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Fire in the Earth System

Assessing the Role of Snow Cover for Post-Wildfire Revegetation Across the Pacific Northwest

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Key Points:

- Summer precipitation, snow cover, and elevation are important drivers of post-fire revegetation success
- Snow cover was a critical explanatory variable for post-fire revegetation in the Oregon and Washington Cascades
- Strong correlations exist between winter snow cover and summer vegetation greenness in the lower snow zone in Montana and Idaho Rockies

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Abstract

Forested, mountain landscapes in the Pacific Northwest (PNW) are changing at an unprecedented rate, largely due to shifts in the regional climate regime. Documented climate warming trends across the PNW include increasing wildfire frequency and severity and an increasingly ephemeral snowpack, especially at moderate elevations. We analyzed 24 high severity wildfires across four distinct PNW mountainous subregions, examining snow-vegetation relationships for two years pre-fire and four years post-fire. To assess the importance of snow cover for revegetation compared to other climatic, topographic, and burn severity-related variables, binary regression tree models were constructed for the dominant pre-fire conifer species within each of the four PNW subregions. Summer precipitation consistently appeared as the most important variable driving post-fire revegetation across all four subregions. Snow cover variables (snow cover frequency and snow disappearance date), along with elevation, were shown to be secondary but significantly influential explanatory variables for revegetation in the Oregon and Washington Cascades. Revegetation was also analyzed using a time series of linear regressions across 200-m elevation bands by measuring correlations between winter snow cover and summer vegetation greenness. Results showed strong positive post-fire correlations at moderate elevations in the western Montana Rockies and at the lowest elevation band in the Idaho Rockies. Considering trends of increasing wildfire activity, lower snowpacks, and earlier snow disappearance dates across the PNW, forests will likely experience more frequent drought conditions that will impact post-wildfire vegetation regrowth.

Plain Language Summary

Wildfires continue to burn more area each year across many regions of the planet, including the Pacific Northwest. There are many short- and long-term effects from these fires, including erosion, debris flows, and water quality issues, which can affect the health of aquatic ecosystems and downstream community water supply. The persistence of these impacts is strongly related to reestablishment and recovery of vegetation in burned areas. However, post-wildfire revegetation in forested, mountainous landscapes is complex and depends on many factors, including fire severity, pre-fire vegetation, elevation, slope, aspect, rain, and snow accumulation and melt. Little is known about the linkages between these drivers and revegetation across the PNW. Our study illustrated that summer precipitation, snow cover, and elevation were all important drivers of revegetation success. In particular, we found that snow cover was a critical explanatory variable for revegetation in the Oregon and Washington Cascades. Given the trends of increasing wildfire activity, lower snowpacks, and earlier snow disappearance dates across the PNW, forests will likely experience more frequent drought conditions, which will impact the success of post-wildfire vegetation recovery.

1. Introduction

Forested, mountain landscapes in the Pacific Northwest (PNW) region of the USA (Washington, Idaho, Oregon, and western Montana) have been changing at an unprecedented rate due to dramatic shifts in the regional climate regime (Halofsky et al., 2020; Littell et al., 2010; Seidl et al., 2017; Spies et al., 2010). A warmer climate is expected to alter upland forest distributions, structure, and function, with substantial implications for water and carbon cycling (Anderson-Teixeira et al., 2013; Berner et al., 2017; Turner et al., 2017). Forest responses to climate change will also be driven by shifts in precipitation regimes, which will influence soil water storage and groundwater (Breshears et al., 2005; Harpold et al., 2012, 2015). Changes in climate have already increased the proportion of winter precipitation that falls as rain rather than

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snow, decreased the spring snow-water equivalent (SWE), and shifted the onset of snowmelt to earlier in the spring (Knowles, 2015; Mankin & Diffenbaugh, 2015; Mote et al., 2005, 2018; Safeeq et al., 2016). In the PNW, snow cover is especially vulnerable to climate change given that the majority of snow accumulates at air temperatures close to 0°C, which can impact precipitation phase (snow or rain) and snowpack ablation rates (Jennings et al., 2018; Nolin & Daly, 2006; Safeeq et al., 2016).

With rising temperatures, decreasing snowpacks and continued build-up of forest biomass, conditions for wildfires across western U.S. forested uplands have also become increasingly favorable (Abatzoglou & Kolden, 2013; Abatzoglou & Williams, 2016; Hanan et al., 2021; Parks & Abatzoglou, 2020; Reilly et al., 2017). Wildfire activity has increased substantially across the western United States in recent decades with evidence for larger and more severe fires (Dennison et al., 2014; Holden et al., 2018; Stavros et al., 2014). Moreover, wildfire season length has increased by about 25-day across the broader western US (Abatzoglou et al., 2020), including a five-fold increase (i.e., 23 days during 1973–1982 to 116 days during 2003–2012) in the PNW over the last four decades, which is primarily attributable to warmer temperatures and drier conditions in the spring and summer (Westerling, 2016). While wildfire activity has intensified rapidly in the past several decades, evidence from longer-term reconstructions of the annual area burned suggests the risks associated with high severity wildfire could continue to rise (Murphy et al., 2018). Additionally, long-term global model projections suggest that fire activity across temperate forest regions of the western U.S. is likely to continue increasing under future climate scenarios (Barbero et al., 2015; Flannigan et al., 2013; Moritz et al., 2012).

After the occurrence of a wildfire, revegetation over the burned area is critical to maintain or re-establish ecosystem functions from forests such as biodiversity, erosion control, water purification, and habitat provision (Crotteau et al., 2013; Hallema et al., 2018; Robinne et al., 2020; Turner et al., 2013). However, climate change projections and shifting wildfire regimes have increased concerns about post-fire regeneration (Bowman et al., 2020; Halofsky et al., 2020) and, as such it is imperative that we broaden our understanding of the role of snowpacks in post-wildfire forest regeneration. This is especially true given that over 80% of western U.S. wildfires from 2000 to 2012 occurred within the seasonal snow zone (Gleason et al., 2013) and there was a 9% annual increase in burned forest area since 1984 (Gleason et al., 2019). Moreover, Gleason et al. (2019) documented that charred forests in the seasonal snow zone experience a four-times greater rate of radiative heating and significantly earlier snowmelt when compared with unburned forests. While previous research has shown the critical importance of snow prior to wildfire (Westerling et al., 2006), and the impact of charred forests on snowmelt patterns, there has been limited research on relationships between snow and post-fire revegetation. A number of studies that examined post-fire seedling regeneration following the 1988 fires in the Yellowstone region found that climate is a major predictor of seedling establishment (Hansen & Turner, 2019; Hansen et al., 2016; Kemp et al., 2019) and although they considered both temperature and precipitation, they did not specifically examine the role of snow. Little et al. (1994) noted that, in the Mount Rainier region, snowpacks lasting into the late spring had a negative relationship with post-fire subalpine fir seedling establishment. McIlroy and Shinneman (2020) focused on regeneration of aspen stands in moisture limited regions from the Great Basin to Yellowstone. They found that winter precipitation, especially snow, was positively correlated with aspen regeneration. In contrast, both Talucci et al. (2019) and Werner et al. (2019) identified negative relationships with between snow accumulation and conifer seedling recruitment. Vanderhoof et al. (2021) and Vanderhoof and Hawbaker (2018) illustrated that snow cover was the main predictor of evergreen versus deciduous post-fire forest regeneration. However, none of these studies evaluated both pre- and post-fire snow-vegetation relationships, which are critical for understanding how fire and climate change are modifying these fundamental relationships.

Our study builds upon underlying ecohydrological relationships that link snow accumulation to summer forest greening. For example, in western U.S. mixed-conifer forests, Molotch et al. (2009) found that photosynthetic activity was significantly correlated with soil water availability, which is often influenced by snowpack accumulation (Barnhart et al., 2020) and snow disappearance date (Harpold et al., 2015; Molotch et al., 2009). Littell et al. (2008) also identified post-snowmelt soil water supply as the most important variable controlling growth in northwestern Douglas-fir dominated forests. Similarly, results from a tree-ring and snow analysis in the Oregon Cascades suggested that late summer moisture stress in Douglas-fir and mountain hemlock was related to snow from the prior winter, in addition to summer vapor pressure deficit

(Ratcliff et al., 2018). However, the dependency on moisture availability often diminishes with increasing elevation as forests shift to an energy-limited state with snowpacks persisting deeper into the growing season (Christenson et al., 2008; Goulden & Bales, 2014).

Considering the connections between snow and soil moisture along with the correlation between soil moisture and forest health, it is logical to hypothesize that a transitive relationship exists between snow and forest health. Indeed, work by Trujillo et al. (2012) supports this notion, as snow accumulation was shown to influence peak summer forest greenness, especially at moderate elevations from 2,000 to 2,600 m. Similarly, common subalpine tree species such as subalpine fir (*Abies lasiocarpa*) and Engelmann spruce (*Picea engelmannii*) have been found to depend on snowmelt water for productivity during the growing season, with longer growing seasons (i.e., earlier snow disappearance dates) leading to lower amounts of carbon sequestration (Hu et al., 2010). Considering trends of decreasing snowpacks and climate projections indicating warmer winters across much of the western U.S., understanding the influences of snowpack on forest productivity will be beneficial as regional climate regimes continue to shift.

