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Green is the New Black: Outcomes of post-fire tree planting across the US Interior West

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ABSTRACT

Reforestation activities such as tree planting are important management tools to offset carbon emissions and restore forest ecosystem integrity. Severe wildfire activity, a key driver of forest loss, is increasing throughout the western United States (US) and creating an immense backlog of areas needing reforestation. Major financial investments and recent policy changes are expected to accelerate rates of tree planting, yet the broad-scale impact and efficacy of post-fire planting activities remain poorly understood. We quantified the outcomes of recent (1987–2022) post-fire plantings in the US Interior West using remotely sensed estimates of forest cover change and in-situ survival records (69,245 seedlings) spanning 297 unique fire events. Overall, planted areas gained forest cover 25.7 % more rapidly than environmentally similar, unplanted sites in the same fires, and planted seedling survival averaged 79.5 % (SD = 23.2 %) after one growing season. However, the effects of planting were highly variable over time and across environmental gradients. Forest cover gain and planted seedling survival were typically highest in cold, wet areas and when planting was followed by wetter-than-average years. Planting season also shaped outcomes, with late summer or fall plantings performing best on warm, dry sites, and spring plantings performing best in cold, wet areas. Forest cover gain was fastest in planting units that burned at low to moderate severity and had > 20 % post-fire forest cover in the surrounding area. Nearly half of all plantings were completed in such areas, where natural regeneration processes are most likely to promote forest recovery even without intervention. Here, we demonstrate that tree planting can enhance post-fire forest recovery rates at broad scales, though its effects are dependent on a range of environmental and operational factors. Our results help inform realistic expectations of planting outcomes, an issue of global relevance as such projects expand to achieve restoration and climate mitigation goals.

1. Introduction

Active reforestation of degraded areas is now recognized as one of the most important strategies for climate change mitigation (Fargione et al., 2018; Griscom et al., 2017), and numerous global initiatives support reforestation efforts (e.g., 2011 Bonn Challenge, 2014 New York Declaration on Forests, Trillion Trees, UN-REDD). Beyond offsetting a portion of carbon emissions associated with anthropogenic climate change (Cook-Patton et al., 2020; Nave et al., 2019), well-planned reforestation activities using native tree species can also restore forest

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ecosystem services such as wildlife habitat, water resource provisioning, erosion mitigation, and timber production (Brancalion and Holl, 2020; Di Sacco et al., 2021; Ellison et al., 2017). Reforestation activities are widely practiced, yet complex questions remain regarding their efficacy (Fargione et al., 2021; Leverkus et al., 2022; Meli et al., 2017). For example, how much does active reforestation accelerate rates of forest regrowth relative to natural recovery processes? Where are reforestation activities most successful? How might reforestation strategies need to be modified to support longer-term forest resilience to altered climate conditions and shifting disturbance regimes?

Factors driving the need for reforestation vary widely among nations (Keenan et al., 2015; Potapov et al., 2022). Across coniferous forests of the western United States (US), an increasingly warm, dry climate and legacies of historical land use have led to increases in fire size and the annual area burned since the 1980s (Coop et al., 2020; Parks and Abatzoglou, 2020; Westerling, 2016). As fire sizes increase, so do the typical sizes of high-severity (i.e., >70 % mortality) and stand-replacing (i.e., near-total mortality) patches (Buonanduci et al., 2023; Chapman et al., 2020; Harvey et al., 2016a; Singleton et al., 2021). Most coniferous tree species in western US forests are obligate seeders (Agee, 1996; Baker, 2009), and the size of some treeless patches can greatly exceed typical seed dispersal distances (McCaughey et al., 1986; Stevens-Rumann and Morgan, 2019). As such, it can take decades to centuries for trees to naturally recolonize patch interiors (Chambers et al., 2016; Hansen et al., 2018). Increases in temperature and aridity associated with climate change are also reducing the likelihood of natural tree regeneration following fire (Davis et al., 2023; Rodman et al., 2020; Stevens-Rumann et al., 2018). Taken together, these increases in severe fire and declines in regeneration potential are driving increases in reforestation needs across the western US. On lands of the USDA (US Department of Agriculture) Forest Service – the primary government agency tasked with managing western US forests (Oswalt et al., 2019) – only about 25 % of total annual reforestation needs were met between 2000 and 2017 (Dumroese et al., 2019). Reforestation following wildfire has been especially challenging; just 6 % of post-fire reforestation needs were met over the last decade, and wildfire is now responsible for over 80 % of the total need nationwide (Dumroese et al., 2019; United States Department of Agriculture, Forest Service, 2022).

Until recently, funding and policy structures severely limited the ability of reforestation activities to keep pace with increases in wildfire and other unplanned events (Dobrowski et al., 2024). However, the Infrastructure Investment and Jobs Act (IIJA) of 2021 (Public Law 117–58), which includes updates to the Repairing Existing Public Land by Planting Necessary Trees (REPLANT) Act, mandated the elimination of the reforestation backlog by 2030 and has helped to alleviate some of the financial barriers to implementation on USDA Forest Service lands. Across the US, these policies and additional directed financial support are now increasing the rate of active reforestation. In 2022, the year after IIJA and the REPLANT Act were signed into law, an estimated 1.4 billion trees (covering a total of 1.1 million ha) were planted for conservation purposes nationwide, nearly 10 % higher than the previous 10-year average (Pike et al., 2023). Still, financial limitations are just one of the barriers to effectively addressing the reforestation backlog. For example, the retirement of experienced reforestation staff, limited workforce availability, and a lack of operational capacity are major barriers to implementation (Dobrowski et al., 2024; Fargione et al., 2021). A myriad of knowledge gaps also exists about how best to prioritize reforestation activities and maximize their return on investment. Expanded monitoring that supports adaptive management will be critical to address these knowledge gaps and optimize success throughout post-fire landscapes (Fargione et al., 2021; North et al., 2019; Stevens et al., 2021).

Though other techniques (e.g., direct tree seeding; Winters and Van Diepen, 2023) are occasionally used, tree planting is the most common active reforestation practice in the US. Tree planting projects typically involve collecting seed from wild trees or trees cultivated in seed orchards (i.e., tree improvement areas), sowing seeds in beds or containers at nurseries, and planting seedlings in a project area (Fargione et al., 2021). The success of such projects can vary widely (Ouzts et al., 2015), highlighting the need to select seedlings and planting strategies that can overcome the expected conditions and limitations of a planting site (Dumroese et al., 2016). More broadly, topography, climate, and weather conditions can influence the performance of planted seedlings (Marsh et al., 2022; Simeone et al., 2019) and natural regeneration (Davis et al., 2023) across large areas. Emerging predictive frameworks (Holden et al., 2022; Rodman et al., 2022b; Stewart et al., 2021) can leverage this information to help anticipate where tree planting might be needed in early stages after fire (North et al., 2019; Stevens et al., 2021; White and Long, 2019). Whereas information describing natural tree regeneration is now widespread (Davis et al., 2023; Stevens-Rumann and Morgan, 2019), data describing the performance of planted seedlings in post-fire environments are exceedingly rare. In a review of existing peer-reviewed literature in the US Interior West (i.e., the 12 states within Forest Service Regions 1, 2, 3, and 4), we found only nine peer-reviewed studies that have investigated the survival or growth of planted or seeded trees in post-fire environments (Table 1). Collectively, these studies reveal meaningful variation in both survival and

Table 1
A summary of peer-reviewed post-fire tree seeding or planting studies in the US Interior West. We used Google Scholar, Web of Science, and targeted journal searches (e.g., *Tree Planters' Notes)* to identify any peer-reviewed studies that reported survival or growth of post-fire seedlings in states that comprise USDA Forest Service Regions 1–4. "No. Monitored Fires" indicates the number of fires included in the study, and "Time Since Planting" gives the number of years that seedlings were monitored for survival or growth after planting. One study was not in a burned area but simulated a post-fire environment through site preparation (Rother et al., 2015). Abbreviations for planted tree species are as follows: PIAL, *Pinus albicaulis*; PIED, *Pinus edulis*; PIFL2, *Pinus flexilis*; PIPO, *Pinus ponderosa*; PIST3, *Pinus strobiformis*; PSME, *Pseudotsuga menziesii*. "Experimental" plantings were conducted using structured experimental designs to test differences among treatments or planting styles, whereas "operational" plantings were completed by managers to accomplish post-fire restoration objectives.

State (s)	No. Monitored Fires	Time Since Planting (No. Years)	Species Planted	Planting Type	Reference
AZ, NM	8	5–9	PIPO	Operational	(Ouzts et al., 2015)
CO	9	1–3	PIPO, PSME	Operational	(Marshall et al., 2024)
CO	1	1–4	PIPO, PIFL2, PSME	Operational	(Marshall et al., 2023)
CO	N/A	1	PIPO, PSME	Experimental	(Rother et al., 2015)
ID	1	1–2	PIAL	Experimental	(Perkins, 2015)
NM	1	< 1	PIED, PIPO, PIST3, PSME	Experimental	(Crockett and Hurteau, 2022)
NM	1	1–3	PIED, PIPO, PIST3, PSME	Experimental/ Operational	(Marsh et al., 2022)
NM	1	1–2	PIPO, PIST3, PSME	Experimental	(Marsh et al., 2023)
WY	1	1–2	PIPO	Experimental	(Winters and Van Diepen, 2023)

growth across project areas and over time. Yet, only two studies in our search reported planted seedling performance across multiple fire events (Marshall et al., 2024; Ouzts et al., 2015), and no studies have monitored planted seedlings for more than nine years (Table 1). Research spanning broad areas and capturing longer-term ecosystem dynamics is needed to better understand and predict planting outcomes.

