

RESEARCH ARTICLE

Evaluating floodplain vegetation after valley-scale restoration with unsupervised classification of National Agriculture Imagery Program data in semi-arid environments

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Abstract

Monitoring vegetation response to valley-scale floodplain restoration to evaluate effectiveness can be costly and time-consuming. We used publicly available National Agriculture Imagery Program (NAIP) data and commonly used ArcGIS software to assess land cover change over time at five study sites located in semi-arid environments of eastern Oregon and north-central California. Accuracy assessments of our unsupervised classifications were used to evaluate effectiveness. Overall accuracy across sites and years ranged from 64.2% to 89.2% with mean and median accuracy of 79.1% and 80.6%, respectively. Further, we compared our classifications with high-resolution uncrewed aerial systems (UAS)-based data collected in the same timeframe. Restored areas classified as dense vegetation were within 4% of the UAS study, water was within 6%, and post-restoration classifications of sparse vegetation and bare ground classes were within 6% and 4% of the UAS study, respectively. This comparison demonstrates that our unsupervised NAIP data classification of land cover change across entire valley-scale restoration projects can be used to monitor riparian vegetation change over time as accurately as UAS-based methods, but at lower cost. Additionally, our methods leverage existing fine-resolution, pre-restoration vegetation density data that were not collected as part of project planning.

KEYWORDS

land cover, valley-scale, NAIP, riparian, floodplain restoration, remote sensing, unsupervised classification, vegetation

1 | INTRODUCTION

Recent decades have seen the implementation of innovative valley-scale restoration projects that functionally link disconnected river channels to their floodplains (Florsheim et al., 2006). These projects are designed to re-couple biological and hydrogeomorphic processes, creating a system designed to be both dynamic in terms of habitat complexity over short time periods (Cluer & Thorne, 2014) and also resilient to large-scale disturbances such as wildfire (Norman et al., 2022; Pugh et al., 2022). A fundamental goal of these

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Research Impact Statement

Our classification of National Agriculture Imagery Program data provides a cost-effective method of determining vegetation response after valley-scale restoration in semi-arid environments.

projects is to reduce the depth to subsurface water (Powers et al., 2019). In some cases, wells have been used to measure this outcome (Flitcroft et al., 2022), but vegetation that requires more consistent access to subsurface water may also serve a similar purpose (McCurdy et al., 2021). It is hypothesized that a key element of valley-scale floodplain restoration is the development of robust vegetation communities that interact with surface and subsurface water to create mosaics of complex habitat across the valley floor (Cluer & Thorne, 2014; Powers et al., 2019). Habitat mosaics in large floodplain-restoration efforts have been demonstrated to contain unique and varied biological communities (Pander et al., 2018). Vegetated islands and wet woodlands or grasslands have been included as possible outcomes of valley-wide floodplain restoration (Cluer & Thorne, 2014; Flitcroft et al., 2022). These complex environments have been shown to host diverse communities of benthic macroinvertebrates in post-restoration environments spread across a larger wetted area (Flitcroft et al., 2022; Jennings et al., 2023).

Evaluation of the effectiveness of valley-wide restoration requires the development of different tools and monitoring methods compared with more traditional forms of river restoration that target stream channels (Flitcroft et al., 2022). Relationships between ecologically important characteristics such as riparian vegetation or biological richness are not well understood in large river systems (Erős et al., 2019). The lack of floodplain monitoring tools likely reflects the absence of a nuanced understanding of hydrogeomorphic floodplain processes and biota. Large floodplain projects are an emerging area of river restoration that is challenging to monitor owing to a variety of practical considerations including: the overall size of the projects; treacherous terrain developed by the process (e.g., unstable saturated sediment and large wood complexes); the cost of monitoring methods and tools; and limited research that identifies specific anticipated outcomes and functional relationships to guide monitoring targets. In practice, there are often few or no data describing the vegetation and water distribution in the restoration area prior to work implementation. Limited budgets for monitoring activities are common and further constrain project-specific effectiveness monitoring particularly as it relates to biota (e.g., vegetation, macroinvertebrates, vertebrates).

Vegetation composition pre- and post-restoration signals changes in species composition, but also alterations in sediment and fluvial processes, and may be monitored using remotely-sensed imagery. For example, in arid and semi-arid environments vegetation is often characterized by meadow and/or shrub communities that reflect patterns of seasonal inundation, resilience to flooding, and depth to groundwater (Stromberg et al., 2007). The vegetation in arid and semi-arid areas enters dormancy or begins senescence during the summer months, but still reflects patterns of hydrologic connectivity (Manning et al., 2020). Plants that are still green in color are typically dense vegetation, like large shrubs and trees, or sparse vegetation in wetland areas or where plants have access to elevated water tables (Ridolfi et al., 2006). In arid environments, vegetation community composition has been mapped with a variety of remote sensing tools (e.g., with Sentinel-2A, Iskin & Wohl, 2022; with NDVI MODIS, Páscoa et al., 2020; with Landsat, Barron et al., 2014; a review, Becker, 2005), allowing for the development of relationships between surface and subsurface groundwater (in southwestern United States see Norman et al., 2014; Wilson et al., 2016; Wilson & Norman, 2018; in eastern Australia, see Fu & Burgher, 2015).

National Agriculture Imagery Program (NAIP) imagery was selected for this project because it is available publicly, has fine spatial (1-m, 0.6-m in 2020 imagery) and spectral (4-band: red, green, blue, and near-infrared) resolution, and numerous studies have evaluated methods for land cover classification using this imagery (Maxwell et al., 2017). However, many of these studies use specialized remote sensing software and ancillary data sources or only use NAIP imagery for validation of satellite imagery (Halabisky et al., 2011, 2016; Weber et al., 2022).

In this study, we explored two research objectives to inform cost-effective approaches for valley-scale monitoring of vegetation density response to restoration in semi-arid environments at floodplain restoration sites in Oregon and California (United States of America, U.S.A.). In particular, our questions are:

- What is the accuracy of vegetation classifications using NAIP data compared to a classification produced from uncrewed aerial systems (UAS) imagery paired with a ground-based site survey?
- How do the densities of vegetation communities change after valley-scale floodplain restoration?

2 | METHODS

2.1 | Study sites

Study sites were selected based on a history of valley-scale floodplain restoration activities, ability to differentiate land cover types (e.g., water, bare ground, dense vegetation, etc.), and availability of comparison data. All sites are located in semi-arid environments of eastern Oregon or central California (Figure 1). In each case, NAIP imagery was available both before and after restoration to evaluate the effect of valley-scale floodplain restoration (Tables 1 and 2).