As western forests continue to experience elevated rates of wildfire activity, these disturbances have the potential to impact long-term forest health by influencing the snowpack-forest greening relationship and the ability of forests to regenerate effectively. Consistent with the known relationship between forest greenness and soil moisture in undisturbed forests, high soil moisture has been positively correlated with post-wildfire vegetation self-replacement and forest recovery (Johnstone et al., 2010). The re-establishment of vegetation in the early years following disturbances is critical to the long-term health of post-fire forest ecosystems (Johnstone et al., 2016). Multiple studies have found post-fire seedling recruitment is predictive of future forest density (Donato et al., 2016; Stevens-Rumann et al., 2018). Importantly, attainment of sufficient tree regeneration is strongly influenced by climatic conditions during the early life stages of newly recruited tree seedlings (Enright et al., 2015). Therefore, local climate conditions, such as snow accumulation and persistence, may be critical factors in determining the resilience of forests undergoing disturbances with increasingly variable climate regimes.

Our study focused on the effects of severe wildfire on the relationship between antecedent snow accumulation and summer greening of vegetation across the Columbia River Basin (CRB) in the northwestern United States. Specifically, we addressed the following research questions:

How important is snow cover for post-wildfire revegetation compared with topographic, climatic, and ecological variables?

To what degree is post-wildfire greening correlated with snowpack across varying mountain regions, pre-fire forest types, and elevation bands across the Pacific Northwest?

2. Materials and Methods

2.1. Study Area

The Columbia River Basin (CRB) is the largest watershed in the Pacific Northwest, encompassing over 670,000 square kilometers (Figure 1). It contains an array of wildfire-prone landscapes (>850 wildfires since 2010), while providing source water to millions of people across seven Western US states and critical habitat for >700 species, making it a unique and important region to study. Mountainous landscapes constitute much of the CRB, including the Cascades in Oregon and Washington and the Rocky Mountains of Idaho and western Montana. Across these four subregions, snow accumulation and snowmelt play a key role in the respective ecohydrology, although each site is defined by unique topographical, climatic, and ecological conditions. Wildfires have the potential to significantly alter watershed hydrology through more variable annual water yields and baseflows, increased peak flows, and altered streamflow timing (Bladon et al., 2014; Hallema et al., 2018; Niemeyer et al., 2020).

Within the CRB, where cold, wet winters contrast with warm, dry summers, such seasonality likely can magnify these hydrologic regimes. Considering the vast amount of land in the northwestern U.S. experiencing shifts in seasonal snowpacks and increased wildfire activity, we used the CRB boundary to provide a relevant framing of the post-wildfire snowpack-revegetation relationship. Specifically, we focused on snow and post-fire revegetation in the CRB because (a) the region has extensive forests in the seasonal snow zone,

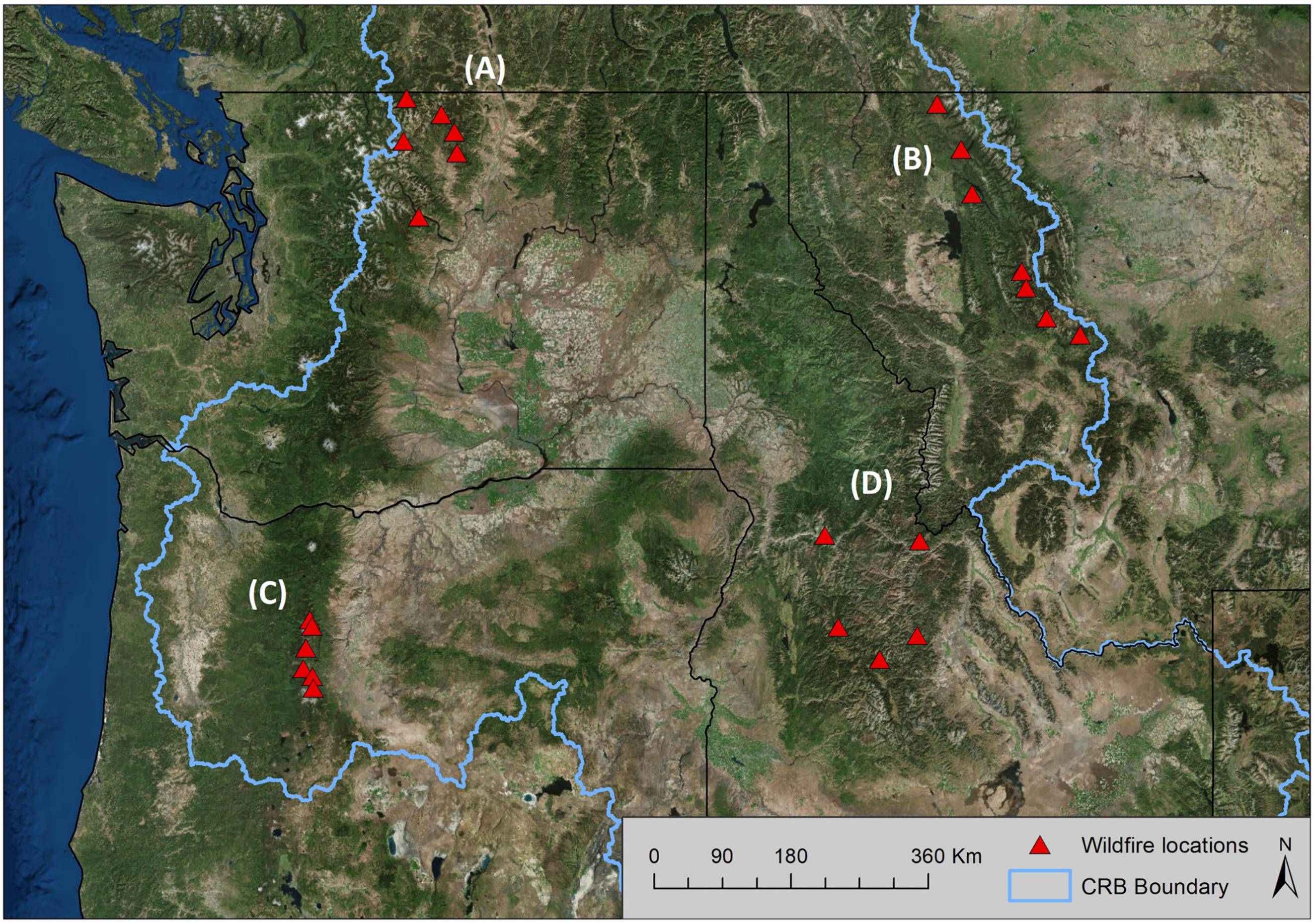

Figure 1. Map of the Columbia River Basin boundary and four subregions of this study: (a) WA Cascades, (b) MT Rockies, (c) OR Cascades, and (d) Central ID.

(b) Pacific Northwest snowpacks have experienced the greatest declines of any seasonal snow region in the western USA, and (c) the extensive CRB land cover change resulting from extensive wildfire has the potential to significantly alter the hydrology of this important river basin.

Table 1 lists the fires used in this study and their characteristics. The fires located in the Washington Cascades subregion extended in latitude from about 48.0°N to 48.9°N and ranged in elevation from about 400 to 2,400 m. This subregion includes the headwaters of major tributaries to the Columbia River, including the Methow, Chelan, Entiat, and Wenatchee Rivers. The fires were located on the eastern slopes of the Cascade Range, where the 30-year normal (1981–2010) annual precipitation decreases with distance east from the Cascade crest due to rain shadow effects, ranging from about 1,800 mm in western, higher elevation forests to about 500 mm over the eastern, lower elevation forests (PRISM Climate Group, 2019). The most extensively burned forest types across the Washington Cascades were interior Douglas-fir (*Pseudotsuga menziesii* var. *glauca*), a mix of Engelmann spruce (*Picea engelmannii*) and subalpine fir (*Abies lasiocarpa*), and whitebark pine (*Pinus albicaulis*).

Fires across the Oregon Cascades subregion spanned latitudes from 44.1°N to 44.7°N and elevations from 700 to 2,100 m. Notable drainages near and in the study area include the McKenzie, Santiam, and Deschutes Rivers. Like the Washington subregion, all wildfires in the Oregon Cascades occurred along the eastern slopes of the range, where average annual precipitation decreases with distance east from the crest of the range. Here, the 30-year normal annual precipitation varied from 2,300 mm in the western, higher elevation forests to 400 mm in the lower elevation forests (PRISM Climate Group, 2019). Burned forests consisted mostly of grand fir (*Abies grandis*), mountain hemlock (*Tsuga mertensiana*), and a mix of western hemlock (*Tsuga heterophylla*) and silver fir (*Abies amabilis*).

Table 1
List of Fires Included in Regression Analyses, Along With Fire Year, Burn Severity, and Area Burned

				%Catchment area in burn severity category			
Region	Fire name	Fire year	Size (km^2)	High	Moderate	Low	Unburned
WA Cascades	Needles	2003	77	40	19	14	27
	Fawn Peak	2003	313	53	17	10	18
	Pot Peak	2004	152	25	28	27	21
	Spur Peak[a]	2006	466	42	26	22	8
	Tripod[a]	2006	242	36	24	22	18
	Tatoosh[a]	2006	199	47	28	19	6
MT Rockies	Bartlett Mountain[a]	2003	112	32	24	25	15
	Blackfoot Lake [a]	2003	74	26	31	27	16
	Little Salmon Ck[a]	2003	134	16	25	37	22
	Robert[a]	2003	221	22	26	29	9
	Snowbank[a]	2003	150	48	20	19	11
	Wedge Canyon[a]	2003	210	31	36	25	6
	Conger Creek	2007	93	26	31	23	19
OR Cascades	B&B[a]	2003	369	5	30	46	18
	Black Crater	2006	38	20	32	32	16
	Biddle Pass	2007	57	25	24	30	20
	GW	2007	55	50	22	12	16
	Pole Creek	2012	109	30	29	30	11
	Waterfalls	2012	51	31	28	31	10
Central ID	Rattlesnake[a]	2007	415	13	16	35	35
	Monumental [a]	2007	1,283	31	17	14	19
	Shower Bath[a]	2007	206	33	17	18	31
	Halstead	2012	770	22	21	31	20
	Mustang	2012	1,528	22	19	27	20

Note. All fires were included in the regression tree component.
[a]Included in the temporal regression component.