Remotely sensed records of forest change, paired with in-situ survey networks, offer the potential to expand monitoring to match the increased pace and scale of post-fire tree planting across the US. The Landsat satellite program has monitored the Earth's surface for over 50 years and is an invaluable source of information to describe ecosystem changes over broad spatial and temporal extents (Wulder et al., 2022). Though the use of Landsat imagery to monitor or inform tree planting efforts is relatively new (e.g., Du Toit et al., 2024; Hoylman et al., 2021), these data have been widely used to describe post-fire vegetation recovery due to natural processes (Celebrezze et al., 2024; Pérez-Cabello et al., 2021; White et al., 2017). Indeed, intra-annual patterns of greenness (i.e., land surface phenology) within Landsat imagery can help to distinguish trees from non-forest vegetation (e.g., grasses, shrubs), as well as isolate forest regrowth following fire (Kiel and Turner, 2022; Menick et al., 2024; Walker and Soulard, 2019). In-situ monitoring data describing the success of tree plantings (e.g., "stake rows" or "survival surveys") have also been collected for decades on USDA Forest Service lands and are commonly used to support management decisions at local to regional levels. To date, these survival data have been underutilized by the scientific community, despite the valuable information that they provide (*but see* Marshall et al., 2024, 2023; Simeone et al., 2019).

Here, we leveraged annual, remotely sensed estimates of forest cover (derived from Landsat imagery), along with in-situ survival surveys of 69,245 tree seedlings from USDA Forest Service monitoring data, to describe the outcomes of post-fire tree planting activities throughout the US Interior West. Together, these datasets span 6706 post-fire tree planting units completed in 297 unique fire events across 10 states. Using these data with Random Forest (RF) models and explanatory variables related to environmental and operational factors, we asked: (Q1) *Does post-fire tree planting enhance remotely sensed rates of forest cover change relative to environmentally similar, unplanted areas? How do the timing of planting, post-planting meteorology, average climate, post-fire forest conditions, and tree species influence* (Q2) *rates of remotely sensed forest cover change within planted areas and* (Q3) *early (i.e., after ca. one growing season) planted seedling survival?*

2. Methods

2.1. Study Area

Our study area included USDA Forest Service lands within the US Interior West that were burned and subsequently planted with tree seedlings to promote forest recovery. The Interior West, as defined here, encompasses 10 states (i.e., Arizona, Colorado, Idaho, Montana, Nebraska, Nevada, New Mexico, South Dakota, Utah, and Wyoming) within four Forest Service Regions (i.e., 1, 2, 3, and 4). Climate varies widely across forests of this area, with average annual temperatures ranging (i.e., 2.5th – 97.5th percentiles) from 1.7 to 20.2 °C (mean = 8.9 °C) and average annual precipitation ranging (i.e., 2.5th – 97.5th percentiles) from 166 to 1070 mm yr^{-1} (mean = 466 mm yr^{-1}) (1991–2020 climate normals; PRISM Climate Group, Oregon State University, 2022). Montane forests predominate in warmer, drier settings and include combinations of ponderosa pine (*Pinus ponderosa* var. *ponderosa* and var. *scopulorum*), Douglas-fir (*Pseudotsuga menziesii* var. *glauca)*, grand fir (*Abies grandis*), western larch (*Larix occidentalis*), and/or white fir (*Abies concolor* var. *concolor*). Subalpine forests predominate in cooler, wetter settings and include combinations of Engelmann spruce (*Picea engelmannii* var. *engelmannii)*, subalpine fir (*Abies lasiocarpa*), limber pine *(Pinus flexilis*), and/or lodgepole pine (*P. contorta* var. *latifolia*). Many additional tree species are present with lower prevalence or in particular locations such as riparian areas.

2.2. USDA Forest Service Tree Planting Policies and Practices

Post-fire tree planting in our study area is informed by national and regional Forest Service directives – specifically, the Forest Service Manual (FSM) Chapters 2470 and 2490, Forest Service Handbook (FSH) 2409.17 with Region 1, 2, 3, and 4 supplements, and the National Forest Management Act of 1976 (Public Law 94–588) as amended by the REPLANT Act. Based on these directives and current practices in the US Interior West, a generalized process for project planning and implementation is summarized below. Sites are selected for tree planting when they have been "denuded or deforested" and natural tree regeneration is insufficient to support site-specific forest management plans. Seeds are initially collected from wild trees in the same seed/breeding zone as the selected planting site, or from tree improvement areas, where available (e.g., Region 1). Collected seeds are then grown into one-, two-, or three-year-old bareroot seedlings or containerized seedlings of various sizes, usually at federal nurseries in Halsey, Nebraska (Charles E. Bessey Nursery), Coeur d'Alene, Idaho (Coeur d'Alene Nursery), or Boise, Idaho (Lucky Peak Nursery). Seedlings are then packaged, stored, and transported to the project area, with methods dependent on factors such as transportation distance, planting season, storage time, and available infrastructure. Prior to planting, site preparation is sometimes used to modify soil, surface fuels, or competing vegetation, either at the level of the planting unit (e.g., mechanical site preparation or prescribed burning) or microsite (e.g., clearing litter or herbaceous vegetation). In post-fire areas, most seedlings are planted by hand, with planting seasons selected to align with periods of suitable weather, abundant soil moisture, and operational feasibility. To protect seedlings from high levels of solar insolation, seedlings are often placed on the north side of stumps, logs, shrubs, or dead trees. Tree tubes or cones are sometimes installed to protect seedlings from harsh microclimatic conditions or mammal herbivory. After three growing seasons, units are either certified to have reached tree densities defined in management plans or are scheduled for retreatment.

2.3. Data – Locations of Post-Fire Planting Units

We used spatial data from the Forest Activity Tracking System (FACTS) (United States Department of Agriculture, Forest Service, 2023) – a consistent data source describing forest management activities on Forest Service lands – to identify the locations and timing of post-fire tree plantings across the Interior West. We selected FACTS polygons where tree planting was reported (i.e., FACTS activity codes 4431 and 4432) and intersected them with fire perimeters in our study area (from 1985 to 2021) from the Monitoring Trends in Burn Severity (MTBS) program (Eidenshink et al., 2007) to focus on planting activities that were completed after fire occurrence. MTBS maps the location and extent of all fire events ≥ 404 ha (1000 ac) in the western US; thus, we did not include plantings that occurred in small fires (i.e., < 404 ha). Small fire events accounted for < 4 % of the total area burned during our study period (National Interagency Fire Center, 2023). Finally, we excluded any plantings that reburned during or after the year of planting completion (9.0 % of all units) (Eidenshink et al., 2007; National Interagency Fire Center, 2023). Because of uncertain locations of individual planted trees and survival surveys within FACTS polygons, we performed all analyses at the level of the planting unit (mean size = 16.0 ha; 2.5th - 97.5th percentiles = 1.0–65.5 ha). Most planting activities (i.e., 55.2 % in our data) occurred within three years of fire, though some occurred as much as 30 years after fire.

2.4. Data – Remotely Sensed Forest Cover

We quantified rates of remotely sensed forest cover change after tree planting using annual, 30-m maps of forest cover from the Rangeland Analysis Platform (RAP) v. 3.0 dataset (Allred et al., 2021). RAP, available throughout the contiguous US, uses intra-annual patterns of greenness in Landsat imagery to map the percent cover of trees and other plant functional groups with relatively high accuracy (e.g., Root-Mean-Square Error = 6.8 % tree cover) (Allred et al., 2021). RAP data have been previously used to characterize vegetation dynamics in burned landscapes (Davis et al., 2023; Rodman et al., 2023) and to describe the outcomes of tree planting after timber harvest (Hoylman et al., 2021). Indeed, comparisons between these data, 2378 post-fire field plots throughout the Interior West, and ancillary spatial datasets indicated that trends in RAP-derived forest cover were related to both tree seedling density and canopy height in post-fire environments (Appendix S1). From RAP, we extracted the mean annual forest cover from 1986 to 2022 in each post-fire planting unit. We then restricted cover data in each unit to dates ≥ 1 year after planting occurred and ≥ 3 years after fire occurrence (hereafter "post-planting years") to reduce the effects of delayed overstory tree mortality (Busby et al., 2024). In cases where multiple plantings were completed in the same unit (9.4 % of all units), we retained only the last recorded activity to focus on a single management event.

We utilized these remotely sensed data to quantify differences in rates of forest cover change between planted and unplanted areas (*Q1*) and drivers of cover change rates across plantings (*Q2*). First, as a general descriptor of change over time, we calculated the mean and 95 % confidence interval (CI) (i.e., 1.96 * the standard error) of forest cover over time across all planting units. To do so, we used all post-fire planting units with forest cover data from at least one post-planting year (n = 6620 planting units completed from 1987 to 2021). Second, within each planting unit, we used the slope coefficient from ordinary least squares (OLS) regression (i.e., predicting annual forest cover as a function of years since planting) to estimate the average change in forest cover year^{-1} (hereafter, "cover change" or "forest regrowth"). We limited cover change calculations to units with forest cover data for ≥ 10 post-planting years (n = 4703 planting units completed from 1987 to 2012) for a more accurate estimation of temporal trends. In Landsat time series, post-fire trajectories can be more easily distinguished with a data duration of at least 10 years, and become increasingly reliable over time (Kiel and Turner, 2022; Menick et al., 2024; Vanderhoof et al., 2021; Walker and Soulard, 2019). Thus, for cover change calculations in *Q1*, we included all post-planting forest cover data through 2022 (i.e., the record length was longer for older plantings), because each pair of a planted unit and matched, unplanted area (described in *Analysis, Q1*) had the same record length, and our focus was on comparing these two groups. For *Q2*, we calculated cover change rates using data for only the first 10 post-planting years, because record length was related to other variables of interest (e.g., Year Planted).

