WHEN LIFE GIVES YOU DATA: LEVERAGING EXISTING DATA SOURCES TO INFORM FUTURE MANAGEMENT OF PINYON–JUNIPER WOODLANDS

by

ALYSON STEEL ENNIS

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Committee Members:

Nichole Barger

Laura Dee

Katharine Suding

Christy McCain

Michael Duniway

Ennis, Alyson Steel (Ph.D. Ecology and Evolutionary Biology)

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Thesis directed by Professor Nichole N. Barger

ABSTRACT

Pinyon–juniper ecosystems in the Western United States exist on vast areas of public lands and are ecologically, economically, and culturally significant. Shifts in climate and land use have driven tree expansion and densification in these systems, creating degraded landscapes and prompting the implementation of tree reduction treatments. In my dissertation, I utilized existing data sources to assess the effects of these treatments and investigate the influence of treatment factors and environmental conditions on treatment outcomes. I first used observational monitoring data and causal inference techniques to assess pinyon–juniper treatment effectiveness in Northwest Colorado. After developing a thorough methodology to account for challenges in data quality, I found that treatments had varied effects on understory vegetation cover—both native and nonnative—and that those effects changed with the method of tree removal and the vegetation cover at a site prior to treatment. I then investigated treatment effectiveness at sites on the Colorado Plateau using meta-analytical methods and existing data from the literature. Findings from my meta-analysis also showed that the effect of treatment on understory vegetation varied by treatment type, although was mostly positive, and included variation in treatment effects by environmental conditions like aridity and elevation. The Northwest Colorado study and the Colorado Plateau study both revealed potential treatment benefits of increased native understory vegetation cover and potential risks of invasive species introduction and proliferation, highlighting tradeoffs of treatment implementation. Together, my dissertation

chapters convey the power of utilizing existing data, particularly to assess landscape-scale restoration treatments carried out on U.S. public lands. My work emphasizes the knowledge that can be gleaned from treatment evaluation and provides data and information to support land managers in promoting more resilient ecosystems in the face of environmental change.

CONTENTS

TABLES

FIGURES

CHAPTER I

INTRODUCTION AND OVERVIEW

Ecological restoration has become a core practice in the management of public lands in the Western United States (U.S.). Increased use of public lands for activities such as energy development, livestock grazing, timber harvest, and recreation is degrading landscapes and threatening the sustainability of ecosystem services (Copeland et al., 2017; Foley et al., 2005; Lawler et al., 2014), necessitating large-scale restoration treatments such as invasive species removal, fuels reduction, and revegetation (Copeland et al., 2018; Pilliod et al., 2017; Redmond et al., 2014a). Restoration treatments vary in their specific goals and objectives, but have an overarching aim to maintain and restore ecosystem processes, functioning, structure, and composition and thus ensure the long-term viability of ecosystem services (Copeland et al., 2018; Kline et al., 2013; Kline and Mazzotta, 2022). Climate impacts have also begun degrading landscapes and changing ecosystem responses to restoration actions. These effects of climate change are becoming more apparent to land managers, decision-makers, and communities, shifting management goals even more strongly towards ecosystem restoration and changing practices to focus on creating resilient landscapes (Chambers et al., 2024; Esposito et al., 2022). As public land use intensifies and climate change impacts continue to alter ecosystems and restoration trajectories, ensuring that restoration treatments are indeed restoring ecosystem structure, function, and diversity becomes paramount.

Adaptive management, the process of learning from and improving upon management practices (Schreiber et al., 2004), is the primary avenue through which managers can assess past restoration treatments and incorporate knowledge into future management plans. With numerous environmental factors shaping the effects of treatments (Copeland et al., 2019; Shackelford et al., 2021; Williams et al., 2017), outcomes become hard to predict, requiring thorough treatment evaluation to inform future planning. Adaptive management provides a structure for analyzing treatment effects, exploring how and which environmental factors significantly influence treatment outcomes, and developing a framework for predicting a site's response to restoration treatments (Herrick et al., 2006; Schreiber et al., 2004). The treatment monitoring and evaluation required for the adaptive management process creates a hurdle, however, as funding and resources are seldom allocated to federal agencies for these steps specifically (Archie et al., 2012; Moir and Block, 2001). Broadening the methods that can be used to assess restoration treatments will support managers in completing the adaptive management cycle and improving the efficiency of these costly management actions (Copeland et al., 2018; Kimball et al., 2015; Munson et al., 2020).

The rise of "big data" and the shift in ecology towards more open science creates ample opportunity to leverage existing, readily available data for the purposes of adaptive management (Hampton et al., 2013; Kachergis et al., 2022; Michener, 2015). There are countless open access sources for environmental data, fed by monitoring networks, remote sensing platforms, and data repositories (Farley et al., 2018), that can be harnessed to answer ecological questions. Many federal land management agencies operate monitoring programs that collect standardized data across spatial and temporal scales (Kachergis et al., 2022; Smith, 2002; Tinkham et al., 2018). Remotely sensed data and other open access data repositories can provide information about environmental variables that may not be included in data collected by monitoring networks (Fattorini, 2014; Zimmermann et al., 2007). In addition to sources for raw data, many methods for utilizing existing data from the scientific literature, such as meta-analysis, are detailed in tutorials and other online resources for open use (Gurevitch et al., 2001; Koricheva et al., 2013; Koricheva and Gurevitch, 2014). This recent uptick of large, open access (or easily accessible) ecological datasets facilitates the process of adaptive management through collaboration and creates new opportunities for partnerships between scientists and managers/decision makers (Carter et al., 2020; Farley et al., 2018; Poisot et al., 2016). By developing, repeating, and fine-tuning methodologies that effectively use available data, scientists can assist managers in evaluating management actions and advance the adaptive management process (McCord and Pilliod, 2022; Remington et al., 2021). Utilizing available resources is essential to future land management, particularly for areas that are especially vulnerable to climate impacts and sensitive to disturbance, like semi-arid regions of the Western U.S.

Occupying a large portion of public lands in the United States, especially in semi-arid and arid regions like the Colorado Plateau, pinyon–juniper ecosystems make up the third most extensive vegetation type in the U.S. Pinyon–juniper communities are co-dominated by pinyon pine and juniper trees and exhibit immense diversity in understory species composition, structure, and functions (Mitchell and Roberts, 1999; Romme et al., 2009). These systems exist across a broad range of landscapes, varying greatly in elevation, topography, climate, and edaphic features. This variation contributes to their biological diversity, creating subcommunities within the pinyon–juniper system like persistent woodlands, wood shrublands, and wooded savannas/grasslands that support diverse wildlife habitats (Romme et al., 2009). Besides being ecologically valuable, pinyon–juniper communities provide economic value, with much of their range open to grazing, resource extraction, and recreation (Miller et al., 2019). These systems are also incredibly culturally valuable, preserving cultural diversity and archaeological resources, and providing pinyon nuts and ceremonial plant materials (Nabhan et al., 2002). As with much of our public lands, pinyon–juniper systems are changing with human use, disturbance, and climate changes.

The expansion of pinyon pine and juniper trees into adjacent ecosystems and increases in tree density (densification) within existing pinyon–juniper systems have occurred over the past century (Miller et al., 2019; Romme et al., 2009; Shinneman and Baker, 2009). Anthropogenic factors like overgrazing and fire exclusion (Archer et al., 2017a; Barger et al., 2009), as well as a period of cool, wet climate in the early 1900s (Miller et al., 2019), created conditions beneficial for tree growth, supporting increases in pinyon–juniper cover. This expansion and densification are reducing understory vegetation cover and creating accumulations of woody fuels (Miller and Tausch, 2001), which is increasing risk of soil erosion and severe wildfire (Gifford et al., 1970; Young et al., 2015), decreasing range quality, and degrading wildlife habitat (Coates et al., 2017; Cole et al., 1997). Land managers have subsequently carried out pinyon–juniper removal and reduction treatments in an effort to improve understory vegetation cover and reduce hazardous fuels, thus restoring wildlife habitat and rangelands, and contributing to fire prevention (Huffman et al., 2009; Redmond et al., 2014a). While benefits to these treatments have been recorded (Fornwalt et al., 2017; Holmes et al., 2017; Johnston and Anderson Jr., 2023; Severson et al., 2017a), there is also uncertainty surrounding the risks associated with treatments and their efficacy considering the number of neutral and even negative treatment effects reported (e.g., increased soil erosion, proliferation of exotic species) (Bombaci and Pejchar, 2016; Coop et al., 2017; Frey et al., 2013; Havrilla et al., 2017; Karban et al., 2022a; Magee et al., 2019; Owen et al., 2009). Understanding the comprehensive effects of pinyon–juniper treatments and what factors influence those effects is essential, as these systems continue to be impacted by changing climate and anthropogenic disturbance. Completing the adaptive management process and thoroughly evaluating treatments will support land managers in carrying out effective and efficient future management plans.

Overview of chapters

Chapter 2, *A causal inference approach to assessing the effects of pinyon–juniper removal treatments*, details my attempt to use existing data from various open access sources to assess pinyon–juniper removal treatment effects on vegetation cover in Northwest Colorado. For my cover response variables, I utilized observational monitoring data from the Bureau of Land Management's Assessment, Inventory, and Monitoring (BLM AIM) program. Treatment details were obtained from the Land Treatment Digital Library (LTDL), and information about relevant environmental covariates was compiled from various open access data sources. I employed pre-regression matching—a causal inference technique aimed at balancing covariate distributions between treatment and control groups—to account for selection bias in the observational AIM data. Unexpected initial results showed tree reduction treatments having a positive effect on tree cover, leading me to more deeply assess each step of my methods and finding inconsistent reporting of treatment completion in the LTDL. Thus, in this chapter, I describe an improved methodology for utilizing AIM and LTDL data, including validating treatment completion with remotely sensed annual fractional tree cover data from the Rangeland Analysis Platform (RAP). The methodology described in this chapter provides a path towards using available data sources to assess the impacts of landscape-scale treatments, which I utilized in my next dissertation chapter.

In **Chapter 3**, *Treatment type and pre-treatment site conditions alter the effect of pinyon–juniper removal on vegetation characteristics*, I carried out the methodology I described in Chapter 2 to evaluate pinyon–juniper treatment effectiveness in Northwest Colorado and investigate how factors such as treatment type and environmental site conditions may influence treatment outcomes. I used the data I collected in Chapter 2 (from AIM, LTDL, RAP, and other sources) and compiled a dataset to assess treatment effects on native herbaceous and cheatgrass (*Bromus tectorum*) cover. Using generalized linear mixed effects models, I found that the effects of treatment on native herbaceous cover were variable, with prescribed fire being the only treatment type that increased native herbaceous cover. Mechanical and manual treatments both had a slightly negative effect on herbaceous cover. Treatment had a positive effect on cheatgrass cover, although magnitude varied by treatment type, with prescribed fire having the most positive effect. Treatment effects were not influenced by environmental variables such as elevation or aridity, but were altered by the percent cover of trees, shrubs, and cheatgrass prior to treatment. The findings from this chapter highlight the potential benefits and risks of pinyon–juniper treatments and support the adaptive management process.

Finally, in **Chapter 4**, *A region-wide meta-analysis of pinyon–juniper treatment effectiveness on the Colorado Plateau*, I completed a meta-analysis to assess the effects of pinyon–juniper treatments on understory vegetation cover on the Colorado Plateau. Using an in-depth literature search, I compiled and extracted data from relevant studies with the goal of finding broad patterns and trends in pinyon–juniper treatments effects. I ran boosted regression tree (BRT) analyses to identify influential moderators for each understory vegetation response (forb, grass, shrub, overall understory, and exotic plant) and included important moderators in subsequent mixed effects meta-regression models. Influential moderators that increased predictive power of BRT models included treatment type, time since treatment, elevation, aridity, mean annual temperature, mean annual precipitation, percent clay in the soil, and percent silt in the soil. Overall, pinyon–juniper treatments increased herbaceous understory (forbs and grasses) and general understory cover, as well as exotic plant cover. Treatments had no significant effect on shrub cover. Treatment type and time since treatment consistently affected treatment outcome for every vegetation response, while the influence of environmental moderators on treatment effects varied by vegetation response. This meta-analysis combined results from 27 different studies and again, my findings highlighted potential benefits and risks to pinyon–juniper treatments, as well as key factors to consider when planning and subsequently assessing future treatments.

CHAPTER II

A CAUSAL INFERENCE APPROACH TO ASSESSING THE EFFECTS OF PINYON–JUNIPER REMOVAL TREATMENTS

Alyson S. Ennis, Brendan K. Hobart, and Nichole N. Barger

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ABSTRACT

Assessing the comprehensive effects of large-scale land treatments (e.g. fire mitigation, habitat improvement, etc.) on federally managed land in the Western United States is challenging due to their large scope and a lack of resources dedicated to monitoring treatment effectiveness. Monitoring programs operated by federal land management agencies provide valuable ecological data which can be utilized to assess the effects of these land treatments. Here, we use observational monitoring data from the Bureau of Land Management's Assessment, Inventory, and Monitoring (AIM) program, treatment information data from the Land Treatment Digital Library (LTDL), and ecological attribute data from a variety of open access sources to assess the effects of pinyon–juniper removal treatments in Northwest Colorado. To account for the inherent bias from observational data in our dataset, we employed pre-regression matching, a causal inference technique aimed at decreasing bias. Upon discovering the unexpected result that tree removal treatments had a neutral or positive effect on tree cover, we reviewed each step of our methods with more scrutiny, finding unreliable reporting of treatment details in the LTDL. We therefore describe an improved methodology for utilizing the LTDL, including validating treatment completion with examination of annual tree cover changes from the Rangeland Analysis Platform, another open access data source. The methodology described here provides a novel path towards using available data sources and statistical techniques to assess the effects of

landscape-scale management actions while emphasizing the importance of data quality and validation.

INTRODUCTION

Approximately 30% of land in the United States is federally owned and managed (Congressional Research Service, 2020). For the past half century, large-scale land treatments such as fuel reduction and wildlife habitat improvement projects have been a key focus for federal land managers, with this trend likely to continue considering the vast amounts of funding for restoration and resilience projects in legislation such as the Inflation Reduction Act (Copeland et al., 2018; Inflation Reduction Act, 2022). Assessing the ecological effects of these treatments is challenging due to their extensive scope and a shortage of resources dedicated to treatment effectiveness monitoring (Clifford et al., 2020). Thus, land managers and other decision makers are constrained in their planning processes by a lack of insight into the comprehensive impact of land treatments. As the western U.S. experiences temperature warming, more variable precipitation patterns, and increased aridity due to climate change, it is more important than ever to learn from the effects of past land treatments in order to facilitate adaptive management (Kharin et al., 2013; Seager and Vecchi, 2010; Sillmann et al., 2013).

A significant challenge to assessing treatment effectiveness and incorporating learned knowledge into management plans is infrequent and incomplete collection of data specific to that purpose (Clifford et al., 2020). Local/small-scale experimental studies can provide a mechanistic basis for ecological responses to treatments, but it is challenging to extrapolate experimental results across the spatial scales and environmental gradients at which treatments are applied. Furthermore, although larger-scale field experiments can elegantly and mechanistically reveal the effects of management, they are extremely costly and rare in practice (Butsic et al., 2017). Thus, we need better methods—that rely on existing, accessible data—for linking management actions to ecological outcomes at relevant scales. Integrating monitoring and remote sensed data can provide a direct and effective way of evaluating treatment effects across a broad range of locations and environmental conditions. Indeed, many federal agencies manage monitoring programs with the goal of collecting extensive observational on-the-ground data (e.g. Bureau of Land Management Assessment, Inventory, and Monitoring; U.S. Forest Service Forest Inventory and Analysis; National Park Service Inventory and Monitoring). Additionally, gaps or shortcomings in monitoring datasets can be augmented with publicly available ecological data—from Digital Elevation Models to climate data to remote-sensing derived data. These data sources can be leveraged to enhance learning about the effects of land treatments, producing knowledge that can be more rapidly incorporated into management actions and decision-making.

Using observational data—such as data from monitoring and remote sensing—to assess treatment effects comes with its own unique challenges, principal of which is a lack of control sites against which to compare treated sites (Butsic et al., 2017). Consider a monitoring dataset in which some of the survey sites fall within past treatments while most are outside of any treatment area. It may be tempting to consider all sites outside of treatment areas as a control group, but because the locations of treatments are typically not randomly assigned, there is a strong risk of introducing bias when evaluating the effects of treatment (Larsen et al., 2019; Reid et al., 2018; Simler-Williamson and Germino, 2022). For example, sites that are more accessible and nearer to roads are often more likely to receive treatment. This selection bias makes the treated sites fundamentally different than many of the control sites, making it very challenging to parse out causal effects of treatment from spurious ones created by confounding variables

(Larsen et al., 2019; Reid et al., 2018). When confounding variables such as accessibility affect both the site selection process for treatment and what ecological effects the treatment may have on a site, false relationships are even more likely to arise. Causal inference approaches allow us to move past these challenges and utilize observational datasets without true controls (Butsic et al., 2017; Larsen et al., 2019; Ramsey et al., 2019).

Causal inference techniques can be applied before and during analyses to reduce bias in a dataset and control for confounding variables. Pre-regression matching—a practical, relatively simple, and increasingly popular approach in conservation science—attempts to balance (i.e., equalize) the distribution of confounding variables between the treatment and control groups to create a less biased dataset for analysis (Stuart, 2010) (Fig. 2.1). More simply, the goal is for the treatment and control groups to have matching distributions for each covariate. When the confounding variables, or covariates, are balanced between treated and control groups, the false relationships that they can create are much less likely to arise in subsequent analyses (Ramsey et al., 2019). The result is a less-biased estimate of treatment effects. In the fields of ecology and natural resource management, matching has been used to evaluate the impact of conservation programs, land management, and restoration actions (Ferraro and Hanauer, 2014; Fick et al., 2021; Herbert et al., 2022; Schleicher et al., 2020; Siegel et al., 2022a, 2022b). Land treatment impact assessment is particularly conducive to the use of matching because the available monitoring data from federal agencies and abundance of open access environmental data can provide information about many different locations within a treatment and many different covariates.

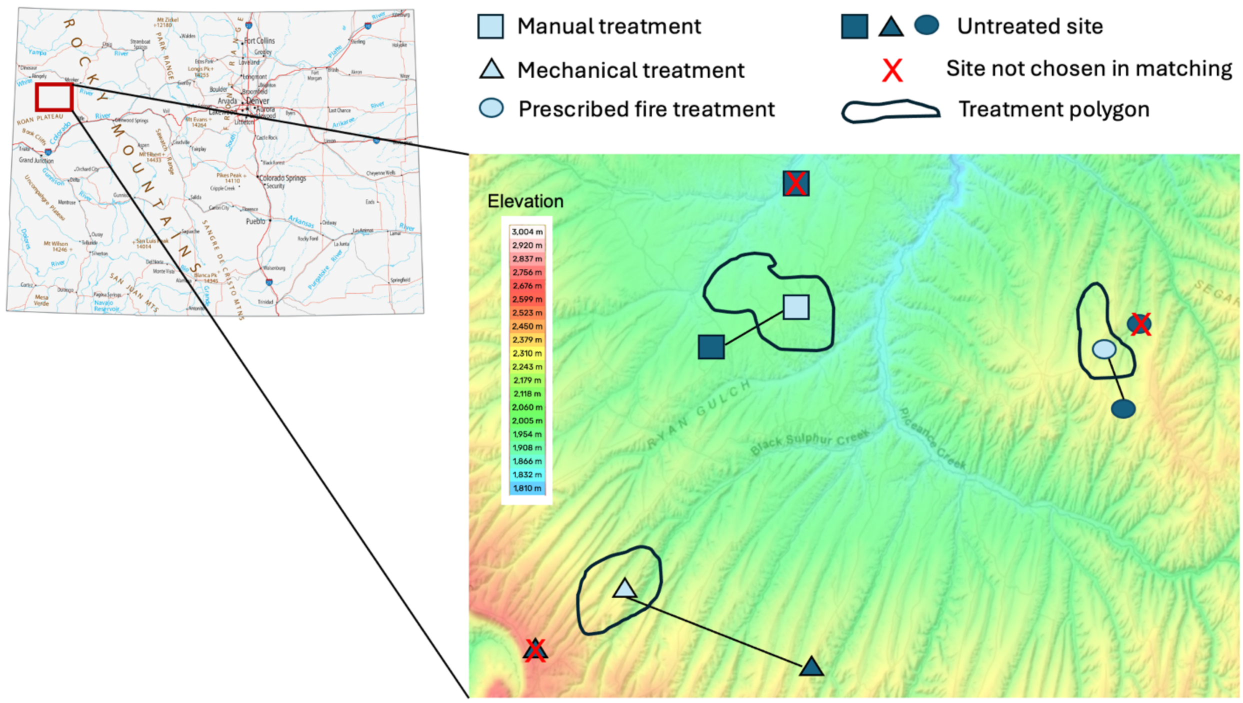

Figure 2.1: Conceptual diagram of the matching process. Monitoring sites within treated areas (lighter blue shapes within black-outlined polygons) are paired with monitoring sites outside of treated areas (darker blue shapes, called untreated or control sites). Sites are paired according to selected covariate values, in this case elevation. A treated site is paired with a control site with the most similar elevation, even if it is further away geographically than a control site with a less similar elevation.

The ecotone between sagebrush steppe and pinyon–juniper woodland provides an opportunity to apply the use of causal inference methods and monitoring data to assess land treatment effectiveness, specifically on land managed by the Bureau of Land Management (BLM). The expansion of pinyon pine and juniper trees (*Pinus edulis*, *Pinus monophylla*, and *Juniperus spp.*) into the adjacent sagebrush steppe in this region is altering fuel loads and their associated risk of high intensity wildfire while decreasing wildlife habitat condition (Mitchell and Roberts, 1999). Expanding tree cover increases the amount of woody fuels which can more readily allow the ignition and spread of wildfire, impacts wildlife habitat for species like the great sage-grouse (*Centrocercus urophasianus*), and is associated with declines in native shrub and herbaceous cover (Archer et al., 2017b; Cole et al., 1997; Miller and Tausch, 2001). The degradation of wildlife habitat, deterioration of rangeland condition for livestock, and increased risk of high intensity wildfire resulting from woodland expansion have led to a broad range of pinyon–juniper removal treatments being implemented across extensive areas of Northwest Colorado and beyond (Redmond et al., 2014a). Because these treatments are being implemented on land managed by the BLM, there is a unique opportunity to make use of data from the BLM's Assessment, Inventory, and Monitoring (AIM) program. This data is not specifically collected for assessing the effectiveness of land treatments, but is a valuable and reliable resource for observational monitoring data due to its structured implementation, broad scope and high frequency of collection, and standardized protocols (Toevs et al., 2011).

We utilized monitoring and treatment data from the BLM, publicly available environmental data, and causal inference methods to assess the average effects of pinyon–juniper removal treatments on vegetation cover in Northwest Colorado. We asked the following questions: (1) What is the effect of treatment on tree cover, and does that effect vary by treatment method? (2) Can we utilize existing and established Bureau of Land Management data to assess treatment effectiveness and what workflow is required to effectively use that data? (3) Is pre-regression matching an appropriate and effective method for assessing the effects of pinyon–juniper removal treatments? Considering the significant investment being made for large-scale land treatments, and the changing climate, it is essential that land managers be able to fully and more conclusively assess treatment effects to support the adaptive management process. Development of a broader set of statistical approaches that harness existing monitoring data, open access environmental data sources, and powerful causal inference methods will support managers with this imperative work.

METHODS

Study area

Our study focused on the northwestern region of Colorado, on land managed by the BLM, including the Colorado River Valley, White River, Kremmling, Grand Junction, and Little Snake BLM field offices. This region of Colorado is within the Colorado Plateau and Southern Rockies ecoregions and contains both sagebrush dominant and pinyon–juniper dominant ecosystems (Omernik, 1987). Our sites are primarily in sagebrush dominant systems—they are generally open, with high shrub cover (20-35%), diverse understories of forbs and grasses, and some amount of pinyon–juniper expansion (5-15% tree cover). Soils at study sites range from deep loamy to deep rocky (Web Soil Survey). The sagebrush systems in this region support significant wildlife habitat for species such as the greater sage-grouse, mule deer, and elk. Habitat fragmentation and degradation in these sagebrush systems are prominent and are driven by anthropogenic impacts (e.g., recreation, oil and gas development, and grazing), as well as pinyon–juniper expansion (Knick et al., 2003; Miller et al., 2000). These impacts, along with a buildup of woody fuels from tree expansion, have led managers to complete pinyon–juniper removal treatments throughout the region (Copeland et al., 2018; Redmond et al., 2014a).

Our study sites consisted of plots from the BLM's AIM Strategy (Toevs et al., 2011). AIM plot locations are randomly selected across BLM-managed lands (Herrick et al., 2022). The particular AIM sites we considered were within the northwest corner of Colorado and ranged in elevation from 1600–2800 meters. Mean annual temperatures in the region range from 2–10°C and mean annual precipitation for the sites ranges from 325–555 millimeters, which primarily falls in the winter months (Daly et al., 2008; PRISM Climate Group, 2014). Each plot is approximately 0.7 acres in size, consisting of three 25 meter transects organized equidistant from each other around a central point (Herrick et al., 2022).

Across the Northwest Colorado region, there are 732 land treatments completed by the BLM according to the Land Treatment Digital Library (LTDL), a repository of BLM treatments assembled by the U.S. Geological Survey (Pilliod and Welty, 2013). These treatments total 550,462 acres across BLM-managed lands, and 132 of those treatments had AIM plots within the treatment boundaries. Of the 132 treatments containing AIM plots, only 72 of those treatments explicitly treated for pinyon–juniper reduction. The 72 pinyon-juniper reduction treatments were completed between 1962–2016 for habitat improvement, fuels reduction, and rangeland health/forage improvement. Other treatments in the region that were not included in this study included herbicide applications, aerial seeding, and brush control.

Data compilation

Data used in our study was compiled almost entirely from public sources. Sites were selected from BLM AIM plots within the study region of Northwest Colorado. BLM AIM data reports numerous metrics collected by seasonal crews according to the AIM protocol. In this study, we used tree cover from AIM as our response variable. Using the LTDL, we inventoried management actions carried out by the BLM and identified AIM plots within areas that had been treated for pinyon–juniper reduction. The LTDL provided spatial information about the treatments, as well as the method by which the trees were removed (Pilliod and Welty, 2013). Since tree removal method is a critical decision point for managers and methods vary in their efficacy, impact, cost, and feasibility, we analyzed the effects of treatments by the removal method. We summarized these methods into the three categories of manual removal, mechanical removal, and prescribed fire. These categories simplify the vast variety of treatment descriptions in the LTDL, while still grouping treatment types that have similar ecological effects and maintaining relevance for land managers. “Manual” treatment was assigned to any tree removal treatment done by hand without any large machinery or fire, “mechanical” was assigned to any removal done by mastication or rollerchopping (in which large machines mulch or cut up trees), and “prescribed fire” was assigned to any removal in which fire was involved, including both pile burning and broadcast burning that are intentionally ignited, but not managed wildfire which is not intentionally ignited. Each treated plot was assigned a treatment type based upon what was listed in the LTDL. Since plots outside of treatment areas (control plots) did not have a treatment type, control plots were assigned a treatment type according to the treated plot to which they were matched in the process of pre-regression matching (see below).

For each AIM plot within the study area, we compiled relevant topographic, climatic, vegetation, and ecological variables in ArcGIS Pro. We calculated elevation, slope, and aspect from the 1/3 arc-second digital elevation model downloaded from the USGS National Map (U.S. Geological Survey, 2023). Aridity index for each plot was collected from the Consultative Group on International Agricultural Research Consortium for Spatial Information (Zomer et al., 2022). The Global Aridity Index is modeled using data from WorldClim Global Climate Data (Zomer et al., 2022). Northwest Colorado occupies two different ecoregions, which we identified from Omernik’s “Ecoregions of the Conterminous United States” and attributed to each AIM plot. We calculated distance to roads using the “near” function in ArcGIS Pro and the Topologically Integrated Geographic Encoding and Referencing (TIGER) Database Primary Roads National Shapefile to find the distance from each AIM site to the nearest road.

