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Assessing the effectiveness of riparian restoration projects using Landsat and precipitation data from the cloud-computing application ClimateEngine.org

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ABSTRACT

Riparian vegetation along streams provides a suite of ecosystem services in rangelands and thus is the target of restoration when degraded by over-grazing, erosion, incision, or other disturbances. Assessments of restoration effectiveness depend on defensible monitoring data, which can be both expensive and difficult to collect. We present a method and case study to evaluate the effectiveness of restoration of riparian vegetation using a web-based cloud-computing and visualization tool (ClimateEngine.org) to access and process remote sensing and climate data. Restoration efforts on an Eastern Oregon ranch were assessed by analyzing the riparian areas of four creeks that had in-stream restoration structures constructed between 2008 and 2011. Within each study area, we retrieved spatially and temporally aggregated values of summer (June, July, August) normalized difference vegetation index (NDVI) and total precipitation for each water year (October-September) from 1984 to 2017. We established a pre-restoration (1984–2007) linear regression between total water year precipitation and summer NDVI for each study area, and then compared the post-restoration (2012–2017) data to this pre-restoration relationship. In each study area, the post-restoration NDVI-precipitation relationship was statistically distinct from the pre-restoration relationship, suggesting a change in the fundamental relationship between precipitation and NDVI resulting from stream restoration. We infer that the in-stream structures, which raised the water table in the adjacent riparian areas, provided additional water to the streamside vegetation that was not available before restoration and reduced the dependence of riparian vegetation on precipitation. This approach provides a cost-effective, quantitative method for assessing the effects of stream restoration projects on riparian vegetation.

1. Introduction

Riparian areas provide critical ecosystem services and are subject to degradation from natural and anthropogenic processes, especially in arid and semi-arid rangelands where water is frequently limiting. A riparian area can cool stream water through shading by streamside vegetation, filter surface and ground water, and otherwise act as an interface between uplands and waters (Gregory et al., 1991; Naiman and Decamps, 1997). Riparian areas also support much of a region's biodiversity (Naiman et al., 1993; Sabo et al., 2005). These ecosystem services, however, are sensitive to herbivory, disturbance (e.g., flood, fire), and human activity. Degradation of riparian areas also can result from stream incision or other forms of disconnection between streams and their floodplains (NRC, 2002).

Degraded riparian areas are common targets of restoration projects (Goodwin et al., 1997; Bernhardt et al., 2005), but evaluating restoration effectiveness has long been a weakness in the field (Kondolf, 1995; Walker et al., 2007; Gonzalez et al., 2015). Riparian restoration projects are frequently underfunded (Ruiz-Jaen and Aide, 2005; Bernhardt et al., 2007) and few projects budget for pre- and post-project monitoring (Bernhardt et al., 2005; Gonzalez et al., 2015). Long-term monitoring efforts are even rarer (Alexander and Allan, 2007; Gonzalez et al., 2015) and monitoring data that do exist are seldom used to assess the effectiveness of individual projects (Alexander and Allan, 2007).

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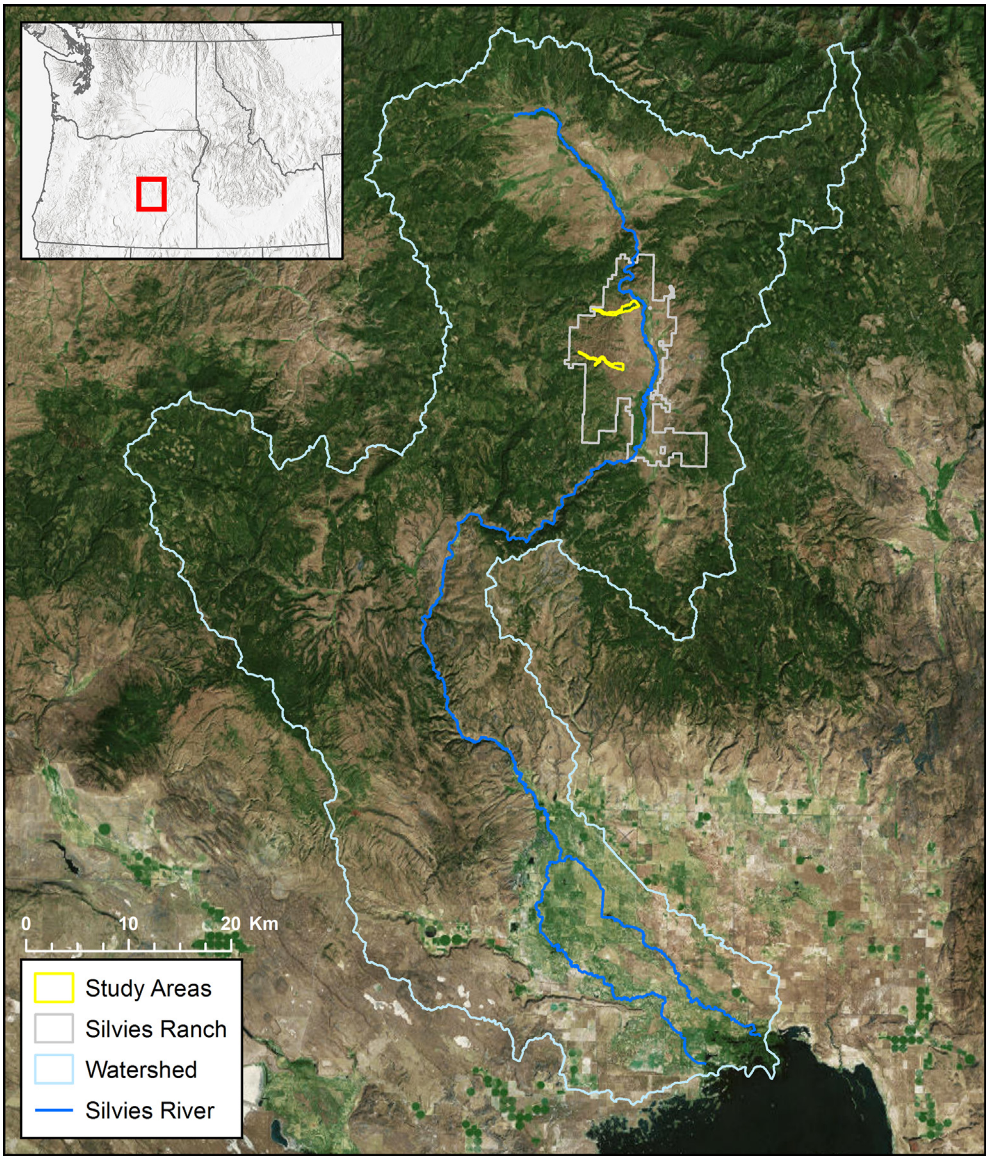

