NATURAL RESOURCES

20-YEAR FOREST HEALTH STRATEGIC PLAN MONITORING REPORT 2024

Strategic Science and Planning Program
Forest Resilience Division

This report summarizes progress to date on monitoring forest changes across eastern Washington and how those changes affect forest health and resilience

FEBRUARY 2024

WASHINGTON STATE DEPARTMENT OF NATURAL RESOURCES

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WASHINGTON STATE DEPARTMENT OF NATURAL RESOURCES

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Suggested Citation: WADNR. 2024, 20-Year Forest Health Strategic Plan: Eastern Washington - Monitoring Report 2024. Washington State Department of Natural Resources. Olympia, WA.

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Published in the United States of America

Contents

GLOSSARY

Vegetation Types:

- **Cold forest:** Upper elevation mixed-conifer forests with high-severity fires every 80-200+ years.
- **Dry forest:** Ponderosa pine and Douglas-fir dominated forests that historically had surface fires every 5-25 years.
- **Moist forest:** Forests that historically had mixed-severity fires every 30-100 years and were composed of fire-resistant (western larch, Douglas-fir) and fire-intolerant (grand fir) trees.
- **Woodland/Steppe:** Grass and shrub lands that may have oak woodlands or ≤ 10% conifer cover.

Forest Structure and Fuels:

- **Large tree:** Overstory diameter ≥ 20 inches.
- **Medium tree:** Overstory diameter 10-20 inches.
- **Small tree:** Overstory diameter < 10 inches.
- **Closed canopy:** At least 60% tree canopy cover.
- **Moderate canopy:** 40-60% tree canopy cover.
- **Open canopy:** Less than 40% tree canopy cover.
- **Surface fuels:** Shrubs, grasses, small trees, woody litter, duff, and downed logs different sizes.
- **Ladder fuels:** Small to mid-sized trees, tall shrubs, or branches of larger trees that can carry fire up from the ground into the crowns of the overstory trees.

Treatment Acres - Reported in two ways (**Box 1**):

- **Total treatment acres** track every forest health treatment conducted, including those that occurred in sequence on the same acre over time. For example, a commercial thinning may have been conducted on an acre prior to a prescribed burn and both treatments would be reflected.
- **Footprint acres** are calculated through spatial analysis to ensure one acre that experienced one or more treatments are only counted once.

Treatments - Defined based on their source and application in the report:

- **Forest Health Treatment Database Treatments:** Any modification of vegetation in a forest that has a forest health objective, although the treatment may have other objectives. These treatments are reported to DNR by partner landowners.
- **Change Detection Treatments:** Changes to vegetation identified by satellite change detection from any treatment regardless of landowner objective. Regeneration, thinning, and broadcast burning treatments are distinguished from wildfires and insect activity.
- **Combined Treatment Database and Change Detection:** In the combined treatment layer, treatments are any management activity to modify vegetation in a forest regardless of landowner objective.

Treatment Types:

- **All treatment types** used in this report are described in detail in **Appendix C**.
- **Fuels treatment or surface fuels treatment:** Manipulation or removal of surface and/or ladder fuels to reduce potential fire intensity (flame length, soil heating, etc.). This may include activities that re-arrange fuels (e.g., felling, lopping, mastication, chipping, piling) and/or activities that remove fuels (e.g., broadcast burning/prescribed fire, pile burning, biomass removal).
- **Managed wildfire:** wildfire that is managed to achieve resource objectives such as fuel reduction under safe conditions and can be suppressed if conditions change.

Other Terms:

- **Priority planning areas** or **Planning Areas:** 20-Year Forest Health Strategic Plan: Eastern Washington priority areas where landscape evaluations, investments, and treatment implementation are focused. Priority planning areas consist of one or more watersheds. See online map.

For additional information on terminology, see this forest health glossary.

20-Year Forest Health Plan: Eastern Washington Monitoring Report 2024

EXECUTIVE SUMMARY

The DNR 20-Year Forest Health Strategic Plan (20-Year Plan) was created in 2017 to address the forest health crisis in eastern Washington. Significant progress has been made in restoring forests across the region, both through active management and natural disturbances including wildfires. Monitoring this progress is a critical component of the 20-Year Plan. This report represents the first major standalone effort towards identifying how forests are changing across eastern Washington, and how those changes impact current and future forest health and resilience.

The 20-Year Plan Monitoring Framework identified three primary levels for monitoring: region, priority planning area, and treatment unit or stand. The regional level covers eastern Washington or larger sub-regions such as northeastern Washington (millions of acres). The planning area level addresses questions within 20-Year Plan planning areas (hundreds of thousands of acres). Finally, the treatment unit or stand level monitors individual treatment projects or changes within stands (<1 to several hundred acres). Here, we summarize efforts across these three levels.

For the regional and planning area sections of this report, we developed and combined two products to monitor disturbances and treatments: change detection (2015-2022) and the forest health treatment database (2017-2022). The change detection product is based on satellite information and captures forest change that resulted in substantial canopy loss. The forest health treatment database consists of forest health treatments reported to DNR by partners and captures lower-intensity treatments missed by change detection. The combined treatment database thus includes all treatments regardless of management objectives.

Monitoring across eastern Washington

For the period of record for the combined treatment database (2017-2022), changes affected 1.5 million footprint acres, or 15% of the forested area in eastern Washington. Wildfires and insect activity accounted for 910,000 of these footprint acres, with management activities accounting for the remaining 571,000 acres.

From 2017 to 2022, a total of 822,000 acres of treatments were implemented across eastern Washington. The most common treatment type was thinning (312,000 acres), followed by regeneration harvest (140,000 acres), fuels rearrangement (106,000 acres), pile burning (106,000 acres), prescribed fire (45,000 acres), and other treatment types (113,000 acres). Because some of these treatments occurred on the same units over time, their total extent was 571,000 footprint acres.

Treatment tracking results suggest that additional surface fuels treatments are needed to keep pace with mechanical thinning and regeneration harvests, as well as to maintain past treatments. Additional monitoring is needed to better assess and quantify this need.

Planning area monitoring

Substantial progress towards landscape restoration goals has been made in the Cle Elum, Glenwood, and South Fork Mill Creek priority planning areas, where detailed analyses were conducted. The rates of treatment and total footprint acres completed in these landscapes are on track to achieve treatment targets identified in the landscape evaluations, and the majority of treatments were in locations with moderate to high treatment priority. However, it is critical to understand not only the rates and location of different treatments, but also their effects on key attributes, including forest structure, fuels, and wildlife habitat.

To assess these treatment effects, we estimated changes in forest structure from 2015 to 2021 using digital aerial photographs. Across the selected planning areas, treatments, wildfires, and insect disturbances increased open-canopy forest with large and medium trees by 6-25%. This led to significant increases in the amount and patch size of White-headed Woodpecker habitat, while Northern Goshawk habitat remained abundant and well distributed. However, 45-70% of the forested area remains closed canopy (>60% cover). Open-canopy forests with large, fire-resistant trees are still in short supply in all three planning areas. Thus, additional changes – from both treatments and disturbances including beneficial wildfire – are needed to shift conditions towards a more resilient condition.

Treatment unit and stand-level monitoring

Across eastern Washington, over 30 stand-level monitoring projects have been initiated with DNR involvement over the last three years. Monitoring projects involve a variety of partners and treatment types, and partners are gradually transitioning to using the DNR monitoring protocol, outlined in the 20-Year Plan monitoring framework. Additionally, DNR is working with many partners to complete intensive photo monitoring of pre- and post-treatment stands to complement field data collection at the stand and project scales. We are working to implement detailed monitoring reports at the project scale, and we include two of these reports as appendices (Squilchuck State Park and Tillicum).

Other monitoring efforts

Since 2020, more than 30 contracts and projects related to monitoring have been completed or initiated. These projects have been critical in advancing the science behind landscape evaluations and monitoring across scales, as well as in effectively communicating the goals of the 20-Year Plan. Highlighted projects include the Work of Wildfire reports introduced following the 2021 fire season, improvements to insect activity mapping, assessing the impacts of forest cover and topography on snowpack, and evalating treatments and wildfire operations, among others.

1. INTRODUCTION

Forests in eastern Washington (EWA) cover approximately 10 million acres and, due to a wide variety of natural disturbances and forest management activities, are very dynamic (**Figure 1**). Previous analyses found that about 3 million of acres need some type of active management or disturbance to sustain forests that are more resilient to wildfire, drought, and other stressors (Haugo et al. 2015, Laughlin et al. 2023). In 2016, the Washington State Legislature passed ESHB 2376 that directed the Washington State Department of Natural Resources (DNR) to develop the 20-Year Forest Health Strategic Plan: Eastern Washington (20-Year Plan) to address this forest health need. In 2017, the Legislature passed SB 5546, instructing DNR to further develop a forest health assessment and treatment framework. The 20-Year Plan resulting from these bills found a need to assess and treat 1.25 million acres.

Since 2017, DNR has made significant progress in analyzing and prioritizing lands across eastern Washington for treatment needs, as well as in communicating and coordinating efforts to increase the pace and scale of forest health treatments in 20-Year Plan priority landscapes. These efforts have been detailed in past legislative reports on the 20-Year Plan. Primary goals of the 20-Year Plan include identifying treatment priorities, implementing treatments, and coordinating forest health efforts. Additionally, a critical goal of the 20-Year Plan is to "develop and implement a forest health resilience monitoring program that establishes criteria, processes, and tools to monitor forest and watershed conditions, assess progress, and reassess strategies over time."

Monitoring is essential for reporting and accountability, building shared understanding and trust, and increasing the effectiveness of forest health treatments over time through adaptive management. In 2020, DNR's Forest Resilience Division (FRD) developed a comprehensive monitoring framework to address two overarching questions: How are forest health conditions and associated forest health indicators changing over time, and what are the outcomes of forest health treatments?

The monitoring framework addresses these questions at three distinct levels:

1. **Region:** eastern Washington or larger sub-regions such as northeastern Washington (millions of acres).
2. **Priority planning area:** 20-Year Plan priority landscapes (hundreds of thousands of acres).
3. **Treatment unit or stand:** individual treatment projects or changes within stands (<1 to several hundred acres).

Since developing the monitoring framework in 2020, we have collaborated with many research, agency, and other partners to develop a range of cutting-edge methods, datasets, and reporting formats to quantify and monitor vegetation change. Primary datasets and tools include tracking of completed forest health treatments, satellite-based change detection, mapping of forest structure and wildlife habitat across eastern Washington, analysis of the work of wildfire and wildfire treatment interactions, and a sampling protocol and data collection system for treatment unit monitoring. We have applied these tools to monitor implementation of the 20-Year Plan at all three levels described in different locations across eastern Washington.

In the December 2022 RCW 76.06.200 report to the legislature, we included several sections that described those monitoring methods, as well as results for treatment activities and outcomes at the three levels. Based on the rapid increase in monitoring datasets and assessments related to the 20-Year Plan, we now plan to compile a standalone monitoring report that summarizes our completed and ongoing monitoring efforts and results every two years. We will still include monitoring information in our legislative reporting. These reports will continue to evolve as we develop and refine methods to realize the full vision laid out in the monitoring framework.

This report is the first standalone monitoring report for the 20-Year Plan. It compiles results from our regional, planning area, and treatment unit/stand-level monitoring efforts into a single document. Based on feedback from partners, we expanded planning area-level monitoring to include analyses of the impacts of treatments on wildlife habitat, forest structural patterns, riparian areas, and treatment location relative to treatment prioritization. We also include summaries of treatment-level monitoring efforts and other monitoring-related reports and projects, including research and development projects.

Figure 1. Examples of recent treatments and changes across eastern Washington. Left: Thinning in the South Fork Mill Creek watershed in northeastern Washington (source: Jessica Walston). Right: 2021 Cedar Creek fire in the Methow Valley (source: Garrett Meigs).

2. MONITORING ACROSS EASTERN WASHINGTON

Here, we assess patterns of change across eastern Washington from treatments, wildfire, and insect disturbances. We first describe the approach and datasets used to assess change across the region. We then summarize change across the region and within all 20-Year Plan priority planning areas. We also provide a summary of the Central Washington Initiative (CWI) as well as a summary of updates to the Pacific Northwest Quantitative Risk Assessment (QWRA). The CWI is an all-hands, all-lands effort to promote resilient landscapes and wildfire-adapted communities across 3.1 million acres in the eastern Cascades. The QWRA is an all-lands comprehensive wildfire risk assessment developed for Oregon and Washington by state and federal land management agencies with support from managers and scientists

Tracking progress towards treatment targets and restoration goals requires reporting both total acres and footprint acres, which we define in Box 1.

Box 1. Treatment and footprint acres

Total treatment acres: track every forest health treatment conducted, including those that occurred in sequence on the same acre over time. For example, a commercial thinning may have been conducted on an acre prior to a prescribed burn and both treatments would be reflected. Total acres track individual actions invested in and implemented at a point in time.

Footprint acres are calculated through spatial analysis to ensure one acre that experienced one or more treatments are only counted once. Footprint acres track the spatial scale of management impact over time and are the primary metric we use for treatment targets in landscape evaluations.

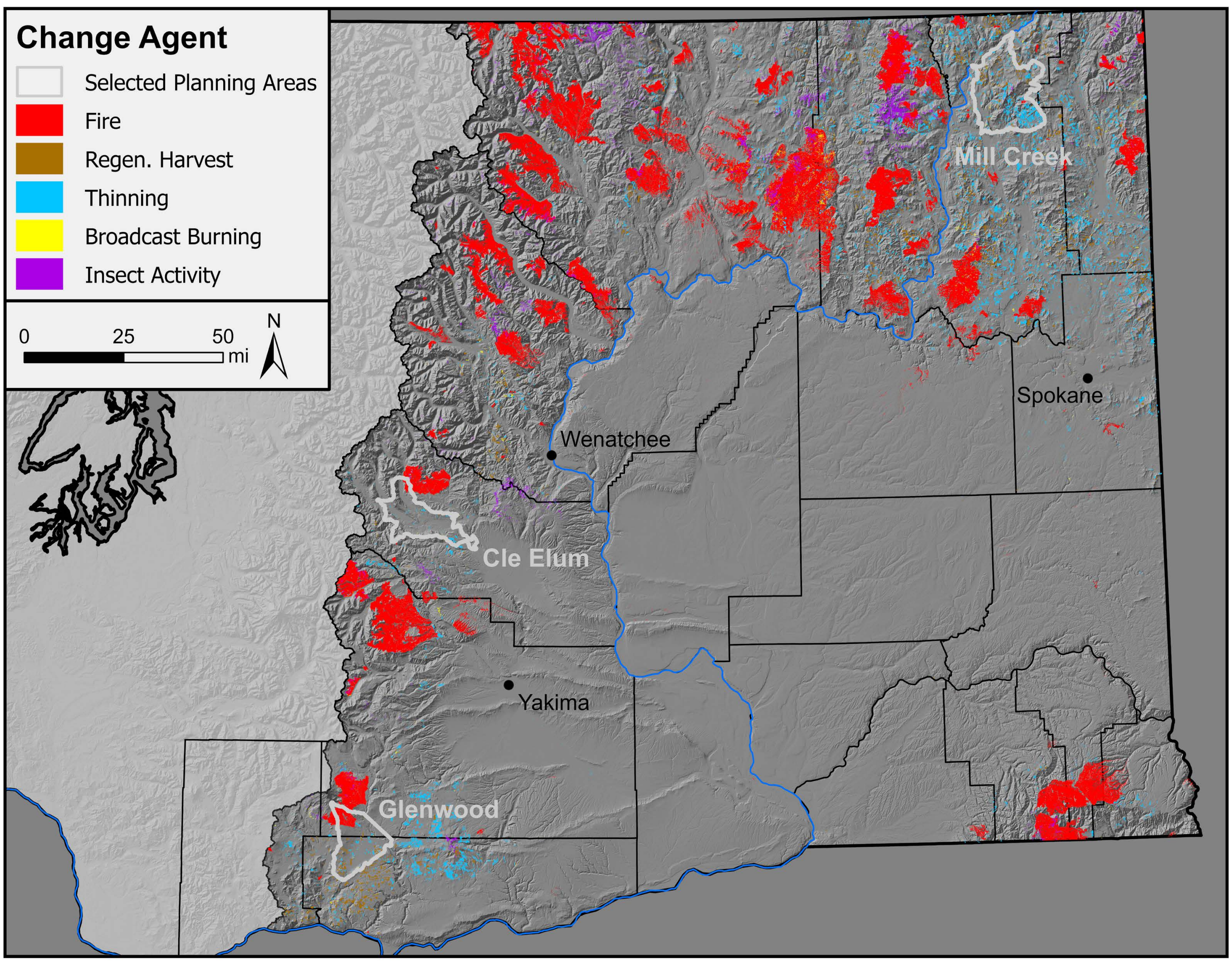


Figure 2. Map of change locations and agents mapped by the remotely sensed change detection product between 2015 and 2022. Selected planning areas are investigated in Section 3 (Planning Area Monitoring). Examples of change patternns at the planning area level are shown in **Figures 7, 15, and 22**. Treatment definitions can be found in **Appendix C**.

2.1 A comprehensive dataset of forest change: combining the change detection and forest health treatment database products

The DNR has developed two separate, complementary products to track treatments and other causes of forest change: satellite-based **change detection**, and a user-reported **forest health treatment database**. Each product has unique benefits and constraints, and together they represent a nearly comprehensive dataset of forest change across eastern Washington.

The change detection product uses annual satellite data to identify areas of likely forest mortality and determines the causal agent with machine learning (**Appendix A**). This product provides an unbiased wall-to-wall view on areas of change across eastern Washington from 2015 through 2022. However, the satellites used (Landsat) have moderate resolution and only provide information on vegetation greenness, not structure. This means that understory treatments, including some fuels management, prescribed fire, and pile burning, are often missed or only partially captured. However, the change detection information is very successful at identifying overstory forest management activities that might be missing from user-reported databases.

In addition to the change detection mapping, the FRD also collects more detailed information on forest health treatments in the forest health treatment database. This database covers 2017–2023 (2022 for this report) and consists of user-reported forest health treatments that is updated twice a year. Data are collected in conjunction with the FRD Forest Health Tracker tool. Treatment details include lead implementer, activity type, and completion date. Lower-intensity treatments not captured in the change detection product are captured in this database. The primary limitation of this product is that the treatments are user-reported and may include inaccuracies or be incomplete. The change detection product enables us to capture most missing treatments; however these treatments may or may not have a forest health objective.

The combination of the two products provides a much more complete view of forest management activities and natural disturbances that move forest conditions towards or away from restoration goals. As of 2023, both datasets are being incorporated into ongoing monitoring reports and efforts (treatment tracking memo, Central Washington Initiative Summary below). We use both datasets for the remainder of this report to assess treatment acres and footprint acres (Box 1). The combined database includes treatments regardless of management objective.

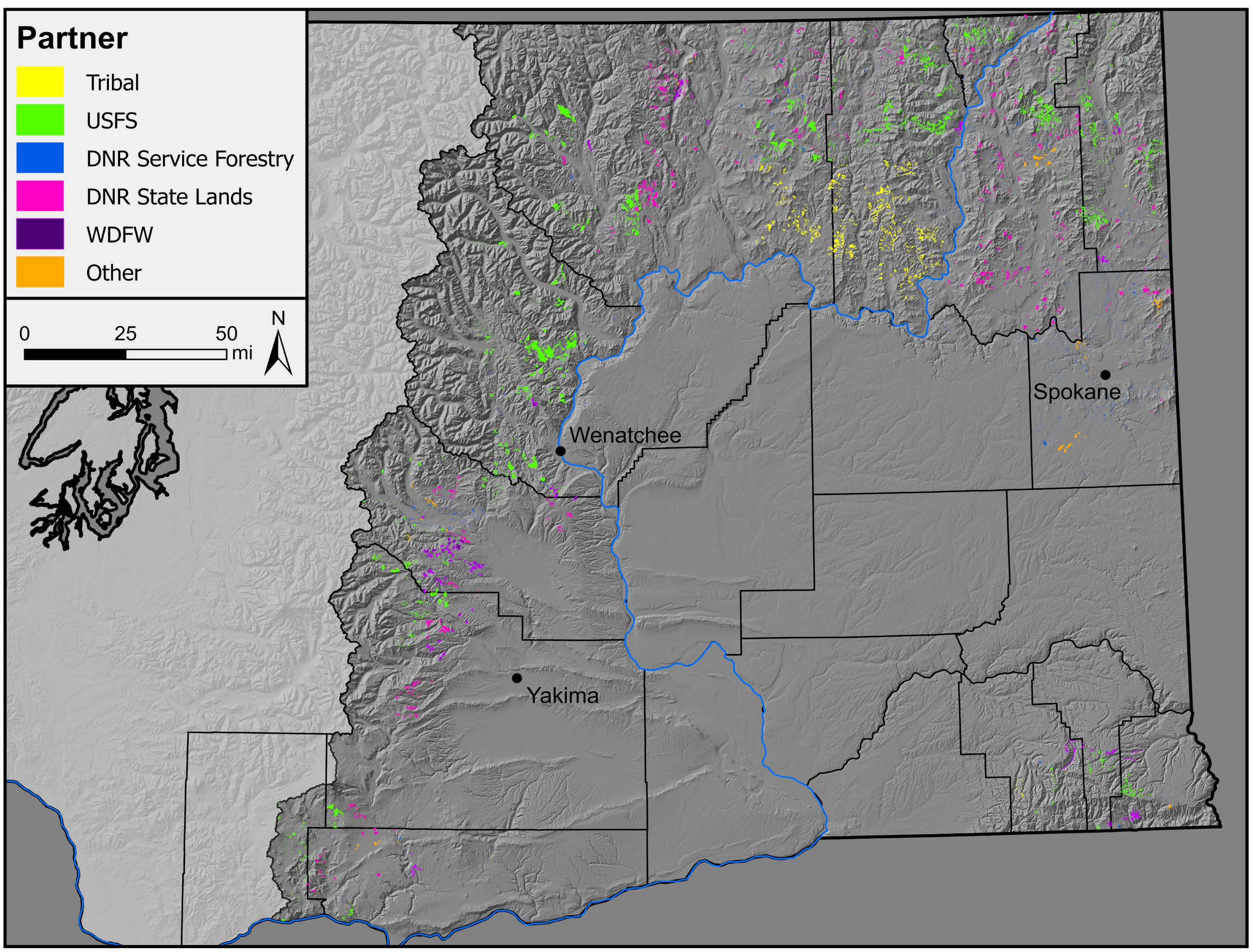


Figure 3. Map of forest health treatments reported by partners between 2017 and 2022. Examples of treatment types at the planning area level are shown in **Figures 7, 15, and 22**. Treatment definitions can be found in **Appendix C**.

2.2 Forest change across eastern Washington

While the 20-Year Plan started in 2017, we chose to evaluate changes across eastern Washington dating back to 2015 to establish a baseline amount of management and disturbance across the region. Details on the period following the implementation of the 20-Year Plan, 2017-2022, are presented in more detail at the end of this section and in section 2.3.