We also calculated pre-treatment vegetation and ground cover using annual percent cover products from the Rangeland Analysis Platform (RAP) (Allred et al., 2021; Jones et al., 2021, 2018; Robinson et al., 2019). Pre-treatment tree, shrub, perennial forb and grass, annual forb and grass, and bare ground cover were calculated for each plot. For AIM plots within treatment areas, annual cover for each functional group was averaged for the five years prior to treatment to estimate pre-treatment vegetation cover. This calculation brought the number of treated sites from 72 to 36 because there is RAP cover data for only as early as 1987. Any treatment that was completed prior to 1992 was unable to be used. Plots outside of treatment areas (control plots) did not have a treatment time, so we could not use the same method to calculate pre-treatment cover. Instead, we averaged annual cover across the five years before the year that the AIM site was monitored in order to smooth interannual variability in vegetation and bare ground cover and maintain consistency with the treated sites. Time since treatment, or age, for treated plots was calculated by subtracting the year that the treatment was completed from the year that AIM data was collected at the plot. These ages were then assigned to control plots according to the treated plot they were matched with during pre-regression matching (see below). Treatments ranged from 1-29 years in age (Fig. S2.1). This compilation of variables gave us a dataset of 1770 AIM plots and their covariate values, 35 of which were within treatment areas (treated plots) and 1735 outside of treatment areas (control plots) (Fig. 2.2).

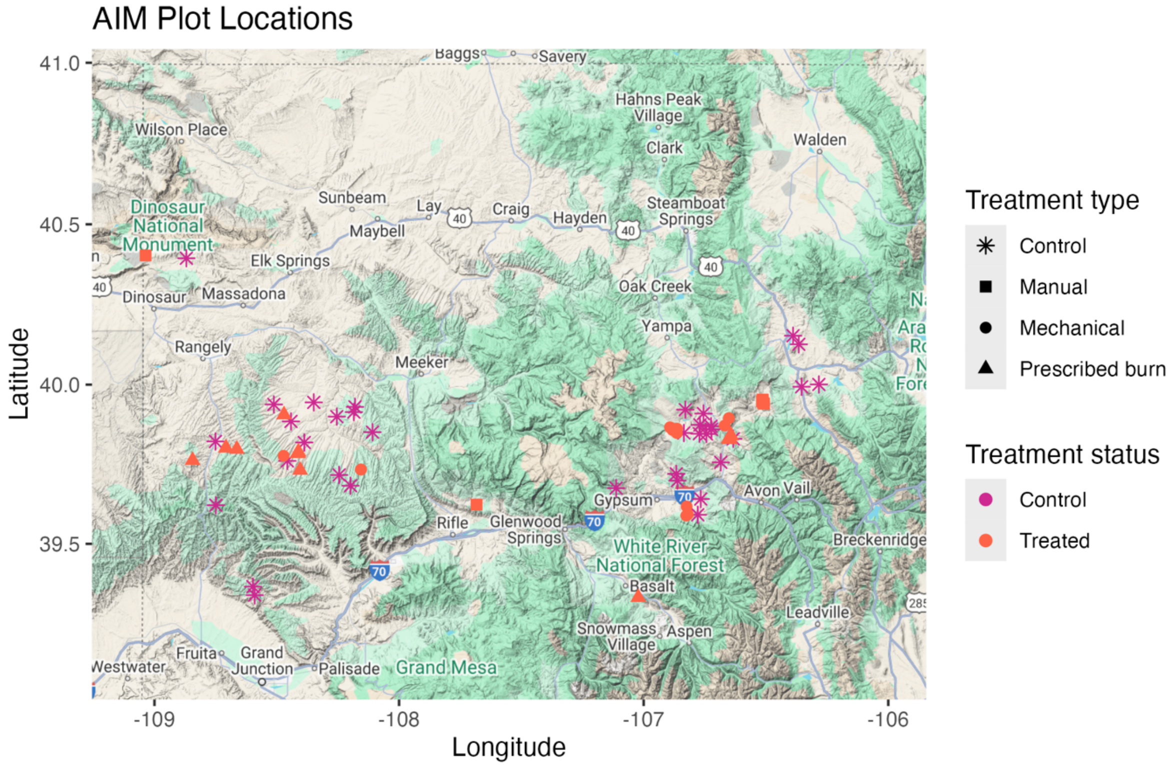

Figure 2.2: Map of AIM plots. Map of AIM plots included in study. Colors indicate treatment status of plots, and shapes represent treatment types.

Pre-regression matching

Utilizing causal inference techniques and the counterfactual—what would occur if treated sites had not been treated—to identify comparable untreated control sites from observational monitoring datasets addresses the selection bias that arises when land managers nonrandomly select sites for landscape-scale treatments and allows us to more reliably assess treatment effects (Larsen et al., 2019). When compiling control sites, it is essential that both the treated and control units have similar covariate averages to ensure their comparability and help eliminate spurious relationships caused by those covariates. Pre-regression matching (matching, henceforth) is completed prior to regression analyses and involves pairing each treated plot with an untreated control plot that is most similar with regard to those confounding variables, therefore improving causality of inference made from analyses of observational data (Fig. 2.1). Matching thus creates a balanced dataset, or a dataset in which the means of the covariate values are approximately the same for both the treated and control sites when considered separately (Ramsey et al., 2019).

The covariates that we used in the matching process for this study included latitude and longitude, topographic factors (elevation, slope, aspect), climatic factors (aridity), ecoregion, distance to roads, and pre-treatment vegetation and ground cover (tree, shrub, perennial forb and grass, annual forb and grass, bare ground). All of these covariates affect both the chances that any given site will be chosen for treatment and the effects of treatment itself, either by explicit consideration by land managers (e.g. topographic factors, distance to roads, pre-treatment vegetation cover) or by acting as proxies for unmeasurable variables (e.g. aridity as an indicator of a site's potential for restoration success (Copeland et al., 2019)) (Fig. 2.3). With the *MatchIt* (Ho et al., 2011) package, we input the dataset of 1770 sites, with the goal of matching each of the 35 treated sites with a comparable control site. We matched by the above covariates using optimal matching with Mahalanobis distance and exact matching by ecoregion. Mahalanobis distance takes correlation between covariates into account and attempts to match treated and control sites that have the most similar values for all covariates (De Maesschalck et al., 2000; Rubin, 1980; Stuart, 2010). Although Mahalanobis distance is typically best used when there are few covariates to be matched upon, because there are considerably more control units than treated units in this dataset, Mahalanobis distance best balanced the covariates for our dataset as compared with other distance measures (Stuart, 2010). We used exact matching for ecoregion because it is a categorical variable with few categories, allowing for treated and control units within the same ecoregion to be paired. All treated sites were matched with a control site and control sites that were not matched to treated units were discarded, creating a dataset of 70 sites. While a sample size of 70 is notably smaller than 1770, the reduction of power is minimal due to analytical precision being predominantly driven by the group with the smaller sample size (Cohen, 1988; Stuart, 2010), which in this case is the treated group.

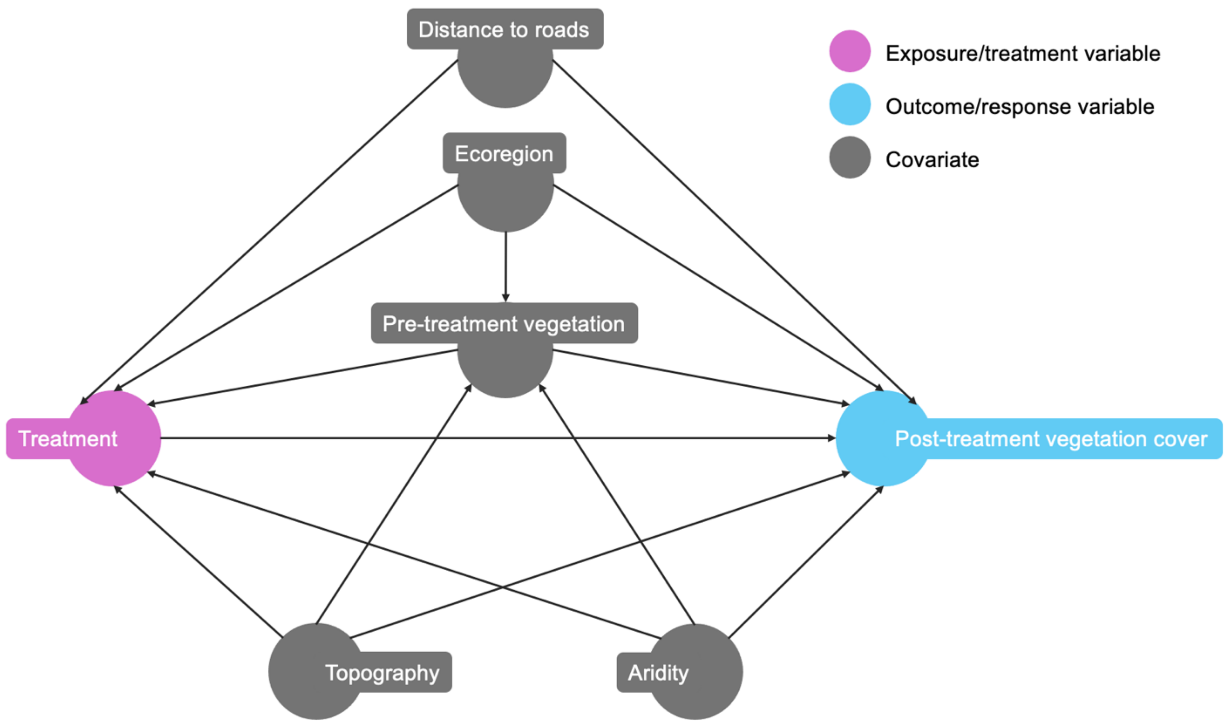

Figure 2.3: Directed Acyclic Graph (DAG). Directed acyclic graph showing relevant covariates included in the matching process. Pre-treatment vegetation summarizes the five vegetation categories included in matching (pre-treatment tree, shrub, perennial forb and grass, annual forb and grass, and bare ground cover). Topography represents the elevation, slope, and aspect variables.

Once the matching process is completed, it is essential to assess the balance of the matched dataset to ensure that the treated and control units in the matched dataset have similar averages for each covariate used in the matching process. To assess covariate balance between treated and control sites, we compared the standardized mean differences (SMDs) for each covariate between treated and control sites. Using the *MatchIt* package, means for each covariate were calculated and standardized for treated and control sites separately. The differences between those standardized means were then calculated and compared between the original dataset and the matched dataset (Fig. 2.4, Table S2.1). Match quality is considered to be high when the SMDs are less than 0.25, meaning that the averages for each covariate are balanced, or very similar between treated and control sites (Rubin, 1973; Stuart, 2010). As illustrated in Fig. 2.4, the SMDs for the covariates we matched upon were considerably decreased by the matching process, with many covariates having SMDs less than 0.1, and all below 0.25, in the matched dataset. With the assurance that match quality in our matched dataset is high and that the covariates are balanced, we have created a less biased dataset (Ramsey et al., 2019).

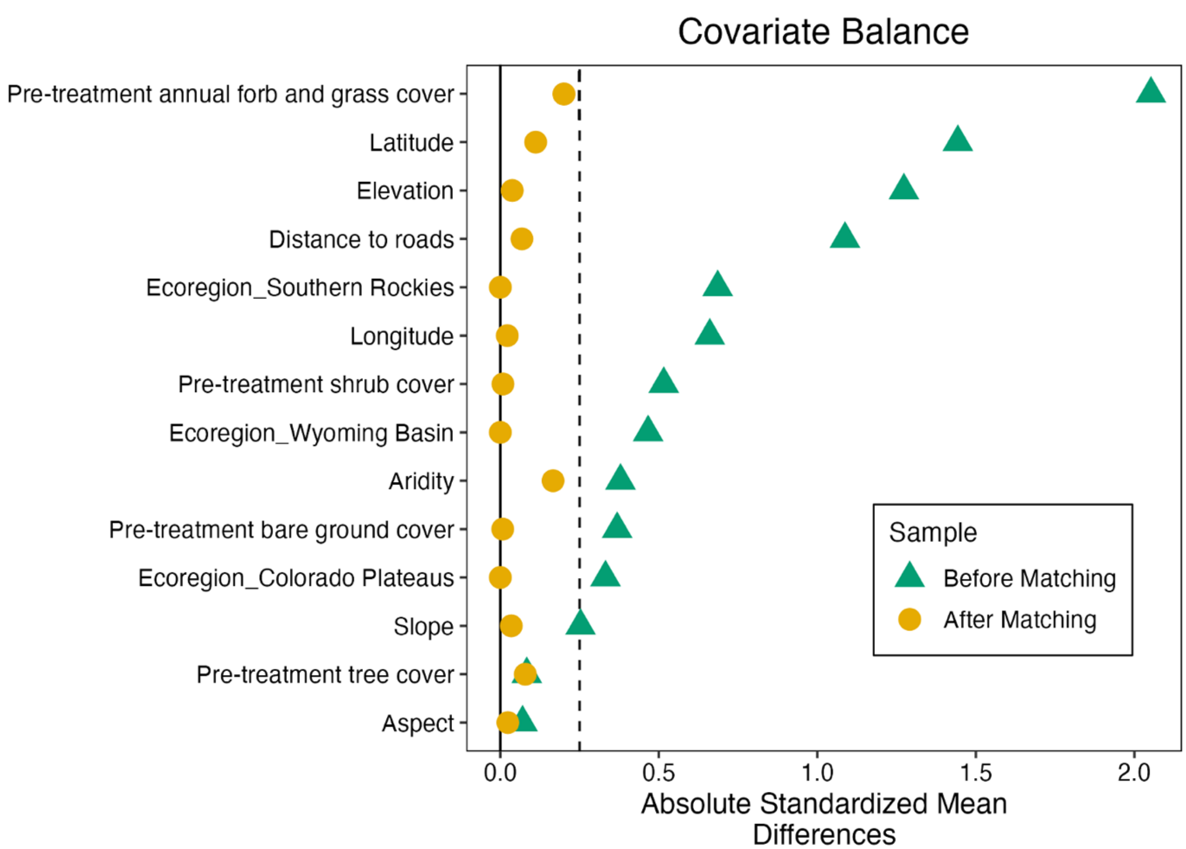

Figure 2.4: Plot of standardized mean differences of each covariate before and after matching. Absolute standardized mean differences displayed for both the unmatched and the matched dataset. The difference in means between the treated and control groups for each covariate is decreased with matching, improving covariate balance. Variables on y-axis are in order of largest unmatched mean differences. Created using *cobalt* (Griefer, 2024) in R (R Core Team, 2018).

One key assumption in the matching process is that there is no unmeasured confounding that is not accounted for in the matching process (Stuart, 2010). In other words, we assume that we have matched on all plausible confounders, or at least on variables highly correlated to plausible unobserved confounders. To test the validity of this assumption, we ran a sensitivity analysis to understand the effects of possible unobserved confounding using the *sensemakr* package in R (Cinelli et al., 2020). Using *sensemakr*, we tested how strong an unobserved confounder would need to be to significantly change the estimated effect of treatment (Cinelli and Hazlett, 2020). We found that even if an unobserved covariate had an effect three times as strong as the strongest observed covariate (pre-treatment shrub cover), our treatment effect would remain much the same (Fig. S2.2). Unlike our main analysis (detailed below, which utilized a Bayesian generalized linear mixed effects model) we had to fit a frequentist generalized linear model for the sensitivity analysis due to package constraints within *sensemakr*. Although these models differ, our sensitivity analysis model captured the key components of our primary analysis that are sensitive to unobserved confounders. Thus, we were confident that we met the assumption that we matched on all important confounders.

Modeling

We used a Bayesian generalized linear mixed effects model (GLMM) to quantify an answer to the question "how do different pinyon–juniper reduction treatments affect tree cover?" We built one model, where the response variable was proportional cover of trees recorded during BLM AIM surveys. In our model, the focal covariates were treatment (binary: "1" indicated that a site received treatment), treatment type (categorical: "manual", "mechanical", and "prescribed fire"), and their interaction. These terms allowed us to evaluate how tree cover varied between treated and control sites for all three treatment types. We included further covariates to account for confounding, all of which were z-standardized (i.e., mean centered and standard deviation scaled) to improve model fitting. These covariates included elevation, slope, aspect, aridity, distance from roads, time since treatment, and pre-treatment vegetation/ground cover percentages (tree, annual forb and grass, perennial forb and grass, shrub, and bare ground). Finally, we included a random intercept for both year and site in each model to appropriately account for lack of independence among sites surveyed within the same treatment area and in the same year.

Using the package brms (Bürkner, 2017) in the R programming language (R Core Team, 2018) , we specified a zero-inflated beta regression model because proportional values for cover were distributed between 0 and 1, and 47% of AIM surveys recorded zero tree cover. We allowed the precision parameter and the zero-inflation component of this model to vary by treatment, treatment type, and their interaction. We specified weakly informative priors for all parameters: for intercept and slope parameters, we used normal distributions with means of zero and standard deviations of two for intercepts and slopes, and for standard deviation parameters, we used a Student T distribution with 3 degrees of freedom, mean of zero, and a standard deviation of 2.5. The prior for slope parameters in the zero-inflation component of the model was a normal distribution with a mean of 0 and standard deviation of 1.

We fit the model on three chains, specified a warmup of 2000 iterations, then ran 6000 iterations. To evaluate the quality of convergence, we visually inspected trace plots, inspected effective sample sizes, and ensured that all R-hat (Gelman–Rubin diagnostic) values were below 1.01 (Gelman and Rubin, 1992). To analyze posterior distributions, we predicted proportional tree cover at control and treated sites for each of the three treatment types (i.e., six derived quantities). We also estimated the effect of each treatment type on tree cover as the predicted difference in outcomes between treated and control sites. To evaluate the overlap of treatment effect parameter distributions with zero, we calculated 50% and 90% credible intervals using the highest density interval method. In presenting results, we use the language of Dushoff et al. (Dushoff et al., 2019) to describe the 'clarity' (rather than 'significance') of model estimates; terms with 90% credible intervals strongly overlapping 0 are said to have 'unclear' effects, whereas those with little or no overlap are said to have a 'statistically clear' effect.

RESULTS

Our final dataset after matching consisted of 35 AIM plots within treatment areas, and 35 paired AIM plots outside of treatment areas. This created a dataset of 70 plots that were balanced across the covariates used in the matching process; all standardized mean absolute differences were <0.25 (Fig. 2.4). Of the 35 treatment plots, 7 occurred within areas treated by manual removal, 12 were within mechanically treated sites, and 16 were treated with prescribed fire.

The following results are from models fit with the matched dataset in which treatments were validated using the Rangeland Analysis Platform (see details in Discussion below). Tree cover was lower in treated sites than untreated sites (Fig. 2.5). Sites that received manual treatments had on average 3% less tree cover (90% credible interval (CrI): -7% – -1.2%) than control sites, showing a small reduction in tree cover. Mechanical removal treatments showed a larger effect, but with higher uncertainty. Sites receiving mechanical removal had approximately 5.5% less tree cover (CrI: -12% – -2%) than control sites, with a wider credible interval than manual removal. Tree removal via prescribed fire also had a negative impact on tree cover with treated sites having 3% less tree cover (CrI: -8% – -0.5%) than control sites.

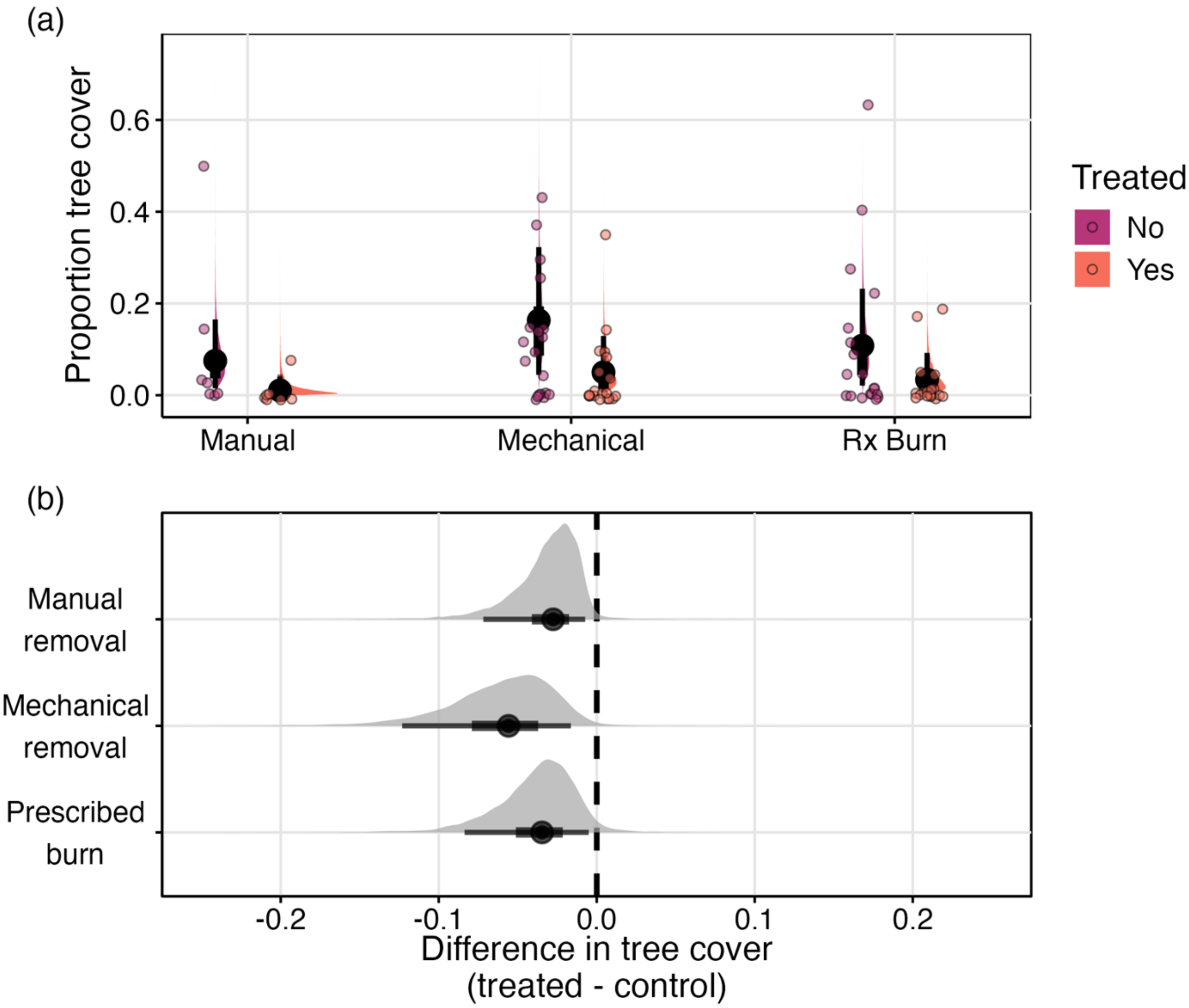

Figure 2.5: Tree cover model results. Differences in tree cover between treated and untreated sites for the dataset of validated treatments only. (a) shows proportion tree cover and posterior distributions for treated and untreated sites for each treatment type. (b) shows effect size for each treatment type.

DISCUSSION

Sizeable financial allocations and calls for adaptive management have prompted the need for a more thorough understanding of the effects and success of management actions. In our study of pinyon–juniper removal treatments in Northwest Colorado, we aimed to use on-the-ground monitoring and treatment data from the BLM, publicly available environmental data, and pre-regression matching to assess treatment effects while also evaluating the application of these methods. Our initial estimates of the effects of tree removal treatments on tree cover were unexpected, showing a neutral and even positive effect of treatment on tree cover, depending on removal method. These results led us to examine our methods in order to assess the validity of these puzzling treatment effects.

While it is possible that pinyon–juniper removal treatments in this study are in fact not reducing tree cover, there are aspects of the methodology that may also be contributing to our unanticipated results. The use of causal inference techniques to assess the ecological effects of landscape-scale tree removal treatments using field data is novel, with pre-regression matching primarily being used for impact evaluation in conservation and other fields (Ferraro and Hanauer, 2014; Schleicher et al., 2020). These methods therefore command a thorough re-examination to ensure they are not skewing the dataset and as a result, our analyses. There is also increased uncertainty in our methods from the various data sources as the uncertainty from each data source compounds with each additional source (McCord et al., 2021). Many of the data sources we used are established and reliable (e.g. PRISM climate data and RAP vegetation cover data), but others are inherently more susceptible to uncertainty or unreliability from human error and/or poor reporting (Pilliod et al., 2017). These details of our methodology were compelling enough to beg further investigation.

There is a strong consensus in the literature about the effectiveness of pinyon–juniper removal treatments in reducing tree cover, therefore eliminating the notion that treatments in this study may be ineffective in that way. The effects of treatments on understory vegetation cover and wildlife vary, but the negative effect of treatment on tree cover has been reported decidedly across regions (Bates et al., 2017; Huffman et al., 2019; Shinneman et al., 2023a), including on the Colorado Plateau, where pinyon–juniper removal has long been practiced and studied (Fick et al., 2022; Havrilla et al., 2017; Huffman et al., 2019, 2017; Redmond et al., 2014a, 2013). A recent review from Shinneman et al. (2023) summarized results from forty-eight studies assessing the effects of pinyon–juniper removal treatments and reported that most studies found negative effects of treatment on tree cover. Logic and evidence clearly support that pinyon–juniper removal reduces tree cover, so we moved on to investigate our causal inference methods.

In the past decade causal inference techniques and specifically pre-regression matching have made their way into the ecology literature, with specific use to assess the impacts of conservation programs (Schleicher et al., 2020). There have been fewer studies that have used matching to assess the effects of active management, so this was one aspect of our methodology that we felt important to thoroughly evaluate. The primary way in which matching would introduce bias into our study is by creating a dataset in which the control sites are not well-matched to the treated sites (Fick et al., 2021; Ramsey et al., 2019). Because we assessed the balance in covariates between the treated and control groups after the matching process and before analysis, we can dismiss this as the case (Fig. 2.4). When inspecting match quality, the distributions of each covariate before and after the matching process can shed light upon how well the control sites are matched with treated sites (Ramsey et al., 2019; Schleicher et al., 2020; Stuart, 2010). Looking at the distributions for each of our covariates, it is clear that the control sites are quality matches for the treated sites (Fig. 2.6). If the control sites are similar to the treated sites in all of the covariates that we matched upon, then they are as similar to the treated sites as we can achieve without directly measuring the treated sites before treatment. This means that they are good representations of the counterfactual, or what would have occurred at a treated site if it had not received treatment (Larsen et al., 2019). Quality matches rule out matching as a source of bias in our dataset (Larsen et al., 2019; Ramsey et al., 2019), so we moved on to further investigate sources of uncertainty in our data sources.

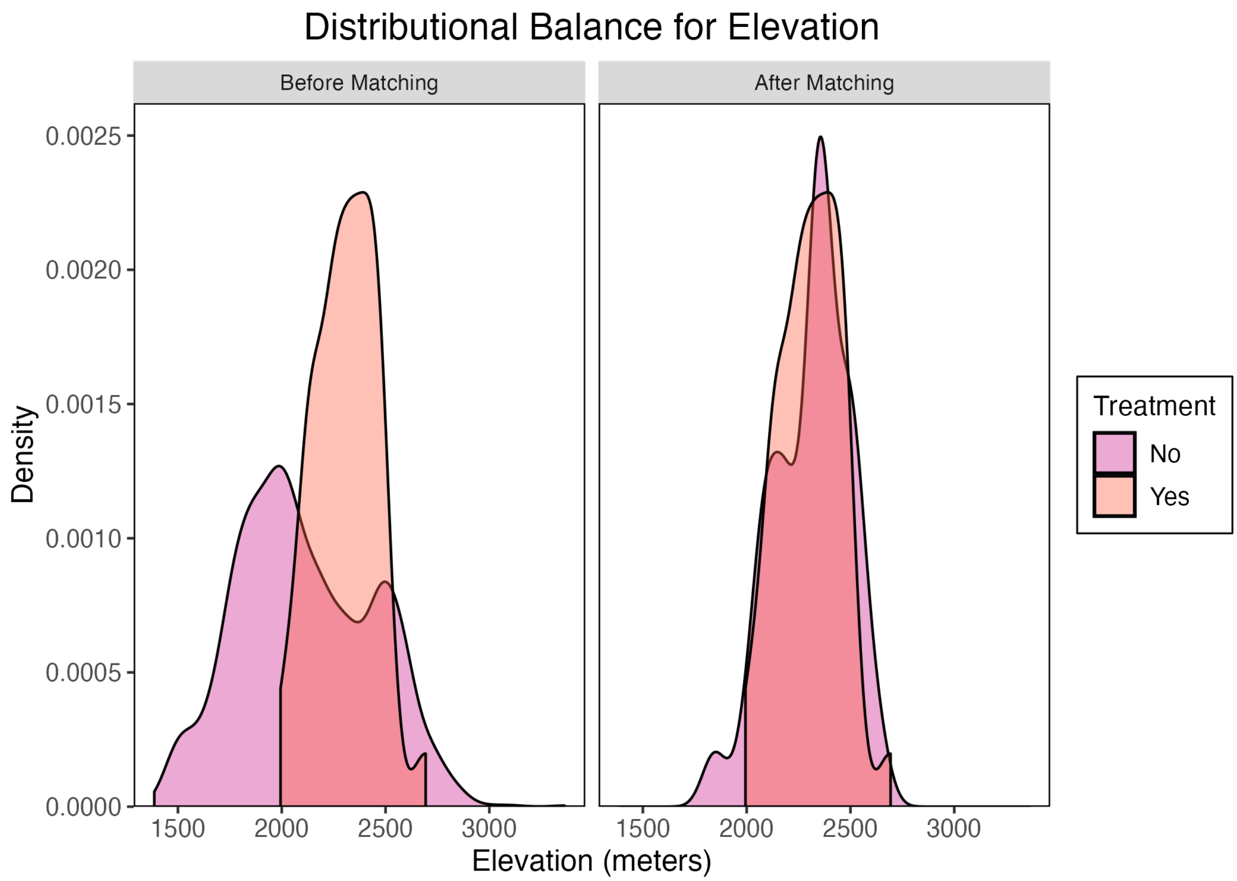

Figure 2.6: Covariate distribution alignment following matching. Distribution of the elevation of treated and control sites before matching (left) and after matching (right). The matched data has much more similar distributions of elevation between treated and control sites, indicating a less-biased dataset.