2.5. Data – Early Survival Surveys

We used tabular FACTS data provided by Forest Service regional offices, supplemented with additional unreported data provided by seven National Forests in Colorado (Marshall et al., 2024), to describe variation in seedling survival rates (*Q3*). These data were collected following a standardized Forest Service monitoring protocol. On each National Forest, a subset of planted trees – a minimum of 100 trees per major tree species (>10,000 trees planted) per planting year, split across up to 10 locations/planting units – were selected and permanently marked for monitoring. Seedlings were then tracked over time to determine survival rates (FSH 2409.14; FSM 2472.4). Based on a subset of Colorado units where tree-level data were available (n = 91), the mean height of monitored seedlings was 15.2 cm at the time of planting and ranged from 6.1 to 33.0 cm (2.5th - 97.5th percentiles). Survival surveys are usually completed by Forest Service staff in the fall season, one and three growing seasons after planting. For each survival survey, we obtained the survey completion date, tree species monitored, the

Table 2
Variables tested to predict remotely sensed forest cover change and in-situ seedling survival in post-fire planting units throughout the US Interior West. Here, we define the "post-planting period" as the first year after the planting date or, for survival surveys completed less than 12 months after planting, the period between the planting date and the date of field surveys.

Variable	Description and Rationale	Cover	Survival
Average Actual Evapotranspiration (AET)	Mean annual AET (mm yr^{-1}) in a planting unit between the 1991 and 2020 water years (Holden et al., 2019). AET describes the simultaneous availability of moisture and energy and is related to productivity.	X	X
Average Climatic Water Deficit (CWD)	Mean annual CWD (mm yr^{-1}) in a planting unit between 1991 and 2020 water years (Holden et al., 2019). CWD describes unmet evaporative demand of the atmosphere and is related to moisture stress.	X	X
Fire Severity	Mean fire severity (the relativized burn ratio; RBR) in a planting unit (Parks et al., 2021). Fire severity can influence competing/facilitating vegetation and microsite conditions.	X	X
Monitoring Period Length	Number of days between completion of planting and survival survey. Survival typically declines with time, and early survival surveys ranged from 3 to 20 months after planting.		X
Ordinal Date of Planting	Numeric representation of the calendar day in which a planting was completed. Season of planting is a key part of the planning process that can adjusted by managers.	X	X
Post-Fire Canopy Cover	Focal mean forest cover (Allred et al., 2021) in a planting unit and the surrounding 300-m radius in the year after the fire. Post-fire forest cover can influence natural recovery potential and microsite conditions.	X	X
Post-Planting AET	AET (z-score relative to 1991–2020 values) in a planting unit during the post-planting period (Holden et al., 2019). AET after planting is an indicator of how AET deviates from longer-term averages at a site.	X	X
Post-Planting CWD	CWD (z-score relative to 1991–2020 values) in a planting unit during the post-planting period (Holden et al., 2019). CWD after planting is an indicator of local heat/aridity and its deviation from longer-term averages at a site.	X	X
Post-Planting Maximum Soil Surface Temperature (SST)	The 95th percentile of maximum daily SST (°C) (Maneta and Silverman, 2013) in a planting unit during the post-planting period. High surface temperatures can girdle small trees and disrupt water movement.	X	X
Post-Planting Minimum SST	The 5th percentile of minimum daily SST (°C) (Maneta and Silverman, 2013) in a planting unit during the post-planting period. Temperatures were	X	X

(*continued on next page*)

Table 2 (*continued*)

Variable	Description and Rationale	Cover	Survival
	restricted to only days without modeled snow cover, as snow can insulate vegetation from cold temperatures. Extremely low temperatures can damage tree tissues, particularly during periods of active growth.		
Post-Planting Minimum Soil Water Availability (SWA)	The 5th percentile of daily volumetric water content (ratio of water volume to soil volume) (Maneta and Silverman, 2013) of the soil in a planting unit during the post-planting period. Low soil moisture can cause both xylem cavitation and embolism.	X	X
Species	Tree species that was planted within a unit. Where multiple species were planted, they were monitored separately. Individual species may respond differently to environmental conditions in post-fire landscapes.		X
Years After Fire	Number of years after the fire in which a planting was completed. Time since fire can influence microsite conditions, such as competing or facilitating vegetation, downed wood loads, and soil properties.	X	X
Year Planted	Calendar year in which a planting occurred. Some managers report declines in survival after ca. 2010.	X	X

total number of marked seedlings, and the number of surviving seedlings. We joined tabular survival data with spatial data describing the locations of post-fire planting units (see *Data – Locations of Post-Fire Planting Units*) using the SUID field, a unique identifier for each planting activity. When multiple plantings were conducted in different years within the same planting unit, we retained survival surveys for all records. To investigate potential sources of error or reporting bias (e.g., underreporting of failed plantings), we compared survival surveys from regional offices with data received from local offices and with remotely sensed metrics (Appendix S2). We found no evidence of errors or systematic bias that would impact inference at the scale of this study.

For subsequent analyses, we focused on survival surveys that (1) were within post-fire planting units; (2) were completed before October 1st, 2022, to align with the availability of potential predictors (see *Data – Potential Predictors of Planting Outcomes*); (3) had $\geq$ 25 marked individuals (across all species) in a given unit; (4) were identified as "one growing season" surveys in Forest Service databases (hereafter referred to as "early survival"); and (5) had species-specific survival estimates for coniferous trees, as angiosperms were poorly represented in the data. We focused specifically on early survival records, because they were the most consistent and widely available in Forest Service monitoring data (e.g., 27 % of units were missing survival data after three growing seasons), and because early survival is highly correlated with longer-term outcomes (Marshall et al., 2024). However, we acknowledge that longer-term data are often used to make management decisions (S. Fox, personal communication), and are more indicative of tree establishment. Conifer species in these data included Douglas-fir, Engelmann spruce, limber pine, lodgepole pine, ponderosa pine, western larch, western red cedar (*Thuja plicata*), western white pine (*Pinus monticola*), and whitebark pine (*Pinus albicaulis*). The final survival dataset included 69,245 monitored seedlings in 1071 planting units (completed from 1999 to 2022) within 161 unique fire events.

2.6. Data – Potential Predictors of Planting Outcomes

Using pre-existing research on post-fire tree planting (Table 1) and tree regeneration in the US Interior West (e.g., Davis et al., 2023; Korb et al., 2019; Stevens-Rumann and Morgan, 2019), we identified 14 potential predictors of forest cover change rates and early seedling survival (Table 2). These predictors were broadly related to the timing of planting, monitoring period length, species selection, post-fire forest conditions, average climate of a planting site, and post-planting weather conditions. Detailed information such as planting methods, the location of seed collection, site preparation techniques, and nursery cultural practices are known to have important influences on the success of plantings (Dumroese et al., 2016; Marsh et al., 2023; Marshall et al., 2023; Pinto et al., 2023), but such data were not consistently available across the study area and were therefore not included in our analyses.

We determined the planting date for each activity using the "DATE_COMPLETED" field FACTS (United States Department of Agriculture, Forest Service, 2023) and used this to create "Year Planted" and "Ordinal Date of Planting" variables. We included Year Planted to test for changes in planting success over time and included Ordinal Date of Planting (i.e., a numeric representation of the calendar date within a year) to test for the effects of planting season. We also quantified "Years After Fire" as the number of years between initial fire occurrence and planting, to test for potential effects of changes in soils, local vegetation, and coarse wood after fire. Because survival could be expected to decline with the length of the survey period, we calculated "Monitoring Period Length" as the number of days between the planting completion and survival survey dates. For survival records in Region 1, where survey dates were unavailable at the time of data acquisition, we assumed a constant survey date of September 21st, one growing season after planting. This is the middle of the typical monitoring season in Region 1 (E. Jungck, personal communication). For survival records, we extracted "Species" as the tree species being monitored in a given survey. While most species were well represented and could be analyzed individually, survival records for five-needle pines (*Pinus* subgenus *Strobus*) were more limited. Because these species often occupy similar niches within a community, we grouped whitebark pine, limber pine, and western white pine into a single "five-needle pine" category.

To describe post-fire forest conditions, we used two variables that captured post-fire forest cover and the severity of the last fire at a planting site. We calculated "Post-Fire Canopy Cover" in the year after fire from RAP as a proxy for seed availability. Following Davis et al. (2023), we calculated the focal mean of forest cover from RAP in a 300-m radius around each 30-m pixel to account for seed dispersal from nearby areas. To characterize "Fire Severity", we developed maps of the Relativized Burn Ratio (RBR; Parks et al., 2014). Relativized indices such as RBR, which account for differences in pre-fire vegetation cover, are preferable in studies spanning a range of vegetation types (Miller and Thode, 2007), and RBR has comparable or greater accuracy than other common fire severity metrics in western US forests (Howe et al., 2022; Parks et al., 2014). To calculate RBR, we first obtained all Landsat scenes (Collection 2, Tier 1, Level 2) that intersected a fire perimeter between May 1st and September 30th using Google Earth Engine (Gorelick et al., 2017). Next, we developed annual, cloud-free images for years immediately before and after the fire year using the mean composite of all clear pixels (Parks et al., 2021). We then calculated RBR following equations in Parks et al. (2014), with a phenology offset developed from a 180-m outward buffer around each fire perimeter. We summarized Post-Fire Canopy Cover and Fire Severity using the mean of all 30-m pixels intersecting a planting unit.