From 2015 to 2022, changes affected 2.1 million footprint acres (2.8 million total acres), or 20% of the forested area in eastern Washington. Most of the changed areas (about 1.6 million footprint acres) (**Figures 2 and 3**) were affected by natural disturbances, particularly wildfire. However, the primary cause of change varied by location. Wildfires were most prevalent in the north central Cascades (see partner StoryMap) and northern Blue Mountain regions, while forest management (commercial and non-commercial thinning, prescribed fire, fuels reduction) was most prevalent in northeastern Washington and the southern Cascades. Insect activity had a large impact on the central Cascades as well as parts of northeastern Washington, especially near Sherman Pass.

The extent of forest affected by all change agents except for wildfire was relatively stable across years (**Figures 4 and 5**). Wildfire extent was more variable from year to year, due in part to record-setting fire seasons in 2015 and 2021. The impacts of wildfires are discussed in more detail in the annual Work of Wildfire reports (see section 5.2.2).

Most changes occurred in drier forests (about 59%), followed by about 25% in cold forests and about 16% in moist forests. In general, this aligns both with the overall distribution of forest types across eastern Washington (56% dry, 20% moist, 24% cold), as well as the historical disturbance regimes and treatment priorities within planning areas. Drier forests are typically more susceptible to drought stress, making them a higher treatment priority than moist and cold forests in many cases.

Federal lands accounted for the vast majority of changed forest areas, with about 1.5 million acres of change. Tribal lands (about 475,000 acres) also experienced substantial change, followed by areas with private nonindustrial ownership (about 212,000 acres), DNR state trust lands (about 192,000 acres), and private industrial land (about 189,000 acres). Federal and tribal lands had notably higher levels of change due primarily to several large wildfires.

For the combined treatment database time period (2017-2022), a total of about 822,000 acres of treatments (571,000 footprint acres) were implemented across eastern Washington (**Figures 4 and 5**). An additional 910,000 footprint acres were changed by wildfires and insect activity. The most common treatment type was thinning (312,000 acres), followed by regeneration harvest (140,000 acres), fuels rearrangement (106,000 acres), pile burning (106,000 acres), prescribed fire (45,000 acres), and other treatment types (113,000 acres).

Of the total treatment area, about 23% was captured by both datasets, 35% was captured only by the change detection product, and 42% was captured by only the treatment database. As expected, the treatments not captured by change detection primarily fell into the fuels rearrangement (25% of missed treatments), pile burning (16% of missed treatments), non-commercial thinning (16% of missed treatments), and tree re-establishment (12% of missed treatments) categories. The treatments not captured by the treatment database primarily were attributed by the change detection maps as 65% thinning, 29% regeneration harvest, and 6% broadcast burning.

2.3 Forest change within priority planning areas

Of the nearly 1.5 million footprint acres of change across eastern Washington since DNR began conducting landscape evaluations in 2017, about 580,000 footprint acres occurred within priority planning areas (**Table 1**). About 39% of the treated footprint acres in eastern Washington over this time period occurred within planning areas (48% of total treatment acres). Footprint acres varied widely among planning areas, from about 500 acres in the Chelan planning area to more than 60,000 acres in the Methow Valley planning area.

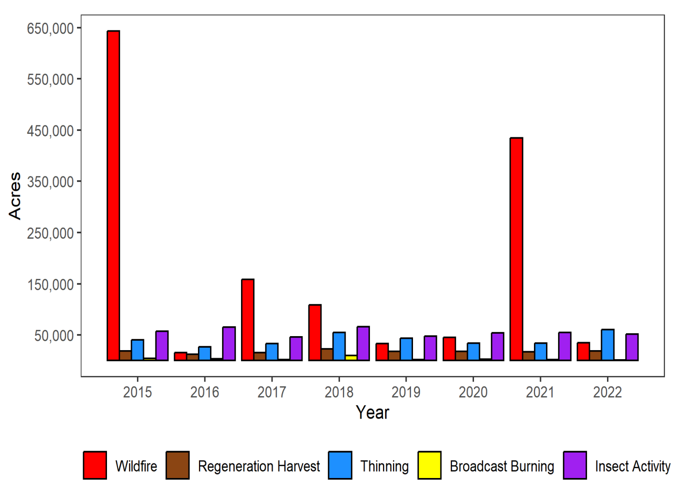


Figure 4. Annual remotely sensed change acres for 2015-2022 from the satellite-based change detection product, by disturbance or treatment category. Note that reported acres in change detection and the forest health treatment database often overlap.

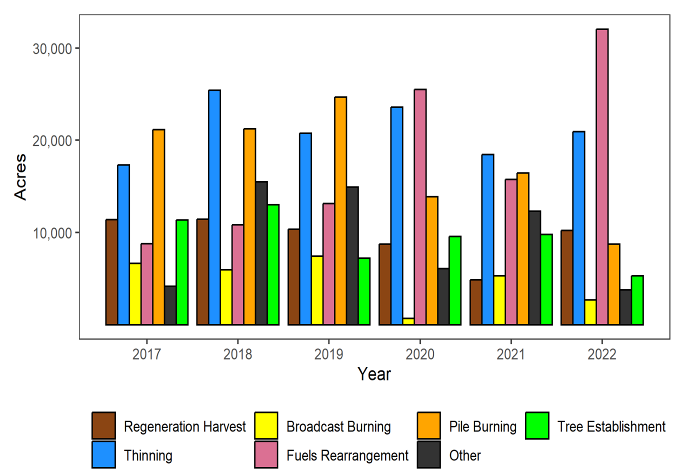


Figure 5. Annual reported change acres 2017-2022 from the forest health treatment database, by treatment category. Note that reported acres in change detection and the forest health treatment database often overlap. Treatment definitions can be found in **Appendix C**.

Table 1 (page 1 of 2). Top 25 priority planning areas sorted by footprint acres changed (2017 – 2022). Planning areas with detailed analysis in this report are shown as bold italic (Cle Elum, Glenwood, Mill Creek). "Total Change Acres" columns represent all changed acres, not footprint acres. Treatment definitions can be found in **Appendix C**.

Planning Area	Total Acres	Forested Acres	Assessed Treatment Need (footprint acres)	Total Footprint Acres	Total Change Acres							
					Regen. Harvest	Thinning	Rx Fire: Broadcast Burn	Rx Fire: Pile Burning	Fuels Rearrangement	Other	Wildfire	Insect Acrivity
Methow Valley	338,246	182,937	49,500 - 75,000	63,699	124	4,718	2,070	3,260	5,639	9,704	50,116	4,445
Asotin	149,152	93,329	Analysis in 2024	48,359	164	3,689	627	3,961	1,372	1,540	44,830	981
Chewuch	94,250	83,846	Analysis in 2024	38,877	NA	230	137	113	NA	NA	38,056	4,534
Tucannon	98,616	80,099	Analysis in 2024	34,948	229	830	31	325	185	155	33,788	5,277
Twisp River	111,918	82,349	26,000 - 36,500	33,283	1	508	62	NA	102	1,318	32,017	5,403
Teanaway	132,120	111,696	38,500 - 60,000	31,398	336	1,854	68	163	632	583	28,438	700
Inchelium	146,263	121,779	Analysis in 2024	29,199	2,536	2,662	38	NA	162	524	25,199	824
Mill Creek	***186,306***	***162,060***	***57,000 - 80,000***	***27,944***	***8,226***	***20,551***	***361***	***8,583***	***6,634***	***2,733***	***469***	***1,099***
Naches-Wenas	180,858	121,981	Analysis in 2024	25,876	245	5,245	3,063	1,987	26	235	17,225	4,385
Loomis	198,991	149,802	Analysis in 2024	19,141	3,650	4,739	1,170	5,225	199	6,005	5,792	13,020
Republic	180,553	144,350	46,500 - 64,000	19,048	1,349	7,945	2,206	5,629	2,988	3,883	23	13,817
Little Naches	95,433	92,914	25,500 - 43,000	18,949	395	5,325	14	708	3,226	NA	14,308	1,165
Chewelah	195,408	158,352	59,000 - 80,000	12,575	2,781	9,255	261	4,511	1,803	1,460	117	220
Mad Roaring Mills	65,008	33,325	13,500 - 20,000	11,332	77	585	483	935	1,038	2,722	8,172	NA

Table 1 (page 2 of 2). Top 25 priority planning areas sorted by footprint acres changed (2017 – 2022). Planning areas with detailed analysis in this report are shown as bold italic (Cle Elum, Glenwood, Mill Creek). “Total Change Acres” columns represent all changed acres, not footprint acres. Treatment definitions can be found in **Appendix C**

Planning Area	Total Acres	Forested Acres	Assessed Treatment Need (footprint acres)	Total Footprint Acres	Total Change Acres							
					Regen. Harvest	**Thinning**	**Broadcast Burning**	**Pile Burning**	**Fuels Rearrangement**	**Other**	**Wildfire**	**Insect Acrivity**
Mt Spokane	121,767	95,814	29,000 - 42,000	10,576	3,048	6,244	96	1,095	972	3,295	NA	223
White Salmon	126,688	104,022	38,000 - 54,000	10,509	8,237	2,308	582	410	939	308	340	NA
Stranger	89,904	72,061	30,000 - 38,000	10,413	3,359	6,992	103	821	348	1,878	NA	20
Deer Park	181,171	90,497	36,000 - 49,000	10,192	1,309	5,831	51	880	2,034	399	2,048	NA
Klickitat	149,649	103,274	43,000 - 55,000	8,887	5,817	3,718	87	198	415	NA	53	NA
Little Pend Oreille	92,994	81,148	30,250 - 43,500	8,705	1,871	4,263	2,202	353	643	2,966	128	142
Glenwood	***104,501***	***83,758***	***23,500 - 32,000***	***8,224***	***4,365***	***2,547***	***976***	***322***	***112***	***1,459***	***NA***	***181***
Cle Elum	***109,396***	***80,300***	***22,000 - 35,500***	***7,563***	***443***	***1,799***	***200***	***1,522***	***2,677***	***576***	***2,395***	***29***
Toroda-Tonata	153,611	117,345	51,000 - 66,000	7,501	894	3,331	414	1,099	245	1,560	32	8,916
Long Lake	103,291	41,253	14,000 - 20,000	7,275	1,334	2,184	32	332	1,977	607	2,093	NA
Trout Lake	117,153	105,015	18,500 - 33,000	6,760	1,607	3,003	92	803	48	2,078	4	724
All Other Planning Areas	1,751,416	1,213,327		71,542	12,366	43,034	3,972	9,809	22,379	4,442	4,516	16,013
Total	**5,274,663**	**3,806,633**		**582,776**	**72,367**	**186,653**	**20,634**	**53,043**	**56,796**	**50,433**	**310,162**	**82,118**

Wildfire was the primary driver of forest change for the planning areas with the most footprint acres (**Table 1**). Fire accounted for most of the change acres for eight of the top ten planning areas. The only planning areas in the top ten where wildfire was not the primary driver of change were Mill Creek and Loomis. More than 20,000 acres of forest health treatments have been completed since 2015 in Mill Creek. The South Fork Mill Creek watershed, which contains many of these forest health treatments, is explored in more detail in the "Planning Area Monitoring" section below. Significant insect activity occurred in Loomis.

Mapped insect activity was mostly sparse across planning areas, with a few notable exceptions. The Republic, Loomis, and Toroda-Tonata priority planning areas each showed more than 8,000 acres of insect activity. These areas have been hit heavily by pine bark beetles and Douglas-fir beetles, as detailed in the forest health highlights reports from recent years (e.g., 2022). The Methow area (Methow Valley, Twisp River, and Chewuch planning areas) also showed higher levels of insect activity, along with some areas of the central Cascades (Naches-Wenas) and Blue Mountains (Tucannon).

The southern Washington Cascades and northeastern Washington planning areas had the most regeneration harvest between 2015 and 2022. These areas also have the highest proportion of industrial lands, where most regeneration harvest is occurring. Thinning was especially prevalent in the Mill Creek planning area and more generally in the northeastern part of the state. Other priority planning areas with high amounts of thinning were Asotin in the Blue Mountains, Highway 97 in the southern Cascades, and Republic in the Okanogan Highlands.

Comparing the total footprint acres affected with assessed treatment needs, many planning areas appear to be on track for meeting total acres treated. However, this comparison does not detail whether change that occurred within planning areas was successful at moving forest characteristics such as structure or wildlife habitat in a positive direction. Many of the acres changed were due to wildfire or insect activity, which can be either beneficial or detrimental in achieving resilience objectives. The "Planning Area Monitoring" section below provides in-depth analyses of three planning areas to better illustrate and understand how changes align with restoration goals.

Finally, it is critical to keep in mind that the forested landscapes of eastern Washington require frequent disturbance to maintain resilient conditions. Many treated areas will need follow-up treatments within 10-20 years to keep tree densities and surface fuels at desired levels. Long-term forest management that produces wood products is also important on many ownerships to sustain a full suite of management tools and local economies. While estimates of treatment need in landscape evaluations account for some of this maintenance need, treatment needs are dynamic over time and will require periodic reassessment.

2.4 Central Washington Initiative Summary

Started in 2022, the Central Washington Initiative (CWI) is an all hands, all lands effort to implement the National Cohesive Wildland Fire Management Strategy, Confronting the Wildfire Crisis Strategy, 20-Year Plan, Bipartisan Infrastructure Law, and Washington House Bill 1168, with the overarching goal of promoting resilient landscapes and communities adapting to changing wildfire conditions. The CWI landscape spans four counties and six high-risk firesheds across 3.1 million acres, including 2.1 million acres of USDA Forest Service lands and 1 million acres of non-Forest Service lands in eastern Washington.

The DNR and Forest Service signed a Memorandum of Understanding (MOU) in June 2022, outlining a shared commitment to working with one another to plan and implement the CWI. The MOU commits both agencies to coordinating programs of work and leveraging funding, as available and appropriate, with a goal of increasing forest and watershed health and resilience on at least 350,000 footprint acres across all lands in Central Washington over the next 10 years. Approximately 200,000 footprint acres are expected to be treated on national forest lands as part of the CWI. This acreage goal was established by meeting the minimum treatment need identified in DNR landscape evaluations for priority landscapes in the initiative area.

CWI treatment accomplishments during the first fiscal year (10/1/2021 - 9/30/2022) include 33,225 footprint acres and 74,660 treatments acres of fuels reduction and terrestrial restoration treatments across all ownerships across the CWI geography. Please see the annual accomplishments report for federal fiscal years 2022 and 2023 with these data and other CWI highlights. The alignment between the Wildfire Crisis Strategy and 20-Year Plan is discussed in detail in a 2023 memo (available online).

2.5 Update to the Pacific Northwest Quantitative Wildfire Risk Assessment (QWRA)

The Pacific Northwest Quantitative Wildfire Risk Assessment (QWRA) is an all-lands comprehensive analysis developed for Oregon and Washington by state and federal land management agencies with support from managers and scientists. The 2023 update was coordinated through the Forest Service Region 6 and the College of Forestry at Oregon State University, with additional leadership provided by DNR, the Oregon Department of Forestry, Bureau of Land Management, National Park Service and Bureau of Indian Affairs.

The QWRA is a suite of products that can support a range of management applications and multiple geographies. While primarily designed for pre-season and active fire prioritization, QWRA products are used differently and adapted to meet the business needs of different users. For a description of how QWRA products are used in the 20-Year Forest Health Strategic Plan, please see the 2022 report to the Legislature.

The 2023 QWRA is an update to the previous QWRA version released in 2018. The new update is driven by the need to reflect changes to fuels on the landscape since the 2018 version and leverage improved fire modeling methods and methodology for mapping highly valued resources and assets (HVRAs), as well as expand the list of included HVRAs. Significant updates to the HVRAs include the addition of Agriculture as a new HVRA and the addition of Rangelands to the Ecological Integrity HVRA. For a detailed description of all HVRAs and changes please see McEvoy et al. (2023).

3. PLANNING AREA MONITORING

3.1 Overview

Understanding how treatments and disturbances are moving landscapes towards or away from resilient conditions is critical to monitoring progress towards the goals of the 20-Year Plan. Tracking treatment and disturbance acres is a critical first step, but quantifying changes in forest structure, composition, and pattern is necessary to assess trends in key indicators of forest health such as fire risk, vulnerability to drought and insects, wildlife habitat, and aquatic functions.

Since developing the 20-Year Plan monitoring framework in 2020, DNR scientists have been working with academic and agency partners to develop robust methods and datasets. In the 2022 legislative report, we included results for two planning areas based on initial change detection methods. In this report, we present results for three planning areas and expand on the 2022 analysis by quantifying structural change relative to resilient reference conditions, changes in wildlife habitat amounts and pattern, and riparian forest structure. Over time, we plan to add changes to drought vulnerability, predicted wildfire behavior, and modeled snowpack and stream flow.

We chose the three planning areas in order to capture a range of ownerships, overall treatment amount, treatment types, and geographic representation. The Cle Elum planning area is dominated by small private landowners and has had a high proportion of small tree thinning and fuel reduction treatments. Glenwood is predominantly private industrial and DNR ownership and has experienced a mix of thinning, regeneration harvest, and wildfire. For the third example, we focused on a sub-watershed of the Mill Creek Planning Area where a large landscape restoration treatment is nearing completion on Forest Service land.

There are two main sections for each of the planning area assessments. The first focuses on treatment implementation over the period since the landscape evaluation for the area was completed (2017-2022). The second assesses changes in forest structure between 2015 and 2021 with respect to overall landscape departure from historical reference conditions, riparian areas, and wildlife habitat. These detailed assessments highlight progress that has been made towards landscape evaluation goals, as well as challenges and needs for ongoing and future treatment.

To analyze changes in forest structure, we mapped forest structure based on the eight forest structural classes used in DNR landscape evaluations. Current amounts of each structure class are compared with target or reference ranges derived from estimates of historical landscape conditions. Canopy cover, height, and other metrics from Digital Aerial Photogrammetry (DAP) datasets were used to generate structure class maps for 2015 and 2021. The 2021 structure class map was created by replacing areas in the 2015 structure class data that changed between 2015 and 2021 with the 2021 structure class data. This method does not account for growth outside of changed areas but is a more conservative approach to minimize the influence of year-to-year differences in DAP structure class results (see **Appendix B** for more details). Note that the large open structure class is likely under-represented in this analysis. Because the analysis is done at the pixel level (66-ft resolution) rather than at the stand level, large open stands often include numerous pixels labeled as other structure classes, especially large closed and medium closed.

Note also that time periods differ between the treatment implementation (2017-2022) and structural change (2015-2021) sections. We report treatment implementation results using the time period of the combined treatment database described above and assess changes relative to the treatment need identified in the landscape evaluations for each planning area, using 2017 as the base year. For structural change, we use 2015 and 2021 DAP data bookends because those are the earliest and latest years with consistent, high-quality imagery. Adjusting imagery dates to match each landscape evaluation would provide less information on overall trends in the area.

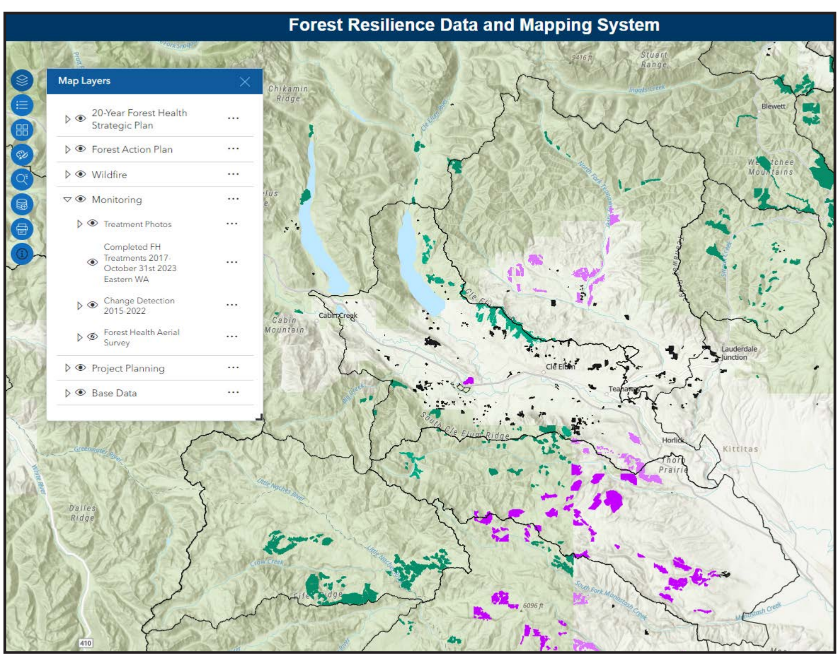


Figure 6. Screenshot of Forest Resilience Data Viewer showing forest health treatments completed in the Cle Elum priority planning area and surrounding planning areas in central Washinton.

Table 2. Changed acres by treatment/disturbance type by vegetation type and tree size class across the Cle Elum planning area (2017-2022). Treatment targets are footprint acres from the [landscape evaluation](). Targets are shown for vegetation types and tree size classes that are overabundant relative to desired conditions or that require maintenance treatments (Dry-Moist Open). Treatment definitions can be found in the glossary and **Appendix C**. *Note that the forest health treatment database is missing some treatment locations and will be updated in collaboration with partners.*

Forest Conditions to Treat		Treatment Need Acres	Acres Changed by Type (2017 - 2022)							
Type	Size Class		Regen. Harvest	Thinning	Fuels Rearrange-ment	Rx Fire: Broadcast Burn	Rx Fire: Pile Burn	Other	Total	Footprint Acres
Dry Dense	Small	500-1,000	16	187	129	9	1	1	344	312
	Medium-Large	8,500-10,500	179	623	579	20	182	175	1,758	1,289
Moist-Cold Dense	Small	1,000-1,500	27	64	73	0	0	0	163	163
	Medium-Large	7,000-13,500	84	302	581	7	202	89	1,265	1,130
Dry-Moist Open	Medium- Large	5,000-9,000	38	348	1,114	140	119	133	1,892	1,370
Other Veg Types	No Target		98	274	202	23	1,018	179	1,795	875
Total Target		22,000-35,500	443	1,799	2,677	200	1,522	576	7,217	5,139
Anticipated Treatment Type	(light blue)	Non-commercial thin + fuels treatment, may be fire only.								
	(blue)	Commercial thin + fuels treatment if access exists. May be non-commercial, fire only, or regeneration harvest.								
	(green)	Maintenance: prescribed fire or mechanical fuels treatment.								

The structure of riparian forests and related riparian functions, forest health, and wildfire risk are major topics of interest in eastern Washington. To inform these discussions, we assessed the structure classes of forest-adjacent to streams in 2015 and 2021. We used DNR stream types and buffers (fish-bearing: 150 ft, non-fish-bearing: 75 ft, rivers and shoreline: 250 ft, unknown: 50 ft) to map these areas. These are not regulatory buffer distances per se, and this analysis does not assess regulatory compliance with Forest Practices rules or regulatory requirements on federal ownerships.

When reading these assessments, we encourage readers to open the web-based [Forest Resilience Data Viewer]() (**Figure 6**) that has spatial layers from landscape evaluations, treatment tracking, and other sources.

3.2 Cle Elum Planning Area Summary

3.2.1 OVERVIEW

This planning area has been a focal point of community wildfire risk reduction and forest restoration in eastern Washington. It has a diverse mix of ownerships, high fire risk, and a large land base of small private landowners and wildland urban interface. The [landscape evaluation]() was completed in 2018 based on 2017 aerial imagery. Many local and regional partners have worked with DNR to implement approximately 7,200 acres of total treatment from 2017-2022 on private and public lands. The successes and lessons learned from the Cle Elum planning area apply to many other planning areas that have a large number of small private landowners as well as surrounding public lands.

