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ORIGINAL ARTICLE

Synthesizing Spectral and Field Observations of Post-fire Conifer Recovery in Dry Conifer Forests

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Abstract

The coniferous forests of the Western Cordillera are particularly affected by recent increases in wildfire extent and severity. After fire, conifer establishment and growth rates are influenced by a wide range of ecological drivers. Understanding the relative influence of ecological drivers on conifer recovery is crucial when modeling landscape dynamics. Past research has examined a wide variety of ecological drivers; however, syntheses of these drivers are rare. This systematic review focuses on forest recovery pathways, which have distinct variability in spatial and temporal measures of conifer establishment and growth. From studies examined, we extracted whether the study identified a recovery pathway and whether field or satellite spectral methods were used. Spectral methods were the most common method to determine the 84 extracted pathways. Among pathways identified, conifer self-replacement was the most common, but the second most common was state change, wherein the forest transitions in landcover type. We also investigated how recovery varied relative to different ecological drivers. Among the > 1000 drivers considered, pre-fire composition and post-fire moisture had consistent positive associations with all recovery metrics, while the association with other drivers varied by metric (stem density versus composition) and/or method (field versus spectral). Our review outlines key gaps for future research, including (1) the accuracy of spectral monitoring to capture structural growth trends, such as stem densities over time, and (2) how the effects of ecological drivers vary across scales, such as post-fire shrub cover at local versus landscape levels. Overall, fusing spectral and field data across spatiotemporal scales improves our understanding of post-wildfire recovery and dynamics, as well as our ability to anticipate the impacts of changing climate and wildfire conditions on recovering forests.

Key words: wildfire; ecosystem recovery; remote sensing; environmental drivers; ecosystem monitoring; disturbance ecology.

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Highlights

- Post-fire moisture and pre-fire forest conditions positively impact all recovery metrics.
- Driver impacts varied by recovery metric and measurement method (spectral vs. field).
- Spectral estimates of post-fire regrowth capture distinct recovery trends.

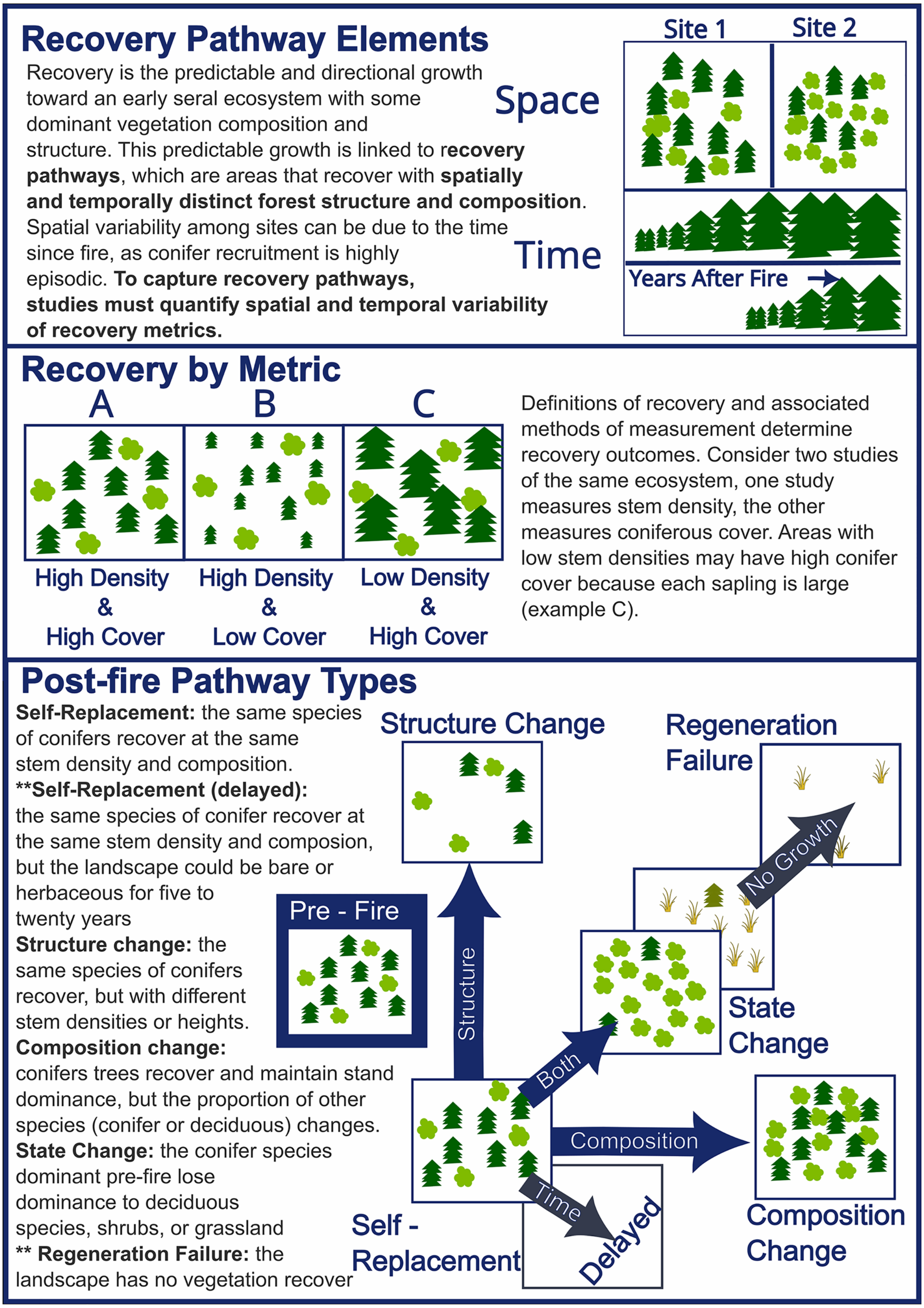
Introduction

The changing climate, coupled with the increased size and severity of wildfires, underscores the need to monitor the spatial and temporal variability of forest recovery after fire (Abatzoglou and others 2021). Throughout the Holocene, pervasive fires have burned in the dry conifer forests that dominate the Western Cordillera (Hessburg and others 2005)—North America's second-largest ecozone (Hessburg and others 2005; Omernik and Griffith 2014). However, as summers of the twenty-first century have become drier and hotter, some regions have experienced significant declines in post-fire conifer establishment and growth (Hansen and Turner 2019; Turner and others 2019). Some studies have documented conifer forests that transition to open grassland (Hamilton and Burton 2023) or mixed forest ecosystems (Kulakowski and others 2013). These changes in forest composition and structure have dramatic impacts on ecosystem functions, including timber provisioning, water cycling, and carbon dynamics (Sánchez and others 2021).

In the decades that follow a high-severity stand-replacing fire, the conifer seedlings that successfully establish generally dominate the forest canopy for the subsequent decades to centuries (Brullsauer and others 1996; Tortorelli and others 2024). Thus, the spatial and temporal variability of conifer establishment and growth in the early post-fire years (that is, < 20 years) indicate future forest composition (Oliver and Larson 1996). Taking advantage of the link between early seedling establishment and young forest growth, recovery studies use conifer stem density or cover at one time to describe pathways of forest recovery specific in composition, structure, and growth rate (Box 1). A pathway describes the spatially variability across metrics of structure or composition, as well as a temporally distinct trend in vegetation growth (Box 1). For example, Coop (2023) sampled vegetation 20–23 years post-fire in the southwest US. They associated spatially variability in post-fire vegetation cover with different forest recovery pathways, such as a pathway leading to a young conifer-dominant forest or a pathway leading to a shrub-dominant landscape (Coop 2023).

Spatial and temporally variability in forest metrics (for example, stem density, species composition, canopy height) reflect general types of conifer recovery pathways (Baltzer and others 2021; Seidl and Turner 2022; White and others 2023). Box 1 defines six pathway types including: self-replacement, delayed self-replacement, structure change, composition change, state change, and regeneration failure. Note that each pathway type has numerous variations. For example, a pathway of composition change could represent an area with an increased deciduous tree response or a different composition of conifer species. Additionally, while spatial variability offers a snapshot of potential pathways, temporal data are essential to confirm trends. A single time-point may mask delayed recovery processes, such as lagged conifer establishment (Box 1, Stevens-Rumann and others 2022). Ultimately, the association of a site with a pathway type depends on the metric measured (for example, stem density), timing of measurement (for example, number of years post-fire), and measurement frequency (for example, single observation versus repeated). For instance, a study that measures conifer growth rates may identify different pathways compared to a study measuring stem density (Box 1). While the spatial and temporal variability of metrics characterizes recovery pathways, understanding *why* these pathways emerge requires examining the ecological drivers behind them.

Recovery pathways are affected by ecological drivers, such as temperature or fire severity, that influence conifer establishment and germinant growth (Drever and others 2006; Littlefield 2019; Baltzer and others 2021). In this review, ''metrics'' refers to variability of a recovery metric (for example, stem density) while ''measures'' refers to variability of an ecological driver. To investigate how driver measures influence recovery metrics, researchers use a range of methods, including benchtop or greenhouse experiments, observational field surveys, and large-scale remote sensing methods. Benchtop or greenhouse experiments control the variability of drivers, isolating the specific impacts on recovery, but extrapolating results to complex landscapes is challenging. For example, it is difficult for a greenhouse study to compare the effect of temperature, easily manipulated in greenhouses, with a driver like fire severity or herbaceous competition, which is challenging to



Box 1. Defining forest recovery pathways and the importance of measurement timing and measurement metric in recovery monitoring.

replicate in a greenhouse setting (Petrie and others 2016). Field studies typically assess a greater diversity of drivers, but are also less common than greenhouse or benchtop studies. In a 2016 review of temperature and moisture effects on ponderosa and lodgepole pine establishment, only 25% of included studies were field-based (Petrie and others 2016).

Although key ecological drivers of recovery are well established, their relative effect on recover remains difficult to quantify for two reasons. First, they operate across diverse spatial and temporal scales (Littlefield and others 2020; Peven and others 2024). Second, a driver's effect on recovery varies with the measurement method, the observed range of the driver, and which other drivers are considered. As a result, while we know temperature and moisture control seedling establishment (Petrie and others 2016), a 2019 review found few post-fire recovery studies integrated climate variables in models (Stevens-Rumann and Morgan 2019). More recent work leveraged regional field plot data to highlight the negative impact of post-fire drought and fire severity on conifer establishment (Davis and others 2019, 2023; Stevens-Rumann and others 2022). Yet, these regional models can also inflate the importance of a single driver while obscuring locally important drivers (Chase and Knight 2013; Peeler and Smithwick 2020). Additionally, plot syntheses require substantial effort and are subject to inherent sampling error (Persson and others 2022). Therefore, regional investigations must account for sampling limitations and methodological variability, as well as consider how drivers impactful at the regional scale interact with drivers important at a site level.

One solution to consider the effects of ecological drivers across scales is to integrate synoptic and large-scale satellite observations within investigations (Pettorelli and others 2018). Satellite observations of land surface reflectance capture the spatial and temporal variability in recovery metrics, and associated measures of ecological drivers, after fire (Kasischke and French 1997; Senf 2022; Wulder and others 2022) while minimizing cost and time investments (Frolking and others 2009a). Further, variability in spectral responses has been linked to variability in ecological driver measures (Frolking and others 2009a). These linkages can synthesize the relationship of pathways and ecological drivers over large areas, such as the Canadian Boreal (White and others 2023). However, since spectral responses do not directly measure forest structure metrics, relationships between spectrally identified recovery and drivers may differ from those identified in the field (Senf 2022). Thus, spectral data require validation using ground-truthing (White and others 2022) or association with trends or values from the established literature (Frolking and others 2009b; White and others 2018, 2019). To capitalize on the advantages of spectral data, we must first compile the spectral and field-based recovery pathways identified in the literature and, for these pathways, determine the relative impact of different ecological drivers.

An improved understanding of what drives pathways of early post-fire vegetation empowers better adaptation and possible management action as forests recover in our altered world (Pritchard and Brockington 2019). This systematic review focuses on the early rate of conifer recovery through establishment, density, basal area, composition, and spectral responses associated with conifer recovery. We focus on early recovery because research suggests that early coniferous growth (up to 30 years) is indicative of young forest (60–80 years) stand structure and composition (Tortorelli and others 2024). Our systematic review specifically asks: What drives early recovery pathways in coniferous dominant forests of the Western Cordillera? In this work, our objectives are to (1) synthesize observed pathways of early forest recovery for dry coniferous forests of the Western Cordillera, (2) outline how spectral responses are used to identify pathways, and (3) assess and synthesize the relative influence of different drivers on recovery measures from both field and spectral methods. Our findings describe the current state of knowledge on early conifer recovery and characterize how the study method (field versus spectral) or metric (stem density vs. composition) affects the findings. As an outcome, we identify knowledge and methodological gaps that frame key questions and recommendations for future post-fire research. We also emphasize the broader applicability of our approach in synthesizing ecological findings from both field and spectral domains.

A Primer on Spectral Remote Sensing for Recovery Monitoring

As a component of our synthesis, we provide a background on data processing and typical methods for using spectral data to monitor forest recovery trends. The use of satellite data to monitor the recovery process, which is a process of incremental change, requires long-term data (that is, > 10 years) of consistent quality. High-quality and long-term datasets, such as the Landsat satellite data series, have revolutionized approaches for both identifying disturbances and monitoring trends of forest recovery. The rise of satellite monitoring has also benefited from increasing data availability and accessibility, particularly the opening of the Landsat archive in 2008. White (2024) noted that between 2008 and 2024, studies using Landsat data to monitor forest recovery have increased sixfold. These recent studies benefit from well-defined approaches for satellite data processing and strong links between various components of forest structure and spectral response (Chu and Guo 2013).