We quantified average climate in each planting unit using Actual Evapotranspiration (AET) and Climatic Water Deficit (CWD) from the TOPOFIRE dataset (Holden et al., 2019). AET and CWD represent two axes of the local energy and water balance (Stephenson, 1998). To calculate these metrics, TOPOFIRE uses inputs of solar radiative forcing and hourly weather data to calculate reference evapotranspiration (i.e., potential evapotranspiration; PET) (Holden et al., 2019). GIS-derived soils data (Ramcharan et al., 2018), precipitation data, and PET are then used to model snowpack and soil moisture over time, as well as evapotranspiration from different ecosystem components (i.e., AET) and the unmet evaporative demand of the atmosphere (i.e., CWD). We extracted daily AET and CWD (ca. 250-m spatial resolution) from TOPOFIRE at the geographic centroid of each planting unit. We then created "Average AET" and "Average CWD" by aggregating daily values to the total in a water year (i.e., October 1st to September 30th) and calculating the mean annual value between 1991 and 2020.

We used daily weather after planting (hereafter "post-planting period") to describe potential influences on seedling survival, growth, and establishment. For cover change records and any survival records with a Monitoring Period Length ≥ 365 days (25.0 % of survival records), we summarized data for the first year after planting. For survival surveys with a Monitoring Period Length < 365 days (75.0 % of survival records), we summarized information between planting completion and the survey date. We used daily data from TOPOFIRE to calculate normalized departures (i.e., z-scores) of AET and CWD relative to longer-term unit-level averages in the 1991–2020 water years. Following Davis et al. (2019), we also developed metrics related to soil surface temperature and soil water availability using Ech2o (v5.6.2-SPAC), a mechanistic ecohydrological model (Maneta and Silverman, 2013). For use with Ech2o, we extracted soil properties for each site from previously calibrated 100-m resolution soil grids (Ramcharan et al., 2018), and temperature and precipitation inputs from TOPOFIRE. We ran Ech2o simulations at a 3-hour timestep and 30-m resolution in a 240-m domain around the centroid of each unit, to reduce computational demands and align with the resolution of other climate variables. We aggregated Ech2o model outputs of soil moisture and soil surface temperature to daily minimum and maximum values. We then used the 95th percentile value of maximum daily soil surface temperatures (i.e., "Post-Planting Maximum SST") and the 5th percentile of minimum daily soil surface temperatures (i.e., "Post-Planting Minimum SST") in the post-planting period to describe temperature extremes experienced by seedlings. We removed dates with modeled snow cover > 0 from Minimum SST calculations, as snow may insulate seedlings from thermal extremes. Finally, we calculated the 5th percentile of daily soil water availability (i.e., "Post-Planting Minimum SWA") to represent hydraulic stress.

2.7. Analysis, Q1 – Planting Effects on Remotely Sensed Forest Cover Change

To compare rates of forest cover change in planted areas and environmentally similar, unplanted areas (*Q1*), we selected a matched, unplanted site for each unit as follows. First, we calculated the mean and standard deviation (SD) of Fire Severity, Average CWD, Post-Fire Canopy Cover (Table 2), and Pre-Fire Canopy Cover within each planting unit. We summarized "Pre-Fire Canopy Cover" as the maximum annual value from RAP between 1986 and the fire year. For fires that occurred in 1985 or 1986 (0.3 % of all units), we did not use Pre-Fire Canopy Cover as a matching variable because pre-fire data were unavailable. For each planting unit, we selected all 30-m pixels within the same fire that (1) were within the unit-level mean ± 1 SD for each of these environmental variables (Fig. S3.1); (2) had no record of tree planting in FACTS; (3) were within USFS lands where data on management history is most reliable; and (4) had no reburns after the planting date (Eidenshink et al., 2007; National Interagency Fire Center, 2023). The mean size of these matched, unplanted areas was 59.8 ha (2.5th - 97.5th percentiles = 0.2 – 453.5 ha). While the inclusion of small planting units or unplanted areas may increase the potential for edge effects and increase sample variance, excluding small (i.e., < 1 ha) planting units or unplanted areas had very little influence on our results (i.e., < 1 % net difference). Thus, we retained all units in the final comparison. We tested for differences between cover change rates of planted units and

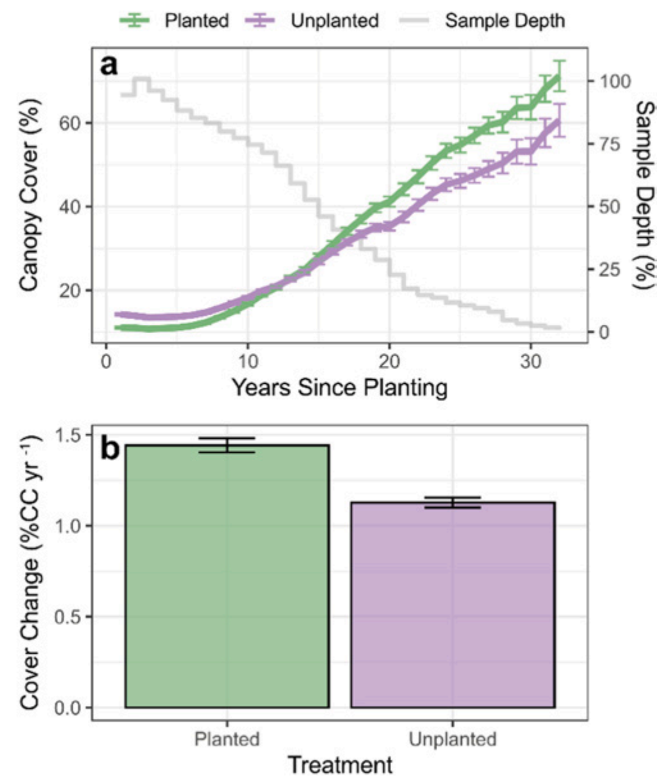

Fig. 1. Remotely sensed (a) forest cover for the first 32 years after planting and (b) average annual change in forest cover after planting in post-fire planting units and environmentally similar, unplanted areas throughout the US Interior West. Error bars in (a, b) give ± one standard error of the mean. Panel (a) includes data from 6620 planting units (n = 293 fires) with at least one year of forest cover data after planting, while panel (b) is restricted to a subset of 4703 planting units (n = 187 fires) with at least 10 years of forest cover data, for better estimation of within-unit temporal trends. In (a), sample depth refers to the percentage of planting units with forest cover data at the specified number of years since planting.

matched, unplanted areas using a paired Wilcoxon signed-rank test (Wilcoxon, 1945), with a one-sided alternative hypothesis that cover change would be greatest in planted units.

2.8. Analysis, Q2 and Q3 – Factors that Influence Cover Change and Early Seedling Survival Rates

We developed two Random Forest (RF) models (Breiman, 2001) to test relationships between response variables (i.e., remotely sensed cover change (*Q2*) and early survival rates (*Q3*)) and potential predictors. We selected variables for inclusion in final models using forward feature selection with spatially stratified cross-validation to reduce overfitting and ensure that models were generalizable across unsampled areas (Meyer et al., 2019, 2018). To do so, we assigned each unit to one of 30 spatial folds (i.e., spatial clusters of planting units in the same general area) using k-means clustering of the geographic centroid coordinates of each unit. Using RF models with these spatial folds in cross-validation, we identified the pair of predictors with the lowest cross-validated error and added predictors from the remaining set until error began to increase. Feature selection using statistical learning models can be sensitive to the spatial structure of holdout data (Erickson et al., 2023). Thus, we ran the above forward feature selection procedure using 10, 20, and 30 spatial folds but found that a relatively consistent set of features were selected regardless of holdout data structure. Final predictors in each model showed no evidence of multicollinearity, with variance inflation factors < 2.