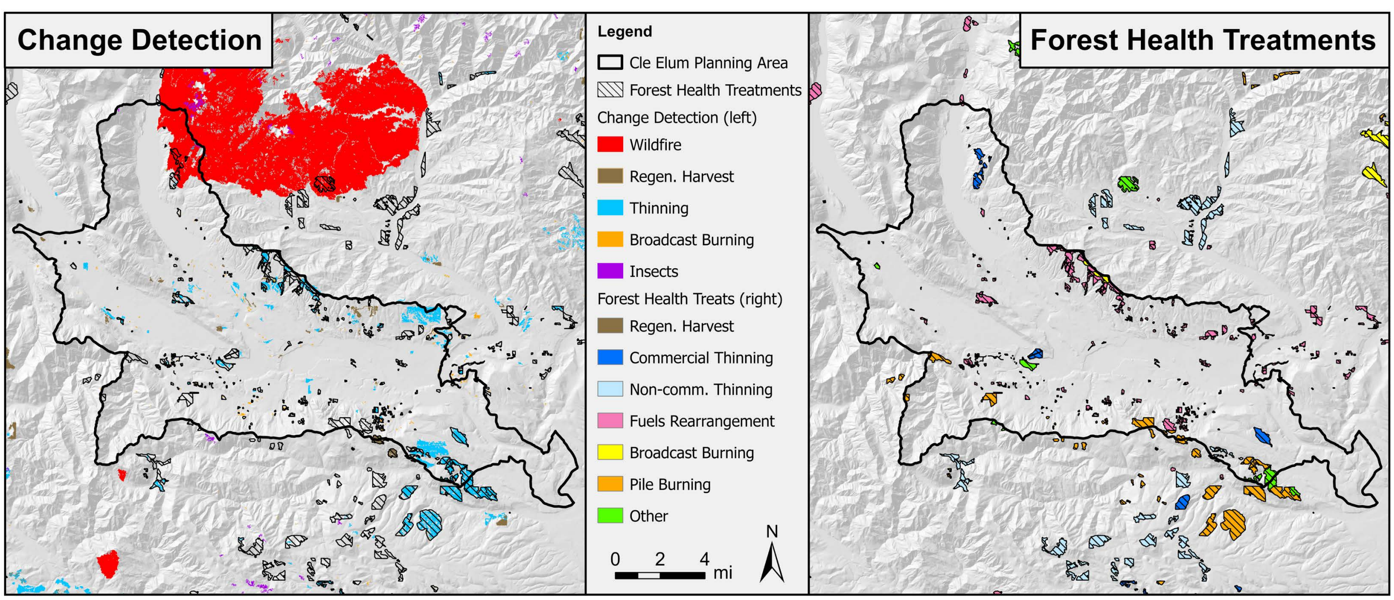


Figure 7. Map of treatment locations identified by the satellite-based change detection product (left, 2015-2022) and forest health treatment database across the Cle Elum planning area (right, 2017-2022). *Note that the treatment database is missing some treatment locations and will be updated in collaboration with partners. Also, the map shows only one treatment in units where multiple treatments occurred.*

Table 3. Footprint acres of treatments and wildfires by land ownership type in the Cle Elum planning area. For each ownership type, proportion of the total forested area is also shown. *Note that the forest health treatment database is missing some treatment locations and will be updated in collaboration with partners.*

Landowner	Treatment Footprint Acres	Wildfire Acres	Percentage in planning area
Private	2,483	70	56
The Nature Conservancy & Municipal	1,200	1,189	13
DNR-Trustlands	789	0	50
Forest Service	697	992	24
WA State Parks	141	0	1
WA Department of Fish and Wildlife	139	0	1

Note that for the Cle Elum planning area, the major difference in amount and types of treatment between the Treatment Implementation (2017-2022) and Structural Change (2015-2021) assessment periods is the inclusion of 2,250 acres of the Jolly Mountain Fire in the structure change analysis. These acres burned before the 2017 imagery used for the Cle Elum landscape evaluation, and thus the landscape evaluation factored in the work of this wildfire within the planning area. Conversely, the about 1,700 acres of treatment that occurred in 2022 were not captured by the structure change analysis. Also, a portion of the 700 acres treated in 2021 were likely completed after the 2021 imagery was collected.

3.2.2 TREATMENT IMPLEMENTATION

Amount of treatment

The Cle Elum landscape evaluation identified a treatment need of 22,000-35,500 acres, which equates to 27-44% of the 80,300 forested acres in the 109,000 acre planning area (**Table 2**). These treatment targets are footprint acres (see Box 1). Treatment need exists in both dry and moist forest types and across all land ownerships. Based on data from DNR's treatment tracking database and satellite-based change detection, 7,217 total acres of treatments have been conducted on 5,139 footprint acres from 2017-2022 (**Table 2, Figure 7**). The Cle Elum collaborative planning dashboard includes a detailed implementation plan and examples of current cross-boundary efforts.

In 2017, the Jolly Mountain Fire burned an additional 2,250 acres in the planning area east of Cle Elum Lake, mostly at low and moderate severity. Fire effects were generally beneficial in this area by reducing tree density and breaking up the large patch of dense forest in that area. However, the treatment targets from the landscape evaluation already account for these fire positive effects because the imagery used for current conditions in the landscape evaluation was collected after the fire in 2017. Thus, the acres burned in the fire are not counted towards the landscape evaluation target and are not shown in **Table 2**. They are, however, factored into the need for maintenance treatment as future work to reduce post-fire fuels.

About half of the footprint acres were implemented on private land (**Table 3**), while another quarter occurred on land managed by The Nature Conservancy and other municipal ownerships (e.g., Roslyn Community Forest). In addition to thinning and mechanical fuel reduction, a number of prescribed fires have been implemented on these ownerships that will greatly enhance the ability of fire managers to protect adjacent communities during future wildfires. The remaining portion occurred on lands managed by the Forest Service, DNR state lands, Washington Department of Fish and Wildlife, Washington

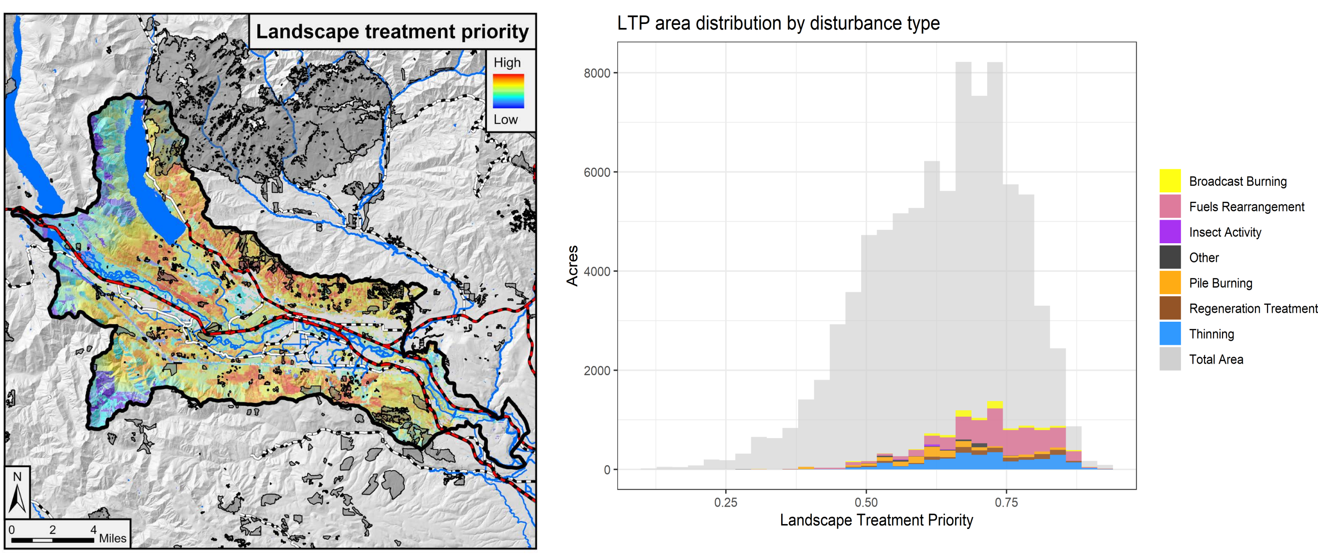


Figure 8. Landscape Treatment Priority (LTP) with all change polygons (shaded areas reflect change detection and forest health treatment database combined) (left). Recent treatments (2017-2022) overlaid with the distribution of LTP across the Cle Elum planning area (right). Treated areas have higher LTP scores relative to the entire landscape, indicating treatments were focused in high-priority locations. *Note that the treatment database is missing some treatment locations and will be updated in collaboration with partners.*

State Parks, and other ownerships. Almost 80% of the treatments were implemented in the target forest types and structure classes identified in the landscape evaluation (**Table 2**).

Overall, treatments have accomplished one quarter of the lower end of the treatment need identified in the landscape evaluation (5,139 of 22,000 footprint acres). However, it is important to note that not all treated acres are in a resilient condition. Depending on starting conditions and landowner objectives, multiple kinds of treatments may be needed to open the canopy, lower tree density, shift species composition, reduce ladder fuels, and decrease surface fuels and restore understory plant communities. On sites where low fire risk is a landowner objective and only mechanical thinning has occurred, prescribed fire or other types of fuels treatments will likely be needed to reduce surface fuels. On sites where drought resistance is a major goal and only understory thinning and/or surface fuel reduction has occurred, mechanical thinning may be needed to open the overstory canopy.

One example is the need for follow-up fire or other fuel reduction treatments in the moderate-severity areas of the 2017 Jolly Mountain Fire. These are needed to prevent a large buildup of surface fuels as fire-killed trees fall over. Field assessment and monitoring will be essential to determining what additional treatments are needed on different sites.

Location of treatments

The landscape evaluation identified high-priority locations for treatment on the south-facing slopes of Cle Elum Ridge, along the eastern half of the southern edge of the Planning area, and in a variety of locations adjacent to Cle Elum and Roslyn (**Figure 8**).

Almost all the treatments since 2017 have been implemented in these high-priority locations (**Figure 8**). Very few treatments were implemented in low-priority areas. The south side of Cle Elum Ridge, in particular, has experienced a lot of treatment, which will enhance the ability of fire managers to protect homes and communities and decrease the risk of a large, high-severity

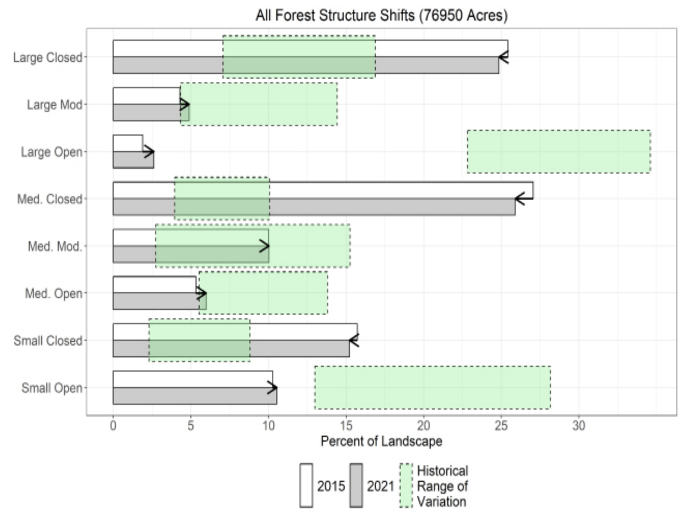


Figure 9. Proportion of the landscape covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the Cle Elum planning area (green shaded area). This graph represents all vegetation types. For information about individual forest types, see **Appendix G**.

fire in the planning area. Combined with the significant amount of treatment acres, this indicates that major progress is being made towards lowering risks from wildfire as well as restoring forests. There is much more work to do, but measurable progress is occurring.

3.2.3 STRUCTURAL CHANGE

Structural change relative to restoration needs

For the Cle Elum planning area, overall shifts in forest structure from 2015 to 2021 show progress towards reference ranges (**Figures 9 and 10**). The direction of change is towards the desired range for all structure classes, although the magnitude is relatively small. The current amounts of dense structure classes (large, medium, and small closed canopy) are all still very high.

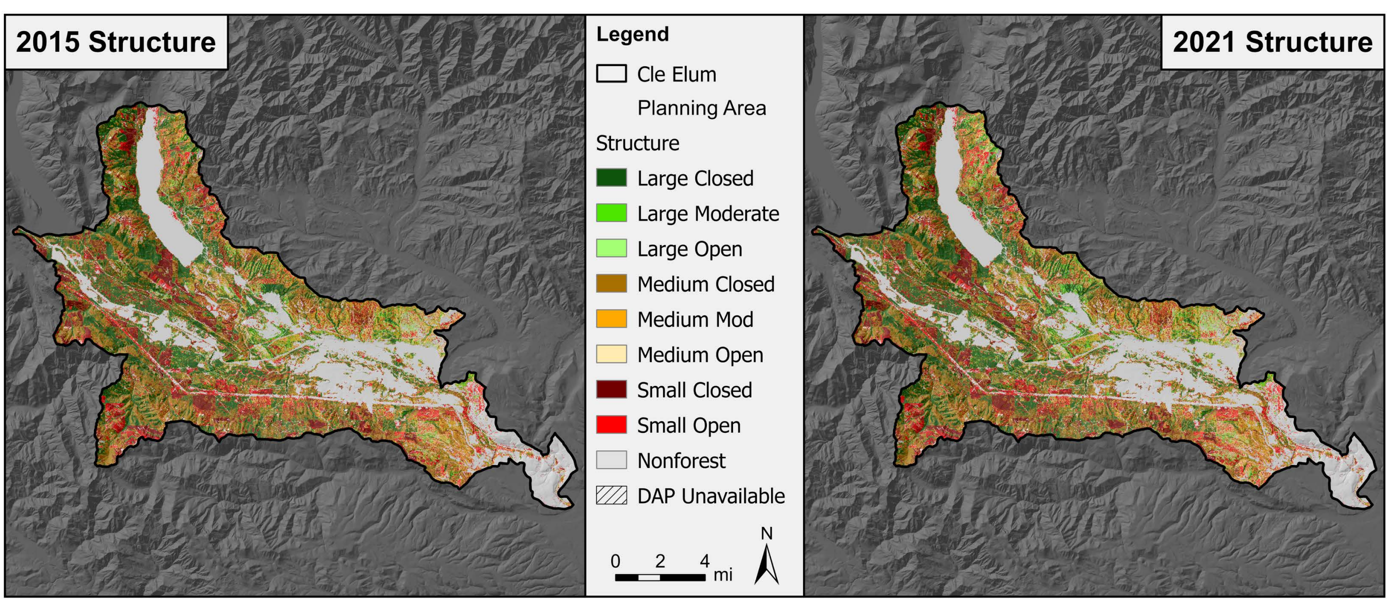


Figure 10. DAP-based forest structure in 2015 (left) and 2021 (right) for the Cle Elum planning area. See document on structural classes for details of the classes and **Appendix B** for details on how forest structure maps were created.

Figure 11. Different treatment types in the Cle Elum planning area. The top two photos show pre (left) and post (right) conditions for a mastication treatment on Nature Conservancy land on Cle Elum Ridge (source: Herman Flamenco). Surface and ladder fuels were treated but the tree canopy was not affected, the bottom left photo shows commercial thinning in the Roslyn Community Forest (source: James Begley), and the bottom right photo shows the same thinned unit after prescribed fire (source: Chris Martin).

The small-open and large-open classes remain low, and this is especially true for the large-open class. The large-open class is characteristic of frequent fire forests. Treatments and wildfire did move the large-moderate and medium-open classes into the low end of the desired range.

Overall, results indicate that there is still too much dense forest in the planning area, particularly in dry forest vegetation types. Closed-canopy forest is less departed in moist and cold forest types (**Appendix G**). A considerable amount of work is still needed to flip the landscape from predominantly closed-canopy forest to a condition dominated by large patches of open- and moderate-canopy forest with large, fire-resistant trees. Note that it is important to maintain closed-canopy patches to sustain a range of habitats and functions. The target landscape condition includes closed-canopy forest on 25-35% of the planning area, but those forests are located in areas that are more likely to sustain dense forest over the long term (e.g., north-facing slopes, valleys, and other sites within moist and cold forest). These sites are mostly lower priorities for treatment in the landscape treatment prioritization (**Figure 8**).

Thinning treatments are not the only tool to accomplish this restoration work. Wildfire can do much of this work in areas farther away from communities and when conditions are safe. Significant treatment before wildfire, however, will increase the likelihood of beneficial wildfire outcomes and management options. Growth of the medium-open and moderate classes will also increase the amount of large-open and moderate classes, especially if open conditions are maintained through fire- and mechanical-based maintenance treatments.

The modest progress in structural change was surprising given the relatively high progress towards the landscape evaluation treatment targets illustrated in the previous section (1/4 of the way towards the lower target of 22,500 acres). A key explanation of this disconnect is that only 56% of the 2017-2021 treatment footprint acres from treatment tracking and change detection resulted in a change in structure class. This percentage was higher for thinning and regeneration treatments (65-80%) but lower for prescribed fire, non-commercial thinning, and fuel re-arrangement treatments (about 40%). In general, canopy cover was not reduced enough to register a change in structure class. This is by design for most prescribed fire, understory tree thinning, mastication, piling, or other surface and ladder fuel treatments (**Figure 11**). In other cases, thinning was too light to register a change. Also, many treatment sites include no-cut areas such as riparian buffers, leave tree patches, and inaccessible

Table 4. Focal wildlife species habitat metrics for the Cle Elum planning area. American Marten represents a cold forest, large-tree, moderate- to closed-canopy habitat type. Northern Goshawk represents a moist to dry forest, large-tree, moderate- to closed-canopy habitat type, while White-headed Woodpecker represents a dry forest, large-tree, open canopy habitat type.

Focal Wildlife Species	Year	Total Acres	Area-Weighted Mean Patch Size (acres)	Mean Nearest Neighbor (feet)	Patch Density
American Marten	2015	1,494	100	480	1.2
	2021	1,497	100	612	1.2
Northern Goshawk	2015	15,258	421	479	1.0
	2021	15,398	420	494	0.9
White Headed Woodpecker	2015	216	32	2593	3.41
	2021	1,044	36	1271	2.26

areas. These results serve as a reminder that treated acres do not necessarily sum to structural change acres.

To be clear, fuels and other treatments that do not change forest structure classes have positive wildfire risk reduction and forest health effects. They are contributing towards the overall progress of the 20-Year Plan. On some sites, more intensive treatments are not possible or consistent with landowner objectives. However, where possible, doing more treatments that significantly reduce canopy cover to less than 40-50% and promote large, fire-resistant trees will move the landscape closer to conditions more likely to be resilient to drought, wildfire, and other stressors over time.

The south-facing slopes of Cle Elum Ridge are a key location for creating more open structure classes both to improve forest health and reduce fire risk for nearby communities. Maps of future moisture deficit shown in the landscape evaluation indicate high levels of moisture stress that are unlikely to sustain dense forest. Relatively large patches of closed-canopy forest are present, especially in the middle and western portion (**Figure 10**). We recognize that significant density reduction has occurred, especially near Roslyn.

Changes in focal wildlife habitat

Relatively little change in habitat for focal wildlife species occurred, reflecting the modest changes in forest structure (**Table 4**). The most notable change was an increase of approximately 800 acres of White-headed Woodpecker habitat. This was created in several thinning projects in areas with medium- to large-sized trees on Cle Elum Ridge and in the southeast portion of the planning area. Overall habitat amount is still very low, however, and patch sizes are small (**Table 4**). Thinning created potential future habitat on additional sites, but the overstory tree size is not large enough to meet the habitat definitions. These medium-open structure class patches (**Figures 9 and**

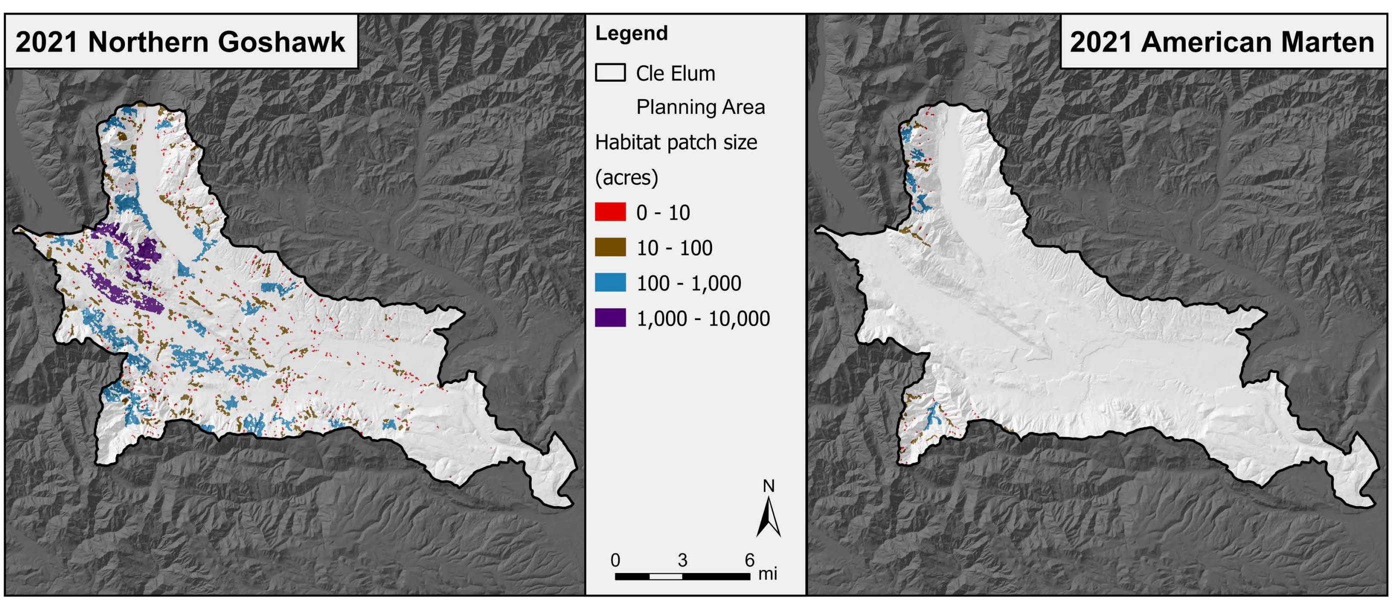


Figure 12. Maps of Northern Goshawk (left) and American Marten (right) habitat in the Cle Elum planning area based on 2021 DAP data. Only 2021 is shown as there is no appreciable different between 2015 and 2021. White-headed Woodpecker is not shown due to its low abundance.

10) will grow into habitat over time if open canopy conditions are maintained.

Northern Goshawk habitat is abundant and showed no appreciable change from 2015-2021 (**Table 4**). It is mostly located on north-facing slopes and in moist forests in the western half of the planning area (**Figure 12**) on sites that generally have the capacity to sustain moderate to high canopy cover. Opportunities to convert some of this habitat to White-headed Woodpecker habitat exist on drier sites. Future treatments are needed to create more of the large-open structure class and larger patches of it. The large tree, dense forest sustainability map in the landscape evaluation can be used to identify areas to maintain goshawk habitat and where conversion to White-headed Woodpecker habitat is warranted. American Marten habitat is moderately abundant within the cold forest of the planning area and did not change from 2015-2021 (**Table 4**).