Satellite images require radiometric calibration and georectification to minimize errors introduced by the sensor, atmospheric effects, and variability in topography. Historically, geographic inaccuracy in satellite geographic positioning made comparing changes in landscapes over time difficult (Gordon 1980). Additionally, time and financial resources limited researchers' capacity to purchase, store, and calibrate the satellite data needed to time-series analysis (Wulder and others 2022). Calibrating satellite data are critical because atmospheric effects can impact land surface reflectance by more than 40% (Dwyer and others 2018). Historically, spectral studies relied on methods established in the literature to pre-process data (Song and others 2001; Franks and others 2013). Recent studies benefit from published analysis-ready data products that calibrate surface reflectance and automatically mask cloudy or hazy pixels (Dwyer and others 2018; Wulder and others 2022).

The release of analysis-ready data products, specifically the Landsat Tier 1 products, facilitates reconstructing long-term time series of spectral responses. Analysis-ready products standardize approaches to infill temporal or spatial data gaps as well as adjust for differences among satellite sensors (Chu and Guo 2013). To successfully curate a time series of spectral responses, users also need to be aware of cloud cover or fog, as both impact spectral responses (Young and others 2017). Most compositing methods have algorithms to detect and remove cloud and fog and extract high-quality pixels for the final mosaiced image. These compositing approaches generally mask pixels assumed to be cloudy or hazy. Then, they merge pixels by maximum, average, or median pixel brightness value for a given range of time (White and others 2014). It is important to know that different approaches, such as the median versus maximum spectral value, will impact final output composites (Epstein and others 2024). In spectral recovery literature, there is no established guideline for best practices in developing image composites, and there have been few studies that compare compositing approaches (White and others 2014; Francini and others 2023).

Historically, studies overcame the complexities of processing satellite data by relying on single images that captured forests of different ages. In these early studies, differences in the spectral response of multiple bands described spatially variable forest age. For example, Jakubauskas and others (1996) compared unique spectral patterns from Landsat TM images to the associated six stages of lodgepole pine forest succession (0–200 years) in the Greater Yellowstone Ecosystem. The overall accuracy for distinguishing successional stages from this the unique spectral patterns of single image was over 80%. As these early studies were generally single-image "snapshots," they did not describe how the spatial variability of forest succession linked to trends of spectral response.

Later studies monitored spectral trends of recovery by capitalizing on known differences in spectral bands accentuated by indices that combine bands (Frazier and others 2018). Spectral indices use ratios and transformations to translate the reflectance of one or multiple bands into a metric of increased ecological relevance. For example, the normalized burn ratio (NBR) combines the near-infrared and shortwave infrared to distinguish green vegetation from bare ground. Fire severity estimates often use NBR. Indeed, NBR is the foundational index for the United States' Monitoring Trends in Burn Severity (MTBS) Project. All MTBS fire severity estimates classify severity with dNBR and RdNBR values (Picotte 2023). These pre- and post-NBR values describe the total loss of vegetation from a fire, indicative of severity. In the same way, the rate and magnitude of NBR change post-fire capture vegetation recovery (White and others 2017; Bright and others 2019).

As spectral recovery of one or multiple spectral indices describes recovering vegetation, many studies have linked spectral rates, magnitudes, or thresholds of change to the recovery of forest structure and ecosystem dynamics (Frolking and others 2009a; Chu and Guo 2013; White 2024). The application of remote sensing to study ecosystem dynamics is succinctly summarized by Senf (2022). Our synthesis concentrates on spectral data of post-fire ecosystem recovery in the conifer forests of the Western Cordillera. For studies with similar methods, such as an assessment of stand development (for example, height, canopy cover) relative to the spectral rate of change, we aim to compare outcomes for spectral response and associated structural recovery quantitatively.

METHODS

Systematic Search

We used a systematic review approach to identify studies investigating pathways and associated drivers from SCOPUS, Web of Science, and AESD before November 11, 2024. Our protocol followed the RepOrting standards for Systematic Evidence Syntheses in environmental research (ROSES) and the Preferred Reporting Items for systematic Reviews and Meta-Analyses (PRISMA, **Appendix A**, (Collaboration for Environmental Evidence 2022). We built and tested our search query in SCOPUS and then expanded the search to Web of Science Core Collection, AESD, and technical reports from both Canadian and US institutions (Table A1). We also incorporated studies identified in past literature reviews and literature articles using snowball searching (Wohlin and others 2022). Search terms capture articles within the SPIDER (S—Sample, PI—Phenomenon of Interest, D—Design, E—Evaluation, R—Research Type) framework (**Appendix A**, Cooke and others 2012). We tested the comprehensiveness of search terms with benchmarking articles selected by the reviewers and field experts.

Exclusion criteria required the study to concentrate on dry-coniferous forests regrowing after high-severity fire. Specifically, forest types of the included studies were located in the Western Cordillera based on the Level Three Ecoregions (Omernik and Griffith 2014), had a continental climate (generally associated with dry conditions, Kottek and others 2006), and were coniferous leading. For studies that relied only on field data, we also required that the study model the forest recovery response with three or more ecosystem drivers (so we could compare relative effects). To capture the emergent literature using spectral monitoring, we included all spectral studies that assessed trends with or without models associated with ecosystem drivers. Out of 2,200 unique studies imported for screening, we excluded 1,997 based on abstracts and 139 based on full text. Of the 68 studies that passed full-text exclusion, we excluded eight studies from quantitative synthesis based on quality appraisal. Quality appraisal addressed the core components of internal and external study validity; studies that passed quality appraisal are focused, extensive, applied, and transparent (Burford and others 2013; Frampton and others 2017). A total of 60 studies, 33 field-based and 27 spectral (Figures 1, S2), published from 1996 to 2024, were included in data extraction (Figures S1 and S2). A complete description of the review protocol following the ROSES framework is included in **Appendix A** (Collaboration for Environmental Evidence, 2022).

Data Extraction

For each field and spectral study, we extracted methods and results describing recovery metrics, pathways, and associated drivers. For all studies, we noted forest type, measure of fire severity, and whether the study used spectral or field methods. We also extracted information on reported recovery trends. For studies that used spectral data to report trends, we extracted the approach used to identify recovery (for example, linear modeling or spectral threshold), the index and/or spectral bands, the number of years to determine pre-fire spectral baseline, the number of years to detect trend (s), and how distinct trends were associated with field observations. We noted when studies reported a distinct recovery pathway, which we defined as spatial variability in a recovery metric that persisted over time. For each pathway of recovery, we extracted metric type (for example, composition versus stem density), year of post-fire observation, the pre-fire forest type, and the post-fire forest type. We categorized types of post-fire forests as (a) mixed-conifer, (b) mixed-growth that includes deciduous and conifer species, or (c) single-species. Additionally, we noted if there were differences in stem density relative to pre-fire composition, or a temporal delay in establishment compared to assumptions or other regions.

Ecosystem Drivers

For studies that considered the relationship between recovery metrics and ecosystem drivers, we extracted information on the recovery metric, model approach, model accuracy, and tested drivers. When studies built multiple models for different species or forest types, we extracted model results for each species and forest type. For each driver, we extracted the direction of effect on the metric of coniferous recovery, the parameter estimates, and how effect was measured (for example, variable importance versus slope parameter), a range for driver significance (for example, very high to not based on p-values or variable importance scores), and degrees of freedom. To be able to calculate driver effect size, we extracted the standard error or the precise p-value. When drivers did not note a parameter value, we determined relationships based on textual reference. When studies tested transformed aspect, we maintained cross-study consistency by ensuring northern aspects

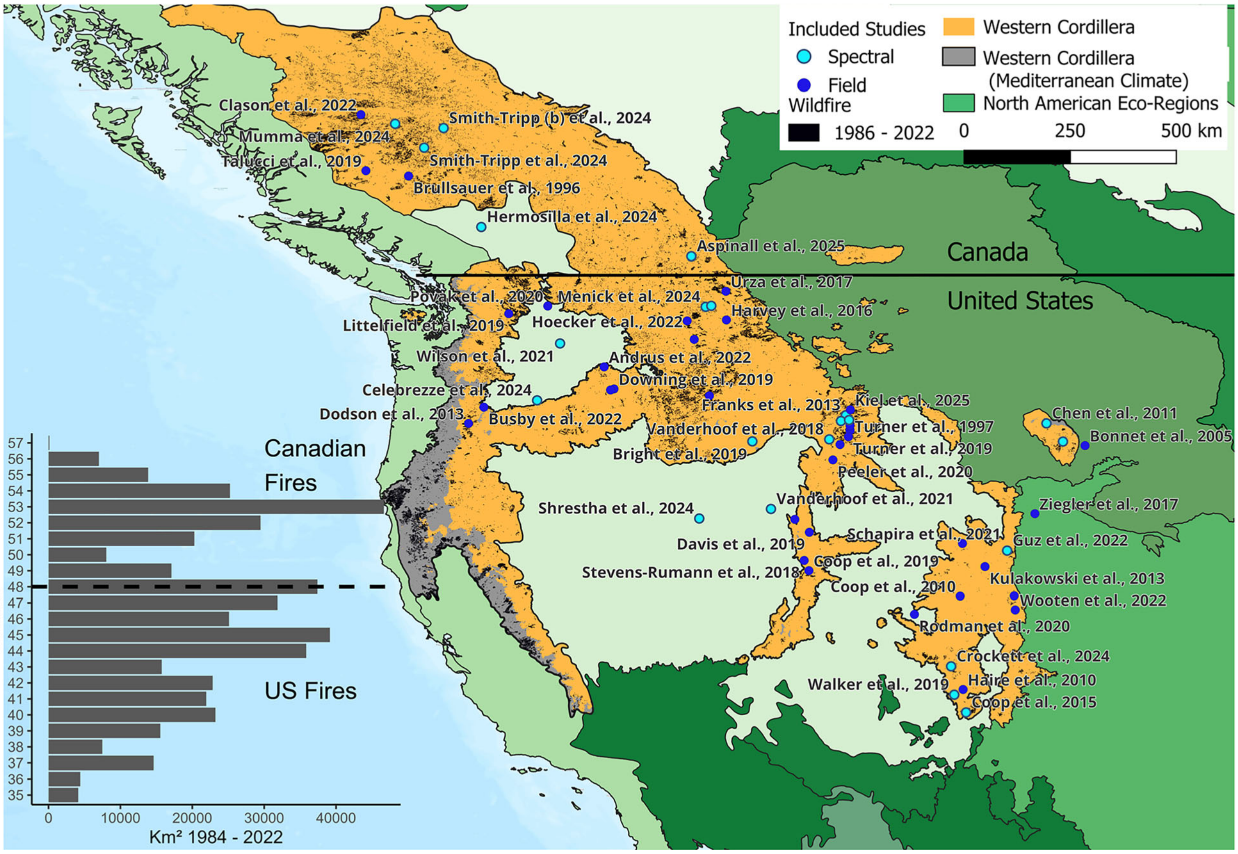


Figure 1. Map of the Western Cordilleran eco-region (shown in orange and red) subset to areas that experience a continental climate (highlighted in orange). Areas with wildfires in this eco-region are shown in black. Total fires (in km^2) from 1984–2022 by latitude band shown at left. Fire locations identified using the Landtrendr algorithm (Kennedy and others 2019), validated with the USGS MTBS (Finco and others 2012) and the Canadian National Fire Database (Skakun and others 2018). Points are the center of the bounding box for studies included in data extraction. Studies that appear outside the Western Cordillera are landscape-level studies. Color denotes if the study is spectral (uses satellite data) or field-based (uses only plot-level data).

were associated with lower values (for example, 0 for a Beers aspect transformation; Ferguson and others 1989). We also noted when drivers were tested as a part of model selection but not included in the final modeling due to model parsimony. Where available, we included estimates of model accuracy of adjusted R^2 or AUC for logistic models. When necessary, we contacted the corresponding author for additional information on the coefficients, approaches, or results. All studies were subject to critical evaluation to minimize bias from confounding factors or study-site selection (see **Appendix A** for more details).

To allow for inter-study comparison despite variability across ecological drivers, we arranged drivers into groups and organized these groups into broader Categories. For the ease of the reader, ''Categories'' are capitalized throughout the text. The eight Categories we describe are: (1) Physical-site Characteristics such as elevation, (2) Abiotic-site Characteristics such as average growing season temperature, (3) Pre-fire Biotic Characteristics such as pre-fire basal area, (4) Fire Impacts such as fire severity, (5) Post-fire Weather such as average post-fire precipitation, (6) Anomalous Post-fire Climate where weather observations were normalized to historic averages, (7) Management, and finally (8) Interaction terms and/or random-effects. In our categorization, we separate post-fire climate measures from anomalous post-fire climate (Post-fire Weather and Post-fire Anomalous Climate, respectively). Post-Fire Anomalous Climate normalizes to site-averaged climate, typically using z-score transformation (Davis and others 2023). For details on associated groupings and categories for individual drivers, see supplemental Table S3. For each group, we tallied the number of models that noted a positive, negative, or neutral effect on the associated conifer recovery metric. We also calculated the frequency that a driver from any given group was both tested and included in the final models.