One of the newer and less corroborated data sources that we used in the compilation of data for this study was the Land Treatment Digital Library (LTDL). The LTDL is a repository of land treatments completed on BLM lands throughout the West (Pilliod and Welty, 2013). Records digitized into the LTDL have often not been validated for completion of the treatment, accuracy of the record, or completeness of the information included in the database (Pilliod et al., 2017). This insight led us to further investigate all of the treatments from the LTDL that had BLM AIM points within their boundaries. We visually inspected changes in tree cover in each treatment polygon by looking at remotely sensed tree cover data from the Rangeland Analysis Platform (RAP), both the raster files and the time series calculated from the RAP online tool (Allred et al., 2021; Jones et al., 2021, 2018; Robinson et al., 2019). For some of the implemented treatments, there was a clear decline in tree cover after the treatment year reported (Fig. 2.7a). For other treatments that were reportedly implemented, there was no decline, and sometimes an increase, in tree cover after the reported treatment year (Fig. 2.7b). An increase in tree cover would likely not be surprising if the increase occurred twenty years after treatment, but the increase often occurred soon after the treatment was reported to have been completed (Fig. 2.7b). Whether this lack of change/increase in tree cover is a result of the treatments that were reportedly implemented not actually being implemented, or treatments were completed and did not reduce tree cover enough to be detectable with RAP, it is impossible to know. This finding was further complicated when two treatments that were reported as "Planned: unknown implementation" (as opposed to "Implemented") clearly exhibited a decline in tree cover after the reported treatment year (although these treatments were not included in our initial analyses), inhibiting one from simply analyzing treatments that were reported as implemented. The unreliable reporting of treatments in the LTDL is an important limiting factor in using this data source to assess treatment effectiveness and creates and extra validation step in the data compilation process.

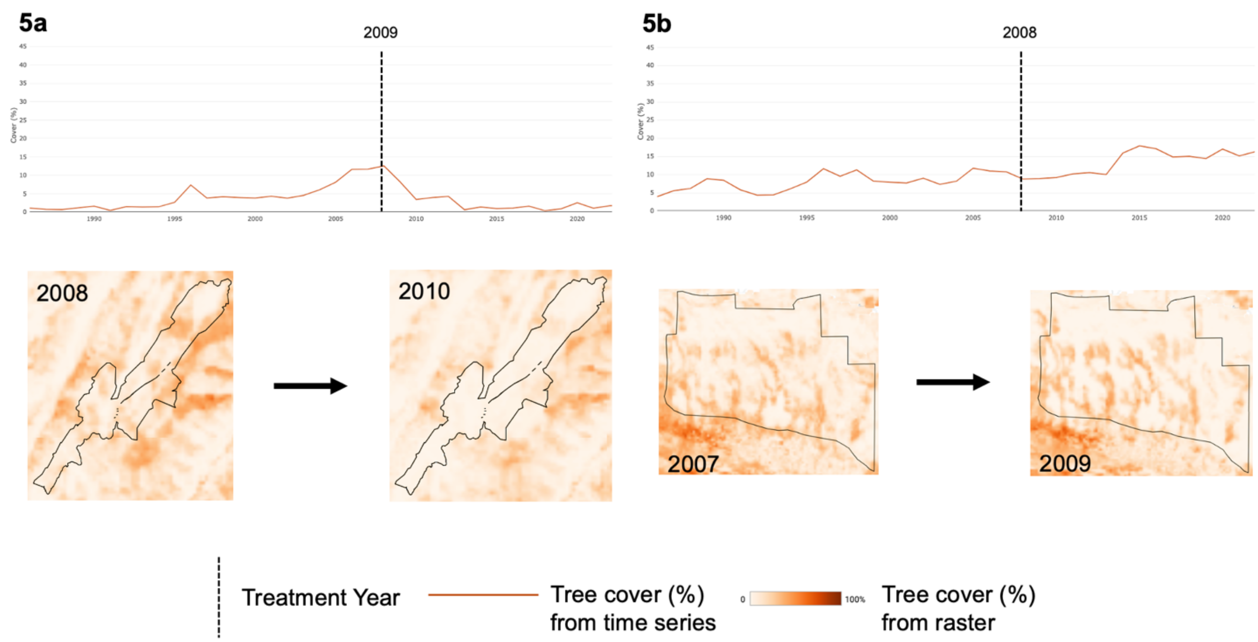

Figure 2.7: Treatment validation. Validation of treatment using tree cover data from the Rangeland Analysis Platform. Time series tree cover and raster tree cover are shown for two BLM pinyon–juniper removal treatments that were both reported completed. (2.5A) shows a treatment that passed treatment validation because of the decline in tree cover after the reported treatment year. (2.5B) shows a treatment that failed treatment validation because there was no decline in tree cover after the reported treatment year.

Our unexpected results and subsequent investigation into the reliability of our data sources highlight the challenges of working with open access observational data. Applying causal inference techniques to observational data in an inventive way cannot overcome challenges with the available data (McCord et al., 2021). In this case, the irregular reporting of treatments within the LTDL data obscured the measurable effects of treatment. While the solution in this specific study is relatively simple—validation of treatment completion via remote sensing cover data (Fig. 2.8)—it is time consuming and may not be so easy in other cases, especially when treatment completion does not have such a clear signal as a reduction in tree cover. Despite these challenges and caveats to using open access data, this workflow offers a less time and resource intensive alternative to more traditional field-based treatment effectiveness monitoring and assessment. Knowledge of important ecological attributes and other confounding factors in the relevant system—as well as some statistical expertise—are important components of the methods outlined here, but this methodology bypasses many hurdles and costs associated with experiments and field data collection campaigns.

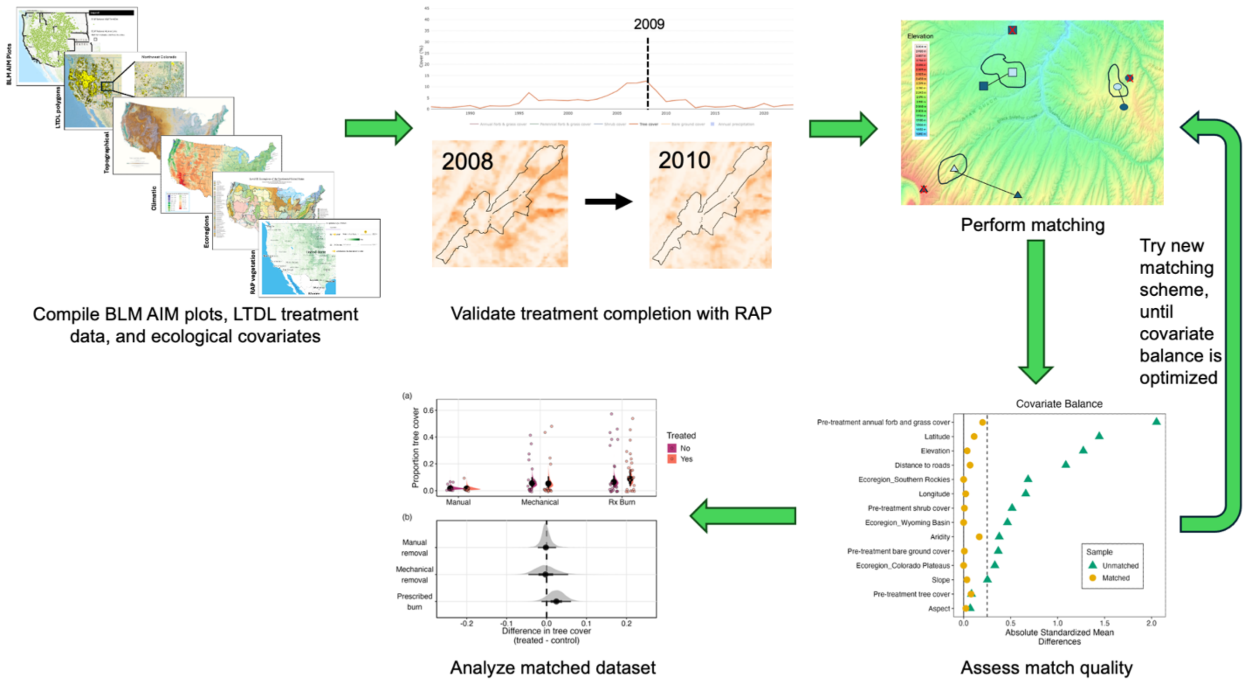

Figure 2.8: Suggested workflow diagram. Diagram illustrating each major step in the methodology described in our study.

Although treatment assessment is not specifically included in the five principles of the Assessment, Inventory, and Monitoring strategy, this existing program has the potential to be better utilized in order to support adaptive management (Kachergis et al., 2022). The rapid onset of ecological changes from global change (Kharin et al., 2013; Seager and Vecchi, 2010; Sillmann et al., 2013) require managers to learn from past land treatments to support the adaptive management process. Tuning monitoring programs to address current management and ecological challenges will greatly aid in this learning process (Lindenmayer and Likens, 2010, 2009). With adaptive monitoring—monitoring that is flexible and modifiable to accommodate changes in ecological patterns, management frameworks, and societal importance—that collects data before and after treatment, assessing treatment effects and incorporating that knowledge into management plans becomes much easier and more efficient (Czaplewski, 1996; McCord and Pilliod, 2022; Ringold et al., 1996).

CONCLUSION

Our endeavor to use entirely pre-existing data sources, observational monitoring data, and causal inference techniques to assess the effects of pinyon–juniper removal treatments on tree cover, while ultimately unsuccessful, provided valuable insights into this novel methodology. The challenges we faced with utilizing the Land Treatment Digital Library as our source of treatment information were surmountable in this case but reflect greater challenges with utilization of increasingly large and available datasets for assessing the impacts of landscape-scale management actions. While promoting data quality and validation as an essential aspect of the data collection process may help mitigate similar challenges and encourage the use of these datasets to answer management questions, longer-term solutions like adaptive monitoring and better integration of monitoring and management are the best steps to be taken towards a more thorough understanding of management effects and support of adaptive management. Considering rapid global change and the sizeable financial allocations for fuel reduction and habitat improvement in the West, it is imperative that management actions—especially large-scale land treatments such as pinyon-juniper removal—are assessed by the extent to which they are meeting managers' goals and objectives, and that managers learn from that knowledge and implement the adaptive management process. For now, until we see these changes in land management and monitoring, the elaboration and refinement of this methodology can support the adaptive management process to improve the efficiency and effectiveness of these large-scale land treatments.

CHAPTER III

TREATMENT TYPE AND PRE-TREATMENT SITE CONDITIONS ALTER THE EFFECT OF PINYON–JUNIPER REMOVAL ON VEGETATION CHARACTERISTICS

Alyson S. Ennis, Brendan K. Hobart, and Nichole N. Barger

ABSTRACT

In the Western U.S., pinyon–juniper woodlands are expanding into adjacent sagebrush steppe ecosystems, altering wildlife habitat, degrading rangelands, and increasing risk of severe wildfire. Land managers have thus implemented tree reduction treatments on public lands, with goals of restoring habitat, improving rangelands, and reducing hazardous fuels. However, there is uncertainty surrounding the potential benefits and risks of treatments, as both positive and negative treatment effects have been recorded for plants, wildlife, and soils. Our goal was to assess pinyon–juniper treatment effects in Northwest Colorado to support the adaptive management process and inform future treatment planning. We leveraged observational monitoring data from the Bureau of Land Management Assessment, Inventory, and Monitoring program by pairing it with data from other open access sources and employing causal inference techniques. We found that treatment caused both increases and declines in native herbaceous vegetation cover, depending on treatment method and pre-treatment vegetation conditions, and increased cheatgrass (*Bromus tectorum*) cover. Our findings illustrate the importance of the treatment evaluation step of adaptive management and provide a novel methodology for the use of data from existing monitoring programs and open access sources.

INTRODUCTION

Woody encroachment—or the expansion of tree species into neighboring vegetation types—is occurring across the globe due to numerous anthropogenic factors such as increased atmospheric CO_2, fire suppression, overgrazing, and other land management practices (Archer et al., 2017b; Barger et al., 2009). Woody encroachment is decreasing biodiversity, changing wildlife habitat, and altering hydrology at a rapid pace (Archer et al., 2017b; Romme et al., 2009). Increased cover of trees in systems not historically dominated by tree species also greatly augments the amount of woody fuels which can more readily allow the ignition and spread of wildfire across the landscape (Miller and Tausch, 2001). In the Western United States (U.S.), encroachment of pinyon–juniper woodlands (*Pinus edulis, P. monophylla,* and *Juniperus spp.*)—the third most expansive vegetation type in the U.S. (Mitchell and Roberts, 1999)— is altering fuels loads, high intensity wildfire risk (Young et al., 2015), and wildlife habitat (Coates et al., 2017; Cole et al., 1997). Increasing pinyon and juniper tree cover is associated with degradation of native shrub and herbaceous cover (Archer et al., 2017b; Cole et al., 1997), habitat for sensitive wildlife species, livestock forage, and soil stability (Wilcox, 1994). Over the past fifty years, a broad range of pinyon–juniper removal treatments have been implemented across extensive areas of public lands in the Western U.S. with the goals of reducing fuels, restoring wildlife habitat, and improving rangelands.

Removal of pinyon pine and juniper trees has been shown to have mixed results (Fick et al., 2022; Shinneman et al., 2023a). In some instances pinyon–juniper removal has measurable benefits, promoting the recovery of herbaceous understory vegetation by reducing competition (Havrilla et al., 2017; Redmond et al., 2013; Stephens et al., 2016) and thereby improving wildlife habitat and rangeland conditions. Studies have found positive effects of treatment for mule deer (Johnston and Anderson Jr., 2023), sage-grouse (Severson et al., 2017a, 2017b), and other avian species (Holmes et al., 2017). Thinning and use of prescribed fire for pinyon–juniper cover reduction has also been shown to reduce hazardous fuels, decreasing the chances of high severity wildfire (Huffman et al., 2009). However, disturbance associated with tree removal may also create an increased risk of invasion by exotic annual grasses such as cheatgrass (*Bromus tectorum*)—which can inhibit the restoration of native understory species (Havrilla et al., 2017)—and degrade soil health, increasing soil erosion (Karban et al., 2022b). In addition to the potential negative effects of treatment on vegetation and soil, many studies have reported neutral or negative impacts of treatment on some bird species (Bombaci et al., 2017; Frey et al., 2013; Magee et al., 2019) and small mammals (Hamilton et al., 2019). Mixed conclusions about the impacts of pinyon–juniper removal led to some uncertainty about the tradeoff between benefits and potential ecological risks of treatments.

Gaining a thorough understanding of the ecological effects of pinyon–juniper removal treatments is further complicated by the potential for such effects to change across environmental gradients. Environmental attributes such as vegetation cover prior to treatment, topography, and climate may influence the outcomes of treatments actions (Davidson et al., 2019; Fick et al., 2022). Topography is an important determining factor in vegetation patterns in the Western U.S., with site features such as elevation and slope playing an important role in mediating soil moisture and temperature, which can affect vegetation change over time (Bochet et al., 2009; Kimball et al., 2015). Variation in climate patterns from local (< 1 km^2) to microsite scales have been shown to shape post-treatment seeding success and vegetation recovery, especially in arid and semi-arid systems (Copeland et al., 2019; Shackelford et al., 2021). Differences in land cover, degradation, and plant functional groups (e.g., the degree of pre-treatment tree dominance) before treatment can also create unique ecological trajectories following treatment (Floyd et al., 2006; Williams et al., 2017). Although the possibility for underlying environmental attributes to mediate treatment effectiveness has been established in the literature, few studies in the expansive pinyon–juniper system have explored this mediation in the context of landscape-scale removal treatments, but see Fick et al., 2022. In contrast to local-scale experiments in which treatments are randomized and/or stratified across environmental gradients, landscape-scale treatments with region-wide management goals encompass sites that naturally vary in environmental attributes (e.g., slope, aspect, etc.). If a site's environmental attributes have a notable impact on the outcomes of treatment, and therefore the effectiveness of treatment, consideration of environmental context in the treatment planning process could help predict how effective a treatment will be and lead to more desirable treatment outcomes and more efficient use of funds (Munson et al., 2020).

Despite the importance of environmental attributes in mediating the effectiveness of pinyon–juniper removal treatments, comprehensive assessment remains challenging due to treatments' large scope and a lack of resources dedicated to monitoring treatment effectiveness (Clifford et al., 2020). While many federal agencies operate monitoring programs that collect observational data, there are hurdles to using existing monitoring data to assess treatment effectiveness due to a lack of true controls (Butsic et al., 2017). Plots from existing monitoring programs exist both within and outside of pinyon–juniper removal treatments, but the plots within treatments may be fundamentally different than the plots outside of treatments due to selection bias (Larsen et al., 2019; Simler-Williamson and Germino, 2022). For example, areas that are perceived as more degraded (e.g., less initial understory vegetation cover) are often more likely to receive treatment, resulting in a critical dissimilarity between plots that were treated and plots that were not. This intrinsic difference makes naïve comparisons between treated and untreated plots dangerous, as spurious relationships can arise when analyzing a biased dataset. Causal inference methods (such as pre-regression matching, used here) provide techniques that can be used prior to or in conjunction with analyses to greatly reduce bias in observational datasets and better demonstrate causal relationships between treatment and response (Butsic et al., 2017; Fick et al., 2021; Larsen et al., 2019; Ramsey et al., 2019).

Our study aimed to assess the effects of pinyon–juniper removal on vegetation cover in Northwest Colorado and evaluate how those effects vary across environmental gradients. We compiled federal monitoring and treatment data with publicly available data to build our dataset of post-treatment vegetation cover, treatment characteristics, and environmental variables. We used pre-regression matching and generalized linear mixed effects models to answer the following questions: 1) How does pinyon–juniper reduction affect understory herbaceous vegetation cover? 2) Does treatment effect vary by tree removal method? 3) Do underlying environmental attributes influence treatment effects? We expected pinyon–juniper treatments to increase understory herbaceous vegetation cover, including both native herbaceous cover and exotic annual cover. We hypothesized that mechanical and prescribed fire removal methods would be most effective in improving native herbaceous understory cover (Stephens et al., 2016; Young et al., 2013a), while prescribed fire would result in the highest percent cover of exotic annuals after treatment (Havrilla et al., 2017). We expected topography and climate to be important underlying environmental attributes, with elevation, aspect, and aridity index having the greatest influence on treatment effects. Given the expensive cost of treatments and climate uncertainty, it is crucial to learn from the effects of past land treatments to facilitate the adaptive management process.

METHODS

Study area

Northwest Colorado provides both the ecological and land management context to answer our study questions using existing monitoring data. Our study area was composed of land managed by the Bureau of Land Management (BLM) within the Kremmling, Little Snake, Grand Junction, and White River BLM field offices. This region of Colorado has very diverse ecosystems ranging from desert to alpine, with much of the BLM-managed land being sagebrush steppe, pinyon–juniper woodlands, and the ecotone between these two systems. These ecotones are the focal systems for our study. Our sites were shrub-dominant, open areas with shrub cover around 20–35%, diverse understories of forbs and grasses, and 5–15% tree cover from pinyon–juniper expansion. Soils in the region range from deep loamy to deep rocky (Web Soil Survey, 2023). Our sites ranged in elevation from 1600–2800 meters. Mean annual temperatures range from 2–10°C and mean annual precipitation ranges from 325–555 millimeters, which predominantly falls in the winter months (Daly et al., 2008; PRISM Climate Group, 2014). The sagebrush steppe in this region of Colorado supports habitat for species like elk (*Cervus canadensis*), mule deer (*Odocoileus hemionus*), and the greater sage-grouse (*Centrocercus urophasianus*). Much of this habitat is experiencing fragmentation and degradation due to anthropogenic impacts (e.g., oil and gas development, livestock grazing, and recreation) and expansion of pinyon–juniper into historically sagebrush-dominated areas (Knick et al., 2003; Miller et al., 2000). Pinyon pine and juniper tree expansion has also increased the amount of woody fuels in the area and thus increased the risk of severe wildfire (Barger et al., 2011; Miller et al., 2000, 2008). These impacts have led managers to carry out pinyon–juniper reduction and removal treatments throughout the region (Copeland et al., 2018; Redmond et al., 2014a).

The specific sites used in our study were plots surveyed by the BLM's Assessment, Inventory, and Monitoring (AIM) program, which has been collecting data across BLM lands for almost 15 years. The locations of plots are randomly selected on BLM land and vegetation data is collected according to the AIM Strategy for Integrated Renewable Resource Management (Toevs et al., 2011). Each AIM plot covers an area of approximately 0.7 acres, with three 25 meter transects placed equidistant from each other around a central point (Herrick et al., 2022; Toevs et al., 2011). Study plots were narrowed down by considering the locations of land treatments within the region. According to the Land Treatment Digital Library (LTDL)—a national repository assembled by the U.S. Geological Survey of land treatments completed by the BLM (Pilliod and Welty, 2013)—there were 732 land treatments within the boundaries of the aforementioned BLM field offices. These land treatments totaled 550,462 acres within Northwest Colorado alone. There were 132 treatments that had AIM plots within their boundaries, of which only 72 were treated specifically for pinyon–juniper reduction. Other treatments in the region that we did not include in this study included aerial and drill seeding, brush control, and herbicide application. The 72 pinyon–juniper reduction treatments that were completed within our study area and included in our dataset were completed between 1992–2016, with treatment goals being fuels reduction, habitat improvement, and rangeland health/forage improvement (Fig. 3.1).

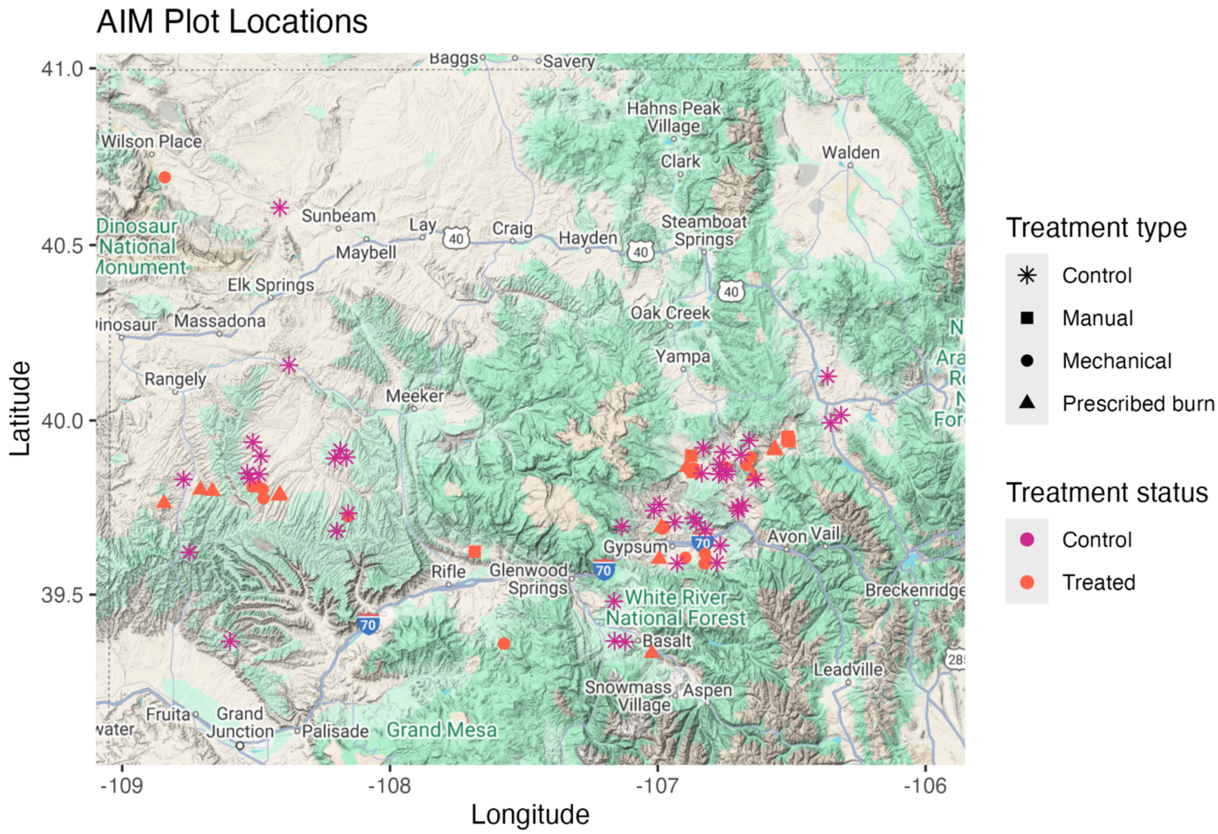

Figure 3.1: Map of AIM plots. Map of AIM plots included in study. Colors indicate treatment status of plots, and shapes represent treatment types.

Data compilation

Our study relies on existing data, so a large component of our methodology was compiling data from primarily publicly available sources. We utilized the standardized metrics collected by seasonal AIM field crews as our response variables, focusing on understory native herbaceous cover and noxious annual grass cover. The AIM plots included in our study recorded cheatgrass as the only noxious annual grass species present in plots, so this response variable will be referred to as cheatgrass hereafter. We identified whether each AIM plot was within or outside of pinyon–juniper removal treatment polygons documented in the LTDL. Plots within treated areas were recorded as "treatment" plots and plots outside of treated areas were recorded as "control" plots. Due to unreliable reporting in the LTDL regarding treatment completion (Chapter II), after identifying treatments that intersected with AIM plots, we verified that these treatments had indeed been completed by visually checking for tree cover reduction using tree cover rasters and time series created from remotely sensed data from the Rangeland Analysis Platform (RAP) (Allred et al., 2021; Jones et al., 2021, 2018; Robinson et al., 2019). Only LTDL treatments that did show a reduction in tree cover were kept in the dataset. The LTDL also provided additional treatment characteristics such as year of completion and removal method (Pilliod and Welty, 2013). We consolidated the various treatment descriptions from the LTDL into three broad categories: manual removal, mechanical removal, and prescribed fire. This simplification maintains distinctions in ecological effects between each treatment type while remaining practical for management applications. Manual treatments included all removal done by hand without heavy equipment or fire, mechanical treatments encompassed removal done by heavy equipment including mastication and rollerchopping (heavy machinery that cuts and mulches trees), and prescribed fire treatments included any removal done with fire such as pile and broadcast burning (in which fire burns across the whole landscape). Control plots, which fell outside of treated areas, were assigned treatment types according to the treated plot they were matched with during the pre-regression matching process (detailed below).

Using ArcGIS Pro, we aggregated topographical, climatic, and vegetation data for each AIM plot in our study region. Elevation, slope, and aspect were derived from the USGS National Map's 1/3 arc-second digital elevation model (U.S. Geological Survey, 2023). We obtained aridity index values from the Consultative Group on International Agricultural Research Consortium for Spatial Information Global Aridity Index (Zomer et al., 2022). The study area spans two distinct ecoregions—Southern Rockies and Colorado Plateau—as defined by Omernik's "Ecoregions of the Conterminous United States," and we assigned each plot to its corresponding ecoregion (Omernik, 1987). Each plot's distance from the nearest road was determined using the "near" function in ArcGIS Pro and road data from the Topologically Integrated Geographic Encoding and Referencing (TIGER) Database. Pre-treatment vegetation characteristics were gathered using RAP, which provided remotely sensed annual percent cover values for trees, shrubs, perennial forbs and grasses, annual forbs and grasses, and bare ground (Allred et al., 2021; Jones et al., 2021, 2018; Robinson et al., 2019). For treated plots, we calculated pre-treatment vegetation conditions by averaging values for each cover type across the five years preceding treatment. Due to RAP data availability beginning in 1987, treatments before 1992 had to be excluded. To estimate similar vegetation cover for control plots, which lack treatment dates, we averaged annual cover values for the five years preceding the year AIM data was collected to account for year-to-year variations and maintain methodological consistency with treated sites. For consistency and simplicity hereafter, "pre-treatment vegetation cover" will refer to both the vegetation cover at treated sites before treatment and the vegetation cover at control sites before AIM data collection. Age, or time since treatment, for treated plots was determined by calculating the number of years between treatment completion and AIM data collection. Given that control plots did not have a treatment completion year, these plots were assigned the same age as the treated site that they were paired with in the pre-regression matching process (detailed below). Treated plots ranged in age from 1–29 (Fig. S3.1). The final dataset encompassed 1898 AIM plots (45 treated, 1853 control) with their associated environmental variables and treatment details, where applicable.