Riparian forest structural changes

16,915 total acres of stream-adjacent forests exist within the Cle Elum planning area. Very few acres experienced structural change from 2015-2021, and these were almost entirely within the Jolly Mountain Fire (**Appendix F**). Over 70% of stream-adjacent forests have high canopy cover while approximately 40% are in the large-tree size class. Although denser forest is necessary to provide shade and other riparian functions, a greater diversity of riparian forest structure is more consistent with conditions found in historical and contemporary areas with active fire regimes (Jager et al. 2021, Everett et al. 2003). Greater structural diversity created by wildfire, thinning, or other disturbances is also likely to enhance aquatic functions and habitat for a range of species, increase snowpack and summer streamflow, accelerate development of large tree structure, and promote mixed broadleaf-conifer riparian forests (Povak et al. 2022, Wine et al. 2018, Sun et al. 2018, Flitcroft et al. 2016, Luce et al. 2012).

We recognize that regulatory requirements and policies guiding riparian forest management are designed to protect important ecological functions. Managing stream-adjacent forests can involve complex tradeoffs and consideration of many factors (Reeves et al. 2018). We provide these landscape-level data on stream-adjacent forest structure to inform discussions around this challenging topic.

3.2.4 CONCLUSIONS

Substantial positive work has been accomplished in the Cle Elum planning area since 2017, but there is more work to do to achieve landscape restoration goals. This analysis highlights several key conclusions that can guide future work:

- The footprint and rate of treatment is on track to achieve the treatment need identified in the landscape evaluation over the course of the 20-Year Plan.
- Treatments are occurring in high-priority locations for wildfire risk reduction and increasing drought resistance.
- More treatments that significantly lower canopy cover are needed to make faster progress towards forest structure restoration goals that will create more fire- and drought-resistant conditions. These treatments should be focused primarily on dry forest sites (**Figure 13**).
- More intensive thinning treatments that promote large, fire-resistant trees on dry sites will increase the amount and patch sizes of White-headed Woodpecker habitat. Existing open canopy areas with medium-sized trees will also grow into this habitat if open conditions are maintained.
- Additional analysis of treatment tracking and monitoring data monitoring work is needed, along with field-based monitoring, to better understand and map which treated areas are in a resilient condition and which acres need additional treatment.

Figure 13. The south side of Cle Elum Ridge above the community of Roslyn. Note the open canopy forest in the foreground but predominance of closed-canopy forest across most of the ridge (source: Derek Churchill).

3.3 Glenwood Planning Area Summary

3.3.1 OVERVIEW

The Glenwood planning area spans a steep elevation gradient from subalpine parkland on Mt. Adams to low-elevation dry forest and shrub-steppe vegetation within the Klickitat River watershed. It has a diverse mix of ownerships, including a high proportion of DNR-managed state trust lands and Industrial private land. Tribal land belonging to the Yakama Nation in the northwest portion represents 8% of the area, and the planning area is within the Yakama Reservation boundary. The landscape evaluation, including the dual-benefit prioritization, was completed in 2020 based on 2017 DAP and GNN layers.

Highlights from the landscape evaluation included the following findings:

- Projected warming over the next 20-40 years will likely shift climate conditions currently suitable for moist and cold forest towards conditions suitable for dry forest throughout the planning area.
- High-priority areas for potential treatments that maximize forest health and wildfire response benefit include locations in the southeast and southwest portions of the planning area and around the community of Glenwood.
- Treating 28-38% of forested acres is recommended to increase resilience and reduce fire risk to communities using a combination of mechanical treatments, prescribed fire, and maintenance treatments.

Nearly 8,400 total acres of treatments and commercial harvest have been completed on private and public lands from 2017 to 2022. This monitoring assessment highlights the progress that has been made towards the landscape evaluation goals, as well as challenges and needs for ongoing and future treatment. The successes and lessons learned from the Glenwood planning area apply to other planning areas that have a mix of industrial, state, private, and Tribal land, and dry forests at high risk of current and future drought stress.

When reading this section, note that the main acreage difference between the Treatment Implementation (2017-2022) and Structural Change (2015-2021) assessment periods is the 11,250 acres burned in the 2015 Cougar Creek Fire (**Figure 14**). An additional 1,900 acres of regeneration harvest, thinning, and prescribed fire also occurred prior to 2017. 2,300 acres treated in 2022 were not captured by the structure change analysis.

3.3.2 TREATMENT IMPLEMENTATION

Amount of treatment

The landscape evaluation identified a treatment need of 23,500–32,000 acres, or between 28-38% of the 83,750 forested acres in the 104,500 acre planning area (**Table 5**). These treatment targets are footprint acres. Treatment need exists in both moist and dry forest types and across private industrial land, state trust lands, and small private landowners. Yakama Nation lands have relatively low treatment needs due to the 2015 Cougar Creek Fire (**Figure 14**) that burned at relatively high elevations in the northwestern portion of the planning area. Based on data from DNR's treatment tracking database and satellite-based change detection, 11,107 total acres of treatments have been conducted on 8,224 footprint acres from 2017-2022 (**Table 5**).

About 40% of the footprint acres occurred on private industrial land (**Table 6**) in the form of regeneration harvests (**Figure 15**). Thinning on state trust lands accounted for an additional one-third of the footprint acres, along with about 10% of the footprint acres having occurred via prescribed burning on the Conboy Lake National Wildlife Refuge (USFWS) and Mt. Adams Community Forest in the central part of the planning area. About 1,300 acres of tree establishment was also implemented following the 2015 Cougar Creek Fire on state trust lands in the northwestern portion of the planning area. Treatment amounts have varied since 2017, with no clear trend over the span. About 2,100 acres of treatments were implemented in 2022. Moreover, several large commercial thinning projects were completed in 2023, and more may be reported in the future.

Combining all footprint acres, about 35% of the total treatment need has been addressed (8,224 of 23,500 acres).

Figure 14. Recent changes in the vicinity of Mt. Adams in the Glenwood Planning areas. Left: View of Mt. Adams and the 2015 Cougar Creek Fire (source: Dave Ryan, Mt. Adams Resource Stewards). Right: prescribed fire in the Mt. Adams Community Forest in (source: Mt. Adams Resource Stewards).

Table 5. Changed acres by treatment/disturbance type by vegetation type and tree size class across the Glenwood planning area (2017-2022). Treatment targets are footprint acres and come from the landscape evaluation. Targets are shown for vegetation types and tree size classes that are overabundant relative to desired conditions or that require maintenance treatments (Dry-Moist Open). Tree regeneration treatments are excluded from the "Other" category. Treatment definitions can be found in the glossary and **Appendix C**. *Note that the forest health treatment database is missing some treatment locations and will be updated in collaboration with partners.*

Forest Conditions to Treat		Treatment Need Acres	Acres Changed by Type (2017 - 2022)							
Type	Size Class		Regen. Harvest	Thinning	Fuels Rearrange-ment	Rx Fire: Broadcast Burn	Rx Fire: Pile Burn	Other	Total	Footprint Acres
Dry Dense	Small	750-1,000	43	6	1	3	0	0	53	44
	Medium-Large	17,000-22,000	2,780	1,536	21	318	170	21	4,847	3,819
Dry-Moist Open	Medium- Large	5,750-9,000	280	333	23	147	33	11	968	861
Other Veg Types	No Target		1,264	672	68	508	119	50	4,094	3,500
Total Target		23,500-32,000	4,366	2,547	113	976	322	82	9,962	8,224
Anticipated Treatment Type		Non-commerical thin + fuels treatment, may be fire only.								
		Commercial thin + fuels treatment if access exists. May be non-commercial, fire only, or regeneration harvest.								
		Maintenance: prescribed fire or mechanical fuels treatment.								

However, it is important to note that not all treated acres should be considered completed in terms of forest health objectives. Much of the acreage changed in the Glenwood planning area was due to regeneration harvests, which will require continued management for density and species selection to maintain resilience through time. The 1,300 acres of tree re-establishment (planting) in the Cougar Creek Fire areas will also need ongoing management. On sites where only mechanical thinning has occurred, follow-up fuels treatments will greatly reduce risk of high intensity wildfire. It is also important to recognize that DNR Trustlands, as well as many private landowners in the Glenwood planning area, have financial and wood production objectives that are an important aspect of the 20-Year Plan.

Location of treatments

The landscape evaluation identified high-priority treatment locations in the southern and southeastern portion of the planning area (**Figure 16**), especially south of the Glenwood highway and southwest of Laurel. This prioritization combines wildfire transmission to homes, wildfire risk to forests, overabundant dense forest structure, and drought vulnerability over time.

Most treatments and other forest management activities since 2017 have been implemented in higher priority areas (**Figure 16**). Very few treatments were implemented in lower priority areas, and those that did occur in low-priority areas were mostly tree re-establishment. While there are a significant number of changed acres, many of these acres were regeneration harvests on industrial land (**Figure 15, Table 6**). Progress is being made on lowering wildfire risks and restoring forests, but much more work is needed, as discussed in the next section.

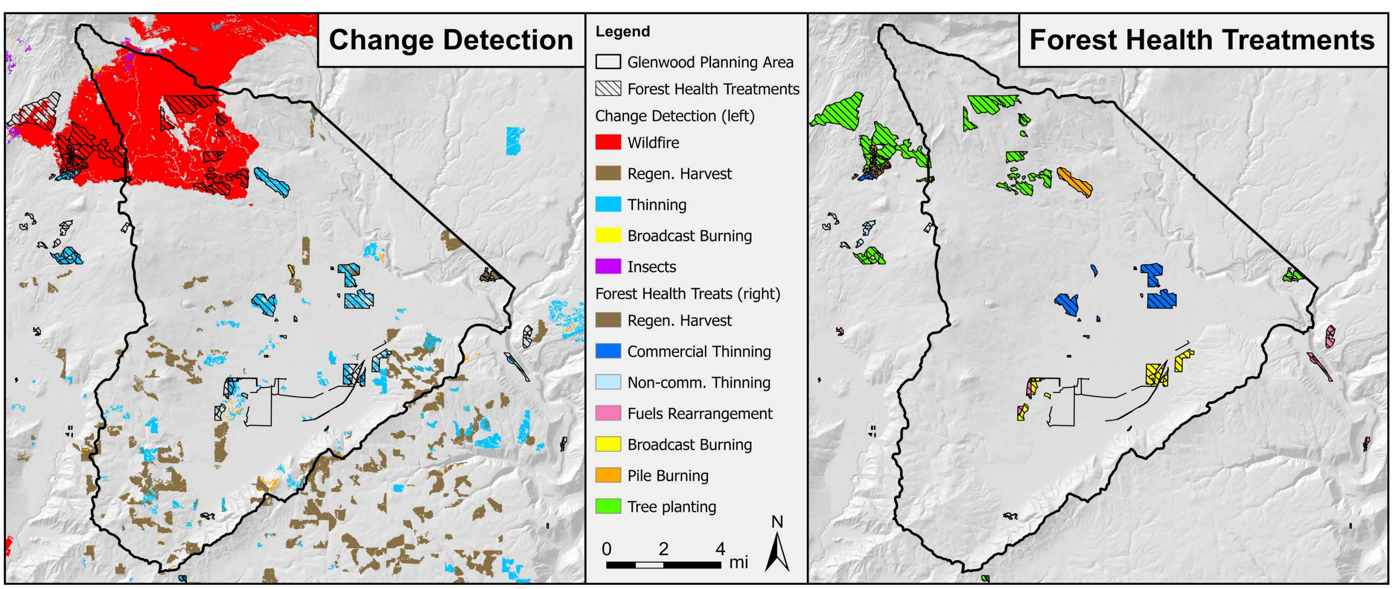


Figure 15. Map of treatment locations identified by the satellite-based change detection product (left, 2015-2022) and forest health treatment database across the Glenwood planning area (right, 2017-2022). *Note that the treatment database is missing some treatment locations and will be updated in collaboration with partners. Also, the map shows only one treatment in units where multiple treatments occurred.*

Table 6. Footprint acres of treatments by ownership type in the Glenwood planning area. For each ownership type, proportion of the total forested area is shown to provide context on the relative contributions of different landowners. Mt. Adams Community Forest treated acres are included in the Municipal-NGO category. DNR-NRCA-NAP: Natural Resource Conservation Areas and Natural Area Preserves. *Note that the forest health treatment database is missing some treatment locations and will be updated in collaboration with partners.*

Landowner	Treatment Footprint Acres	Percentage in planning area
Municipal-NGO	2	<1
DNR-NRCA-NAP	1	2
DNR-Trustlands	2,297	33
US Fish and Wildlife	650	6
Industrial	2,827	33
Private	625	16
State (Other)	176	1
Yakama Nation	63	8
Forest Service	43	<1

3.3.3 STRUCTURAL CHANGE

Structure change relative to restoration need

Between 2015 and 2021, treatment activities within the planning area moved forest structure towards the historical range of variation for the region across all vegetation types (**Figures 17 and 18**). The treatments resulting in the most significant structural changes were regeneration harvests on industrial lands in the southern portion of the planning area (**Figures 15 and 18**). Additional significant changes resulted from two commercial thinning projects completed in 2018 on state trust lands (254 acre Camp Draper and 302 acre Bacon Island) and several areas of prescribed burning within the Conboy Lake National Wildlife Refuge and Mt. Adams Community Forest (**Figure 19**).

Most of the Glenwood planning area consists of dry and moist mixed-conifer forest types. Large and medium closed structure classes within these forest types showed the most significant declines in abundance, while the largest increases were seen in all open structure classes. The only movement away from historical ranges of variation was an increase in the open class for moist mixed-conifer forests. A lot of work is still needed to bring the forest structure in the area within ranges that will promote future resilience to wildfire, drought, and other stressors (see the landscape evaluation). The focus should remain on shifting medium and large stands from dense to open structure while maintaining existing open stands.

About 60% of treatment footprint acres from 2017 to 2021 resulted in detectable changes of structure class. The percentage was higher for thinning and regeneration harvest areas (60-80%), but lower for areas treated with prescribed fire (44-53%). This follows expected patterns, in that thinning and regeneration harvest are expected to have larger impacts on canopy cover than prescribed burning. These numbers serve as a reminder that treated acres do not necessarily sum to structural change acres.

At least 12,500 additional acres of treatments are required to reach the restoration goals outlined in the Glenwood landscape evaluation (**Table 5**). Because much of the existing treatment acreage was regeneration harvest, the actual number of acres required is likely to be higher. Most of the additional treatment need is in dry medium-to-large dense forests, although work is also needed in dry and moist medium-to-large open forests. Additional projects within state trust lands with higher treatment

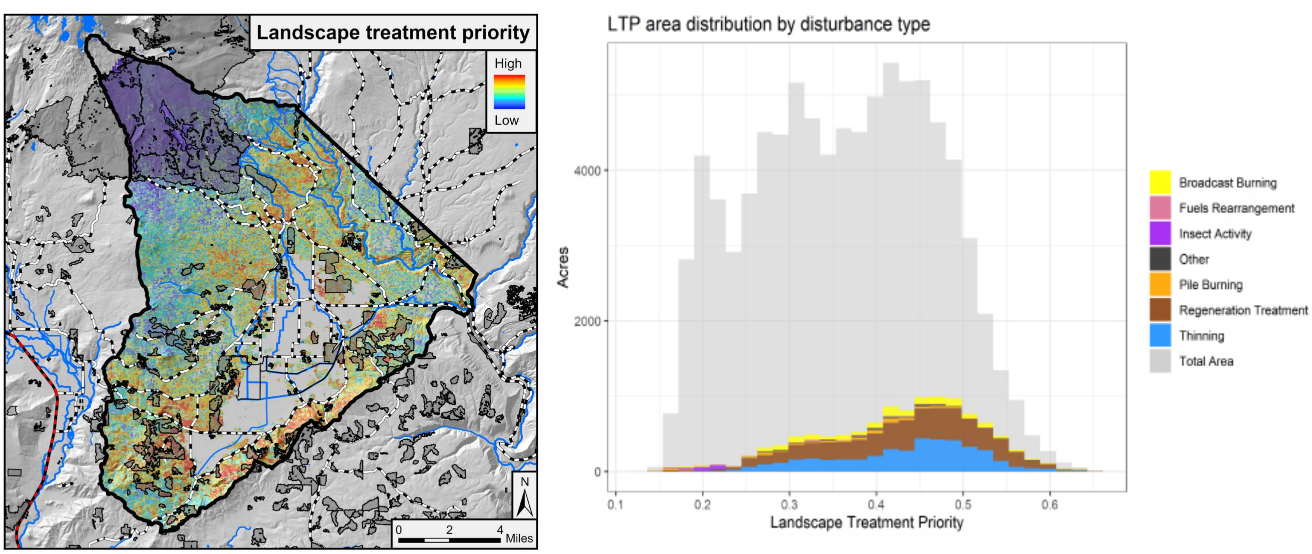


Figure 16. Landscape Treatment Priority (LTP) with all change polygons (shaded areas reflect change detection and forest health treatment database combined) (left). Recent treatments (2017-2022) overlaid with the distribution of LTP across the Glenwood planning area (right). Treated areas have higher LTP scores relative to the entire landscape, indicating treatments were focused in high-priority locations. *Note that the treatment database is missing some treatment locations and will be updated in collaboration with partners.*

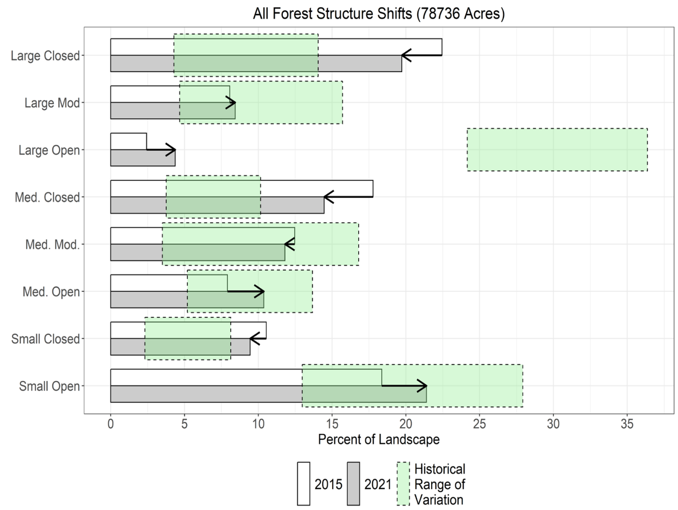


Figure 17. Proportion of the landscape covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the Glenwood planning area (green shaded area). This graph represents all vegetation types. For information about individual forest types, see **Appendix G**.

priority could accomplish much of this work. Areas of private industrial lands, state trust lands, and small private landowner property south of the Glenwood Highway would also benefit from thinning or other treatments that are consistent with landowner objectives.

Changes in focal wildlife habitat

A goal identified in the Glenwood landscape evaluation is to increase the habitat for species such as White-headed Woodpecker that require large trees and open canopies in dry forests. Over 1,500 additional acres of these areas have been created, and the structure of habitat across the landscape has changed considerably. Treatments have expanded patch sizes and decreased patch density across the landscape (**Figures 20 and 21**). The mean

Figure 19. Photo of prescribed burning within the Mt. Adams Community Forest (source: Dave Ryan, Mt. Adams Resource Stewards).

distance between patches has also decreased slightly. Overall, this means that along with increased overall habitat abundance, habitat connectivity has also increased slightly.

Habitat for species such as Northern Goshawk that require high canopy cover, large trees, and dry or moist forests remained roughly the same between 2015 and 2021 (**Figure 20**). This habitat type is abundant across the planning area, with about 16,000 estimated acres. Additional treatments can shift more oshawk habitat into White-Headed Woodpecker habitat. Retaining goshawk habitat in areas with lower moisture stress and fire risk will make it more durable over time. The large-dense forest sustainability map in the Landscape Evaluation can be used to help identify locations with moderate to high sustainability.

Changes in habitat for American Marten, which is a focal species for large-tree, cold forest habitat, was not assessed here due to the small amount of cold forest within this landscape and the low of amount of habitat within cold forest due to the 2015 Cougar Creek Fire.

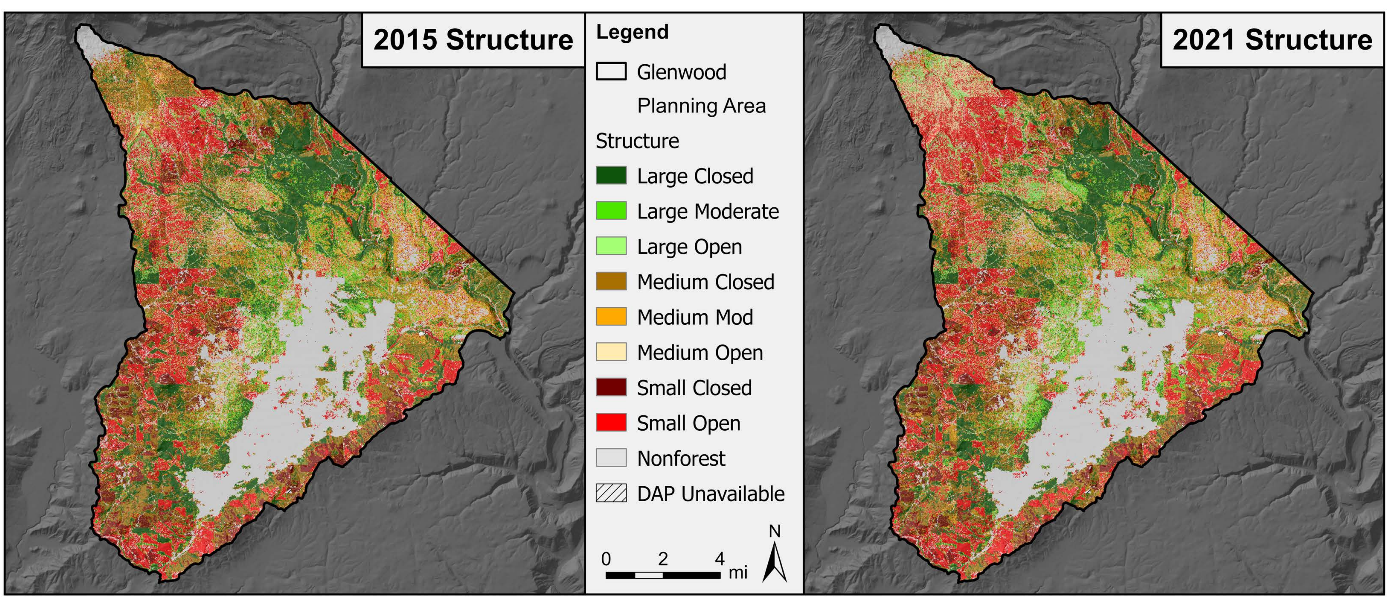


Figure 18. DAP-based forest structure in 2015 (left) and 2021 (right) for the Glenwood planning area. See document on structural classes for details of the classes and **Appendix B** for details on how forest structure maps were created.