2.1.1 | Whychus Canyon

Whychus Canyon (WC) is located in eastern Oregon at the boundary between the Cascades and Intermountain ecological provinces and, more specifically, the area where the eastern Cascade Range joins the Columbia Basin (Campbell et al., 2003). The upland areas of this region are dominated by ponderosa pine (*Pinus ponderosa*). Riparian areas and wet meadows support a greater diversity of grasses, shrubs, and trees, including black cottonwood (*Populus trichocarpa*), compared with upland areas (Crowe et al., 2004). Whychus Creek has its headwaters in the glaciers of the Three Sisters peaks of the Cascades and flows approximately 66 km before reaching its confluence with the Deschutes

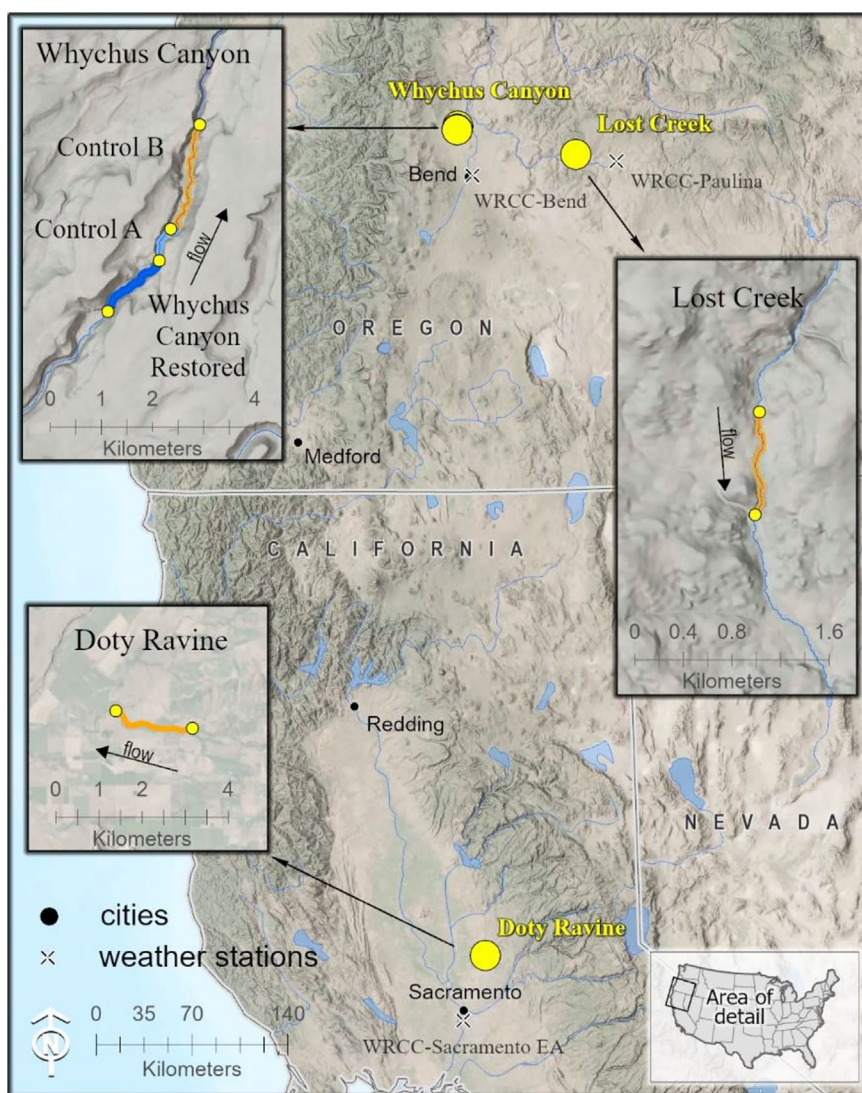


FIGURE 1 Restoration site locations in eastern Oregon and north central California, U.S.A. (yellow dots on main map). The study site reach lengths are delineated between upstream and downstream yellow dots in the insets. Locations of Western Regional Climate Center weather stations are symbolized by X's. WRCC, Western Regional Climate Center.

TABLE 1 Summary of restoration status, date of restoration, total restored area, and pour point of restored area for the study sites. Total restored area is the area directly affected by restoration action. Pour point area is the area of the watershed draining to the study site.

Site	State	Status	Restoration date	Total restored area (ha)	Pour point area (ha)
Doty Ravine	CA	Restored	2016	48.2	6349
Lost Creek	OR	Restored	October 2012	4.6	2179
WC Restored	OR	Restored	Summer 2016	18.0	61,534
WC Control A	OR	Unrestored	N/A	8.8	61,664
WC Control B	OR	Unrestored	N/A	39.3	61,942

TABLE 2 Summary of National Agriculture Imagery Program (NAIP) data acquisition dates for the imagery used in this analysis.

Site	Year					
	2009	2012	2014	2016	2018	2020
Doty Ravine	3 July	5 July		10 July	21 July	9 July
Lost Creek	25 June	10 June		25 June		4 July
WC Restored	30 June		30 June			25 June
WC Control A	30 June		30 June	21 June		25 June
WC Control B	30 June			21 June		25 June

River (USFS, 2010). Whychus Creek within WC has been affected by water removal for irrigation as well as channelization and straightening. Restoration actions at WC were designed to increase habitat diversity and reconnect relic valley-floor floodplain habitats (Edwards et al., 2020). Three study sites were located in WC and ranged in elevation from 790 to 830 m (USGS, 2024).

Average monthly air temperature, precipitation, and snowfall data were retrieved from the Western Regional Climate Center (WRCC) for the Bend station located 40 km southeast of WC (Figure 1). Climate normals for this station were determined by WRCC from data collected between 1928 and 2005 (WRCC, 2024). WC has average annual precipitation of 29.5 and 82.3 cm of snow. Rainfall occurs throughout the year with the majority occurring between November and June. Snowfall is concentrated between the months of November and April (Figure 2a). January is the coldest month with average minimum temperature of -5.7°C and average maximum of 4.8°C whereas hottest temperatures occur in July with average maximum temperature reaching 27.8°C and average minimum of 7.6°C .

Restoration at WC-Restored (Latitude: 44.37, Longitude: -121.42) was completed in 2016. At WC-Restored, wood was added to the stream coincident with the redistribution of sediments to fill low areas and spread water across the valley floor. The type of valley-floor restoration performed at WC-Restored is implemented to facilitate self-forming and dynamic wetland-stream complexes (Flitcroft et al., 2022). WC-Restored and two unrestored control sites were part of a separate field survey executed using UAS and analyzed by McCurdy et al. (2021). The two unrestored control sites included in our study at WC were Control A (Latitude: 44.37, Longitude: -121.41) and Control B (Latitude: 44.39, Longitude: -121.41). We compared our vegetation classification using NAIP imagery (more description in *Data Sources*) with the results of the McCurdy et al. (2021) study. WC-Restored had an 18-ha restoration area and 1.6-km reach length, Control A had an 8.8-ha potential restoration area with a 0.7-km reach length, and Control B had a 39.3-ha potential restoration area and a 2.8-km reach length (Table 1).

2.1.2 | Lost Creek

Lost Creek (Latitude: 44.19, Longitude: -120.33) is located in eastern Oregon between 1227 and 1242 m elevation in the foothills of the Ochoco Mountains (USGS, 2024). Restoration activities took place in 2012 with the intended purpose of stabilizing an incised channel and restoring floodplain connectivity using subsurface rock grade-control structures, or check dams (Norman et al., 2016, 2022), and cross-vane/step-pool structures. Average monthly normal temperature, precipitation, and snowfall data were retrieved from the WRCC for the Paulina station located 30 km east of Lost Creek (Figure 1). Climate normals for this station were determined by WRCC from data collected between 1961 and 2005 (WRCC, 2024). Lost Creek has average annual precipitation of 28.6 cm with 56.6 cm of snow. Rainfall occurs throughout the year with the majority occurring between October and June. Snowfall is concentrated between the months of November and April (Figure 2b). January is the coldest month with average minimum temperature of -8.0°C and average maximum of 3.8°C . Warmest temperatures occur in July, with average maximum temperature reaching 30.4°C and average minimum of 6.3°C (WRCC, 2024). Lost Creek had a 4.6-ha restoration area and a 0.95-km reach length (Table 1).