To assess the relative impact of driver groups across studies, we normalized estimated parameters across models. For each model, we first normalized reported driver parameters so that the driver with the largest effect or importance was 1, and the least important parameter was 0. We then multiplied normalized values by the overall accuracy of the model and the direction of model effect. For these normalized values, a value closer to one describes a driver that positively impacted the metric of recovery and was associated with a highly accurate model (generally $R^2 > 0.7$). Comparatively, a vital driver included in a model with low accuracy would be closer to zero. Finally, a value close to -1 describes a driver that negatively impacted the metric of recovery and was associated with a highly accurate model. Normalization allowed comparison between statistical approaches, such as random forest and linear regression.

Results

Overview of Results

Our meta-analysis and narrative review synthesized findings from 60 studies investigating forest recovery pathways and drivers in the Western Cordillera of North America (see Supplemental Table S1 for a list of selected studies). We begin with a summary of the included literature, highlighting metrics and methods used to identify pathways, years of post-fire assessment, and methods for determining fire severity. We then address objective (1), identifying key recovery pathways from the included literature, with an emphasis on the application of spectral data to discern these pathways. Then, we address objective (2), assessing the relative importance of drivers of recovery. Typically, studies relate spatial variability in recovery metrics to ecological drivers. While the spatial variability of the recovery metric does not explicitly capture a pathway, this spatial variability is often implied to represent a pathway. Thus, we present results of recovery drivers in relation to their measurement metric, such as stem density, seedling/sapling presence, and spectral recovery associated with coniferous growth. We first outline how individually measured drivers are categorized into broader driver groups, as well as the frequency at which groups are assessed. Subsequently, for each driver group, we consider its overall importance across models, considering how the specific metric measured (for example, stem density or spectral response) influences the relative importance of different driver groups.

Studies Included in Review

One-third of the total burned area in the western Cordillera is in Canada, but studies are disproportionally located in the USA (Figure 1). Research is predominantly field-based, but 27 studies (44% of extracted) use spectral data to monitor and/or model recovery (Figure 1). Half of the extracted studies, both field and spectral, describe distinct recovery pathways related to species composition, forest structure, or temporal trends. 43 studies (70%) also modeled variable recovery responses in relation to different drivers; of these, 13 (32%) investigated how different ecosystem drivers impacted spectral metrics of conifer recovery.

The most common pre-fire forest type for extracted studies is mixed conifer (41%), followed by ponderosa pine and Douglas-fir dominated forest (13%). The time frame for post-fire assessment averaged 15 years. Note some studies had longer observation windows (> 60 years), which we retained because they emphasized ecological relationships of early forest succession in the generally underrepresented Canadian extent of the cordillera. When studies include a metric of field-based recovery, the most common metric is stem density (41%), followed by seedling presence (13%). All studies assessed high-severity wildfires, but varied in approaches used to identify fire severity. The most common method to estimate fire severity was RdNBR (15%), followed by a combination of dNBR and MTBS (13%, Supplemental Table S1).

Objective 1: Distinct Recovery Pathways of the Western Cordillera

Our systematic review identified 29 studies that reported 103 different recovery pathways. Of these studies, 73% used spectral data to identify pathways. From the extracted literature, the most commonly observed pathways suggest self-replacement (62%, Figure 2). The second most reported pathway (12%) was state changes, where the pre-fire dominant conifer species lose dominance to deciduous trees and shrubs, grass, or bare ground. Spectral studies reported self-replacement and state changes at a greater frequency than field-based studies (80% of state change pathways were identified by spectral studies). Additionally, pathway identification is more common with spectral

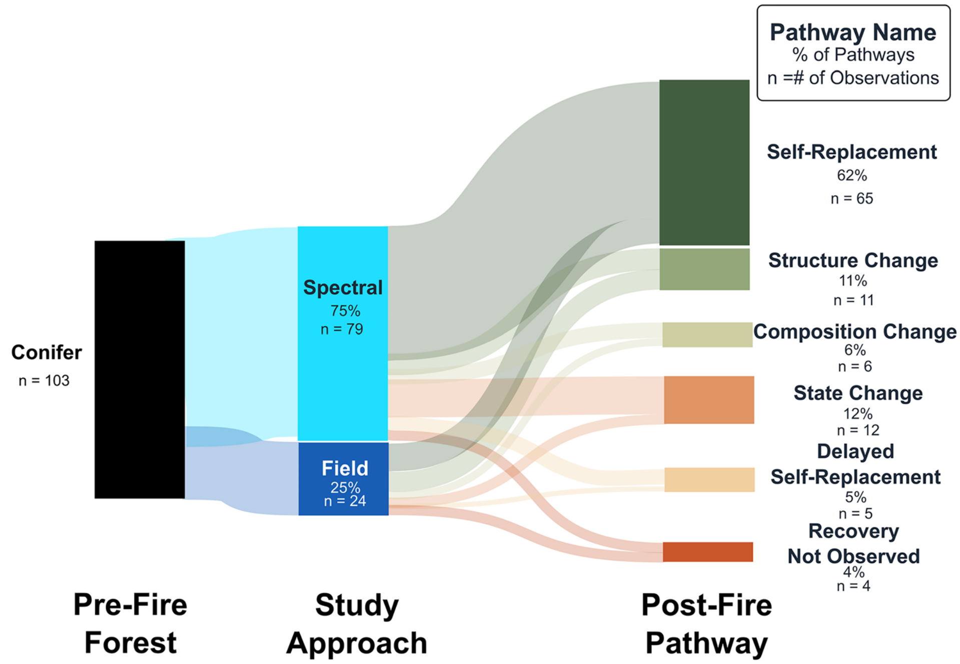


Figure 2. Sankey diagram representing the literature identified recovery pathways. Lines are colored by type of recovery pathway. Studies that use spectral data and field data are divided. Line width represents the frequency the pathways was extracted from spectral and field studies (n = 103).

methods than with field-based studies. When studies did not observe recovery during the observation window, recovery outcomes were described as binaries between 'recovered' or 'not-recovered' (Vanderhoof and others 2018; Davis and others 2019; Kiel and Turner 2022; Menick and others 2024).

Self-replacement pathways included areas with recovery delay. For example, Kiel and others (2025) found three distinct recovery pathways, including two pathways of slow or delayed recovery, where conifers required decades to establish at densities > 500 stems per hectare. Spectral studies often associated slow rates of spectral recovery with delayed conifer establishment. For example, Menick (2024) used snow-season NDVI values to differentiate between areas with successful conifer establishment 29–34 years after fire in northwestern Montana. They found positive NDVI trends were delayed from the original fire event, which they attribute to an associated delay in coniferous recovery. The pathway of delayed coniferous recovery is also noted in other spectrally based studies (Vanderhoof and others 2018; Smith-Tripp and others 2024a).

Objective 2: Discerning Recovery Pathways with Spectral Data

Spectral studies are diverse in their approaches to identify recovery pathways, complicating interstudy comparison and applying findings at scale. Differences lie in data processing, methodology, and associated field observations (see Table 1). Most of the studies included in the review used data acquired from the Landsat satellite series (23 of 27). Most studies create seasonal composites of satellite surface reflectance (20 out of 27), but compositing approaches and definition of growing season vary (Table 1). For example, Menick and others (2024) used maximum composites for the growing season, May–October, to assess canopy recovery in northwest Montana. In eastern Oregon, Washington, and Idaho, Celebrezze and others (2024) defined the growing season as June–August. Studies also used varying years to establish pre-fire spectral baselines to gage post-fire changes. Baseline periods vary from immediately before the fire (Buma 2012) to 10 years prior (Celebrezze and others 2024; Smith-Tripp and others 2024b), with a median of 3 years. Some studies exclude the year before the fire to avoid mixed signals from pre-fire drought (Vanderhoof and Hawbaker 2018; Vanderhoof and others 2021).

Table 1. Description of Methods Used to Process Spectral Data and Identify Spectral Trends among Included Studies Systematic Review (n = 27)

Variable	Value	Number of papers (n = 27)
Landsat spectral composite approach	Maximum	8
	Mean	2
	Median	4
	Median, maximum	1
	Other	12
Spectral metrics	All landsat bands	1
	Combination of bands/indices	7
	EVI	2
	MODIS summer LAI	1
	NBR	8
	NDVI	9
	NDVI (growing season)	1
	NDVI (snow cover)	2
	SAVI	1
	SWIR (band 5)	1
	Green chromatic coordinate	1
Years to establish baseline	1	2
	2–4	15
	5 +	5
	Other	5
Observation window	1–5	7
	11–20	6
	21 +	2
	6–10	11
	Other	3
Method to assess spectral recovery	Change	5
	Cut-off	2
	Other	1
	Phenology	2
	Relative change	3
	Slope	9
	Supervised classification	2
	Unsupervised classification	3
Field or lidar verified structural attribute	Combination of measures	7
	Composition	9
	Density	3
	No field assessment	8
	Seedling presence	1

Studies also used different spectral indices to identify trends: NDVI is the index most assessed (12 of 27), while NBR or index combinations are equally frequent (8 of 27). For these indices, post-fire spectral trends and associated pathways were identified from (1) temporal slopes (n = 9), (2) relative or absolute change (n = 8), (3) classification or clustering (n = 5), and spectral brightness thresholds (n = 2). Thirteen studies validated spectral differences using field data, light detection and ranging (lidar) imputed structure estimates, or high-resolution imagery. Trends were identified from spectral satellite observations taken 1 and 30 years after the fire event, averaging 9 years. Interestingly, Epstein and others (2024) found no accuracy differences when using different observation windows (5, 10, or 15 years) to calculate spectral recovery rates associated with either dense or sparse conifer recovery.

Synthesizing the association of spectral trends to pathways was challenged by the diversity of data processing, selected spectral indices, and methodologies. Instead of a quantitative comparison, we provide a narrative synthesis of how different spectral trends describe structural recovery pathways. First, studies generally used a single spectral index to model recovery, and support that areas with higher spectral index values have more vegetation cover (Buma 2012; Vanderhoof and Hawbaker 2018; Vanderhoof and others 2018; Kiel and Turner 2022; Menick and others 2024; Smith-Tripp and others 2024b). Additionally, higher spectral recovery rates indicate more vegetation regrowth, but not necessarily coniferous regrowth (Smith-Tripp and others 2024b). For example, Celebrezze and others (2024) found that the recovery rate of NDVI and NBR did not distinguish between shrub and conifer dominant areas, with areas dominated by grass having slower recovery rates. Grass was not universally associated with slower spectral recovery rates—both Chen and others (2011) and Mitchell and Yuan (2010) found that grass had higher initial recovery rates compared to dense Ponderosa pine stands after the 2002 Jasper fire in South Dakota. Chen and others (2011) also considered which index best described differences in land cover postfire and suggested that the integrated forest index (IFI) and the NBR displayed the most variability across ponderosa pine, mixed conifer, and grassy study sites. Although Chen and others (2011) is the only study to test IFI, the value of NBR for differentiating among distinct trends is noted by several different studies (Celebrezze and others 2024; Menick and others 2024; Smith-Tripp and others 2024a, 2024b). Notably, while studies compared the effectiveness of different indices for modeling recovery (for example, NDVI vs. NBR, Celebrezze and others 2024) no study tested how using a single index versus multiple indices impacted study outcomes.

Objective 3: The Relative Influence of Recovery Drivers

Models linking spatial and temporal recovery to ecosystem drivers vary in the metric measured and modeling approach. Many studies include multiple models for specific forest types (for example, lodgepole pine and Engelmann spruce; (Littlefield 2019) or regions (for example, southwest Washington vs. Montana Rockies; Wilson and others 2021). In total, we extracted the directional association of ecosystem drivers and recovery metrics from 152 distinct models. Modeling details, including tested drivers and effects, are noted in Table S4. Two-thirds of models are derived from field-based studies (99 out of 150). Across all models, the most common statistical approach is generalized linear regression (40%), while random forest and boosted regression are the second and third most common (11 and 10%, respectively). Metrics of stem density, spectral response, and seedling/sapling presence are the most common metrics used as response variables in models of ecological drivers (41, 35, 13%). For the most common recovery metrics, spectral response and stem density, assessments of model accuracy are similar (average stem density model accuracy = 0.54, average spectral model accuracy = 0.56). Our presentation of results focuses on the most tested recovery metrics: stem density, spectral response, and seedling/sapling presence.

Variability in recovery metrics is modeled using many different ecological drivers. To facilitate synthesis, we placed the more than 1000 extracted drivers in 31 ecological similar groups within 8 categories (Table S3). Notably, while we focus on naturally recovering forests, select studies include comparison to planted or salvaged areas (Andrus and others 2022; Clason and others 2022). We include these studies for completeness (Post-Fire Management), but focus our discussion on drivers present in unmanaged stands. Of these eight categories, Fire Impacts represent almost half ($n = 459$) of tested drivers, while Post-fire Weather and Post-Fire Management were the least common (Figure 3). Within the category of Fire Impacts, the post-fire seed source, which described distance (distance to edge) or abundance (cone abundance) of live seed sources, was the most frequently tested ($n = 148$). Physical-site Characteristics ($n = 336$), including elevation and aspect, were the second most commonly modeled drivers (Figure 3). The frequency of different driver groups included in models varied by measurement metric. Models that were developed for spectral metrics include more drivers (parameters) than field methods (median number of drivers for spectral is 9 vs. 6 for field). Among categories of driver groups, field methods more frequently consider Abiotic-site Characteristics and Physical-site Characteristics. Conversely, spectral methods more frequently consider Pre-fire Conditions, Post-fire Weather, and Post-fire Anomalous Climate.