Following variable selection, we used a similar, spatial cross-

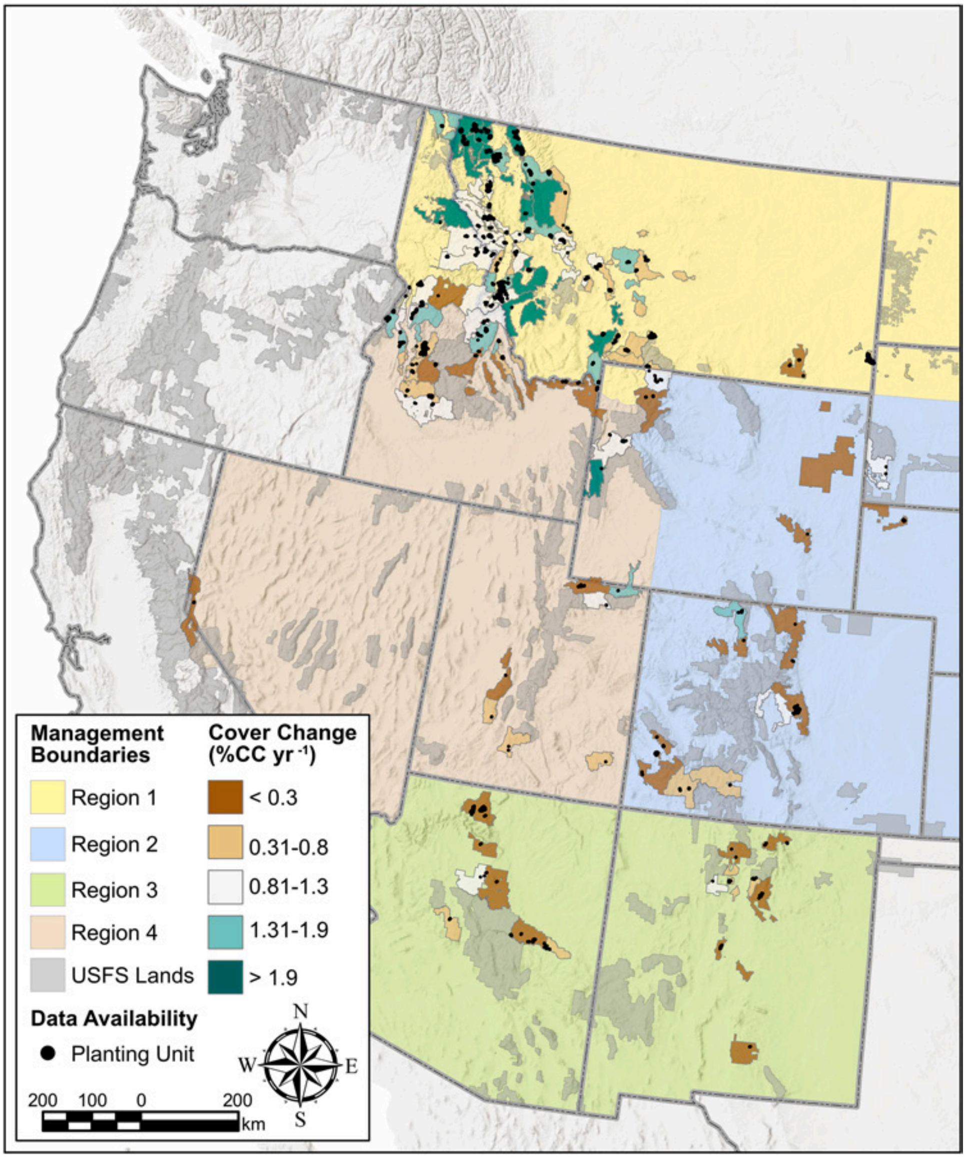

Fig. 2. Remotely sensed rates of forest cover change (i.e., average annual change in cover) in post-fire tree planting units in the US Interior West. Values give the mean rate of cover change across all planting units within each USDA (United States Department of Agriculture) Forest Service Ranger District. Planting units (n = 4703 in 187 fires) were restricted to those in Forest Service Regions 1–4, and with ≥ 10 years of forest cover data after planting. CC: Canopy Cover; USFS: USDA Forest Service.

validation procedure to tune model parameters that can influence model flexibility (i.e., "mtry", "min.node.size"). Throughout model development, we used 1000 trees and a maximally selected rank statistic for split variable selection (Wright et al., 2017). To summarize the effects of final variables in each model, we calculated relative variable importance (i.e., the permutation-based mean decrease in accuracy statistic, scaled to sum to 100) (Wright and Ziegler, 2017) and developed accumulated local effects (ALE) plots, which illustrate the individual effect of each variable on predicted values of the response (Molnar et al., 2018). All analyses were performed in R v. 4.2.3 (R Core Team, 2023). We developed RF models and calculated variable importance using the 'ranger' (Wright and Ziegler, 2017) and 'spatialRF' (Benito, 2021) packages, performed variable selection and model tuning using the 'caret' (Kuhn, 2008) and 'CAST' (Meyer et al., 2023) packages, and developed ALE plots using the 'iml' package (Molnar et al., 2018).

3. Results

3.1. Q1) Does Planting Enhance Rates of Remotely Sensed Forest Cover Change?

Post-fire tree planting activities in the US Interior West drove increases in forest cover over time (Fig. 1). When comparing planted units to environmentally similar unplanted areas within the same fires, mean forest cover was slightly higher in unplanted areas for the first 5–10 years but was consistently higher in planted areas after 13 years (Fig. 1a). On average, post-fire planting units had 25.7 % higher rates of remotely sensed forest cover change (mean difference = 0.29 % forest cover year^{-1}) than unplanted areas (Fig. 1b), and differences were greater than zero based on a paired Wilcoxon signed-rank test ($p < 0.001$). However, unit-level differences in cover change were variable across the study area, with 63.7 % of units having faster rates of cover increases than matched, unplanted areas (Fig. S3.2).

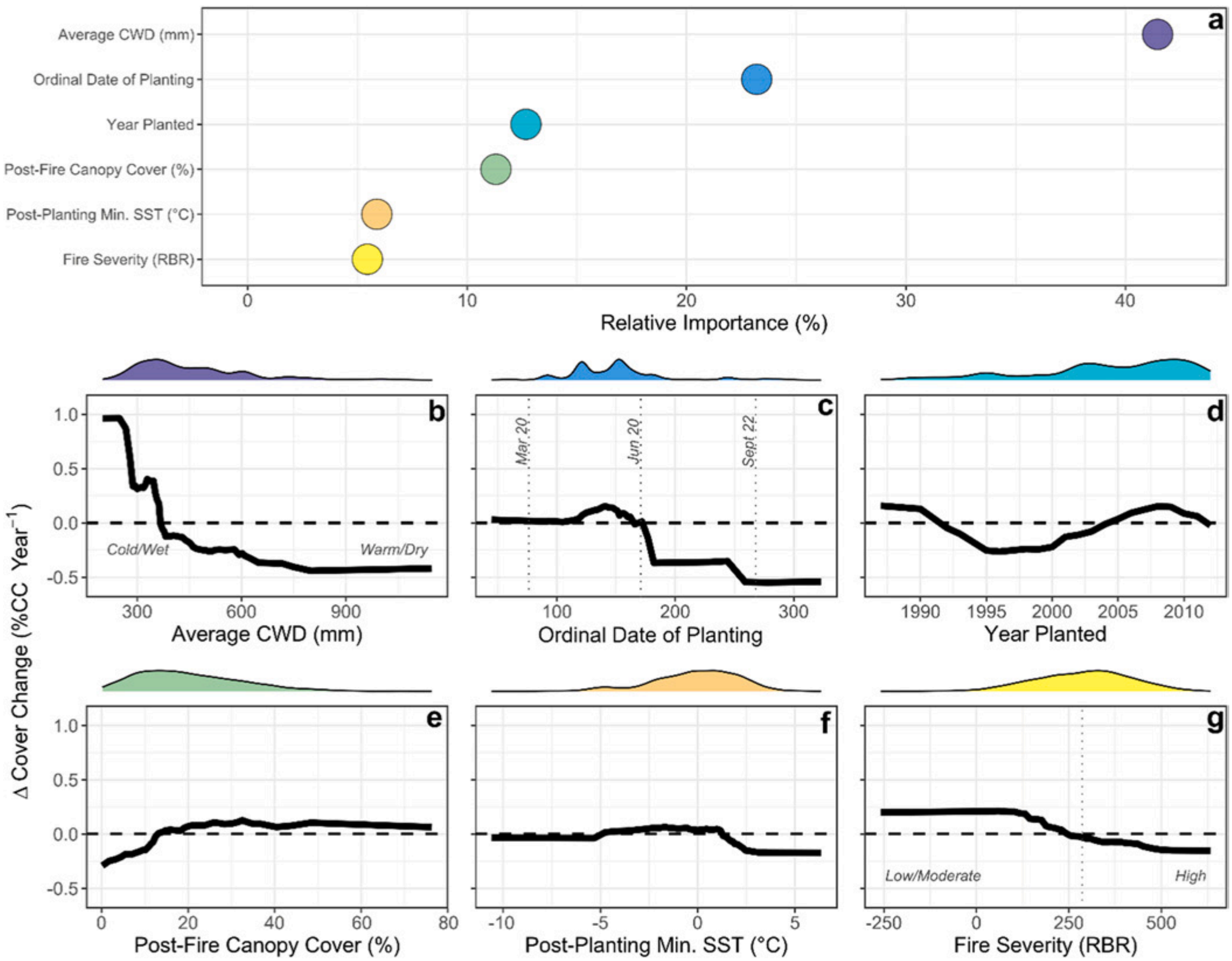

Fig. 3. Plots of (a) relative variable importance and (b-g) accumulated local effects showing results of the Random Forest model predicting rates of forest cover change after post-fire tree planting in the US Interior West. In panels (b-g), the y-axis gives the change in predicted values (relative to the overall response mean) at a given value of the corresponding predictor variable (x-axis), after accounting for the effects of other covariates. When solid black lines are above dashed lines, they indicate a higher-than-average rate of forest regrowth at the value of the corresponding variable (x-axis). Density plots above panels (b-g) show the distribution of the predictor variable across units. CC: Canopy Cover; CWD: Climatic Water Deficit; RBR: Relativized Burn Ratio; SST: Soil Surface Temperature.

3.2. Q2) Factors Influencing Forest Cover Change Following Post-Fire Tree Planting Projects

Variation in remotely sensed forest cover change rates was related to geographic gradients and biophysical predictors. Within planting units, the mean rate of forest gain was 1.42 % (forest cover) yr^{-1} (standard deviation (SD) = 1.26 %) and most units ranged from −0.22 % (2.5th percentile) to 4.30 % yr^{-1} (97.5th percentile) (Fig. S3.2). Rates of cover change were 3.5 times higher in wetter, northern portions of the study area (i.e., 1.55 % forest cover yr^{-1} in Idaho and Montana) than in drier, southern areas (i.e., 0.35 % forest cover yr^{-1} in Arizona and New Mexico) (Fig. 2). Variation in cover change was best explained by an RF model that included six variables (ranked from high to low relative importance) including Average Climatic Water Deficit (CWD), Ordinal Date of Planting, Year Planted, Post-Fire Canopy Cover, Minimum Post-Planting Soil Surface Temperature (SST), and Fire Severity (Fig. 3a). The RF model explained 29 % of the variation in remotely sensed rates of forest cover change (i.e., out-of-bag $R^2 = 0.29$; R^2 from spatial CV (cross-validation) = 0.14), but prediction error was relatively high (i.e., out-of-bag RMSE (root-mean-squared-error) = 0.99 % forest cover $year^{-1}$; RMSE from spatial CV = 1.09 % $year^{-1}$).