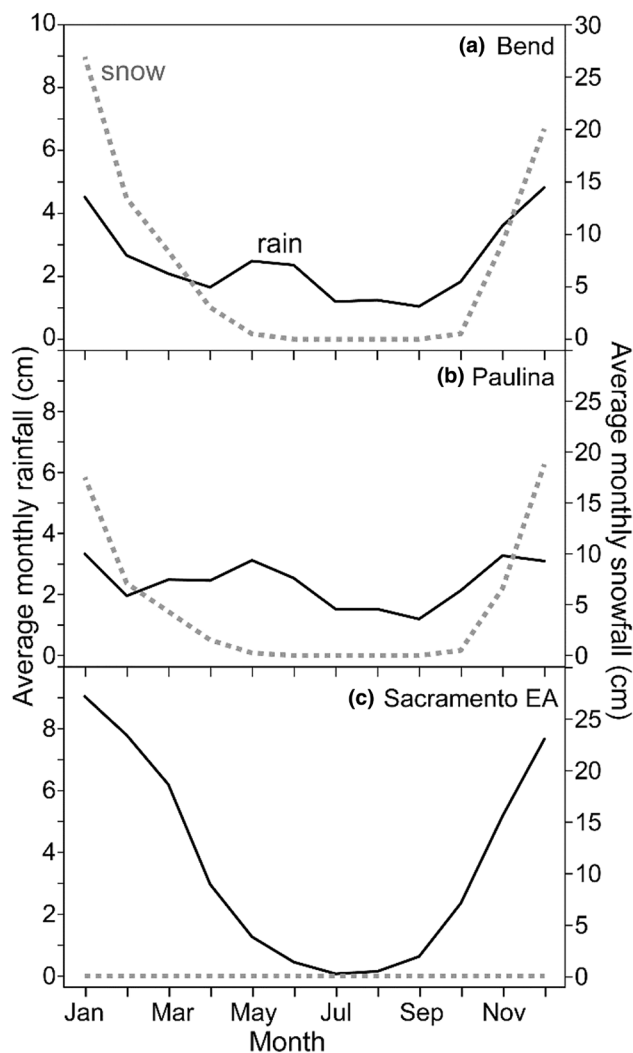


FIGURE 2 Timing of average annual precipitation and snowfall at (a) Bend (Whychus Canyon [WC], OR), (b) Paulina (Lost Creek, OR) and (c) Sacramento Executive Airport (Doty Ravine, CA) based on WRCC data.

2.1.3 | Doty Ravine

Doty Ravine (Latitude: 38.94, Longitude: -121.29) is located in the 62-km² Doty Ravine Creek Basin in the Sierra Nevada foothills of north-central California, with a study site elevation ranging from 47 to 50 m (Ciotti et al., 2021; USGS, 2024). Restoration at this site included levee removal and installation of beaver dam analogs (e.g., Pollock et al., 2014) in 2016. The site was also modified by a natural flood pulse event in February 2018. Average monthly normal temperature, precipitation, and snowfall data were retrieved from the WRCC for the Sacramento Executive Airport (Sacramento EA) station located 50 km southwest of Doty Ravine (Figure 1). Climate normals for this station were determined by WRCC from data collected between 1941 and 2016 (WRCC, 2024). Doty Ravine has average annual precipitation of 43.8 cm and no snow. Rainfall occurs throughout the year, with the majority occurring between October and April (Figure 2c). January is the coldest month with minimum average temperature of 3.2°C and maximum average temperature of 11.9°C; warmest temperatures occur in July, with average maximum temperature reaching 33.7°C and minimum average temperature of 14.6°C (WRCC, 2024). It has a 48-ha restoration area and 1.6-km reach length (Ciotti et al., 2021; Table 1).

2.2 | Data sources

NAIP imagery was available for download at all sites for 2009, 2012, 2014, 2016, 2018, and 2020 (Table 2) from USGS Earth Explorer (USGS, 2021). The individual NAIP imagery frames associated with each study site were downloaded for analysis. Throughout the United

States, NAIP imagery is collected within a window of opportunity defined by time of day, time of year, and clear weather (Maxwell et al., 2017). As such, some years of imagery data were excluded at some sites for blurriness or containing excessive shadows in images collected too early in the morning or too late in the afternoon. The exact dates of the available imagery that were used for analysis at each site are presented in Table 2.

We selected ArcGIS as our imagery analysis tool because of its ubiquity among federal, academic, and non-governmental organizations. This choice was intended to circumvent the organizational and technical barriers that have been previously identified as problems preventing adoption and incorporation of new tools, including lack of trained staff, insufficient software and tools, and lack of technical knowledge (Ye et al., 2013). Although we selected ArcGIS as our tool for this study, QGIS is an open-source GIS application with many of the same features that could potentially be used to complete the classifications described in this study (Khan & Mohiuddin, 2018).

2.3 | Vegetation classification

The individual NAIP raster imagery frames were mosaicked for each site and year as needed to develop full coverage for each site. After mosaicking, we produced two additional layers for use as inputs to our classification model.

We used the image segmentation function (in ArcMap 10.5.1 software), which groups pixels based on proximity and similarity of spectral characteristics. Each segment represents a single value that was evaluated as an input for the classification. The image segmentation tool was used with the default settings of Spectral: 15.5, Spatial: 15, and Segment: 20.

A Normalized Difference Vegetation Index (NDVI) raster was created using the NDVI tool in ArcMap 10.5.1. NDVI is the normalized difference of the near-infrared and red bands and can aid with identifying vegetation density. We incorporated the NDVI raster as an input layer for the unsupervised classification to assist with classifying vegetation densities (Pettorelli et al., 2005; Reed et al., 1994).

When determining whether to use unsupervised or supervised classification methods, we chose not to use a supervised classification method because the imagery had been collected over a long time period using different sensors. A new training set would have been required for each sampling event, negating the processing-time benefits associated with supervised classifications.

The IsoCluster Unsupervised Classification ArcGIS tool was used to perform the classification with the following six inputs: segmented image, NDVI raster, and the red, green, blue, and near-infrared NAIP bands. Unsupervised classification allows the ArcGIS software to assign the image pixels to cluster classes based on statistical difference and spectral characteristics. The IsoCluster function clusters the multivariate data combined in a list of input bands (ArcGIS, 2024). The IsoCluster Unsupervised Classification produced 50 cluster classes with a minimum class size of 20 and a sample interval of 10. Preliminary evaluation found that fewer initial cluster classes (e.g., 5–10 classes) resulted in greater overall classification error, and we achieved an output with less error after manually reclassifying a greater number of cluster classes (e.g., 50 classes). The initial cluster classes were then manually reclassified to 5 classes (sparse vegetation, dense vegetation, bare earth, water, and shadow) by comparing the classification to the original NAIP imagery displayed as false color composite (Appendix S2). We selected these classes because they could be visually differentiated in the NAIP imagery and verified with the McCurdy et al. (2021) classification maps. We visually differentiated the classes by creating a false-color composite (FCC) image. Dense vegetation, sparse vegetation, and bare earth were visually classified as areas of opaque pink, dispersed pink, and blue/gray, respectively. Areas containing water were visually classified as light to dark blue. Doty Ravine results were reduced to six classes rather than five, because it was the only study site that also included a paved road (Appendix S2).