Post-fire seed source is the most frequent driver grouping included in stem density and seedling/sapling presence models. Post-fire seed source describes the distance to or overall lack of seed source (for example, distance to the forest edge and remaining live basal area, Table S3). To ensure this driver grouping aligned with a lack of seed source, some drivers, such as the proportion of the landscape that is unburned, were inverted. Once transformed, the effects of post-fire seed source generally skewed negative, with some examples of positive impacts. For instance, Povak and others

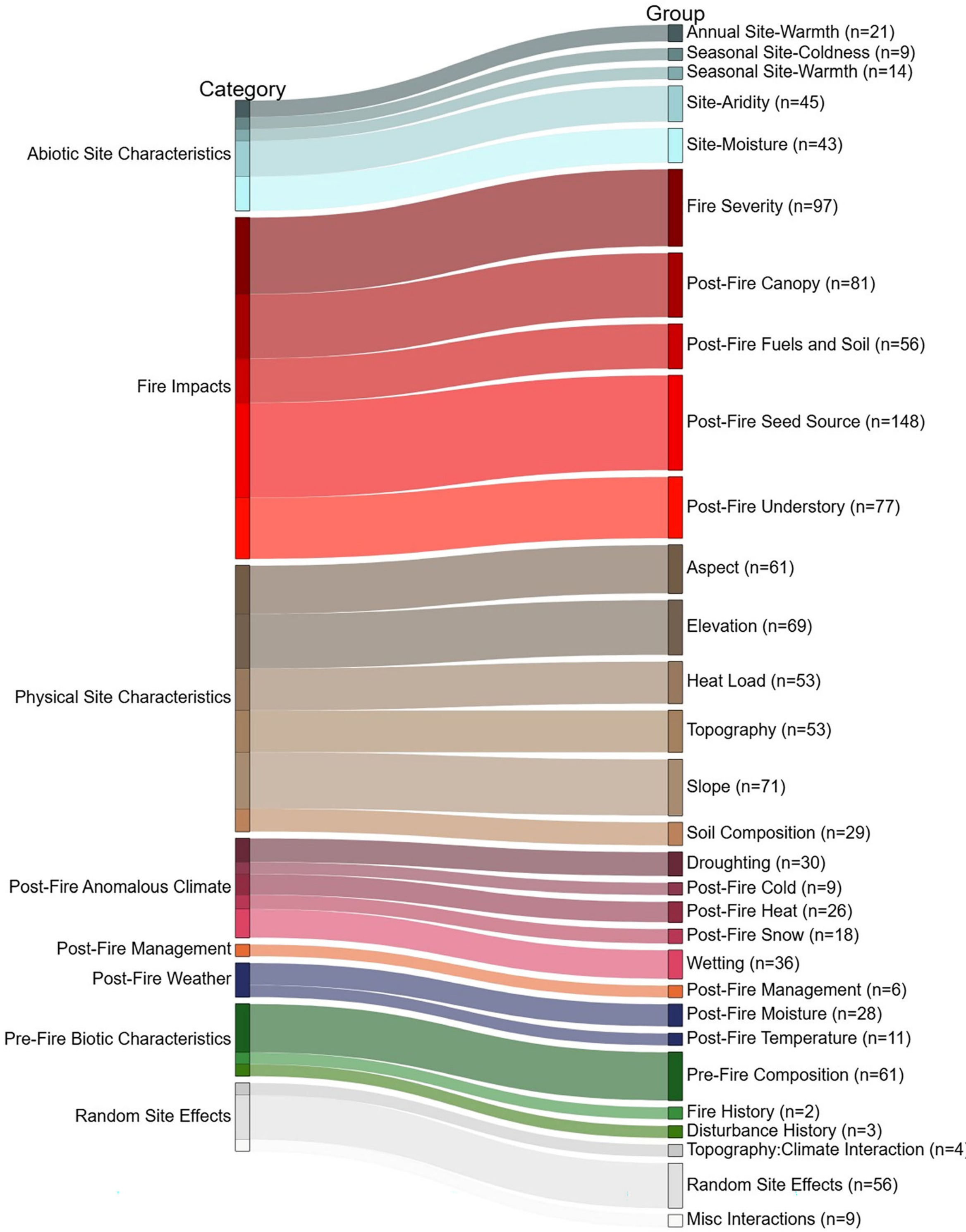


Figure 3. Frequency of different groupings (arranged by Category) of driver factors across all papers. Labels are the groupings, and numbers are the total number of times a driver within the group was extracted.

(2020) found that distance-to-edge was negatively correlated with post-fire stem densities in a mixed conifer forest. Yet, Peeler and Smithwick (2020) found that lodgepole seedling density was positively correlated proportion of burned landscapes. Spectral studies found a consistent negative impact

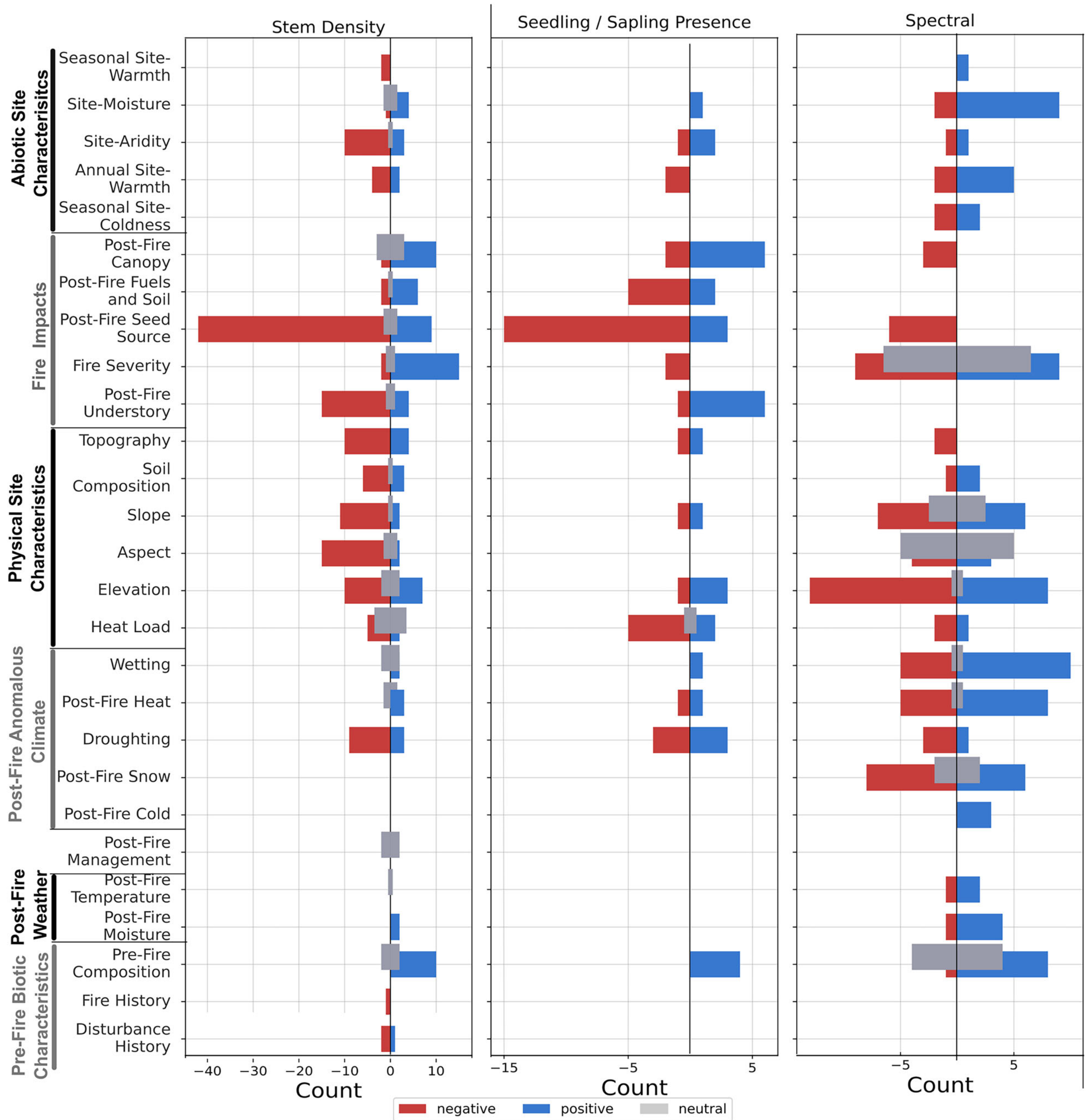


Figure 4. Number of models investigating the spectral and structural recovery of interior dry conifer forests. Values are colored by the number of models where driver association is negative (red) or positive (blue) for the recovery metric (note scales on the *x*-axis vary) with neutral (gray) offset. Positive spectral recovery is either (**a**) a positive impact on recovery rate, OR (**b**) a recovery rate positively correlated with coniferous stems. The y-axis labels are each driver group within each driver Category.

of seed source, but most spectral studies tested fire severity, not seed source.

Effects of drivers, such as fire severity, differed among recovery modeling approaches. Across the western US, the spectral recovery of lodgepole pine forests was negatively correlated with satellite estimated fire severity (Shrestha and others 2024), but in field-based models, post-fire lodgepole pine stem densities are positively associated with field estimated fire severity (Turner and others 1997; Coop and others 2010; Hoecker and Turner 2022). Overall, a greater proportion of field-based metrics have positive correlations with fire severity, whereas spectral studies note a neutral and/or variable effect (Figure 4). Another driver with variable impact across metrics was aspect: densities are generally lower on southern aspects in field-based studies (Hoecker and Turner 2022; Ziegler and others 2017), whereas the effect is often neutral in spectral recovery models (Vanderhoof and others 2021; Wilson and others 2021) or non-significantly negative (Bright and others 2019).

The effect of ecological drivers also varies by forest type or region. Fire severity positively correlates with stem density recovery across all forest types, but Douglas-fir and ponderosa pine forests are negatively correlated (Figure S3). Similarly, elevation has a variable impact on recovery by species and region. For coniferous species in Pacific Northwest forests, Littlefield (2019) found species presence was positively correlated with elevation for alpine species like Engelmann spruce and western larch, but negatively correlated with Douglas-fir and ponderosa pine. Across the northwest US region, Wilson and others (2021) used variable importance to assess the impact of elevation on spectral recovery of Douglas-fir; they found elevation to be the most important driver for spectral recovery for Douglas-fir forests in central Idaho, but in western Montana, post-fire precipitation anomalies had a greater relative impact.

Pre-fire composition and site-moisture are two of the few driver groups that consistently positively impact all recovery metrics (Figure 5). Standardized models suggest pre-fire composition had a greater positive impact on stem density (field) than spectral recovery (weighted effect of 0.32 vs 0.11 for spectral recovery). Conversely, post-fire moisture had a greater positive effect on spectral recovery (weighted effected of 0.41 vs. 0.36). Site-moisture also had a consistent and positive influence on models of spectral recovery but had little to no influence among the eight models of field-measured stem density that included site-moisture (weighted ranking spectral = 0.32 vs. weighted ranking stem density = 0.00). For some driver groups, such as wetting and post-fire heat, spectral recovery studies suggested a strong positive influence. However, none of the included studies based on field data included parameter estimates for wetting or post-fire heat.

Overview of Findings

Our systematic review investigated the distinct early (< 20 years) recovery pathways and associated ecological drivers after high-severity fire in dry conifer forests. Our approach merged findings from different disciplines: field-based studies as well as studies that use spectral responses from satellite image time series data. From the included studies, we found that distinct pathways identified by spectral and structural literature are generally similar and reflect those of prior syntheses (Baltzer and others 2021; Stevens-Rumann and others 2022). These pathways described distinct spatial and temporal trends by species composition, forest structure, and establishment rate. However, recovery pathways were predominantly defined by studies with both pre-fire and multiple post-fire observations—namely, studies that used time series of spectral data.

After synthesizing pathways, we investigated which ecological drivers' impact on the spatial and temporal variability in recovery metrics. We found that the number of ecological drivers included in the literature is diverse (more than 1000 unique drivers were tested across 60 studies, Figure 5). Importantly, more recent literature has incorporated post-fire weather and climate conditions, addressing a limitation noted in the last systematic review of coniferous recovery (Stevens-Rumann and Morgan 2019). Overall, the relative importance of ecological drivers varied by method (spectral vs. field-based), metric (stem density vs. seedling presence, Figure 5), species (lodgepole pine vs. Douglas-fir, Figure S3), and region (Oregon vs. Montana). Further, satellite and field-based studies focus on different drivers: spectral studies are more likely to include post-fire measures of climate conditions, while field-based studies are more likely to include post-fire measures of soil and understory condition.