Pre-regression matching

To address selection bias in landscape-scale treatments, we employed causal inference techniques and the counterfactual to identify comparable control sites for each treated site from our observational data (Larsen et al., 2019). Pre-regression matching (matching) occurs before analyses and pairs treated plots with control plots that are similar in regard to key confounding variables/covariates. Matching ensures that the treated sites and control sites are comparable and mitigates spurious relationships caused by confounding variables (Fick et al., 2021). This process creates a balanced dataset where covariate averages are approximately equal between treated and control sites, even in the absence of a traditional randomized experiment (Ramsey et al., 2019). We incorporated the following covariates in our matching process: plot latitude and longitude, topographic attributes (elevation, slope, aspect), aridity index, road proximity, pre-treatment vegetation characteristics (percent cover of trees, shrubs, perennial and annual forbs and grasses, and bare ground), and ecoregion (Fig. S3.2).

Using the *MatchIt* package (Ho et al., 2011), we paired 45 treated sites with control sites using optimal matching with Mahalanobis distance and exact matching by ecoregion (De Maesschalck et al., 2000; Rubin, 1980; Stuart, 2010). All 45 treated sites were paired with comparable control sites and unpaired control sites were discarded, creating a dataset of 90 sites. The 45 treated sites were within 23 unique treatments. The matching process reduced our dataset from 1853 to 90 sites, but analytical precision remains largely intact with the smaller dataset as precision is primarily determined by the smaller group size, which in this case is the treated group (Cohen, 1988; Stuart, 2010). To validate the matching quality and assess the covariate balance between the treated and control groups in the matched dataset, we examined the standardized mean differences (SMDs)—or the difference in means between the treated and control groups—for each covariate. High quality matching is achieved when SMDs are below 0.25 (Rubin, 1973; Stuart, 2010). Our matched dataset showed substantial improvement from the unmatched data, with most SMDs below 0.1 and all below 0.25 (Table S3.1 and Fig. S3.3). Upon confirmation that the matching process reduced bias in observed variables (Ramsey et al., 2019), we were able to move on to analyses. To test if the presence of unobserved confounding variables would alter treatment effects, we ran a sensitivity analysis using the *sensemakr* package in R (Cinelli et al., 2020). This analysis showed that even if an unobserved covariate had an effect three times as strong as the strongest observed covariate (pre-treatment shrub cover), our treatment effect would remain much the same (Fig. S3.4).

Modeling

To quantify how treatment type and site-level environmental attributes influenced the effect of pinyon–juniper removal treatments on understory herbaceous vegetation, we used a set of generalized linear mixed effects models (GLMMs). Response variables were obtained from BLM AIM data. All models for native herbaceous cover were fit with a beta distribution (to account for proportions as the response variable) (Damgaard and Irvine, 2019) and the dispersion parameter was always a function of the focal predictor and treatment status. Models for cheatgrass cover were fit with a binomial distribution and the dispersion parameter was always a function of the focal predictor and treatment status. We modeled cheatgrass cover as binary due to a high prevalence of zeroes and to simplify model interpretation. Simply the presence of cheatgrass is significant due to its high invasibility and rapid rate of spread (Duncan et al., 2004), so sites with zero cheatgrass cover were kept as zeroes and sites with greater than zero cover were changed to ones. In all models, we included the year that AIM data was collected and treatment polygon as random effects to account for non-independence between sites sampled in the same year and within the same treatment. We also included, in every model, a suite of "controlling" covariates: elevation, slope, aspect, aridity, distance to roads, and pre-treatment cover values (tree, shrub, perennial forb and grass, annual forb and grass, and bare ground cover). Models were fit and diagnosed using the *glmmTMB* package in R (Brooks et al., 2017; R Core Team, 2018)(Magnusson et al. 2017, R Core Team 2018) and model results were interpreted and plotted with the *ggeffects* package (Lüdecke, 2018).

We began our modeling process by testing the significance of treatment age, or time since treatment, owing to its importance in assessing treatment effects (Fornwalt et al., 2017; Havrilla et al., 2017). Our sample size precluded us from including too many model parameters, so we chose to test age first in order to determine its inclusion in future models. We fit models for native herbaceous cover and cheatgrass cover with age, treatment status, and their interaction as the focal predictors, and additional controlling covariates of treatment type and environmental attributes to account for any additional variation remaining in the dataset after the matching process. These model results showed that treatment effect did not shift with treatment age (i.e. the interaction between treatment and age was not significant, $P = 0.355$), so we did not include age as a predictor in any future models.

Next, we fit models to understand how the effect of treatments on native herbaceous and cheatgrass cover varied by treatment type ("manual", "mechanical", and "prescribed fire"). This consisted of one model each for native herbaceous, native forb, native grass, and cheatgrass, with treatment type as the focal predictor, including main effects for treatment type and treatment and their interaction.

We proceeded to fit nine models each for native herbaceous cover and cheatgrass cover, where each model was designed to evaluate the effect of a different environmental attribute on treatment effects. Each of these models included a focal, continuous environmental variable, treatment status, and the interaction between these variables. They also included treatment type and its interaction with the focal environmental attribute. For example, the models in which elevation was the focal predictor included treatment, elevation, and treatment type main effects, plus interactions between elevation and treatment and elevation and treatment type. Finally, after fitting models for native herbaceous cover and cheatgrass cover, we broke down native herbaceous cover into native forb cover and native grass cover and fit models for only the environmental attributes that had significant effects on native herbaceous cover. The focal attributes for these models were pre-treatment tree cover and pre-treatment shrub cover.

For simplicity and interpretability, we categorized pre-treatment tree, shrub, and annual forb and grass cover into low, medium, and high categories in the following results figures. Low, medium, and high categories were determined by assessing the distribution of pre-treatment cover in our dataset. Low tree cover was approximately 2%, medium was 20%, and high was 40%; low shrub cover was 16%, medium 40%, and high 70%; no annual forb and grass cover was <1%, low was 10%, and high was 25%.

RESULTS

Treatment type

Native herbaceous cover: Pinyon–juniper removal treatments had mixed effects on native herbaceous cover depending on treatment type, with mechanical removal having a slightly negative effect on cover, manual removal having a mostly neutral effect, and prescribed fire having a positive effect on cover in treated sites (Fig. 3.2). Sites treated with mechanical removal had on average 29% native herbaceous cover (95% CI: 22% – 36%) versus untreated sites which had on average 38% cover (CI: 30% – 45%). Manually treated sites had on average 20% native herbaceous cover (CI: 11% – 34%) whereas paired untreated sites had 28% (CI: 20% – 35%). Tree removal by prescribed fire had a clear positive effect on native herbaceous cover, with treated sites having an average of 42% cover (CI: 33% –52%) and untreated sites having an average of 30% (CI: 23% –38%).

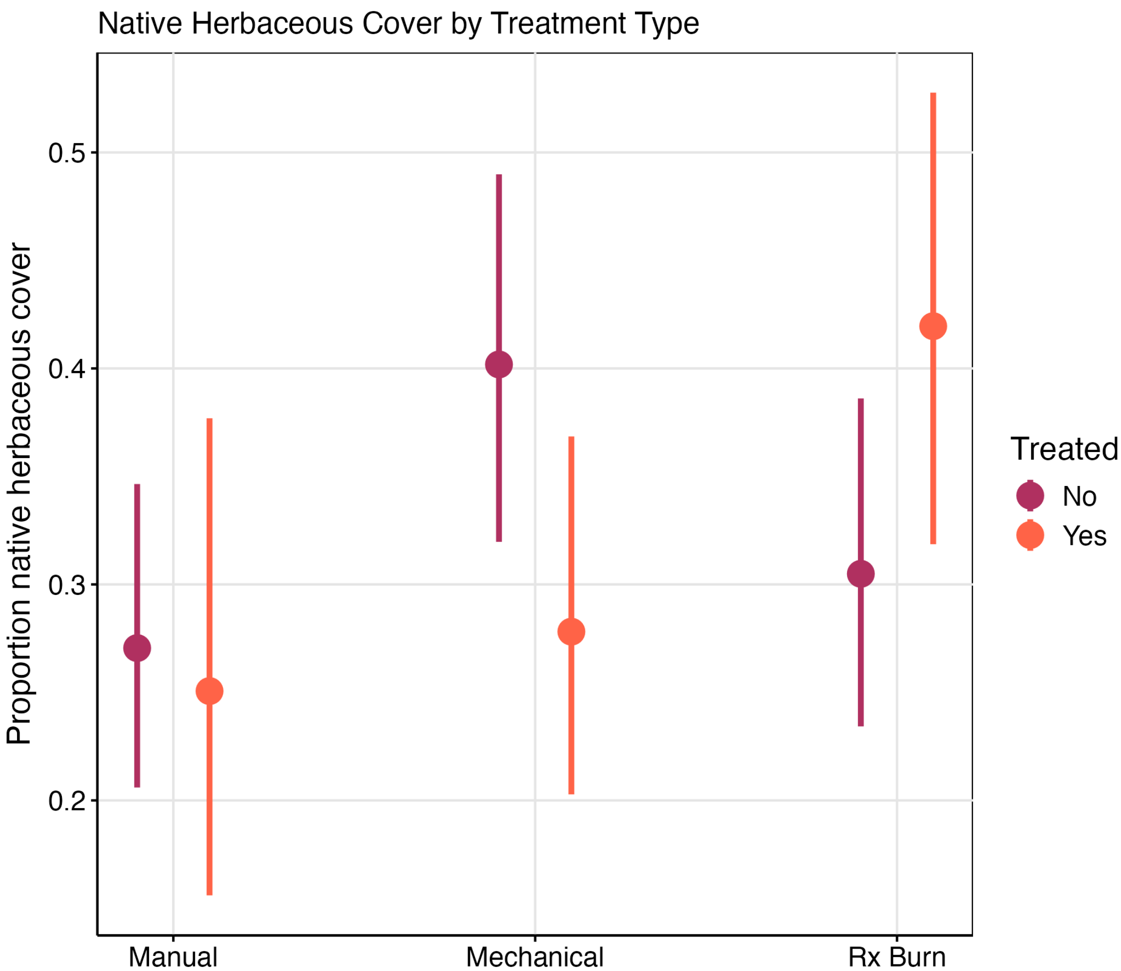

Figure 3.2: Native herbaceous cover x treatment type model results. Effects of treatment type on native herbaceous cover.

Native forb & native grass cover: When we assessed the effects of treatment type on native forb and native grass cover individually (i.e., splitting native herbaceous cover into grass and forb responses), treatment type showed similar effects to native understory overall, but with some differentiation between the two more specific cover types (Fig. 3.3). Mechanical treatment had negative effects on both forb and grass cover: treated sites were on average 6% lower in native forb cover and 7% lower in native grass cover (Fig. 3.3). Manual treatment also showed a negative effect on forb and grass cover, although the magnitude of effects was the opposite and grass cover was more negatively affected. Forb cover was 1% higher at untreated sites and grass cover was 6% higher at untreated sites versus manually treated sites. Finally, prescribed fire had a positive effect on forb cover and a stronger positive effect on grass cover. Burned sites 2% higher forb cover and 10% higher grass cover than untreated sites.

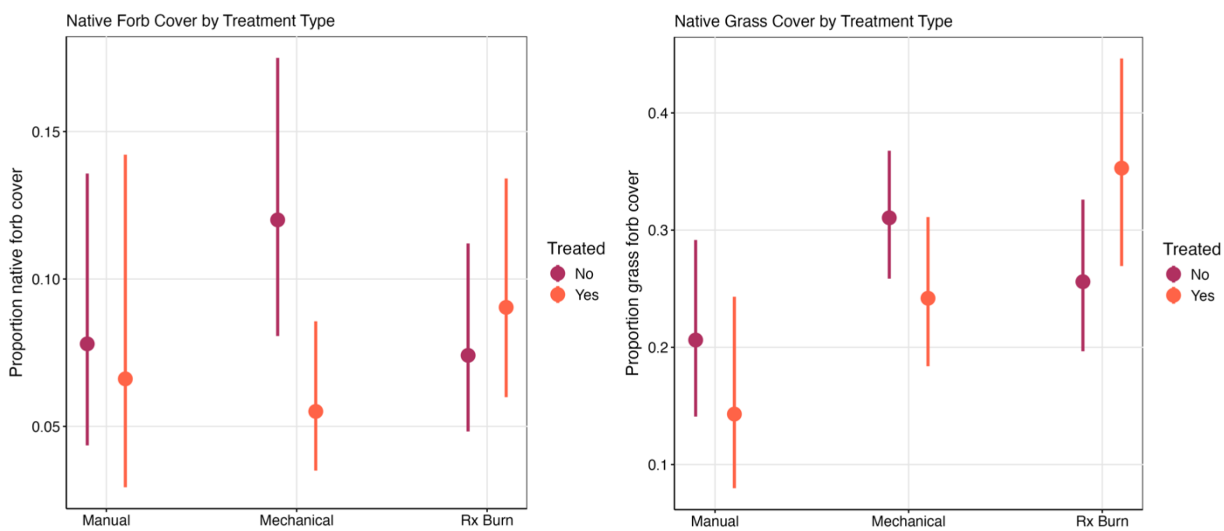

Figure 3.3: Native forb and grass cover x treatment type model results. Treatment type effects on native forb and grass cover (i.e., splitting native perennial cover into two categories).

Cheatgrass cover: The effect of treatment on cheatgrass cover was very clear, with a positive effect for each treatment type (Fig. 3.4). Prescribed fire treatments had the strongest positive effect, with treated sites having a 51% (CI: 12% – 88%) probability of cheatgrass occurrence whereas untreated sites had an almost 0% (CI: 0% – 11%) chance of occurrence. Mechanical treatment had a less positive effect on cheatgrass cover, with treated sites having on average 88% (CI: 35% – 98%) probability of occurrence and untreated sites having 45% (CI: 9% – 87%) probability of occurrence. Manual removal had the least clear effect on cheatgrass presence, although it was still positive. Sites that received manual treatment had a higher probability of cheatgrass occurrence at 52% (CI: 6% – 98%) versus 0% (CI: 0%-77%) at untreated sites.

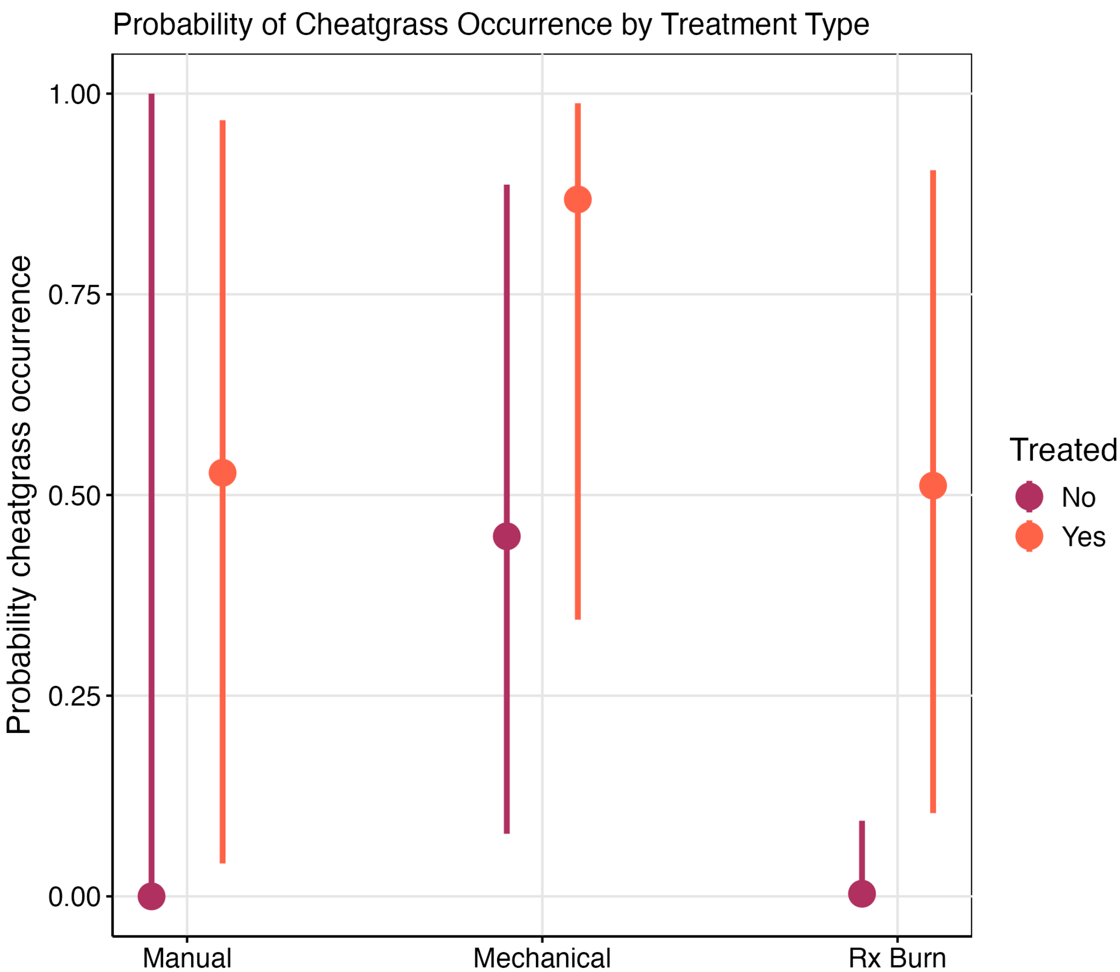

Figure 3.4: Cheatgrass cover x treatment type model results. Effect of treatment type on cheatgrass cover.

Environmental attributes

The effects of pinyon–juniper removal treatments did not change with any of the topographic or climatic variables that were included in our models (Table 3.1). This included elevation, slope, aspect, and aridity. Conversely, treatment effects were influenced by (i.e., interacted with) pre-treatment vegetation cover, where pre-treatment tree, shrub, and annual forb and grass cover altered the effect of treatments on understory herbaceous vegetation cover. Sites with higher pre-treatment tree cover experienced a more positive effect of treatment on native herbaceous cover, whereas sites with lower pre-treatment tree cover showed a negative effect of treatment on native herbaceous cover ($\beta_{\text{treatment*pre-treatment tree}} = 0.42$, $p = 0.0523$) (Table 3.1, Fig. 3.5). Relative to the mediating effect of pre-treatment tree cover, pre-treatment shrub cover had the opposite influence on treatment effects ($\beta_{\text{treatment*pre-treatment shrub}} = -0.49$, $p = 0.0046$). Sites with low pre-treatment shrub cover (~16%) had higher native herbaceous cover after treatment than before treatment, whereas sites with high pre-treatment shrub cover (~70%) had lower native herbaceous cover after treatment than before (Table 3.1, Fig. 3.6).

Model structure	β_{gradient} (SE)	$\beta_{\text{treatment}}$ (SE)	$\beta_{\text{interaction}}$ (SE)	$P_{\text{interaction}}$
Native perennial herbaceous cover model set				
Herbaceous cover ~ elevation + treatment + method + elevation:treatment + elevation:method	0.38 (0.45)	-0.09 (0.24)	0.06 (0.32)	0.84
Herbaceous cover ~ slope + treatment + method + slope:treatment + slope:method	-0.83 (0.56)	-0.10 (0.17)	0.21 (0.22)	0.34
Herbaceous cover ~ aspect + treatment + method + aspect:treatment + aspect:method	0.17 (0.24)	-0.03 (0.17)	0.11 (0.15)	0.47
Herbaceous cover ~ aridity + treatment + method + aridity:treatment + aridity:method	-1.32 (1.04)	-0.07 (0.13)	0.02 (0.61)	0.97
Herbaceous cover ~ pre-treatment tree + treatment + method + pre-treatment tree:treatment + pre-treatment tree:method	-0.86 (0.22)	-0.05 (0.16)	0.42 (0.22)	0.05

Herbaceous cover ~ pre-treatment shrub + treatment + method + pre-treatment shrub:treatment + pre-treatment shrub:method	0.82 (0.25)	0.15 (0.18)	-0.49 (0.17)	<0.01
Herbaceous cover ~ pre-treatment pfg + treatment + method + pre-treatment pfg:treatment + pre-treatment pfg:method	1.75 (0.56)	-0.01 (0.17)	-0.37 (0.37)	0.32
Herbaceous cover ~ pre-treatment afg + treatment + method + pre-treatment afg:treatment + pre-treatment afg:method	0.89 (0.50)	0.08 (0.25)	0.34 (0.48)	0.48
Herbaceous cover ~ pre-treatment soil + treatment + method + pre-treatment soil:treatment + pre-treatment soil:method	-0.19 (0.63)	-0.02 (0.18)	0.25 (0.31)	0.42
Cheatgrass cover model set				
Cheatgrass cover ~ elevation + treatment + method + elevation:treatment + elevation:method	-1.39 (1.25)	1.08 (0.75)	0.66 (1.28)	0.60
Cheatgrass cover ~ slope + treatment + method + slope:treatment + slope:method	-0.16 (2.07)	0.95 (0.59)	-0.55 (0.68)	0.42
Cheatgrass cover ~ aspect + treatment + method + aspect:treatment + aspect:method	-0.16 (0.34)	0.94 (0.49)	-0.46 (0.45)	0.31
Cheatgrass cover ~ aridity + treatment + method + aridity:treatment + aridity:method	-0.28 (4.96)	1.26 (0.57)	3.69 (2.52)	0.14
Cheatgrass cover ~ pre-treatment tree + treatment + method + pre-treatment tree:treatment + pre-treatment tree:method	-2.55 (2.14)	1.46 (0.72)	1.44 (1.06)	0.17
Cheatgrass cover ~ pre-treatment shrub + treatment + method + pre-treatment shrub:treatment + pre-treatment shrub:method	-0.27 (1.11)	1.14 (0.63)	-0.29 (0.61)	0.63
Cheatgrass cover ~ pre-treatment pfg + treatment + method + pre-treatment pfg:treatment + pre-treatment pfg:method	2.52 (2.33)	1.13 (0.57)	-0.25 (0.97)	0.79
Cheatgrass cover ~ pre-treatment afg + treatment + method + pre-treatment afg:treatment + pre-treatment afg:method	1.10 (2.74)	7.07 (3.0)	9.21 (5.38)	0.02
Cheatgrass cover ~ pre-treatment soil + treatment + method + pre-treatment soil:treatment + pre-treatment soil:method	2.69 (2.62)	1.09 (0.57)	-0.62 (0.97	0.53
Native forb and grass cover model set				
Native forb cover ~ pre-treatment tree + treatment + method + pre-treatment tre:treatment + pre-treatment tree:method	-0.78 (0.27)	-0.22 (0.22)	0.43 (0.27)	0.11

Native forb cover ~ pre-treatment shrub + treatment + method + pre-treatment shrub:treatment + pre-treatment shrub:method	0.46 (0.47)	0.04 (0.30)	-0.37 (0.26)	0.15
Native grass cover ~ pre-treatment tree + treatment + method + pre-treatment tree:treatment + pre-treatment tree:method	-0.81 (0.26)	0.08 (0.16)	0.33 (0.23)	0.14
Native grass cover ~ pre-treatment shrub + treatment + method + pre-treatment shrub:treatment + pre-treatment shrub:method	0.81 (0.26)	0.21 (0.19)	-0.41 (0.18)	0.02

Table 3.1: Environmental attribute model estimates, standard errors, and significance. Estimates and standard errors for environmental attribute models for each response variable. Each model also included all controlling covariates that were not part of the focal terms (elevation, slope, aspect, aridity, and pre-treatment tree, shrub, perennial forb and grass, annual forb and grass, and bareground cover).

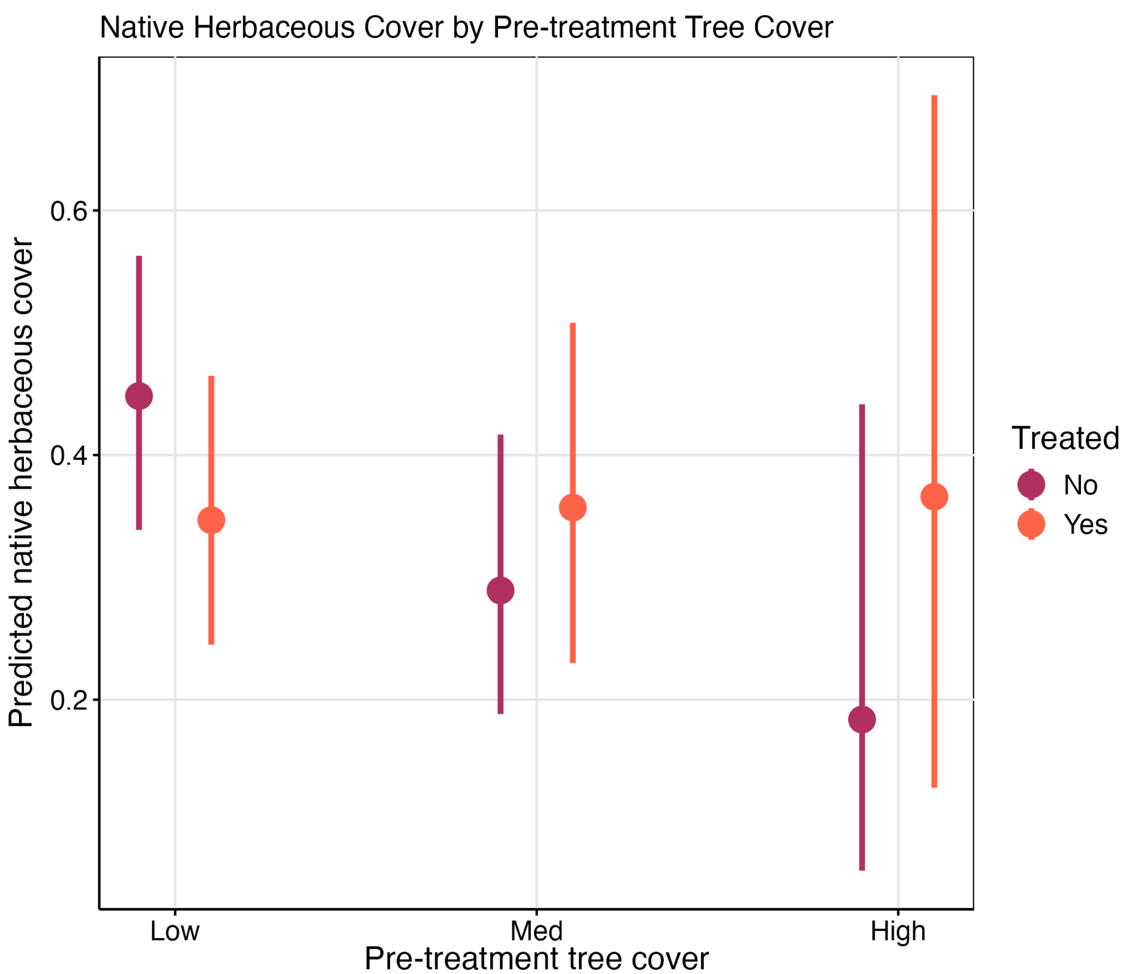

Figure 3.5: Native herbaceous cover x pre-treatment tree cover model results. Effect of pre-treatment tree cover on native herbaceous cover. Low cover represents approximately 2% tree cover, medium 20%, and high 40%.

