FINAL REPORT

Roles of pre-fire vegetation, soil, and climate in Great Basin ecosystem recovery

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List of abbreviations and acronyms

AIM: Assessment, Inventory, and Monitoring

BLM: Bureau of Land Management

GEE: Google Earth Engine

MTBS: Monitoring Trends in Burn Severity

NBR: Normalized burn ratio

NDMI: Normalized difference moisture index

NDPDI: Normalized difference perennial dominance index

NDVI: Normalized difference vegetation index

NRCS: Natural Resources Conservation Service

NRI: Natural Resources Inventory

R&R: Resilience and resistance

TCA: Tasseled cap angle

Keywords:
Remote sensing, Landsat, time-series analysis, Great Basin, sagebrush, shrublands, rangelands, wildfire, resilience, resistance, restoration, ESR, spatiotemporal, invasive plants, cheatgrass, biodiversity, plant diversity

Abstract:

Great Basin shrublands in the United States are rapidly converting to annual grass-dominated ecosystems, driven primarily by increased wildfire activity. Post-fire vegetation recovery trajectories vary spatially and temporally and are influenced by the effects of topography, climate, soils, and pre-fire vegetation. Our study leverages spatially continuous Landsat data alongside spatial environmental datasets to evaluate drivers of post-fire vegetation recovery. We first evaluated the spectral diversity hypothesis, which suggests that variation in remotely sensed spectral values relates to plant species diversity. In turn, plant species diversity is theorized to be an important predictor of ecological resilience to disturbance and resistance to invasive species. Weak relationships between spectral diversity measures and plant species diversity led us to explicitly model plant species richness with Landsat spectral information and environmental variables. We applied the model of plant species richness to produce annual maps of predicted species richness from 1994–2017.

We assessed post-fire recovery in terms of the impacts of frequent fire activity on post-fire communities, whether post-fire seeding improves recovery outcomes, and by explicitly modeling post-fire plant communities. We found that repeated fires had a cumulative effect leading to increased annual herbaceous invasion and diminished perennial plant components. Meanwhile, on average, post-fire seeding treatments had negligible influence upon post-fire perennial plant recovery. Importantly, post-fire recovery trajectories varied significantly across the region, underscoring the importance of spatial evaluations of recovery patterns. The model of post-fire recovery produced strong validation statistics when averaged across all fires and more tempered results when applied to new fires not included in model development. Notably, plant species richness was not a strong enough predictor variable to be included in the final model.

Spatially continuous analyses are important as they can account for variability in post-fire recovery of Great Basin shrublands. While such analyses have previously been hampered by data and computing limitations, our results suggest that these approaches are increasingly tractable. Most importantly, spatially explicit approaches such as this provide valuable maps to land managers that can inform data-driven post-fire management.

Objectives:

Our overarching objective was to **determine post-fire plant community recovery based on pre-fire vegetation, soil properties, climate, fire characteristics, and rehabilitation treatments**. Our completed project addresses the Resilient Landscapes goal of the 2014 National Cohesive Wildland Fire Management Strategy as well as "public benefits of ensuring health and safety of public and other lands" and "protection of life, critical infrastructure and natural and cultural resources." It addresses these items by 1) assessing the relationship between remotely sensed spectral diversity and plant species diversity, 2) evaluating pre-fire plant species diversity as a predictor of post-fire vegetation recovery, 3) comparing aerial versus drill seeding efficacy in plant community recovery across landscapes and time, and 4) developing spatially and temporally robust metrics of recovery using remote sensing and field-based measurements.

Background:

Fire and associated post-fire rehabilitation treatments interact with other drivers, such as climate, soil, pre-fire vegetation composition and structure, and invasive plants to influence ecosystem function. Both wildland fire and post-fire rehabilitation treatments affect numerous ecosystem properties, but little is known about the extent and magnitude of these effects in rangeland ecosystems and how they vary across regional geographies. This lack of knowledge greatly impairs the success of rehabilitation treatments and the efficient use of limited financial and human resources.

Post-fire emergency stabilization and rehabilitation is a major activity undertaken by the Bureau of Land Management (BLM) in the Great Basin, with average of $33.7 million (2000-2013) spent annually —86% of which is spent in Great Basin states (BLM 2014). Meanwhile, annual average acres burned have increased nationally from an average of 2.9 million acres during the 1980s to 6.6 million acres from 2010–2015—including 1.2 million acres per year in sage-grouse habitat between 2012 and 2014 (Figure 1) (USDI 2015).

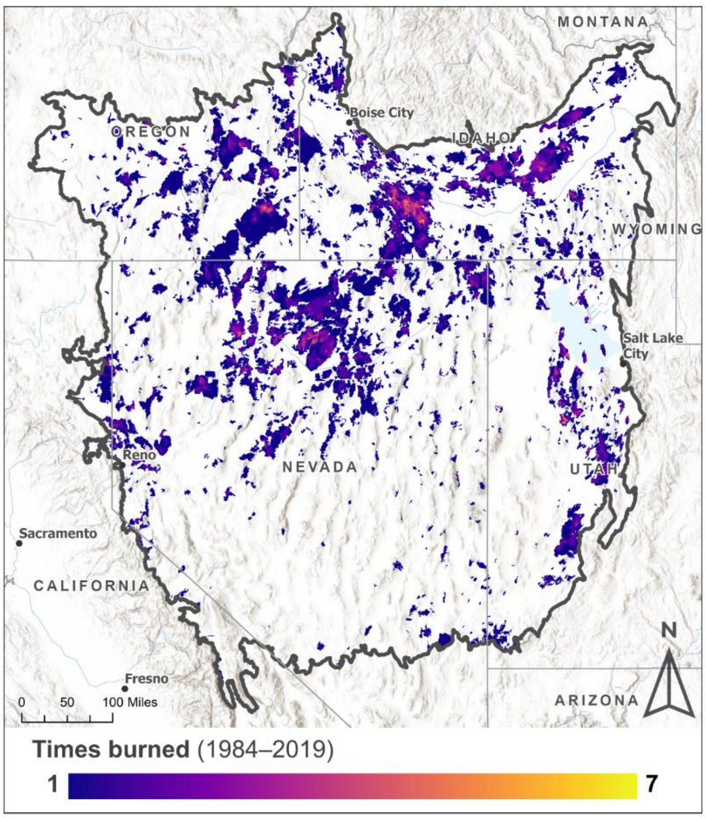

Figure 1: Map of the study area, comprising the Great Basin and Snake River Plain level III ecoregions. The study is overlaid onto a map of fire frequency derived from Monitoring Trends in Burn Severity fire perimeters.

Post-fire rehabilitation program goals include stabilizing sites and reducing erosion, preventing/reducing annual grass (*Bromus tectorum*) invasion, and establishing desirable plant communities and critical habitat for threatened or endangered species, such as sage grouse (USDI BLM 2007). The most commonly used methods for rehabilitating shrubland ecosystems are aerial or drill seeding. Recent literature suggests that these expensive treatments are not consistently effective at displacing cheatgrass populations or reestablishing sage-grouse habitat, and treatment success varies with elevation and precipitation (Arkle et al. 2014, Knutson et al. 2014, Mahood and Balch).

When rehabilitation treatments fail, BLM managers often express concern about numerous proximate causes (Newingham personal communication). However, soil characteristics and climate are generally not identified as contributing to treatment failure. Considering that soils affect the distribution, composition, and productivity of plant communities, a better understanding of the role of soils in post-fire succession and rehabilitation is necessary to improve post-fire management outcomes. Another important attribute when discussing treatment failure and post-fire succession is climate. Climate has been shown to alter fire regimes (Robichaud et al. 2009, Li and Guo 2010) and lead to greater opportunity for invasion by cheatgrass (Bradley 2009). Yet, little is known about how climate interacts with post-fire rehabilitation treatments. Considering climate's influence on ecosystems, fire regimes, and invasion by introduced species, examining landscape patterns of post-fire ecosystem responses along climate gradients will allow us to take into consideration a site's long-term potential for invasion and ultimately its restoration success.

In addition to soils and climate, pre-fire vegetation plays a driving role in Great Basin post-fire communities, particularly pre-fire functional group composition and species diversity. Sites with high cover of perennial native grasses and forbs tend to better recover their perennial grasses and forbs components following fire (Barker, Pilliod, Rigge, & Homer, 65 2019; R. F. Miller, Chambers, Pyke, Pierson, & Williams, 2013; Rhodes, Bates, Sharp, & Davies, 2010). For sites with few perennial native species prior to fire, the converse is true (Chambers, et al. 2007; Barnard et al., 2019). Past research has demonstrated that spectral diversity indices are related to vegetation diversity in a given area; as the number and structural complexity of plant species increases, so does the spectral diversity (e.g., Heumann et al. 2015, Möckel 2016). If species diversity increases ecosystem resilience and resistance (R&R) (Folke et al. 2004), then spectral diversity indices may be suitable indicators of ecosystem R&R to disturbance, and ultimately ecosystem response to fire.