Recovery Pathways Limited by Knowledge Gaps in Pre-fire Composition and Post-fire Growth Trends

Field-based and remote sensing scientists predominantly define recovery pathways by their composition, including conifer self-replacement or state-shifts (where composition shifts to different tree species, shrubland, or grassland, Box 1, Figure 2). Fewer studies describe pathways of density change and/or temporal delay, likely because identifying these pathways requires estimates of pre-fire composition and multiple observations post-fire. As a result, pathways of structural change are seldom identified, nor are measures of pre-fire conditions incorporated in recovery models. Spectral data offer a lens into both pre-fire conditions as well as post-fire monitoring; however, the accuracy of spectral

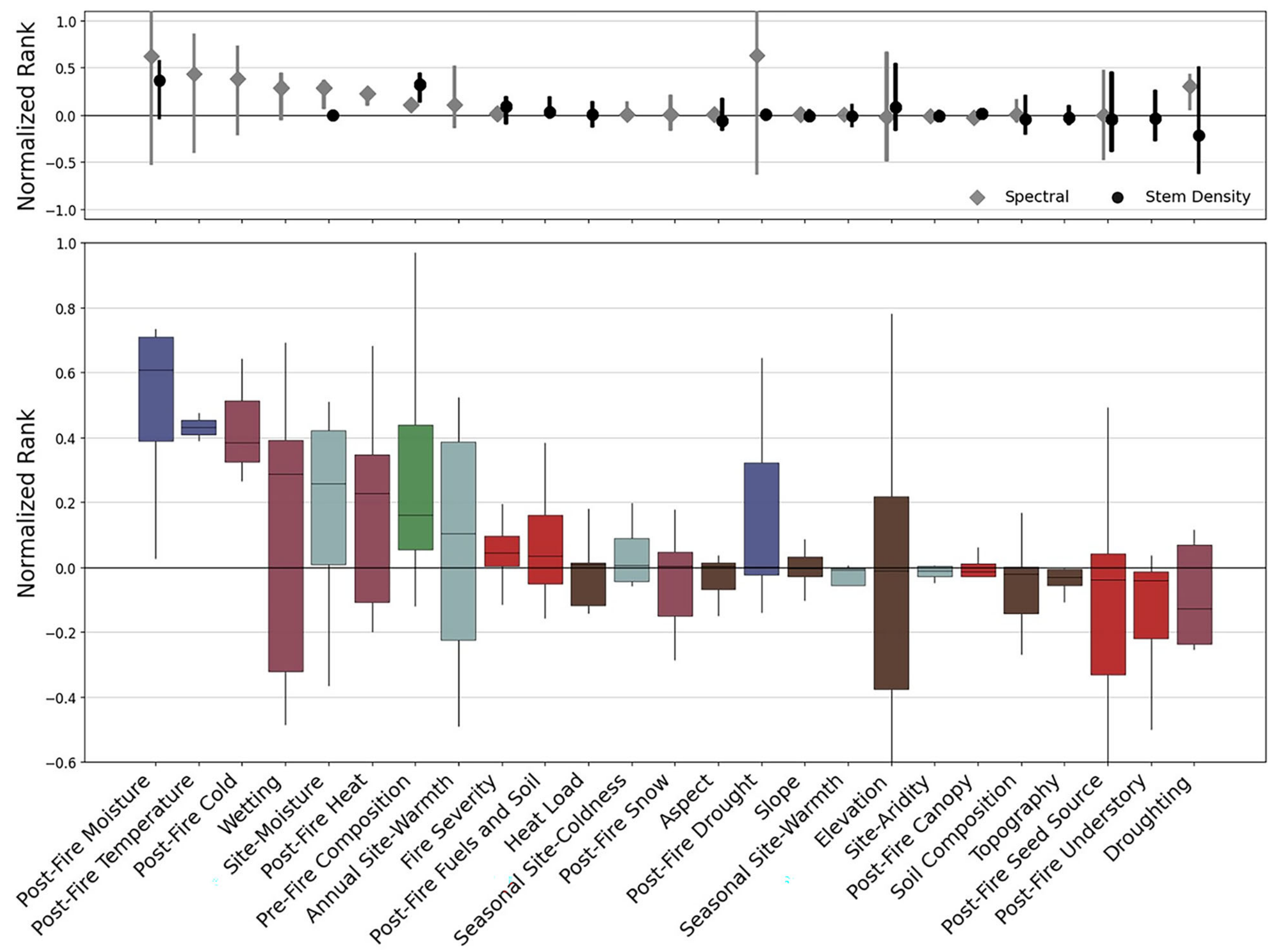


Figure 5. Relative importance of drivers with parameters normalized by model and model accuracy between − 1 and − 1. Values of − 1 or 1 describe a driver with the largest effect size or greatest importance in a model that captures 100% of variability, whereby negative values have a negative effect and positive values have a positive impact on the associated conifer recovery metric. Driver groups are shown only when $N > 3$. (**A**) Diamonds and bars are the median and interquartile ranges for spectral and stem-based models. (**B**) Boxes show interquartile ranges and median values for each driver group across all approaches. Boxes are colored by driver Category (see legend at left).

data for characterizing the pre-fire conditions and post-fire trends is not well established.

Spectral data pre-dating fire could provide estimates of pre-fire composition and structure. Field-based studies often estimate pre-fire structure based on post-fire observations, but high fire severity results in less structure to measure (Harvey and others 2013; Downing and others 2019; Turner and others 2019). This means pre-fire spectral observations are instrumental when the pre-forest stand is completely consumed. Vanderhoof and Hawbawker (2018) compared pre- and post-fire growing season values of NDVI, and suggested that areas with increases in the magnitude of change between winter and summer NDVI may be areas with an increased deciduous composition. Given variability between spectral response and structural estimates, assessing the accuracy of pre-fire spectral observations to capture pre-fire metrics of forest structure is also essential (Ireland and Petropoulos 2015; Wilson and others 2021; Celebrezze and others 2024). Such research should also consider which pre-fire measures to quantify: identifying density changes requires pre- and post-fire density estimates, but both pre-fire density and cone abundance may impact conifer growth (Turner and others 2019).

Time series of post-fire field observations are rare. Thus, recovery pathways were predominantly identified by studies that used spectral data. Our review included two studies that initially labeled slow rates of spectral recovery and later field validated high stem densities as locations of delayed coniferous establishment (Menick and others 2024;

Smith-Tripp and others 2024a). However, neither of these studies validated temporal trends with time series from plots at the same location. Such validation is likely important, as research in other ecozones suggests spectrally identified trends may not coincide with those identified in the field. For example, a study in the US Great Basin that aligned spectral and field-based trends of post-fire recovery found that spectral trends did not capture the field-observed trend of post-fire exotic vegetation encroachment (Barker and others 2019). As we continue to rely on spectral data for post-fire monitoring, it is important to investigate the capacity for spectral and field-based trends to align. These investigations should also consider the spatial scale associated with trends—a region with slow conifer establishment at the scale of a Landsat (900 m^2) pixel could encompass smaller field plots with rapid conifer establishment. Additionally, a spectral response validated as conifer growth at one location may not apply to other regions or time periods.

Effect of Recovery Drivers Varies by Metric and Method

The frequency that a driver is tested and its associated impact on recovery varies by metric (stem density vs. composition) and method (spectral vs. field). Across all metrics, ecological drivers that describe moister conditions are associated with faster recovery rates and higher conifer densities (Brullsauer and others 1996; Haire and McGarigal 2008; Dodson and Root 2013; Malone and others 2018). Comparatively, the relative impact of aspect differs by method: stem densities are consistently lower on southern aspects, but aspect often plays a neutral role in spectral recovery. Finally, while post-fire understory was the second most common driver in the Fire Impacts category, none of the included spectral studies tested the impact of this driver.

Spectral models highlight some ecological drivers that are rarely considered by field-based studies. For example, field-based studies highlight the negative impact of post-fire drought on post-fire seedling establishment (Davis and others 2019, 2023) and stem densities after fire (Clark-Wolf and others 2022). However, spectral studies that consider both post-fire moisture and temperature suggest that post-fire temperature can have a larger impact on recovery than moisture (Bright and others 2019; Guz and others 2021). For example, Vanderhoof and others (2021) found that the NDVI recovery rate for the winter season, indicative of greater conifer densities, was positively associated with cool summer temperatures, but observed no relationship with summer aridity.

In some cases, the effect of an ecological driver could result from different data sources among spectral and field studies. Buma (2012) correlated in-field stem density with thresholds of NDVI and found that areas where NDVI corresponded to high-stem density did not correlate with aspect. Buma (2012) suggested that the influence of aspect on coniferous recovery was muted because aspect is used to convert atmospheric reflectance to surface reflectance.

Standardizing Recovery Drivers Across Spatial Scales

Spatial scale of measurement and analysis impacts research outcomes for both recovery pathways and associated ecological drivers. Spectral recovery metrics are estimated at the pixel level, which in the case of Landsat, represents a 900 square meter area. This spatial unit is commensurate with information requirements for forest management and as such, has proven useful for large-area assessments of post-disturbance recovery (White and others 2017; White 2024). However, spectral recovery can capture the influence of recovering vegetation such as shrubs and grasses, in addition to trees. As ecological drivers may impact different vegetation in different ways, examination of the association between spectral recovery and ecological drivers must take this into account. It is likewise critical to consider the spatial scale used to estimate ecological drivers, as the scale at which a driver is quantified could mediate its impact on recovery. For example, cover immediately around a plot may provide a microclimate conducive to seedling establishment (Downing and others 2019), while extensive shrub cover throughout an area may outcompete coniferous growth (Laughlin and others 2023). Peeler and others (2020) demonstrated the importance of scale; their research found that the accuracy and effect of models varied by the spatial extent used to quantify seed source. Specifically, sub-alpine fir regeneration density was lowest when the distance to the seed source was quantified within a 50–100 m radius of the field plot. The importance of spatial scale may explain the variable ecological drivers across studies. Consider shrub cover, where some studies found post-fire shrub cover had the greatest negative impact on post-fire regeneration (Littlefield and others 2020), but other studies found a positive effect (Downing and others 2019; Boag and others 2020) or neutral effect (Andrus and others 2022). Leveraging spectral data to create spatially continuous estimates of ecological drivers, future research could ask at what spatial scale drivers like shrub cover shift from being facilitative to competitive.

Pre-selection of ecological drivers, such as post-fire drought, may obscure the impact of other drivers. We found that droughting had the most consistent negative association across all recovery metrics, while post-fire moisture had the strongest positive association. Post-fire drought is frequently attributed to decreases in post-fire stem densities, failed seedling establishment, and decreased rates of spectral recovery (Rodman and others 2020; Schapira and others 2021; Guz and others 2022; Braziunas and others 2023). However, some studies that tested both temperature and moisture found a greater impact of post-fire temperature (Clark-Wolf and others 2022). Further, when studies normalized precipitation to historical climate (that is, tested ''wetting''), the impact of moisture was more variable. Thus, which drivers are considered and how they are processed impact the observed response within a recovery model. This finding raises another critical question: Are there consistent and standardized sets of ecological drivers that should be incorporated into recovery models? For example, a standard set of climate variables, including climate anomalies, would improve knowledge synthesis efforts and thus our understanding of recovery.

Considering the Limitations of Selected Studies

The methods we used to identify, select, and extract data from studies include limitations that must be considered in the context of our results. First, as we focused on research in the first several decades, recovery pathways identified in synthesis skewed toward those identified by spectral studies. We acknowledge the extensive research using longer time series from dendrochronology or field-based space-for-time to understand recovery pathways (Johnson and Fryer 1989; Brullsauer and others 1996; Gendreau-Berthiaume and others 2018). However, the value of spectral studies is their capacity for post-fire monitoring amidst rapidly changing ecological conditions. Yet, extracting and synthesizing findings of spectral studies can be challenging due to the diversity of approaches prevalent in the literature.

Generalizing across studies of spectral monitoring of recovery pathways is challenged by diversity in metrics of conifer recovery. While the challenge to define recovery is not isolated to remote sensing (Baltzer and others 2021; Stevens-Rumann and others 2022), the variability in definitions of recovery complicates the already challenging process of linking field observations to the spatial scale of spectral responses (Frolking and others 2009a; Bartels and others 2016). For example, Celebrezze and others (2024) found that the spectral recovery rate of grass was slower than that of shrubs and conifers. But, across the western US, Vanderhoof and others (2021) grouped grass and shrubs together and found this group's spectral recovery to be faster higher than that of conifers. The different outcomes of spectral recovery rates among Vanderhoof and others (2021) and Celebrezze and others (2024) underscore that the definition of recovery impacts study outcomes.

Beyond challenges associated with definitions of recovery, spectral monitoring for recovery pathways is also challenged by the use of different satellite source data, image compositing methods, and definitions of growing season, which means findings are not always generalizable. For example, faster rates and/or greater amplitudes of spectral recovery after fire are often linked to a dominance of grass, forbs, or deciduous shrubs post-fire over conifers (Mitchell and Yuan 2010; Vanderhoof and Hawbaker 2018). Yet, this relationship is not universal. Additionally, different phenology (both spatial and species-based) produces unique spectral responses that can highlight conifer dominance, but phenology differs regionally; peak conifer spectral response for Colorado is in June (Buma 2012), whereas August was the peak spectral response in Arizona and New Mexico (Crockett and Hurteau 2024). Variability in spectral phenology, as well as amplitudes and rates, could be the result of forest region and type, but could also reflect variability in underlying data processing (Wilson and others 2021; Crockett and Hurteau 2024). Slow spectral recovery rates identified as grass by Celebrezze and others (2024) used mean growing season NDVI and NBR. However, in the dry Western Cordillera, grass senesces in summer months, which means NDVI and NBR drop after the grass turns brown. This senescence causes a lower growing season mean NDVI value compared to shrubs, deciduous, and conifer trees (Walker and Soulard 2019). Thus, in grassy areas, NDVI compiled from mosaics of mean brightness would have lower rates of spectral recovery compared to mosaics compiled from maximum brightness values.