Fires in the Idaho Rockies subregion spanned latitudes from 44.3°N to 45.5°N and elevations from 700 to 2,900 m. Centered in the Sawtooth and Salmon River Ranges, the study area includes lands in the heart of the Salmon River sub-watershed, within the greater Snake River basin. Wildfires in this subregion occurred across forested landscapes that received 400–1,270 mm of annual precipitation according to the 30-year normal (PRISM Climate Group, 2019). Like the Washington Cascades, the burned forest types in the Idaho region consisted primarily of Douglas-fir, Engelmann spruce-subalpine fir, and whitebark pine.

Fires in the Western Montana Rockies subregion spanned latitudes ranging from 46.9°N to 48.9°N and elevations from about 1,000 to 2,400 m. The fires in this study area were distributed latitudinally in the primarily north-south oriented Flathead River watershed and occurred mainly in the Lewis Range and Flathead Range. Across the Western Montana wildfires, 30-year average annual precipitation varied from about 500 to 1,800 mm and was largely dependent on elevation (PRISM Climate Group, 2019). In this region, burned forests were composed primarily of Douglas-fir and Engelmann spruce-subalpine fir.

2.2. Data Descriptions

Snow cover characterization was estimated using a new snow cover frequency (SCF) product as described in Crumley et al. (2020) and Nolin et al. (2021). SCF was derived from the Moderate Resolution Imaging

Spectroradiometer (MODIS) snow cover product, which uses daily satellite imagery to identify snow-covered land at a resolution of 500 m. For each unique pixel, SCF was calculated by dividing the total number of snow-covered days by the total number of valid observations over a user-defined timespan. The SCF metric has previously been related to SWE (Crumley et al., 2020) based on the assumption that a pixel with high SCF likely received higher SWE compared to pixels with low SCF under the same climatic conditions. Unlike SWE data from Snow Telemetry (SNOTEL) sites, the SCF data are gridded and spatially consistent and contiguous. Nolin et al. (2021) found that MODIS-derived SCF was far more sensitive to differences between high, average, and low snow years than SNOTEL-derived SCF. Snow disappearance date (SDD) was also considered for this study as a proxy for spring snowmelt timing. However, a preliminary analysis showed a much stronger relationship between SCF and greenness compared to the relationship between SDD and greenness. SDD had low interannual variability and low (daily) precision whereas SCF ranged from 0.00 to 1.00 and had higher precision. Thus, we chose to use only SCF as a snow metric. For this study, we calculated SCF annually from January 1 to July 1. For more detailed information on the SCF algorithm and its derivation in Google Earth Engine, see Crumley et al. (2020).

Pre- and post-fire forest greenness was measured using the Enhanced Vegetation Index (EVI) MODIS product (Huete et al., 2002). EVI is calculated using red, infrared, and blue wavelength bands to estimate canopy greenness. EVI is relatively sensitive to physiological differences in vegetation canopy features, such as leaf area index, phenology and stress, chlorophyll content, and canopy structure (Huete et al., 2002; Waring et al., 2006). As a result, EVI has lower canopy background variation and improved sensitivity over dense vegetation compared to other vegetation indices (e.g., NDVI), which has facilitated its use for previous post-fire vegetation monitoring studies (Lu et al., 2015). We recognize that while EVI is preferred for dense vegetation conditions, the NDVI may be more sensitive to biomass changes in the post-fire environment, when vegetation is sparse (Lu et al., 2015). However, it was important to be consistent in the vegetation index we used, therefore we used EVI for both pre- and post-fire greenness estimates.

We acquired EVI images as 16-day composites at a resolution of 500 m. For each year, we compiled and processed EVI composites between June 1 and October 1 to extract the maximum summer EVI value for each pixel. The June–October date range was selected to increase the likelihood of capturing the peak photosynthetic activity across the variety of forest types in the study region.

Wildfire burn severity and burn perimeter data were acquired from the Monitoring Trends in Burn Severity (MTBS) project (https://www.mtbs.gov/). MTBS burn severity data are developed from pre-fire and post-fire 30 m resolution Landsat images optimally selected for peak photosynthetic activity and proximity of dates between years. For both pre- and post-fire images, the Normalized Burn Ratio (NBR) (Key & Benson, 2006) is calculated using the near infrared (NIR) and shortwave infrared (SWIR) bands as:

$$\mathrm{NBR} = \frac{\mathrm{NIR} - \mathrm{SWIR}}{\mathrm{NIR} + \mathrm{SWIR}} \tag{1}$$

This ratio is an effective metric for measuring burn severity as the NIR wavelength is especially sensitive to changes in photosynthetic activity, while SWIR is sensitive to post-wildfire soil condition alterations such as shifts in soil water content and presence of ash and charred wood (Miller & Thode, 2007). We used NBR to quantify burn severity according to the relativized delta Normalized Burn Ratio (RdNBR) (Miller & Thode, 2007). To do this, we differenced the pre- and post-fire NBR images to produce an NBR change (dNBR) image. The dNBR image was then relativized using the following formula:

$$\mathrm{RdNBR} = \frac{\mathrm{dNBR}}{\sqrt{\left|\frac{\mathrm{NBR}_{\mathrm{prefire}}}{1000}\right|}} \tag{2}$$

The relative nature of this product is rooted in the inclusion of pre-fire NBR, thereby reducing the vegetation density bias that exists in the absolute dNBR product (Miller & Thode, 2007). We selected and used the RdNBR product since fires were analyzed across varying landscapes and timeframes. RdNBR data were resampled to 500-m spatial resolution using ENVI 5.4 software. Pixels were resampled using the pixel aggregate method, which calculates the average of underlying 30-m pixels within each 500-m pixel, weighted by the fraction of the underlying pixel falling within the 500-m pixel. Along burn perimeters, 500-m pixels were only generated when the 30-m data covered the resampled pixel centroid.

To characterize pre-fire species compositions, we used the LANDFIRE Existing Vegetation Type (EVT) data set (Rollins, 2009). The EVT data layer combines Landsat imagery, field data, decision tree models, and biophysical gradient data. We resampled the 30-m EVT categorical data to 500 m using a majority resampling method. Because the majority resampling method only used a 9 × 9-pixel window to calculate the majority value, we conducted three resampling iterations to achieve a representative 500-m vegetation type layer, resampling the original 30-m data to resolutions of 90, 270, and 500 m.

We quantified pre-fire canopy coverage using the LANDFIRE Existing Vegetation Cover (EVC) data set. Like the EVT layer, 30-m Landsat imagery is combined with training data to produce a vertically projected percent canopy cover layer for tree, shrub, and herbaceous vegetation types. Original grid cell values ranged from 100 (0% tree cover) to 109 (90%–100% tree cover) representing decile ranges of tree cover. We reclassified these values as the midpoint of each percentage range to make them more interpretable. For example, an original value of 100 (0% tree cover) was reclassified as zero, an original value of 102 (20%–30% tree cover) was reclassified as 25, and an original value of 108 (80%–90% tree cover) was reclassified as 85. Since this study was concerned with forested land cover, all grid cells containing only herbaceous and shrub cover were reclassified to zero before further analysis. Following these reclassifications, the EVC layer was resampled to 500 m to match the other data layers by using the pixel aggregate method in ENVI 5.4.

To quantify elevation, we used a digital elevation model (DEM) generated using topographic data from NASA's Shuttle Radar Topography Mission (SRTM). The original data were resampled from 30 to 500 m to maintain consistency among data layers. The original DEM was also used to generate slope and aspect layers, which were then resampled to 500 m to match the MODIS resolution. The aspect layer was reclassified broadly to indicate the pixel's aspect, with values ranging from 1 (north-facing) to 6 (south-facing) with intermediate values indicating either east- or west-facing slopes.

Between the dates of snow disappearance and peak summer greenness, rainfall provides critical additional moisture that may be transpired by regenerating vegetation. To provide a quantitative estimate of this input, we used PRISM monthly precipitation data at 800-m spatial resolution (Daly et al., 2002; PRISM Climate Group, 2019). Summer total precipitation amounts were created by summing the monthly precipitation amounts for June, July, and August.

2.3. Binary Regression Tree Analysis

To determine the degree of importance of several topographic, climatic, and ecological variables to post-fire revegetation, we constructed a series of binary regression trees for each of the four CRB subregions. Tree creation was performed in R using the recursive partitioning (rpart) package (Therneau et al., 2019). Regression trees are especially useful when dealing with complex processes involving many interacting variables. Past studies have successfully used regression trees to monitor post-disturbance regrowth, although without the inclusion of snow cover variables (Chen et al., 2011; Liu, 2016). Binary regression trees use a machine-learning approach to construct a regression model through a series of recursive splits into subgroups until no further improvements can be made in the model. Tree construction is initiated by splitting the data set into two subgroups using the single variable that most effectively splits the data. From this point, each subgroup is partitioned with separately applied iterations, ultimately creating a full regression tree with an abundance of terminal groups. The full tree is then pruned back to a level of complexity that minimizes the cross-validated error.