Metrics and methods that combine soils, climate, and pre-fire vegetation information may prove helpful for guiding post-fire vegetation management. In an effort to prioritize post-fire rehabilitation of vegetation in the Great Basin, scientists and resource managers have developed a R&R framework (Chambers et al. 2014, Miller et al. 2015, Pyke et al. 2015) in which ecosystems fall along a gradient of resilience to disturbance and resistance to annual grass invasion. This framework suggests that 1) soil moisture and temperature regimes, 2) pre-fire vegetation, 3) burn severity, 4) weather, and 5) post-fire management all affect ecosystem trajectories. While scientific evidence supports some of these theories, other components of the framework remain fairly conceptual. In addition, this conceptual framework has not been evaluated in regard to post-fire successional trajectories over broad spatial and long temporal scales.

Materials and methods

Plant species diversity

Spectral diversity

Spectral diversity has been used as a proxy for species diversity in diverse regions (Figure 2) (Rocchini et al., 2010; Warren et al., 2014). To evaluate and establish relationships of spectral diversity in the Great Basin, we used remotely sensed data from Landsat and field measurements of species richness from the BLM's Assessment, Inventory and Monitoring (AIM) and NRCS's Natural Resources Inventory (NRI) datasets (Herrick et al., 2017). Additionally, we supplemented the AIM and NRI datasets by collecting 43 post-fire field plots stratified by aerial and drill seeding (using Land Treatment Digital Library data) and moderate and high fire severity (using Monitoring Trends in Burn Severity) (Herrick et al., 2017). All new post-fire field data collection was covered by JFSP funds. In total, we analyzed 10,471 field plots in the Great Basin and Snake River Plain.

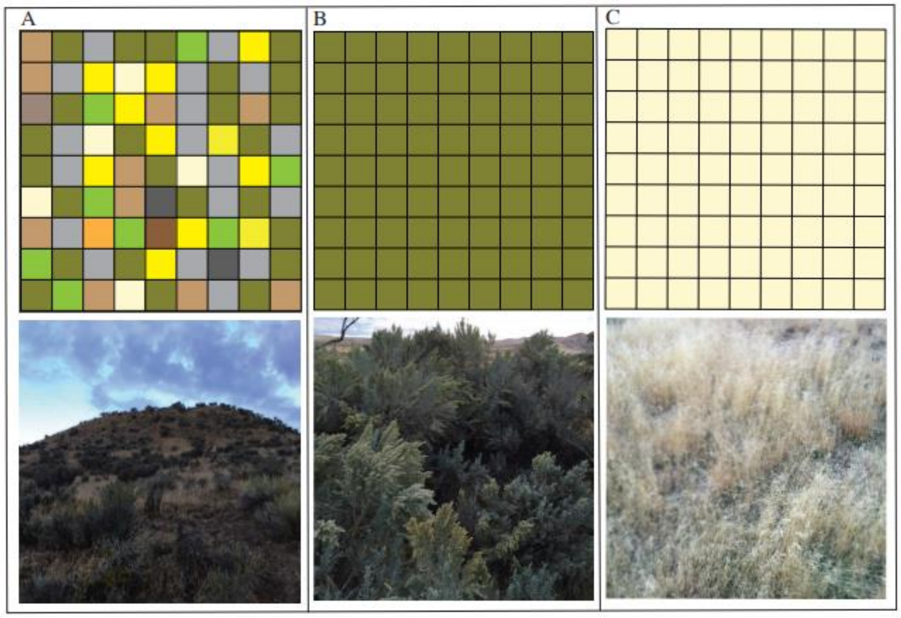

Figure 2: Conceptual relationship between spectral diversity and plant diversity in shrubland systems. Panel A is an intact ecosystem with high spectral and species diversity. Panel B is a sagebrush-dominated system with low species and spectral diversity. Panel C is a cheatgrass-dominated system with low species and spectral diversity.

Landsat data were accessed using Google Earth Engine's (GEE) Python API. We created annual composite images of collection 1, tier 1 surface reflectance images using Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper (ETM), and Landsat 8 Operational Land Imagery (OLI) for each year of the Landsat archive from 1984–2019 corresponding to the green-up period from April 1–June 15. Landsat data were also harmonized between sensors and cloud-masked. (Roy et al., 2016).

To derive the spectral diversity variables, we first calculated a suite of vegetation and ecological indices. Using each of these vegetation indices and the Landsat bands, we calculated spectral diversity measures based on Warren et al. (2014), including standard deviations, coefficients of variation, richness, and Shannon's H using a 100-meter focal grid. We also conducted unsupervised classification of the Landsat composites and calculated Shannon's H and richness values. In total, we analyzed 94 measures of spectral diversity. Ultimately, we related the spectral diversity measures to AIM and NRI species inventory data (referred to as species richness hereafter) by calculating Pearson correlation values. We also trained two Random Forest models using the same data inputs to account for variable interactions.

Species richness modeling

In addition to evaluating relationships between spectral diversity and plant species richness, we also modeled plant species richness directly using both the Landsat remote sensing variables and environmental variables. In total, we analyzed 220 predictor variables including spectral diversity, raw Landsat variables, soils, climate, fire, and topography variables. For modeling, we used Random Forest packages in R to perform variable selection, model training, and model validation. We then applied the Random Forest model to produce maps of predicted species richness across our study area for each year between 1994–2017. We also evaluated the relative importance of the predictor variables to assess drivers of species richness.

Post-fire recovery

We selected seven fires from the Monitoring Trends in Burn Severity (MTBS) dataset to analyze post-fire recovery (Table 1). The fires were spatially distributed across the Great Basin and satisfied the selection criteria that:

1. The fire occurred between 1995–2003.
2. The fire primarily burned in shrubland plant communities.
3. A significant portion of the initial fire perimeter has not burned since.
4. The fire received significant post-fire aerial and/or drill seeding.

We used ArcGIS Pro version 2.X to produce spatial polygons with attributes for the number of times each polygon has burned and which years it burned (Figure 3). Spatial polygons of aerial and drill seeding were compiled from the Land Treatment Digital Library (https://ltdl.wr.usgs.gov).

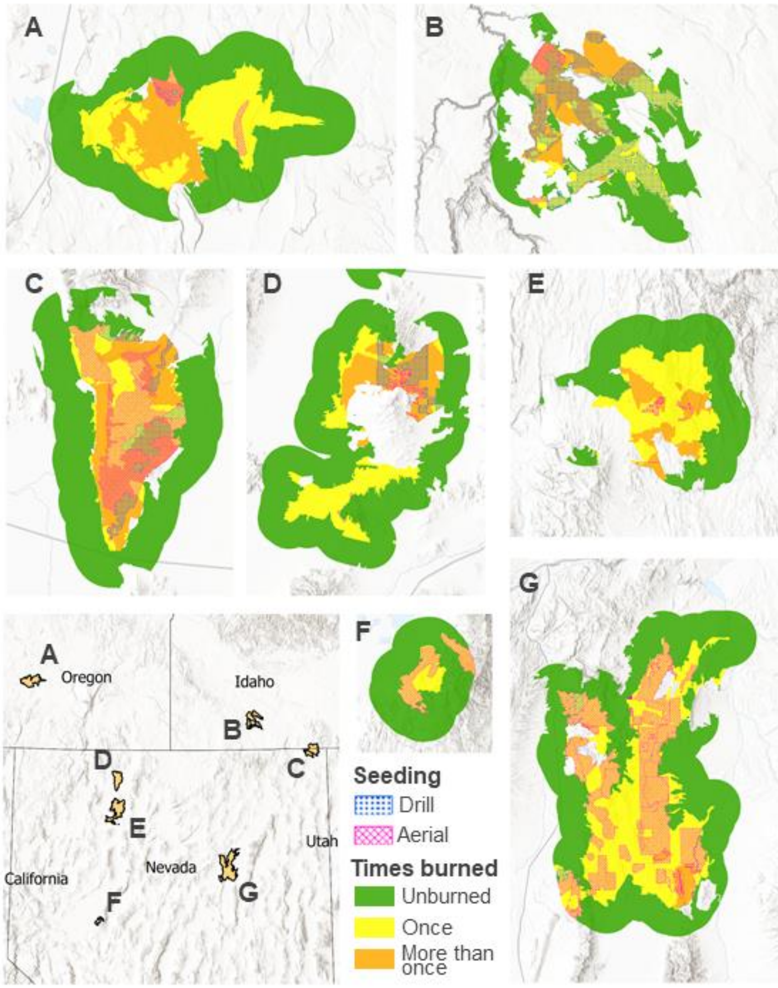

Figure 3: Numbers of times burned and post-fire seeding (drill or aerial) for each fire. A) Big Juniper (2001), B) Tuana Complex (1995), C) Bilk Creek (2000), D) Sombrero (1999), E) West Basin (2000), F) Shirttail (1999), G) Sadler Complex (2000). The areas that are not represented by a polygon either fell outside of the buffered area or have burned since the fire of interest.