Fig. 1. General study area of Silvies Valley Ranch, and tributary creeks and study riparian areas.

The development of metrics and standards for evaluating restoration effectiveness (i.e., assessing whether or not restoration objectives were met) has proven difficult (Bernhardt et al., 2007; Kondolf et al., 2007) and rigorous evaluations have been even more difficult to implement (Alexander and Allan, 2007; Gonzalez et al., 2015). Both spatial (Hobbs and Norton, 1996; Gonzalez del Tanago and García de Jalón, 2006; Aguiar et al., 2011) and temporal (Kondolf and Micheli, 1995; Trowbridge, 2007) scales prove challenging in evaluating effects of restoration work. Stream or riparian restoration projects are generally implemented on a local scale (e.g., a meander bend of a river) (Lake et al., 2007). However, environmental or ecological effects of restoration often can be seen outside of project boundaries, including upstream and downstream reaches and streamside areas (Aguiar et al., 2011). Riparian vegetation in particular is characterized by hydrophilic plants and thus inextricably linked to regional and local scale climate and hydrology (Stromberg et al., 2007; Orellana et al., 2012; Boudell et al., 2015). Riparian vegetation is strongly influenced by both longitudinal and lateral surface and subsurface connectivity to the floodplain (Gonzalez del Tanago and García de Jalón, 2006; Lake et al., 2007). These linkages are even more pronounced in arid environments such as rangelands (Patten, 1998; Perry et al., 2012).

Many restoration projects are assessed through metric trajectories, or changes over time (Palmer et al., 2005; Gonzalez et al., 2015), yet these evaluations require both baseline pre-restoration data and long-term monitoring of the completed project. Although Kondolf & Micheli (1995) recommend both a historical study of pre-restoration conditions and a minimum of 10 years of post-restoration monitoring, Gonzalez et al. (2015) found that just 16% of projects monitoring trajectories included pre-restoration data, and only 22 of 169 total projects reviewed included more than six years of post-restoration monitoring. The long-term effects of restoration will seldom be seen in such short time frames (Trowbridge, 2007), especially in projects intended to foster natural ecological processes like succession (Walker et al., 2007), plant community development (Weisberg et al., 2013), and resilience from natural disturbance (e.g., beaver, flood).

Satellite remote sensing has been used extensively to assess wetland and riparian vegetation conditions at regional and local scales (Ozesmi and Bauer, 2002; Goetz, 2006; Smith et al., 2014; Lawley et al., 2016). Long-term remote sensing of riparian vegetation requires satellite observations of sufficient history and spatial resolution to characterize both baseline conditions and trajectories with respect to natural and anthropogenic change agents, such as climate, hydrology, and land