2.4 | Vegetation classification accuracy assessment

We produced a confusion matrix to determine the accuracy of each IsoCluster Unsupervised Classification. A confusion matrix is used to compare the predicted classification with the validated classification and provides the framework for the production of several accuracy metrics. The purpose of the confusion matrix is to provide an assessment of the relation between the unsupervised classification and the ground condition (Foody, 2002). We validated the classification using the false-color composite NAIP imagery as our ground condition with 300 spatially distributed random validation points (Appendix S1). This number of validation points was determined based on 50 accuracy points for each of a maximum of 6 land cover classes. The 300 validation points were spatially distributed across all 5 land cover types for the study sites and included the 6 land cover types at Doty Ravine. The validation points were not visited on the ground but were visually differentiated in the NAIP image as previously described. Each image was individually assessed in ArcGIS for classification accuracy and the validation point attribute table was updated to indicate if the classification was correct or, if not, the correct classification was noted. The final attribute table was exported to Microsoft Excel to produce the confusion matrix and accuracy metrics. Areas for each cover-class type were calculated for each site and year. This process was repeated on classifications for each year at each site.

We used the confusion matrix data to produce several accuracy metrics to evaluate each NAIP classification including an F1 mean, an overall accuracy, and a kappa score. The Producer's and User's accuracies are calculated from the confusion matrix and are used to assess the accuracy associated with an individual cover-class type. The Producer's accuracy is the percentage of validation points that were correctly put into a given class. The User's accuracy is the percentage of classified points that were correctly put into a given class (Al-Ali et al., 2020). An F1 value is a harmonic mean that represents both the Producer's and User's accuracy as a single metric. The F1 value ranges from 0 to 1, with higher scores representing better classification performance (Powers, 2011). The overall accuracy metric is used to broadly state the total percentage of validated points that were correctly classified for a given image. A Kappa coefficient is used to determine the agreement between the classified and validated values and was calculated according to Cohen (1960). A Kappa value of 1 represents perfect agreement, while a value of 0 represents no agreement.

2.5 | Comparison data

An opportunity existed at Whychus Canyon to compare the 2020 NAIP imagery analysis that was used in this project with an intensive, coupled field and UAS monitoring study completed by McCurdy et al. (2021). On July 10, 2020, McCurdy et al. (2021) collected 6-band orthoimagery of WC-Restored, WC-Control A, and WC-Control B using a UAS platform. They also collected UAS photo-plot imagery and performed in situ rapid vegetation assessments. The rapid assessments assigned 40 points to WC-Restored and 20 points to each of WC-Control A and B. Each point was visited in person and assigned to one of six cover class types to be used for their classification accuracy assessment. The purpose of their study was to assess the areas of surface water and inundation, the extent of large wood throughout the study area, determine sediment size, and assess land cover (McCurdy et al., 2021).

2.6 | Comparison study

We compared the results of our classification to the results of McCurdy et al. (2021) at Whychus Canyon to determine how effective our NAIP classification is compared with their UAS image classification. Control A and Control B served as unrestored control sites in the McCurdy et al. (2021) study. We also used these control sites to compare our classification technique in unrestored areas.

McCurdy et al. (2021) used UAS photo plots and a ground-based vegetation assessment to produce classification maps with seven land cover classes including: water, upland tree/shrub, low riparian tree/shrub, mid-height riparian tree/shrub, high riparian tree/shrub, visible herbaceous, and bare/other.

We compared our NAIP classification from imagery collected June 25, 2020 to the results of their UAS-based classification. We merged the McCurdy et al. (2021) tree/shrub classes greater than 9.1 cm into a single dense vegetation category; herbaceous classes and vegetation less than 9.1 cm tall were merged into a sparse vegetation category; and, finally, water-related classes were merged into a water category. The McCurdy et al. (2021) other/bare category was compared directly to our bare earth category. The McCurdy et al. (2021) imagery was collected using a combination of UAS and ground-based methods, and water boundaries were manually delineated during post-processing. Their methods eliminated the need for a shadow category; however, shadows were unavoidable with the NAIP-based approach.

The total area for each land cover class was calculated for our classification of 2020 NAIP imagery of WC-Restored, Control A, and Control B. The percent coverage for each class of the total area in the NAIP-based 2020 imagery classification was calculated and compared to the same percent coverage by class in McCurdy et al. (2021). A comparison could not be performed at Lost Creek or Doty Ravine because separate drone-based classification studies were not available at those sites. The percentage of each land cover type was compared to determine the effectiveness of our NAIP classifications versus the UAS classifications. We used a symmetrized percent difference (SPD) metric, described in Iskin and Wohl (2024) as the absolute value of the difference between two classifications divided by the sum of those classifications multiplied by 100 (Equation 1), to compare the percent cover of classes between our NAIP classification and the UAS classification (from McCurdy et al., 2021).

$$\text{Symmetrized Percent Difference (SPD)} = \left(\frac{|\text{Classification 1} - \text{Classification 2}|}{\text{Classification 1} + \text{Classification 2}} \right) \times 100. \quad (1)$$

2.7 | Post-classification change analysis

We performed a post-classification change-detection analysis using methods similar to Mundia and Aniya (2005) to assess the pre- and post-restoration vegetation density changes at WC-Restored, Lost Creek, and Doty Ravine. The analysis was not performed at WC-Control A or WC-Control B because no restoration had occurred at these locations. We identified the most recent classification that occurred prior to restoration and compared that classification to the 2020 NAIP classification. The change analysis was performed by first converting both

the pre-restoration and post-restoration classification rasters into polygon vectors and dissolving their features by their classified attribute fields. The pre- and post-restoration classifications were then analyzed with the Intersect function in ArcGIS. The total area changed from one land cover type to another land cover type was calculated in the attribute table (Mundia & Aniya, 2005). Additional data summarization was performed in Microsoft Excel.

3 | RESULTS

3.1 | IsoCluster unsupervised classification accuracy

Overall classification accuracy percentages for all study locations and imagery years ranged from 64.2% to 89.2% with median accuracy of 80.6% and mean accuracy of 79.1% (Table 3). WC kappa scores were generally higher at WC-Restored, ranging from 0.76 in 2014 and 2020 to 0.83 in 2009. However, kappa scores in the unrestored reaches were lower, ranging from 0.61 in 2014 to 0.83 in 2020 at Control A and from 0.53 in 2009 to 0.81 in 2020 at Control B (Appendix S1). The F1 harmonized mean metric showed that the classification method was most accurate for classifying dense vegetation across all years and study reaches at WC. At WC-Restored, the classification underperformed for bare ground in 2009 and 2020 and for water in 2014. The F1 metric was lowest for bare ground and sparse vegetation at Control A and for sparse vegetation at Control B (Table 3).

Lost Creek kappa scores ranged from 0.51 in 2012 to 0.65 in 2020, resulting from difficulty distinguishing between water and shadows (Appendix S1). Similarly, the F1 metric showed that the classification could not reliably classify water in 2012 and 2016 or shadows in 2016. However, the bare, sparse and dense vegetation classes were reliably classified (Table 3).

Kappa scores at Doty Ravine ranged from a low of 0.45 in 2020 to 0.84 in 2018. The low kappa score for 2020 was driven by misclassifications of shadows, bare ground, and sparse vegetation. The F1 metric showed consistently high accuracy for dense vegetation; however, the classification did not perform well for sparse vegetation and water (Table 3). Detailed information regarding misclassifications and Producer's and User's accuracies for all sites and years are provided in Appendix S1.

3.2 | IsoCluster unsupervised classification vegetation composition

3.2.1 | WC Restored—Restoration in 2016

Three time periods of NAIP imagery were available and of sufficiently high quality for land cover classification—2009, 2014 and 2020 (Figure 3). The percentage of land cover identified as shadow for each year was 19%, 9%, and 3% in 2009, 2014, and 2020, respectively. Dense vegetation cover prior to restoration was similar in 2009 and 2014 (11% and 14%, respectively) as was sparse vegetation cover (47% and 53%, respectively). In 2020, after restoration, sparse vegetation increased to 27%. Water increased from 2% in 2009 and 2014 to 14% of total land cover in 2020, and dense vegetation cover decreased from previous highs of 47% and 53% in 2009 and 2014, respectively, to 34% in 2020. (Figures 3 and 4; Table 4).