Table 1: Summary of fires analyzed. Adjoining fires burned in the same year as the fire of interest and were within the 5-kilometer buffer.

Fire name	Year	Acres burned	Adjoining fires
Tuana Complex	1995	80,638	Three Creek (1995)
Shirttail	1999	11,976	New Pass Complex (1999)
Sadler Complex	1999	183,908	Mineral, Railroad Pass, Dido Complex (1999)
Sombrero	1999	128,143	Dun Glenn Complex (1999)
Bilk Creek Complex	2000	69,694	N/A
West Basin	2000	56,396	Choke Cherry (2000)
Big Juniper	2001	95,148	N/A

The normalized difference perennial dominance index

Many vegetation modeling studies in the Great Basin use shrub or sagebrush cover percentages as their response variable (Barnard et al., 2019; Rigge et al., 2019). While these metrics are often appropriate at local scales, at the regional extent there are locations for which vegetation community health is not synonymous with shrub or sagebrush cover. Here, we introduce an alternative metric, the normalized differenced perennial dominance index (NDPDI). Inspired by the normalized differenced vegetation index (Tucker, 1979), this index differences percent cover of perennial plants (shrubs and perennial forbs and grasses) against annual plants (annual forbs and grasses) (eq. 1).

$$NDPDI = \frac{Perennial\,\% - Annual\,\%}{Perennial\,\% + Annual\,\%} + 1 \qquad \text{[eq. 1]}$$

The NDPDI is bound from 0–2, with values of less than 1 being dominated by annual plants and values greater than 1 being dominated by perennial plants. One of the advantages of such an approach is that it is unbiased for low or high vegetation cover systems. For example, high elevation mountain sagebrush systems naturally have much higher cover than valley salt desert shrub. It is also sensitive to relatively minor shifts in dominance. One notable limitation of NDPDI is that it treats all perennial functional groups the same which can wash over important distinctions. Yet, in many portions of the region simply establishing perennial plants in the post-fire environment is viewed as a restoration success. Thus, we propose the index as a scalable indicator of plant community health for the Great Basin and Snake River Plain.

Post-fire recovery and number of times burned

To investigate the effect of the number of times burned on post-fire vegetation trajectories, we analyzed NDPDI, annual herbaceous vegetation, and bare ground trends derived from the Rangeland Analysis Platform Vegetation Cover dataset (Allred, 2021). To produce the images of NDPDI, we summed the vegetation classes of perennial herbaceous and shrub components (to represent perennial cover percentage) and used the annual herbaceous class to represent annual cover percentage. We then exported the annual data for NDPDI, annual herbaceous, and bare ground by polygons that were unburned, burned once, burned twice, burned three times, and burned four times. To evaluate trends, we produced time-series plots and calculated post-fire linear regression coefficients for NDPDI, annual herbaceous, bare ground. We assessed trends for all fires grouped together and for each fire individually.

Influence of post-fire seeding on recovery

To assess the effect of seeding on post-fire vegetation recovery, we evaluated spatial polygons that were classified as being drill seeded or aerial seeded using the Land Treatment Digital Library; areas that did not fall within a spatial polygon were assumed to have been unseeded (Pilliod et al., 2017). For the post-fire seeding impacts analyses, we excluded areas that burned multiple times following the approach of Knutson et al. (2014). Similar to the assessment of number of times burned, we exported annual data for NDPDI, annual herbaceous, and bare ground for drill, aerial, and unseeded polygons (Allred et al., 2021). To evaluate trends, we produced time-series plots and calculated post-fire linear regression coefficients for NDPDI, annual herbaceous, bare ground. Again, we assessed trends for all fires grouped together and for each fire individually.

Modeling post-fire recovery trajectories using environmental variables

We had three objectives for modeling post-fire recovery: 1) train a model of post-fire vegetation recovery, 2) evaluate environmental variables as drivers of post-fire vegetation recovery, and 3) apply the model to predict vegetations recovery for a contemporary fire. We defined post-fire recovery as the 15-year post-fire NDPDI value, which became the response variable in our model. Our model evaluated 106 candidate environmental predictor variables, including climate, soils, topographic, fire, and pre-fire vegetation variables. We produced the model and evaluated the importance of the environmental variables using the Random Forest package in R (Liaw & Wiener, 2007; R Core Team, 2018). We concluded by applying the model to the Saddle Draw Fire—which burned 284,065 acres in Oregon in 2014—to produce a map of the predicted projection of post-fire NDPDI for the year 2029.

Results and Discussion

Plant species diversity

Relationships between spectral diversity and plant species richness

The relationships between spectral diversity and plant species richness were generally weak (Table 2). The best performing spectral diversity predictor was the Shannon's H index of normalized difference vegetation index (NDVI) binned at increments of 0.05 (40 bins), with additional spectral diversity measures derived from NDVI consistently among the strongest predictors. However, even the Shannon's H index of NDVI had a Pearson correlation of only 0.27. Overall, "pure" spectral values (non-spectral variability measures), such as mean NDVI, better predicted species richness than any of the spectral diversity measures, albeit only slightly so. The first model, which used only the spectral diversity measures, reported a variance-explained (pseudo-R^2) of 17.65%. The second model, which used spectral diversity measures and the "pure" spectral data, reported a variance-explained of 22.58%.

Table 2: Summary of fires analyzed. Adjoining fires burned in the same year as the fire of interest and were within the 5-kilometer buffer.

Variable	Pearson correlation (R)
NDVI_40ShanH	0.27
NDVI_40Rich	0.26
NBR_40ShanH	0.25
NDMI_40ShanH	0.25
NDVI_sd	0.25
NDVI_20Rich	0.24
NBR_40Rich	0.24
NDMI_40Rich	0.24
kmeans500_Rich	0.24
NBR_sd	0.23

One primary reason that the spectral diversity relationships are likely weak in the Great Basin is the broad spatial extent. Importantly, Schmidtlein & Fassnacht (2017) noted that little attention had been paid to whether relationships hold across space and time during the development of the spectral diversity hypothesis. One example of how the regional spatial extent of this project likely confounds spectral diversity relationships is in regard to phenology. In our analysis, we subset the Landsat data to the period from April 1–June 15 to coincide with the green-up period. However, the green-up period varies significantly across latitudes, elevations, and aspects within the region. As a result, measured spectral diversity may be more of a function of topographic variability or environmentally-driven phenological variability than plant diversity. This assertion is supported by spectral diversity progenitor Rocchini et al. (2014) who stated that at regional and continental scales environmental parameters better predict biodiversity than spectral diversity.

Environmental model of species richness

The predictive model incorporating environmental variables as well as spectral information was a much better predictor of plant species richness than spectral diversity measures alone. The final model after variable reduction included 21 predictor variables related to topography, soils, climate, fire characteristics, as well as spectral information. This combined environmental and spectral variable model had an R^2 value of 0.52, a root mean square error of 6.69, and mean absolute error of 5.03 based on a validation set of 1,561 plots (Figure 4). Of the predictor variables, many precipitation and aridity variables ranked highly, with 11 of the 21 variables in the model being either measures of precipitation or aridity. Relatively few spectral variables were selected for the final model and none of the spectral diversity predictors were selected.