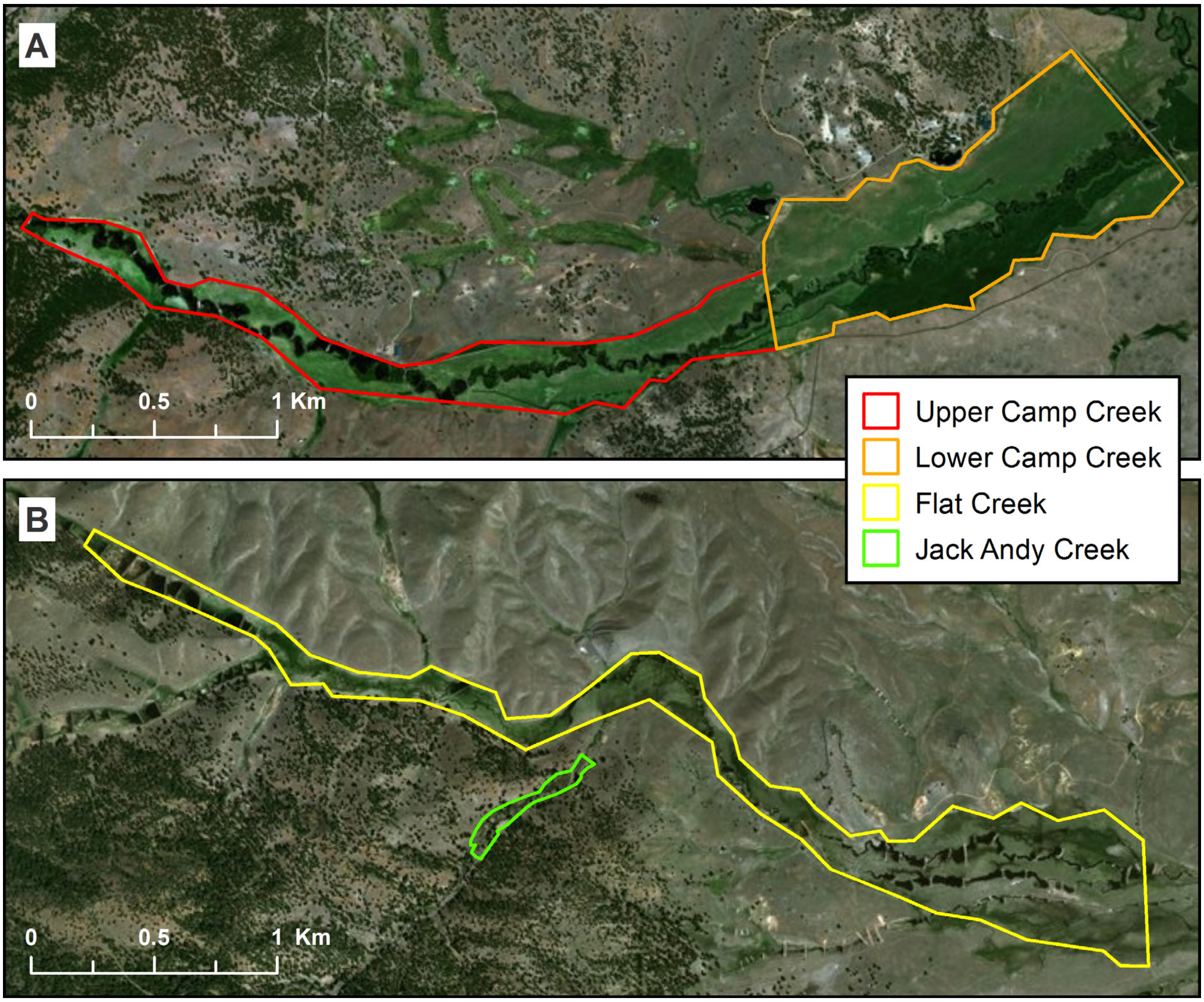

Fig. 2. Delineated riparian study areas. (a) Upper (left) and Lower (right) reaches of Camp Creek. (b) Flat Creek (larger polygon) and Jack Andy Creek (smaller polygon).

management (Dawson et al., 2016). Landsat is ideally suited to meet these requirements due to its extensive and continuous archive (30+ years), overpass frequency (8–16 day), and spatial resolution (30 m pixel size) (Gutman and Masek, 2012; Huntington et al., 2016).

Since opening the Landsat archive, ecological applications of Landsat data have exponentially increased (Wulder et al., 2012; Kennedy et al., 2014). Software platforms such as Google Earth Engine (Gorelick et al., 2017) now provide remote sensing and climate data archive access and massively parallel cloud-computing capabilities. This cloud-based access and processing has led to significant advancements and data discoveries related to high resolution land cover and water extent mapping, as well as visualizations that would not be otherwise possible (Hansen et al., 2013; Pekel et al., 2016; Kennedy et al., 2018). These new capabilities and advancements have changed the paradigm of remote sensing and ecosystem monitoring over long time histories and at high resolution.

Here we present a method and case study to assess the effectiveness of riparian restoration using a freely available, on-demand, cloud-computing web application to access, process, and download 30+ years of Landsat and gridded precipitation data for restoration locations. We compared statistical relationships between riparian vegetation vigor and precipitation data for both pre- and post-restoration periods. The approach we present overcomes some of the barriers in accessing large geospatial datasets and provides a simple but rigorous quantitative approach that can be used by scientists, practitioners, and managers to assess the effectiveness of a restoration project for improving riparian vegetation.

2. Materials and methods

2.1. Study site

This study focuses on streamside areas adjacent to three streams tributary to the Silvies River, located on the Silvies Valley Ranch, in eastern Oregon (Fig. 1). Streamside areas were identified as areas that had the potential for inundation given their proximity to the channel, slope, and topography (e.g., valley form). These areas were likely to support riparian vegetation following restoration. Each stream had a number of artificial beaver dams (ABDs) installed between 2008 and 2011, but none had pre-restoration vegetation or hydrologic data collected and no systematic post-restoration data were collected (Davee et al., 2017). ABDs are densely spaced, low-head weirs constructed from rock and other materials that pond water up to the valley floor, thereby raising water tables, slowing the movement of water through the landscape, increasing valley bottom storage and shallow groundwater levels, and promoting surface and groundwater interactions within restoration areas (Pilliod et al., 2018). Such changes ultimately lead to replacement of upland shrubland vegetation (i.e., typical of sagebrush steppe) with riparian vegetation and grasses, as well as increases in vegetation vigor and evapotranspiration (Loheide and Gorelick, 2005;

Essaid and Hill, 2014).