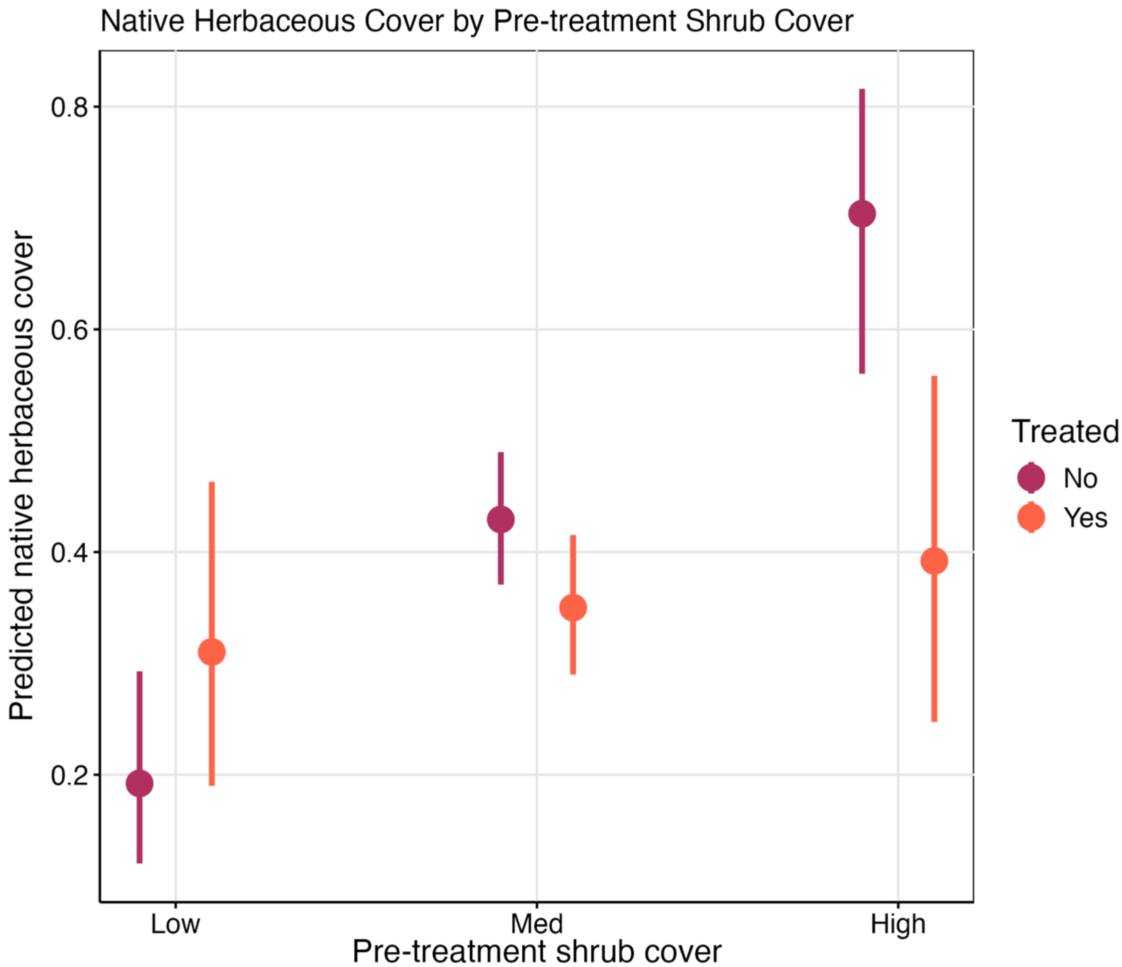

Figure 3.6: Native herbaceous cover x pre-treatment shrub cover model results. Effect of pre-treatment shrub cover on native herbaceous cover. Low cover represents approximately 16% cover, medium 40%, and high 70%.

The only underlying environmental attribute that influenced the effect of treatments on cheatgrass cover was the presence of annual forbs and grasses prior to treatment ($\beta_{\text{treatment*pre-treatment cheatgrass}} = 9.21$, $p = 0.0183$) (Fig. 3.7). Annual forb and grass cover from RAP includes nonnative species (Allred et al., 2021; Jones et al., 2021, 2018; Robinson et al., 2019), so our metric of pre-treatment annual forb and grass cover includes cheatgrass cover. If annual forbs and grasses, including cheatgrass, were not present before treatment occurred, then there was a higher likelihood that the site would remain free from cheatgrass after treatment. If annual forbs and grasses were already at the treatment site, even at low levels, then our models predicted that there would almost certainly be cheatgrass present after treatment.

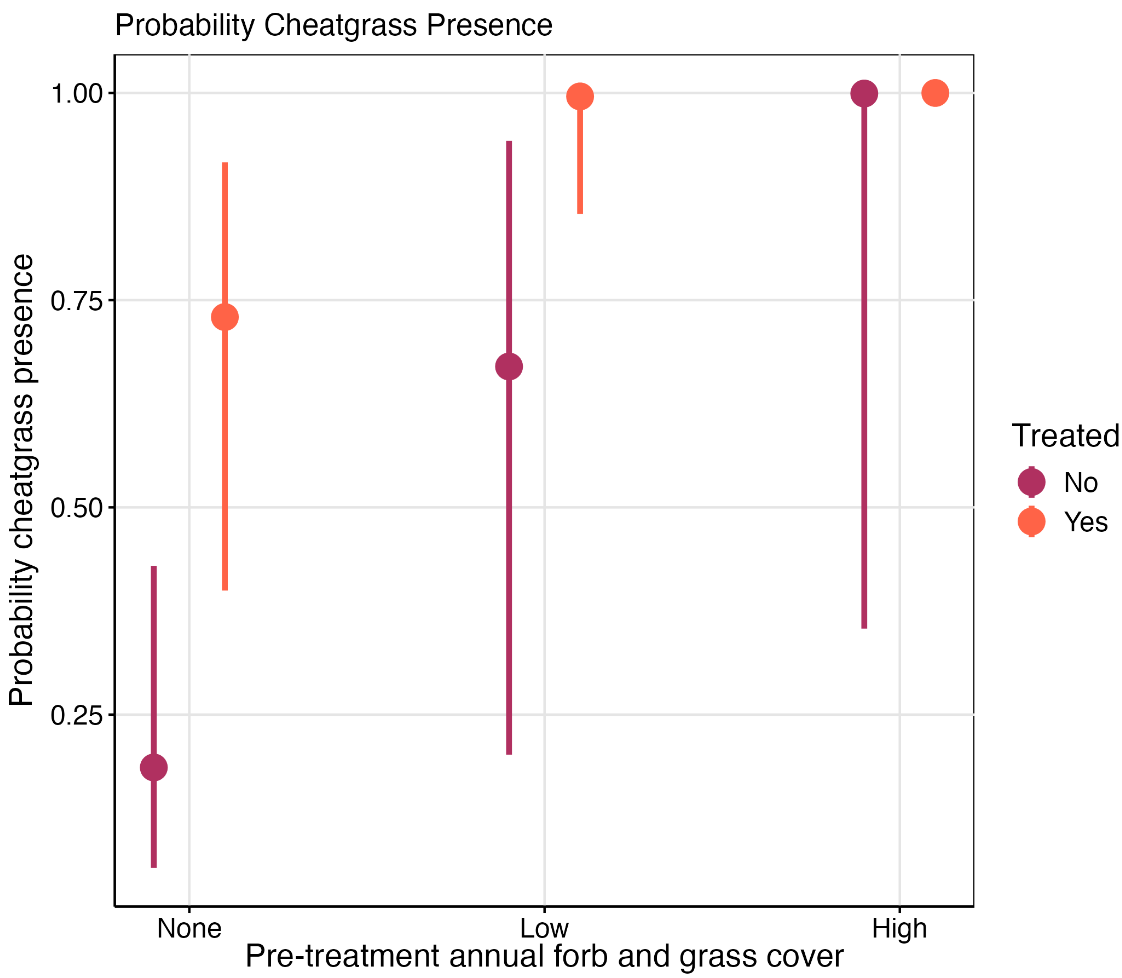

Figure 3.7: Cheatgrass cover x pre-treatment annual forb and grass cover model results. Effect of pre-treatment annual forb and grass cover on cheatgrass cover. No cover represents <1% annual forb and grass cover, low 10%, and high 25%.

DISCUSSION

Understanding the effectiveness of common restoration methods—and how such effectiveness varies across environmental gradients—is paramount to successful adaptive management. Pinyon–juniper removal is a widespread, prominent restoration action in the Western U.S., yet most research on treatment effectiveness is largely limited to small-scale experimental contexts. Our landscape-scale research revealed two predominant factors that mediate pinyon–juniper treatment effects on understory vegetation: treatment type and pre-treatment vegetation cover influenced the effects of tree removal on understory vegetation (both native herbaceous cover and cheatgrass grass cover) while treatment effects did not change across elevational, slope, aspect, or aridity gradients. Our results highlight the potential for both risks and benefits from treatments and the difference in outcomes that can occur with different removal methods and pre-treatment site conditions.

Treatment type

The method by which trees are removed for pinyon–juniper treatments is a significant factor in treatment planning and consideration of desired outcome (Copeland et al., 2018; Stephens et al., 2016). Differences in treatment results have been shown for mechanical treatments like mastication and rollerchopping (Fick et al., 2022; Havrilla et al., 2017; Johnston and Anderson Jr., 2023; Redmond et al., 2014a), prescribed fire (Huffman et al., 2013; Miller and Tausch, 2001; Overby et al., 2000), and manual treatments like lop & scatter, in which trees are cut with chainsaws and removed material is scattered across the landscape (Almalki et al., 2023; Brockway et al., 2002; Ross et al., 2012). The strong effects of prescribed fire increasing native forbs and grasses in our study has also been shown in experimental studies (Havrilla et al., 2017; Huffman et al., 2013) and is likely a result of a reduction in all vegetation cover and increased soil nutrient availability at burned sites. Steep declines in vegetation cover reduce competition for herbaceous understory cover, and prescribed fire has been shown to result in a pulse of increased soil nutrients (Alcañiz et al., 2018; Halpern et al., 2014). Mechanical and manual treatments have shown more uncertainty in their effects, in our study and other experimental studies (Bristow, 2010; Ernst-Brock et al., 2019; Havrilla et al., 2017; Huffman et al., 2017; Redmond et al., 2013). When separating herbaceous understory into different functional groups, effects on native forb versus grass cover differ, which may clarify the negative impacts of some removal methods. Reductions in native understory cover after tree removal have been shown in both the short and long term (Bristow, 2010; Ernst-Brock et al., 2019), particularly for forb species (Ernst-Brock et al., 2019). Previous studies have found that vegetation recovery after pinyon–juniper treatment is driven by short-lived species—primarily exotic annual species—that better capitalize on disturbance, rather than perennial species that may be more challenging to recover or reestablish after disturbance (Huffman et al., 2013; Redmond et al., 2014b). Additionally, pinyon–juniper removal treatments in our study area primarily focus on removal of trees that have begun to grow into open sagebrush systems, ultimately resulting in only a small change in tree cover. These sites may require more intensive treatment to create more pronounced change in conditions that support native herbaceous growth (Huffman et al., 2017), or different monitoring approaches to detect treatment effects that may be patchy and irregular across the landscape.

In contrast to the mixed results of treatment on native herbaceous cover, treatments had a clear, consistent positive effect on cheatgrass cover. With any kind of disturbance comes risk for invasion by exotic annual grasses in the Western U.S. (Bishop et al., 2019; Duncan et al., 2004), so it is not surprising that all treatment types had a positive effect on cheatgrass cover (Bybee et al., 2016; Coop et al., 2017; Redmond et al., 2014b). Prescribed fire had the strongest positive effect; burning removes greater amounts of vegetation from the landscape and potentially deteriorating the seed bank, creating increased disturbance and ample space for cheatgrass proliferation (Allen et al., 2008; Havrilla et al., 2017; Korb et al., 2004). Even manual treatments—which don't use heavy machinery or fire and thus are associated with less disturbance—resulted in an increase in cheatgrass cover at treated sites, highlighting the critical risk of noxious species invasion with treatment. Method of tree removal is an important decision point in the treatment planning process and should be given consideration in the context of feasibility and resource availability, but also in the context of a treatment method's ecological effects.

Environmental attributes

The environmental context of a site is another key consideration in the pinyon–juniper treatment planning process, with pre-treatment vegetation conditions of a site influencing treatment effectiveness where underlying attributes like topography and climate do not. Our investigation showed no change in treatment outcomes across gradients of elevation, slope, aspect, or aridity. In past work, these attributes have been shown to affect vegetation: divergent climate change responses in vegetation at different elevations (Gao et al., 2019; Lamprecht et al., 2018), more northerly aspects in the northern hemisphere being more forested (Holland and Steyn, 1975; Yang et al., 2020), variation in plant traits across an aridity gradient (Welles and Funk, 2020). Yet, here, they did not shape treatment effectiveness, potentially due to the small range of environmental attributes within our study sites. Pre-treatment vegetation cover, on the other hand, did change how any given site responded to treatment. Sites with higher pre-treatment tree cover exhibited a larger positive treatment effect on native herbaceous cover (Fig.

3.5). Higher tree cover in pinyon–juniper woodlands is often associated with sparse understories and exposed bare ground (Archer et al., 2017b; Cole et al., 1997; Romme et al., 2009). When tree cover is reduced from high percent cover to low cover, there is a larger impact, creating more light availability and less competition for soil nutrients and moisture (Bates et al., 2000; Brockway et al., 2002). This impact is less prominent when tree cover is reduced at sites with already low tree cover pre-treatment.

Similar to pre-treatment tree cover, percent shrub cover prior to treatment also altered how pinyon–juniper removal affects native herbaceous cover, although with an inverse relationship (Fig. 3.6). Higher pre-treatment shrub cover resulted in a less positive effect of treatment on native herbaceous vegetation. The increased prevalence of shrubs at a site before it is treated may lead to a negative impact of treatment on native herbaceous cover in a number of ways. High shrub cover may inhibit herbaceous growth after treatment by limiting the availability of light, soil moisture, and nutrients for use by herbaceous species (Beck et al., 2012; Davies et al., 2012). Additionally, prominent shrub cover can lead to reduced herbaceous understory vegetation (Davies et al., 2007; Eldridge et al., 2011), diminishing the availability of propagules for herbaceous regrowth (Nunes and Byrne, 2022).

Finally, the least surprising instance of pre-treatment vegetation influencing treatment effects is the presence of annual forb and grass cover before treatment resulting in higher cheatgrass cover post-treatment. If there are exotic species at a site prior to being treated, the disturbance associated with treatment can facilitate proliferation of the species after the treatment is complete (Bybee et al., 2016; Coop et al., 2017). This emphasizes the importance of surveying for cheatgrass presence before implementing any treatment at a site and utilizing management actions such as herbicide application to mitigate cheatgrass establishment and spread.

The results from our analyses align with other studies that have investigated how environmental attributes and pre-treatment vegetation conditions might influence or improve prediction of large-scale restoration treatments effectiveness (Copeland et al., 2019; Davidson et al., 2019; Fick et al., 2022; Williams et al., 2017). For instance, a study by Fick et al. (2022) in the pinyon–juniper system used remote sensing data from RAP for their vegetation cover response variables and found edaphic setting (encapsulated by soil geomorphic units), aridity index, and pre-treatment tree cover had a strong effect on outcomes of many functional groups (Fick et al., 2022). Our sample size was unable to accommodate the many categories that would be included in a land potential or soil type variable, but we view pre-treatment vegetation cover as a related metric. Land potential is a measure of a site's potential productivity and resilience (Herrick et al., 2016), which partially shapes and informs vegetation characteristics of a site (Duniway et al., 2010). Thus, taken together, our study and previous research suggest that considering both a site's current and potential vegetation communities is important to help support a more thorough and science-based decision-making process (Herrick et al., 2006).

Management implications

In response to calls for increased adaptive management on public lands in the Western U.S., we illustrate the power of using easily accessible data sources to support the adaptive management process. In this case, the BLM carried out management and indirectly conducted treatment monitoring through the AIM program. This study represents the evaluation phase, frequently a key missed step in the adaptive management process and one that seldom receives direct support from federal funding sources (Archie et al., 2012). Upon producing and sharing knowledge from research like ours, the cycle will ideally begin again with an improved decision-making process for future treatments (Schreiber et al., 2004). Here, we provide a new method for taking advantage of existing monitoring programs and adapting them to better align with treatment effectiveness monitoring (e.g., collecting AIM data at a site before and after treatment), which contributes directly to adaptive management practices (Smith et al., 2023).

CONCLUSION

Gaining insights into the underlying factors that contribute to the effectiveness of pinyon–juniper removal treatments is an important question for the future of pinyon–juniper woodlands, sagebrush steppe systems, and the ecotone between them (Hartsell et al., 2020; Remington et al., 2021). Here, we utilized observational monitoring data from the BLM AIM program in conjunction with environmental variables from open access data sources to investigate if treatment outcomes were altered by attributes such as site topography, climate, or pre-treatment vegetation cover. Our results highlight how vegetation conditions prior to treatment and tree removal method influence the effect of removal treatments and emphasize the importance of considering these factors in the treatment planning process (Fig. 3.8). It is important to recognize that while our findings support the planning process for managers interested in treatment effects on vegetation, there are numerous other goals that are likely important to managers, including increased wildlife use and fuels reduction. Our findings speak to the effectiveness of treatments in meeting vegetation management goals, but may not clarify how well treatments meet other management goals.

While the methods we employed in this study allowed us to use existing data to assess the effects of pinyon–juniper removal in Northwest Colorado, the process was ultimately complex and time-intensive. Tuning federal agencies' existent monitoring/assessment programs to accommodate more direct treatment effectiveness monitoring would facilitate adaptive management and science-based decision making (Shinneman et al., 2023b; Smith et al., 2023; Stauffer et al., 2022). Uncertainty surrounding global change and the future of sagebrush steppe and pinyon–juniper woodlands make learning from management actions and incorporating new knowledge into decision making more critical than ever (Simonson et al., 2021).

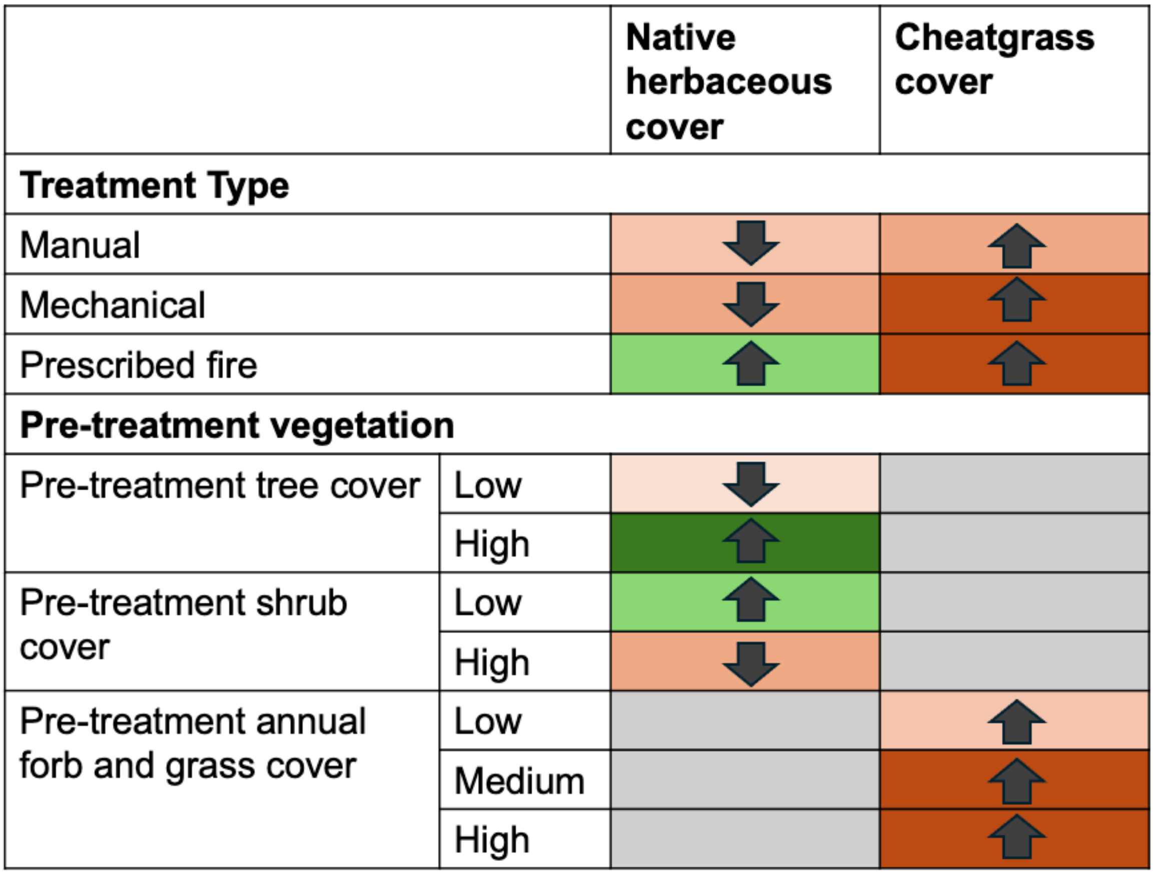

Figure 3.8: Stoplight chart. Chart summarizes treatment effects on native herbaceous and cheatgrass cover. Green colors represent positive effects/benefits of treatment while orange colors represent negative effects/risks. Darker shades signify stronger effects in either direction (i.e., mechanical and prescribed burn treatment in darker orange have stronger negative effects on cheatgrass cover than manual treatment in lighter orange). Arrows represent whether treatment increases (upward facing arrow) or decreases (downward facing arrow) cover.

CHAPTER IV

A REGION-WIDE META-ANALYSIS OF PINYON–JUNIPER TREATMENT EFFECTIVENESS ON THE COLORADO PLATEAU

Alyson S. Ennis and Nichole N. Barger

ABSTRACT

Pinyon–juniper systems cover large swaths of the Colorado Plateau, supporting wildlife habitat, rangelands, cultural resources, and other ecosystem services. These and neighboring ecosystems are experiencing vast ecological change with increased land use, management actions, and climate impacts. One such change is the expansion and densification of pinyon pine and juniper trees which is increasing hazardous fuels buildup and degrading wildlife habitat and rangelands. Pinyon–juniper reduction treatments have been implemented across Colorado Plateau public lands to counteract expansion and densification. Management goals include reduction of woody fuels, restoration of wildlife habitat, and rangeland improvement. There is uncertainty surrounding the effectiveness of these treatments given the number of both positive and negative treatment effects reported in the pinyon–juniper literature. While there have been some syntheses and reviews that have summarized this literature, none have focused on the Colorado Plateau or used meta-analytical methods. Our goal in conducting this meta-analysis was to aggregate studies about pinyon–juniper treatment effects on understory vegetation on the Colorado Plateau in order to find broad patterns or trends in treatment outcomes. We found that overall, treatments increased understory vegetation cover, including exotic plant cover. The magnitude of increase differed by time since treatment, treatment method, and environmental conditions (aridity, elevation, and mean annual temperature). These results, which were more unequivocal than those from previous syntheses, can feed into the adaptive management process

as treatment evaluation and support managers in carrying out treatments that improve the function and resilience of pinyon–juniper systems.

INTRODUCTION

Pinyon–juniper ecosystems cover millions of acres of the Colorado Plateau in the Western United States (U.S) (Mitchell and Roberts, 1999) and make up some of the most iconic landscapes in the American Southwest. These communities, co-dominated by pinyon pine (*Pinus edulis*) and juniper (*Juniperus spp.*) trees, support many ecosystem services. A multitude of wildlife species rely on pinyon–juniper communities for habitat, from big game species like elk (*Cervus canadensis*) and pronghorn (*Antilocapra americana*) to birds and small mammals, including at-risk species like the pinyon jay (*Gymnorhinus cyanocephalus*) (Finch and Ruggiero, 1993; Paulin et al., 1999). Pinyon–juniper woodlands provide numerous resources for humans, such as fuelwood (Samuels and Betancourt, 1982), pinyon nuts, cultural plant materials for indigenous peoples (Koyiyumptewa et al., 1993), rangeland for livestock grazing, and recreation. Pinyon–juniper systems are extremely diverse, occupying a variety of topographies, climate conditions, and geologies across their broad geographic range (Romme et al., 2009). Even within the Colorado Plateau, which is only a subsection of the pinyon–juniper ecosystem's range, there is a spectrum of species compositions, vegetation structures, and land use histories. Akin to diversity within the system, pinyon–juniper communities are experiencing a diverse set of ecological changes, both subtle and dramatic, as a consequence of continued human use, disturbance, and climate changes (Miller et al., 2019; Miller and Wigand, 1994; Romme et al., 2009).

In the past century, pinyon–juniper communities have been subject to a wide range of disturbances, climate impacts, and land uses (Miller and Wigand, 1994; Romme et al., 2009). A combination of climate conditions, fire exclusion, and overgrazing throughout the early 1900s resulted in increases in tree density ("densification") of existing woodlands and expansion of pinyon pine and juniper trees into adjacent, non-wooded systems (Barger et al., 2009; Miller et al., 2008). Expansion and densification often degrade landscapes, reducing native understory vegetation, increasing bare ground that is susceptible to erosion, and creating an accumulation of woody fuels (Archer et al., 2017a; Miller and Tausch, 2001). Reduction of native understory vegetation—and subsequent soil erosion—degrades wildlife habitat while creating opportunities for invasive species proliferation (Coates et al., 2017; Cole et al., 1997). Accumulation of woody fuels from increased tree cover and fine fuels from invasive species like cheatgrass (*Bromus tectorum*) jointly increase the threat of fire ignition and facilitate more severe wildfire (Bradley et al., 2018). Increased risk of catastrophic wildfire threatens the resilience and longevity of both human infrastructure and pinyon–juniper ecological communities broadly (Redmond et al., 2023). These consequences of pinyon–juniper expansion and densification have resulted in attempts to restore communities to their historical structure, function, and diversity through landscape-scale treatments.

A large percentage of pinyon–juniper ecosystems are on public lands managed by federal land management agencies. Because of this, large-scale restoration treatments have been carried out within the pinyon–juniper system. These treatments focus on removal of pinyon pine and juniper trees through various methods, with the goals of restoring wildlife habitat, reducing hazardous fuels, and improving rangelands (Redmond et al., 2014a). However, there is a lack of consensus about the effectiveness of pinyon–juniper treatments. Studies from the scientific literature report positive, neutral, and negative treatment outcomes on vegetation, soils, and wildlife (Shinneman et al., 2023a). There are clear tradeoffs associated with pinyon–juniper treatments. Benefits such as improvement in understory vegetation have been shown (Havrilla et al., 2017; Huffman et al., 2013; Stephens et al., 2016), but so have risks like increased soil erosion and invasive species cover (Coop et al., 2017; Havrilla et al., 2017; Karban et al., 2022a). Uncertainty surrounding treatment effectiveness is further complicated by the sheer diversity of pinyon–juniper systems (Romme et al., 2009). This diversity makes it challenging to predict how any given site will respond to treatment and consideration of possible environmental conditions that may influence treatment effectiveness makes the planning process laborious and convoluted. Finally, there is a conspicuous lack of effectiveness monitoring for pinyon–juniper treatments, as federal funding is seldom allocated specifically for that purpose (Archie et al., 2012). Taken together, this uncertainty leaves many questions about the benefits and risks of treatment, complicating the treatment planning process for land managers. Given the intrinsic value of pinyon–juniper systems, the immense diversity within this vegetation type, and climate uncertainty in the Western U.S., finding ways to better inform decision-making around treatments is essential for the future of these systems (McCord and Pilliod, 2022; Schreiber et al., 2004).

Due to the prevalence and cultural significance of pinyon–juniper systems, there are many studies in the scientific literature that have investigated the impacts of pinyon–juniper treatments on vegetation, soils, and wildlife. These studies span broad spatial and temporal scales. They utilize treatments that were completed using different tree removal methods and that cover a variety of environmental conditions. Many of the factors that differ between studies influence the effects of treatments and thus treatment outcomes. Treatment type—whether trees were removed manually with chainsaws, mechanically using heavy machinery, or with prescribed fire—changes how treatment impacts the landscape (Fornwalt et al., 2017; Karban et al., 2022a; Stephens et al., 2016). Environmental conditions (e.g., aridity, elevation) influence how sites respond to restoration actions (Copeland et al., 2019; Shackelford et al., 2021). The pinyon–juniper literature therefore provides a valuable source of existing data to investigate the influence of these factors.

In recent years, reviews of the pinyon–juniper literature have been published, aiming to synthesize results and gain a more thorough understanding of treatment effectiveness (e.g., Shinneman et al., 2023; Jones 2019; Miller et al., 2019). However, these reviews have employed vote-counting techniques rather than statistical meta-analysis methods and have been broad in scope. In the review from Shinneman et al. (2023), less than 6% of studies took place on the Colorado Plateau. This leaves a large gap to be filled in the study of pinyon–juniper treatments on the Colorado Plateau, a region especially sensitive to disturbance and vulnerable to climate impacts (Copeland et al., 2017; Schwinning et al., 2008). Furthermore, while vote-counting methods are effective for summarizing results, they do not consider the magnitude of effects or study precision, limiting the power of their findings. Meta-analytical methods offer the opportunity to utilize this literature to quantitatively assess ecosystem response to pinyon–juniper treatments (Arnqvist and Wooster, 1995). With statistical meta-analysis, we can leverage this existing data source (i.e., the pinyon–juniper treatment body of literature) to find patterns in treatment effects and consider explanations for differences in effects among studies.