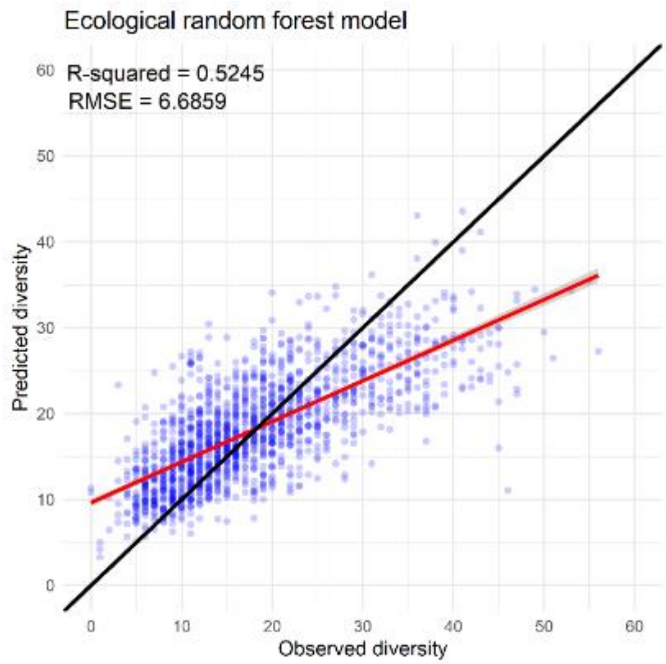

Figure 4: Model predictions from the environmental model of species richness plotted against observed species richness counts from AIM and NRI plots. The 1:1 line is displayed in black and a linear regression fit is displayed in red.

The combined environmental/spectral model accomplished the project's aim of producing spatially explicit estimates of plant diversity, which were ultimately to be incorporated as a predictor of post-fire vegetation recovery in our subsequent analyses. The fact that the model is generally supported by the literature lends confidence to its outputs. Specifically, the stronger performance of the combined environmental/spectral model relative to spectral diversity supports the assertion of Rocchini et al. (2014) that environmental parameters predict plant diversity at broad spatial extents. Additionally, many of the most important variables in the model are supported by other studies (Anderson & Inouye, 2001; Maurer et al., 2020; Chambers, Pyke, et al., 2014; Shinneman & Baker, 2009; Colwell et al., 2016). It is worth bearing in mind that in the context of this project, the plant species richness maps are simply a means to test whether species richness predicts post-fire recovery in the Great Basin. However, it is likely that these maps will have broader utility within the Great Basin rangeland management community as well.

Table 3: Variables selected for the environmental model of species richness, their variable importance, and the direction of the relationship.

Rank	Variable	Importance (%IncMSE)	Direction
1	Mean annual dryness index	16.7	⇩
2	Mean annual precipitation	15.4	⇧
3	Annual winter precipitation	13.2	⇧
4	Slope percent	12.2	⇧
5	Mean snow water equivalent	11.4	⇧
6	Annual 5-degree warming days	11.2	⇩
7	Annual annual dryness index	11.2	⇩
8	Landsat band 1 mean	9.6	⇩
9	Mean summer precipitation	9.5	⇧
10	Topographic diversity	9.2	⇧
11	Mean spring precipitation	9.2	⇧
12	Mean TCA	9.0	⇧
13	Elevation	8.9	⇧
14	Mean NDVI	8.9	⇧
15	Mean minimum temperature 0-degree cooling days	8.7	⇧
16	Years since fire	8.6	⇩
17	Annual precipitation	8.3	⇧
18	Annual snow water equivalent	8.0	⇧
19	Annual winter minimum temperature	7.9	⇧
20	Landsat band 3 mean	7.2	⇩
21	Annual summer precipitation	6.6	⇧

Evaluating change in species richness between two time periods (1994–1996 and 2015–2017) revealed both losses and gains in species richness (Figure 5). We chose to create a mean image for each of those date ranges to reduce the influence of the interannual variability. In general, species richness decreased in the west central portion and increased in the southern portion of the Great Basin. These trends almost certainly affect biodiversity of higher-level taxa, such as insects and birds. Previous models of bird assemblages in the Great Basin found that bird diversity was closely related to plant taxonomic composition, even more so than vegetation structure or primary productivity (Fleishman & Mac Nally, 2006). Few studies have evaluated the effects of plants diversity on higher trophic levels in the Great Basin; however, relationships are well established elsewhere (Cardinale et al., 2006; Scherber et al., 2010).

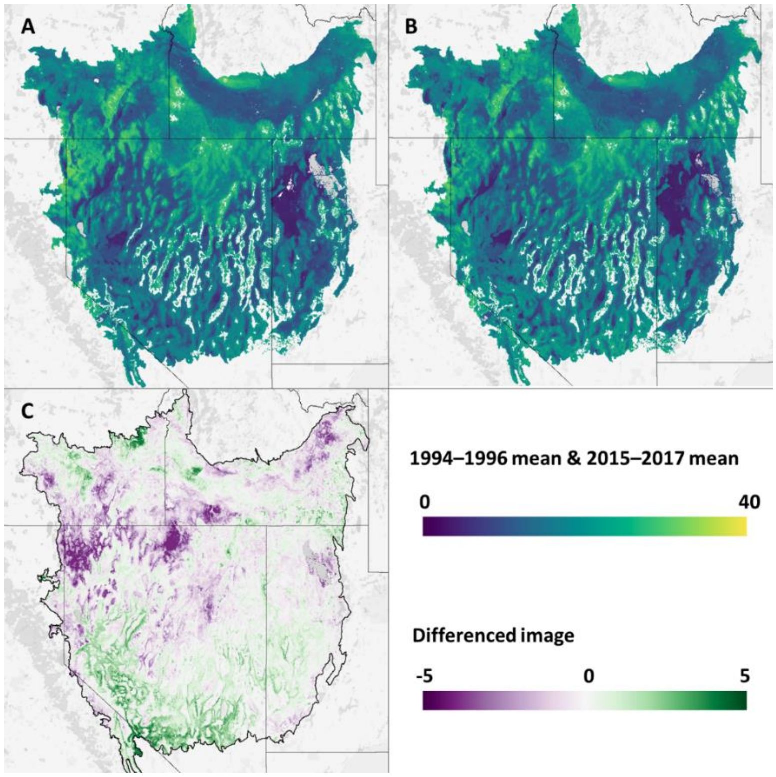

Figure 5: Mean images of species richness between 1994–1996 (A) and 2015–2017 (B). The map of species richness change through time (C) shows increases in the southern Great Basin species richness and declines across much of the northern Great Basin.

Post-fire recovery

Effect of number of times burned on post-fire vegetation

With regard to the effect of number of times burned on post-fire vegetation, each subsequent fire generally increased annual herbaceous cover, decreased NDPDI, and decreased bare ground (Figure 6). The most significant changes occurred after the first fire. Prior to fire, areas that burned once had similar trajectories to areas that were unburned. However, following fire, those same areas had steep declines in NDPDI and increase in annual herbaceous cover. Although there were additional declines in NDPDI for each additional time burned, post-fire slopes were largely flat (Figure 6). In each case bare ground declined throughout the time-series, suggesting that some of the increase in annual herbaceous can be attributable to infilling. Notably, even areas that didn't burn had declines in NDPDI and increases in annual herbaceous cover, suggesting baseline declines in native plant communities in the study region even in the absence of fire.

Our finding that each additional time burned resulted in increased degradation (increases in annual herbaceous cover and decreases in NDPDI) supports the findings of Mahood & Balch (2019). They studied sites that had burned 0–3 times in north central Nevada and found that repeatedly burned locations had successively lower alpha-diversity and native perennial cover percentage. In turn, invaded locations have been found to be twice as likely to burn and four times as likely to burn multiple times over a fifteen year period (Bradley et al., 2018). Lending support to those studies, we found that areas that burned multiple times also had elevated cover of annual herbaceous plants prior to the fires we analyzed, indicating that annual herbaceous cover is both a driver and response to fire. While it is well-established that fire degrades shrublands in the Great Basin, this is the first study to our knowledge to evaluate the impact of repeated burning in a spatially-explicit approach in the Great Basin.