The Silvies Valley Ranch encompasses the majority of a large alluvial valley, as well as some steeper, adjacent uplands in the headwater reaches of the Silvies River, which drains to Malheur Lake. The landowner purchased the property in 2007 with the intent to establish a sustainable grass-fed cattle grazing operation and eco-tourism resort. Eager to return sparsely vegetated valley floors to productive grasslands, as well as to offer fishing and bird-watching to future guests, the landowners set out to address the pervasive channel incision that had dried upland valley floors, converting what was thought to have been herbaceous wet meadows into sparse, upland species (e.g. *Artemisia* spp., *Chrysothamnus* spp., *Purshia tridentata, Festuca idahoensis)*.

To reverse this conversion, the landowners built 376 ABDs in six intermittent tributary drainages over the course of six years. The earliest in-stream structures were installed in the winter of 2008, and installation in the four study areas continued through 2011. The structures are maintained periodically by both the landowner and the resident beaver populations, with the majority still operating as initially designed. In the valley bottoms on either side of the structures, sagebrush and other upland species were mechanically removed, and have been replaced by a mix of grasses. Cattle are now regularly grazed in the valley bottoms alongside the treated areas, and the areas are hayed seasonally. The landowners report large increases in hay production since installing the structures (Davee et al., 2017). Whereas the pre-installation channels had been incised up to 5 m and went dry most years, the post-installation channel is perennially wet and the water level in some channels has risen by more than 3.5 m.

2.2. Study areas and data retrieval

Riparian areas for this study were selected based on the length of time since the installation of the ABDs, with the most recent ABDs installed at least five years previously. After a field visit to the ranch to identify potential study areas, we selected four study areas: Upper Camp Creek, Lower Camp Creek, Flat Creek, and Jack Andy Creek (Fig. 2). In each study area, a riparian area polygon was delineated on the basis of high resolution background imagery (e.g. National Agriculture Imagery Program).

Analyses were based on the relationship between the satellite-derived normalized difference vegetation index (NDVI) and precipitation. NDVI is a measure of pixel greenness, or vegetation photosynthetic potential. NDVI has been used as a proxy for ecosystem performance in forests (Wylie et al., 2008, 2014) and rangelands (Wylie et al., 2012; Rigge et al., 2013b), and changes in NDVI over time have been used to examine the effect of best management practices on riparian vegetation in rangelands (Rigge et al., 2013a). In the Great Basin, NDVI is used extensively for quantifying vegetation vigor, plant cover, and consumptive water use of groundwater dependent vegetation (McGwire et al., 2000; Devitt et al., 2011; Huntington et al., 2016; Carroll et al., 2017). Summer (June, July, and August; JJA) NDVI was chosen to maximize the vegetation signal derived from shallow groundwater (Dawson and Pate, 1996; Huntington et al., 2016), whereas water year precipitation was chosen because it is a good indicator of shallow groundwater levels and groundwater discharge (i.e. baseflow) during this period (Huntington and Niswonger, 2012; McEvoy et al., 2012; Abatzoglou et al., 2014).

We used Climate Engine (ClimateEngine.org), a freely available remote sensing and climate cloud-computing application (Huntington et al., 2017) powered by Google Earth Engine (Gorelick et al., 2017), to process and download spatially and temporally averaged Landsat 4, 5, 7, and 8 derived annual NDVI values for each polygon from 1984 to 2017. NDVI was computed within Climate Engine using U.S. Geological Survey (USGS) Landsat at-surface reflectance product collections hosted by Google Earth Engine (USGS, 2018a,b). Climate Engine automatically applies cloud masks provided by Landsat at-surface reflectance collections (Zhu and Woodcock, 2012; Foga et al., 2017) for data masking. Spatially and temporally averaged NDVI values were computed within Climate Engine and downloaded for respective polygons as median values for Landsat images acquired in the summer (JJA) of each year.

Daily precipitation data from METDATA (Abatzoglou, 2013) was aggregated to water year totals (October 1– September 30) and downloaded for each study area via Climate Engine. METDATA is a hybrid of daily North American Data Assimilation System (NLDAS) (Mitchell et al., 2004; Xia et al., 2012) and monthly Parameter Regression on Independent Slopes Model (PRISM) data (Daly et al., 2008), and is available at a 4 km grid resolution. Two of the study areas were contained entirely within a single METDATA grid cell; in those cases, the total precipitation over the water year for respective cells were used. The Upper and Lower Camp Creek study areas each spanned two different METDATA cells, and the mean water year precipitation over the two cells was used for these study areas.

2.3. Statistical analyses

Using the pre-restoration (1984–2007) NDVI and precipitation data, we examined the relationship between precipitation and NDVI using linear regression to determine a best-fit regression line for each study area. Using MATLAB's Curve Fitting Toolbox (MathWorks, Natick, Massachusetts), we determined the 95 percent confidence intervals, the 95% prediction interval, the R^2, F-statistic, and p-value for the linear regression. We then compared post-restoration data (2012–2017) to pre-restoration (1984–2007) regressions. If the post-restoration data fit the pre-restoration relationship, the residuals between the post-restoration observations and the pre-restoration regression would be normally distributed with a mean of zero. We tested this hypothesis with a single-sample *t*-test on post-restoration residuals. This test shows whether the post-restoration relationship between NDVI and precipitation is statistically significantly different from the pre-restoration relationship.