To address the uncertainty surrounding the effects of pinyon–juniper treatments on understory vegetation on the Colorado Plateau, we compiled a database of pinyon–juniper treatment literature and used meta-analysis to synthesize regional patterns in existing data. We focused on vegetation and ground cover with the goal of quantifying overall effects of pinyon–juniper removal treatments on understory species and exotic species. We also aimed to detail which predictors—both environmental conditions and other key factors such as tree removal method—are most influential in determining these treatment effects. Specifically, we tested the hypotheses that (a) pinyon–juniper treatments result in an increase in herbaceous understory vegetation cover while having mixed/neutral effects on shrub cover, (b) treatments increase exotic species cover, (c) vegetation responses to treatment shift with tree removal method, time since treatment, and environmental conditions associated with changes in soil moisture (e.g., elevation and aridity index (Mata-González et al., 2002; Wang et al., 2019)). Testing support for these hypotheses is critical to assessing the effects of pinyon–juniper treatments, which can in turn help optimize resources allocated to completing treatments and minimize uncertainty around how climate change will influence treatment outcomes and the pinyon–juniper system as a whole.

METHODS

Literature search and data extraction

To search the existing literature and compile relevant studies, we used the Web of Science database. Our searches included all combinations of the following search terms: "pinyon–juniper" OR "pinon–juniper" AND "vegetation treatment", "treatment", "management", "thinning", "fuels management", and "land treatment". To select articles for review, we screened abstracts to ensure that studies assessed outcomes of pinyon–juniper removal and were completed in the Colorado Plateau region. The following criteria were then applied to articles during a second, more thorough screening to identify eligible studies:

1) Specific study locations were within the Colorado Plateau ecoregion.
2) The study specifically investigated the effects of pinyon–juniper removal treatments via field studies, not effects after wildfire or of treatments that were carried out in a pinyon–juniper system but did not reduce tree cover or via remote sensing methods.
3) Studies must have reported percent cover or proportion of vegetation and ground cover. This included studies that may have focused on treatment effects on another focal group (e.g., wildlife, soils), but also reported effects of treatment on vegetation and ground cover.
4) Articles needed to include figures or tables from which data could be extracted. This data had to include at least average effects (i.e., means), with average effects and a measure of variance (e.g., standard deviation, standard error) being optimal.

In some cases, individual articles contained multiple sub-studies. For example, a single article might compare the effects of multiple different treatment types or assess treatment effects over multiple years. To account for potential non-independence between sub-studies within the same article, each article was given a unique identifier to test for non-independence during analyses.

Once relevant articles were compiled (Fig. S4.1 and Appendix S4.1), we extracted data from figures and tables within each article using ImageJ software (Schneider et al., 2012). Mean, standard deviation, standard error, confidence intervals, and sample size were extracted from each study, where provided, for both treatment and control study sites. We extracted data for the following vegetation response variables: forb, grass, shrub, overall understory, and exotic plant cover. Although overall understory cover was only reported in four articles, we felt it was an important metric to report and included it in our analyses. Information regarding relevant moderators—variables that moderate the effect of treatment—was gathered from articles as well as open access data sources (Table 4.1). Time since treatment (calculated by subtracting the year treatment was completed from the year data was collected), treatment type (tree removal method), and elevation were collected from the articles themselves. Treatment types included mastication (large tractor with mechanical axe that mulches trees), rollerchopping (large tractor with rotating blades that cut down trees), chaining (two large tractors with heavy chain between them, uprooting trees), broadcast burning (trees are cut and debris scattered, and then fire is ignited across landscape), pile burning (trees are cut and debris is gathered into piles which are then burned), and lop & scatter (trees are cut down via chainsaw and debris is scattered across the treatment area). Climate variables (mean annual temperature and precipitation) were obtained from the PRISM Climate Group (PRISM Climate Group 2014). Soils data (percent clay, percent silt, percent sand) were gathered from the U.S. Geological Survey (Watson and Belitz, 2024). We used the Global Aridity Index to obtain aridity for each site (Zomer et al., 2022).

Moderator	Levels or Range	Description
Time since treatment	1–40 years	Number of years between treatment completion and data collection; reported in article; for articles that provided year ranges, the average year was reported for this metric
Treatment type	Broadcast burn, chaining, lop & scatter, mastication, pile burn, rollerchopper	Method of tree removal; reported in article
Seeding	Yes, No, Unknown	If treatments included a seeding treatment or not; reported in article
Elevation	1585–2250 meters	Average elevation reported in article
Aridity	0.109–0.343 (unitless)	Aridity index; from CGIAR Global Aridity Index 0.05–0.20: arid 0.20–0.50: semi-arid
Mean annual temperature	7–13 degrees Celsius	Average annual temperature, 30-year normal; from PRISM Climate Data
Mean annual precipitation	272–693 millimeters	Average annual precipitation, 30-year normal; from PRISM Climate Data
Percent clay	14–29%	Percent clay in soil; from USGS
Percent silt	22–40%	Percent silt in soil; from USGS
Percent sand	37–62%	Percent sand in soil; from USGS

Table 4.1: Moderator details. Details of moderator variables included in boosted regression tree analyses and subsequent mixed effects meta-regression models.

Calculation of meta-analysis metrics

To summarize the quantitative results from each study, we calculated effect size and within-study variance. For our effect size metric, we used the log response ratio (lnRR) of each study, calculated using treatment and control means from each study with the following formula: $\ln(X_{\text{treated}} / X_{\text{control}})$, where X_{treated} is the mean vegetation response after treatment and X_{control} is the mean vegetation response in the untreated control. A positive lnRR indicates that treatment increased the vegetation cover variable whereas a negative lnRR indicates that treatment decreased vegetation cover. The log response ratio provides a standardized measure that effectively summarizes treatment effect and with a simple calculation can be transformed into the percent change in vegetation response with treatment (Hedges et al., 1999).

Studies varied in their precision, so we calculated within-study variance in order to account for such precision in our analyses (Hedges et al., 1999). Variance was calculated using the following formula:

$$\sigma^2 = \left[\frac{SD^2_{treated}}{(n_{treated})(X^2_{treated})}\right] + \left[\frac{SD^2_{control}}{(n_{control})(X^2_{control})}\right]$$

$X_{treated}$ and $X_{control}$ are the mean vegetation cover with and without treatment, $SD_{treated}$ and $SD_{control}$ are the standard deviation of treatment and control means, and $n_{treated}$ and $n_{control}$ are the number of samples or replicates of treatment and control measurements. Within-study variance was used to weight studies according to their precision. For studies that only reported means, with no measure of variance (standard deviation, standard error, or confidence interval), variances were imputed using Taylor's Law (Nakagawa 2015)—the relationship between mean and variance—for our dataset.

Boosted regression tree predictor exploration

Boosted regression tree (BRT) analysis allowed us to assess the relative importance of our possible moderators and their potential interactions for effect size (lnRR) for each of our five vegetation cover responses separately. BRT analysis sequentially fits and aggregates multiple decision trees using a forward stepwise approach, enhancing predictive accuracy and helping us narrow down our set of moderators (De'ath, 2007). We ran BRTs using the 'gbm.step' function from the *gbm3* (Ridgeway et al., 2024) and *dismo* packages (Hijmans et al., 2024) in the R software environment (R Core Team, 2018), following the methodology outlined in Elith and Leathwick (2017). We started with the following predictors in our dataset, collected from articles and open access data sources: treatment type, time since treatment, elevation, mean annual temperature, mean annual precipitation, aridity, and soil percent clay, silt, and sand (Table 4.1). Initial BRT models included all moderators and weights were assigned based on within-study variance. We then performed model simplification using the 'gbm.simplify' function, as recommended in Elith and Leathwick (2017). Our subsequent simplified BRT models retained only the most influential moderators, ranking them based on their relative influence (scaled to sum to 100% for each model, indicating the proportion of variation explained by each moderator). This relative influence metric was derived as the average contribution across all trees in a given BRT model (Friedman & Meulman, 2003). Finally, potential interactions among moderators in the simplified BRT models were assessed using the 'gbm.interaction' function (Elith and Leathwick, 2017). No interactions were reported.

Mixed multi-factor meta-analysis

After using BRT to select important moderators to include in the models for each of our vegetation responses, we conducted our meta-analysis using mixed effects meta-regression models with restricted maximum likelihood estimation of parameters using the 'rma.mv' function in the *metafor* package (Viechtbauer, 2010). The response variable for each model was the effect size, or lnRR, for each vegetation response. First, we fitted models with only random effects to estimate the overall treatment effect size for each vegetation response model (i.e., the weighted overall lnRR of vegetation response to pinyon–juniper treatment). Each effect size was weighted by within-study variance and residual between-study variance (paper identifier) was included as a random effect. Next, for each of our five vegetation responses, we fit a series of mixed effects multiple meta-regression models to examine the relative importance of moderators selected from our BRT analyses. This series included a comprehensive model containing all moderators as fixed effects, along with subset models in which one additional fixed effect was incorporated. Time since treatment and treatment type were included in comprehensive models for all vegetation types, even if not identified as influential in BRT analyses, due to their importance in the treatment planning and evaluation process (Chambers et al., 2021; Fornwalt et al., 2017). Each model also accounted for residual between-study variation by including paper identifier as a random effect. To explore residual heterogeneity, we conducted separate univariate models for each vegetation response as well. Because the response variable for each model was effect size (lnRR), when interpreting model outputs, significance of moderator variables indicated that the variable moderated treatment effects on the vegetation response. For example, if elevation was significant in the model for understory cover, then it affected the size of the effect of treatment on understory vegetation cover, not understory vegetation cover itself.

RESULTS

Summary of articles

Our final database included 27 articles from the 70 that went through the screening process (Appendix S4.1 and Table S4.1). These articles described studies that took place within all Colorado Plateau states: 7 in Arizona, 9 in Colorado, 4 in New Mexico, and 7 in Utah (Fig. 4.1). The publication years in our final database spanned 50 years, from 1973–2023. There was high variety in moderator values amongst articles, with studies looking at treatment effects from 1–40 years after treatment and from mechanical, manual, and prescribed fire treatment types. Studies spanned 1585–2250 meters in elevation, with average annual temperatures ranging from 7–13ºC and average annual precipitation from 272–693 millimeters.

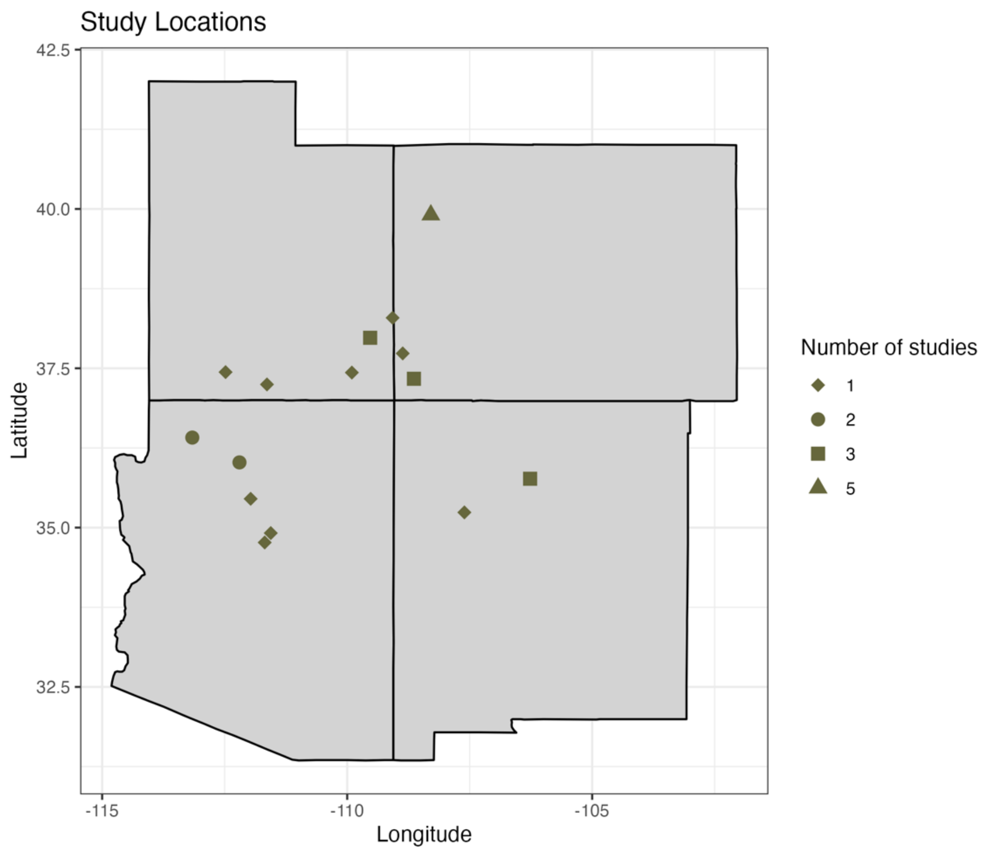

Figure 4.1: Study map. Map of study locations on the Colorado Plateau. Shapes indicate the number of studies at each point. Total studies = 27.

BRT moderator exploration

Exploration of moderator importance with BRT analyses identified various combinations of time since treatment, treatment type, elevation, aridity, mean annual temperature, mean annual precipitation, percent clay, and percent silt as moderators with significant explanatory power in simplified BRT models (Fig. 4.2). Percent sand was dropped during the simplification process for every model. BRT analyses did not identify any significant interactions amongst moderators and thus no interactions were included in our mixed effects meta-regression models. After BRT exploration, moderators identified as important for each of our vegetation responses were included as fixed effects in meta-analysis models.

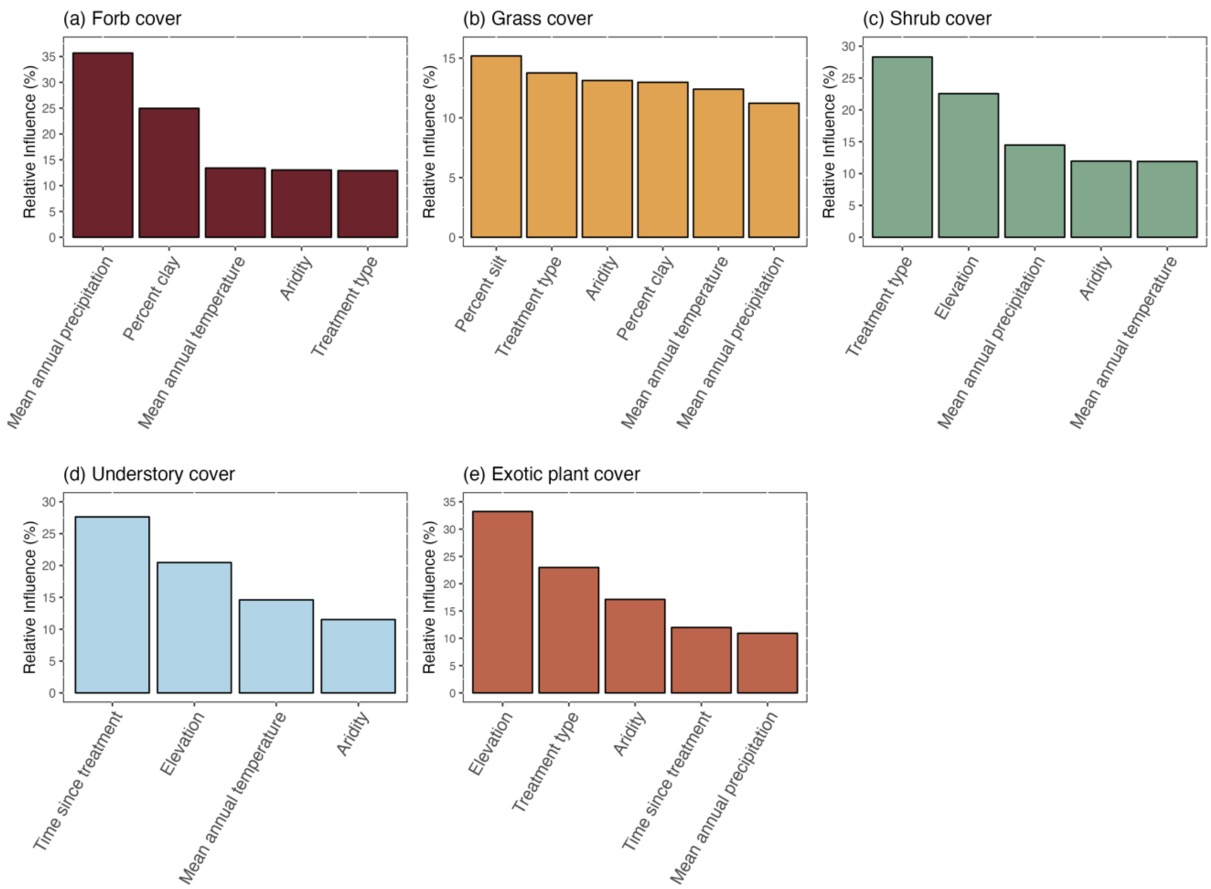

Figure 4.2: BRT analysis results. Results from simplified boosted regression tree analyses showing the relative influence (in percentage) of moderators on the effect size (lnRR) of treatment for each vegetation response.

Mixed multi-factor meta-analysis

Pinyon–juniper treatments had overall positive effects on forb (+ 98%, $p < 0.001$), grass (+ 82%, $p = 0.007$), understory (+ 170%, $p = 0.012$), and exotic plant (+ 619%, $p < 0.001$) cover (Fig. 4.3). Treatment effects on shrub cover were not significantly different from zero (– 2%, $p = 0.892$) (Fig. 4.3c). Meta-regression models in conjunction with BRT analysis, however, showed that plant cover responses to treatment were context-dependent and changed with time since treatment, treatment type, aridity, elevation, and mean annual temperature. In the following results, it is important to note that aridity is measured by aridity index, in which larger values mean a site is **less** arid (Zomer et al., 2022). When grass, understory, and exotic species cover increase as aridity index increases, that is interpreted as cover increasing as sites become **less** arid. Test statistics of mixed effects meta-regression models are reported in Table 4.2. In the figure illustrating effects of environmental conditions, only moderators that significantly altered treatment effects are shown graphically.

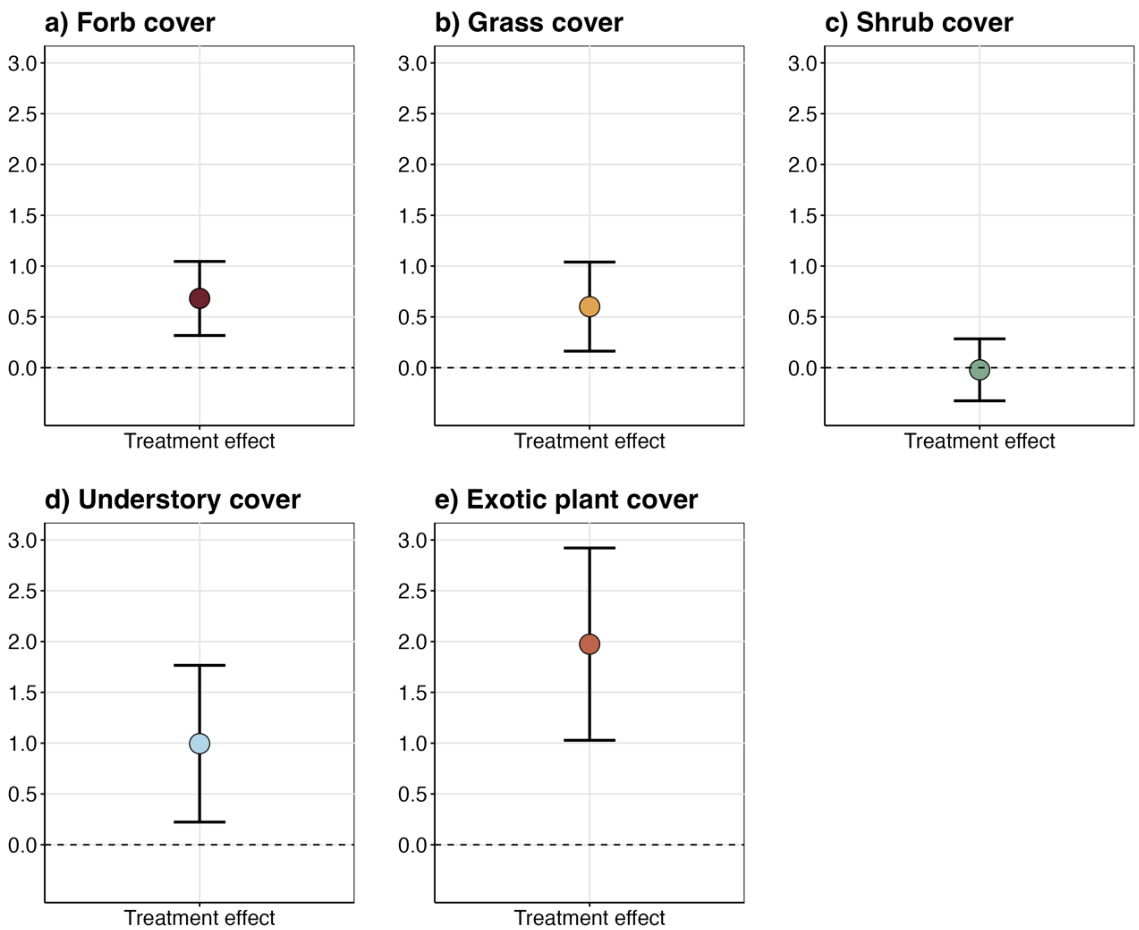

Figure 4.3: Overall treatment effects. Weighted mean effect size for overall treatment effect on each vegetation response. Effect size of treatment (lnRR) is on the y-axis.

	Forb cover			Grass cover			Shrub cover			Understory cover			Exotic plant cover		
	Q_E (*df* 54) = 750.43 $p < 0.001$			Q_E (*df* 56) = 666.36 $p < 0.001$			Q_E (*df* 61) = 246.84 $p < 0.001$			Q_E (*df* 22) = 95.36 $p < 0.001$			Q_E (*df* 44) = 289.26 $p < 0.001$		
	Q_M (*df* 11) = 146.53 $p < 0.001$			Q_M (*df* 12) = 134.15 $p < 0.001$			Q_M (*df* 11) = 21.55 $p = 0.03$			Q_M (*df* 8) = 108.17 $p < 0.001$			Q_M (*df* 10) = 156.86 $p < 0.001$		
	Q_M	*df*	p-val	Q_M	*df*	p-val	Q_M	*df*	p-val	Q_M	*df*	p-val	Q_M	*df*	p-val
Treatment type	32.38	6	< 0.001	34.01	6	< 0.001	10.08	6	0.12	16.83	4	< 0.01	50.78	6	< 0.001
Time since treatment	114.21	1	< 0.001	95.50	1	< 0.001	6.92	1	0.01	51.10	1	< 0.001	78.79	1	< 0.001
Elevation	–	–	–	–	–	–	2.01	1	0.16	1.42	1	0.23	0.81	1	0.37
Aridity	< 0.01	1	0.96	16.96	1	< 0.001	0.14	1	0.71	0.32	1	0.57	2.29	1	0.13
Mean annual temperature	< 0.01	1	0.97	0.03	1	0.88	1.65	1	0.20	1.28	1	0.26	–	–	–
Mean annual precipitation	0.39	1	0.53	< 0.01	1	0.93	0.08	1	0.77	–	–	–	2.14	1	0.14
Percent clay	0.31	1	0.58	0.16	1	0.69	–	–	–	–	–	–	–	–	–
Percent silt	–	–	–	1.60	1	0.21	–	–	–	–	–	–	–	–	–
Percent sand	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–

Table 4.2: Test statistics. Test statistics for moderator variables in mixed effects meta-regression models for each vegetation response.

Forb cover: Forb cover generally increased with treatment (Fig. 4.3a). Time since treatment had a significant positive effect on treatment outcome, increasing forb cover by 15% ± 1.4% (P < 0.001) for every year after treatment (Fig. 4.4a). Treatment effect also changed with treatment type (Fig. 4.5a). Broadcast burning increased cover by 133% ± 31% (p = 0.002), lop and scatter by 96% ± 29% (p = 0.008), and mastication by 123% ± 25% (p < 0.001). Rollerchopping increased forb cover by 83% ± 44% (p = 0.097), although this effect was only marginally significant. The effects of chaining and pile burning on forb cover were not significantly different from zero. Moderators other than time since treatment and treatment type included in the forb meta-regression models (mean annual precipitation, percent clay, mean annual temperature, and aridity) also did not significantly affect forb cover after treatment (Table 4.2).

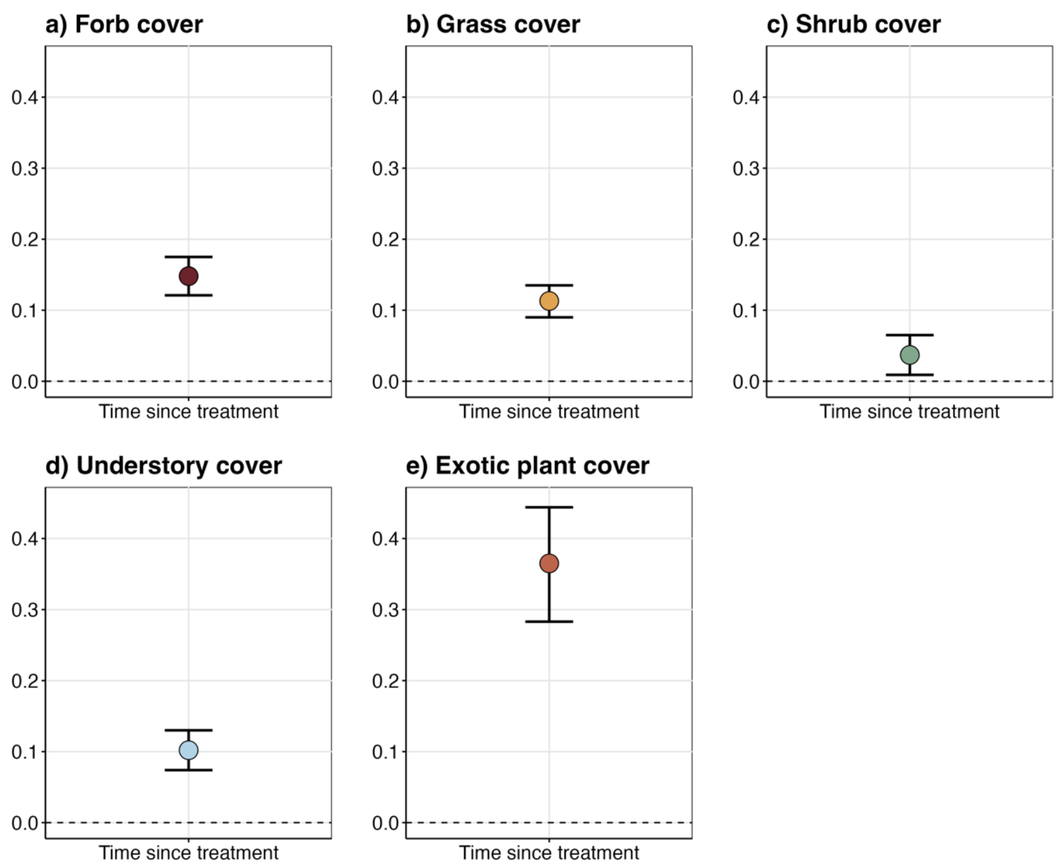

Figure 4.4: Time since treatment effects. Weighted mean effect sizes for time since treatment for each vegetation response. Effect size of time since treatment on the log response ratio (lnRR) is on the y-axis. Because models were fit with the log response ratio (lnRR) as the response, these values represent how much time since treatment influences the treatment effect on each vegetation response.