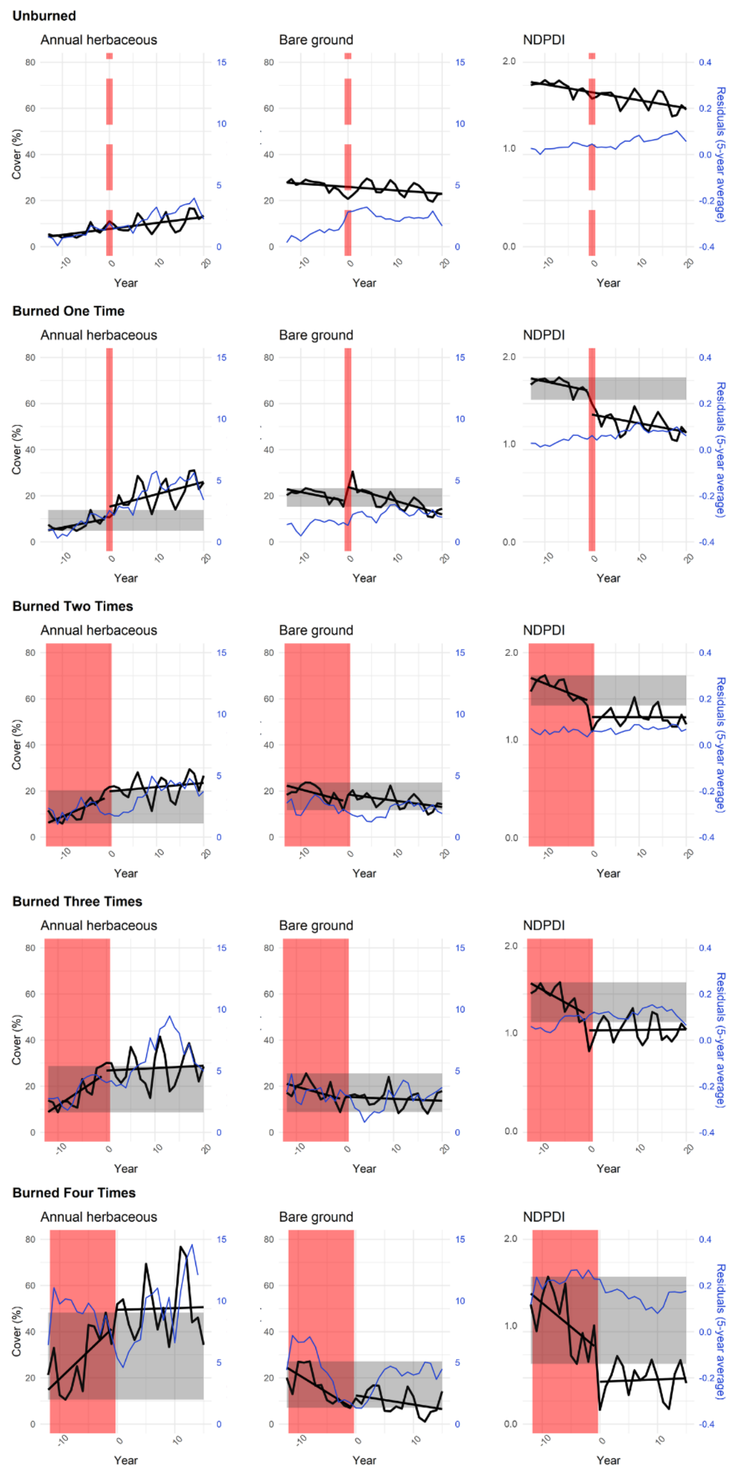

Figure 6: Time-series plots for pixels that were unburned, burned once, burned twice, burned three times, and burned four times. Red bars depict the year of the fire of interest and are dashed for unburned. For areas that burned multiple times the entire period of fire is depicted in red. Grey boxes represent the pre-fire envelope for each variable.

The specific fire events analyzed had variable post-fire outcomes in response to repeated fire (Figure 7; Table 3). Among areas that burned once, those within the West Basin fire had the highest post-fire NDPDI value of 1.82 (high perennial dominance), whereas those within the Shirttail, Sombrero, and Bilk Creek fires all had values <1 (annual herbaceous dominance). In general, the West Basin fire recovered anomalously well regardless of the number of times burned. The Bilk Creek and Sombrero fires are in close spatial proximity to one another and had similar trajectories in response to repeated burning. Both of those fires had 15-year post-fire NDPDI intercepts <1.0 for all areas that had burned, indicating significant degradation. Like the West Basin Fire, the Big Juniper fire in the northwestern portion of the Great Basin maintained an NDPDI value of >1.0 even in areas that burned twice, however those areas had lower NDPDI than adjacent unburned areas.

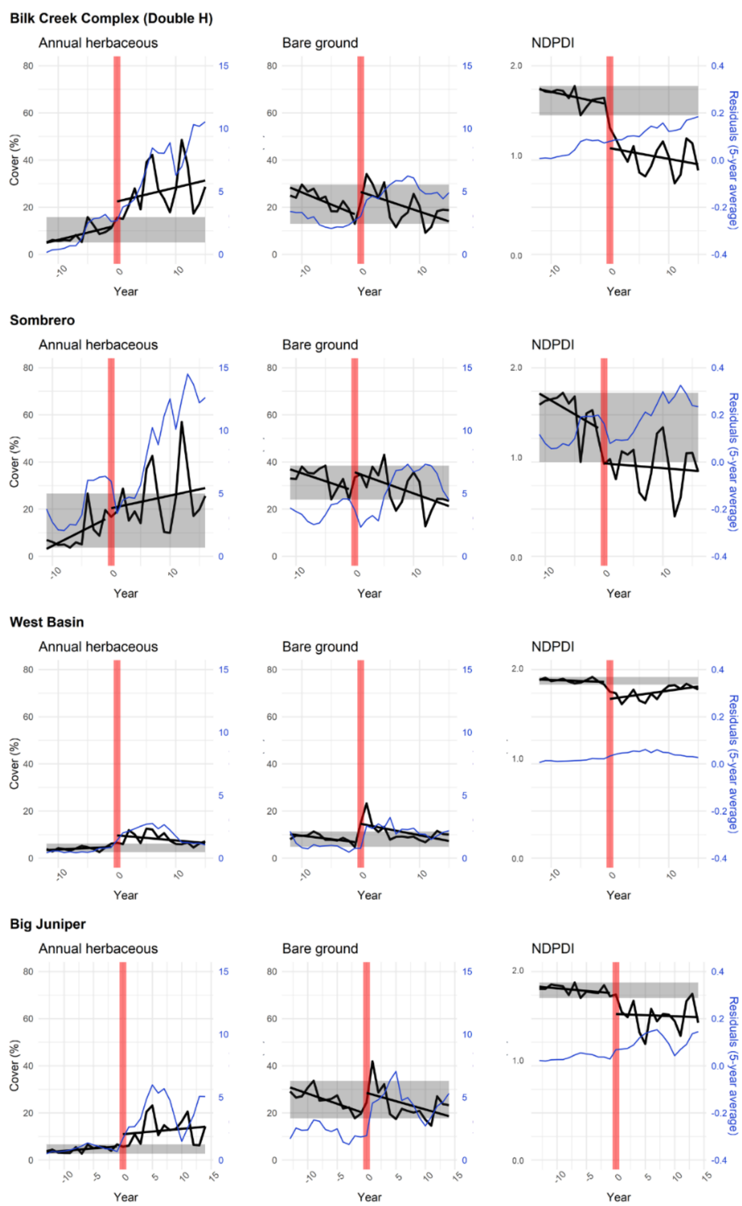

Figure 7: Time-series plots for pixels in four of the seven fires of interest. Fires were selected for plotting based on their location to depict some of the variability in recovery trajectories. Red bars depict the year of the fire of interest. For areas that burned multiple times the entire period of fire is depicted in red. Grey boxes represent the pre-fire envelope for each variable.

The effects of repeated burning on post-fire vegetation varied widely across the region, suggesting variable R&R in the different locations. The Bilk Creek and Sombrero fires both burned geographically near the study area evaluated by Mahood & Balch (2019) and our findings for those fires closely matched theirs—the first fire dramatically increased annual herbaceous cover and each subsequent fire incrementally led to slightly more dominance by annual herbaceous plants. However, trajectories varied for fires in the northern and eastern Great Basin, with the Big Juniper, Sadler, Tuana, and West Basin fires all maintaining perennial dominance even burning as many as three times. Current maps of resilience and resistance based on soil temperature and moisture suggest that locations in the northern Great Basin would be expected to have stronger post-fire recovery than in the central Great Basin (Maestas et al., 2016). While the soil-based resilience and resistance maps are coarse, our results support the general patterns.

Table 4: Post-fire linear regression slopes and 15-year intercepts of NDPDI for each fire for the number of times burned.

	Unburned		**One time**		**Two times**		**Three times**		**Four times**	
Fire	**Slope**	**15-int**	**Slope**	**15-int**	**Slope**	**15-int**	**Slope**	**15-int**	**Slope**	**15-int**
Big Juniper	0.00	1.76	0.00	1.52	0.02	1.51	N/A	N/A	N/A	N/A
Bilk Creek	-0.01	1.50	-0.01	0.97	0.01	0.83	0.00	0.62	0.00	0.49
Sadler	0.00	1.69	0.00	1.42	0.01	1.46	N/A	N/A	N/A	N/A
Shirttail	-0.01	1.32	0.02	0.85	N/A	N/A	N/A	N/A	N/A	N/A
Sombrero	-0.01	1.34	-0.01	0.92	0.01	0.89	N/A	N/A	N/A	N/A
Tuana	-0.01	1.62	0.00	1.53	0.00	1.34	0.00	1.33	N/A	N/A
West Basin	0.00	1.82	0.01	1.82	0.01	1.77	0.01	1.77	N/A	N/A

Effect of post-fire seeding on post-fire vegetation

When looking across all fires, seeding had little impact on post-fire recovery (Figure 8). Post-fire recovery slopes of NDPDI were most steeply negative for unseeded areas, but the intercepts (0-intercept: 1.41; 15-intercept: 1.27) were also higher than seeded areas, suggesting that the unseeded areas maintained their perennial component better than those that were seeded. Aerial seeding resulted in relatively moderate NDPDI intercepts (0-intercept: 1.33; 15-intercept: 1.20) and the slopes were only slightly less steep than unseeded. Drill seeding had the lowest post-fire NDPDI intercepts (0-intercept: 1.21; 15-intercept: 1.20) but also had the flattest slopes suggesting more stability through time.