While regression trees are often used to create prediction models, we used regression trees to better understand the underlying processes driving post-fire revegetation. In developing the regression tree, the relative importance of each independent variable was calculated by summing the goodness of split values each time a variable was used for a split. The relative importance measures were then scaled to sum to 100, so they could be interpreted as a percentage of influence when building the final regression tree.

To accompany the relative importance values, we also report R^2 values for both the complete and pruned regression trees. Of interest are the R^2 values associated with the appropriately pruned tree, which was trimmed back to the number of splits where the cross-validated error reached a minimum. Without pruning, R^2 values would continually increase with each additional split even if the fit of the regression model was not improved. Therefore, it is important to only consider the R^2 values for the tree size at which point any further splitting would not improve the model fitness. To summarize, R^2 values reported in the results reflect how well the pruned regression tree models fit the datasets.

To determine the relative influence of a suite of environmental variables on post-fire regrowth, regression trees were grown and pruned for each of the four CRB mountain regions using the cross-validation pruning process. Since the dependent variable of this analysis was post-disturbance revegetation, we only considered pixels with a 50% decrease in EVI from pre-to post-fire, as revegetation was not expected in pixels where a minimal decrease in vegetation density had occurred. We used the dependent variable to estimate post-fire revegetation of highly burned pixels using the normalized EVI-based recovery metric, as follows:

$$\mathrm{EVI}_{\mathrm{recovery}} = \frac{\mathrm{EVI}_{\mathrm{post4}} - \mathrm{EVI}_{\mathrm{post1}}}{\mathrm{EVI}_{\mathrm{pre1}} - \mathrm{EVI}_{\mathrm{post1}}} \quad (3)$$

The EVI recovery variable was quantified by first calculating the difference between EVI at four years and one year post-fire, which served as a proxy for post-fire vegetation growth. The four-year post-fire timeframe was dictated by the overlap of MODIS data availability (2001–2016) and the final year of high wildfire activity within the study area which occurred in 2012. This value was divided by the difference between the pre-fire EVI and the one-year post-fire EVI to standardize the growth to reflect revegetation with respect to pre-fire conditions. For instance, if the pre-fire EVI was 0.4, the one-year post-fire EVI was 0.2, and the four-year post-fire EVI was 0.3, the EVI recovery value would be 0.5, indicating 50% revegetation compared with pre-fire conditions. While we could not quantify the specific revegetation type, this analytical approach provided a useful approximation of vegetation health and vigor across severely burned post-fire landscapes.

We assigned the threshold for vegetation density loss at 50%, thereby only including severely burned pixels in the regression tree analysis. Regression trees were grown using lower vegetation loss thresholds (40%, 30%, and 25%); however, with each respective decrease in threshold, cross-validated R^2 values decreased, indicating that the selected independent variables were not as well suited to explain revegetation within low-to moderately burned forests. Any significant increase in the threshold over 50% would have resulted in too few data points (<100) for meaningful regression tree results.

All independent variables were derived and compiled using remotely sensed data (Table 2). Climatic variables included both snow cover and precipitation-related statistics. The SCF anomaly during the first post-fire snow season was calculated by subtracting the average SCF over the available data years (2001–2016) from the post-1 SCF value. Additionally, over the three immediate post-fire years, the average SCF anomaly was calculated to capture longer term snowpack effects. Only three post-fire years were included in this variable to complement the dependent variable, which measures peak EVI during the fourth post-fire year.

To capture the effects of non-snow precipitation, the summer (June–August) precipitation anomaly during the year immediately following the wildfire was calculated using the 800-m PRISM data. Similar to SCF, this variable was constructed by subtracting the average summer precipitation from 2001 to 2016 from the first post-fire year summer precipitation. The summer precipitation anomalies for the three years immediately following the fire were averaged to create the "post-3" mean summer precipitation anomaly variable.

Topographical explanatory variables considered during tree construction were elevation, slope, and southness. To measure vegetation effects on regrowth, three variables were included. Pre-fire forest cover was created from the EVC canopy cover layer. Although we only included high burn severity pixels in regression tree construction, burn severity (RdNBR) was also included to capture variability that occurred above the burn severity threshold. Additionally, burn severity standard deviation was calculated to approximate distance to seed source, with the assumption that greater variability in burn severity allows for more effective seed dispersal into high severity burn zones. This variable was constructed through two processing steps. First, for each 30-m pixel, standard deviation was calculated over an encompassing 16 × 16-pixel neighborhood (480 × 480 m) centered on each respective pixel. The 16 × 16 pixel dimensions were chosen in anticipation of the second step, resampling from 30 to 500 m to match the resolution of the accompanying variables. Resampling was conducted using the nearest neighbor method, so that in the final image the

Table 2
List of Variables and Associated Details Used in the Construction of Regression Trees

Variable	Role	Units	Variable description
Revegetation	Dependent	Unitless	Reflects post-fire revegetation using the following formula: $(EVI_{post4}–EVI_{post1})/(EVI_{pre1}–EVI_{post1})$
SCF post-1 anomaly	Explanatory	Unitless	Difference between SCF post-fire year 1 and SCF average from 2001 to 2016
SCF post-3 mean anomaly	Explanatory	Unitless	Average SCF anomaly over first 3 post-fire years
Summer precipitation post-1 anomaly	Explanatory	Millimeters	Difference between summer (June–August) precipitation post-fire year 1 and summer precipitation average from 2001 to 2016
Summer precipitation post-3 mean anomaly	Explanatory	Millimeters	Average summer precipitation anomaly over first 3 post-fire years
Elevation	Explanatory	Meters	SRTM elevation data
Slope	Explanatory	Unitless	SRTM-derived slope data
Southness	Explanatory	Unitless	Degree of southness ranging from 1 (north-facing) to 6 (south-facing).
Pre-fire vegetation cover	Explanatory	Unitless	Percentage value reflecting pre-fire canopy coverage
RdNBR variability	Explanatory	Unitless	Standard deviation of 16 × 16 grid of 30 m cells within each 500 m cell
RdNBR	Explanatory	Unitless	Relativized measure of burn severity

value of each 500 m pixel indicates the standard deviation of the underlying 16 × 16 window of 30 m burn severity data.

2.4. Temporal Regression Analysis

To measure the degree of correlation between snowpack and forest greening before and after a wildfire, we conducted a series of linear regressions spanning pre- and post-fire years for selected wildfires within each subregion (Table 1, noted with an asterisk). These fires were selected because they covered large areas and the forests experienced moderate to high burn severity. Multiple fires were combined for each subregion except for the Oregon Cascades, where the extensive B&B Complex Fire was large enough in area to provide a sufficient sample size. As with the regression tree analysis, data were separated by forest types to account for varying phenologies and fire-adaptive traits. The same dominant forest types were used from the regression tree models to maintain consistency between analyses. For each forest type within each of the selected wildfires, maximum EVI was plotted versus SCF for the two years preceding each fire and the four years following each fire. Regression statistics were not calculated during the disturbance year, as maximum summer EVI values were likely unrepresentative if early or mid-summer fires occurred before peak forest productivity. The timeframe for this portion of the analysis was dictated by the overlap of MODIS data and the occurrence of high wildfire activity across the study area. Complete MODIS data were only available from 2001 to 2016, so the number of pre- or post-fire years was limited for some wildfires. For example, one of the most active wildfire years was 2003, which only allowed for two years of pre-fire MODIS data.

Since our study was focused on forested landscapes, we only included pixels if the pre-fire forest cover was greater than 30%. Data points were further constrained to moderately and highly burned forest by only including pixels where summer maximum EVI decreased by at least 25%. The EVI loss metric was used as a threshold rather than burn severity (RdNBR) to maintain consistency with the regression tree analysis. However, burn severity data were used to inform the 25% EVI loss threshold choice. EVI loss percentage was plotted against burn severity values for each subregion to determine the EVI loss value that best represented the moderate burn severity threshold (RdNBR > 315) recommended by Miller and Thode (2007). While the regression tree analysis only included high burn severity pixels, this portion of the analysis was expanded to include moderate burn severity pixels, primarily to include enough data points within each forest type for a robust time series of linear regressions. Lastly, within each forest type, data were stratified into 200-m elevation bands to quantify the variability in correlations with elevation.

3. Results

3.1. Regression Tree Analysis

3.1.1. Washington Cascades Subregion

For the six wildfires from the Washington Cascades included in our study, we developed regression tree models for the three dominant pre-fire forest types, including Douglas-fir, Engelmann spruce/subalpine fir mix, and whitebark pine. Overall, our analyses indicated that summer precipitation in the first post-fire year was the most influential variable for regenerating vegetation for all three primary forest types, with other explanatory variables shifting in importance depending on forest type (Figure 2).

In the lowest elevation Douglas-fir forest type, the regression tree model described the variability in vegetation regrowth moderately well ($R^2 = 0.42$; $p < 0.01$). Summer precipitation variables had the highest relative importance (RI), describing a combined 34% of the post-fire vegetation regrowth. Snow cover variables (RI = 26%) and elevation (RI = 19%) were moderately influential variables. All other independent variables had little influence (RI < 10%) on post-fire revegetation.

In the mid-elevation Engelmann spruce/subalpine fir forest type, the model also performed moderately well in describing the post-fire vegetation regrowth ($R^2 = 0.42$; $p < 0.001$). Summer precipitation variables were again the most important regression tree variable (RI = 37%). Multiple moderately influential variables were suggested by the model, including slope (RI = 14%), burn severity (RI = 12%), burn severity heterogeneity (RI = 10%), elevation (RI = 10%) and snow cover (RI = 10%). Southness and pre-fire canopy cover displayed minimal contributions (RI < 10%) to the regression tree construction.