3.2.2 | WC Control A—Unrestored control

Four time periods of NAIP imagery were available and of sufficient quality for land cover classification—2009, 2014, 2016, and 2020 (Table 2). Dense vegetation coverage ranged from 46% to 50% and water coverage ranged from 2% to 4%. However, bare ground stayed constant at 23%, 19% and 20% in 2009, 2014, and 2016, respectively, but increased to 40% in 2020. Sparse vegetation stayed constant at 15% and 16% in 2009 and 2014, respectively, before decreasing to 8% and 1% in 2016 and 2020, respectively. Shadow cover was constant at 13% for both 2009 and 2014, then increased to 22% in 2016 before decreasing to 7% in 2020. (Figure 4).

3.2.3 | WC Control B—Unrestored control

Three time periods of NAIP imagery were available and of high quality for land cover classification—2009, 2016, and 2020 (Table 2). Sparse vegetation, dense vegetation, water, and bare earth coverage stayed constant at ranges between 18%–19%, 37%–38%, 3%–6%, and 31%–35%, respectively, across all study years. Shadow coverage across all years was 6% in 2009 then increased to 11% in 2016, before decreasing to 3% in 2020. (Figure 4).

TABLE 3 F1 accuracy and overall classification accuracy for each vegetation class at each site over time. The F1 value is a harmonic mean representing both the Producer's and User's accuracy in a single metric. Overall classification accuracy for IsoCluster Unsupervised Classification analysis of NAIP imagery by site and year. The score ranges for both metrics range from 0 to 1, with higher scores representing better classification performance. Post-restoration years in bold face. Blanks represent years with low-quality imagery.

Site/vegetation type	Year					
	2009	2012	2014	2016	2018	2020
Doty Ravine						
Water	0.42	0.38		0.38	0.76	0.38
Sparse vegetation	0.80	0.37		0.38	0.67	0.44
Dense vegetation	0.86	0.92		0.91	0.94	0.84
Bare	0.85	0.78		0.85	0.94	0.25
Shadow	0.79	0.55		0.29	0.63	0.31
Road	0.95	1.00		0.95	1.00	0.95
Overall	0.825	0.776		0.806	0.889	0.642
Lost Creek						
Water	n/a	0.27		0.17		n/a
Sparse vegetation	0.80	0.61		0.67		0.80
Dense vegetation	0.65	0.70		0.82		0.65
Bare	0.63	0.67		0.67		0.63
Shadow	0.58	0.67		0.24		0.58
Overall	0.726	0.646		0.713		0.788
WC Restored						
Water	0.85		0.64			0.82
Sparse vegetation	0.82		0.73			0.81
Dense vegetation	0.91		0.90			0.87
Bare	0.69		0.80			0.77
Shadow	0.90		0.88			0.80
Overall	0.879		0.842			0.824
WC Control A						
Water	0.88		0.68	0.85		0.86
Sparse vegetation	0.51		0.55	0.79		0.50
Dense vegetation	0.95		0.81	0.93		0.96
Bare	0.50		0.61	0.53		0.67
Shadow	0.67		0.74	0.86		0.89
Overall	0.802		0.737	0.877		0.892
WC Control B						
Water	0.62			0.76		0.76
Sparse vegetation	0.47			0.73		0.69
Dense vegetation	0.75			0.88		0.93
Bare	0.77			0.71		0.92
Shadow	0.67			0.88		0.88
Overall	0.661			0.831		0.867

3.2.4 | Lost Creek—Restoration in 2012

Four time periods of NAIP imagery were available and of high quality for land cover classification—2009, 2012, 2016, and 2020 (Table 2). Over this time period, dense vegetation coverage increased steadily from 9% in 2009 to 29%, 43%, and 55% in 2012, 2016, and 2020, respectively. As dense vegetation coverage increased, sparse vegetation coverage decreased from 52% in 2009 to 37%, 35%, and 23% in 2012, 2016, and 2020, respectively. Bare ground coverage decreased from 28% in 2009 to a low of 19% in 2016 before increasing slightly in 2020 to 21%.

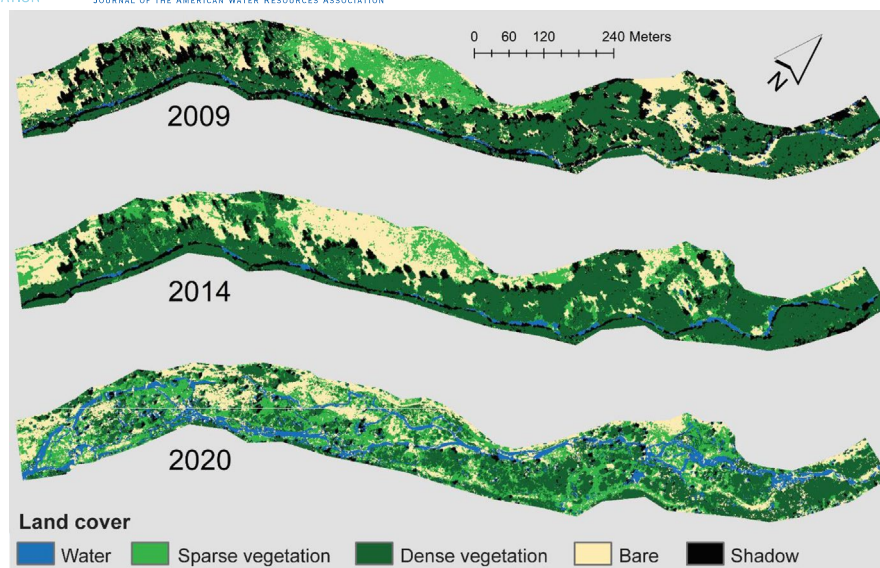


FIGURE 3 IsoCluster Unsupervised Classification of NAIP imagery for WC-Restored for the years 2009, 2014, and 2020.

Water cover fluctuated from 0%, 2%, 1%, and 0% in 2009, 2012, 2016, and 2020, respectively. Shadow coverage decreased from 10% in 2009 to 8%, 3%, and 1% in 2012, 2016, and 2020, respectively. (Figure 5).

3.2.5 | Doty Ravine—Restoration in 2016 and flood pulse in 2018

Five time periods of NAIP imagery were available and of high quality for land cover classification—2009, 2012, 2016, 2018, and 2020 (Table 2). Shadow coverage stayed constant, ranging between 4% and 9% across all years. Water coverage was 1% in 2009, increased to 2% in 2012 and 2016, then decreased to 1% in 2018 and 2020. Dense vegetation was 26% in 2009, then increased and stayed between 42% and 48% from 2012 to 2018 before increasing to 58% of the total area coverage in 2020 imagery subsequent to the restructuring flood pulse in 2018. Sparse vegetation was 26% in 2009 then dropped by 17% to 9% in 2012. This occurred at the same time that dense vegetation increased by 19% between 2009 and 2012. Sparse vegetation stayed constant at 13% in 2016 and 2018 before increasing to 31% in 2020. Bare ground coverage was constant between 33% and 37% from 2009 to 2018 before decreasing to 1% in 2020. The reduction in bare ground coverage and increase in both sparse and dense vegetation coverage occurred 2 years after a flood pulse modified the study reach (Ciotti et al., 2021). This study reach also had paved roads within the classification area that remained constant at 1% coverage in all images. (Figure 6).