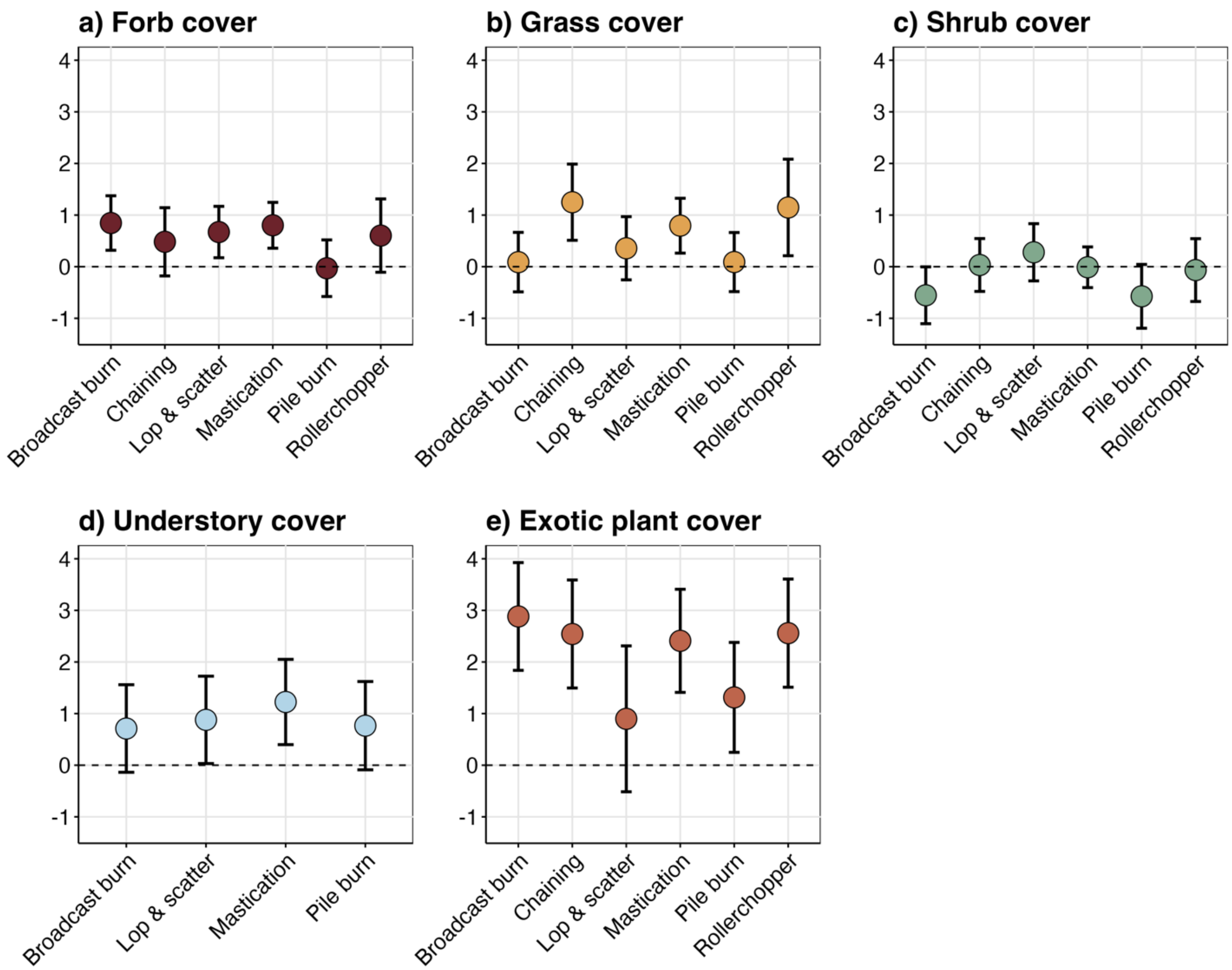

Figure 5: Treatment type effects. Weighted mean effect sizes for each treatment type for each vegetation response. Effect size of each treatment type on the log response ratio (lnRR) is on the y-axis. Because models were fit with the log response ratio (lnRR) as the response, these values represent how much each treatment type influences the treatment effect on each vegetation response.

Grass cover: Treatment had an overall positive effect on grass cover (Fig. 4.3b). The effect of treatment increased as time since treatment increased, with grass cover increasing by 12% ± 11%

($p < 0.001$) in treated sites each year after treatment (Fig. 4.4b). Treatment effects were significantly altered by treatment types (Fig. 4.5b). Chaining increased grass cover the most, by more than twofold (249% ± 46%, $p < 0.001$), followed by rollerchopping (215% ± 61%, $p = 0.016$), and mastication (121% ± 31%, $p = 0.003$). Broadcast burning, lop and scatter, and pile burning had treatment effects that were not significantly different from zero. Aridity index significantly influenced the effect of treatment on grasses, with cover increasing by 77% ± 26% ($p = 0.012$) as aridity increased by one unit (Fig. 4.6a). Percent clay, percent silt, mean annual temperature, and mean annual precipitation did not significantly change treatment effects (Table 4.2).

Shrub cover: Treatment effect did not significantly differ from zero for shrub cover (Fig. 4.3c). However, shrub cover was altered with time since treatment, increasing by 4% ± 1% ($p = 0.009$) per year (Fig. 4.4c). Treatment type had only marginal effects on shrub cover (Fig. 4.5c). Broadcast burn decreased shrub cover by 74% ± 32% ($p = 0.049$) and pile burning by 78% ± 37% ($p = 0.069$). The remaining treatment types did not have a significant effect on shrub cover. The effects of treatment on shrub cover became more positive as mean annual temperature increased, nearly doubling shrub cover (99% ± 40%, $p = 0.041$) (Fig. 4.6b). Other moderators included in the comprehensive meta-regression model (mean annual precipitation, elevation, and aridity) did not significantly change treatment effects (Table 4.2).

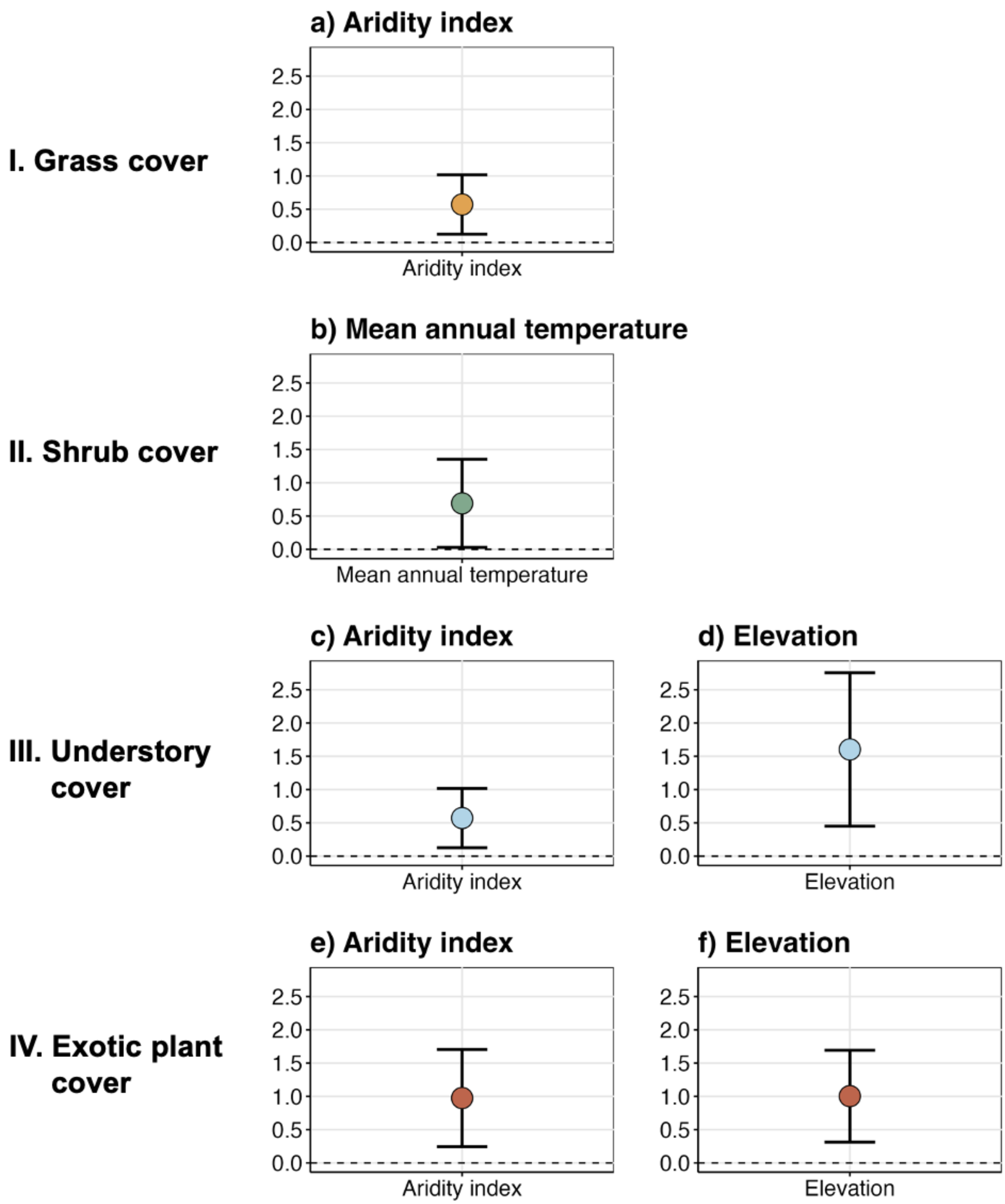

Figure 4.6: Environmental moderator effects. Weighted mean effect sizes for significant environmental moderators for each vegetation response. Effect size of environmental moderators on the log response ratio (lnRR) is on the y-axis. Because models were fit with the log response ratio (lnRR) as the response, these values represent how much each environmental moderator influences the treatment effect on each vegetation response. Note: Plots for the aridity moderator are in the scale of aridity index, in which higher values indicate **less** aridity.

Overall understory cover: Treatment increased overall understory cover, although with more uncertainty due to its small sample size (Fig. 4.3d). Time since treatment had a positive relationship with understory cover, increasing it by 11% ± 1% ($p < 0.001$) as time since treatment increased (Fig. 4.4d). Treatment effects on understory changed by treatment type (Fig. 4.5d), with lop and scatter increasing cover by 141% ± 54% ($p = 0.042$) and mastication by 240% ± 52% ($p = 0.004$). Pile burning increased understory cover by 115% ± 55% ($p = 0.079$). Broadcast burning did not change treatment effects on understory cover. Increases in elevation and aridity index both altered treatment effects on understory cover, increasing cover by almost fourfold (397% ± 80%, $p = 0.006$) and onefold (94% ± 21%, $p < 0.001$), respectively (Fig. 4.6c & 4.6d).

Exotic species cover: Exotic plant cover drastically increased with treatment (Fig 4.3e) and with time since treatment, by 44% ± 4% ($p < 0.\ 001$) per year (Fig. 4.4e). Every treatment type except lop and scatter significantly influenced the effect of treatment on exotic cover. Broadcast burn increased cover by over sixteen-fold (1,685% ± 70%, $p < 0.001$), chaining by over eleven-fold (1,171% ± 71%, $p < 0.001$), rollerchopping by over eleven-fold (1,192% ± 71%, $p < 0.001$), mastication by over tenfold (1,013% ± 67%, $p < 0.001$), and pile burning by over twofold (272% ± 72%, $p = 0.016$) (Fig. 4.5e). Elevation and aridity again altered treatment effects on cover, increasing exotic plan cover by 173% ± 42% ($p = 0.004$) and 165% ± 45% ($p = 0.009$), respectively (Fig. 4.6e & 4.6f).

DISCUSSION

Across a large body of research, pinyon–juniper treatment effects on understory vegetation and exotic plant cover vary, with possible benefits of increasing native forb and grass cover counteracted by potential risk of exotic species introduction and proliferation. During the treatment planning process, accommodating these tradeoffs is a complex task, creating challenges for land managers and decision makers. In our study, we utilized boosted regression tree analysis and meta-analytical techniques to summarize the effects of pinyon–juniper treatment on cover of five different vegetation classes and assess the influence of ten different moderators on treatment effects. In contrast to previously published vote-counting-style reviews which primarily reported non-significant effects of treatment on understory vegetation, our meta-analysis showed positive effects of treatment on understory vegetation. However, our results did align with previous reviews about positive treatment effects on exotic plant cover (Jones, 2019; Shinneman et al., 2023a). Instead of reporting the numbers of positive, negative, and non-significant results from relevant articles, we provide quantitative effect sizes for treatment effects on forb, grass, shrub, overall understory, and exotic plant cover, and showing that treatment type, time since treatment, and environmental conditions all influenced treatment outcomes.

Treatment type

Treatment type was an influential moderator for four out of five vegetation types and when included in meta-regression models, significantly altered treatment effects. The six different treatment types included in our meta-analysis disturb landscapes to very different degrees, with divergent amounts of ground cover left behind (plant cover or as mulch), and impacting soils to varying extents (Miller et al., 2019). Deciding how to remove trees for a treatment is already an important decision point in the treatment planning process and the more knowledge and evidence provided to support this critical decision, the higher the likelihood that treatments will meet management goals.

Herbaceous understory cover (forb and grass cover) experienced the most positive effects from mechanical treatments (chaining, mastication, and rollerchopping) and manual treatments (lop and scatter). Mechanical treatments have consistently been shown to increase forb and grass cover (Bates et al., 2017; Brockway et al., 2002; Rubin and Roybal, 2018; Williams et al., 2017), reducing tree cover to release valuable resources and leaving behind mulch and other plant materials to create favorable conditions for seedling establishment after treatment (Stoddard et al., 2008; Young et al., 2013b). Lop and scatter treatments are similar in their reduction of tree cover and creation of favorable microsites for seedling establishment, but sites treated with lop and scatter techniques may not experience the same drastic changes or resource release as more intensive removal methods like mechanical treatments.

Prescribed fire treatment types had more nuanced effects on forb and grass cover. Broadcast burning had a very positive effect on forb cover, whereas the effect on grass cover was non-significant. Broadcast burning reduces vegetation cover more completely than other treatment types, creating ample opportunity for herbaceous vegetation to reestablish and utilize newly available resources (Halpern et al., 2014). Pile burning did not have statistically significant effects on forb or grass cover in our models, but did have the most negative effects of any treatment type on forb and grass cover. While pile burn treatments remove trees similarly to mechanical and manual treatments, woody material is gathered into piles instead of spread on the ground, creating treatment sites that lack valuable protected microsites for new seedling establishment. Furthermore, any addition of soil nutrients from fire is limited to the areas in and around burn piles (Alcañiz et al., 2018), where the intense heat created from burning such conglomerate fuels can reduce microbial activity (Korb et al., 2004), destroy the seed bank (Neary et al., 1999), and increase soil erosion (Hubbert et al., 2015), thereby counteracting positive impacts from nutrient release.

Pinyon–juniper treatments overall had no significant effect on shrub cover, although investigating effects by treatment type revealed more varied results. Mechanical and manual treatment types had decidedly neutral effects on shrub cover, but prescribed fire treatments, although only marginally significant, negatively affected shrub cover. The sensitivity of many shrub species—including sagebrush (*Artemisia spp.*)—to fire makes the use of burning as a tree removal strategy a risky endeavor (Ziegenhagen and Miller, 2009). Low intensity fire may not pose a threat to shrubs within treatment areas, but high intensity fire can cause direct mortality (Miller et al., 2014). Other treatment types may not result in a noticeable effect of treatment on shrub cover, because shrubs are less negatively impacted by tree expansion (Archer et al., 2017a), prompting much less positive response after tree removal. Treatment effects on overall understory cover after treatment removal were positive, with each treatment type showing increases in understory cover, although some effects were only marginally significant. Fewer studies in our meta-analysis reported overall understory cover, so only four treatment types were represented for this cover type, but the effects generally aligned with results for herbaceous and shrub cover.

Introduction and facilitation of exotic species is a common risk associated with land treatments, including pinyon–juniper treatments (Bybee et al., 2016; Redmond et al., 2014b), and our findings reflect that. Nearly all treatment types increased exotic plant cover. Lop and scatter treatments, which create much less disturbance because they are completed manually without heavy machinery or fire, had non-significant effects on exotic cover. Chaining, mastication, rollerchopping, broadcast burning, and pile burning all had significant positive effects on exotic plant cover. These treatment types typically involve high disturbance, allowing for more ruderal exotic species to proliferate within treated sites (Coop et al., 2017). Without management actions to mitigate exotic species introduction and subsequent invasion, it is thus likely that most pinyon–juniper treatments which use mechanical or prescribed fire removal methods will increase exotic cover.

Treatment type has been shown to be a significant factor in influencing pinyon–juniper treatment effects and is also a crucial decision point during the treatment planning process. Expanded knowledge about the nuanced effects of various tree removal methods supports land managers in choosing treatment types that will meet their management goals. When planning treatments and considering the resources required to complete them, the distinction in effects of different treatment methods can illuminate which treatments are actually worthwhile. Lop and scatter treatments did not significantly increase exotic plant cover, but had the least positive effects on forb and grass cover. The improvements in forb and grass cover that are associated with broadcast burning and mechanical treatments are tempered by the drastic increase in exotic plant cover. The unequivocal increase of exotic plant cover after treatment suggests that spending resources on mitigation measures for invasive species before, during, and/or after treatment is worthwhile.

Time since treatment

Time since treatment, measured as the number of years between treatment and data collection, was not an influential moderator for every cover type, but significantly altered treatment effects in every meta-regression model. As time since treatment increased, so did forb, grass, shrub, overall understory, and exotic plant cover. All treatments inherently involve some amount of disturbance to the landscape, likely resulting in neutral or even negative initial effects on forb, grass, and shrub cover (Ernst-Brock et al., 2019; Owen et al., 2009). As sites rebound from disturbance impacts, vegetation can take advantage of the resources made available by tree removal and begin to recover (Bybee et al., 2016; Roundy et al., 2014). The largest positive impact of time since treatment was for exotic plant cover, further solidifying this outcome as a risk of treatment. If exotic species are introduced to a site during treatment, or given the opportunity to spread in disturbed areas, they will inevitably proliferate unless mitigation measures are taken (Duncan et al., 2004). None of the studies in our meta-analysis reported any actions taken to reduce or prevent exotic plant growth, although it has been shown that prevention and mitigation actions can decrease the risk of invasion and spread of exotic species (Lehnhoff et al., 2019). Importantly, while our results represent the influence of time since treatment as continuous by each year that time since treatment increases, it is likely that vegetation cover does not continue to increase at the same rate each year and that treatment effects stabilize over time.

Environmental moderators

The environmental conditions of a site influence how that site responds to disturbance, land use, and management actions. Site-level climatic conditions have been shown to affect the success of seeding treatments (Davidson et al., 2019), the degree of site degradation can modify restoration trajectories (Williams et al., 2017), and topography is an important mediator of soil moisture, which is required for vegetation recovery (Bochet et al., 2009; Fick et al., 2022). We found three environmental moderators—aridity, elevation, and mean annual temperature—that altered pinyon–juniper treatment outcomes. Soil texture (soil percent clay, silt, and sand) was not significant in our models, but it is important to note that soil depth has been found to be a significant explanatory variable for treatment effectiveness in pinyon–juniper systems (Fick et al., 2022). We did not include this variable in our models, but intend to in future iterations of this study.

Aridity had a significant influence on treatment effects for grasses, overall understory, and exotic plants. Although land within the Colorado Plateau is categorized as 'drylands', there is some variability in aridity (Schwinning et al., 2008). Sites from studies included in our meta-analysis ranged in aridity from 0.109–0.343 on the aridity index scale. On this scale, smaller values indicate more arid sites, with an aridity index of 0.05–0.20 being considered arid and 0.20–0.50 being considered semi-arid. Grass, understory, and exotic species cover increased with higher aridity index; in other words, treatments resulted in higher plant cover at less arid sites. Precipitation, soil moisture, and water availability are inextricably linked with plant cover, and increased plant cover is associated with more moisture (Wang et al., 2019).

Elevation and mean annual temperature, the other two important environmental moderators, also had positive relationships with vegetation cover. Sites at higher elevations saw greater increases in general understory and exotic plant cover with treatment. With higher elevation comes cooler and wetter conditions, creating more optimal environs for plant growth (Mata-González et al., 2002). Mean annual temperature altered treatment effects on shrub cover only, with higher temperatures leading to more shrub cover. This aligns with the trend of woody expansion with increasing average temperatures in the last century (Archer et al., 2017a). Woody species like shrubs (and pinyon pine and juniper trees) are able to take advantage of longer growing seasons and enhanced photosynthesis to increase growth (Peguero-Pina et al., 2020).

These findings regarding the influence of these environmental moderators on the effects of pinyon–juniper treatments are impactful in the context of climate change, as future projections predict that the Colorado Plateau will become hotter and experience more variability in precipitation patterns with climate change (Copeland et al., 2017; Schwinning et al., 2008). This would create greater hurdles for managers as they attempt to restore understory cover with restoration treatments. As temperatures increase and water availability becomes more unpredictable, we may see more negative impacts on understory species and shifts towards more shrub-dominant systems. Treatment outcomes may become more unpredictable, and treatments may be less likely to meet management goals.

Management implications and conclusions

Our findings clarify some of the uncertainty surrounding the effects of pinyon–juniper treatments on understory vegetation. Where vote-counting-style reviews have reported that a majority of treatments have non-significant effects on understory vegetation cover (Jones, 2019; Shinneman et al., 2023a), we provide support for the implementation of pinyon–juniper treatments, quantifying the improvement of forb, grass, and overall understory cover with treatment. Our results align with other literature syntheses in regards to increases in exotic species cover, further emphasizing the importance of mitigation measures to prevent nonnative introduction and spread (Bybee et al., 2016; Redmond et al., 2014b). By focusing on the Colorado Plateau, our meta-analysis characterizes treatment effects more specifically for this vulnerable region, filling an important knowledge gap.

Findings from our meta-analysis can be incorporated into the decision-making process to aid in prediction of treatment outcomes at a given site and provide more nuance as to how managers can meet their management goals (Fig. 4.7). There are likely numerous other factors that may shape how a site responds to restoration treatments, but with deeper knowledge of treatment effects and some of the moderators influencing those effects, managers can be more empowered in their decision-making. Drastic changes are often required to create change in degraded landscapes (Hobbs and Cramer, 2008), and improvement in understory vegetation cover with treatment and with time show that initial negative ecological or aesthetic effects immediately post-treatment should not drive denouncement of pinyon–juniper treatments. Given uncertainty surrounding pinyon–juniper treatments, our findings provide more evidence in support of these management actions and the managers carrying them out.

	Forb cover	Grass cover	Shrub cover	Understory cover	Exotic plant cover
Overall treatment effect	↑	↑		↑	↑
Time since treatment	↑	↑	↑	↑	↑
Treatment type					
Broadcast burning	↑		↓	↑	↑
Pile burning			↓	↑	↑
Chaining	↑	↑			↑
Mastication	↑	↑		↑	↑
Rollerchopping	↑	↑			↑
Lop & scatter	↑	↑	↑	↑	
Aridity		↓		↓	↑
Elevation				↑	↑
Mean annual temperature			↑		

Figure 4.7: Stoplight chart. Summary of results for managers. Colors indicate treatment effects with darker shades representing larger effects and lighter shades representing smaller effects. Green colors show treatment benefits and red colors show treatment risks. Beige represents non-significant effects, and gray represents moderators for which no data was available. Arrows show if cover increased or decreased with treatment.

As part of the evaluation step in the adaptive management process, our meta-analysis illustrates the efficacy and power of using existing data to inform land management. While treatment effectiveness monitoring specifically for treatment evaluation is incredibly valuable, it is often impractical and costly for federal agencies already encumbered by limited budgets and large workloads (Archie et al., 2012). The abundance of open access (or easily accessible) ecological data extends beyond remote sensing platforms and monitoring networks to the existing scientific literature. While new individual studies are valuable and of utmost importance to continue the progress of science, aggregation of existing studies promotes discovery of broader patterns and trends, and with more statistical power (Cohn and Becker, 2003; Hedges and Pigott, 2001; Valentine et al., 2010). Finally, meta-analyses can encourage collaborations between managers and scientists to effectively answer challenging management questions.

CHAPTER V

CONCLUSIONS AND REFLECTIONS

It is clear that pinyon–juniper removal treatments offer both ecological benefits and risks. Overall, such treatments often increase native understory vegetation cover—a common management goal—but they are also associated with significant increases in exotic plant cover, particularly cheatgrass. While the chapters of this dissertation highlight the complexity inherent in large-scale land treatments, additional work is needed to further support managers in their decision-making and treatment planning processes. Numerous unmeasured factors may influence treatment outcomes, many of which are not yet well understood.

The timing of treatment implementation and subsequent monitoring is a key factor in treatment planning, and one of the more straightforward variables to integrate. Chapter Three demonstrates that treatment effects on understory cover tend to become more positive over time; however, it does not address potential lag effects or how these effects may change over longer periods. The positive impact on native understory cover may increase in magnitude for five to seven years post-treatment before leveling off. Incorporating climate conditions into treatment timing is another increasingly viable strategy. As the southwestern U.S. becomes warmer and precipitation patterns more variable (Sillmann et al., 2013), anticipating climate conditions in the immediate and subsequent years following treatment can help improve outcomes(Shackelford et al., 2021; Simonson et al., 2021). Given projections of intensified drought (Bradford et al., 2020), which may limit understory response, incorporating climate considerations into treatment planning is increasingly important.

The methodologies employed in this dissertation account for as many confounding or influential variables as data availability allows, but many relevant factors remain unobserved.

Elements such as funding availability and timing, grazing allotments, and societal pressures contribute to the socio-ecological context of treatment planning and may also affect treatment outcomes. Similarly, ecological factors like biotic interactions and fine-scale environmental conditions—which are difficult to capture in datasets—likely play a role as well. While these variables are challenging to include in statistical analyses, they warrant thoughtful consideration when evaluating landscape-scale treatments on public lands. Although not explicitly analyzed in this dissertation, awareness of these variables informed the selection of covariates that were included in analyses. With this work, I hope to support managers in promoting treatment benefits while mitigating risks by encouraging deeper consideration of treatment methods, site conditions, and unmeasured factors.

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APPENDICES

APPENDIX TO CHAPTER II

Figure S2.1: Distribution of treatment ages for treated plots only. Age (or time since treatment) was calculated by subtracting the reported year of treatment completion (from the Land Treatment Digital Library) from the year Assessment Inventory and Monitoring data was collected at the plot.

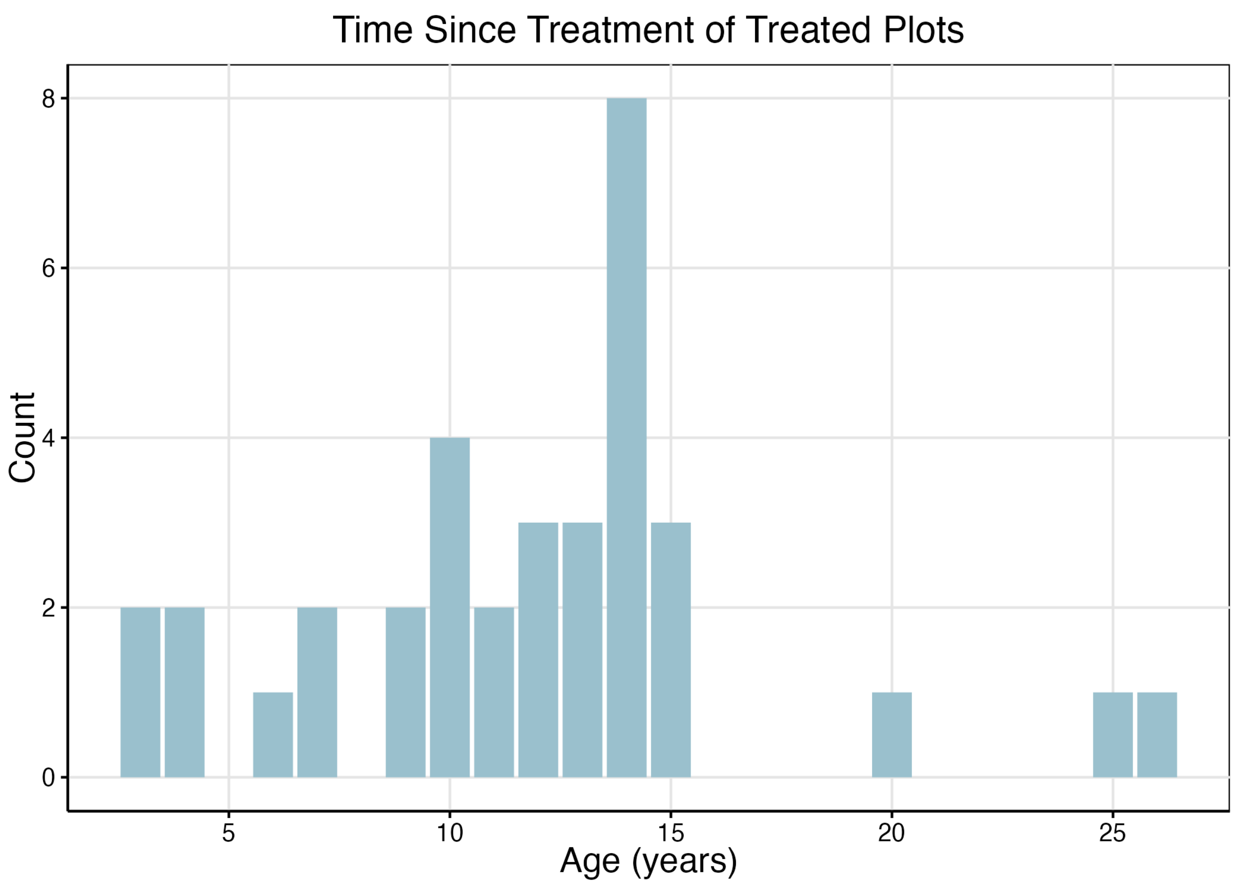


Table S2.1: Mean values and standardized mean differences for each covariate included in the matching process in the dataset before matching and after matching.

