm). In addition, the orthomosaics we generated had shadows with NDVI values $> 0$, which likely contributed to an overestimation of NDVI. Future studies should investigate these issues, and develop an NDVI processing workflow to mask out shadows. Despite the inaccuracies we observed in UAV NDVI, the high-resolution UAV raster was useful for distinguishing green foliar cover from non-vegetation classes during the classification workflow.

Due to its finer spatial resolution, UAV NDVI is better suited than Landsat NDVI for surveying riparian habitat. Riparian habitat patches in our restoration sites and elsewhere can be very narrow, thus making up a small portion of a 30-m Landsat pixel. In contrast, UAVs can retrieve the NDVI values that correspond only to the riparian habitat, avoiding the spectral signature from adjacent non-riparian areas. On the other hand, if a restoration site or riparian habitat patch is large, then UAV surveys conducted over several days with different light and flight conditions can result in significant errors related to BRDF (Rasmussen et al., 2016; Stark et al., 2016). Future research should assess the magnitude of error caused by temporal variations in UAV NDVI.

Multispectral sensors are commonly used to map NDVI for precision agriculture (Loures et al., 2020; Tsouros et al., 2019), but applying them to assess restored riparian vegetation health is novel. In precision agriculture, NDVI is used to locate areas that require changes in irrigation or fertilizer application. Similarly, in restoration sites, high-resolution UAV NDVI can track spatial-temporal trends in vegetation health at different scales, enabling managers to target actions at appropriate scales, and
potentially reduce management costs. Restoration management applications of UAV NDVI include detection of hydric stress or plant die-off caused by pests. In the arid Delta, where water is scarce, optimization of water use in restoration sites is particularly important. Restoration site-scale UAV NDVI assessments can show spatial-temporal trends in plant water use, including impacts of seasonal groundwater and surface water fluctuations on riparian vegetation, which can inform timing and magnitude of environmental flows. Patch- and plot-scale NDVI can be used to fine-tune irrigation to optimize water use. Additionally, UAV NDVI could help restoration managers track the advance of the saltcedar beetle, portending invasive saltcedar defoliation.

**Comparison of efficiency**

UAV-based survey costs and time requirements exceeded those of ground surveys in the first year, when we purchased expensive equipment (drones, sensors, and licenses) and spent considerable time learning data collection, processing, and analysis methods. In the second year, UAV-based surveys became slightly more cost- and time-efficient than ground surveys. Yet, due to differences in the data types that each method provides, we do not recommend that UAV surveys replace ground surveys; instead, we view them as complementary approaches, as Dufour et al., (2013) also suggested. Each restoration site has different monitoring data requirements and limitations, as we found in our study.

Before deciding whether to conduct UAV-based vegetation surveys, users must consider the implications of multispectral sensors’ limited ability to accurately quantify individual target species. If habitat structure, understory, or ground cover layers are important to monitor, then ground surveying is required (in the absence of UAV lidar). If mapping aerial cover of vegetation groups, rather than individual species, will suffice, then UAVs can map large areas more readily than ground surveys.

UAV surveys have a recognized potential of becoming a standard tool for evaluating vegetation response to restoration (Kamm & Reed, 2019). However, UAV-based vegetation mapping still involves ground truthing. UAV image classification of riparian restoration sites with a diversity of plant species requires in-depth knowledge and existing species composition data during the sample-training phase. In some studies, integrating data from the DEM or cloud model into the classification workflow helped distinguish between shrubs and tree species (Cruzan et al., 2016); we recommend applying this approach to sites with diverse canopy heights.

In addition, standardized, repeatable workflows from data acquisition to image classification are required for tracking short- and long-term changes in riparian vegetation. Online workflow-sharing platforms can help practitioners create site-specific protocols (Gillan et al., 2020). However, UAV is a rapidly evolving technology. Because new equipment and software are continually being developed, established UAV survey protocols and processing workflows can quickly become obsolete. In contrast, ground protocols are stable and repeatable, but are labor intensive, typically covering very small areas compared to UAVs. Given these trade-offs, at the current time, ground methods complemented with UAV surveys are the gold standard to monitor riparian restoration sites.

**Conclusions**

We developed and demonstrated an efficient workflow that successfully used UAVs to map vegetation classes and NDVI in riparian restoration sites. Few studies have quantified riparian cover types using UAV survey methods (Cornejo-Denman et al., 2018; Dunford et al., 2009; Michez et al., 2016). Our study is the first to use UAV multispectral imagery to classify arid land riparian vegetation cover using automated methods.

Because UAV imagery is inherently limited to the canopy top, ground surveys more accurately map understory. Nevertheless, UAVs are useful and accurate for monitoring changes in restored riparian vegetation species cover and health over time. In the future, when UAV-based lidar becomes more affordable, its use in combination with high-resolution spectral imagery will improve UAV-based vegetation classification.

UAV-based NDVI data compare well to satellite-based NDVI. Due to its finer spatial resolution, UAV-based NDVI is better suited for evaluating riparian vegetation, which typically occurs in narrow, linear bands. Satellite-based NDVI lumps these vegetation bands into pixels that exceed their width and therefore include multiple vegetation types.

We hypothesized that UAV-based vegetation surveys are more time- and cost-efficient than ground surveys for assessing restored riparian vegetation. We found that first-year labor and equipment costs of UAV vegetation monitoring exceeded those of ground surveys due to one-time drone and sensor acquisition expenses and process development and learning. However, by the second year, the costs of UAV surveys were slightly less than that of ground surveys.

Although ground surveys will always be needed to ground-truth UAV data, over time UAV mapping can gradually replace ground surveying at previously surveyed sites. The accuracy and efficiency of UAV-based photogrammetry and NDVI for mapping restored riparian vegetation warrant its further development for widespread application.
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Data Availability Statement

Project data are freely available in the ScienceBase-Catalog, Minute 319/323 chapter in the following link https://www.sciencebase.gov/catalog/item/5f3aaf5a82ce8df5b6c4075c.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Figure S1. Spectral profile of landcover types in the Herradura site

Table S1. UAV-derived land cover class area and percent cover of total site for the three restoration sites.