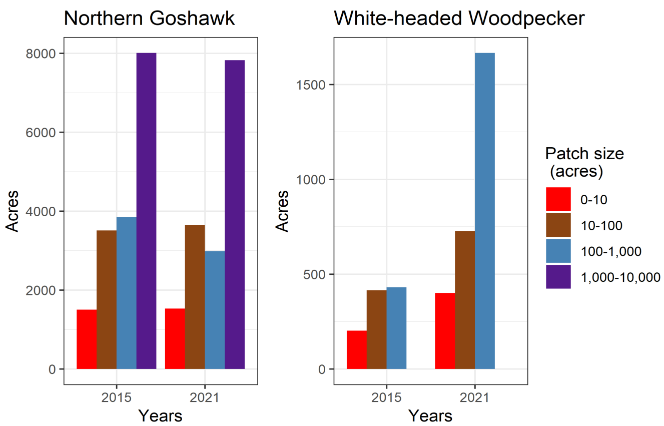


Figure 20. Acres of Northern Goshawk and White-headed Woodpecker habitat by patch size across the Glenwood planning area (2015-2021). For White-headed Woodpecker, total acres increased from 1,048 in 2015 to 2,795 in 2021, area weighted mean patch size increased from 194 to 249 acres, and mean nearest neighbor distance between patches decreased from 1,887 to 1,516 feet. For goshawk, total acres decreased from 16,871 to 15,994, area weighted mean patch size increased from 2,771 to 2,869 acres, and mean nearest neighbor distance between patches decreased from 477 to 458 feet.

Riparian forest structural changes

Nearly 8,600 acres of the Glenwood planning area are in stream-adjacent forests. Structural changes within these zones mirrored those for the planning area, with the largest decrease in large and medium closed-canopy forests and the largest increases in all open structure classes due to changes in riparian areas affected by the 2015 Cougar Creek Fire. Approximately 60% of stream-adjacent forests have high canopy cover while approximately 45% are in the large-tree size class (**Appendix F**). Especially in dry forest areas, reducing density in some of these stream-adjacent forests will restore historical riparian conditions (Everett et al. 2003), and likely increase resistance to large patches of high-severity wildfire, as well as drought mortality (Gaines et al. 2022, Jager et al. 2021, Reeves et al. 2018). We recognize that regulatory requirements and policies guiding riparian forest management are designed to protect important ecological functions. Managing stream-adjacent forests can involve complex tradeoffs and consideration of many factors. We provide these landscape-level data on stream-adjacent forest structure to inform discussions around this topic.

3.3.4 CONCLUSIONS

- Significant positive work has been accomplished in the Glenwood planning area, including several large commercial thinning projects on state trust lands and nearly 1,000 acres of prescribed burning in the Conboy Lake National Wildlife Refuge and Mt. Adams Community Forest.
- The total footprint acres completed and rate of treatment are on track to achieve treatment targets identified in the landscape evaluation.
- Many treatments are occurring in high-priority zones as outlined in the landscape evaluation.
- Regeneration harvest is common on private industrial lands in the southern portion of the planning area, where treatment needs are also high.
- Habitat for species such as White-headed Woodpecker that require large trees with open canopies in dry forests has increased by over 1,500 acres. Habitat for species like Northern Goshawk that require high canopy cover, large trees, and dry or moist forests has been maintained throughout the area.
- Future work will continue to address the need to thin dry dense forests with medium-large trees to reduce wildfire risk and promote drought resilience as the area shifts to a drier climate.

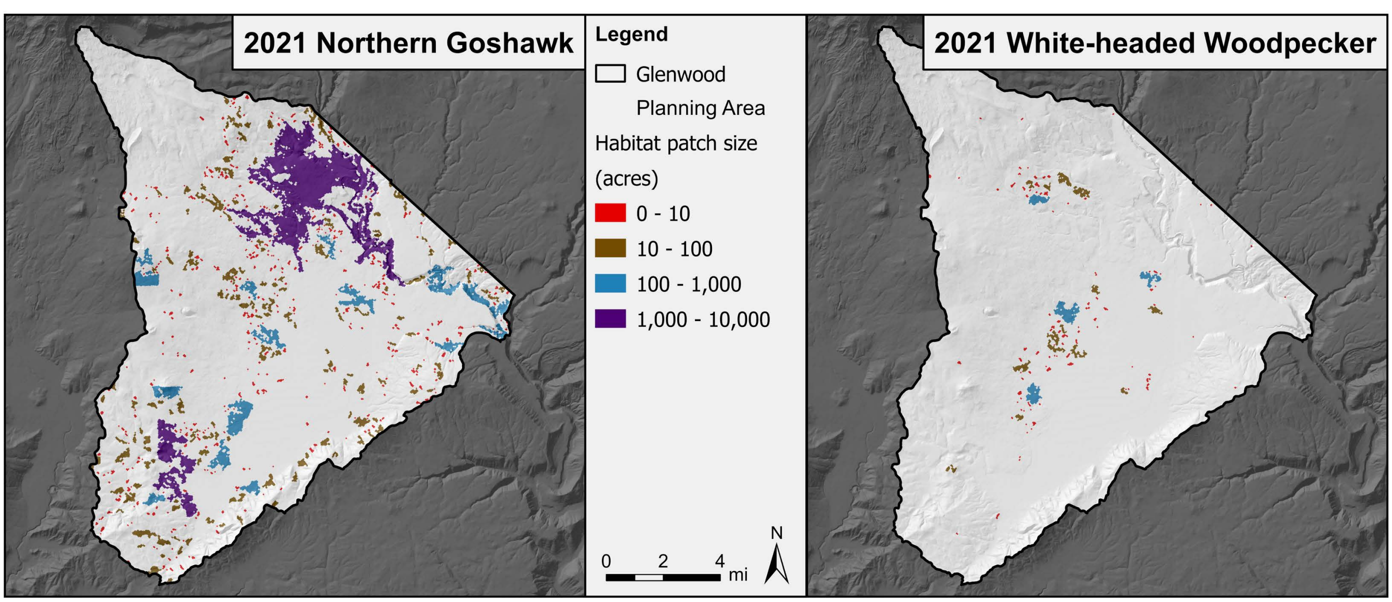


Figure 21. Maps of Northern Goshawk (left) and White-headed Woodpecker (right) habitat in the Glenwood planning area based on 2021 DAP data. American Marten habitat is not shown due to its low abundance.

Table 7. Changed acres by treatment/disturbance type by vegetation type and tree size class across the Mill Creek planning area (2017-2022). Treatment targets are footprint acres and come from the [landscape evaluation](). Targets are shown for vegetation types and tree size classes that are overabundant relative to desired conditions or that require maintenance treatments (Dry-Moist Open). Footprint acres for the South Fork Mill Creek Sub-watershed are also shown. Treatment definitions can be found in the glossary and **Appendix C**. *Note that the forest health treatment database is missing some treatment locations and will be updated in collaboration with partners.*

Forest Conditions to Treat		Treatment Need Acres	Acres Changed by Type (2017 - 2022)									
Type	Size Class		Regen. Harvest	Thinning	Fuels Rearrange-ment	Rx Fire: Broadcast Burn	Rx Fire: Pile Burn	Insect Activity	Other	Total	Footprint Acres	SF Mill Creek Footprint
Dry Dense	Small	1,000-2,000	40	102	8	5	5	5	2	167	127	18
	Medium-Large	46,000-58,000	4,955	11,308	3,577	183	5,168	151	1,187	26,530	15,664	5,093
Moist-Cold Dense	Medium-Large	8,000-14,000	1,694	5,012	1,715	55	1,840	159	118	10,592	6,371	3,036
Dry-Moist Open	Medium-Large	2,000-6,000	492	703	202	52	265	19	22	1,756	1,259	31
Other Veg Types	No Target		1,045	3,088	1,134	66	1,306	722	1,521	8,882	4,523	1,491
Total Target		57,000-80,000	8,226	20,214	6,635	362	8,583	1,057	2,850	47,927	27,944	9,669
Anticipated Treatment Type	(light blue)	Non-commercial thin + fuels treatment, may be fire only.										
	(blue)	Commercial thin + fuels treatment if access exists. May be non-commercial, fire only, or regeneration harvest.										
	(green)	Maintenance: prescribed fire or mechanical fuels treatment.										

3.4 Mill Creek Planning Area Summary

3.4.1 OVERVIEW

This large planning area has experienced a relatively high amount of management activity, with 17% of the 158,574 forested acres receiving treatment since 2017. The [landscape evaluation]() was completed in 2018 based on 2015 LiDAR. Due to the high level of treatment, this planning area was assessed in the 2022 [monitoring report](). Significant progress has been made towards structural restoration goals. Many additional treatment acres have been reported since 2022.

The [Mill Creek A-Z Stewardship Project]() is on the Colville National Forest (CNF) within this planning area. This innovative project is one of the first large landscape restoration projects (largely) completed on the CNF, although additional fuel reduction, prescribed fire, and other treatments will occur. It thus offers an excellent opportunity to monitor treatment outcomes relative to the landscape-level goals of the 20-Year Plan. The Mill Creek A-Z Project was planned before the 20-Year Plan, and a landscape evaluation was not available during the NEPA planning process. However, the project did seek to follow landscape restoration principles.

In this section, we will begin with treatment numbers for the whole planning area, but then focus on the South Fork of Mill Creek, which is one of the main project areas of the Mill Creek A-Z project. This 26,749 acre sub-watershed is located in the southeast corner of the planning area. It is predominantly in Forest Service ownership (92%), with the remainder split between private and state trust lands. Almost all the area is forested. Vegetation types are a mix of dry and moist mixed-conifer

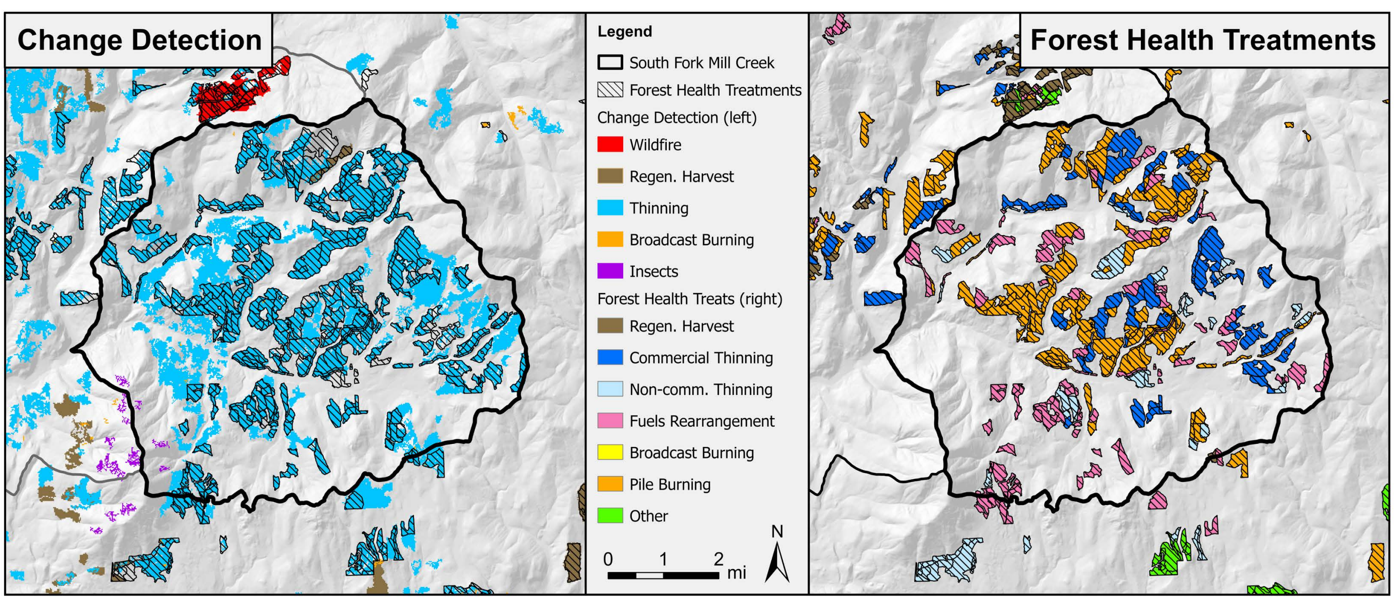


Figure 22. Map of treatment locations identified by the satellite-based change detection product (left, 2015-2022) and forest health treatment database across the South Fork Mill Creek area (right, 2017-2022). *Note that the treatment database is missing some treatment locations and will be updated in collaboration with partners. Also, the map shows only one treatment in units where multiple treatments occurred.*

forest, with some western red-cedar potential vegetation types in draws and valley bottoms and a small amount of cold forest.

In the South Fork Mill Creek sub-watershed, there were about 500 acres of treatments prior to the Treatment Implementation time period (2017-2022), and about 6,500 acres of mostly thinning, fuels rearrangement, and pile burning in 2022 that were not included in the assessment of structural changes covering 2015-2021.

3.4.2 TREATMENT IMPLEMENTATION

Amount and location of treatment

Entire Planning Area:

The Mill Creek landscape evaluation identified a treatment need of 57,000-80,000 acres, which equates to 36-50% of the forested area (**Table 7**). These treatment targets are footprint acres (see description of footprint vs. total acres in Box 1). Treatment need exists in both dry and moist forest types and across small private, private industrial, Forest Service, and DNR ownerships. Based on data from DNR's treatment tracking database and satellite-based change detection, 47,927 total acres of treatments have been conducted on 27,944 footprint acres from 2017-2022 (**Table 7, Figure 22**). This equates to 40% of the lower end of the treatment target range. As discussed above in the Cle Elum monitoring assessment, however, not all treated acres are in a resilient condition.

South Fork Mill Creek:

From 2017 to 2022, treatments occurred on 36% (9,669 acres) of this sub-watershed. (**Table 7, Figure 22**). Almost all treatment has occurred on the CNF as part of the Mill Creek A-Z Project. The great majority of treated acres received a commercial (7,000 acres) or non-commercial thin (2,675 acres), as well as a follow-up piling of fuels and burning of the piles. Almost no regeneration treatment or prescribed fire treatments have occurred. Almost all the regeneration harvest in the larger planning area occurred outside of the South Fork of Mill Creek sub-watershed on non-USFS ownerships. Note that about 1,350 acres of treatments were reported for 2023 that are not included in these numbers. Additional treatments are planned for 2024 and beyond.

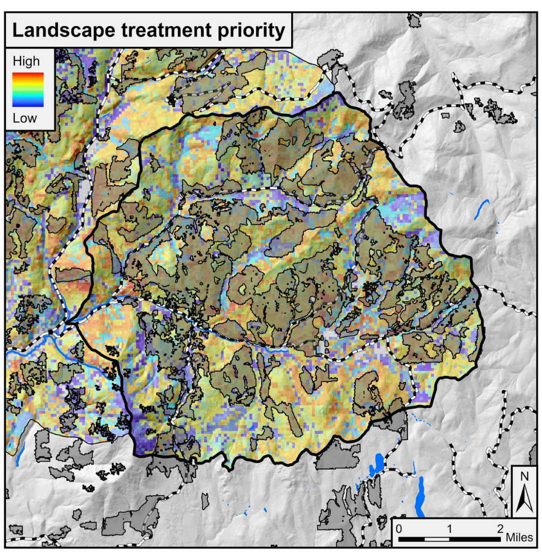
Specific treatment targets for this sub-watershed are not provided in the landscape evaluation, as targets are derived for the whole planning area and are not broken down by smaller areas. However, the fact that about half of the acres have been treated indicates that sufficient treatment has likely occurred to shift the landscape into a resilient condition. Almost 80% of the footprint acres of treatments were implemented in the target forest types and structure classes identified in the landscape evaluation (**Table 7**). These forest structure classes are overabundant relative to desired conditions (e.g., dense small and dense medium/large classes), as well open canopy conditions that need maintenance treatments to keep fuel levels low.

Overall, most of the treatments were implemented in moderate- to high-priority areas for treatment (**Figure 23**). Higher priority areas are generally on drier south-facing slopes as well as denser north-facing slopes with higher fire risk. Given the high level of treatment, however, some areas of moderate and lower priority were also treated. Also, a range of objectives and factors determine treatment location. While the resilience and wildfire risk reduction objectives that make up the Landscape Treatment Prioritization are major drivers of treatment location on USFS land, they are not the only factors.

3.4.3 STRUCTURAL CHANGE

Structural change relative to restoration needs

Overall shifts in forest structure from 2015 to 2021 show major progress towards reference ranges (**Figures 24 and 25**). The direction of change is towards the desired range for all structure classes. The current amount of the moderate-closed structure classes is smaller but is still much higher than the desired range.



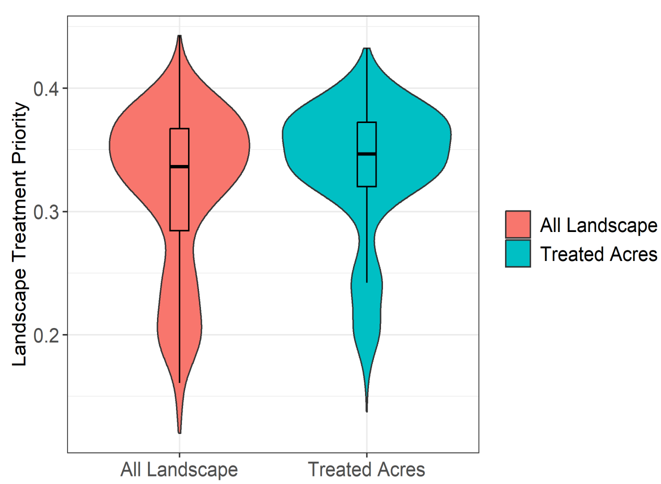


Figure 23. Left: Landscape Treatment Priority (LTP) with all change polygons across the South Fork Mill Creek area (shaded areas reflect change detection and forest health treatment database combined). Right: Comparison of the distribution of landscape treatment priority scores (LTP) for the South Fork Mill Creek area with treated areas. See this online guide for a description of how to interpret violin plots. The overall higher scores of the treated areas indicate that treatments were generally focused in moderate- to high-priority locations. *Note that the treatment database is missing some treatment locations and will be updated in collaboration with partners.*

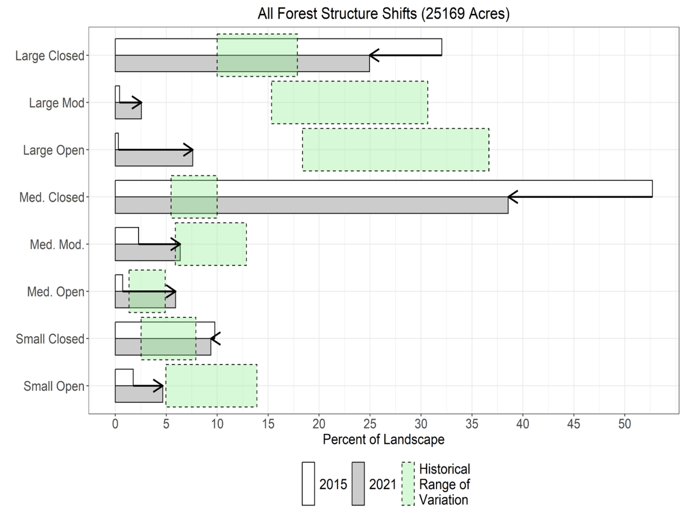


Figure 24. Proportion of the landscape covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the Mill Creek planning area (green shaded area). This graph represents all vegetation types. For information about individual forest types, see **Appendix G**.

The large-closed class was reduced, while the large-open and moderate classes increased, resulting in no net loss of large-tree structure. Treatments pushed the moderate-open class from below to slightly above the desired range, but this class will grow into large-open or moderate over time. Importantly, there are now a number of large patches of open canopy forest with medium to large trees, including a ~1,400 acre patch on primarily south-facing slopes in the middle of the sub-watershed. These patches are large enough to restore resilient landscape patterns that underlie characteristic low and moderate intensity fire behavior as well as reducing likelihood of large insect outbreaks (Hessburg et al. 2015). They also facilitate larger prescribed fires, use of big box wildfire management strategies, and provide anchor points for fire management operations.

Results indicate that there is still too much dense forest in the sub-watershed, particularly in dry forest vegetation types. Close to 70% of the landscape is still in a closed-canopy condition, whereas a resilient condition for this mix of dry and moist forest vegetation types is 30-40% in closed-canopy and 60-70% in open to moderate cover. The overall proportion of the landscape in large-tree classes is also lower than target ranges. Growth of the medium classes should address this need relatively quickly because many medium classes are approaching the large tree threshold (>20" overstory DBH), although a large high-severity fire or drought-related insect outbreak could reduce large tree structure quickly.

The large remaining need for structural change despite the high proportion of treatment (36%) reported above is due to two factors. First, 20-25% of the treatment acres did not result in structural change because treatment boundaries typically contain no-treat areas, as well as pre-existing canopy openings that do not change structure class. Second, the 2021 structure classes (**Figure 24**) do not include 6,500 total acres of treatments that were conducted in 2022, as well as some of 2021 treatments that were completed after the DAP imagery was collected. Thus, the actual amount of footprint acres driving change in forest structure (**Figure 25**) is closer to 20-30% of the total sub-watershed. Subsequent DAP imagery will capture 2022 and 2023 treatments and show the landscape moving closer to the target ranges. It is important to note, however, that this analysis does not account for forest growth in the portions of the landscape that were not treated.

The restoration work in this landscape has increased the likelihood of positive, complementary outcomes when a wildfire does occur (**Figure 26**). Ideally, moderate- and low-severity wildfire will further reduce density and surface fuels, while some patches of high-severity fire will create openings, early-seral plant communities, and opportunities for regeneration of broadleaf species and more climate-adapted conifers.

Prescribed fire, or wildfire under moderate weather conditions managed to achieve the same outcomes as prescribed fire, would greatly increase the odds of beneficial effects of subsequent wildfire events. Additional piling and pile burning

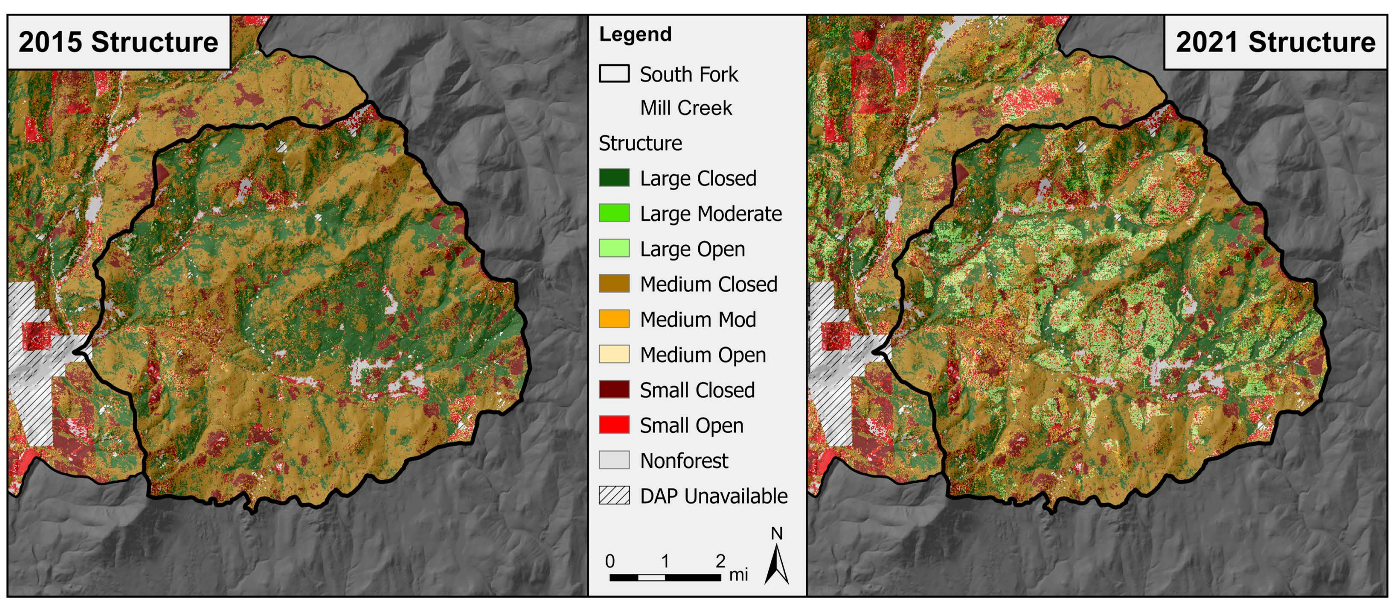


Figure 25. DAP-based forest structure in 2015 (left) and 2021 (right) for the South Fork Mill Creek area. See document on structural classes for details of the classes and **Appendix B** for details on how forest structure maps were created.