Covariate	Unmatched dataset			Matched dataset		
	Treated Means	Control Means	SMDs	Treated Means	Control Means	SMDs
Latitude	39.8118	40.0465	-1.4431	39.8118	39.8299	-0.1117
Longitude	-107.5095	-108.1152	0.6608	-107.5095	-107.4893	-0.0220
Elevation (meters)	2305.2366	2111.9066	1.2730	2305.2366	2310.9633	-0.0377
Slope (degrees)	7.6629	8.7931	-0.2531	7.6629	7.5085	0.0346
Aspect (degrees)	178.9687	187.6190	-0.0702	178.9687	181.9008	-0.0238
Aridity	2534.8571	2459.6161	0.3792	2534.8571	2567.8857	-0.1664
Distance to roads (meters)	373.4842	825.4107	-1.0872	373.4842	345.1810	0.0681
Pre-treatment tree cover (%)	11.2057	12.2341	-0.0835	11.2057	10.2343	0.0789
Pre-treatment shrub cover (%)	28.9486	22.2562	0.5156	28.9486	29.0571	-0.0084
Pre-treatment perennial forb and grass cover (%)	19.7143	17.4245	0.3686	19.7143	20.6971	-0.1582
Pre-treatment annual forb and grass cover (%)	2.2629	7.1960	-2.0522	2.2629	2.9429	-0.1929
Pre-treatment bare ground cover (%)	12.8686	16.1788	-0.5517	12.8686	12.9143	-0.0076
Colorado Plateau Ecoregion	0.4571	0.6225	-0.3318	0.4571	0.4571	0.0000
Southern Rockies Ecoregion	0.5429	0.2013	0.6857	0.5429	0.5429	0.0000
Wyoming Basin Ecoregion	0.0000	0.1763	-0.4673	0.0000	0.0000	0.0000

Figure S2.2: Values for the effect of treatment without consideration of an unobserved confounder (black triangle), and with adjustment for an unobserved confounder (red diamonds) that is one, two, and three times as strong as the strongest observed covariate (z_match_shr, or z-scaled pre-treatment shrub cover). The red dotted line signifies a treatment effect of zero. Thus, even an unobserved covariate which is three times as strong as pre-treatment shrub cover would not nullify or change the direction of the treatment effect.

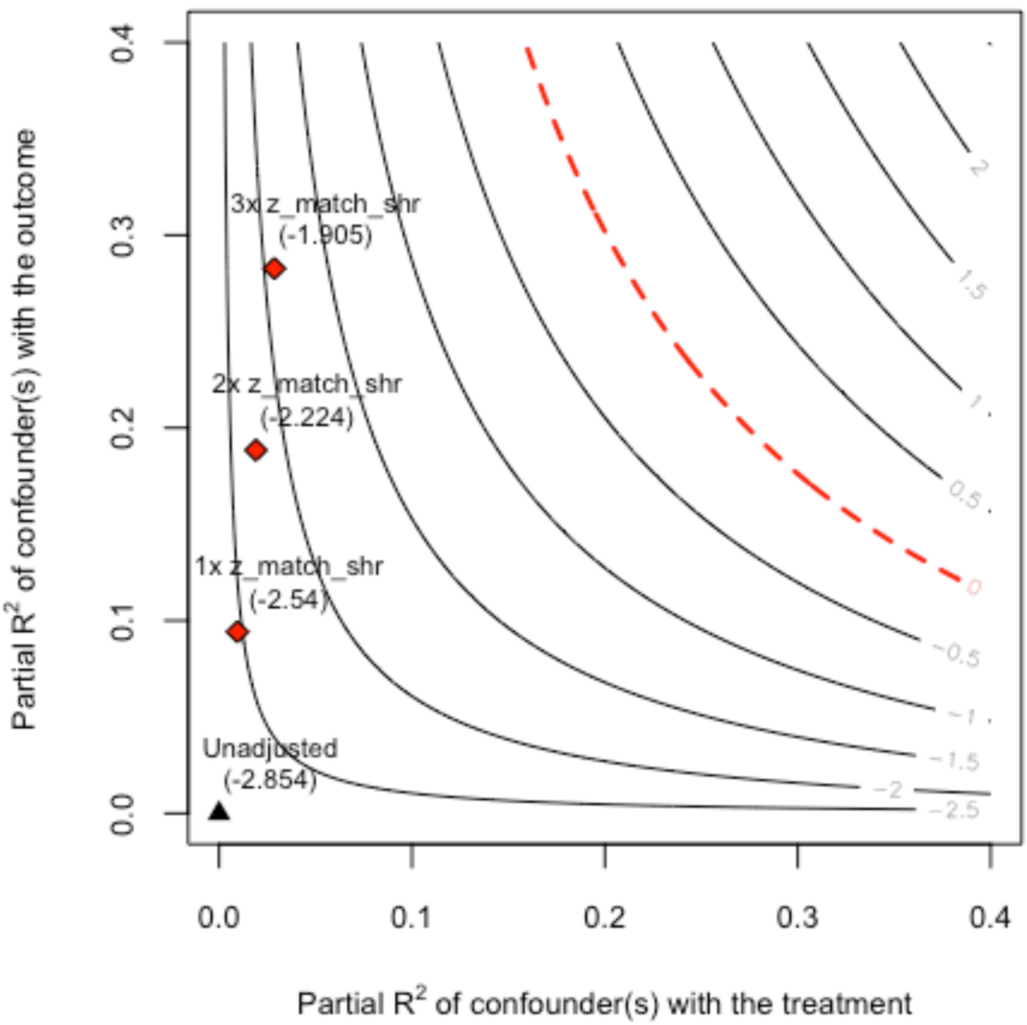


Figure S3.1: Distribution of treatment ages for treated plots only. Age (or time since treatment) was calculated by subtracting the reported year of treatment completion (from the Land Treatment Digital Library) from the year Assessment Inventory and Monitoring data was collected at the plot.

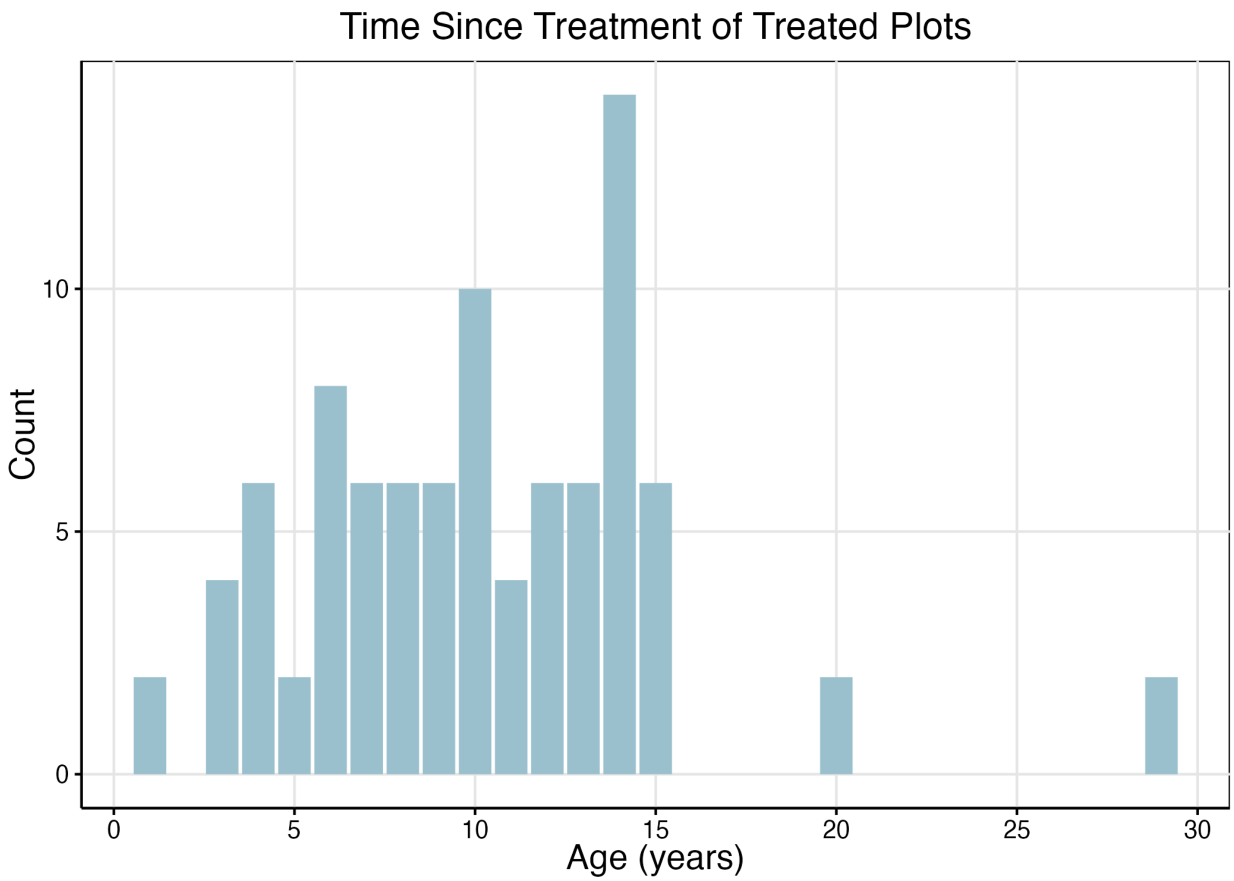


Table S3.1: Mean values and standardized mean differences for each covariate included in the matching process in the dataset before matching and after matching.

Covariate	Unmatched dataset			Matched dataset		
	Treated Means	Control Means	SMDs	Treated Means	Control Means	SMDs
Latitude	39.7912	40.0681	-1.3437	39.7912	39.8043	-0.0632
Longitude	-107.4019	-108.0549	0.7664	-107.4019	-107.3695	-0.0380
Elevation (meters)	2280.7340	2128.0372	0.9824	2280.7340	2278.9410	0.0115
Slope (degrees)	7.9115	8.6087	-0.1279	7.9115	7.5820	0.0604
Aspect (degrees)	185.9756	186.3839	-0.0036	185.9756	183.4160	0.0225
Aridity	2472.3125	2543.6788	-0.3151	2472.3125	2530.8572	-0.2385
Distance to roads (meters)	332.5470	812.9160	-1.2443	332.5470	307.6223	0.0646
Pre-treatment tree cover (%)	11.1278	12.2035	-0.0909	11.1278	8.9717	0.1821
Pre-treatment shrub cover (%)	28.8529	22.3761	0.4814	28.8529	29.1835	-0.0246
Pre-treatment perennial forb and grass cover (%)	18.7130	17.8523	0.1597	18.7130	19.7759	-0.1972
Pre-treatment annual forb and grass cover (%)	2.4066	6.9520	-1.6444	2.4066	2.9270	-0.1883
Pre-treatment bare ground cover (%)	13.3730	16.0179	-0.4129	13.3730	13.9985	-0.0977
Colorado Plateau Ecoregion	0.333	0.6037	-0.3318	0.3333	0.3333	0.0000
Southern Rockies Ecoregion	0.6444	0.2246	0.6857	0.6444	0.6444	0.0000
Wyoming Basin Ecoregion	0.0222	0.1717	-0.4673	0.0222	0. 0222	0.0000

Figure S3.2: Directed acyclic graph showing relevant covariates included in the matching process. Pre-treatment vegetation summarizes the five vegetation categories included in matching (pre-treatment tree, shrub, perennial forb and grass, annual forb and grass, and bare ground cover). Topography represents the elevation, slope, and aspect variables.

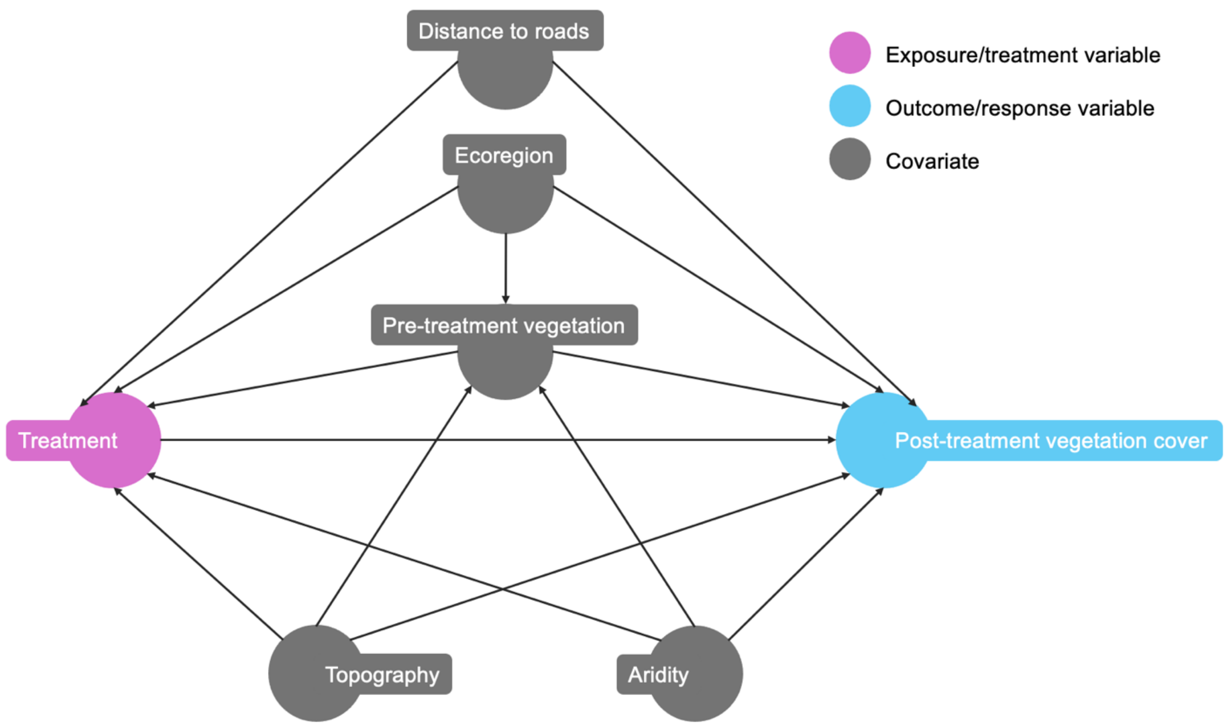


Figure S3.3: Love plot of standardized mean differences of each covariate before and after matching. Absolute standardized mean differences displayed for both the unmatched and the matched dataset. The difference in means between the treated and control groups for each covariate is decreased with matching, improving covariate balance. Variables on y-axis are in order of largest unmatched mean differences. Created using *cobalt* (Griefer, 2024) in R (R Core Team, 2018).

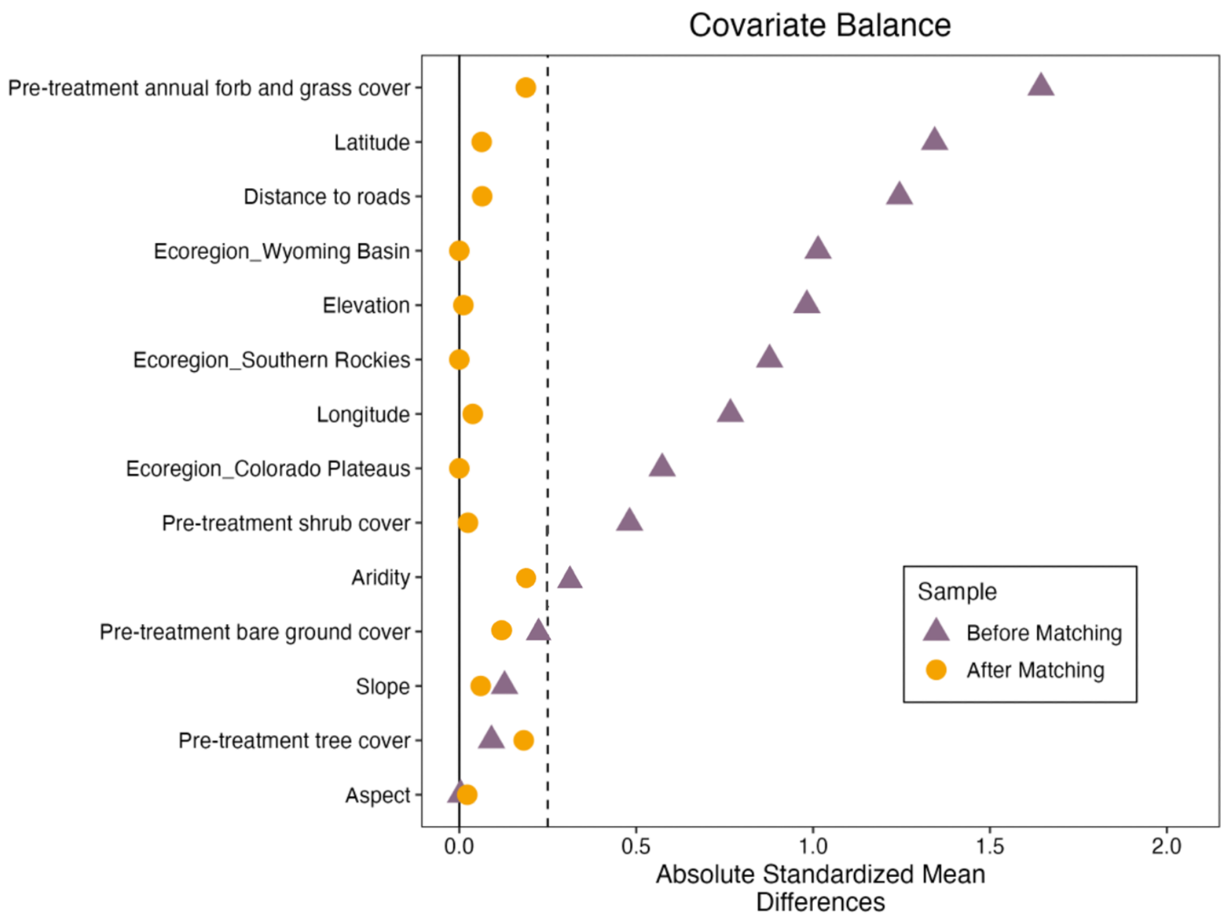
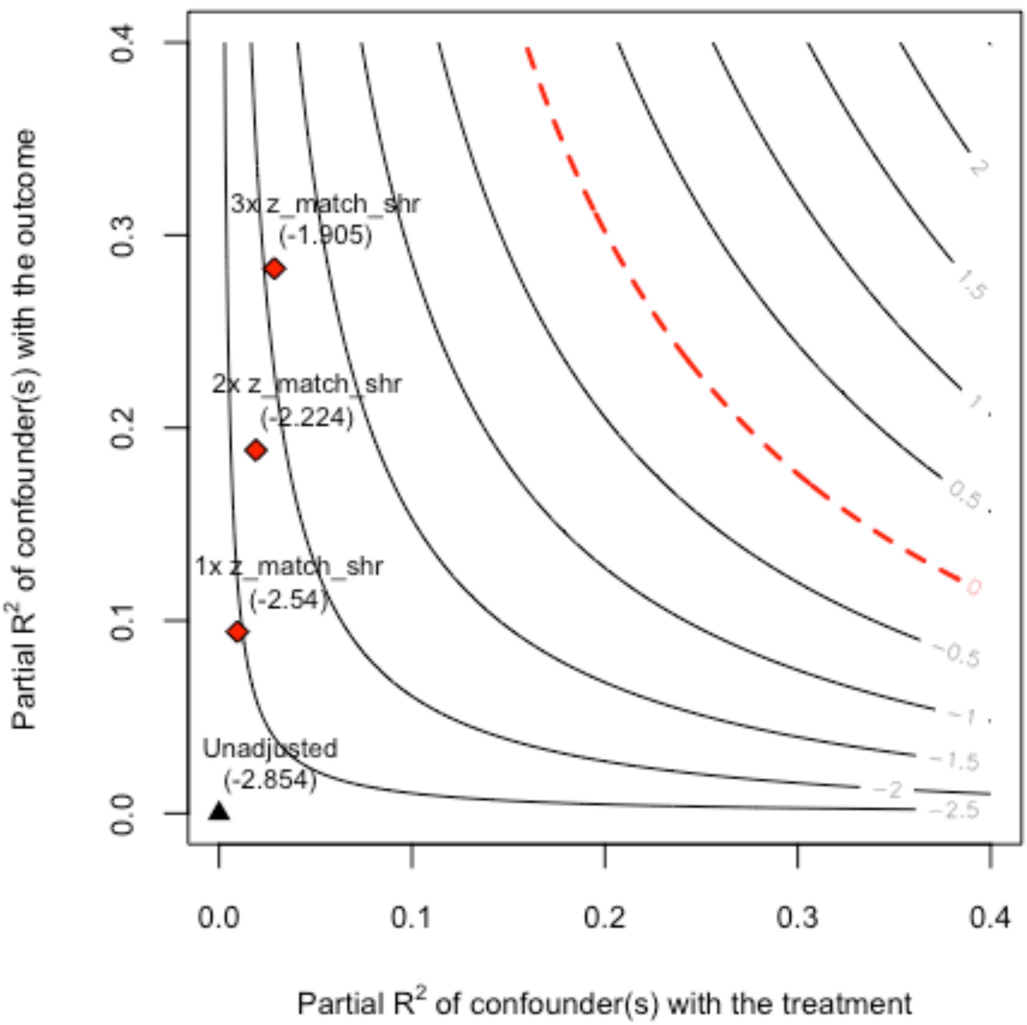
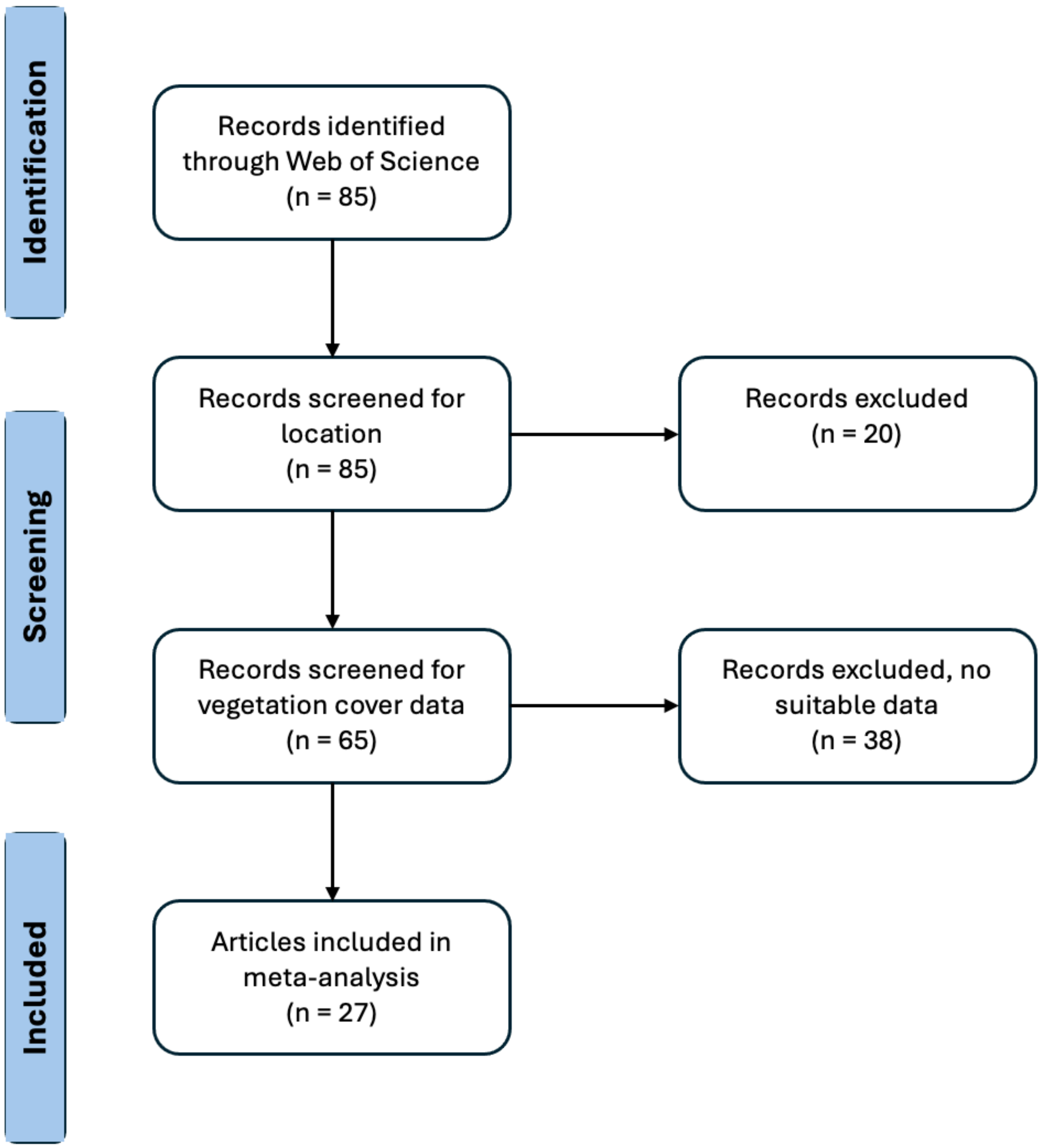


Figure S3.4: Values for the effect of treatment without consideration of an unobserved confounder (black triangle), and with adjustment for an unobserved confounder (red diamonds) that is one, two, and three times as strong as the strongest observed covariate (z_match_shr, or z-scaled pre-treatment shrub cover). The red dotted line signifies a treatment effect of zero. Thus, even an unobserved covariate which is three times as strong as pre-treatment shrub cover would not nullify or change the direction of the treatment effect.



APPENDIX TO CHAPTER IV

Figure S4.1: PRISMA flow diagram (Moher et al., 2009) illustrating the iterative screening process.



Appendix S4.1: Bibliographic references for articles included in meta-analysis (n = 27).

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Table S4.1: Table of study details.

Citation	State of study site(s)	Treatment year(s)	Data collection year(s)	Time since treatment (years)	Sample size (n)	Data collection method
Almalki et al., 2023	NM	2009	2014, 2019	5 & 10	70	Line-point intercept
Bombaci et al., 2017	CO	2012	2013	1 & 2	112	Quadrat
Brockway et al., 2002	NM	1996	1997	1 & 2	8	Line-point intercept
Faist et al., 2015	CO	2004-2006	2012	6-9	27	Quadrat
Fornwalt et al., 2017	CO	2003-2006	2007, 2012	2-4 & 6-9	12	Quadrat
Frey et al., 2013	UT	2005	2006, 2007, 2009	1, 2, &4	75	Quadrat
Gallo et al., 2016	CO	1950-1980	2014	>40	22	Quadrat
Gifford 1973	UT	1967	1968-1971	1-4	10	Line-point intercept
Haskins & Gehring 2004	AZ	1995	2000	5	8	Line-point intercept
Havrilla et al., 2017	UT	2009	2010, 2011, 2015	1, 2, & 6	10	Line-point intercept
Huffman et al., 2013	AZ	2006	2007, 2008, 2011	1, 2, & 5	12	Quadrat
Huffman et al., 2017	AZ	2003	2014	10	6	Quadrat
Huffman et al., 2019	AZ	2006	2007, 2011, 2017	1, 5, & 11	12	Quadrat
Jacobs & Gatewood 1997	NM	1994	1996, 1997	2 & 3	15	Line-point intercept
Johnston & Anderson 2023	CO	2011	2013, 2016, 2017	1, 2, 5, & 6	91	Line-point intercept
Karl et al., 2014	UT	2009	2010	1	30	Line-point intercept
Kleintjes et al., 2004	NM	1997	1999, 2001	2 & 4	20	Line-point intercept
O'meara et al., 1981	CO	1962, 1969, 1976	1977	1, 8, & 15	30	Line-point intercept
Overby et al., 2000	AZ	1995	1997	2	5	Quadrat

Owen et al., 2009	CO	2003 & 2005	2006	1-4	25	Quadrat
Redmond et al., 2013	UT	1963-1988	2006	18-43	17	Quadrat
Redmond et al., 2014	UT	2010	2012	2	10	Line-point intercept
Rhoades et al., 2012	CO	2001-2006	2008	3-5	18	Quadrat
Ross et al., 2012	UT	2007-2009	2010	1 & 2	10	Line-point intercept
Rubin & Roybal 2018	AZ	2014	2016	2	30	Quadrat
Stephens et al., 2016	CO	2011	2013	2	70	Line-point intercept