In addition to the limitations of spectral studies, a large proportion of studies identified in our systematic review included linked datasets and were ultimately excluded from later syntheses. For example, we included Stevens-Rumman and others (2018), which combined data from more than ten previously published studies, specifically investigating the role of post-fire climate on post-fire stem densities. Studies that combined datasets could not test variables that were not measured at all plots, namely, variables of post-fire understory vegetation and soil composition. These understory and plot-level variables had large effects within the individual studies that we excluded from our extraction (Rother and Veblen 2016, 2017). We selected Stevens-Rumman and others (2018) as the spatial extent of their study better complemented the spatial scale of spectral studies. However, including the published studies included in Stevens-Rumman and others (2018) may have increased the frequency of testing and relative importance of other drivers, such as post-fire shrub cover. Across all studies, these linked datasets further underscore the need for a standard set of ecological drivers in recovery models, including post-fire understory, soil conditions, and a standardized set of post-fire climate variables.

Future Research Priorities: Key Questions and Recommendations

Our recovery synthesis framed key questions for future research. Addressing these questions will help to improve our characterization of recovery pathways and our understanding of ecological drivers across scales. The following section first summarizes questions and then introduces the recommendations and data needs for future research. We include summary tables of both questions and recommendations (Tables 2 and 3). We believe that following these recommendations will improve knowledge synthesis of recovery dynamics across field and spectral disciplines.

Characterizing recovery pathways: Future research that uses spectral data to characterize recovery pathways must also determine how accurate both pre- and post-fire forest structure estimates are when derived from spectral data. Comparing studies of recovery is difficult because metrics are inconsistent across both field and remote sensing-based studies. Spectral studies often combine in-field observation and spectral data to develop binary spectral thresholds for areas of 'high' and 'low' post-fire stem density—the magnitude of these spectral responses will vary based on pre-processing approaches and study area (Buma 2012; Kiel and Turner 2022). Instead of classification, spectral data could provide continuous estimates of forest structure, such as pre-fire basal area (White and others 2023) or post-fire canopy cover (Menick and others 2024). Yet, are these pre-fire spectral estimates of recovery metrics such as basal area or overall productivity (Vanderhoof and Hawbaker 2018) accurate enough to characterize areas where forest composition or structure change as a result of fire? Secondarily, after a fire, are unique trends in vegetation consistent between field and spectral approaches? (Table 2). Synthesizing the outcomes of studies that test these questions requires establishing more consistent pre-processing and compositing approaches across spectral studies.

Recommendations for characterizing recovery pathways: A first step for establishing spectral data to estimate pre- and post-fire forest structure is the use of consistent source satellite data such as the

Table 2. Key Outstanding Research Questions Associated with each Review Objective

Review objective	Key outstanding research questions framed by review
Characterizing forest recovery pathways	What pre-fire metrics are needed to characterize and comparer pre- and post-fire conditions? What accuracy is sufficient for comparison?
	Are pre-fire estimates of forest composition and structure sufficiently accurate to characterize areas where forest composition and structure change as a result of fire?
	Is there consistent alignment between field and spectrally observed trends of post-fire vegetation development?
	How do methodological inconsistencies in data processing influence the assessment of recovery outcomes?
	For spectral methods, how does the technique of pre-processing data, the selected spectral index, and the method to identify trends influence recovery outcomes?
Quantifying ecological drivers of forest recovery	How does spatial scale alter the association between recovery metrics and ecological drivers?
	What ecological drivers are important to consider in models of recovery across spatial scales?
	How can we standardize approaches to derive and report ecological drivers?

Table 3. Considerations and Recommendations for Future Research to Enable Synthesis and Meta-Analysis

Component of Study	Considerations and recommendations
Spectral data processing	Methods to process spectral data must be consistent in data source (such as analysis-ready datasets) and metrics measured
	Measures of spectral change between summer and winter help capture composition
	Structural estimates based on models of lidar-satellite fusion help capture structure and facilitate upscaling field observations
Measuring ecological drivers	Methods to assess post-fire conditions, such as canopy, understory, and soil, must be standardized
	Climate anomalies must be explicit in definitions of a ''normal'' climate and climate extremes (e.g., heat events, drought)
	Measurement accuracy should consider the impact of changing spatial scale
	Collaborations between field and remote sensing scientists will improve understanding of ecological drivers across spatiotemporal scales
Study reporting	Reporting of the method to measure recovery metric and drivers must be consistent to enable synthesis
	Model statistics, including accuracy and standard errors, must be explicit to enable meta-analysis

analysis ready Landsat datasets (Dwyer and others 2018) or the more recent harmonized Landsat-Sentinel dataset (Claverie and others 2018). These sources correct for atmospheric and sensor effects to produce surface reflectance that is required to support analysis over space and time (Song and Kim 2001). For estimating forest structure with spectral data, data processing approaches should highlight the spectral phenology response, including time-series analyses based on the amplitude of change between winter and summer spectral indices (Vanderhoof and Hawbaker 2018; Menick and others 2024; Shrestha and others 2024). For estimating forest structure, we suggest leveraging spatially complete structural estimates provided by lidar data to circumvent often mismatching spatial resolutions between field plots and spectral data (Senf 2022). For example, Menick and others (2024) used lidar data estimates across a large region of the US northwest to model temporal trends in post-fire canopy cover, validating their model with high resolution aerial imagery. In boreal forests, airborne lidar has been used to characterize post-fire recovery (Bolton and others 2015) and to validate spectral models of recovery (White and others 2018, 2022). As the spatial extent of lidar data continues to expand, so do possible collaborations to integrate historic opportunistic field samples as ground verification of spectral trends from one time (the original field sample) to the next (the later lidar acquisition). While the accuracy of lidar-satellite imputed forest estimates can vary (Hermosilla and others 2024), temporally and spatially complete remote sensing data layers can contextualize field observations. Further, repeat lidar acquisitions can help bound the accuracy of data layers (Montesano and others 2023). These spatially and temporally continuous recovery metrics can then be linked to ecological drivers, which can operate at different spatial scales (Davis and others 2020).

Quantifying ecological drivers: Fusing field and spectral approaches helps bridge spatial and temporal scales of both recovery pathways and ecological drivers. Across all studies, we found that landscape-level drivers such as post-fire weather and anomalous climate conditions had the strongest impact in recovery models. However, we did not investigate whether the spatial scale of the study impacted observed outcomes. Are measures of post-fire climate the most important drivers across scales? Or, are estimates of post-fire canopy more important at a local level? An essential question to address alongside these research questions is which drivers are important to consider in models of recovery across scales? (Table 2). Finally, as drivers such as climate anomalies will differ based on the definitions of ''normal'' climate, these investigations should also consider the best, or at least consistent, methods of deriving ecological drivers (Table 3).

Recommendations for quantifying ecological drivers: Acknowledging the difficulty of questions around ecological drivers, we recommend that future investigations start with a driver with existing standardization efforts across scales and methods. One good example is soil burn severity. We found that few studies, field or spectral, consider metrics of soil burn severity, even though soil burn severity mediates resprouting of post-fire shrubs and deciduous trees (Pausas and Keeley 2017; Baltzer and others 2021). Typical satellite-based estimates of burn severity, such as dNBR or RdNBR, poorly capture the spatial variability or depth of soil burn severity (Kasischke and others 2008). The US currently attempts to standardize satellite-derived severity using in-field observations. These attempts improve burn severity map accuracy, but the accuracy decreases as the distance from in-field samples increases (Wilson and Prentice 2024). The soil depth a wildfire burns to depends on the weather during the fire event, slope, aspect, and vegetation, which can all be estimated from remote sensing datasets (Seydi and others 2024). Recent efforts suggest that integrating information from remote sensing datasets, such as topography and surrounding vegetation, could improve the spatial accuracy of soil burn severity mapping (Wilson and Prentice 2024). As a first step to standardizing ecological driver quantification, future work could test how improved spatially continuous soil burn severity maps alter conclusions across scales: local to landscape and across methods: field or remote sensing.

Conclusions

In this study, we highlighted the pathways of forest recovery after fire in dry conifer forests and their associated ecological drivers. We synthesized outcomes from both field-based and spectral-based assessments, with both forms of inquiry concluding that self-replacement was the most commonly observed pathway. Alternative pathways were primarily related to changes in vegetation composition. As the scale of fire disturbance has increased, remote sensing methods are increasingly used to identify recovery pathways. However, the diversity in definitions of recovery and underlying spectral responses means identifying these distinct recovery pathways is difficult. Remote sensing can also help inform on pre-fire conditions as well as monitor temporal trends post-fire. Ultimately, for remote sensing to bridge site-level observations to the landscape level, spectral approaches must be better standardized, and the accuracy of structural forest estimates from spectral data must be better quantified. Spatial and temporal variability in recovery estimated from spectral data can identify pathways at increasingly earlier time points across large regions. Similarly, by incorporating spatially continuous estimates that fuse spectral and field observations, we may better understand how underlying ecological drivers, such as shrub cover, vary across scales. By synthesizing findings across methods of spectral and field investigations of post-fire dynamics, we can better predict and prepare for ecosystem change after fire in western North America, as well as in disturbed ecosystems globally.

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Data Availability

Data are available at data https://doi.org/10.5281/zenodo.17518232.

Open Access

References

Abatzoglou JT, Battisti DS, Williams AP, Hansen WD, Harvey BJ, Kolden CA. 2021. Projected increases in western US forest fire despite growing fuel constraints. Commun Earth Environ 2:1–8. https://doi.org/10.1038/s43247-021-00299-0.

Andrus RA, Droske CA, Franz MC, Hudak AT, Lentile LB, Lewis SA, Morgan P, Robichaud PR, Meddens AJH. 2022. Spatial and temporal drivers of post-fire tree establishment and height growth in a managed forest landscape. Fire Ecol. https://doi.org/10.1186/s42408-022-00153-4.

Baltzer JL, Day NJ, Walker XJ, Greene D, Mack MC, Alexander HD, Arseneault D, Barnes J, Bergeron Y, Boucher Y, Bourgeau-Chavez L, Brown CD, Carrière S, Howard BK, Gauthier S, Parisien M-A, Reid KA, Rogers BM, Roland C, Sirois L, Stehn S, Thompson DK, Turetsky MR, Veraverbeke S, Whitman E, Yang J, Johnstone JF. 2021. Increasing fire and the decline of fire adapted black spruce in the boreal forest. Proc Natl Acad Sci U S A 118:e2024872118. https://doi.org/10.1073/pnas.2024872118.

Barker BS, Pilliod DS, Rigge M, Homer CG. 2019. Pre-fire vegetation drives post-fire outcomes in sagebrush ecosystems: evidence from field and remote sensing data. Ecosphere 10:e02929. https://doi.org/10.1002/ecs2.2929.Lastaccessed06/05/2025.

Bartels SF, Chen HYH, Wulder MA, White JC. 2016. Trends in post-disturbance recovery rates of Canada's forests following wildfire and harvest. For Ecol Manag 361:194–207. https://doi.org/10.1016/j.foreco.2015.11.015.

Boag AE, Ducey MJ, Palace MW, Hartter J. 2020. Topography and fire legacies drive variable post-fire juvenile conifer regeneration in eastern Oregon, USA. For Ecol Manag. https://doi.org/10.1016/j.foreco.2020.118312.

Bolton DK, Coops NC, Wulder MA. 2015. Characterizing residual structure and forest recovery following high-severity fire in the western boreal of Canada using Landsat time-series and airborne lidar data. Remote Sens Environ 163:48–60. https://doi.org/10.1016/j.rse.2015.03.004.

Braziunas KH, Kiel NG, Turner MG. 2023. Less fuel for the next fire? Short-interval fire delays forest recovery and interacting drivers amplify effects. Ecology. https://doi.org/10.1002/ecy.4042.

Bright BC, Hudak AT, Kennedy RE, Braaten JD, Khalyani AH. 2019. Examining post-fire vegetation recovery with Landsat time series analysis in three western North American forest types. Fire Ecol. https://doi.org/10.1186/s42408-018-0021-9.

Brullsauer AR, Bradfield GE, Maze J. 1996. Quantifying organizational change after fire in lodgepole pine forest understorey. Can J Bot 74:1773–82. https://www.scopus.com/inward/record.uri?eid=2-s2.0-0030303599&doi=10.1139%2fb96-214&partnerID=40&md5=d2faba0b6f840b4f436ca16b584c3782

Buma B. 2012. Evaluating the utility and seasonality of NDVI values for assessing post-disturbance recovery in a subalpine forest. Environ Monit Assess 184:3849–3860. https://doi.org/10.1007/s10661-011-2228-y.

Burford B, Lewin S, Welch V, Rehfuess E, Waters E. 2013. Assessing the applicability of findings in systematic reviews of complex interventions can enhance the utility of reviews for decision making. J Clin Epidemiol 66:1251–1261. https://doi.org/10.1016/j.jclinepi.2013.06.017.

Celebrezze JV, Franz MC, Andrus RA, Stahl AT, Steen-Adams M, Meddens AJH. 2024. A fast spectral recovery does not necessarily indicate post-fire forest recovery. Fire Ecol. https://doi.org/10.1186/s42408-024-00288-6.

Chase JM, Knight TM. 2013. Scale-dependent effect sizes of ecological drivers on biodiversity: why standardised sampling is not enough. Ecol Lett 16(Suppl 1):17–26. https://doi.org/10.1111/ele.12112.Lastaccessed04/08/2025.

Chen XX, Vogelmann JE, Rollins M, Ohlen D, Key CH, Yang LM, Huang CQ, Shi H. 2011. Detecting post-fire burn severity and vegetation recovery using multitemporal remote sensing spectral indices and field-collected composite burn index data in a ponderosa pine forest. Int J Remote Sens 32:7905–7927. https://doi.org/10.1080/01431161.2010.524678.