When assessed across all fires together, post-fire aerial and drill seeding did not improve recovery 15 years following fire, and in some cases had worse outcomes (Figure 8). Similarly, Knutson et al. (2014) found that native perennial grass cover did not increase on seeded sites except in instances of drill seeding competitive non-native perennial grasses. Rather, they found that precipitation and elevation were more important drivers of recovery than seeding. Drill seeding of non-native perennial grass cultivars may help to explain why our results showed that drill seeding was more effective than aerial seeding. A similar post-fire seeding study found none of the 313 study plots met all guidelines for sage grouse breeding habitat (Arkle et al., 2014). Environmental variables often drive post-fire recovery, particularly climate and topography (Kulpa et al., 2012; Svejcar et al., 2017). Thus, while seeding has some demonstrated impact on post-fire recovery, just as often the projects have no better outcomes than those left unseeded.

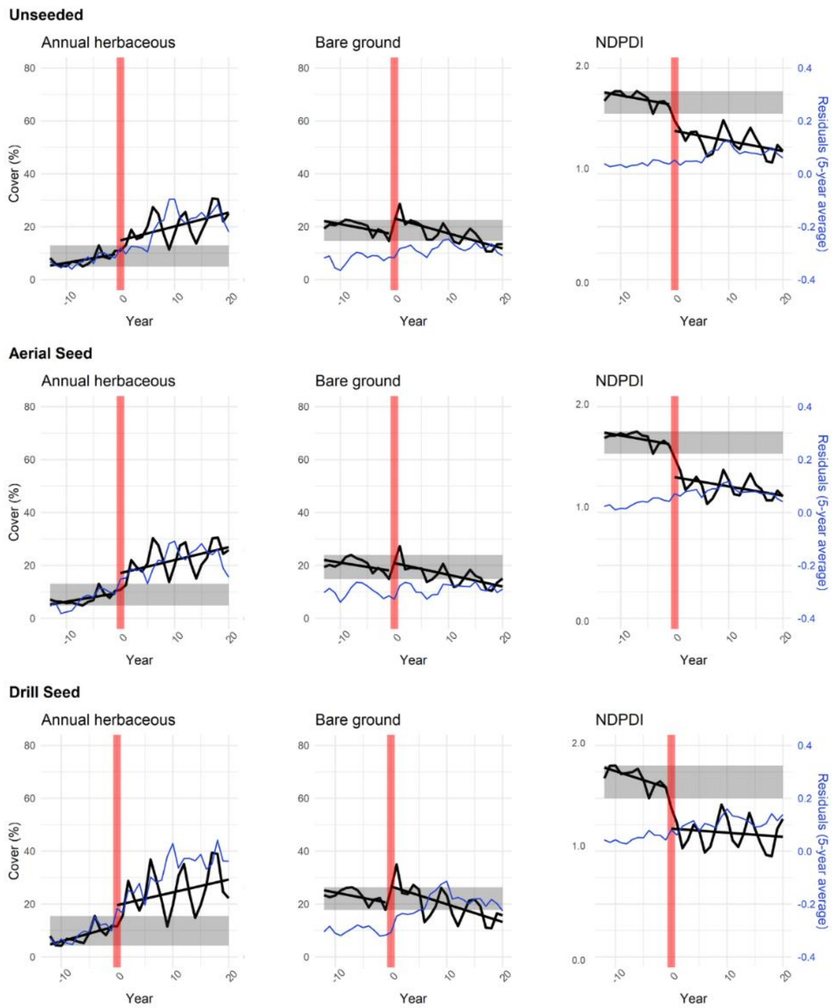

Figure 8: Time-series plots for pixels that were unburned, burned once, burned twice, burned three times, and burned four times. Red bars depict the year of the fire of interest and are dashed for unburned. For areas that burned multiple times the entire period multiple times the entire period of fire is depicted in red. Grey boxes represent the pre-fire envelope for each variable.

Similarly, when evaluating fires individually, unseeded areas generally had higher post-fire NDPDI than aerial or drill seeded areas (Table 4). The only exception to that pattern was the Tuana Complex. However, multiple fires had positive post-fire slopes for seeded areas despite negative slopes in unseeded areas. For example, drill seeded areas in the Sombrero, Sadler, and Tuana fires all had positive slopes of NDPDI, suggesting that some recovery may be occurring. The only fire with a positive NDPDI slope following aerial seeding was the West Basin fire with all other fires registering negative post-fire slopes, indicating ongoing decline.

It is possible that our finding that seeding had little positive influence on post-fire trajectories is partially related to the motivation for managers to apply seeding to areas that most severely burned. Additionally, there are known limitations of the MTBS dataset in the Great Basin, particularly the inclusion of unburned islands and fingers within the fire perimeters with commission errors as high as 15% (Sparks et al., 2015). Thus, while the MTBS fire perimeters likely include some component of unburned areas and additional low burn severity areas, post-fire managers are unlikely to apply seeding to those areas. This is evident in our results, as it seems unlikely that applying aerial seeding would cause worse outcomes than applying no seeding at all. Nonetheless, at the broad spatial extent of our study it is unlikely that these individual caveats outweigh our finding that post-fire seeding did not appreciably improve vegetation outcomes in the fires analyzed.

Table 5: Post-fire linear regression slopes and 15-year intercepts of NDPDI for each fire for each seeding strata.

	Unseeded		**Drill**		**Aerial**	
Fire	**Slope**	**15-int**	**Slope**	**15-int**	**Slope**	**15-int**
Big Juniper	0.00	1.52	N/A	N/A	-0.00	1.38
Bilk Creek	-0.01	1.02	-0.02	0.94	-0.01	0.94
Sadler	0.00	1.46	0.01	1.34	-0.00	1.39
Shirttail	-0.02	1.03	N/A	N/A	-0.02	0.77
Sombrero	-0.01	0.92	0.01	0.89	-0.01	0.82
Tuana	0.00	1.45	0.00	1.56	-0.01	1.59
West Basin	0.01	1.81	N/A	N/A	0.01	1.74

Modeling post-fire vegetation recovery

The model of post-fire vegetation recovery reported strong accuracy statistics, with an R^2 of 0.83 (Figure 9). A scatterplot of model predictions vs. actual datapoints are displayed in Figure 9. Leave-one-fire-out model validation reported a more modest average R^2 of 0.34, suggesting that the model generalizes only somewhat well to fires that it was not trained on and that it may not be as predictive as the “all-fire” model results would otherwise suggest (Table 5). The model included 17 predictor variables and the variables are summarized in Table 6. Among the 17 variables, pre-fire vegetation variables of NDPDI and annual herbaceous cover were both highly ranked. Additionally, several summer aridity/precipitation measures were also important, including post-fire summer precipitation, post-fire summer dryness index, and average 5-degree warming degree days. Relatedly, heat-load index and slope northness are both related to potential evapotranspiration. Both measures of fire severity were included, albeit with opposite directionality.

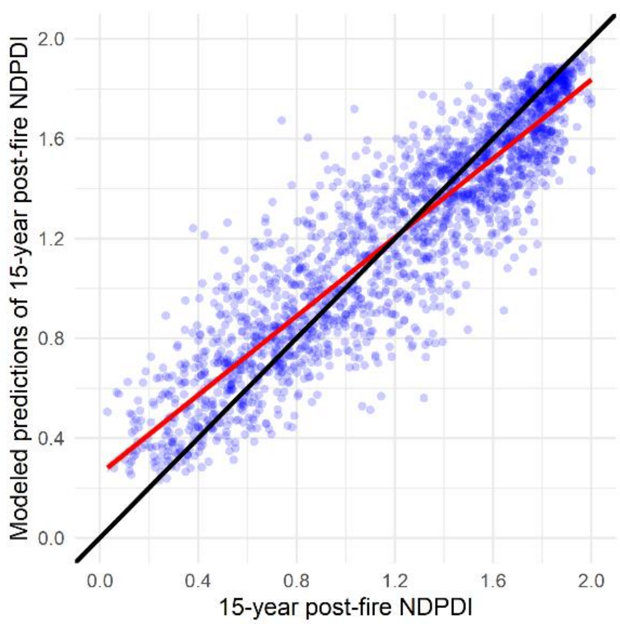

Figure 9: Model predictions plotted against the validation set for 15-years after fire. The red line indicates the linear regression fit through the datapoints and the black line is the 1:1 line.