3.3 | Comparison of NAIP IsoCluster unsupervised classification with UAS classification

The results of the NAIP IsoCluster Unsupervised Classification compared with the McCurdy et al. (2021) UAS classification results were slightly different at each of the WC study reaches (Table 4). At WC-Restored, our classification identified 6% less sparse vegetation, 4% less bare ground and 6% more water compared with McCurdy et al. (2021). In the unrestored Control A area, our classification identified 33% less sparse vegetation, 30% more bare ground, 3% less dense vegetation and 1% less water compared to the UAS classification. In the other unrestored area, Control B, our classification identified 24% less sparse vegetation, 17% more bare earth, 4% more dense vegetation and 1% more water coverage. The values in Table 4 do not sum to zero as a result of rounding. The differences between the two classifications can be partially attributed to the uncertainty associated with shadows in the NAIP images and possibly from the 15-day difference between the dates of imagery collection for the two classifications.

There was only an 8.5% symmetrized percent difference for sparse vegetation in the WC-Restored; however, SPD was 94.4% and 38.7% at Control A and Control B, respectively. This suggests that both classifications were similar for sparse vegetation post-restoration, but that our unsupervised classification differed greatly from the ground-based classification at unrestored control sites. The SPD for dense vegetation was 0.0%, 2.0%, and 5.7% at WC-Restored, Control A and Control B, respectively. The water class had SPD values of 27.3%, 11.1%,

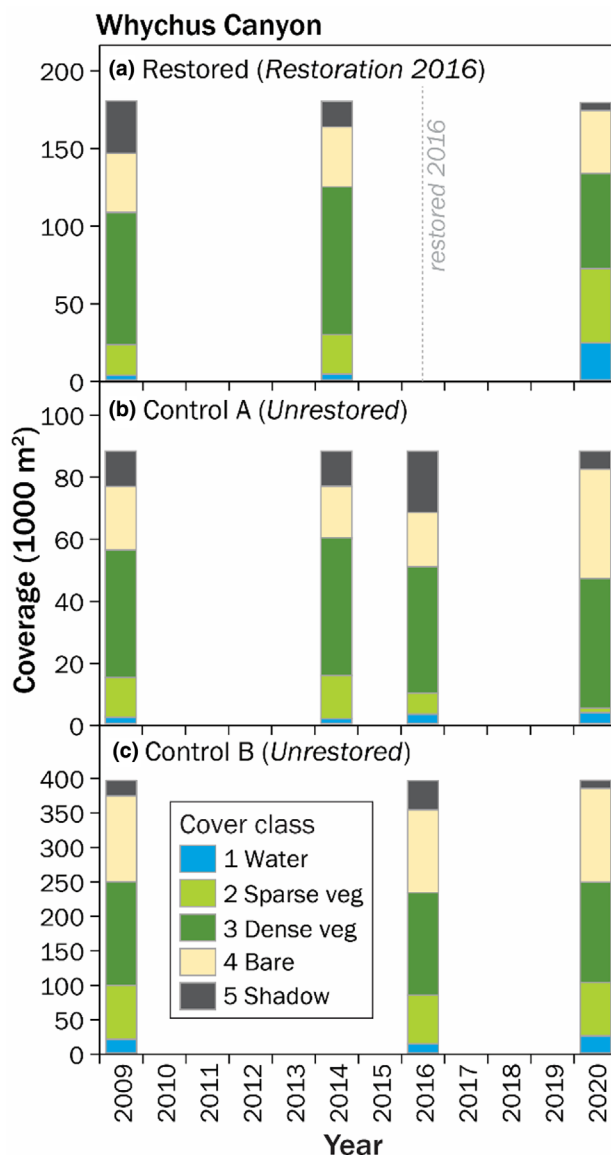


FIGURE 4 Total area of each cover class (m²) identified using IsoCluster Unsupervised Classification of NAIP imagery for (a) WC-Restored, (b) Control A, and (c) Control B in Oregon.

and 0.0% at WC-Restored, Control A, and Control B, respectively. This difference may be related to post-classification manual delineation of water by the McCurdy et al. (2021) study and shadows in the NAIP images. The bare ground class had SPD values of 6.1%, 60.0%, and 32.1% at WC-Restored, Control A, and Control B, respectively, which are expected to arise from the same sources as seen previously with sparse vegetation. Our classification had a 100% SPD for the shadow classification because there were no shadows associated with the UAS imagery.

3.4 | Post-classification change analysis

3.4.1 | WC Restored—2014–2020

We compared the classification of the 2014 pre-restoration imagery to that of the 2020 post-restoration imagery. Of the total area of land cover which changed after restoration (10.59 ha), 19.94% constituted a change from dense vegetation to sparse vegetation. Other changes representing the majority of change were bare to sparse (11.54%), dense to bare (11.31%) and dense to water (11.16%) (see Appendix S3).

TABLE 4 Comparison between results of IsoCluster Unsupervised Classification of NAIP imagery and UAS-collected classification data from McCurdy et al. (2021) at three WC sites: WC-Restored, Control A, and Control B. Differences do not sum to zero owing to rounding.

	Cover class	Percent cover in each class		Difference
		This study	McCurdy et al. (2021)	
Restored	Shadow	3	0	3
Post-restoration	Sparse vegetation	27	32	-6
	Dense vegetation	34	34	0
	Water	14	8	6
	Bare ground	23	26	-4
	Shadow	7	0	7
Control A Unrestored	Sparse vegetation	1	35	-33
	Dense vegetation	48	50	-3
	Water	4	5	-1
	Bare ground	40	10	30
	Shadow	3	0	3
Control B Unrestored	Sparse vegetation	19	43	-24
	Dense vegetation	37	33	4
	Water	6	6	1
	Bare ground	35	18	17
	Shadow	3	0	3

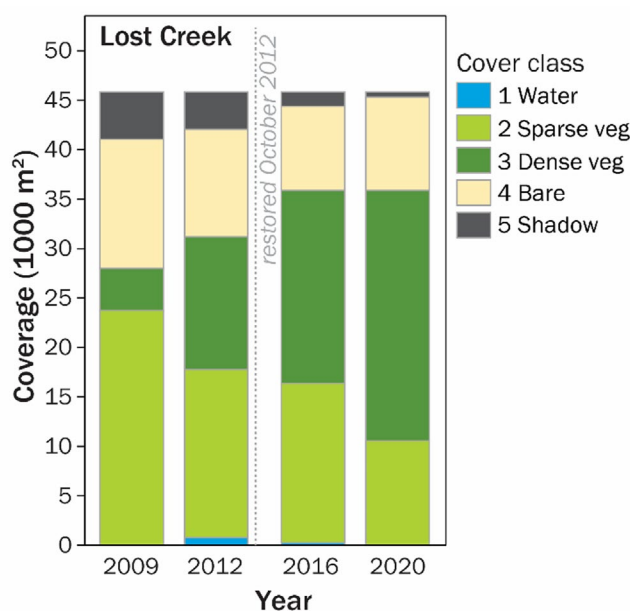


FIGURE 5 Total area of each cover class (m^2) identified using IsoCluster Unsupervised Classification of NAIP imagery for the valley-scale floodplain rehabilitation site at Lost Creek, Oregon.

3.4.2 | Lost Creek—2012–2020

We compared the classification of the 2012 pre-restoration imagery to that of the 2020 post-restoration imagery. Of the total area of land cover which changed after restoration (2.67 ha), 33.33% constituted a change from sparse vegetation to dense vegetation. Other changes representing the majority of observed change were bare to sparse (10.24%) and bare to dense (14.46%) (see Appendix S3).