Among all the vegetation types and regions, the regression tree model for whitebark pine-dominated pixels in the Washington Cascades was most effective at describing the variation in post-fire revegetation ($R^2 = 0.76$). Snow cover and summer precipitation variables were the four most important factors in constructing the regression tree, combining for an RI of 85%. Summer precipitation was again the most influential variable with an RI of 48%. Snow cover also contributed significantly to regression tree construction (RI = 38%). All other variables were suggested by the model to be minimally influential for post-fire revegetation (RI < 5%).

3.1.2. Oregon Cascades Subregion

Regression tree models for the Oregon Cascades were grown and pruned for the three dominant pre-fire forest types within the perimeters of the six selected fires. Listed from lowest to highest average elevation, these species were grand fir, western hemlock/silver fir mosaic, and mountain hemlock. The grand fir model fit the data quite well ($R^2 = 0.70$). Summer precipitation, snow cover, and topography were all shown to be relatively important explanatory variables for post-fire regrowth.

For grand fir-dominated pixels, snow cover was shown to be most important explanatory variable (RI = 35%). Summer precipitation (RI = 29%) and slope (16%) were also significant contributors to model construction. All other independent variables were shown to have little influence (RI < 10%) on post-fire revegetation.

For pixels where pre-fire forest type was a mosaic of western hemlock and silver fir, the model performed moderately well ($R^2 = 0.32$). Summer precipitation, snow cover, and topographic variables were responsible for 100% of the regression tree construction. Summer precipitation variables were shown to be the most important regression tree components (RI = 38%), while snow cover variables were nearly as important (RI = 31%). Various moderately influential variables were suggested by the model, including slope (RI = 14%), burn severity (RI = 12%), burn severity heterogeneity (RI = 10%), and elevation (RI = 10%). All other explanatory variables had RI = 0%, suggesting negligible importance for post-fire re-vegetation.

The regression tree model grown for mountain hemlock-dominated pixels was moderately effective in describing the variation in post-fire revegetation ($R^2 = 0.57$). Summer precipitation explained the most variance in post-fire regrowth, with a combined RI of 52%. Snow cover (14%) and elevation (12%) were

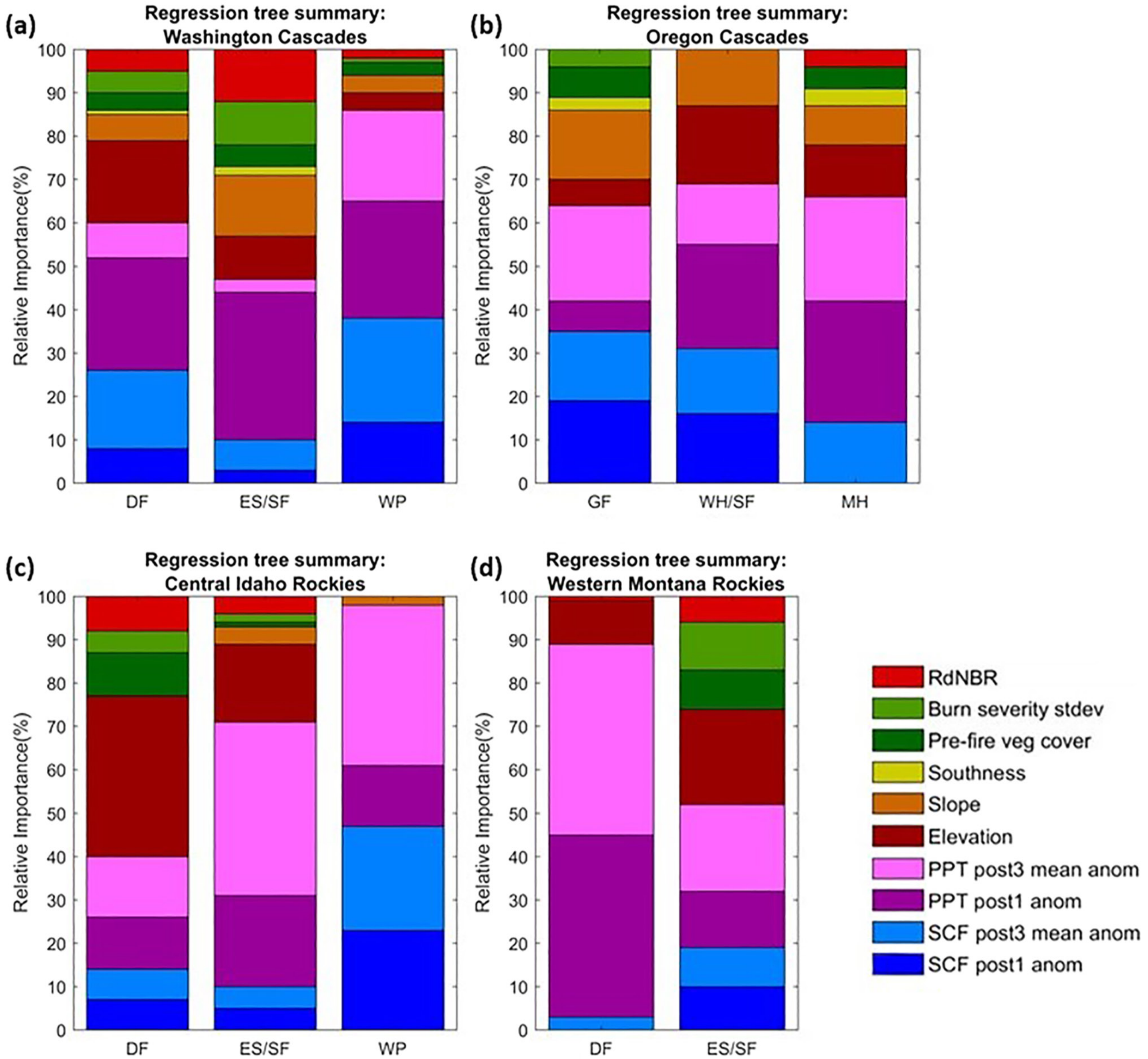

Figure 2. Regression tree relative importance values for each of the dominant vegetation types in (a) Washington Cascades, (b) Oregon Cascades, (c) central Idaho Rockies, and (d) western Montana Rockies. The dominant vegetation types include Douglas-fir, Engelmann spruce/subalpine fir, whitebark pine, and mountain hemlock.

moderately influential explanatory variables. All other variables were minimally influential for post-fire revegetation (RI < 10%).

3.1.3. Central Idaho Rockies Subregion

Regression tree models for the central Idaho Rockies subregion were generated for the three dominant pre-fire forest types within the five selected fire perimeters. Listed from lowest to highest average elevation, these were Douglas-fir, Engelmann spruce/subalpine fir mix, and whitebark pine. While regression tree results are notably different depending on pre-fire forest type, summer precipitation appears to be the most important variable on a regional scale (Figure 2).

The Douglas-fir regression tree model described the variability in vegetation regrowth moderately well ($R^2 = 0.43$; $p < 0.001$). The central Idaho Douglas-fir regression tree was the only model for which elevation was the most important explanatory variable (RI = 37%). Summer precipitation (RI = 26%), snow cover (RI = 14%), and pre-fire canopy cover showed moderate contribution to regression tree construction. All other independent variables were shown to have relatively little influence (RI < 10%) on post-fire revegetation.

For pixels where pre-fire forest type was mosaic of Engelmann spruce and subalpine fir, the goodness of fit was similar to the Douglas-fir model ($R^2 = 0.39$). Summer precipitation was the primary explanatory variable used to build the regression tree (RI = 61%). Elevation (RI = 18%) and snow cover (RI = 10%) were the only other moderately important variables for Engelmann spruce/subalpine fir. All other potential explanatory variables displayed minimal importance (RI < 5%) for regression tree construction.

The regression tree model for whitebark pine-dominated pixels in central Idaho was by far the least effective at describing the variation in post-fire revegetation ($R^2 = 0.13$; $p < 0.01$), while the Washington Cascades whitebark pine regression tree was the most effective model. Although the low R^2 value suggests a weak model, the results show similar relationships as the same forest types in the Washington Cascades. Summer precipitation was the most influential variable (RI = 51%), while snow cover was also highly influential for model construction (RI = 47%). All other variables were suggested by the model to be minimally influential for post-fire revegetation (RI < 5%). With such a low R^2 value, these results suggest other factors to play considerable roles in post-fire revegetation for whitebark pine-dominated land cover.

3.1.4. Western Montana Rockies Subregion

Regression tree models for the western Montana Rockies subregion were generated for the two dominant pre-fire forest types within the five selected fire perimeters. The two primary forest types were Douglas-fir at lower elevations and an Engelmann spruce/subalpine fir mix at higher elevations. For both forest types, summer precipitation is shown to be the most important variable for post-fire revegetation (Figure 2).

The Douglas-fir regression tree model was not as effective at modeling the data as in other subregions, but still provided statistically significant results ($R^2 = 0.33$; $p < 0.001$). Among all forest types and subregions, summer precipitation was the most important explanatory variable in the western Montana Rockies (RI = 86%). The only other noteworthy explanatory variable was elevation (RI = 10%) All other independent variables were shown to have low impact (RI < 5%) on post-fire revegetation.