Table 6: Leave-one-out validation statistics for the model of post-fire recovery. The name of the fire in the table represents the fire that was left out of the model training and the subsequent validation of predictions upon the fire. Validation statistics are reported as the coefficient of determination (R2 and root mean square error (RMSE)

Fire	R^2	RMSE
Big Juniper	0.29	0.33
Bilk Creek Complex	0.40	0.49
Sadler Complex	0.37	0.38
Shirttail	0.46	0.31
Sombrero	0.34	0.31
Tuana Complex	0.28	0.38
West Basin	0.23	0.39
Total	0.34	0.37

Table 7: Variable importance rankings and directionality for all variables in the model of 15-year post-fire NDPDI.

Rank	Variable	Importance (%IncMSE)	Direction
1	Pre-fire NDPDI	320.2	⇧
2	Post-fire summer precipitation	298.3	⇧
3	Post-fire summer dryness index	247.1	⇩
4	Average summer precipitation	168.2	⇧
5	Pre-fire annual herbaceous cover	160.4	⇩
6	Slope northness	133.0	⇧
7	Average cooling 0-degree-days	93.5	⇧
8	Average winter temperature	88.7	⇩
9	Average spring precipitation	77.3	⇧
10	Heat load index	75.9	⇩
11	RdNBR (burn severity index)	72.8	⇩
12	dNBR (burn severity index)	63.6	⇧
13	Average warming 5-degree-days	58.5	⇩
14	Post-fire snow water equivalent	56.4	⇧
15	Average winter precipitation	48.9	⇧
16	Average annual dryness index	48.6	⇩
17	Post-fire mean annual precipitation	46.4	⇧

The model of post-fire recovery should be considered experimental, however its strong performance demonstrates promise for future applications. A similar machine learning approach was applied to predict post-fire restoration outcomes following the Soda Fire and reported R^2 values of 0.58–0.79 across their models (Barnard et al., 2019). While we ultimately chose not to take the additional leap of modeling resilience and resistance explicitly, our validation statistics lend confidence that our approach may be able to be extended to produce maps of resilience and resistance.

The fact that many of the predictor variables selected for our model are documented drivers of post-fire vegetation recovery lends further confidence to the model. For example, Arkle et al. (2014) similarly found that latitude, climatic, and topographic variables affected the probability of post-fire vegetation communities meeting greater sage grouse brood-rearing habitat requirements. Previous studies have also identified soil properties as important drivers of post-fire recovery (Maestas et al., 2016; Roundy et al., 2018), however our model did not find any soils variables to be important. Pre-fire vegetation plays a driving role in Great Basin post-fire communities and pre-fire NDPDI and annual herbaceous cover were two of the most important variables in our models. (Barker, Pilliod, Rigge, & Homer, 2019; R. F. Miller, Chambers, Pyke, Pierson, & Williams, 2013; Rhodes, Bates, Sharp, & Davies, 2010; Chambers, et al. 2007; Barnard et al., 2019). Ultimately species richness was not found to be a highly important variable in the model (Figure 10).

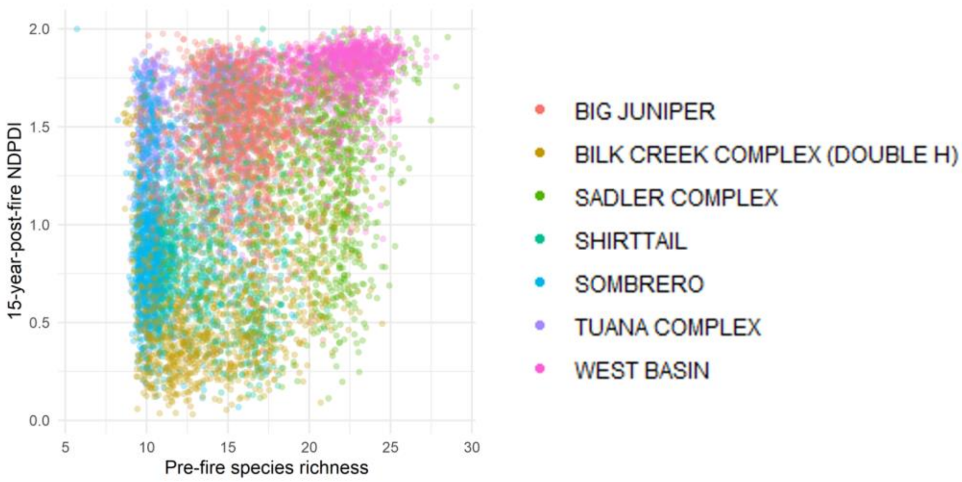

Figure 10: Relationship between pre-fire species richness and post-fire vegetation recovery. The relationship was not strong enough to warrant inclusion in the post-fire recovery model.

When the post-fire vegetation model is applied to the Saddle Draw Fire (2014), mapped predictions revealed that, while diminished NDPDI can be expected across the fire, it will not be uniform (Figure 11). In particular, the projections suggest that southern aspects and locations that had relatively high pre-fire NDPDI may have the most significant decreases in NDPDI following fire. Our post-fire vegetation recovery model predictions for the Saddle Draw Fire suggest that post-fire trajectories are spatially variable and governed by ecological drivers. Importantly, some of the sites that had the highest NDPDI values pre-fire were projected to maintain relatively high NDPDI fifteen years following fire. However, while using machine learning to evaluate drivers of post-fire recovery is valuable, mapping post-fire condition should be considered novel. Similar studies have, as yet, not gone as far as spatially explicit predictions of post-fire recovery (Barnard et al., 2019). That said, we believe that improvements in vegetation time-series mapping from Landsat and improved modeling of important data inputs make this type of modeling increasingly defensible and, indeed, an imperative of 21st century restoration planning (Allred et al., 2021; Jones et al., 2020).

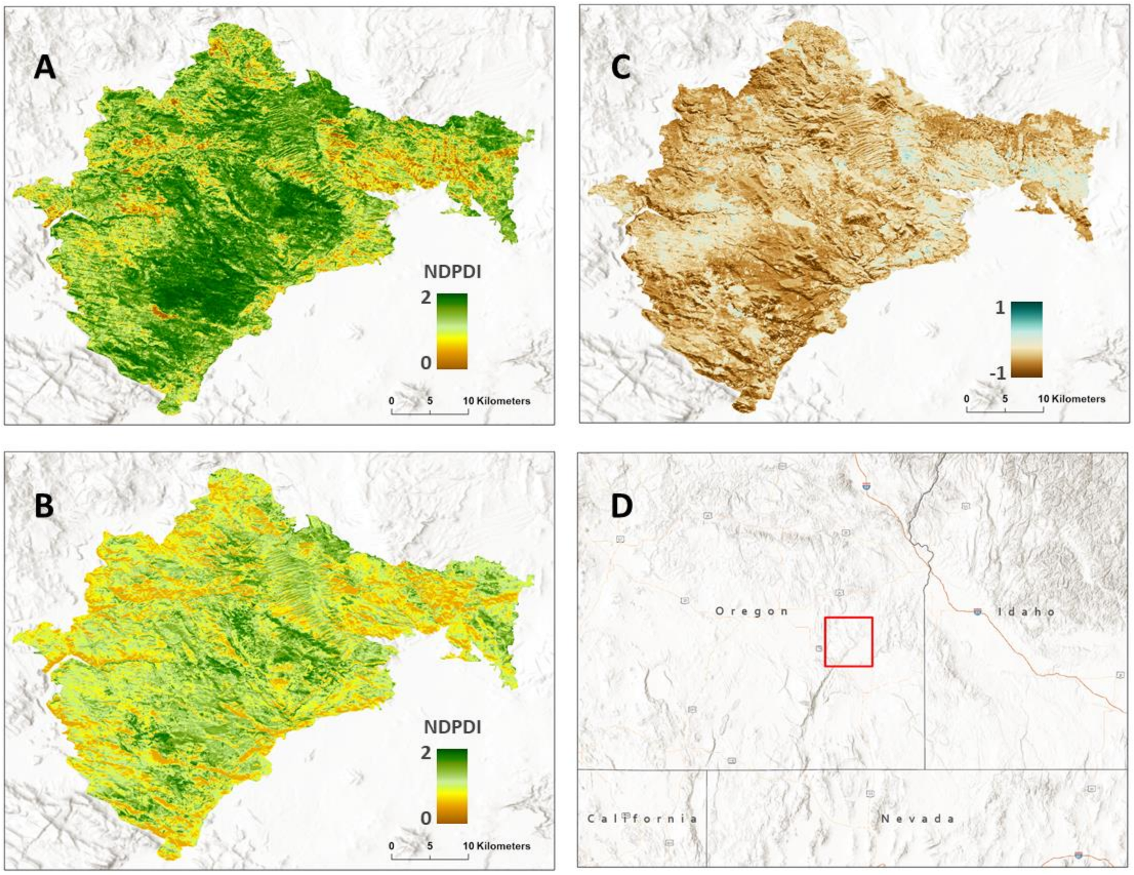

Figure 11: Maps of NDPDI for the Saddle Draw Fire. A) Pre-fire NDPDI (median of NDPDI between 2011–2013), B) modeled predictions of 15-year post-fire NDPDI corresponding to the year 2029, and C) differenced image of B – A.