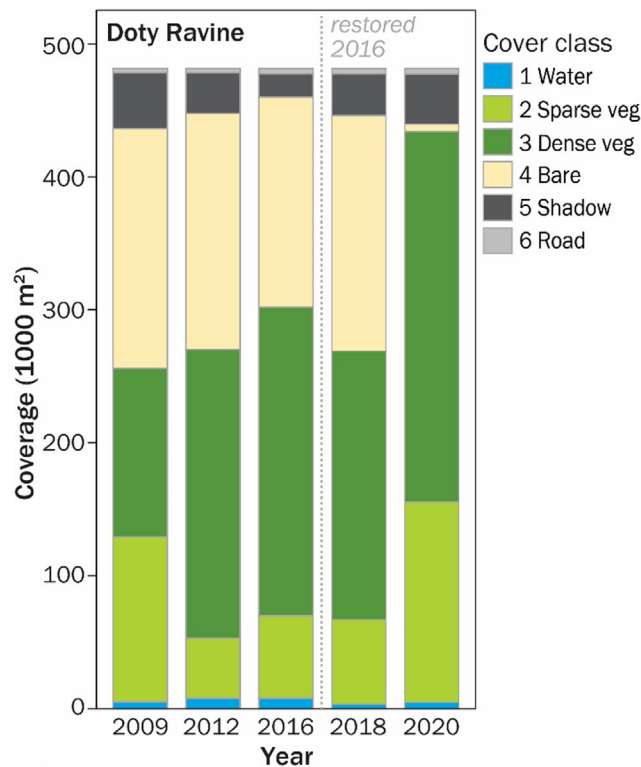


FIGURE 6 Total area of each cover class (m^2) identified using IsoCluster Unsupervised Classification of NAIP imagery for the valley-scale floodplain rehabilitation site at Doty Ravine in California.

3.4.3 | Doty Ravine—2016–2020

We compared the classification of the 2016 pre-restoration imagery to that of the 2020 post-restoration imagery. Of the total area of land cover which changed after restoration (27.05 ha), 38.39% constituted a change from bare to sparse vegetation. Other changes representing the majority of change were bare to dense (16.73%), sparse to dense (14.14%) and dense to sparse (8.51%) (see Appendix S3).

4 | DISCUSSION

4.1 | Temporal change detection and accuracy

Empirical evaluation of the changes in floodplain surface complexity through quantification of vegetation classes at a valley scale is challenging due to the large size of floodplain restoration projects, the difficulty in traversing project areas (particularly after vegetation begins to mature), and the cost of effective data collection (Flitcroft et al., 2022). This makes remote sensing and data processing tools valuable for both implementation and effectiveness monitoring at valley-scale floodplain sites. In this study, we found that the IsoCluster Unsupervised Classification of NAIP imagery offered strong overall accuracy, as well as effective class-specific (e.g., dense vegetation) identification. These two strengths of the method mean that pre- and post-restoration monitoring can be completed, even when pre-data collection was not part of the project planning process. Recent work from Kolarik et al. (2023, 2024) and Shrestha et al. (2024) found utility in Landsat and Sentinel imagery for hind-casting vegetation change in mesic environments. Although the return time for these satellite images is within days instead of years, the spatial resolution of Landsat and Sentinel (30 m and 10 m, respectively) is insufficient to capture the spatial heterogeneity inherent in these highly dynamic, valley-scale floodplain sites. Additionally, tracking dense vegetation development facilitates evaluation of succession over time in arid or semi-arid environments. The ability to track vegetation progression on the floodplain may also be a meaningful way to understand soil moisture and depth to groundwater (Stromberg et al., 2007) (although additional targeted research to fully understand these relationships in arid floodplain restoration sites is needed). Ultimately, NAIP imagery was both cost-effective and allowed for long-term monitoring that can facilitate learning about the success or failure of valley-scale floodplain restoration projects.

The NAIP imagery processed with an IsoCluster Unsupervised Classification was consistently effective at differentiating among areas of dense vegetation, sparse vegetation, and barren land at post-restoration study areas. Evaluating the effectiveness of floodplain restoration is

linked to the structure (e.g. open patch, shrub vs. tree-dominated) and type of vegetation that establishes at a site (Göthe et al., 2016). In semi-arid environments, vegetation clearly reflects surface and subsurface water availability with linkages to wetland characteristics (Stromberg et al., 2007). These results show that this method can be applied in semi-arid regions for rapid evaluation of dense vegetation response to floodplain restoration over time.

The IsoCluster Unsupervised Classification of NAIP imagery had consistently high overall accuracy assessments and was also particularly effective at classification in the dense vegetation category. High overall accuracy demonstrates that the tool can effectively process the NAIP imagery to capture site conditions in a given year. This facilitates overall assessments of change over time across the different classification types, which is a key aspect of monitoring. The effectiveness of the tool at identifying the dense vegetation classification is particularly useful for tracking plant succession from establishment to more dense communities. Post-classification change detection was useful for identifying land cover changes resulting from restoration activities. Dense vegetation was distinguishable in both pre- and post-restoration imagery. The clear identification of dense vegetation may also aid in quantifying the amount of dense vegetation removed during the implementation of valley-floor floodplain restoration, as well as the rate at which vegetation colonizes and develops at the site.

Availability of NAIP imagery can facilitate long-term monitoring of vegetation succession, but such monitoring of restoration sites is uncommon (Bash & Ryan, 2002). More often, implementation monitoring (to quantify the amount of work that was completed) is performed (Bash & Ryan, 2002), but evaluating whether the goals of a restoration project were successfully achieved over the long-term is expensive, rarely funded, and may not target effective metrics (Rubin et al., 2017). In our analysis, even though NAIP imagery was not available for every year owing to data quality (e.g., blurriness, shadows, etc.), gaps of a few years were not a significant concern. This reflects the goal of considering long-term effects of restoration on vegetation, which itself may take several years to grow to maturity. Rather, we found that access to enough NAIP imagery over time to capture trends in vegetation, combined with a relatively simple “desktop” analysis method, can facilitate cost-effective, long-term monitoring of vegetation across entire valley-scale restoration projects.

Inundation of the valley floor is a common goal of floodplain restoration (Cluer & Thorne, 2014; Powers et al., 2019). As such, being able to effectively identify the wetted area, particularly at baseflow conditions, would allow for evaluation of restoration effectiveness. The IsoCluster Unsupervised Classification method was effective at identifying surface water when channels were wide, or when they were not covered with vegetation. Thus, this method allows for effective quantification of water in pre-restoration conditions, and immediately post-restoration before vegetation has begun to grow. As vegetation matures adjacent to water edges, the edges become obscured by vegetation or shadows from vegetation. As a result, this method is not useful for determining change in the wetted portion of a study area over the long term should vegetation grow along water edges. Other tools and remotely sensed datasets may need to be implemented to effectively identify surface water (Bijeesh & Narasimhamurthy, 2020) once water-adjacent vegetation begins to mature.