For the Engelmann spruce/subalpine fir forest type, the model goodness of fit was similar to that of Engelmann spruce/subalpine fir pixels in other subregions ($R^2 = 0.39$; $p < 0.001$). Summer precipitation was again the dominant explanatory variable used to build the regression tree (RI = 33%). Elevation (RI = 22%), snow cover (RI = 19%), and burn severity heterogeneity were moderately influential for the Engelmann spruce/subalpine fir model. All other potential explanatory variables displayed minimal importance (RI < 10%) for regression tree construction.

3.2. Temporal Regression Analysis

In the following sections we highlight the degree of linear correlation between maximum summer EVI and antecedent SCF for two pre-fire years and four post-fire years. Regression statistics were calculated across elevation bands for the dominant forest types within each of the four subregions and plotted in the form of heatmaps. R values were plotted rather than R^2 values to indicate the direction of the linear relationship. Each heatmap displays R values from a unique forest type, and rows correspond to elevations bands, indicated by y-axis values. For example, an elevation band labeled as "1,400" contains pixels ranging in elevation from 1,400 to 1,600 m for the indicated forest type. Fire disturbance year is indicated by the vertical bold line between years "pre1" and "post1."

Since, the objective of this portion of the research was to examine how the strength of linear SCF-EVI relationships shifted following wildfire, exact R values are not displayed on the heatmaps. Relative shifts in correlation strength and direction are illustrated by color, with red indicating a positive relationship, blue indicating a negative relationship, and darker colors representing stronger correlations. Light-colored cells correspond to correlation coefficients close to zero.

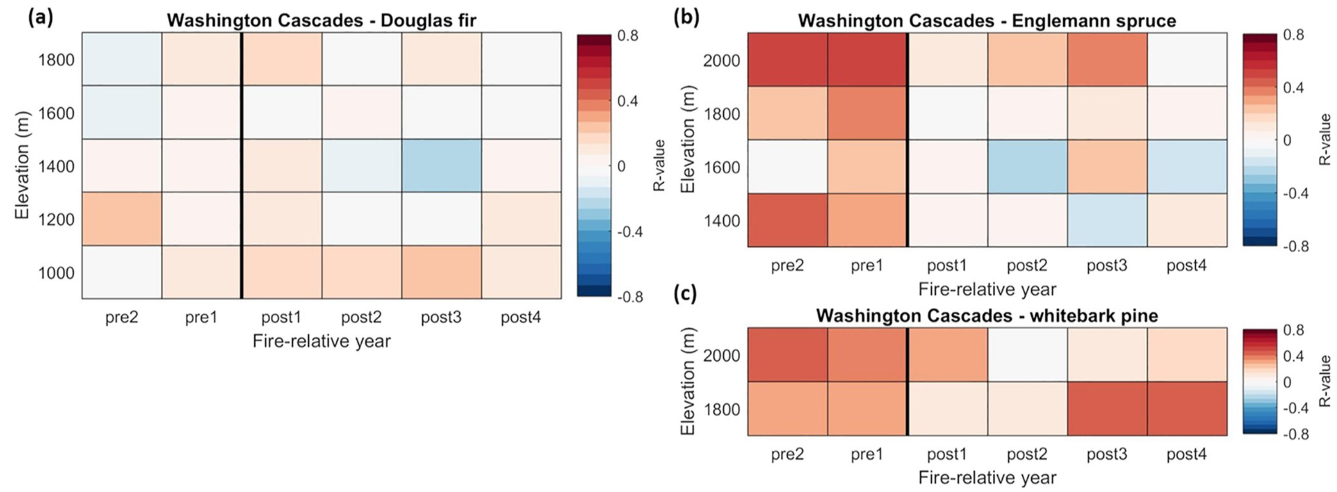

Figure 3. Temporal regression results for the Washington Cascades fires for pixels classified pre-wildfire as (a) Douglas-fir, (b) Engelmann spruce/subalpine fir, and (c) whitebark pine. Here, and for the similar figures, each row corresponds to a 200 m elevation band, while each column represents a fire-relative year. The vertical black line indicates the fire occurrence year, with two pre-fire years to the left and four post-fire years to the right. The R values represent the correlation between Enhanced vegetation index and Snow cover frequency .

3.2.1. Washington Cascades Subregion

Overall, correlations between EVI and SCF across the Washington Cascades forest types were weakly to moderately positive (Figure 3). Douglas-fir pixels displayed weak correlations at all elevation bands both before and after wildfire occurrence ($-0.20 \leq R \leq 0.20$). Engelmann spruce showed positive correlations before the fire, especially at the highest elevation band ($R = 0.51$). Correlations became significantly weaker in the first post-fire year at all elevations ($R < 0.10$). Post-fire correlations were weak across all elevations except for the 2,000 m band during the third post-fire year, where a moderately positive correlation was observed ($R = 0.35$).

The whitebark pine forest zone exhibited a similar pattern as Engelmann spruce, with an apparent moderate, positive pre-fire correlation during both pre-fire years. R values were 0.30 for both pre-fire years at 1,800 m, while R values at 2,000 m were 0.46 during the first pre-fire year and 0.35 and during the second pre-fire year. Following fire occurrence, R values generally decreased at both elevations to a weak, positive state. Only during the third ($R = 0.43$) and fourth ($R = 0.41$) post-fire years did the 1,800 m band return to a moderately positive correlation between EVI and SCF.

3.2.2. Oregon Cascades Subregion

Interestingly, we only observed a strongly negative SCF-EVI relationship in the Oregon Cascades region (Figure 4). Before wildfire occurrence, grand fir-dominated pixels showed a moderately negative SCF-EVI relationship at all elevation bands, with R values ranging from 0 to -0.28. The immediate post-fire year showed no correlation ($R < 0.05$) between SCF and EVI at all elevations. The second, third and fourth post-fire years exhibited strong negative correlations at the 1,000 m band, with R values of -0.56, -0.62, and -0.55, respectively.

Western hemlock/silver fir-dominated pixels showed moderate, negative correlations between SCF and EVI before and after fire occurrence at both elevation bands. During the first pre-fire year, both the 1,200 m band ($R = -0.46$) and the 1400-m band ($R = -0.38$) displayed moderately negative correlations. Relationships were weak post-fire until the fourth year, when the 1,200 m band ($R = -0.38$) and the 1,400 m band ($R = -0.58$) once again displayed moderately negative correlations.

Prior to fire occurrence, mountain hemlock-dominated pixels displayed low SCF-EVI correlations across both elevation bands. Of the three dominant forest types in the Oregon Cascades, mountain hemlock was the only forest type where, we observed a positive post-fire correlation. During the first post-fire year, the 1,600 m band showed a moderately positive SCF-EVI correlation ($R = 0.49$). The second and third post-fire

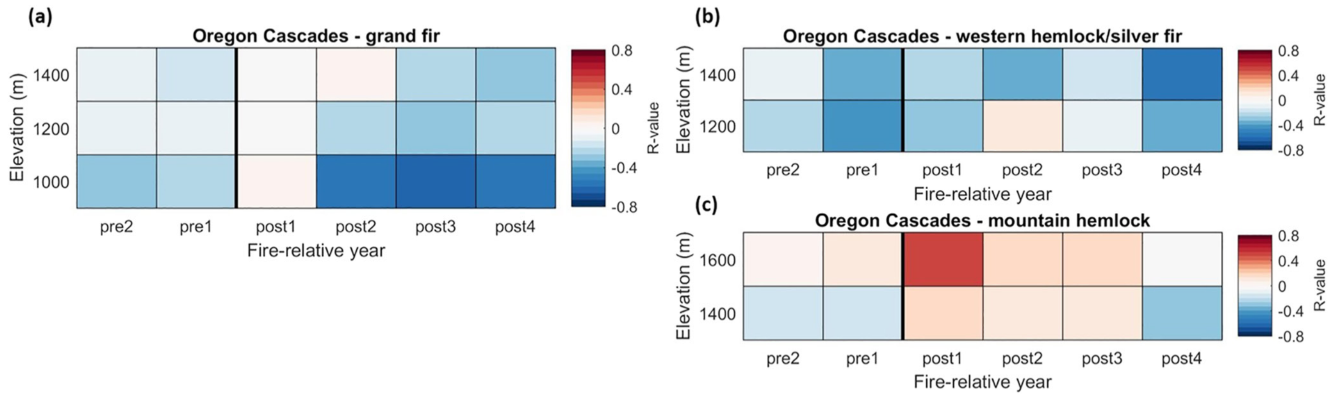

Figure 4. Temporal regression results for Oregon Cascades fires for pixels classified pre-wildfire as (a) grand fir, (b) western hemlock/silver fir, and (c) whitebark pine. The R values represent the correlation between Enhanced vegetation index and snow cover frequency.

years showed weakly positive correlations ($R < 0.15$), while the fourth post-fire year showed a moderate, negative correlation at the 1,400 m band ($R = -0.32$).

3.2.3. Central Idaho Rockies Subregion

In the Idaho Rockies subregion, Douglas-fir pixels displayed ambiguous elevational and temporal correlation trends. During the second pre-fire year, correlations were moderately negative at 1,400 m ($R = -0.36$) and 1,600 m ($R = -0.32$) and moderately positive at 2,000 m ($R = 0.34$) and 2,200 m ($R = 0.42$). Moderate positive correlations were also observed during the first post-fire year at 1,200 m ($R = 0.45$) and 2,200 m ($R = 0.44$). Correlations were weak across all elevation bands for the second, third and fourth post-fire years (Figure 5).