To provide control areas, we performed analyses on Flat Creek (an ephemeral and intermittent stream) and Lower Camp Creek (a perennial stream). Of the four areas evaluated, Flat Creek is the most dependent on precipitation for streamflow and vegetative growth, whereas Camp Creek is the least dependent. In these control analyses, the pre-restoration data were split into two datasets: an early pre-restoration (1984–2002) and a late pre-restoration (2003–2007). The same analyses were run on these two pre-restoration datasets, establishing a statistical relationship between precipitation and NDVI for the early data and using the residuals for the later pre-restoration data to assess whether those later pre-restoration data fit the earlier pre-restoration relationship. Following the control, the post-restoration residuals (2012–2017) were also tested against the early pre-restoration data. All analyses were conducted in MATLAB using a 0.05 alpha level as a basis for statistical significance.

2.4. Restoration assessment

We used the statistical analyses to assess whether the riparian restoration was successful in each study area. Fig. 3 provides a conceptual illustration using synthetic data. If NDVI were entirely dependent on precipitation, the pre-restoration linear regression would perfectly predict the value of NDVI in response to a year's precipitation. Because NDVI is also influenced by other factors, the observed values tend to be scattered around the line with values both above and below the regression line (Fig. 3a). If riparian restoration were unsuccessful (i.e., the relationship between precipitation and NDVI remains unchanged), the post-restoration data would continue to fit that pre-restoration pattern (Fig. 3b). With a successful restoration, the post-restoration NDVI values would be greater than the values predicted by the pre-restoration regression (Fig. 3c).

The statistical tests described above provide a quantitative basis for the assessment of restoration effectiveness. We assessed riparian

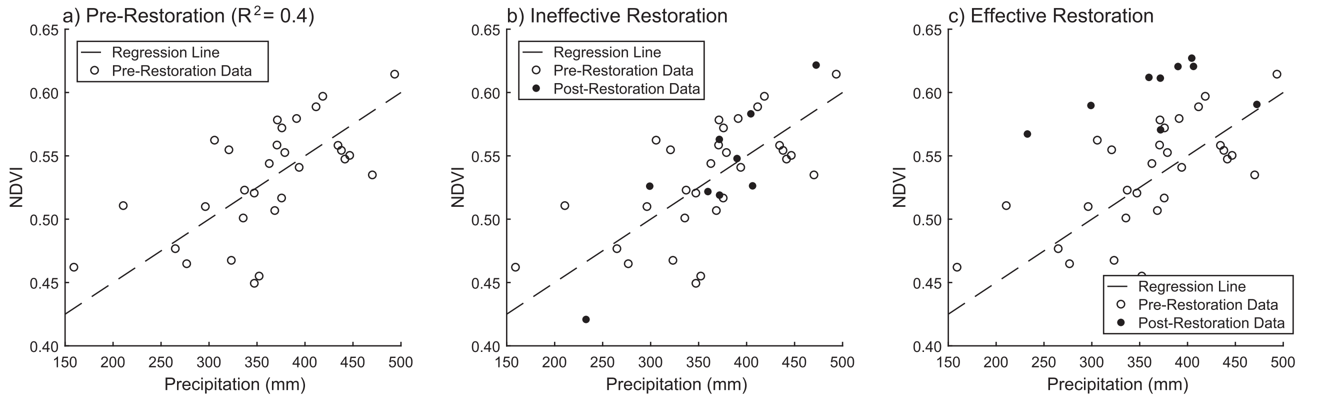

Fig. 3. Synthetic data illustrating the restoration assessment. a) pre-restoration data indicating the linear relationship between annual precipitation and NDVI ($R^2 = 0.4$). b) sample data showing an ineffective riparian restoration. A *t*-test shows that these data are not significantly different from the pre-restoration data ($p = 0.74$; t-statistic = 0.35). c) sample data showing an effective riparian restoration. A *t*-test shows that these data are significantly different from the pre-restoration data ($p < 0.005$; t-statistic = 3.75).

restoration as effective if two criteria were met: a) the post-restoration NDVI values were greater than the values predicted by the pre-restoration relationship (indicating an increase in photosynthetic potential, or productivity), and b) the *t*-test showed a statistically significant difference between the pre-restoration and post-restoration data (indicating a change in the functional relationship between precipitation and vegetation).

3. Results

For each study area, we found a statistically significant ($p < 0.05$) linear relationship between pre-restoration precipitation and pre-restoration NDVI, although the slopes and intercepts of the various relationships varied by a factor of 2 (Table 1; Fig. 4). In each study area, we also found that post-restoration residuals were statistically distinct from pre-restoration data (Table 2).

Fig. 5 shows data from the control areas at Flat Creek and Lower Camp Creek, in which 19 years of pre-restoration data were used to establish the pre-restoration relationship and the following 5 years (still pre-restoration) were tested for a change in that relationship. In this case, the 19 years of early pre-restoration data (1984–2002) were sufficient to establish statistically significant relationships (Table 3a). *T*-tests performed on the residuals of five years of late pre-restoration data (2003–2007 control) showed that they were not from a statistically distinct population (Table 3b). In contrast, we found that post-restoration data (2012–2017) came from a statistically distinct population (Table 3c).