Figure 26. Left: Mosaic of closed and open canopy forest created by treatments in the South Fork Mill Creek sub-watershed. Note the large patch of large-tree open canopy forest in the foreground (source: Jessica Walston). Right: Thinning treatment on a productive, mixed conifer stand in the Colville National Forest before piling and burning. Note the high levels of slash and activity fuels (source: Derek Churchill).

will also reduce fuels. Based on the treatment tracking data from 2017 2022, pile burning has occurred on roughly half of the thinned acres, and no prescribed fire has occurred. Thus, surface fuel loads are likely high on a considerable number of acres.

Prescribed fire and additional piling and pile burning are planned for this project area. Each unit is assessed post-harvest for fuel treatment needs. Units with higher need receive priority for piling, which are usually north aspect and higher productivity sites. Lower productivity sites on dry, south aspects generally don't need piling due to less activity fuel. However, prescribed fire on dry sites is planned to reduce excessive litter and duff that have accumulated due to fire exclusion. Under current burn windows, managers estimate that it will takes up to 10 years to complete prescribed-fire treatments after thinning contracts are closed, which can be several years after the thinning is completed. Managing a wildfire to do this work under moderate weather conditions can be much faster.

Changes in focal wildlife habitat

In many eastern Washington landscapes, habitat for species that require large-tree, open canopy forest is in short supply, while habitat for closed-canopy species is highly available because of past fire suppression and forest management. The significant changes in forest structure from treatment offer an excellent opportunity to assess how habitat amount and pattern for these habitat types has shifted.

White-headed Woodpecker habitat has significantly increased from being almost non-existent in this landscape to now accounting for 12% of the sub-watershed (3,000 acres) (**Figures 27 and 28**). Importantly, there are now moderate (10-100 acre), large (100-1000 acre), and very large (1000+ acres) patches of this habitat type (**Figure 27**). The average distance between habitat patches (mean nearest neighbor) decreased from 3,071 to 957 feet, indicating that habitat is now better distributed across the landscape (**Figure 28**). Further monitoring of this habitat is needed, however, to assess whether fine-scale habitat components were retained, created, or are likely to develop over time. These include large, old ponderosa pine trees and snags; a mosaic of tree clumps, regeneration thickets, and openings; and restored understory plant communities (shrubs, grasses, etc.; **Figure 29**).

The amount of Northern Goshawk habitat (large tree, closed-canopy) has decreased from 43% to 32% of the landscape (from 11,500 to 8,500 acres). Several of the very large patches (1,000-5,000 acres) have changed to moderate and large patches (**Figure 27**). Northern Goshawk habitat is still abundant and patches are well distributed through the landscape (**Figure 28**), even with the large patches of thinning treatments. Mean nearest neighbor between patches did not appreciably change.

Furthermore, locations where Northern Goshawk habitat was treated are generally in drier locations with higher moisture stress and landscape treatment priority (e.g., south-facing slopes) where large-tree dense forest is less sustainable over time (**Figure 30**). The remaining goshawk habitat is located on more sustainable sites overall (e.g., north-facing slopes, valley bottoms, draws).

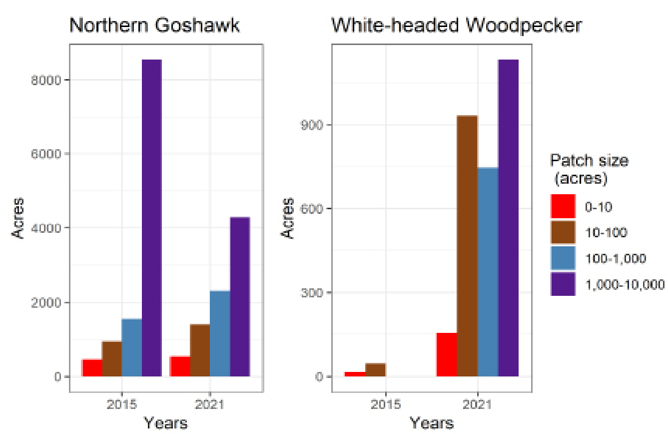


Figure 27. Acres of Northern Goshawk and White-headed Woodpecker habitat by patch size across the South Fork Mill Creek area (2015-2021). For White-headed Woodpecker, total acres increased from 61 in 2015 to 2,960 in 2021, area weighted mean patch size increased from 13 to 487 acres, and mean nearest neighbor distance between patches decreased from 3,071 to 957 feet. For goshawk, total acres decreased from 11,455 to 8,530, area weighted mean patch size decreased from 3,257 to 1,192 acres, and mean nearest neighbor distance between patches increased from 319 to 354 feet.

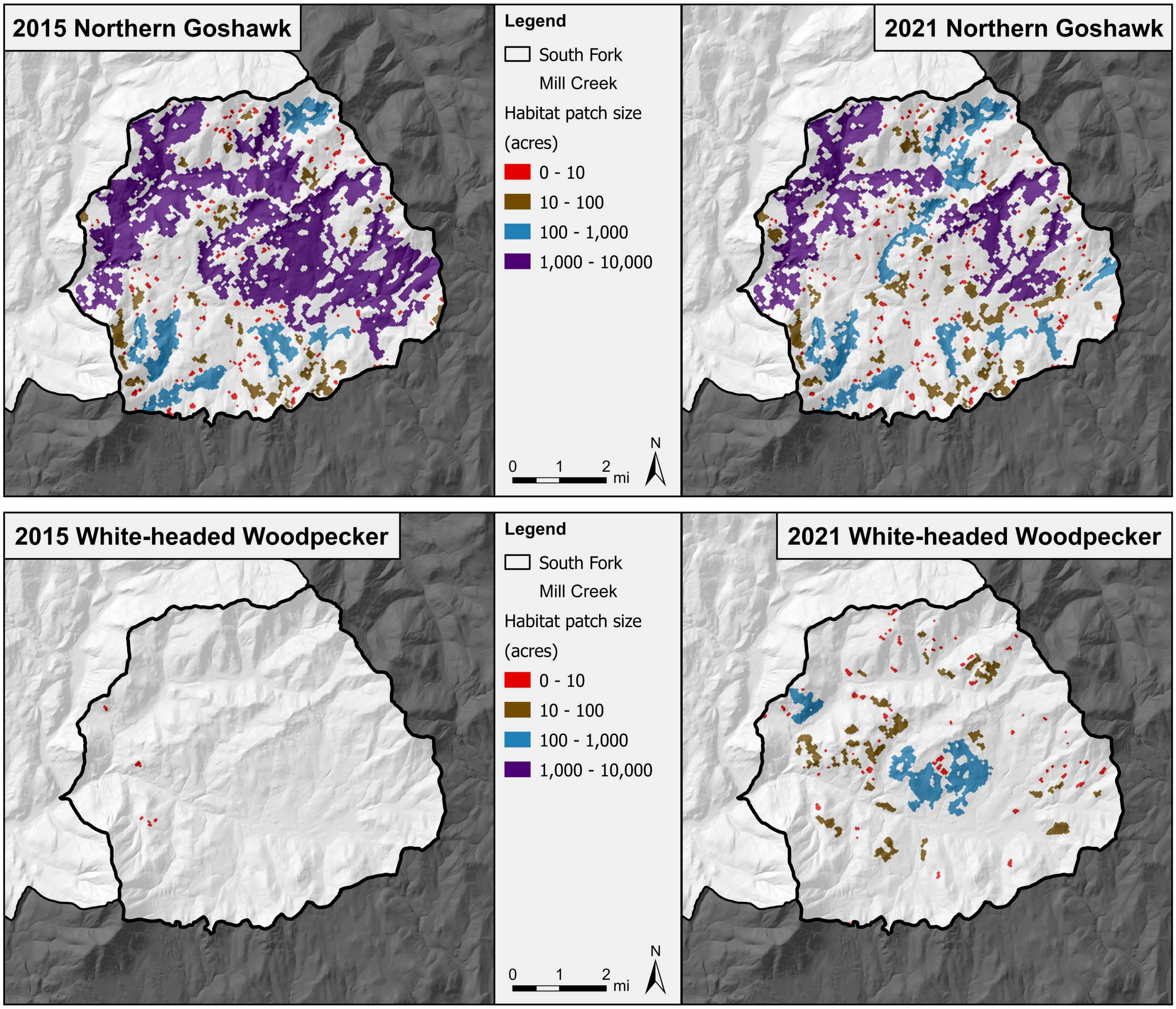


Figure 28. Maps of Northern Goshawk habitat in 2015 (upper left) and 2021 (upper right) and White-headed Woodpecker habitat in 2015 (lower left) and 2021 (lower right) in the South Fork Mill Creek area based on DAP data.

Figure 29. Treated units that contain key habitat components for White-headed Woodpecker and other wildlife species. These include large and old trees, snags, shrubs, broadleaf trees, downed logs, thickets of small trees, openings, and tree clumps of varying sizes (sources - left: Ken Bevis; right: Derek Churchill).

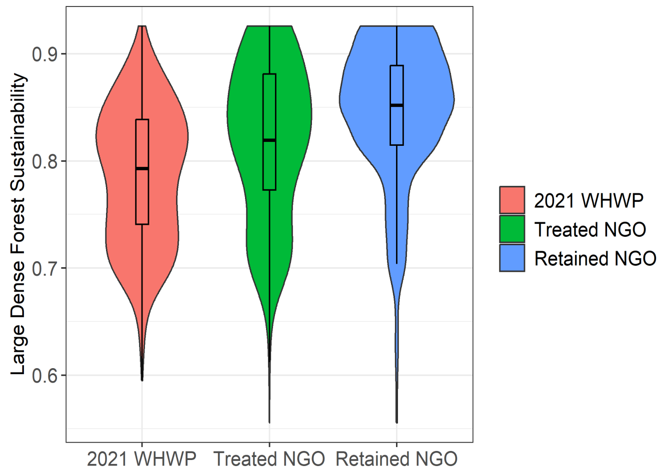


Figure 30. Distribution of large, dense forest sustainability scores for White-headed Woodpecker habitat that was created from 2015-2021, Northern Goshawk (NGO) habitat that was thinned, and Northern Goshawk habitat that was not treated and thus retained. The large dense forest sustainability score is based on current and future water balance deficit and quantifies the ability of a site to sustain higher density forest. Higher scores for the retained NGO habitat indicate that it is located on sites with higher moisture levels and lower drought stress such as north-facing slopes and draws. See this online guide for a description of how to interpret violin plots.

Conversely, the White-headed Woodpecker habitat generally occurs on drier sites where open canopy conditions are much more likely to sustain large trees over time. These are, however, opportunities to shift more Northern Goshawk habitat in drier areas into White-headed Woodpecker habitat.

Changes in habitat for American Marten, which is a focal species for large-tree, cold forest habitat, was not assessed here due to the very small amount of cold forest, and thus habitat potential, within this landscape.

Riparian forest structural changes

Over 3,100 acres of stream-adjacent forest exist within the South Fork of Mill Creek sub-watershed. A small amount of large- and medium-closed classes shifted to more open canopy classes between 2015 and 2021 (**Appendix F**). Over 80% of these areas are still closed-canopy, however, while approximately 50% are in the large-tree size class. Although denser forest is necessary to provide shade and other riparian functions, a greater diversity of stream-adjacent forest structure is more consistent with conditions found in historical and contemporary landscapes with active fire regimes (Jager et al. 2021, Everett et al. 2003). Greater structural diversity created by wildfire, thinning, or other disturbances is also likely to enhance aquatic functions and habitat for a range of species, increase snowpack and summer streamflow, accelerate development of large tree structure, and promote mixed broadleaf-conifer riparian forests (Povak et al. 2022, Jager et al. 2021, Wine et al. 2018, Sun et al. 2018, Luce et al. 2012). We recognize that regulatory requirements and policies guiding riparian forest management are designed to protect important ecological functions. Managing stream-adjacent forests can involve complex tradeoffs and consideration of many factors. We provide these landscape-level data on stream-adjacent forest structure to inform discussions around this topic.

3.4.4 CONCLUSIONS

- Landscape-scale restoration work in the Mill Creek South Fork sub-watershed is close to completion and thus offers an excellent opportunity to evaluate treatment outcomes relative to the landscape-level restoration goals.
- 36% of the planning area has been treated, generally with a combination of thinning, fuel re-arrangement, and pile burning. Treatments are generally in moderate- to high-priority landscape treatment areas.
- Major progress towards restoring a landscape dominated by large-tree, open canopy forest has occurred from 2017-2021, but more work remains. Treatments implemented in 2022-2023 will show more progress. No net loss of large-tree structure occurred.
- The restoration work in this landscape has increased the likelihood of positive, complementary outcomes when a wildfire does occur. However, prescribed fire or wildfire under moderate weather conditions managed to achieve the same outcomes, would increase the odds of beneficial effects of subsequent wildfire events.
- Treatments dramatically increased the amount and patch sizes of habitat for White-headed Woodpecker. Habitat for Northern Goshawk was reduced but is still abundant and well distributed. The remaining goshawk habitat is generally located on sites with lower moisture stress that will be more sustainable over time.
- Further monitoring with 2023 DAP can assess if additional restoration is needed, as well as fine-scale habitat features within treated areas.

4. TREATMENT UNIT AND STAND-LEVEL MONITORING

Stand-level treatment monitoring is a key component of the 20-Year Plan. Monitoring at this scale allows for a detailed understanding of the impact of forest health treatments on the landscape. Additionally, if (or when) the stand is tested by wildfire, these monitoring sites are critical to understanding how treated areas are influencing the resiliency of Washington forests. Stand-level monitoring is typically time intensive and expensive. The hours of effort to collect these data are not feasible under internal current staffing levels. DNR is working to address these and other barriers.

4.1 Stand-Level Monitoring

DNR has begun increasing the pace and scale of stand-level monitoring across the state. After the onboarding of a new monitoring coordinator, the protocol was revised to be more accessible to partners and their internal goals while also supporting DNR's needs and the 20-Year Plan. The Forest Service, Washington State Parks, and several other partners are collaborating with DNR to transition their monitoring efforts to the FRD protocol. More than 30 stand-level monitoring projects have been initiated with some level of DNR involvement over the last three years (**Table 8**). Supporting a statewide effort to increase the pace and scale of stand-level monitoring is a priority of DNR. Work to reduce barriers to the implementation and effectiveness of monitoring is ongoing. The collaborative nature of stand-level monitoring has partners engaged and excited about the potential of a single dataset that can be used for a more comprehensive understanding of treatments from a stand-level perspective.

Table 8. Number of stand-level monitoring projects with DNR involvement, by partner, within the last three years.

Partner	Number of projects
Internal (includes private land)	6
Forest Service	16
State Parks	3
Tribal	2
Municipalities	6
Others (non-profits/collaboratives)	2
Total	35

Figure 31. Example pre- (top) and post-treatment (bottom) images for Squilchuck State Park (source: John Marshall).

Figure 32. Panorama photographs of Dirtyface Peak, north of Lake Wenatchee. The top image shows the image taken in 1934 by Robert Cooper (Osborne Panorama), and the bottom image was taken in 2023 by John Marshall.

Treatment monitoring for 2023 varied across the state. More than 100 plots were collected using the FRD protocol and Survey123, a tool that allows partners to use smartphones and tablets to record plot information, including GIS data, and sync the data with a DNR plot database. A diverse set of projects were monitored, including commercially marginal timber programs, pre-commercial thinning, prescribed fire, fuels reduction, and commercial harvest. Projects across eastern Washington were monitored in partnership with the Good Neighbor Authority, Washington State Parks, Tribes, universities, and municipalities. Other monitoring efforts that did not use the FRD protocol occurred across the state in collaboration with division staff. Overall, partners are beginning to engage more with stand-level monitoring.

In addition to stand-level data, a more intense photo monitoring effort is underway. John Marshall, a local forestry and landscape photographer, has been taking terrestrial and aerial photos at many sites across the state. He will typically capture both pre- and post-treatment images (**Figure 31**). An additional collection of photos has been developed by almost all natural resource professionals using smartphones. Photographs of forests and other important natural resources have been captured by everyday employees, but all too often, these photos are stored locally on the user's phone or computer with little metadata to provide insight to the image. When staff move to different jobs, these photos are thus lost or not replicable over time. To support natural resource professionals, the FRD Opportunistic Protocol was developed to provide a place to store, catalog, and geo-reference photos to facilitate repeat photo monitoring over time.

4.2 Osborne Panoramas

Time sequence, geo-referenced photos capture changes and provide a visual record of the history of a forest. A set of Forest Service fire lookout panoramas (known as Osborne Panoramas) were taken in the early 1920's and 30's to provide landscape markers for fire lookout staff. Little did the original photographers know that they were also capturing an important moment in time. These photos are a catalog of the historical conditions at broad vista points across the state. John Marshall has been retaking these Osborne Panoramas, and the comparison to the original can illustrate the departure from the historical range of variability in forest structural conditions (**Figure 32**). The DNR has purchased a complete set of these photos, but there are still more to be recaptured. Continued support will result in the annotation and organization of these photos to allow easy top-down comparisons of the historical and current photos. The Forest Service will house a copy of the originals and the retakes in its public library. Ultimately, we hope that a record will be housed in the National Archives of Records and Administration.

Figure 33. Before (left) and after (right) treatment photos in Squilchuck State Park (source: John Marshall).

4.3 Treatment Project Reports

Several project areas have been monitored recently using stand-level monitoring protocols: Bullfrog, Virginia Ridge, Tillicum, Squilchuck State Park (**Figure 33**), and Trout Lake. The Bullfrog and Virginia Ridge reports were included in the 2022 legislative report, and their reports are available online. Two additional reports, Tillicum and Squilchuck State Park, are included in **Appendices E and F**. The Trout Lake project on the Colville National Forest saw DNR treat 2,973 acres under the Good Neighbor Authority. Staff worked collaboratively with the Forest Service to determine a simple monitoring protocol to answer their initial monitoring questions and were supported by project objectives that aimed to improve forest health, reduce fuels, and create landscape-level connectivity. Preliminary results indicate that all timber sale units observed an increase in average DBH, and that species composition shifted towards more fire-tolerant species as prescribed. Basal area and trees per acre targets were not as successful, with four of the seven timber sale units resulting in higher than desired targets identified in the prescription. More detailed discussion of the monitoring results will be available in the project monitoring report later in 2024.

5. ADDITIONAL MONITORING EFFORTS

5.1 Overview

Over the past five years, DNR scientists have worked with academic and agency partners to develop key methods, datasets, and tools for 20-Year Plan monitoring. More than 30 internally and externally led projects have been completed or put into motion since the start of the 2020-2021 biennium (**Appendix H**). The FRD has utilized funding from House Bill 1168 for many projects that have covered a wide range of topics including:

1. Monitoring effectiveness of treatments at reducing wildfire severity, treatment implementation, social components of the 20-Year Plan, and effects of treatments on snowpack and streamflow.
2. Developing tools and datasets to monitor structure class change, map tree species composition, assess operational feasibility and potential economic outputs, wildlife habitat, and model fuels and fire behavior.
3. Addressing major knowledge gaps in treatment need across eastern Washington, treatment longevity, treatment effectiveness at reducing wildfire intensity, and post-fire management.

5.2 Highlights

5.2.1 EVALUATING FUEL TREATMENT EFFECTIVENESS FOLLOWING THE SCHNEIDER SPRINGS (WA) AND BOOTLEG (OR) FIRES

Building on the 2021 Work of Wildfire assessment, we established a project with research partners at the University of Washington to evaluate fuel treatment effectiveness on two large 2021 wildfires: the Schneider Springs Fire that burned in Washington and the Bootleg Fire that burned in Oregon. Key findings from the work led by Chamberlain et al. (in review) include: treatments generally reduced burn severity; treatments that included prescribed fire were particularly effective; a consistent, scalable framework that accounts for fire weather, fuels, and topography is essential to quantify drivers and effects at the scale of individual fires and to compare among fires.

Another extension of the 2021 Work of Wildfire assessment is an in-depth investigation of fire effects on mature and old forests in both- open and closed-canopy conditions and across multiple forest types within the Schneider Springs Fire. We evaluated burn severity across forest types and structure classes based on pre-fire DAP, LiDAR, and Landsat imagery. Key findings include: burn severity proportions generally aligned with historical estimates across forest types, despite several very large patches (≥400 ha) of high-severity fire; burn severity was disproportionately higher in locations with mature/large trees compared to locations with young/small trees, particularly in moist and cold forest types; burn severity tended to be lower in locations with recent treatments and closer to roads (**Figure 34**).

Ongoing monitoring efforts on the Schneider Springs Fire will assess delayed tree mortality, sensitivity of burn severity maps to different pre-fire structure and composition, and post-fire management priorities in collaboration with Forest Service and academic researchers.

Figure 34. Effects of the Schneider Springs Fire showing relatively low severity and high survival of large trees in an area with recent thinning and prescribed burning (source: Garrett Meigs).

5.2.2 ASSESSING FIRE EFFECTS IN THE CONTEXT OF THE 20-YEAR FOREST HEALTH STRATEGIC PLAN: WORK OF WILDFIRE RAPID ASSESSMENTS

In the wake of the extensive 2021 fire season, we established the Work of Wildfire Rapid Assessment to evaluate fire effects in the context of the 20-Year Forest Health Strategic Plan. Here, we provide highlights from the 2021 and 2022 fire seasons. Our analysis of the 2023 fire season is planned for Winter/Spring 2024.

2021 Highlights [reproduced from 2021 report]

In eastern Washington, 2021 was the second largest in terms of forested acres burned (463,345 acres) and third largest fire season in recent history in terms of total acres burned. Many communities suffered from smoke and evacuations, although fortunately impacts to homes and structures were minimal. In terms of the landscape resilience and forest health goals associated with the 20-Year Plan, 2021 fires had beneficial outcomes in many places while moving conditions in the wrong direction in others. Specific outcomes of each wildfire depended on management objectives, fire weather, fuel conditions, fire management operations, past forest health treatments, and terrain.