Engelmann spruce pre-fire pixels showed minimal SCF-EVI correlations at 1,800 and 2,000 m, but showed strong, positive post-fire correlations at the 2,200 m band. For the 2,200 m band, the strongest correlation occurred during the first post-fire year ($R = 0.60$) and weakened during the second ($R = 0.48$) and third ($R = 0.45$) post-fire years. Whitebark pine results showed little correlation at all elevation bands. Only the highest elevation band during the first post-fire year showed a moderately positive correlation ($R = 0.39$).

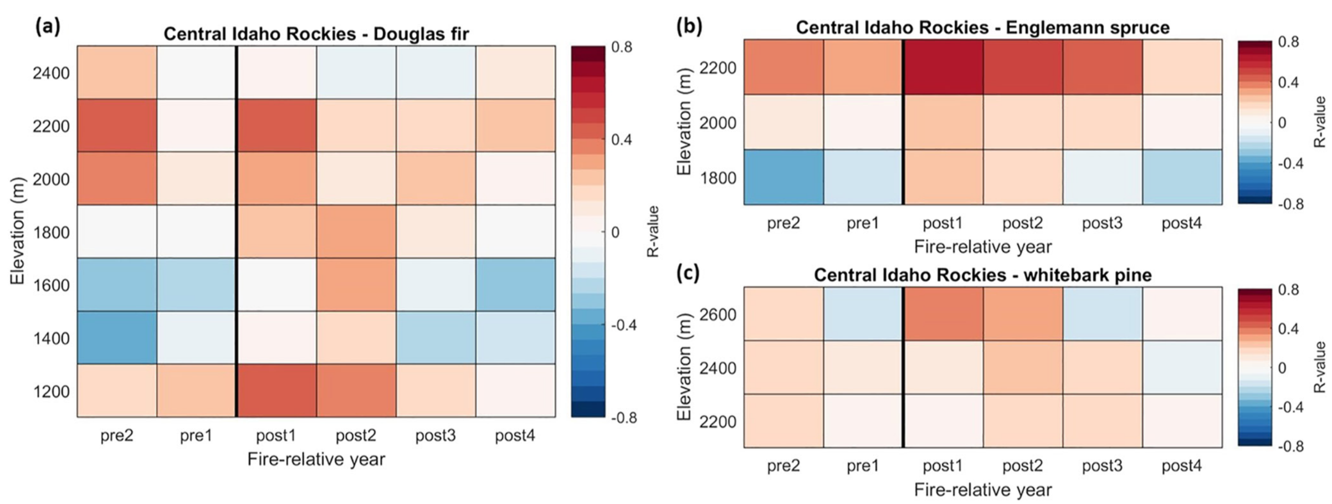

Figure 5. Temporal regression results for central Idaho Rockies fires for pixels classified pre-wildfire as (a) Douglas-fir, (b) Engelmann spruce/subalpine fir, and (c) whitebark pine. The R values represent the correlation between Enhanced vegetation index and snow cover frequency.

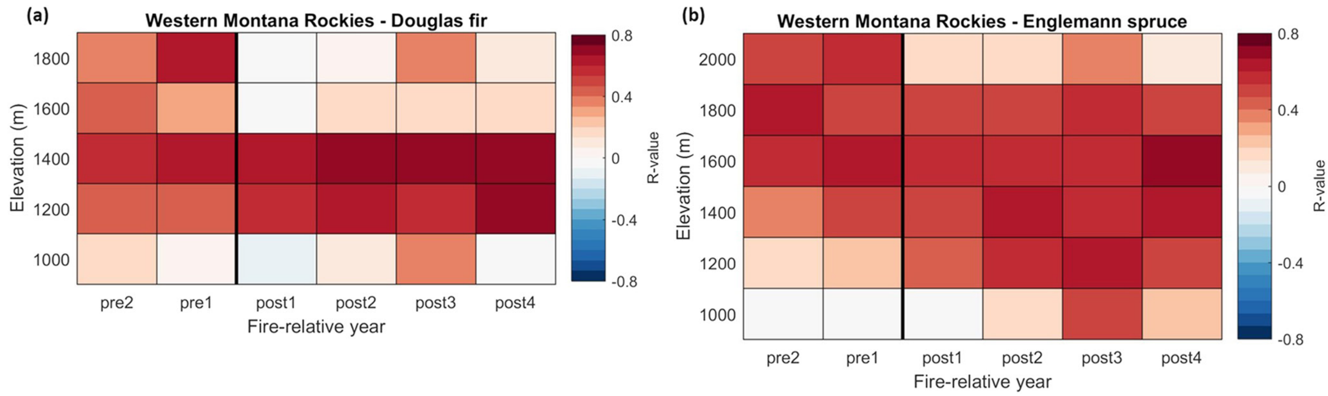

Figure 6. Temporal regression results for western Montana Rockies fires for pixels classified pre-wildfire as (a) Douglas-fir and (b) Engelmann spruce/subalpine fir.

3.2.4. Western Montana Rockies Subregion

Results for the western Montana Rockies subregion showed remarkably strong and positive SCF-EVI correlations for both dominant forest types across multiple elevation bands (Figure 6). Douglas-fir-dominated pixels displayed moderate strength before fire occurrence at all elevations except the lowest band (1,000 m), where minimal correlation was observed ($R < 0.20$). Elevation did not appear to have an influence on pre-fire correlation strength, as R-values were strongly positive at both the 1,400 m ($R = 0.64$) and 1,800 m ($R = 0.66$) elevation bands. Post-fire correlation patterns for Douglas-fir pixels were significantly different depending on elevation band. At 1,000 m, correlations remained generally weak following fire occurrence. The 1,200 m band exhibited a persistent strong, positive relationship for all post-fire years ($R \geq 0.57$), reaching a maximum of $R = 0.67$ during the fourth post-fire year. A similar pattern occurred at the 1,400 m band, but to a slightly stronger degree. All post-fire correlations were strong ($R \geq 0.62$), with a maximum of $R = 0.70$ during the fourth post-fire year. The two highest elevation bands for Douglas-fir shifted from a pre-fire moderately positive correlation to weak post-fire SCF-EVI correlations.

Engelmann spruce displayed correlation magnitudes and post-fire shifts similar to Douglas-fir. At the lowest elevation of 1,000 m, pre-fire correlations were nearly zero ($-0.1 < R < 0.1$) and remained weak following fire occurrence except for the third year, during which SCF appeared to be positively correlated with EVI ($R = 0.47$). The 1,200 m band showed slightly positive correlations for the two years preceding fire occurrence ($R = 0.17$, 0.24), followed by a post-fire shift towards a stronger SCF-EVI relationship. Correlations reached a maximum during the third post-fire year ($R = 0.60$) and were moderately strong during all other post-fire years. Pre-fire correlations from 1,400 to 2,000 m were consistently moderately positive, ranging from $R = 0.39$ to 0.66. Post-fire correlations were moderately strong between elevations of 1,400 m and 1,800 m, with R values ranging from 0.49 to 0.69. At the highest elevation band (2,000 m), correlations were once again weakly positive.

4. Discussion

Both portions of our analysis suggested that post-wildfire revegetation in forested, mountainous landscapes is a complex, geographically dependent process. There were considerable differences among all subregions and pre-fire forest types for both the variables of importance from the regression tree analysis and the correlation strength from the temporal linear regression analysis. The role of snow cover for influencing post-fire revegetation differed within each subregion depending on the dominant pre-fire conifer species. Additionally, for individual species of conifers, the importance of snow cover was dependent on the geographic location of the wildfire. Specifically, forests dominated by Douglas-fir or Engelmann spruce displayed varying revegetation patterns across the Montana Rockies, Idaho Rockies, and Washington Cascades.

Our regression tree results indicated that summer precipitation variables, followed by snow cover variables, had the greatest influence on post-fire revegetation for moderately and highly burned forests. These findings are consistent with past studies conducted in Mediterranean climates, where precipitation has previously been noted as a strong driver of short-term post-fire regeneration (Meng et al., 2015; Röder et al., 2008; Viana-Soto et al., 2017). However, we had hypothesized that snow cover would have a stronger influence on forest greening due to observations of these linkages in previous studies (Hu et al., 2010; Trujillo et al., 2012). Regardless, assessing snow cover and summer precipitation as independent explanatory variables provided a more comprehensive and representative modeling of drivers of post-fire revegetation dynamics. We posit several explanations for a stronger relationship between forest greening and summer precipitation. One explanation may be related to the shallow rooting depths of seedlings, which may be disconnected from spring snowmelt, which is often stored in deeper soil layers (Cavender-Bares & Bazzaz, 2000; Williams et al., 2009). This explanation is in turn influenced by the geology, soil structure, and saprolite depth underlying the burned area, which will differ depending on region and elevation. Another explanation is the timing of precipitation relative to evaporative demand that affects seedling establishment. Post-fire changes in soil hydraulic properties can also influence the effects of snowmelt and summer precipitation on vegetation growth. High burn severity can impact soil physical properties resulting in increased preferential flow and deep drainage, which would contribute to a greater proportion of snowmelt or summer precipitation bypassing the soil matrix, which would then be unavailable to recovering vegetation (Stoof et al., 2014).