4. Discussion

All four study areas showed statistically significant pre-restoration relationships between precipitation and NDVI, indicating water-limited

Table 1
Pre-restoration statistical data (all statistical tests are based on 22 degrees of freedom):

Study Area	Pre-Restoration Precipitation-NDVI Linear Regression			
	Regression Slope (mm^{-1})	Regression Intercept	R^2	p-value
Upper Camp Creek	4.00×10^{-4}	0.334	0.431	4.93×10^{-4}
Lower Camp Creek	5.77×10^{-4}	0.451	0.288	6.84×10^{-3}
Flat Creek	7.23×10^{-4}	0.231	0.521	6.88×10^{-5}
Jack Andy Creek	3.01×10^{-4}	0.386	0.337	2.93×10^{-3}

vegetation. The strengths of those pre-restoration relationships varied, likely influenced by topography, soils, local groundwater dynamics and other geomorphic features of the study areas. We interpret the slope of the pre-restoration regression equation as representing the strength of precipitation dependence, and the pre-restoration intercept as indicative of the availability of alternative sources of water. Lower Camp Creek, for example, lies alongside the Silvies River and has the greatest regression intercept (extrapolated NDVI at zero precipitation) of the four study areas. The local water table in this study area is higher due to the proximity of the perennial stream, and the vegetation in this area can access more water than the vegetation in other study areas. In contrast, Flat Creek is the study area most dependent on precipitation, with both the greatest sensitivity to precipitation (as indicated by the greatest pre-restoration slope) and the least access to other sources of water (as indicated by the lowest pre-restoration intercept). Precipitation explains more of the NDVI variance at Flat Creek than any of the other study areas ($R^2 = 0.521$), and the significance of the correlation between precipitation and NDVI is also greatest at Flat Creek ($p < 10^{-4}$).

In all four study areas, the post-restoration data were statistically distinct from the pre-restoration precipitation-NDVI relationship, regardless of the pre-restoration correlation, slope, or significance. In all cases, the post-restoration precipitation data fall within the range of data used to establish the pre-restoration relationship (Fig. 6). Just as importantly, the control analyses of Flat Creek and Lower Camp Creek did not indicate changes in the riparian community when no restoration had occurred. We examined temperature (water year mean temperature, also acquired from ClimateEngine.org) and autocorrelation as potential confounding processes. Temperature and NDVI were not significantly correlated at any of the study areas – R^2 values for the temperature-NDVI relationship ranged from 0.001 to 0.12. Further, there was no statistically significant autocorrelation (assuming a one-year lag) within NDVI or precipitation in either the pre-restoration (1984–2007) or post-restoration (2012–2017) periods.

Instead of simply comparing pre- and post-restoration Landsat images to assess a change in vegetation vigor, this method focuses on the relationship between NDVI and precipitation and uses all available Landsat imagery for the time period of interest. Increases in NDVI are usually associated with increased consumptive water use by riparian vegetation (Groeneveld et al., 2007; Beamer et al., 2013; Nguyen et al., 2015). The statistical analysis presented here shows that this additional water is not provided by precipitation, so it must come from some other source. In the case of Silvies Ranch, the ABDs were installed to raise the level of water in the channel, thereby raising the elevation of the water table adjacent to the stream channel. The higher water tables result in a