Cold, wet sites (CWD < 400 mm yr^{-1}) typically had the fastest rates of remotely sensed forest cover change after planting (Fig. 3b). Planting season also had a strong relationship with cover change, where spring plantings completed between late-April (Ordinal Date = 120) and mid-June (Ordinal Date = 170) had the greatest forest gains overall (Fig. 3c). However, an interaction between these terms indicated that spring plantings had particularly high rates of cover change on cold, wet sites. In contrast, late summer or fall plantings (Ordinal Date ≥ 200) had the highest rates of cover change on moderate to dry sites (i.e., CWD ≥ 400 mm yr^{-1}) (Fig. 4a). Rates of forest cover change also varied through time, such that plantings completed in the late 1990s and in the early 2010s showed the lowest rates of forest regrowth (Fig. 3d), likely because these periods were followed by years of extreme, regional drought in 2000, 2002, 2012, 2013, and 2021 (i.e., negative soil moisture anomalies; Williams et al., 2022). Fire Severity and Post-Fire Canopy Cover also had meaningful relationships with cover change (Figs. 3e, 3g, 4b). These variables indicate that forest gains were most rapid when fires burned at low to moderate severity (i.e., relativized burn ratio [RBR] < 282) and when some trees survived the fire (i.e., > 20 % Post-Fire Canopy Cover). Though natural regeneration and forest recovery are more likely in such settings, 45.0 % of planting units had at

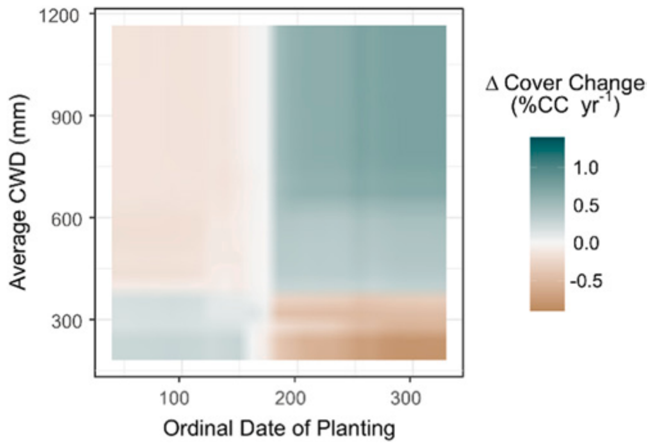

Fig. 4. Bivariate interaction plot showing results of the Random Forest model predicting remotely sensed rates of forest cover change after post-fire tree planting in the US Interior West. Colors give the change in predicted values (relative to the overall response mean) for given values of the corresponding variables (x- and y-axes), after accounting for relationships with other covariates in the model. When colors are green, they indicate a higher-than-average rates of forest cover change at the value of the corresponding variables (x- and y-axes). For other bivariate interactions, see Fig. S4.1. CC: Canopy Cover; CWD: Climatic Water Deficit.

least 20 % Post-Fire Canopy Cover in the surrounding area, and 45.4 % of units were in areas that burned at low to moderate severity in the last fire (Fig. 3g). Removing areas with a history of multiple fires before planting only marginally reduced these numbers (i.e., < 5 %). Plantings followed by periods with cold (i.e., Minimum SSTs < −5 °C) or warm (i.e., Minimum SSTs > 1.5 °C) nighttime temperatures had slightly lower cover change rates (Fig. 3f).

3.3. Q3) Factors Influencing Seedling Survival in Post-Fire Tree Planting Projects

Early survival of planted tree seedlings (i.e., after one growing season) varied markedly throughout the US Interior West based on in-situ monitoring data. Mean early survival was 79.5 % (SD = 23.2 %), with most records ranging from 16 % (2.5th percentile) to 100 % (97.5th percentile). Overall, < 1 % of unit-level records had full mortality after one growing season and 14.1 % had full survival. Survival was generally greatest in the north (e.g., 83.1 % average survival in Idaho and Montana), and lowest in the south (68.4 % survival in Arizona and New Mexico), though there was meaningful variation within each region and through time (Fig. 5). The RF model of early seedling survival indicated that these geographic patterns were best described by six explanatory variables (ranked from high to low relative importance) including Average CWD, Ordinal Date of Planting, Post-Planting CWD, Year Planted, Average Actual Evapotranspiration (AET), and the Monitoring Period (Fig. 6). Because Species was not selected for model inclusion, we aggregated survival records across species for our final analysis. This model explained 42 % of the variation in the survival (i.e., out-of-bag R^2 = 0.42; R^2 from spatial CV = 0.20) with modest prediction error (i.e., out-of-bag RMSE = 17.7 %; RMSE from spatial CV = 20.8 %).

Average CWD was the strongest single predictor in the RF model of seedling survival (Fig. 6a). Plantings in cold, wet areas (i.e., CWD < 400 mm yr^{-1}) had 20–30 % higher survival, on average, than plantings in warm, dry areas (i.e., CWD > 750 mm yr^{-1}) (Fig. 6b). Average Actual Evapotranspiration (AET) had a weakly negative relationship with survival (Fig. 6f). Taken together, findings related to AET and CWD suggest that survival is highest in wet areas, where evapotranspiration is limited by energy rather than moisture. Plantings during spring or early summer months (i.e., Ordinal Date < 190) also tended to have higher survival rates overall (Fig. 6c). Post-Planting CWD was another primary driver of seedling survival; when plantings were followed by moderately to highly wet conditions (i.e., z-score < 1), survival increased by nearly 20 % (Fig. 6b). However, both Average CWD and Ordinal Planting Date interacted with Post-Planting CWD, such that cold, wet areas and projects completed during the late summer or fall season were less sensitive to drought in the post-planting period (Fig. 7). Across the study area, 2011–2013 and 2021–2022 were years with notably low survival (Fig. 6f); many of these years experienced intense drought across the Interior West (Williams et al., 2022). Monitoring Period Length helped to account for differences in survey length across units, and survival declined with increased time since planting (Fig. 6g).

4. Discussion

Our results highlight the potential for recent (i.e., 1987–2022) tree planting efforts to significantly boost forest recovery in burned areas across the US Interior West. We found that post-fire tree planting enhanced rates of remotely sensed forest regrowth by 25.7 %, and early survival rates (i.e., after one growing season) of planted seedlings averaged 79.5 %. While plantings generally promoted forest recovery, we also found considerable variability in project outcomes. Only 63.7 % of planting units gained forest cover faster than matched, unplanted areas in the same fires, and there were notable differences in cover change and early survival within and among regions. Climatic gradients, planting season, post-fire forest conditions, and drought events in the post-planting period all helped to explain this variability, providing insight into factors that influence the outcomes of tree planting projects throughout our study area.

4.1. Environmental and Operational Factors Related to Planting Outcomes

Average Climatic Water Deficit (CWD) and Ordinal Date of Planting (i.e., planting season) were the strongest predictors of forest cover change and seedling survival in our statistical models. We found that units on cold, wet sites (i.e., Average CWD < 400 mm $year^{-1}$) had the highest rates of cover change and early seedling survival. As an indicator of moisture stress experienced by plants, low Average CWD has been positively associated with forest recovery after a range of disturbance types in the US West (Hoylman et al., 2021; Menick et al., 2024; Rodman et al., 2022a), and with the presence or abundance of natural seedling establishment after fire (Davis et al., 2023; Korb et al., 2019; Stevens-Rumann and Morgan, 2019). Nevertheless, plantings on warm, dry sites will continue due to national policy (e.g., National Forest Management Act of 1976) and local management plans. To enhance growth and survival on such sites, managers might select seedlings from more drought-adapted populations (Dixit et al., 2021; Marshall et al., 2024; Moran et al., 2024; Young et al., 2020) and species (North et al., 2019; Williams and Dumroese, 2013), apply nursery practices that enhance resilience to drought (Pinto et al., 2023), and target aspects or microsites that enhance survival (Marsh et al., 2023; Marshall et al., 2023). They might also adjust planting seasons. Indeed, we found that the spring and early summer months (i.e., before June 30th) were the best time to plant seedlings in cold, wet areas, whereas late-season plantings were more successful in warm, dry areas. These patterns were generally consistent across the US Interior West, despite differences in precipitation seasonality. In warm areas, high surface temperatures and aridity limit seedling establishment, whereas frost injury may be a more important constraint in cold areas (Davis et al., 2019; Grossnickle, 2012). Thus, late-season plantings could have more positive outcomes on warm, dry sites, where moisture stress is a critical concern.