Regardless of their relative importance, both snow cover and summer precipitation variables still displayed a predominantly positive influence on vegetation regrowth across forest types and subregions. These correlations were expected, as recent studies have revealed similar relationships between regeneration and annual precipitation or wet season precipitation (Harvey et al., 2016; Meng et al., 2015; Stevens-Rumann et al., 2018). Elevation also appeared to be a significant driver of revegetation, exhibiting a negative influence for most forest types, consistent with post-fire forest reproduction patterns in the Sierras and the Alaska boreal forest (Johnstone et al., 2010; Van Mantgem et al., 2009). Temporal regression results also illustrate an elevational component to the post-fire snow cover-greening relationship, most notably in the western Montana Rockies subregions where post-fire correlations were strongest at moderate elevations. For continental snowpacks, like the Montana Rockies, SCF may not accurately represent snow water equivalent at higher elevations due to the cold, dry climate that would enable thin snowpacks to persist well into the growing season, hence the lower correlations.

Snow cover influences on post-fire revegetation appeared to be most strongly linked in the Oregon and Washington Cascades, as suggested by our regression tree results. While the relative importance values did not indicate correlation direction, these relationships were likely positive, as post-fire revegetation has been shown to be positively related to soil moisture availability (Johnstone et al., 2010; Meng et al., 2015), which in turn has been shown to positively correlated with snow accumulation and persistence (Harpold & Molotch, 2015; Molotch et al., 2009). We hypothesize that the warmer, maritime snowpacks of the Oregon and Washington Cascades, relative to the colder, continental snowpacks of Montana and Idaho might explain this difference. Annual linear regressions suggested a remarkably strong positive relationship between SCF and peak summer EVI at moderate elevations (1,200–1,600 m) in the western Montana Rockies where Douglas-fir and Engelmann spruce-dominated forest stands experienced moderate or high severity fire. The mid-elevation Montana Rockies was the only region where a strong, positive correlation persisted for all four post-fire years. These results are especially noteworthy for Engelmann spruce-subalpine fir forests, where field studies have shown post-fire drought stress to result in significant declines in seedling establishment (Bell et al., 2014; Harvey et al., 2016; Stevens-Rumann et al., 2018). Considering this apparent negative relationship between soil moisture availability and seedling density and the negative correlations between snow cover and post-fire vegetation density suggested here, such subalpine forests in Montana may be at greater risk for delayed post-fire revegetation and decreased forest densities under a warming climate.

An important note regarding these findings is the different interpretations of the two regression analyses. Regression tree results illustrated the broader, potentially lagged impact that post-fire snow cover conditions can have on revegetation relative to pre-fire forest conditions, since snow cover variables during the first three post-fire years are used to explain the variance in post-fire revegetation four years following wildfire occurrence. Compared to the time series of linear regressions, regression tree results are more robust against local differences in topography, climate, and pre-fire forest density since the EVI recovery metric is relativized to pre-fire conditions and since SCF and summer precipitation variables are presented as anomalies rather than originally observed values. On the other hand, the time series of SCF-EVI linear regressions illustrated the immediate influence of snow cover on post-fire greening, measuring an absolute, seasonal correlation between snow cover and summer vegetation productivity. While, results are subject to local variations in pre-fire forest densities within each subregion, more information is offered regarding how correlations shift with elevation before and after fires.

It is worth pointing out that the relatively coarse 500-m spatial resolution of the MODIS EVI and SCF data will not be able to capture local variations in pre- and post-fire green biomass and snow cover. Although we did not investigate the specific effects of spatial resolution, results may be less accurate over areas of complex topography and mixed pixels. Future results could perhaps be refined with finer scale remote sensing data. We note by using EVI as a post-fire greenness metric, we are obtaining information about revegetation but not forest regeneration. Without lidar vegetation structure information or in situ observations, we cannot confirm that the post-fire greenness is the result of regrowing forest. It is also important to note that post-fire EVI greenness is likely responding to the full composition of revegetation, including grasses, shrubs, and trees (Vanderhoof et al., 2021). While the results of this study may not provide information about specific vegetation types in the post-fire period, our findings demonstrate that early seral response is affected by snow.

Interestingly, the apparent importance of snow cover for revegetation differed between the two regression analyses for some subregions and forest types. Our results from the regression time series suggested snow cover had a strong direct influence on post-fire greening in the western Montana Rockies. However, the regression tree results did not portray snow cover as an important variable for revegetation, although regression tree models in Montana explained EVI recovery only moderately well ($R^2 < 0.40$). In contrast, while the Oregon and Washington Cascades displayed overall weak correlations from the temporal regression analysis, a stronger dependence was suggested by regression tree findings, potentially indicating a lagged effect of post-fire moisture conditions on vegetation recovery. The linkage between snow cover and post-fire greening in Montana has potential implications for post-fire ecosystem transitions or vegetation shifts (Davis et al., 2019, 2020; Parks et al., 2019). Frequent and long-duration hydraulic stress induces higher tree and seedling mortality and lower elevation forests are more vulnerable due to drier conditions (Simeone et al., 2019). Specifically, due to climate change and declining snowpacks, our study supports the growing concern that the resilience to fire in some regions and forest types may be increasingly compromised, resulting in extensive and enduring areas of altered vegetation (Coop et al., 2020).

From a broader perspective, as wildfire activity continues to increase and intensify in the PNW, understanding the main drivers of revegetation over severely burned forested landscapes is vital for guiding future post-fire forest management decisions. Results here and from previous studies consistently suggest that drought stress during the early post-fire years significantly curbs the resilience of western U.S. montane forests (Donato et al., 2016; Enright et al., 2015; Harvey et al., 2016; Van Mantgem et al., 2009). Determining how prevalent tree species in geographically distinct subregions respond to a range of post-fire snowpack conditions is especially important for PNW forests, where trends towards earlier spring snowmelt are evident (Knowles, 2015; Mote et al., 2018). Additionally, this knowledge may be used to facilitate adaptive post-fire management policies and decisions to ensure long-term forest health. For example, depending on the subregion and species composition, reseeding efforts following low snow winters might employ more drought tolerant species or, replanting could be delayed 1–2 years until snowmelt and soil moisture conditions are more favorable for seedling propagation. However, considering trends towards lower frequency of suitable climate years and increased frequency of severe fires in the PNW, other approaches may be necessary to adapt to this combination of shifts described as the "interval squeeze model," in which vulnerable tree species may be unable to effectively self-replace before the occurrence of another severe wildfire (Enright et al., 2015). Across western North America, the combination of climate change and high severity fire is already leading to low seedling establishment ponderosa pine and Douglas-fir and models indicate a further significant increase in fire-catalyzed ecosystem transitions in montane forested environments (Davis et al., 2019, 2020). Where snowpacks have declined, this ecosystem transition is likely to look like a shift from forest to non-forest (Sean A. Parks et al., 2019) and more specifically, from evergreen to deciduous vegetation (Vanderhoof et al., 2021). Even without a pre-fire understanding of snow-forest linkages, we need to understand the drivers and relationships that affect post-fire regrowth in order to assess hydrological impacts (Robinne et al., 2020), especially in areas of high burn severity where runoff, soil erosion and "black water" runoff can negatively affect peak flows, sediment transport, and water quality (Bladon et al., 2014).

The positive relationship between snow cover and regenerating vegetation suggested here, along with past field studies of post-fire seedling densities indicate a potential shift toward decreased forest densities following severe wildfires (Harvey et al., 2016; Stevens-Rumann et al., 2018). Fire-intolerant and drought-intolerant species inhabiting large swaths of montane and subalpine landscapes, such as Engelmann spruce, subalpine fir, western hemlock, and silver fir appear to be the most vulnerable to a diminishing snowpack. Shifts in species compositions of northwestern forests have been shown to be a legitimate possibility stemming from post-fire moisture stress and increased fire frequency (Bell et al., 2014; Donato et al., 2016; Stevens-Rumann et al., 2018). When severe wildfires are followed by low snowpacks, early snowmelt or low summer precipitation, drought stress intensifies and provides an opportunistic window for more drought-tolerant species (e.g., lodgepole pine, whitebark pine) to establish. Increasing fires and declining snowpacks can also lead to an expansion of low elevation invasive species in montane regions (Stevens & Latimer, 2015). Post-fire soil moisture deficiency may even lead to a successional transition from conifer to deciduous tree compositions (Johnstone et al., 2010).

These findings do not imply inherently beneficial or detrimental post-fire vegetation trends. With shifting climate trends in the PNW, migration of vegetation types and accompanying fire regimes may be the most adaptive path forward for forested landscapes. Fires can be viewed as an opportunity for forests to re-organize into ecosystems better structured to survive warmer winters, longer fire seasons, and greater drought stress. One of the major challenges moving forward is how to reconcile ecological forces of a changing climate with goals of ongoing post-fire management practices, where are often oriented towards re-establishing forests as they existed pre-disturbance.

5. Conclusions

As climate change continues to impact area burned, burn severity, and precipitation regimes, it is increasingly critical to understand the dominant drivers of post-fire vegetation recovery. Our research suggests that snow cover has a strong influence on post-fire vegetation greening. However, the effect varied depending on subregion and dominant pre-fire conifer species, with the most notable impacts at low to moderate elevations in the Washington Cascades, Oregon Cascades, and western Montana Rockies. Additionally, positive relationships between snow cover and summer precipitation with post-fire greening suggest that active post-fire revegetation efforts will help facilitate recovery, especially during years when severe wildfires are followed by early snowmelt years or below average summer precipitation. Given the current projections for climate change, the role of snowpacks in affecting post-fire vegetation recovery will become increasingly important in the Western US. As such, we advocate for similar studies in the future—perhaps, supported and validated with field research—to enable post-fire management and policy decisions that will promote healthy and resilient forests.

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Data Availability Statement

Data and code used for this manuscript are publicly available at Zenodo. https://doi.org/10.5281/zenodo.5515749.

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