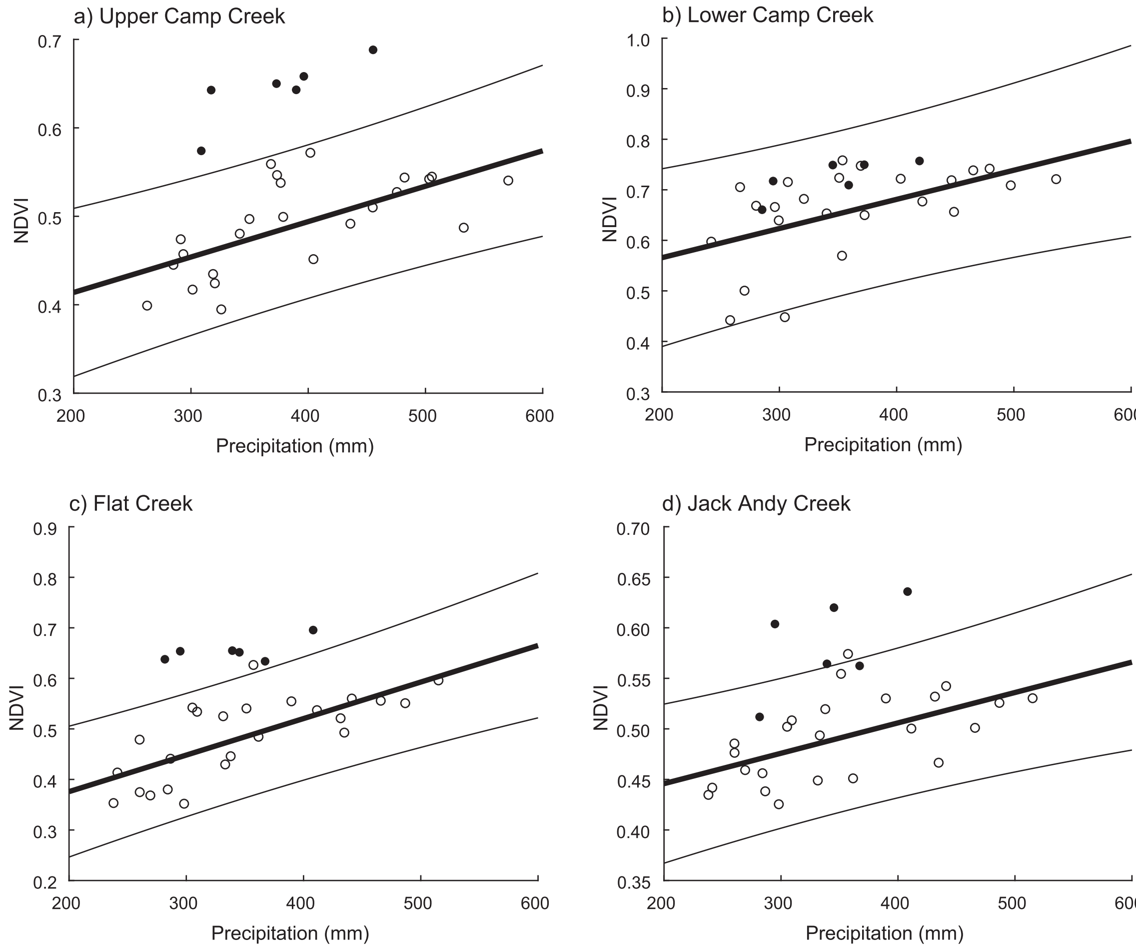

Fig. 4. Pre-restoration (open circles) and post-restoration (filled circles) data for each watershed. In each panel, the best-fit regression line is indicated by the bold line, and the 95% prediction interval indicated by the solid lines. Pre- and post-restoration statistics for each watershed can be found in Tables 1 and 2, respectively.

Table 2
Post-restoration statistical analysis (all statistical tests based on 5 degrees of freedom):

Study Area	Post-Restoration Tests of Precipitation-NDVI Regression		
	Statistically significant change?	P-value	t-statistic
Upper Camp Creek	Yes	1.32×10^{-5}	16.91
Lower Camp Creek	Yes	5.90×10^{-4}	7.70
Flat Creek	Yes	1.46×10^{-5}	16.57
Jack Andy Creek	Yes	1.88×10^{-3}	5.97

vadose zone that drains less effectively, increasing the time over which two sources of water (increased soil moisture and higher groundwater) are available to the riparian community. The analysis presented here offers quantitative and statistically supported evidence for the claim that the restoration work effectively achieved that goal.

Taking advantage of recent advances in cloud-computing, this method evaluates riparian restoration at spatial and temporal scales that have proven challenging in the past (Kondolf and Micheli, 1995; Hobbs and Norton, 1996; Aguiar et al., 2011). Norman et al. (2014) regressed Landsat-derived NDVI against springtime precipitation to examine the effects of gabions in cienegas, but limitations in data processing required them to use a single Landsat image for each year, and their nearest usable precipitation gauge was 35 km away from the study site. Climate Engine's easy access to distributed processing of Landsat images and gridded meteorological data make it possible to interrogate the local record from 1984 to the present, establishing a baseline condition that is not just a snapshot in time, but a long-term, quantifiable relationship that captures a wider range of conditions than short-term pre-project monitoring might. This analysis does require several years of post-restoration data, so it cannot be used as an assessment tool immediately following the completion of a contemporary project. However, the method can be applied quickly and inexpensively to projects that were implemented as recently as five years ago. As time passes, the method can also be applied repeatedly to monitor the project over the longer timescales (i.e., the decadal monitoring recommended by Kondolf and Micheli, 1995) that are seldom considered in the initial budgeting. Finally, the method could potentially be applied to consider riparian areas undergoing terrestrialization, although grouping the pre- and post- terrestrialization data will be more challenging.

This statistics-based remote sensing approach is a powerful tool to quantitatively and defensibly assess the effectiveness of one aspect of stream restoration projects. The method does not depend on on-site monitoring and instead uses existing satellite data accessed through ClimateEngine.org. Climate Engine is designed to make these data-intensive calculations and extractions accessible to a wide audience of users, and the analysis presented here requires no specialized skills in either remote sensing or Geographic Information System (GIS) programming. Climate Engine is currently available at no charge for non-commercial activity, making it an attractive option to (usually resource-limited) NGOs and government agencies that typically sponsor restoration projects. Similarly, the statistical analysis, although performed in MATLAB for this paper (see supplemental material for

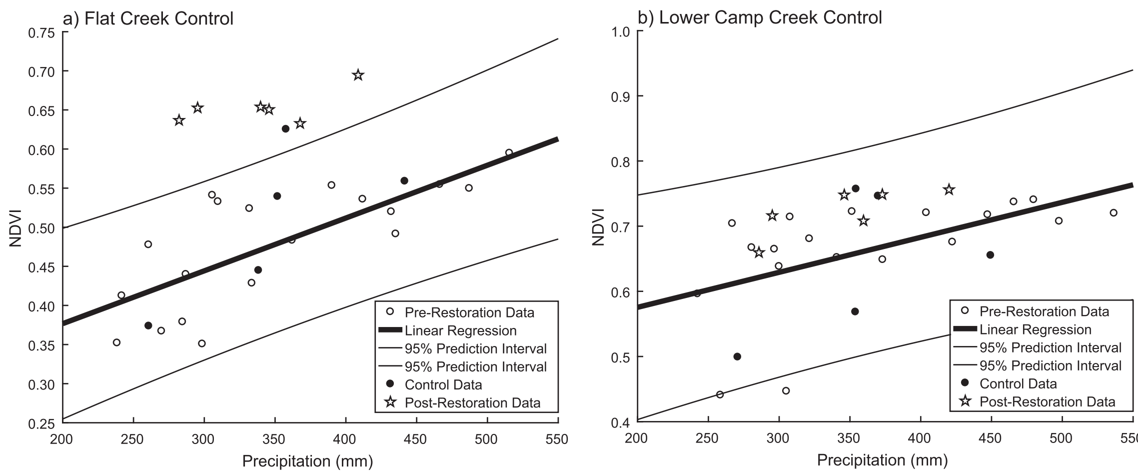

Fig. 5. Control tests on (a) Flat Creek and (b) Lower Camp Creek study areas. The control data (filled black circles) came from the pre-restoration population, but were not used to establish the pre-restoration regression between precipitation and NDVI.