Chu T, Guo X. 2013. Remote sensing techniques in monitoring post-fire effects and patterns of forest recovery in boreal forest regions: a review. Remote Sens 6:470–520. https://doi.org/10.3390/rs6010470.

Clark-Wolf K, Higuera PE, Davis KT. 2022. Conifer seedling demography reveals mechanisms of initial forest resilience to wildfires in the northern Rocky Mountains. For Ecol Manag. https://doi.org/10.1016/j.foreco.2022.120487.

Clason AJ, Farnell I, Lilles EB. 2022. Carbon 5–60 years after fire: planting trees does not compensate for losses in dead wood stores. Front for Glob Chang. https://doi.org/10.3389/ffgc.2022.868024.

Claverie M, Ju J, Masek JG, Dungan JL, Vermote EF, Roger J-C, Skakun SV, Justice C. 2018. The harmonized Landsat and sentinel-2 surface reflectance data set. Remote Sens Environ 219:145–161. https://doi.org/10.1016/j.rse.2018.09.002.Lastaccessed06/12/2025.

Collaboration for Environmental Evidence. 2022. Guidelines and Standards for Evidence synthesis in Environmental Management. www.environmentalevidence.org/information-for-authors. October 10. Last accessed 2024

Cooke A, Smith D, Booth A. 2012. Beyond PICO: the SPIDER tool for qualitative evidence synthesis. Qual Health Res 22:1435–1443. https://doi.org/10.1177/1049732312452938.

Coop JD. 2023. Postfire futures in southwestern forests: climate and landscape influences on trajectories of recovery and conversion. Ecol Appl. https://doi.org/10.1002/eap.2725.

Coop JD, Massatti RT, Schoettle AW. 2010. Subalpine vegetation pattern three decades after stand-replacing fire: effects of landscape context and topography on plant community composition, tree regeneration, and diversity. J Veg Sci 21:472–487. https://doi.org/10.1111/j.1654-1103.2009.01154.x.

Crockett JL, Hurteau MD. 2024. Climate limits vegetation green-up more than slope, soil erodibility, and immediate precipitation following high-severity wildfire. Fire Ecol. https://doi.org/10.1186/s42408-024-00264-0.

Davis KT, Dobrowski SZ, Higuera PE, Holden ZA, Veblen TT, Rother MT, Parks SA, Sala A, Maneta MP. 2019. Wildfires and climate change push low-elevation forests across a critical climate threshold for tree regeneration. Proc Natl Acad Sci U S A 116:6193–6198. https://doi.org/10.1073/pnas.1815107116.

Davis KT, Higuera PE, Dobrowski SZ, Parks SA, Abatzoglou JT, Rother MT, Veblen TT. 2020. Fire-catalyzed vegetation shifts in ponderosa pine and Douglas-fir forests of the western United States. Environ Res Lett. https://doi.org/10.1088/1748-9326/abb9df.

Davis KT, Robles Kemp KB, Higuera PE, Chapman T, Metlen KL, Peeler JL, Rodman KC, Woolley T, Addington RN, Buma BJ, Cansler CA, Case MJ, Collins BM, Coop JD, Dobrowski SZ, Gill NS, Haffey C, Harris LB, Harvey BJ, Haugo RD, Hurteau Kulakowski D, Littlefield CE, McCauley LA, Povak N, Shive KL, Smith E, Stevens JT, Stevens-Rumann CS, Taylor AH, Tepley AJ, Young DJN, Andrus RA, Battaglia MA, Berkey JK, Busby SU, Carlson AR, Chambers ME, Dodson EK, Donato DC, Downing WM, Fornwalt PJ, Halofsky JS, Hoffman A, Holz A, Iniguez JM, Krawchuk MA, Kreider MR, Larson AJ, Meigs GW, Roccaforte JP, Rother MT, Safford H, Schaedel M, Sibold JS, Singleton MP, Turner MG, Urza AK, Clark-Wolf KD, Yocom L, Fontaine JB, Campbell JL. 2023. Reduced fire severity offers near-term buffer to climate-driven declines in conifer resilience across the western United States. Proc Natl Acad Sci U S A 120(11):e2208120120.

Dodson EK, Root HT. 2013. Conifer regeneration following stand-replacing wildfire varies along an elevation gradient in a ponderosa pine forest, Oregon, USA. For Ecol Manag 302:163–170. https://doi.org/10.1016/j.foreco.2013.03.050.

Downing WM, Krawchuk MA, Meigs GW, Haire SL, Coop JD, Walker RB, Whitman E, Chong G, Miller C. 2019. Influence of fire refugia spatial pattern on post-fire forest recovery in Oregon's Blue Mountains. Landsc Ecol 34:771–792. https://doi.org/10.1007/s10980-019-00802-1.

Drever CR, Peterson G, Messier C, Bergeron Y, Flannigan M. 2006. Can forest management based on natural disturbances maintain ecological resilience? Can J for Res 36:2285–2299. https://doi.org/10.1139/x06-132.

Dwyer JL, Roy DP, Sauer B, Jenkerson CB, Zhang HK, Lymburner L. 2018. Analysis ready data: enabling analysis of the Landsat archive. Remote Sens 10:1363. https://doi.org/10.3390/rs10091363.

Epstein Seielstad CA, Moran CJ. 2024. Impact and recovery of forest cover following wildfire in the Northern Rocky Mountains of the United States. Fire Ecol. https://doi.org/10.1186/s42408-024-00285-9.

Ferguson D, Morgan P, Johnson F. 1989. Proceedings—Land Classifications Based on Vegetation: Applications for Resource Management. United States Department of Agriculture https://dn790007.ca.archive.org/0/items/CAT91960227/CAT91960227.pdf

Finco M, Quayle B, Zhang Y, Lecker J, Megown KA, Kenneth Brewer C. 2012. Monitoring Trends and Burn Severity (MTBS): Monitoring wildfire activity for the past quarter century using landsat data. In: Morin, Randall S; Liknes, Greg C, comps Moving from status to trends: Forest Inventory and Analysis (FIA) symposium 2012; Baltimore: MD.

Frampton GK, Livoreil B, Petrokofsky G. 2017. Eligibility screening in evidence synthesis of environmental management topics. Environ Evid. https://doi.org/10.1186/s13750-017-0102-2.

Francini S, Hermosilla T, Coops NC, Wulder MA, White JC, Chirici G. 2023. An assessment approach for pixel-based image composites. ISPRS J Photogramm Remote Sens 202:1–12. https://doi.org/10.1016/j.isprsjprs.2023.06.002.

Franks S, Masek JG, Turner MG. 2013. Monitoring forest regrowth following large scale fire using satellite data: a case study of Yellowstone National Park, USA-. Eur J Remote Sens 46:551–569. https://doi.org/10.5721/EuJRS20134632.

Frazier RJ, Coops NC, Wulder MA, Hermosilla T, White JC. 2018. Analyzing spatial and temporal variability in short-term rates of post-fire vegetation return from Landsat time series. Remote Sens Environ 205:32–45. https://doi.org/10.1016/j.rse.2017.11.007.Lastaccessed04/08/2025.

Frolking S, Palace MW, Clark DB, Chambers JQ, Shugart HH, Hurtt GC. 2009a. Forest disturbance and recovery: a general review in the context of spaceborne remote sensing of impacts on aboveground biomass and canopy structure. J Geophys Res-Biogeosci. https://doi.org/10.1029/2008JG000911.

Frolking S, Palace MW, Clark DB, Chambers JQ, Shugart HH, Hurtt GC. 2009b. Forest disturbance and recovery: a general review in the context of spaceborne remote sensing of impacts on aboveground biomass and canopy structure. J Geophys Res. https://doi.org/10.1029/2008jg000911.

Gendreau-Berthiaume B, Macdonald SE, Stadt JJ. 2018. Importance of the canopy in determining on-going regeneration and stand successional development in lodgepole pine forests. J Veg Sci 29:213–225. https://doi.org/10.1111/jvs.12622.

Gordon SI. 1980. Utilizing Landsat imagery to monitor land-use change: a case study in Ohio. Remote Sens Environ 9:189–196. https://doi.org/10.1016/0034-4257(80)90028-0.Lastaccessed03/24/2025.

Guz J, Gill NS, Kulakowski D. 2021. Long-term empirical evidence shows post-disturbance climate controls post-fire regeneration. J Ecol 109:4007–4024. https://doi.org/10.1111/1365-2745.13771.

Guz J, Sangermano F, Kulakowski D. 2022. The influence of burn severity on post-fire spectral recovery of three fires in the Southern Rocky Mountains. Remote Sens. https://doi.org/10.3390/rs14061363.

Haire SL, McGarigal K. 2008. Inhabitants of landscape scars: succession of woody plants after large, severe forest fires in Arizona and New Mexico. Southwest Nat 53:146–161. https://doi.org/10.1894/0038-4909(2008)53[146:IOLSSO]2.0.CO;2.

Hamilton NP, Burton PJ. 2023. Wildfire disturbance reveals evidence of ecosystem resilience and precariousness in a forest-grassland mosaic. Ecosphere. https://doi.org/10.1002/ecs2.4460.

Hansen WD, Turner MG. 2019. Origins of abrupt change? Postfire subalpine conifer regeneration declines nonlinearly with warming and drying. Ecol Monogr 89:e01340. https://doi.org/10.1002/ecm.1340.

Harvey BJ, Donato DC, Romme WH, Turner MG. 2013. Influence of recent bark beetle outbreak on fire severity and postfire tree regeneration in montane Douglas-fir forests. Ecology 94:2475–2486.

Hermosilla T, Wulder MA, White JC, Coops NC, Bater CW, Hobart GW. 2024. Characterizing long-term tree species dynamics in Canada's forested ecosystems using annual time series remote sensing data. For Ecol Manag. https://doi.org/10.1016/j.foreco.2024.122313.

Hessburg PF, Agee JK, Franklin JF. 2005. Dry forests and wildland fires of the inland Northwest USA: contrasting the landscape ecology of the pre-settlement and modern eras. For Ecol Manag 211:117–139. https://doi.org/10.1016/j.foreco.2005.02.016.

Hoecker TJ, Turner MG. 2022. A short-interval reburn catalyzes departures from historical structure and composition in a mesic mixed-conifer forest. For Ecol Manag. https://doi.org/10.1016/j.foreco.2021.119814.

Ireland G, Petropoulos GP. 2015. Exploring the relationships between post-fire vegetation regeneration dynamics, topography and burn severity: a case study from the Montane Cordillera Ecozones of Western Canada. Appl Geogr 56:232–248. https://doi.org/10.1016/j.apgeog.2014.11.016.Lastaccessed06/09/2025.

Jakubauskas ME. 1996. Thematic mapper characterization of lodgepole pine seral stages in Yellowstone National Park, USA. Remote Sens Environ 56:118–132. https://doi.org/10.1016/0034-4257(95)00228-6.

Johnson EA, Fryer GI. 1989. Population dynamics in lodgepole pine-engelmann spruce forests. Ecology 70:1335–1345.

Kasischke ES, French NHF. 1997. Constraints on using AVHRR composite index imagery to study patterns of vegetation cover in boreal forests. Int J Remote Sens 18:2403–2426. https://doi.org/10.1080/014311697217684.

Kasischke ES, Turetsky MR, Ottmar RD, French NHF, Hoy EE, Kane ES. 2008. Evaluation of the composite burn index for assessing fire severity in Alaskan black spruce forests. Int J Wildland Fire 17:515. https://doi.org/10.1071/wf08002.

Kiel NG, Turner MG. 2022. Where are the trees? Extent, configuration, and drivers of poor forest recovery 30 years after the 1988 Yellowstone fires. For Ecol Manag. https://doi.org/10.1016/j.foreco.2022.120536.

Kiel NG, Mavencamp EF, Turner MG. 2025. Sparse subalpine forest recovery pathways, plant communities, and carbon stocks 34 years after stand-replacing fire. Ecol Monogr 95:e1644. https://doi.org/10.1002/ecm.1644.Lastaccessed09/30/2025.

Kottek M, Grieser J, Beck C, Rudolf B, Rubel F. 2006. World Map of the Köppen-Geiger climate classification updated. Meteorol Z 15:259–263. https://doi.org/10.1127/0941-2948/2006/0130.

Kulakowski D, Matthews C, Jarvis D, Veblen TT. 2013. Compounded disturbances in sub-alpine forests in western Colorado favour future dominance by quaking aspen (Populus tremuloides). J Veg Sci 24:168–176.

Laughlin MM, Bakker JD, Churchill DJ, Gregory MJ, DeMeo T, Alvarado EC, Harvey BJ. 2023. Trends in forest structure restoration need over three decades with increasing wildfire activity in the interior Pacific Northwest US. For Ecol Manag. https://doi.org/10.1016/j.foreco.2022.120607.

Littlefield CE. 2019. Topography and post-fire climatic conditions shape spatio-temporal patterns of conifer establishment and growth. Fire Ecol. https://doi.org/10.1186/s42408-019-0047-7.

Littlefield CE, Dobrowski SZ, Abatzoglou JT, Parks SA, Davis KT. 2020. A climatic dipole drives short- and long-term patterns of postfire forest recovery in the western United States. Proc Natl Acad Sci U S A 117:29730–29737. https://doi.org/10.1073/pnas.2007434117.