Our classification method underestimates all land cover and water areas owing to the presence of shadows in the imagery, but still provides useful estimates of land cover change. Shadows have consistently presented problems with remotely sensed imagery (Campos et al., 2014; Shahtahmassebi et al., 2013), and this study is no exception. Shadows in NAIP imagery presented a challenge in this analysis. In a study by Assal et al. (2014), shadow classes produced by unsupervised classification were omitted because they represent unknown cover types. However, our objective was to compare the accuracy between our classification of NAIP imagery and a classification based on UAS imagery. As such, we felt it was important to leave in the shadow class as it represents an important distinction between the methods. NAIP imagery is collected within an approximate window of dates and at the discretion of the contractor, based on cloud cover and other time constraints. As a result, imagery for some years is collected early in the morning or late in the afternoon. In higher-latitude locations such as Oregon, this can cause shadows that cover large percentages of the study area, necessitating the omission of entire years of NAIP data. As noted by Maxwell et al. (2019), inconsistencies from collection date and lighting from different times of day present a problem with the use of NAIP imagery, especially when imagery is only collected once every 2 years. As such, the timeliness of reporting vegetation change using NAIP imagery may need to be considered over longer time frames, based on image availability (such that data can be compared every 4, 6, or possibly 8 years). Although the use of LiDAR-derived canopy height models (Chamberlain et al., 2021; Jarron et al., 2020) and manual delineations could be used to help identify the true cover type in the shadow classes, the use of ancillary data and post-processing was beyond the scope of this study.

Prior to restoration, sparse vegetation and bare earth classifications from the IsoCluster Unsupervised Classification of NAIP Imagery were inconsistent, with unexpected variability in classifications pre-restoration that did not reflect dynamic vegetation conditions. Rather, the results were more likely variable owing to inaccurate classifications resulting from similarities in the spectral signature of sparse vegetation and bare earth. Other studies have found that different tools and techniques may be effective at differentiating between sparse vegetation and bare earth (e.g., AVIRIS, Ashner & Heidebrecht, 2002). However, differentiation of vegetation types and bare earth was consistent with what would be expected in the post-restoration image classification. This finding may be capturing the effect of changes in groundwater depth that can affect vegetation condition, allowing for enhanced classification of sparse vegetation and bare earth. This interpretation is consistent with the finding by Manning et al. (2020) that plants near stream channels in arid environments tend to be denser than in upland areas, thereby reflecting patterns of hydrologic connectivity. One of the goals of valley-scale floodplain restoration is to make the depth to groundwater shallow, with the hypothetical goal of facilitating vegetation establishment and long-term growth. Our finding of consistent transition of bare earth to sparse vegetation in post-restoration floodplain sites (Appendix S3) suggests that this goal is being achieved at our study sites.

Although NAIP imagery is available on a biannual basis, there may be differences in the day of year on which the data were collected, possibly confounding trend detection over time. Imagery collected at the beginning, middle, or end of the vegetation growing season could result in different classifications, particularly between bare earth and sparse vegetation. This difference in vegetation reflectance may be particularly pronounced in arid or semi-arid environments. In this study, the dates of image acquisition by year typically fell within a 2-week window of time (within sites over years). Thus, our comparisons likely reflect a similar period in the growing season over time. Considering the date of imagery collection in the interpretation of restoration monitoring results would enhance overall evaluation of vegetation change over time at restored sites.

A limitation of this study was the inability to differentiate between native and non-native riparian vegetation. Floodplain restoration may facilitate invasion by non-native plant species, ultimately decreasing ecological benefits (D'Antonio et al., 2016). Field-based surveys to evaluate the composition of the vegetation communities would yield a more nuanced assessment of vegetation community composition post-restoration (Paillex et al., 2017; Rondeau et al., 2023; Wilson & Norman, 2022). Combined with monitoring of other aspects of the floodplain environment, our unsupervised classification, along with vegetation community composition studies, would allow a more comprehensive assessment of floodplain vegetative response.

4.2 | Comparison study

Vegetation recovery and change in the years following restoration is a key metric for evaluating the success of a restoration action. However, in situ field measurement and mapping of vegetation change is costly. Using NDVI and the IsoCluster Unsupervised Classification tool in ArcMap (10.5.1), we successfully classified vegetation change over time in response to restoration actions in semi-arid environments. Overall accuracy of the IsoCluster Unsupervised Classification compared to McCurdy et al. (2021) found strong similarity at the WC-Restored site, where the percentage of land cover determined to be dense vegetation was identical. Sparse vegetation and bare ground were under-represented by our methods by 6% and 4%, respectively. However, water was over-represented by 6%. The over-representation of water in the data is most likely related to the difficulty our classification method had with differentiating among water, shadow, and emergent vegetation in shallow water. Although the method still had some difficulties separating sparse vegetation and bare ground, it seems that the sparse vegetation was still vigorous at WC-Restored during the McCurdy et al. (2021) sampling period and had not yet become brown from senescence. This finding of consistency in post-restoration vegetation classification between methods may reflect stronger differentiation between sparse and dense vegetation and bare ground that could be due to a higher water table supporting vegetation in the post-restoration reach during dry summer months.

Whychus Control A and Control B were both unrestored reaches of the WC complex that were evaluated as part of the McCurdy et al. (2021) study, and were compared to our methodology. Surface water in Control A and Control B reaches exists as a single-thread channel without the numerous bifurcations and meanders observed at WC-Restored. As such, the IsoCluster Unsupervised Classification and the McCurdy et al. (2021) study found nearly identical classifications of water (within 1% of areal coverage). The IsoCluster Unsupervised Classification methodology also provided similar results for dense vegetation as the McCurdy et al. (2021) study with 3% less for Control A and 4% more for Control B. As observed in earlier evaluations of our methods, comparisons between the studies found that the greatest discrepancies in classification occurred with the bare earth and sparse vegetation classes at the Control A and Control B sites. These sites had very similar reflectance values, which may be why the differences with the IsoCluster Unsupervised Classification were similar at both of these sites.

The use of IsoCluster Unsupervised Classification of NAIP images facilitates monitoring of valley-scale floodplain restoration efforts to empirically evaluate the effectiveness of such efforts. Remote sensing has been demonstrated to be effective for floodplain monitoring using other methods (Roni et al., 2019), and this approach adds a low-cost and highly accessible method to the available tools.

5 | CONCLUSION

Innovative, inexpensive monitoring of post-restoration valley-scale vegetation presents an opportunity to evaluate the effectiveness of these projects over time. Our IsoCluster Unsupervised Classification of NAIP imagery was useful in assessing successional progress of vegetation recovery at large-scale floodplain restoration sites in semi-arid environments, through the consistent classification of dense vegetation composition. We were able to more effectively differentiate between vegetation and bare ground in the post-restoration imagery than in pre-restoration imagery. These findings are consistent with one of the goals of floodplain restoration, to increase vertical and lateral hydrologic connectivity. Enhanced hydrologic connectivity should be reflected in denser vegetation composition in the post-restoration floodplain.

Another benefit of using existing NAIP imagery was access to pre-restoration data from imagery collected using consistent methods, allowing for pre- and post-restoration comparisons. Inconsistency in data collection and limited pre-data are common limitations in long-term monitoring of restoration projects. By accessing long-term datasets, we were able to explore a longer time series of floodplain vegetation,

thus allowing us to identify predictable patterns in vegetation composition change. Ultimately this approach offers a cost-effective monitoring alternative for floodplain environments targeting changes in vegetation cover and river channel movement over time.

Future work may include developing floodplain heterogeneity metrics similar to those of Iskin and Wohl (2022, 2023, 2024). Although development of these models was outside the scope of our study, they would provide valuable information to managers at a spatial scale needed for evaluating habitat change in floodplain restoration projects.

AUTHOR CONTRIBUTIONS

Jay W. Munyon: Conceptualization; data curation; formal analysis; investigation; methodology; project administration; resources; software; validation; visualization; writing – original draft; writing – review and editing. **Rebecca L. Flitcroft:** Conceptualization; funding acquisition; project administration; supervision; validation; writing – original draft; writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The NAIP data that support the findings of this study are available in USGS Earth Explorer at <https://earthexplorer.usgs.gov/>.

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SUPPORTING INFORMATION

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

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