Key takeaways from the 2021 Work of Wildfire report are:

- The 2021 wildfires had both positive and negative effects on resilience and wildfire risk reduction objectives.
- Individual wildfire events spanned a wide range of forest conditions across eastern Washington.
- Forest health treatments burned at low, moderate, and high severity.
- Wildfire managers utilized some forest health treatments to manage wildfires more effectively and safely.

2022 Highlights [reproduced from 2022 report]

The 2022 wildfire season had significant and widespread impacts on communities and ecosystems across Washington state. The fires affected air quality and community health, local and regional transportation networks, timber resources, recreation, and local businesses due to smoke, road closures, and evacuations. There are also ongoing risks of cascading effects including delayed tree mortality, soil stability, and debris flows. While these

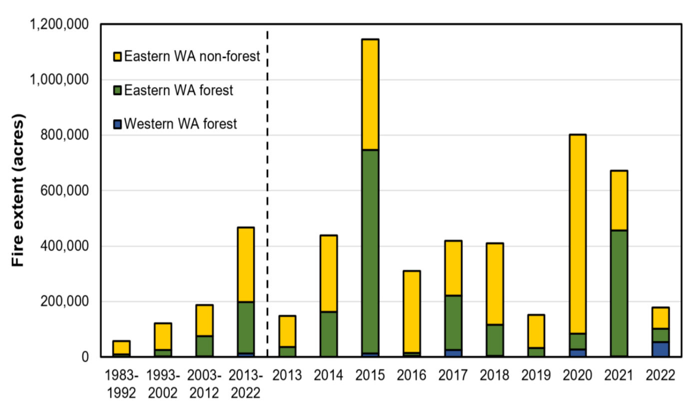


Figure 35. Total fire extent (acres) across Washington State from 1984 to 2022 by decadal average and individual year (2013-2022; bars to the right of the dashed line). Fire perimeters are compiled by the WA DNR Wildland Fire Management Division. 2015, 2020, and 2021 have been the largest fire years to date [reproduced from 2022 report].

socio-economic impacts were extensive, the 2022 fires also had both negative and positive effects on forest health, landscape resilience, and wildfire risk reduction objectives.

The 2022 report broadened the Work of Wildfire framework to encompass eastern and western Washington, which have distinct, historical fire regimes and contemporary fire effects on forest health. In 2022, eastern Washington experienced less forest fire than in recent major fire years, especially in dry forests. In contrast to typical patterns, fire extent in forested areas was higher in western Washington (53,600 acres) than in eastern Washington (48,000 acres) (**Figure 35**). In addition, low-severity fire was relatively more abundant in western Washington than in eastern Washington (48% vs. 39% of total, respectively). The emergence of multiple, late-season fire events and wind-driven blow-up days in western Washington (**Figure 36**) is a reminder of the historical role of large fires, serves as a precursor of likely impacts in the years to come, and underscores the need for proactive strategies to protect communities and infrastructure.

5.2.3 COLLECTING DATA ON THE BENEFIT OF FOREST HEALTH TREATMENTS TO FIRE OPERATIONS: THE WILDFIRE INTERACTION WITH TREATMENTS AND SUPPRESSION (WITS) SURVEY

The Washington Legislature directed DNR to prioritize forest health treatments that have the dual benefit of 1) improving forest health and 2) providing strategic opportunities for fire suppression activities (HB1784). This requirement was implemented in the 20-Year Plan framework by integrating the Potential Operational Delineations (PODs) analysis coupled with a spatial prioritization that helps managers prioritize forest health treatments with a dual benefit intent.

The integration of dual benefit into the planning process underlying the 20-Year Plan is a recent addition; the first landscape evaluations with dual benefit analyses were published in 2020. Since then, DNR staff have collaborated with Gretchen Engbring (Stanford University) and other partners to develop methods addressing four questions:

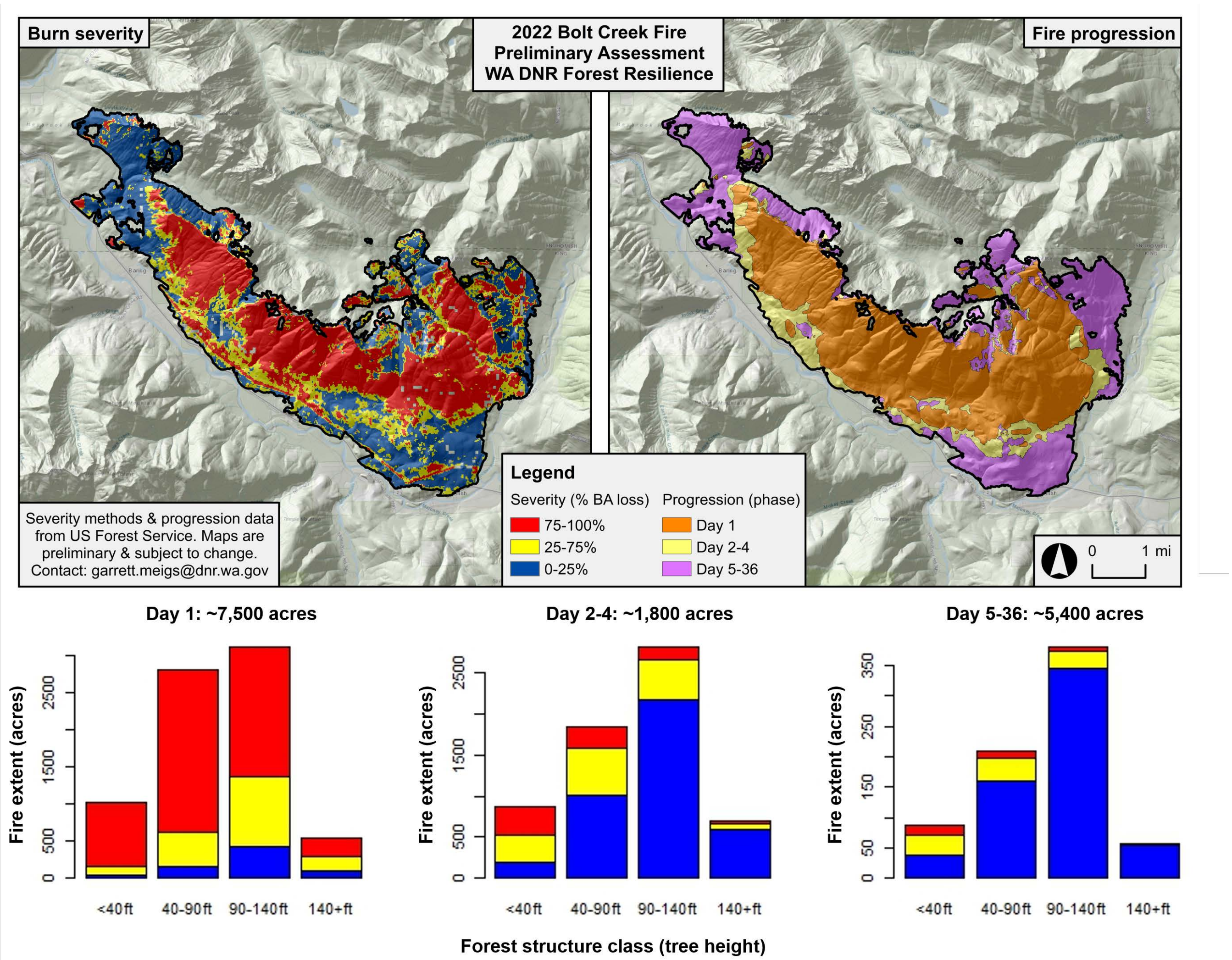


Figure 36. Bolt Creek Fire severity and spread phases across four structural stages and three burn phases. Upper left panel shows burn severity, while upper right panel shows fire progression across the three phases. Lower panels show burn severity by structural stage for each burn phase. Remotely sensed, overstory tree height was used to classify these four stages using the following thresholds: very young: <40 feet; young: 40-90 feet; mature: 90-140 feet; and old growth >140 feet. Severity estimates are preliminary and will change due to delayed tree mortality and other factors [reproduced from 2022 report].

1. Are forest health treatments benefitting fire managers?
2. If so, what benefits do forest health treatments provide during fire suppression?
3. How does treatment type, wildfire behavior, and/or suppression action affect perceived benefits?
4. Do operations intentionally utilize treatment areas during suppression activities?

Fuels reduction treatments, such as thinning, prescribed burning, and mastication, are common strategies for forest managers to reduce the risk of future high-severity fire and to provide safe areas for firefighters to directly engage with wildfires. Studies have demonstrated that treatments can reduce the impact on values at risk and increase ecosystem resilience to fire disturbance. However, more is needed to know about the utility of these treatments during suppression activities and how operational decisions influence ecological outcomes. Wildfire managers often work with local land managers to identify treatment locations and adjust tactics to utilize these areas. These tactical decisions are based on firefighters' local knowledge and expertise, and are often discussed in the field, making the decisions and resulting outcomes challenging to track.

Capturing treatment benefits for fire suppression is more nuanced and challenging than quantifying treatment effects on forest health. The latter can be measured based on post-treatment vegetation structure relative to a desired condition. Quantifying the benefits of treatments to fire operations is challenging in several ways. First and foremost, identifying and weighing "benefit" is inherently subjective and may differ depending on the experience, background, and specific location of individuals at the time of the fire-treatment interaction. Data collection typically relies on surveys or interviews with wildfire staff to provide multiple perspectives on the benefit of treatment at a specific fire interaction. Additionally, depending on the size of the treatment and/or fire, there can be multiple perspectives and outcomes to the same interaction. Therefore, data collection is sensitive to both time and perspective, as fire staff frequently rotate through incidents, making for a small window of opportunity to capture first-hand observations.

Collecting information about fuel conditions before and after the treatment as well as data on the specific fire suppression tactics that took place during a given fire-treatment interaction, can provide context to analyze the results and hypothesize why some treatments provided perceived benefits while others did not. However, these data are not readily or systematically available. The Wildfire Interaction with Treatments and Suppression (WITS) survey was developed to understand the relationship between wildfire suppression tactics and resulting fuel treatment effectiveness. This survey is intended to be deployed when a wildfire intersects with a known treatment. Intended respondents of the WITS survey are wildland fire operations staff on DNR jurisdiction fires and treatments within DNR-managed lands, or private lands, that were cost-shared by DNR's Service Forestry. A pilot survey deployment was conducted in northeast Washington during the 2023 wildfire season, specifically on the Oregon and Gray Fires in Spokane County. Analysis of the results of this pilot is underway. It will focus on lessons learned from the 2023 WITS deployment, including the survey questions, notification system, and deployment process for the 2024 fire season.

Figure 37. Example output from the Bugnet insect mapping project, showing interannual insect activity according across eastern Washington according to three analytical options.

5.2.4 BUGNET: IMPROVING MAPS OF INSECT ACTIVITY USING REMOTE SENSING

We partnered with the EMAPR lab at Oregon State University to develop Landsat-based maps of insect activity across Washington forests. The new maps complement existing aerial surveys by leveraging Landsat satellite time series and statistical analyses to identify locations likely affected by prominent insect agents, including bark beetles and defoliators.

The new insect mapping system is called Bugnet. Bugnet leverages common change detection techniques, but it builds on prior efforts by thinning the processing area of regions that are not suitable for insects and disease in forests, grouping clusters of pixels with similar changes in space and time, and integrating data from the aerial detection surveys (ADS) and high-resolution imagery. The EMAPR lab developed three options with increasing degrees of complexity and established a validation framework to refine final insect map layers. All the options use ADS polygons to guide their sampling. The Bugnet workflow also provides insight into the possible insect and disease agents by attributing Bugnet polygons with the distance to the nearest ADS polygon locations.

The general spatial patterns vary among the three Bugnet options. Option 1 is generally speckled and noisy, Option 2 is segmented and discrete, and Option 3 is intermediate between Options 1 and 2. In addition, Option 1 results in more extensive and cyclical patterns of damage, whereas Options 2 and 3 result in more muted interannual patterns, with Option 3 exceeding Option 2 in all years (**Figure 37**).

5.2.5 MODELING SPECIES COMPOSITION USING A COMPREHENSIVE FIELD PLOT DATABASE AND REMOTE SENSING

The Natural Resource Spatial Informatics Group (NRSIG) at the University of Washington School of Environmental and Forest Sciences has developed a comprehensive database of field plots in Washington state using physical, climate, digital aerial photogrammetric (DAP), and spectral metrics. NRSIG's objective is to develop a resource of plots and statewide rasters available to researchers for modeling and creation of prediction rasters. Plot sources include Forest Service Forest Inventory and Analysis plots (with precise locations), DNR Remote Sensing Forest Resource Inventory System plots, and Forest Service Region 6 LiDAR plots. Work to incorporate field plots in Oregon and California into the normalized database is ongoing.

In addition to a database of field plots, NRSIG has produced statewide 66-foot resolution rasters with environmental variables and forest structural metrics. Sources for statewide rasters include digital elevation models, Natural Resource Conservation Service SSURGO, PRISM Climate Group at Oregon State University, ClimateNA from British Columbia University, multiple years of DAP provided by DNR, and Continuous Change Detection and Classification (CCDC) based on Sentinel satellite data.

NRSIG is developing models using the comprehensive plot database in combination with the statewide raster products to develop wall-to-wall rasters of predicted forest species and structure. Models of species composition will be used by DNR in the future for monitoring changes over time resulting from natural disturbances and active forest management. Additionally, model accuracies are being used to determine the feasibility of Small Forest Landowners to participate in a theoretical carbon program without the need for additional field plots.

The modeling framework developed by NRSIG has robust model development procedures and documentation. It is intended to facilitate rapid creation of statewide prediction rasters for new response variables or iteration with updated input data (such as new DAP or change detection products building on CCDC). A comprehensive site for exploring models, accuracy reports, and metadata is under development and is expected to be available in spring 2024.

5.2.6 COMBINED EFFECTS OF FOREST COVER AND TOPOGRAPHY ON SNOW DEPTH IN THE EASTERN CASCADES, WASHINGTON

The challenge of managing forest health in the face of climate change and the associated impacts of wildfire and drought is at the forefront of the DNR 20-Year Plan. Reduced snowpack, earlier spring melt, and associated changes in streamflow timing and quantity threaten salmonid populations and other aquatic species and functions.

DNR commissioned a study to explore the interplay between forest cover, topography, and snow depth in Washington State's Eastern Cascade Mountains. Partnering with leading experts, the research aims to assess how forest thinning, primarily implemented for wildfire risk reduction and climate adaptation, impacts hydrologic systems in these fire-prone ecosystems.

Utilizing LiDAR datasets and previous ground monitoring efforts, the study focused on a transition zone within the Cascade Mountains characterized by varied climates from warmer, wetter conditions on western slopes to colder environments on the eastern slopes.

Key findings underscore the significance of both forest canopy and topographic attributes in influencing snow depth distribution across the Eastern Cascades. In moderate- to low-elevation forests (less than3,000 ft), distance to canopy edge emerged as a dominant predictor of snow accumulation. Reducing canopy cover decreases snow interception by tree canopies (**Figure 38**), increases accumulation, and thus the amount of water that ends up in the soil. However, only in gaps within topographically shaded areas (e.g. north-facing slopes) did snow last longer and melt out later in the season. Without shading, elevated melt rates from increased solar radiation and wind negate the gains from greater snow accumulation due to reductions in canopy cover. Prolonging snow melt later into the spring is important for stream flow timing and maintaining high soil and fuel moistures later into the summer. At higher elevations (more than 1,000 m), topographically shaded forest gaps amass more snow, regardless of gap size, signifying a different dynamic than in lower elevations.

The full report (available online) outlines in detail the project's overview, methods, analysis results, and management implications. Moreover, it provides comprehensive access to software, code, and data necessary to replicate this analysis, along with guides for calculating topographic and forest metrics using snow-off LiDAR data, aiding future forest treatment planning across the Eastern Cascades.

This research has important implications for forest management strategies. It highlights the important relationships between forest structure, topography and snow accumulation, emphasizing the need for a nuanced approach to thinning and gap creation treatments. Reducing canopy cover over large areas through thinning and fire has the potential to increase overall snowpack and water entering the soil. Most importantly, focusing on topographically shaded areas is critical to extending the duration of the snowpack and maintaining the hydrological regimes that salmon are accustomed to. However, these cooler, shaded areas are often prioritized for maintaining denser forest

Figure 38. Left: Aerial view of the Cle Elum Ridge study site. Right: Susan Dickerson-Lange (University of Washington) and Emily Howe (The Nature Conservancy) measuring snow depth at the Cle Elum Ridge site (source: Mark Stone/University of Washington)..

cover for closed-canopy wildlife and other functions. Thus, balancing wildfire risk reduction, wildlife habitat for closed-canopy species with snow accumulation and duration becomes paramount in balancing landscape resilience and aquatic system health in the face of a warmer, drier future with more wildfire and drought risk.

The insights gleaned from this study pave the way for more informed decision-making in forest management, aiding planners, policymakers, and partners in devising strategies that strike a balance between mitigating wildfire hazards and safeguarding critical water resources and biodiversity in the Eastern Cascades. DNR has partnered with the Pacific Northwest National Lab and Forest Service PNW Research Station to examine these tradeoffs over large spatial scales (see partner report). More information on the effects of treatments on snowpack and streamflow in western WA is reported by Sun et al. (2022).

5.2.7 RAPID ANALYSIS OF FUEL TREATMENT EFFECTIVENESS

The extent to which treatments reduce wildfire intensity and effectiveness is a central monitoring question of the 20-Year Plan. It is challenging and time consuming, however, to statistically analyze and determine whether treatments change wildfire outcomes compared with untreated areas due to the many factors that drive wildfire behavior. Relatively little is known about how treatments affect landscape level fire behavior beyond the footprint of treatments. Managers, stakeholders, and legislators need timely, actionable information on how treatments change fire behavior to improve and better integrate landscape treatment design, prioritization, and wildfire response strategies.

The DNR Forest Resilience Division partnered with Dr. Alina Cansler from the University of Montana, Confederated Tribes of the Colville Reservation forest managers, Forest Service fire managers, and other researchers to launch a project to develop methods and systems to rapidly assess treatment outcomes after each wildfire season. This project is being funded by the Joint Fire Science Program and is in its initial stages. It builds off recent analysis of treatment effects on the Schneider Springs fire described above and past studies (e.g., Cansler et al. 2022).

The project will develop research tools to:

1. Inform landscape-scale fuel treatment strategies by using empirical data to assess how the density, spatial configuration, topographic locations, and types of treatments impact burn severity and burn severity pattern in the context of environmental setting, fire weather, and management actions. It will also examine how the transmission of fire into and out of treatments impacts fire behavior and resulting burn severity.
2. Empower managers and scientists in the PNW to conduct rapid and consistent empirical assessments of treatment effectiveness at treatment- and landscape-levels by developing a landscape treatment effectiveness tool that integrates geospatial datasets, analyses, and visualization of standardized and user-defined datasets.
3. Improve our understanding of management use of treatment areas during wildfires through surveys of managers to determine how incident fire management actions interact with treatments and resulting tactical and ecological outcomes.

6. CONCLUSIONS AND NEXT STEPS

Significant progress has been made in restoring forests across eastern Washington as part of the 20-Year Plan, both through active management and natural disturbances including wildfires. This report represents the first major standalone effort towards identifying how forests are changing across eastern Washington, and how those changes impact current and future forest health and resilience. Across the three monitoring levels, we found that treatments are doing significant positive work towards meeting restoration needs. Here, we detail our findings for each of these levels.

6.1 Monitoring across Eastern Washington

From 2017 to 2022, changes affected 1.5 million footprint acres, or 15% of the forested area in eastern Washington. Wildfires and insect activity accounted for 910,000 footprint acres, with management activities accounting for the remainder. During this same time period, a total of 822,000 acres of treatments have been implemented across eastern Washington. The most common treatment type was thinning (312,000 acres), followed by regeneration harvest (140,000 acres), fuels rearrangement (106,000 acres), pile burning (106,000 acres), prescribed fire (45,000 acres), and other treatment types (113,000 acres). Some of these treatments occurred on the same units. These treatments cumulatively encompassed 571,000 footprint acres. About 392,000 acres of treatments have occurred within 20-Year Plan priority planning areas between 2017 and 2022. This represents about 48% of total treatment acres across eastern Washington.

Although treatments and natural disturbances have been extensive, the number of acres treated is not the only or most important metric to measure progress towards resilient landscapes. It is also critical to assess changes in forest structure, fuels, wildlife habitat, and other key indicators of forest health. Treatment tracking results suggest that additional surface fuels treatments are needed to keep pace with mechanical thinning and regeneration harvests, as well as to maintain past treatments. Surface fuels treatments, particularly prescribed fire, reduce wildfire risk and increase the likelihood of beneficial wildfire.

6.2 Planning Area Monitoring

In the priority planning areas selected for detailed analysis (Cle Elum, Glenwood, South Fork Mill Creek), the rates of treatment and total footprint acres completed are on track to achieve treatment targets identified in the landscape evaluations. Most treatments in these planning areas were in locations with moderate to high treatment priority. Across these three planning areas, treatments, wildfires, and insect disturbances increased open-canopy forest with medium and large trees by 6-25%. These changes significantly increased the amount and patch size of White-headed Woodpecker habitat, while Northern Goshawk habitat remained generally abundant and well-distributed. At the same time, 45-70% of the forested area remains closed canopy (>60% cover). Because open-canopy forests with large, fire-resistant trees are still in short supply in all three planning areas, additional treatments that reduce canopy cover will result in faster progress towards more fire- and drought-resistant conditions.

In all three planning areas, treatments have increased the likelihood of positive, complementary outcomes when a wildfire does occur. Beneficial wildfire can thus accomplish a significant portion of the needed restoration work in areas farther away from communities and when conditions are safe. Additional prescribed fire and other surface fuels treatments will greatly increase the odds of positive wildfire outcomes.

6.3 Treatment Unit and Stand-level Monitoring

Over 30 stand-level monitoring projects have been initiated with DNR involvement over the last three years. DNR is working with many partners to complete intensive photo monitoring of pre- and post-treatment stands in addition to field data collection at the stand and project scales. We have acquired updates to the panorama photos taken from fire lookouts (Osborne panoramas) in the 1930s and will continue to acquire additional photos. The comparison to the originals can illustrate the departure from the historical range of variability in forest structural conditions at stand and landscape scales. We are working to implement detailed monitoring reports at the project scale, two of which are included as appendices in this report (Squilchuck State Park and Tillicum). Many more treatments than could be included in this report are recently completed, in progress, or planned. Further improvements to monitoring methods and data will help us to better understand progress towards forest resilience goals.