Weather also strongly influenced early survival in post-fire planting projects across the US Interior West. When post-planting conditions were moderate to wet (i.e., Post-Planting CWD z-score < 1), we found that early survival increased by around 20 % (Fig. 6d). This is consistent with experimental plantings that show that watering can enhance

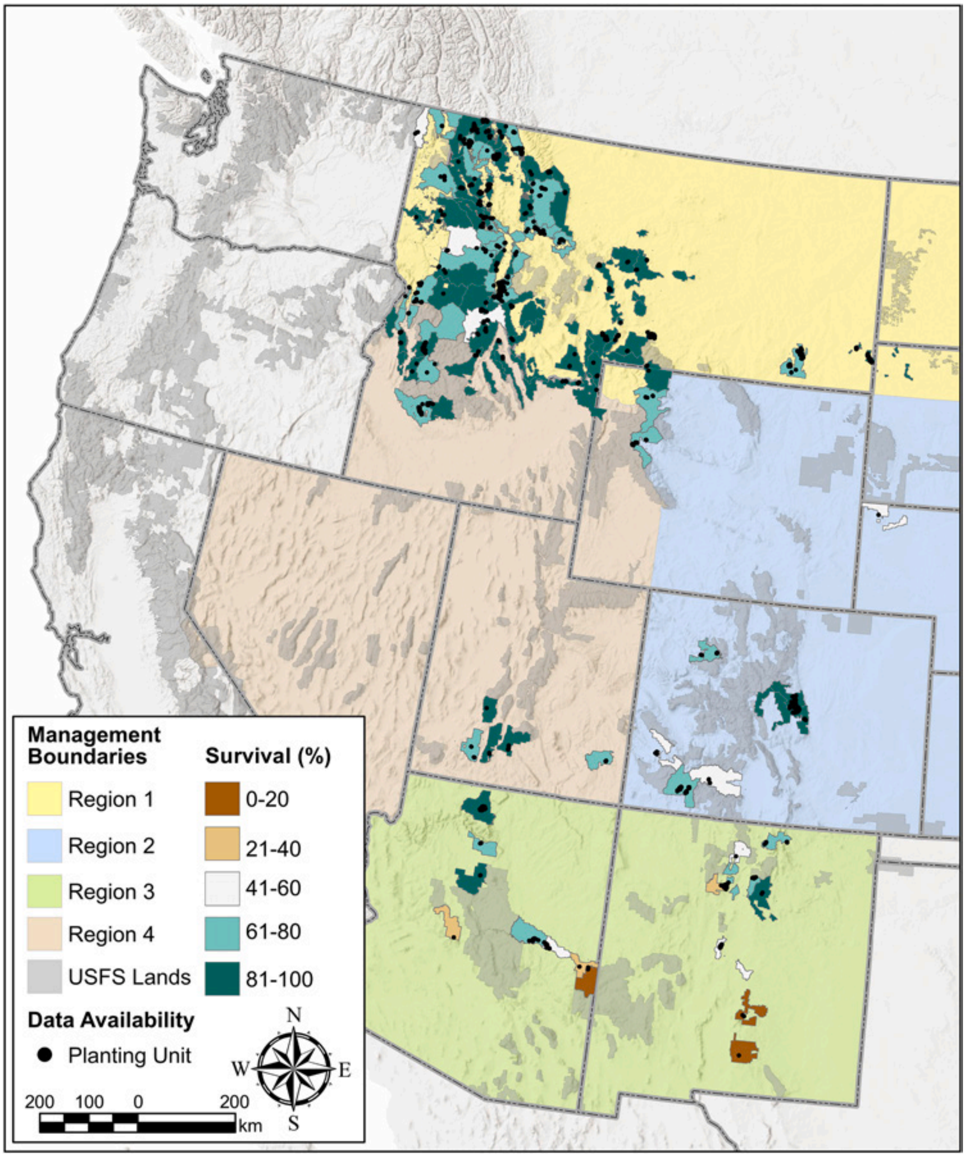

Fig. 5. Early seedling survival rates (i.e., one growing season after planting) from in-situ monitoring data within post-fire tree planting units in the US Interior West. Mapped survival rates give the value across all planting units within a USDA (United States Department of Agriculture) Forest Service Ranger District. Planting units (n = 1071 in 161 fires that burned from 1988 to 2021) were restricted to those in Forest Service Regions 1–4, and where field-inventoried survival data were available. CC: Canopy Cover; USFS: USDA Forest Service.

survival, whereas warm, dry conditions reduce survival (Rother et al., 2015). Similarly, post-fire moisture availability is strongly related to natural seedling establishment (Davis et al., 2023; Harvey et al., 2016b; Stevens-Rumann et al., 2018; Young et al., 2019) and remotely sensed patterns of vegetation recovery after fire (Bright et al., 2019; Vanderhoof et al., 2021). Unfortunately, the process of planning and implementing the various stages of reforestation – including collecting or growing seeds, raising seedlings, and planting trees – may take several years, so it can be difficult for managers to plan projects around uncertain weather events. However, factors such as typical environmental conditions at a site and the expected frequency of future drought events (e.g., McCullough et al., 2016; Triepke et al., 2019), could be readily incorporated into spatial prioritization tools (Holden et al., 2022; Rodman et al., 2022b; Stewart et al., 2021) to assess risk of planting failure. In addition, when flexibility in the timing of planting exists, leading indicators such as the El Niño Southern Oscillation (e.g., League and Veblen, 2006; Littlefield et al., 2020) may help forecast when early season conditions will be favorable for seedlings. Planting season is another important factor that managers can control, and we found that late summer or fall plantings may be less susceptible to drought events in the first year after planting (Fig. 7b).

Post-Fire Canopy Cover and Fire Severity also explained variation in our model of forest cover change (Fig. 3). Cover change was typically fastest in planting units that burned at low- to moderate-severity (i.e., relativized burn ratio (RBR) < 282; Parks et al., 2021) and had at least 20 % forest cover post-fire, likely because surviving trees influenced patterns of remotely sensed recovery. For example, sites with adjacent, surviving trees often have more abundant tree regeneration due to greater seed availability (Chambers et al., 2016; Gill et al., 2020). Growth and crown expansion of large, surviving trees could also have a strong influence on satellite-derived estimates of forest regrowth (Vanderhoof et al., 2021). Though natural forest recovery processes may be more likely in such areas, about 45 % of the planting units included in our data were in low- or moderate-severity areas or where forest cover after fire exceeded 20 %. Such areas might be planted due to accessibility, recreational value, or high suitability for timber production.

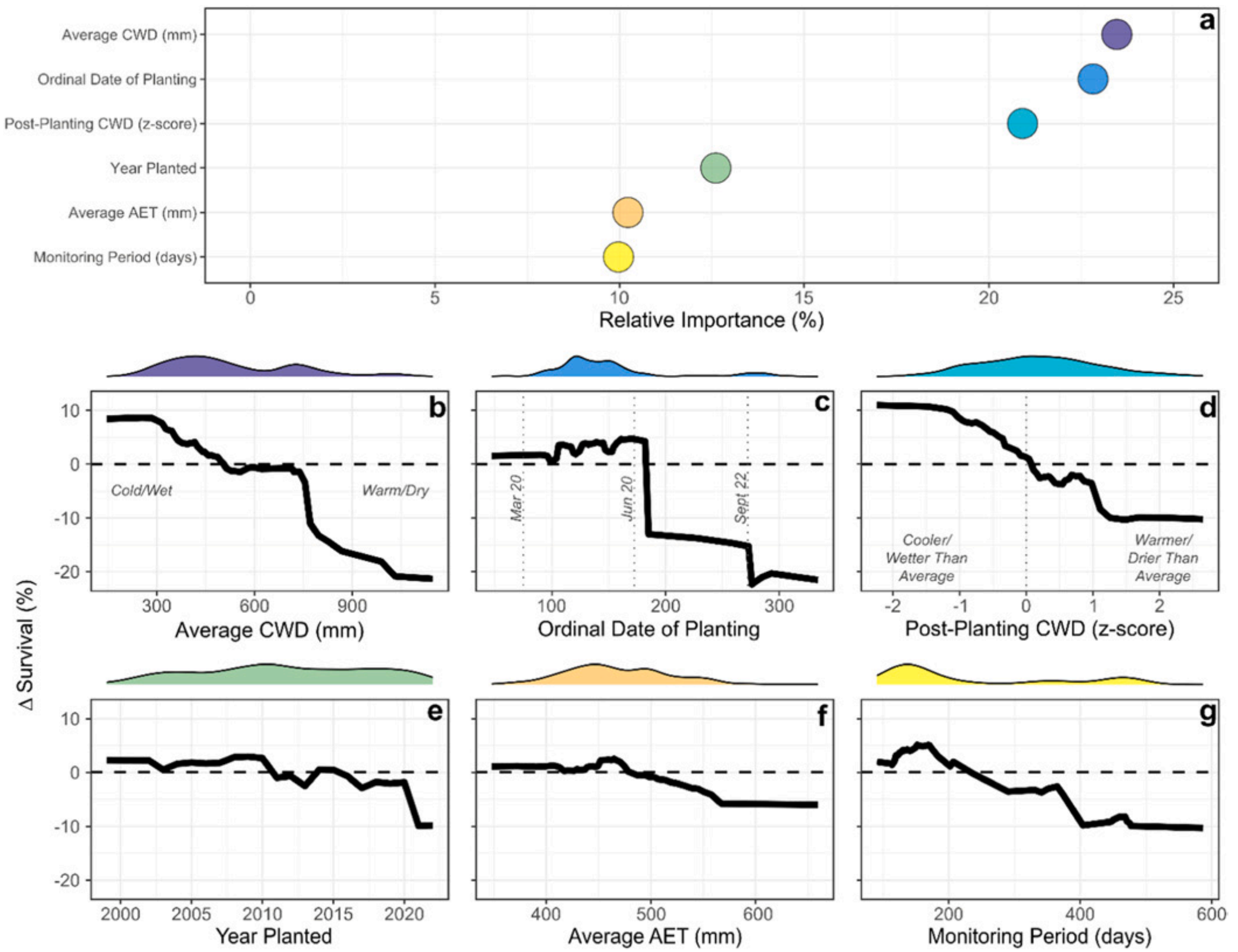

Fig. 6. Plots of (a) relative variable importance and (b-g) accumulated local effects showing results of the Random Forest model predicting early seedling survival rates (typically one growing season after planting) from in-situ monitoring data after post-fire tree planting in the US Interior West. In panels (b-g), the y-axis gives the change in predicted values (relative to the overall response mean) for a given value of the corresponding variable (x-axis), after accounting for the effects of other variables. When solid black lines are above dashed lines, they indicate a higher-than-average survival rate at the value of the corresponding variable (x-axis). Density plots above panels (b-g) show the distribution of the predictor variable across units. AET: Actual Evapotranspiration; CWD: Climatic Water Deficit.