Table 3
Statistical analyses on the control study areas. (a) pre-restoration (1984–2002) relationships, (b) control (2003–2007) *t*-tests, and (c) post-restoration (2012–2017) *t*-tests.

(a) Pre-Restoration (1984–2002) Precipitation-NDVI Linear Regression (17 d.f.)				
Study Area	Regression Slope	Regression Intercept	R^2	P-value
Flat Creek	6.75×10^{-4}	0.242	0.566	2.01×10^{-4}
Lower Camp Creek	5.37×10^{-4}	0.468	0.311	0.0130
(b) Pre-Restoration Control (2003–2007) Residual Tests for Changes in the Precipitation-NDVI Regression (4 d.f.)				
Study Area	Statistically Significant?	P-value	t-statistic	
Flat Creek	no	0.411	0.916	
Lower Camp Creek	no	0.737	−0.360	
(c) Post-Restoration (2012–2017) Residual Tests for Changes in the Precipitation-NDVI Regression (5 d.f.)				
Study Area	Statistically Significant?	P-value	t-statistic	
Flat Creek	yes	9.04×10^{-6}	18.27	
Lower Camp Creek	yes	7.68×10^{-4}	7.27	

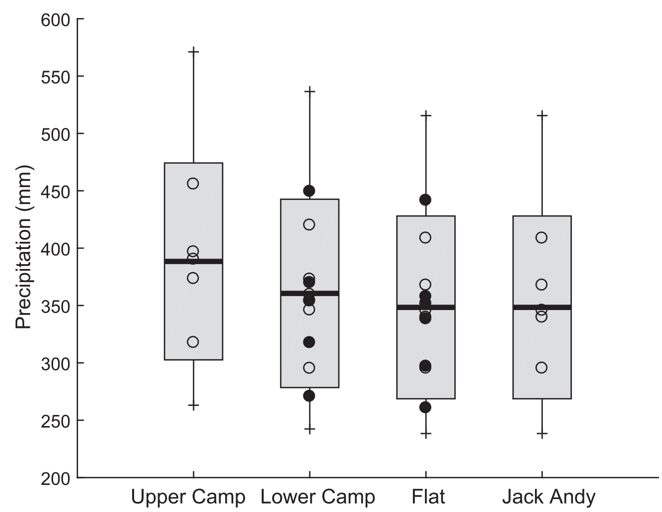

Fig. 6. Pre- and post-restoration precipitation at study areas. The heavy black line in each column indicates mean pre-restoration precipitation, with the shaded box indicating ± one standard deviation and the lines indicating the full range (minimum to maximum) of pre-restoration observations. Post-restoration precipitation observations are indicated by the open circles. For Lower Camp Creek and Flat Creek, control data are indicated with filled circles.

program scripts), can be carried out in Excel or in *R* at limited or no cost, respectively.

This paper offers a proof-of-concept for a quantitative, statistically sound assessment of stream and riparian restoration work, but it is also important to recognize its limitations. It examines only one aspect of those projects, and it relies on spatially integrated data to do so. The project must be large enough that data aggregated on a 30 m pixel size are representative of both the pre-restoration and restored area, and the spatial scale of the precipitation data must be fine enough that those data accurately represent the rainfall at the restoration site. The method identifies changes in the relationship between spatially and temporally integrated vegetation vigor and precipitation, but it does not identify the mechanisms by which those changes occurred. Since the method relies on spatially integrated data, the boundaries of the polygons enclosing the study areas are particularly important. In this case, the proof-of-concept goal of this manuscript was achieved by drawing polygons based on post-restoration riparian areas. In using this method to examine other projects, however, we recommend drawing the polygons based on the project goals established before any restoration work is undertaken. The proof-of-concept here was also demonstrated in a semi-arid water-limited setting, where there is a marked distinction in greenness between upland and riparian vegetation. Further testing is warranted before applying the method in more mesic settings. Finally, the remote sensing analysis cannot take the place of on-site data collection to evaluate other aspects of the projects, nor can it evaluate the success of effective riparian restoration in achieving specific project goals. Wildlife surveys, for example, are still needed to assess the creation of habitat, and on-site surveys are still required to evaluate projects intended to halt ongoing incision. However, this method does offer a way to perform some post-restoration analysis in a data-limited environment for projects in which pre- and post-restoration on-site data collection was limited or absent.

5. Conclusions

Using remote sensing and climate data freely available via a cloud-computing application (ClimateEngine.org) along with relatively simple statistical analyses, we demonstrate that restoration work at Silvies Valley Ranch was effective in providing additional water to the riparian vegetation community, thereby increasing vegetation vigor.

We infer that this additional water was provided by shallow groundwater that was raised by the installation of ABDs along four streams. The change shown in this study is not merely an observed change in the vegetation, but a change in the functional relationship between precipitation and vegetation. The change to that relationship is quantified and shown to be statistically significant. Although this analysis is limited to vegetation, it can be performed with freely available data and common inexpensive software, and it does not depend upon on-site monitoring, either before or after restoration. The approach and analysis presented in this paper offers a powerful and cost-effective way to evaluate effectiveness of one aspect of restoration projects, especially projects that are implemented with little or no monitoring.

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Conflicts of interest

None.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ecoleng.2018.06.024. These data include Google maps of the most important areas described in this article.

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