Conclusions (Key Findings) and Implications for Management/Policy and Future Research:

Maintaining native shrublands under pressures of invasion by annual herbaceous plants and increasingly frequent fire is imperative to the biological integrity of Great Basin ecoregion and regional-scale analyses and data products are essential tools for managers (Chambers et al., 2019; Jones et al., 2020). Fundamental field-based studies have helped to elucidate environmental covariates of R&R and the capability now exists to build on those studies to provide spatially explicit information to managers and to scale that information to regional extents (Chambers et al., 2014, 2019; Ricca & Coates, 2020; NfRCS, 2021). Remotely sensed datasets like Landsat satisfy the need for spatially comprehensive information across a temporally rich time period and recently have been leveraged to produce annual maps of rangeland fractional cover (Jones et al., 2018; Rigge et al., 2020). This project was designed to address the management need for maps by applying rangeland fractional cover datasets to analyze shrubland R&R and post-fire response at the broad scale of the Great Basin.

The NDPDI, then, can be thought of as a coarse indicator of shrubland and perennial grassland biotic integrity intended to be used in the context of rangeland fractional cover maps to assess R&R (Allred et al., 2021; Rigge et al., 2020). As the baseline maps are available annually, analyzing trajectories in NDPDI following wildfire and other disturbance events is suitable for assessing general R&R at a regional extent. While this project has elicited important insights and demonstrated the potentially for spatial approaches to post-fire vegetation assessment in the region, future analyses should be more comprehensive in nature. For example, a more comprehensive study might analyze all fires in the MTBS dataset across the region and assess post-fire trajectories of NDPDI. This type of analysis could be used to validate existing R&R datasets (Maestas et al., 2016), elucidate environmental and spatial drivers of R&R, and develop more dynamic maps of R&R to be leveraged by managers in the post-fire environment.

Our results suggest that additional resources are needed to effectively restore Great Basin plant communities following fire. The difficulty of revegetating burned sites with native plants has been well-documented by previous studies (Arkle et al., 2014; Knutson et al., 2014; Kulpa et al., 2012). Our findings confirm those results and suggest that frequent failure of restoration projects may be more related to seed sources, weather or climate conditions, or timing of restoration than mechanism of seeding (aerial vs. drill). It is essential that agencies support and maintain ongoing work delineating seed zones, collecting and increasing locally adapted seed, and improving general restoration methods (Davies et al., 2017; Fisk et al., 2018; Leger et al., 2021; Shaw & Pellant, 2013). It is worth emphasizing that there have been significant strides in Great Basin restoration ecology during in the intervening years following the treatments analyzed here. However, new challenges related to climate change and increasing annual herbaceous plants combined with the documented difficulty of restoring native shrublands underscore the need for ongoing resources for fire response and fire science.

Our finding that repeated fire leads to cumulative degradation of perennial plants and invasion by annual herbaceous plants further demonstrates the importance of restoration at broad scales. In state-and-transition theory in the Great Basin, mid-elevation sites that are dominated by annual herbaceous plants have likely already transitioned to a cheatgrass-dominated state (Bagchi et al., 2013). In cheatgrass-dominated sites, frequent fire maintains cheatgrass dominance by preventing perennial plants from establishing. As a result, there are often few management options available for cheatgrass-dominated sites aside from mitigating impacts of fire (Bagchi et al., 2013; Svejcar et al., 2017). Thus, it is imperative to prioritize management in sites that are at-risk of transitioning to cheatgrass-dominance and to maintain intact habitat. In this regard, spatial conservation strategies help to organize diverse stakeholders around landscape- and regional-scale management objectives.

Following large rangeland fires, comprehensive strategies for post-fire management and restoration enable managers to efficiently and effectively allocate resources. Toward that end, maps provide common frames of reference for diverse stakeholders to address landscape- and regional-scale conservation issues (Falkowski et al., 2017; Maestas et al., 2016). The Cheatgrass Challenge in Idaho is one example of such a strategy. That group, led by the NRCS-Idaho, has implemented a strategy of “defend the core, grow the core, and mitigate impacts” for managing rangeland plant communities (NRCS, 2021). For groups that have developed spatial strategies in advance, when large fires affect a field office, managers are much better equipped to respond to the threat. In the past three-years, significant progress has been made in the region using satellite-derived spatial products to scale-up field monitoring information (Allred et al., 2021; Rigge et al., 2020). NDPDI builds upon those efforts and can help managers to identify sites that are at-risk of transitioning to annual dominance. With further research and development, NDPDI has the potential to provide a next-generation approach for mapping R&R at regional extents.

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Appendix B: List of Completed/Planned Scientific/Technical Publications/Science Delivery

StI Jensen's Master's thesis:

- Master's thesis defense presentation: Leveraging the Landsat archive to characterize plant species diversity and post-fire recovery in Great Basin shrublands
- Master's thesis: Leveraging the Landsat archive to characterize plant species diversity and post-fire recovery in Great Basin shrublands

Public presentations:

Jensen, E.R., Filippelli, S., Newingham, B.A., Vogeler, J. (2020, August). Of pixels and plant diversity: Modeling plant species diversity using Landsat time-series and machine learning. Contributed talk at Ecological Society of America, Virtual Conference

Jensen, E.R. (2019, November). A Remote Sensing Approach to Resilience and Resistance in Sagebrush Systems of the Great Basin. Poster presentation at CSU GradShow, Fort Collins, CO

Jensen, E.R. (2019, September). Remote sensing models of shrubland plant biodiversity in the Great Basin. Poster presentation at GIS in the Rockies, Denver, CO

Jensen, E.R., Vogeler, J.C., Newingham, B, Falkowski, M.F. (2019, April). A Remote Sensing Approach to Resilience and Resistance in Sagebrush Systems of the Great Basin. Poster presentation at US – International Association of Landscape Ecology annual meeting, Fort Collins, CO

Planned manuscripts:

- Planned manuscript submission to Ecosphere: Evaluating post-fire recovery based on management and environmental variables using satellite-derived datasets in Great Basin Shrublands
- Planned manuscript submission to TBD peer-reviewed journal: Characterizing plant species diversity using spectral heterogeneity and environmental variables in Great Basin shrublands

Web applications for spatial products:

- Web application for visualizing and analyzing NDPDI
    - One pager describing NDPDI and the application
- Web application for visualizing species richness maps

Additional science delivery:

- StI Jensen has stepped into the role of Outreach Coordinator for the Rangeland Analysis Platform (RAP) and will assess the feasibility and utility of incorporating NDPDI into the RAP.

Appendix C: Metadata

Plant species richness dataset

Metadata were produced according to FGDC v. 2 Content Standard for Digital Geospatial Metadata (CSDGM) protocols and were uploaded to the project submission. This dataset is available and will be maintained as a public Google Earth Engine Image Collection asset at this link. While we had initially planned to use the USGS ScienceBase repository for storing project datasets, Google Earth Engine will better facilitate future analysis of this dataset and has become standard in the period since writing the Data Management Plan.

NDPDI dataset

The Rangeland Analysis Platform's Vegetation Cover, v2 dataset has FGDC v. 2 Content Standard for Digital Geospatial Metadata (CSDGM) metadata, which was also written by StI Jensen, available at this link. The NDPDI dataset only takes the additional step of using the Vegetation Cover dataset to calculate the normalized difference of the perennial and annual bands of that dataset, as described in this report. Similarly to the plant species richness dataset, the NDPDI dataset is publicly available as a Google Earth Engine Image Collection asset at this link.