Malone SL, Fornwalt PJ, Battaglia MA, Chambers ME, Iniguez JM, Sieg CH. 2018. Mixed-severity fire fosters heterogeneous spatial patterns of conifer regeneration in a dry conifer forest. Forests. https://doi.org/10.3390/f9010045.

Menick C, Tinkham W, Hoffman C, Vanderhoof M, Vogeler J. 2024. Snow-cover remote sensing of conifer tree recovery in high-severity burn patches. Remote Sens Environ. https://doi.org/10.1016/j.rse.2024.114114.

Mitchell M, Yuan F. 2010. Assessing forest fire and vegetation recovery in the black hills, South Dakota. Gisci Remote Sens 47:276–299. https://doi.org/10.2747/1548-1603.47.2.276.

Montesano PM, Neigh CSR, Macander MJ, Wagner W, Duncanson LI, Wang P, Sexton JO, Miller CE, Armstrong AH. 2023. Patterns of regional site index across a North American boreal forest gradient. Environ Res Lett 18:075006. https://doi.org/10.1088/1748-9326/acdcab.Lastaccessed06/09/2025.

Oliver CD, Larson BC. 1996. Forest Stand Dynamics. Nashville: Wiley.

Omernik JM, Griffith GE. 2014. Ecoregions of the conterminous United States: evolution of a hierarchical spatial framework. Environ Manag 54:1249–1266. https://doi.org/10.1007/s00267-014-0364-1.

Pausas JG, Keeley JE. 2017. Epicormic resprouting in fire-prone ecosystems. Trends Plant Sci 22:1008–1015. https://doi.org/10.1016/j.tplants.2017.08.010.

Peeler JL, Smithwick EAH. 2020. Seed source pattern and terrain have scale-dependent effects on post-fire tree recovery. Landsc Ecol 35:1945–1959. https://doi.org/10.1007/s10980-020-01071-z.

Persson HJ, Ekström M, Ståhl G. 2022. Quantify and account for field reference errors in forest remote sensing studies. Remote Sens Environ 283:113302. https://doi.org/10.1016/j.rse.2022.113302.Lastaccessed06/09/2025.

Petrie MD, Wildeman AM, Bradford JB, Hubbard RM, Lauenroth WK. 2016. A review of precipitation and temperature control on seedling emergence and establishment for ponderosa and lodgepole pine forest regeneration. For Ecol Manag 361:328–338. https://doi.org/10.1016/j.foreco.2015.11.028.

Pettorelli N, Schulte to Bühne H, Tulloch A, Dubois G, Macinnis-Ng C, Queirós AM, Keith DA, Wegmann M, Schrodt F, Stellmes M, Sonnenschein R, Geller GN, Roy S, Somers B, Murray N, Bland L, Geijzendorffer I, Kerr JT, Broszeit S, Leitão PJ, Duncan C, ElSerafy G, He KS, Blanchard JL, Lucas R, Mairota P, Webb TJ, Nicholson E. 2018. Satellite remote sensing of ecosystem functions: opportunities, challenges and way forward. Remote Sens Ecol Conserv 4:71–933. https://doi.org/10.1002/rse2.59.

Peven G, Engels M, Eitel JUH, Andrus RA. 2024. Montane springs provide regeneration refugia after high-severity wildfire. Ecosphere. https://doi.org/10.1002/ecs2.70009.

Picotte JJ. 2023. Assessing Vegetation Burn Severity Across a Range of Scales and Metrics. https://media.proquest.com/media/hms/PRVW/1/BE1jW?_s=YKVV6LC6%2B9KI9fj5iGaoRsgZzss%3D#view=FitV. Last accessed 04/08/2025

Pritchard R, Brockington D. 2019. Regrow forests with locals' participation. Nature 569:630–630. https://doi.org/10.1038/d41586-019-01664-y.

Rodman KC, Veblen TT, Battaglia MA, Chambers ME, Fornwalt PJ, Holden ZA, Kolb TE, Ouzts JR, Rother MT. 2020. A changing climate is snuffing out post-fire recovery in montane forests. Glob Ecol Biogeogr 29:2039–2051. https://doi.org/10.1111/geb.13174.

Rother MT, Veblen TT. 2016. Limited conifer regeneration following wildfires in dry ponderosa pine forests of the Colorado front range. Ecosphere. https://doi.org/10.1002/ecs2.1594.

Rother MT, Veblen TT. 2017. Climate drives episodic conifer establishment after fire in dry ponderosa pine forests of the Colorado front range, USA. Forests. https://doi.org/10.3390/f8050159.

Sánchez JJ, Marcos-Martinez R, Srivastava L, Soonsawad N. 2021. Valuing the impacts of forest disturbances on ecosystem services: an examination of recreation and climate regulation services in U.S. national forests. Trees for People 5:100123. https://doi.org/10.1016/j.tfp.2021.100123.

Schapira ZH, Stevens-Rumann CS, Shorrock D. 2021. Subalpine tree seedlings: assessing aging methodology and drivers of establishment. For Ecol Manag. https://doi.org/10.1016/j.foreco.2021.119516.

Seidl R, Turner MG. 2022. Post-disturbance reorganization of forest ecosystems in a changing world. Proc Natl Acad Sci U S A 119:e2202190119. https://doi.org/10.1073/pnas.2202190119.

Senf C. 2022. Seeing the system from above: the use and potential of remote sensing for studying ecosystem dynamics. Ecosystems 25:1719–1737. https://doi.org/10.1007/s10021-022-00777-2.

Seydi ST, Abatzoglou JT, AghaKouchak A, Pourmohamad Y, Mishra A, Sadegh M. 2024. Predictive understanding of links between vegetation and soil burn severities using physics-informed machine learning. Earths Future 12:e2024EF004873. https://doi.org/10.1029/2024EF004873.

Shrestha S, Williams CA, Rogers BM, Rogan J, Kulakowski D. 2024. Divergent biophysical responses of western United States forests to wildfire driven by eco-climatic gradients. Biogeosciences 21:2207–2226. https://doi.org/10.5194/bg-21-2207-2024.

Smith-Tripp S, Coops NC, Mulverhill C, White JC, Gergel S. 2024a. Early spectral dynamics are indicative of distinct growth patterns in post-wildfire forests. Remote Sens Ecol Conserv. https://doi.org/10.1002/rse2.420.

Smith-Tripp SM, Coops NC, Mulverhill C, White JC, Axelson J. 2024b. Landsat assessment of variable spectral recovery linked to post-fire forest structure in dry sub-boreal forests. ISPRS J Photogramm Remote Sens 208:121–135. https://doi.org/10.1016/j.isprsjprs.2024.01.008.

Song C, Woodcock CE, Seto KC, Lenney MP, Macomber SA. 2001. Classification and change detection using Landsat TM data. Remote Sens Environ 75:230–244. https://doi.org/10.1016/s0034-4257(00)00169-3.

Song T-H, Kim HK. 2001. Measurement of gas temperature distributions in a test furnace using spectral remote sensing. In: ICHMT Third International Symposium on Radiative Transfer. Connecticut: Begellhouse https://doi.org/10.1615/ichmt.2001.radiationsymp.340

Stevens-Rumann CS, Morgan P. 2019. Tree regeneration following wildfires in the western US: a review. Fire Ecol. https://doi.org/10.1186/s42408-019-0032-1.

Stevens-Rumann CS, Kemp KB, Higuera PE, Harvey BJ, Rother MT, Donato DC, Morgan P, Veblen TT. 2018. Evidence for declining forest resilience to wildfires under climate change. Ecol Lett 21:243–252. https://doi.org/10.1111/ele.12889.

Stevens-Rumann CS, Prichard SJ, Whitman E, Parisien M-A, Meddens AJH. 2022. Considering regeneration failure in the context of changing climate and disturbance regimes in western North America. Can J for Res 52:1281–1302. https://doi.org/10.1139/cjfr-2022-0054.

Tortorelli CM, Young DJN, Reilly MJ, Butz RJ, Safford HD, Venuti NE, Welch KR, Latimer AM. 2024. Post-fire resurveys reveal predictability of long-term conifer recruitment in severely burned California dry forests. For Ecol Manage 566:122100. https://doi.org/10.1016/j.foreco.2024.122100.

Turner MG, Romme WH, Gardner RH, Hargrove WW. 1997. Effects of fire size and pattern on early succession in Yellowstone National Park. Ecol Monogr 67:411–433. https://doi.org/10.1890/0012-9615(1997)067[0411:EOFSAP]2.0.CO;2.

Turner MG, Braziunas KH, Hansen WD, Harvey BJ. 2019. Short-interval severe fire erodes the resilience of subalpine lodgepole pine forests. Proc Natl Acad Sci U S A 166:11319–11328.

Vanderhoof MK, Hawbaker TJ. 2018. It matters when you measure it: using snow-cover normalised difference vegetation index (NDVI) to isolate post-fire conifer regeneration. Int J Wildland Fire 27(12):815–830.

Vanderhoof MK, Burt C, Hawbaker TJ. 2018. Time series of high-resolution images enhances efforts to monitor post-fire condition and recovery, Waldo Canyon fire, Colorado, USA. Int J Wildland Fire 27:699–713. https://doi.org/10.1071/WF17177.

Vanderhoof MK, Hawbaker TJ, Ku AD, Merriam K, Berryman E, Cattau M. 2021. Tracking rates of postfire conifer regeneration versus deciduous vegetation recovery across the western United States. Ecol Appl 31(2):e0223. https://doi.org/10.1002/eap.2237.

Walker JJ, Soulard CE. 2019. Phenology patterns indicate recovery trajectories of ponderosa pine forests after high-severity fires. Remote Sens. https://doi.org/10.3390/rs11232782.

White JC. 2024. Characterizing forest recovery following stand-replacing disturbances in boreal forests: contributions of optical time series and airborne laser scanning data. Silva Fennica. https://doi.org/10.14214/sf.23076.

White JC, Wulder MA, Hobart GW, Luther JE, Hermosilla T, Griffiths P, Coops NC, Hall RJ, Hostert P, Dyk A, Guindon L. 2014. Pixel-based image compositing for large-area dense time series applications and science. Can J Remote Sens/j Can Teledetect 40:192–212. https://doi.org/10.1080/07038992.2014.945827.Lastaccessed04/08/2025.

White JC, Wulder MA, Hermosilla T, Coops NC, Hobart GW. 2017. A nationwide annual characterization of 25 years of forest disturbance and recovery for Canada using Landsat time series. Remote Sens Environ 194:303–321. https://doi.org/10.1016/j.rse.2017.03.035.Lastaccessed05/05/2025.

White JC, Saarinen N, Kankare V, Wulder MA, Hermosilla T, Coops NC, Pickell PD, Holopainen M, Hyyppä J, Vastaranta M. 2018. Confirmation of post-harvest spectral recovery from Landsat time series using measures of forest cover and height derived from airborne laser scanning data. Remote Sens Environ 216:262–275. https://doi.org/10.1016/j.rse.2018.07.004.

White JC, Saarinen N, Wulder MA, Kankare V, Hermosilla T, Coops NC, Holopainen M, Hyyppä J, Vastaranta M. 2019. Assessing spectral measures of post-harvest forest recovery with field plot data. Int J Appl Earth Obs Geoinf 80:102–114. https://doi.org/10.1016/j.jag.2019.04.010.

White JC, Hermosilla T, Wulder MA, Coops NC. 2022. Mapping, validating, and interpreting spatio-temporal trends in post-disturbance forest recovery. Remote Sens Environ 271:112904. https://doi.org/10.1016/j.rse.2022.112904.Lastaccessed05/05/2025.

White JC, Hermosilla T, Wulder MA. 2023. Pre-fire measures of boreal forest structure and composition inform interpretation of post-fire spectral recovery rates. For Ecol Manag 537:120948. https://doi.org/10.1016/j.foreco.2023.120948.

Wilson SG, Prentice S. 2024. Digital soil mapping of soil burn severity. Soil Sci Soc Am J 88:1045–1067. https://doi.org/10.1002/saj2.20702.Lastaccessed04/08/2025.

Wilson AC, Nolin AW, Bladon KD. 2021. Assessing the role of snow cover for post-wildfire revegetation across the Pacific Northwest. J Geophys Res Biogeosci. https://doi.org/10.1029/2021JG006465.

Wohlin C, Kalinowski M, Romero Felizardo K, Mendes E. 2022. Successful combination of database search and snowballing for identification of primary studies in systematic literature studies. Inf Softw Technol 147:106908. https://doi.org/10.1016/j.infsof.2022.106908.Lastaccessed06/27/2025.

Wulder MA, Roy DP, Radeloff VC, Loveland TR, Anderson MC, Johnson DM, Healey S, Zhu Z, Scambos TA, Pahlevan N, Hansen M, Gorelick N, Crawford CJ, Masek JG, Hermosilla T, White JC, Belward AS, Schaaf C, Woodcock CE, Huntington JL, Lymburner L, Hostert P, Gao F, Lyapustin A, Pekel J-F, Strobl P, Cook BD. 2022. Fifty years of Landsat science and impacts. Remote Sens Environ 280:113195. https://doi.org/10.1016/j.rse.2022.113195.

Young NE, Anderson RS, Chignell SM, Vorster AG, Lawrence R, Evangelista PH. 2017. A survival guide to Landsat preprocessing. Ecology 98:920–932. https://doi.org/10.1002/ecy.1730.

Ziegler J, Hoffman C, Fornwalt P, Sieg C, Battaglia M, Chambers M, Iniguez J. 2017. Tree regeneration spatial patterns in Ponderosa Pine forests following stand-replacing fire: influence of topography and neighbors. Forests 8:391.