Surprisingly, Fire Severity and Post-Fire Canopy Cover were not included in the final models of seedling survival, suggesting that their effects on survival may have differed across project sites. For example, high-severity fire can be associated with increases in shrubby vegetation on some sites, which has been found to both facilitate and compete with tree seedlings (Guiterman et al., 2018; Marsh et al., 2023). High forest cover can moderate microclimatic conditions experienced by seedlings (Davis et al., 2018; Wolf et al., 2021), but despite this microclimatic buffering, growth and survival of planted seedlings are not consistently higher in such areas, perhaps due to species traits (Hill et al., 2024). Indeed, shade-intolerant and early-seral tree species can benefit from low forest cover (Davis et al., 2023; Hoecker and Turner, 2022). Plantings in severely burned areas with low forest cover may become increasingly common over the upcoming years (Dobrowski et al., 2024), pointing to an urgent need to understand the drivers of planted seedling survival in these harsh sites.

4.2. Rates of Forest Cover Change and Early Seedling Survival

Overall forest cover change rates and early seedling survival numbers presented here generally align with findings from prior research. While we are aware of no other studies that have assessed the effects of post-fire tree planting on remotely sensed forest regrowth, planting is known to enhance recovery following other severe disturbances (Meli et al., 2017). For example, after clearcutting, tree planting led to increases in both forest height (+5.25 m) and forest cover (+15 %) relative to unplanted areas across the US West over a ca. 30-year period (Hoylman et al., 2021). Similarly, we found that areas planted following wildfires had about 15 % higher forest cover than unplanted areas after 30 years (Fig. 1a). Seedling survival rates previously reported following operational or experimental post-fire plantings range from 0 to > 90 % (Marsh et al., 2022; Marshall et al., 2024; Ouzts et al., 2015; Rother et al., 2015). Here, we report an average of ca. 80 % seedling survival. While this average is near the upper end of previously reported ranges, we attribute this to our study's unique focus on early seedling survival across a broad spatial extent. We focused on early survival because these data were the most consistent and widely available in USFS survival surveys. However, survival declines with time (Fig. 6g), and survival rates from longer-term studies are generally lower than short-term studies. (e.g., 25 % average survival from 5 to 9 years after planting in the Southwest; Ouzts et al., 2015). Additionally, much of the existing research on post-fire tree planting in the Interior West is from more arid states such as New Mexico (Table 1), where survival tends to be lowest (Fig. 5). Over half of the units included in our data

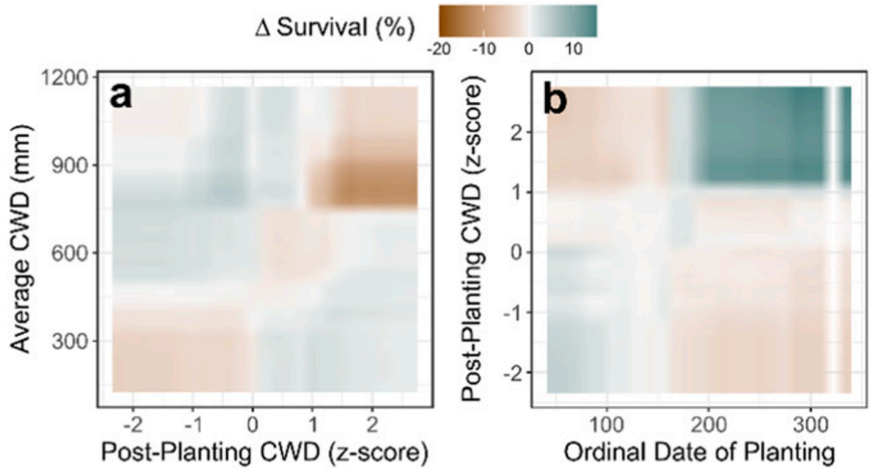

Fig. 7. Selected bivariate interaction showing results of the Random Forest model predicting early seedling survival rates (typically one growing season after planting) from in-situ monitoring data of post-fire planting units in the US Interior West. Colors give the change in predicted values (relative to the overall response mean) for given values of the corresponding variables (x- and y-axes), after accounting for the effects of other variables in the model. When colors are green, they indicate a higher-than-average cover change rate at the value of the corresponding variables (x- and y-axes). For other bivariate interaction plots, see Fig. S4.2. CWD: Climatic Water Deficit.

were from Montana and Idaho, where survival is comparatively high (Fig. 5).

4.3. Study Limitations and Future Research Needs

We assessed a wide range of environmental and operational variables that can influence forest regrowth and seedling survival at broad scales, but there are many additional factors that likely influenced planting success in our study area. The principles of the Target Plant Concept, which include matching seed collection, seedling production, and fine-scale planting practices with the expected environmental conditions at a site, are strongly related to planting outcomes (Dumroese et al., 2016). For example, drought-conditioning (Dixit and Burney, 2024; Pinto et al., 2023) or cold-hardening practices at the nursery (Grossnickle, 2012) can help to prepare seedlings for environmental extremes. Stock type (e.g., bare root seedlings vs. containerized seedlings; McDonald, 1991), seedling size/age (Dixit and Burney, 2024; Pinto et al., 2012, 2011), and fine-scale planting practices (Crockett and Hurteau, 2022; Marsh et al., 2023; Marshall et al., 2023; Rojas-Arévalo et al., 2021) can also have critical influences on survival and growth. Unfortunately, data on these various stages of the reforestation pipeline (*sensu* Fargione et al., 2021) were not consistently available for this study. Linking seed collection, nursery production, and project implementation data to project outcomes across broad areas is a critical area for future research.

Uncertain locations of planted trees or survival surveys within larger planting units likely weakened the relationship between response variables and covariates in our models, as both environmental conditions and planting outcomes can vary within units (Marshall et al., 2023), and survival can also be highly stochastic in local areas. However, despite a range of uncertainties in both response variables and predictors, we note that our model accuracies (e.g., out-of-bag R^2 values of 0.29 [cover change] and 0.42 [survival]) are within the general ranges reported in prior research. For example, environmental factors explained 2–70 % of the variation in post-fire spectral recovery (i.e., rates of recovery in Landsat-derived spectral indices) due to natural processes (Bright et al., 2019; Meng et al., 2015), and correctly classified recovery trajectories ca. 70 % of the time (Vanderhoof et al., 2021). Topographic variables explained 16 % of the variance (i.e., R^2 from random cross-validation) and 30 % of the deviance in planted seedling survival throughout the 2011 Las Conchas Fire, New Mexico (Marsh et al., 2022), whereas more detailed ecohydrological models explained ca. 70 % of the variance in planted seedling survival in sites across Montana and Idaho (Simeone et al., 2019).

Average CWD was the strongest predictor in each RF model, but some of this explained variation may reflect inter-regional variation in planting and nursery practices, including transportation distance and planting density. Southwest (i.e., Region 3) forests – which often have high Average CWD values – primarily utilize the Lucky Peak Nursery in Boise, Idaho for seedling production, requiring significant transportation distances of seedlings to project sites. Likewise, many Southwest forests have shifted to planting in the late summer or early fall, and it has been difficult to acquire seedlings that are conditioned for this planting season (J. Youtz, personal communication). Remotely sensed rates of forest cover change increase with seedling density (Fig. S1.2). Thus, variations in planting densities within and among regions may also influence cover change rates in ways that are difficult to disentangle from Average CWD and other drivers. Nevertheless, Average CWD is also negatively correlated with cover change and survival within most regions (where operational factors are more consistent), indicating that site conditions play an important role in planting outcomes.

5. Conclusion

Active reforestation is an issue of global relevance (Griscom et al., 2017; Meli et al., 2017), and tree planting following fire is of particular interest in the United States (Cook-Patton et al., 2020; Dumroese et al., 2019; United States Department of Agriculture, Forest Service, 2022), yet very little is known about the effectiveness of these efforts at regional to national scales. To address this need, we used a combination of remotely sensed forest cover change and in-situ survival records spanning nearly 300 individual fire events to describe the outcomes of recent (1987–2022) post-fire tree plantings across the US Interior West. The novel spatiotemporal extent of these data yielded important insights into the environmental and operational factors that influence success of planting. Average survival rates of planted seedlings were nearly 80 % after one growing season, and tree planting significantly enhanced rates of forest regrowth after wildfire in our study area. However, the effects of planting also varied markedly across broad environmental gradients, highlighting the need for consistent, post-planting monitoring that spans large areas and extended time periods. Understanding the drivers of such variability and its influence on forest ecosystem recovery is critical as rates of tree planting are likely to accelerate globally to achieve climate mitigation and restoration goals.

CRediT authorship contribution statement

Kyle C Rodman: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Paula J. Fornwalt:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Zachary A. Holden:** Writing – review & editing, Writing – original draft, Software, Methodology, Data curation, Conceptualization. **Joseph E. Crouse:** Writing – review & editing, Visualization, Methodology, Investigation, Formal analysis. **Kimberley T. Davis:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Laura A.E. Marshall:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Michael T. Stoddard:** Writing – original draft, Validation, Formal analysis, Data curation. **Robert A. Andrus:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Marin E. Chambers:** Writing – review & editing, Writing – original draft, Conceptualization. **Teresa B. Chapman:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Sarah J. Hart:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Catherine A. Schloegel:** Writing – review & editing, Writing – original draft, Conceptualization. **Camille S. Stevens-Rumann:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.foreco.2024.122358.

Data availability

Data, analytical code, and model outputs from this study are available through Zenodo via the following link: https://doi.org/10.5281/zenodo.13962941

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