6.4 Next steps and ongoing efforts

Building on the momentum to date, we will continue to collaborate with partners to develop and implement the monitoring framework. Here, we highlight several priorities for current and future efforts:

- Additional analyses of treatment tracking, change detection, and forest structure data are needed to better understand and map which treated areas are meeting landowner objectives and resilience goals. Combining field-based monitoring with GIS datasets will be necessary for this effort. These analyses will help inform where additional treatments are needed in the short-term, as well as help estimate long-term treatment and maintenance needs.
- We will continue to increase resources and reduce barriers to implementing stand-level monitoring efforts. Increasing the pace and scale of stand-level monitoring and integrating it with planning area and regional monitoring efforts is a priority for the DNR Forest Resilience Division.
- Incorporating improvements, such as insect activity and tree mortality mapping, to change detection products will help provide a more complete view of forest changes from stand to regional scales.
- Accurate maps of species composition remain a major missing dataset for evaluating treatment need, climate adaptation planning, and overall monitoring. Ongoing projects (see section 5.2.5) will continue to move us towards this essential dataset.
- Structure class mapping will be refined using additional LiDAR and field plot datasets. With better structure class data, we anticipate being able to track growth in addition to treatments and disturbances.

LIST OF APPENDICES

Appendix A. Change detection methods

Appendix B. Structure class modeling methods

Appendix C. Change detection and forest health treatment categories

Appendix D. Tillicum project monitoring report

Appendix E. Squilchuck State Park project monitoring report

Appendix F. Figures of structural change in riparian areas

Appendix G. Figures of departure for major vegetation types for the Cle Elum, Glenwood, and South Fork Mill Creek planning areas

Appendix H. List of DNR FRD completed and ongoing monitoring projects

ACKNOWLEDGMENTS

We are grateful for the time and support of key partners, collaborators, and reviewers. Specifically, we would like to thank members of the monitoring sub-group of the Forest Health Advisory Committee for their time and effort in assisting with this effort. Committee members have provided invaluable ideas and feedback that have greatly improved the 20-Year Plan monitoring framework and all the related methods and results. Katie Fields, Sam Steinshouer, James Pass, Albert Durkee, Jay McLaughlin, and Bill Gaines provided helpful reviews of the report. Additionally, we would like to acknowledge the work of Kevin Ceder and Jonathan Kane on DAP accuracy assessments and modeling. Finally, we appreciate the timely and insightful feedback from DNR colleagues in the Forest Resilience Division.

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Appendix A. Change Detection Methods

1. Overview

The DNR Forest Resilience Division (FRD) Change Detection product was created with the goal of producing a wall-to-wall unbiased annual view of forest changes across the 20-Year Forest Health Strategic Plan (20-Year Plan) area. The FRD has an existing tool, the Forest Health Tracker, that has enabled the creation of a treatment location database with data provided by various partners. However, not all forest health treatments are included in this database (due to reporting lags, incomplete reported data, or missing spatial information), and it entirely excludes natural disturbances such as insect activity and wildfire. As such, the need was identified for a remotely sensed product to fill data gaps by mapping all potential causes of forest change across the 20-Year Plan area. The resulting Change Detection products accomplishes this goal by using satellite data to map and attribute forest mortality across forested areas of eastern Washington.

The change detection product is created using a three-step approach, (1) mapping potential change locations, (2) attributing changes to different disturbance or treatment types, and (3) post-processing model predictions to improve the final mapped product. Potential change locations were mapped using the USFS Landscape Change Monitoring System (LCMS) product. Changes were attributed to wildfire, insect activity, regeneration harvest, thinning, and broadcast burning using a supervised machine learning model. Post-processing was completed to add in known wildfire locations, filter out unreasonably small change areas, and remove incorrectly predicted post-fire change. All steps are detailed in the following sections.

For the final change detection product, about 80% of known disturbance areas were successfully mapped. The lowest proportion of detected pixels (52%) was for insect activity, which is a known challenge in remotely sensed change mapping. The DNR FRD has an ongoing contract to improve insect mapping capabilities (see the main 2024 Monitoring Report). Other class-level detection proportions ranged from 78% (broadcast burning) to 97% (wildfire). The final change detection product produced in 2023 for the 2024 Monitoring Report has an overall attribution accuracy of 86%, with individual class accuracies ranging from 81% (Regeneration Harvest) to 90% (Broadcast Burning).

2. Landsat-based mapping of forest change

To determine areas of change across eastern Washington, we use the Landscape Change Monitoring System (LCMS) data (USDA Forest Service 2023) from the USFS Geospatial Technology and Applications Center (GTAC). LCMS products use Landsat and Sentinel 2 satellite data to assess changes in forest conditions across the United States and include annual maps of forest losses and gains, with losses split into areas of fast or slow loss. LCMS data are produced using an ensemble modeling approach (Cohen et al. 2018; Healey et al. 2018) utilizing both CCDC (Zhu and Woodcock, 2014) and LandTrendr (Kennedy et al. 2010; Kennedy et al. 2018), which are temporal segmentation algorithms that analyze time series for breaks in natural temporal patterns (i.e., changes in canopy greenness over time). See the LCMS methods documentation (Housman et al., 2021) for more details about the product.

LCMS forest loss and gain data for 2015 – 2022 were downloaded for the change detection analysis in August 2023 from Google Earth Engine (Gorelick et al., 2017). Products were downloaded for eastern

Washington and downloaded tiles mosaicked together with GDAL by first combining tiles into a virtual raster using *gdalbuildvrt* and then translating the virtual raster to a GeoTIFF using *gdal_translate*. The result is a 30m resolution multi-band raster for fast forest loss, slow forest loss, and forest gain, where each band represents detected changes for an individual year.

3. Models to attribute change types

Mapped change locations were attributed to disturbance and active management categories using a Random Forest model, which is a form of supervised machine learning. Data on known change types (the response variable) and a dataset of predictor variables were used to train the model. The resulting model was then used to predict the change type of all change locations mapped by the LCMS data. Finally, several simple post-processing steps were applied here to further improve disturbance maps. Datasets and modeling methods are described below in detail.

3.1 Model response variable

Known disturbance polygons were used as the response variable for the attribution Random Forest model. Polygon datasets used for the model training included the DNR Large Fires dataset (2016 – 2021), USFS Aerial Detection Surveys (ADS; 2017 – 2021), DNR State Lands completed harvest information (2016 – 2023), DNR Forest Practices harvest data (expiration dates 2016 – 2038), and DNR FRD Forest Health Treatment database (2017 – 2023). The ADS data were used to label insect activity, while all the DNR datasets were combined to label regeneration harvest, thinning, and broadcast burning. The years differed for each dataset based on comparison with the raw LCMS data.

All the training data sources contain polygon boundaries rather than pixels. Polygon datasets are challenging to use for prediction because not all pixels within the polygons are equally affected by the labeled disturbance, or even affected at all. For instance, ADS polygons are drawn around large areas of insect activity, but there may be a considerable amount of undisturbed forest within those boundaries. To get around this issue, the ADS and DNR datasets were filtered and refined to make it more likely that pixels labeled as those disturbances experienced forest structural changes. For ADS polygons, only areas where bark beetles or defoliators with greater than or equal to 10 trees per acre affected were included. The full list of insects included is found in Table 1. DNR harvest and treatment data were limited to completed treatments and were relabeled into simple categories (Table 2). Once harvest and treatment data were reclassified, the datasets were merged, with more severe disturbance types taking priority in areas of overlap (e.g., regeneration harvest if both regeneration harvest and thinning occurred in the same pixel). Finally, because predictions were made at the pixel scale, all filtered and merged datasets were converted to raster format for the analysis using the *terra* package (Hijmans 2023) in R (R Core Team, 2023).

Table 1. ADS codes and descriptions included as insect activity in training the Random Forest attribution model.

Code	Description
1	Douglas-fir Beetle
2	Douglas-fir Engraver
3	Engelmann Spruce Beetle
4	Fir Engraver
5	Western Balsam Bark Beetle, Sub-Alpine Fir

6B	Mountain Pine Beetle, Whitebark Pine
6L	Mountain Pine Beetle, Lodgepole Pine
6P	Mountain Pine Beetle, Ponderosa Pine
6W	Mountain Pine Beetle, Western White Pine
7	Pine Engraver Ips
8	Western Pine Beetle
88	Western Pine Beetle, Pole-sized Ponderosa
9	Silver Fir Beetle
AB	Balsam Wooly Adelgid
BS	Western Spruce Budworm
LS	Black Pine Needle Scale
SM	Satin Moth
SF	Sawfly, True Fir
SP	Sawfly, Ponderosa Pine
CH	Larch Casebearer
AS	Spruce Aphid
TM	Douglas-fir Tussock Moth

Table 2. DNR harvest and treatment data classes. Simple classes were used to train the Random Forest attribution model. Predicted classes were then grouped into final classes.

Original Label	Simple Class	Final Class
Forest Practices Data		
EVEN-AGE	Regeneration Harvest	Regeneration Harvest
EVEN R/W	NA	NA
EVEN/SALVAGE	Regeneration Harvest	Regeneration Harvest
R/W SALVAGE	Regeneration Harvest	Regeneration Harvest
RIGHT-OF-WAY	NA	NA
SALVAGE	Regeneration Harvest	Regeneration Harvest
UN/SALVAGE	Moderate Thinning	Thinning
UNEVEN-AGE	Moderate Thinning	Thinning
UNEVEN R/W	NA	NA
State Lands Data		
COMMRCL_THIN	Moderate Thinning	Thinning
VARIABL_THIN	Moderate Thinning	Thinning
SELECT_PROD	Moderate Thinning	Thinning
VRH	Regeneration Harvest	Regeneration Harvest
UNEVNAGE_MGT	Moderate Thinning	Thinning
CLEAR_CUT	Regeneration Harvest	Regeneration Harvest
SHELTER_INT	Regeneration Harvest	Regeneration Harvest
SEEDTREE_INT	Regeneration Harvest	Regeneration Harvest
SHELTER_REM	Regeneration Harvest	Regeneration Harvest
SEEDTREE_REM	Regeneration Harvest	Regeneration Harvest

TEMP_RET_REM	Regeneration Harvest	Regeneration Harvest
TEMP_RET_1ST	Regeneration Harvest	Regeneration Harvest
PILE	Other	Thinning
LAND_USE_CONV	NA	NA
PATCH_REGEN	Regeneration Harvest	Regeneration Harvest
Forest Health Tracker Data		
Precommercial Thin	Light Thinning	Thinning
Thinning for Hazardous Fuels Reduction	Light Thinning	Thinning
Jackpot Burning - Scattered concentrations	Pile Burning	NA
Burning of Piled Material	Pile Burning	NA
Slashing - Pre-Site Preparation	Other	Thinning
Piling of Fuels, Hand or Machine	Other	Thinning
Site Preparation for Planting - Burning	Other	Thinning
Single-tree Selection Cut (UA/RH/FH)	Moderate Thinning	Thinning
Chipping of Fuels	Other	Thinning
Shelterwood Establishment Cut (with or without leave trees) (EA/RH/NFH)	Moderate Thinning	Thinning
Commercial Thin	Moderate Thinning	Thinning
Shelterwood Removal Cut (w/ leave trees) (EA/NRH/FH)	Regeneration Harvest	Regeneration Harvest
Road Maintenance - Vegetation Reduction	Other	Thinning
Underburn - Low Intensity (Majority of Unit)	Broadcast Burning	Broadcast Burning
Seed-tree Seed Cut (with and without leave trees) (EA/RH/NFH)	Regeneration Harvest	Regeneration Harvest
Rearrangement of Fuels	Other	Thinning
Invasives - Pesticide Application	Other	Thinning
Salvage Cut (intermediate treatment, not regeneration)	Moderate Thinning	Thinning
Pruning to Raise Canopy Height and Discourage Crown Fire	Other	Thinning
Yarding - Removal of Fuels by Carrying or Dragging	Other	Thinning
Two-aged Seed-tree Seed and Removal Cut (w/res) (2A/RH/FH)	Regeneration Harvest	Regeneration Harvest
Site Preparation for Planting - Mechanical	Other	Thinning
Site Preparation for Natural Regeneration - Manual	Other	Thinning
Prune	Other	Thinning
Broadcast Burning - Covers a majority of the unit	Broadcast Burning	Broadcast Burning
Liberation Cut	NA	NA
Group Selection Cut (UA/RH/FH)	Regeneration Harvest	Regeneration Harvest
Sanitation Cut	Moderate Thinning	Thinning

Stand Clearcut (w/ leave trees) (EA/RH/FH)	Regeneration Harvest	Regeneration Harvest
Planting	Planting	NA
Lop and Scatter	Other	Thinning
VRH	Regeneration Harvest	Regeneration Harvest
UNEVNAGE_MGT	Moderate Thinning	Thinning
SEEDTREE_REM	Regeneration Harvest	Regeneration Harvest
SHELTER_REM	Regeneration Harvest	Regeneration Harvest
VARIABL_THIN	Moderate Thinning	Thinning
SEEDTREE_INT	Regeneration Harvest	Regeneration Harvest
COMMRCL_THIN	Moderate Thinning	Thinning
PATCH_REGEN	Regeneration Harvest	Regeneration Harvest
HAND_CUT	Light Thinning	Thinning
FOLIAR_BROAD	Other	Thinning
PILE_BURN	Pile Burning	NA
HAND_PLANT	Planting	NA
MASTICATION	NA	NA
FOLIAR_DIRECT	Other	Thinning
GROUND_HERB	Other	Thinning
GROUND_MECH	Other	Thinning
Non-Commercial	Light Thinning	Thinning
Hand Crew	Light Thinning	Thinning
Hand Crew/Chipper/Masticator	Light Thinning	Thinning
Hand Crew/Masticator	Light Thinning	Thinning
Handcrew	Light Thinning	Thinning
Masticator	NA	NA
Mechanized Logging	NA	NA
Helicopter	NA	NA
Hand Crew - Chipper	Light Thinning	Thinning
Mastication	NA	NA
Commercial	Moderate Thinning	Thinning
Fire	Broadcast Burning	Broadcast Burning
Commercial _thinning	Moderate Thinning	Thinning
Broadcast Burn	Broadcast Burning	Broadcast Burning
Biomass Removal	NA	NA
Thinning	Moderate Thinning	Thinning
Machine Pile Burn	Broadcast Burning	Broadcast Burning
Hand Pile Burn	Pile Burning	NA
Mowing	Other	Thinning
Hand Pile	Other	Thinning
Shaded Fuel Break	Moderate Thinning	Thinning
PCT	Light Thinning	Thinning

Stand Improv - Non-comm	Light Thinning	Thinning
Stand Improv - Commercial	Moderate Thinning	Thinning
PreCommercialThin	Light Thinning	Thinning
PileAndBurn	Pile Burning	NA
Hand Crew/Chipper	Light Thinning	Thinning
Handcrew & Chipper	Light Thinning	Thinning
LAND_USE_CONV	NA	NA

3.2 Model predictor data

Landsat-derived metrics of forest greenness were used as predictors in the attribution model (Table 3). A suite of vegetation indices, including Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Shortwave Infrared (SWIR), Normalized Burn Ratio (NBR), and Tasseled Cap Wetness, Greenness, and Brightness (TCW, TCG, TCB), were compiled in Google Earth Engine (GEE; Gorelick et al., 2017). The indices were calculated on each Landsat image over the study period, and then the mean values were calculated for each year. Mean value rasters were downloaded from GEE and tiles mosaicked using GDAL. Four sets of predictors were calculated from the downloaded annual indices: magnitude change, the standard deviation of magnitude, magnitude change within a 90x90m neighborhood, and the standard deviation of change in magnitude within a 90x90m neighborhood. Magnitude change was calculated as the change in index value the year of the disturbance relative to the mean of three prior years. Landsat metrics were extracted at change locations, matching years between Landsat and change detection layers.

In addition to Landsat-derived predictors, the probability of fast or slow loss, as well as gain, from LCMS was extracted for each location where change was labeled. Additionally, the mean and standard deviation of fast or slow loss probability was calculated for 90x90m neighborhood around each pixel and those values were also considered as predictors.

The final dataset used for modeling included data from 2017 to 2021, covering the same period as the response variables. Change locations were limited to forested locations (see the forest mask product in the DNR data dictionary) in eastern Washington. For model development, each change location was limited to one year of change over the study period and one known disturbance agent. If any years were labeled with fast loss, that was the year of change for that pixel. Otherwise, the last year where change was detected was used as the year of change. If more than one disturbance existed in a change pixel, they were prioritized as follows: fire, regeneration harvest, thinning, broadcast burning, and insect activity. The final model dataset had Landsat and LCMS predictor variables for the year change was detected, along with one known disturbance type.

Table 3. Predictors in the Random Forest attribution model.

Predictor Variable Code	Predictor Variable Name	Description
Pixel Variables		
Prob_FastLoss	Probability of Fast Loss	Probability of fast forest loss from the LCMS model.
Prob_SlowLoss	Probability of Slow Loss	Probability of slow forest loss from the LCMS model.

Prob_Gain	Probability of Gain	Probability of forest gain from the LCMS model.
NDVI_Magnitude	NDVI Magnitude Change	Change in NDVI the year change was detected relative to the three years prior.
NDWI_Magnitude	NDWI Magnitude Change	Change in NDWI the year change was detected relative to the three years prior.
NBR_Magnitude	NBR Magnitude Change	Change in NBR the year change was detected relative to the three years prior.
SWIR_Magnitude	SWIR Magnitude Change	Change in SWIR the year change was detected relative to the three years prior.
TCG_Magnitude	TCG Magnitude Change	Change in TCG the year change was detected relative to the three years prior.
TCB_Magnitude	TCB Magnitude Change	Change in TCB the year change was detected relative to the three years prior.
TCW_Magnitude	TCW Magnitude Change	Change in TCW the year change was detected relative to the three years prior.
Neighborhood Variables (90x90m area around each pixel)		
Prob_FastLoss_mean	Mean Prob. of Fast Loss	Mean probability of fast forest loss.
Prob_SlowLoss_mean	Mean Prob. of Slow Loss	Mean probability of slow forest loss.
Prob_Gain_mean	Mean. Prob. of Gain	Mean probability of forest gain.
Prob_FastLoss_sd	Std. Dev. Prob. of Fast Loss	Standard deviation probability of fast forest loss.
Prob_SlowLoss_sd	Std. Dev. Prob. of Slow Loss	Standard deviation probability of slow forest loss.
Prob_Gain_sd	Std. Dev. Prob. of Gain	Standard deviation probability of forest gain.
NDVI_Magnitude_sd	Std. Dev. NDVI Magnitude Change	Standard deviation of the magnitude change in NDVI.
NDWI_Magnitude_sd	Std. Dev. NDWI Magnitude Change	Standard deviation of the magnitude change in NDWI.
NBR_Magnitude_sd	Std. Dev. NBR Magnitude Change	Standard deviation of the magnitude change in NBR.
SWIR_Magnitude_sd	Std. Dev. SWIR Magnitude Change	Standard deviation of the magnitude change in SWIR.
TCG_Magnitude_sd	Std. Dev. TCG Magnitude Change	Standard deviation of the magnitude change in TCG.
TCB_Magnitude_sd	Std. Dev. TCB Magnitude Change	Standard deviation of the magnitude change in TCB.

TCW_Magnitude_Sd	Std. Dev. TCW Magnitude Change	Standard deviation of the magnitude change in TCW.

3.3 Modeling

The Random Forest model predicting simple classes (Table 2) was fit using the *parsnip* package with the *ranger* engine (Kuhn and Vaughan, 2023) in R (R Core Team, 2023). To ensure an even sample from each disturbance class, the training sample was a random subset of each class with 60% of the number of pixels in the smallest class. The resulting training sample had 1,705 pixels for each class. Validation and testing datasets were each comprised of 20% of the number of pixels in the smallest class. Training, validation, and testing samples did not include any of the same pixels. However, note that because the sample were taken from polygons, the data do not represent entirely independent observations. In the future, spatial sampling procedures may be introduced to deal with this issue.

The final predictors used are shown in Table 3. The Random Forest model was trained with 40 trees (*trees*) and a minimum of 40 data points per node required for further splitting (*min_n*). Hyperparameters (number of trees and minimum node size) were determined iteratively, by cycling through various arguments and choosing the combination that produced the highest model accuracy. Variable importance is displayed in Figure 1. The resulting confusion matrix showing classification errors by change agent for the result attribution model is shown in Table 4.

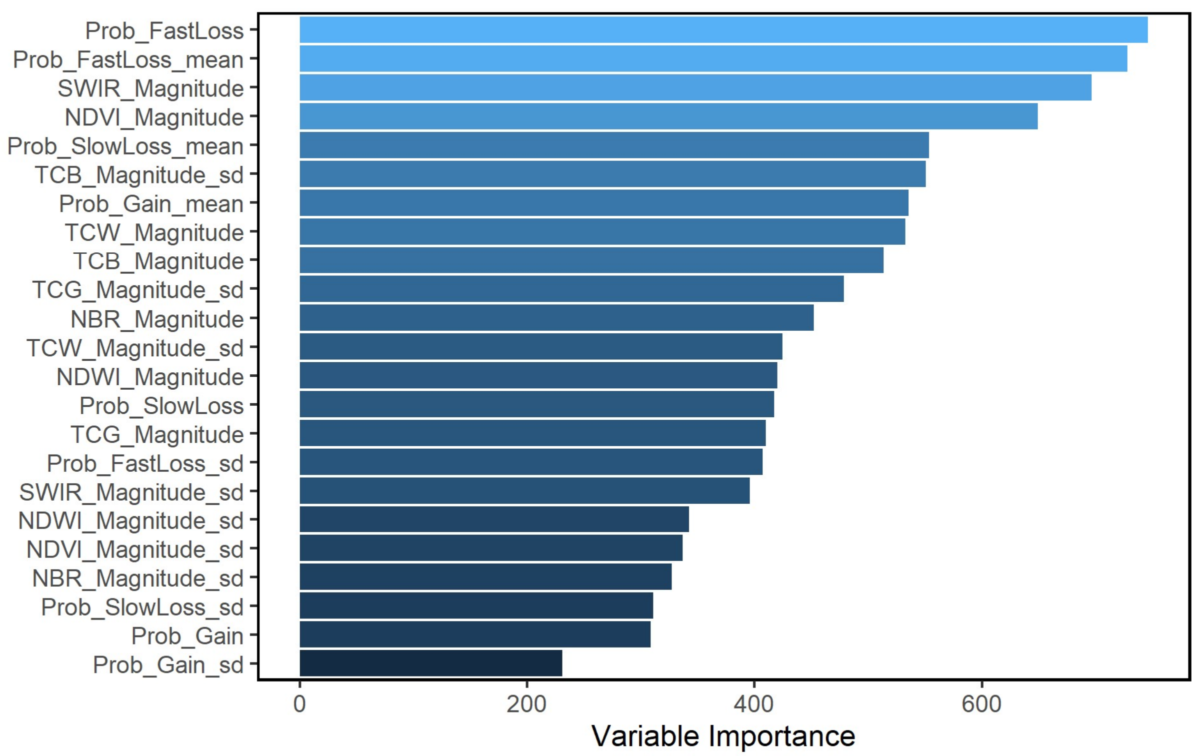

Figure 1. Variable importance of predictors used in the change detection attribution model. Predictor variable descriptions are found in Table 3. Variable importance is the mean decrease in Gini score. A higher value indicates higher variable importance.

Table 4. Confusion matrix showing accuracy of the final Random Forest model, both for the full classes modeled ("Accuracy") and the simple classes after joining all thinning classes ("Simple Accuracy"). Note that most errors between regeneration harvest and thinning are with thinning or regeneration harvest. These two categories are not fully distinct, so this is expected.

	Wildfire	Regen. Harvest	Mod. Thin.	Light Thin.	Other	Broad. Burn	Insect Activity	Accuracy	Simple Accuracy
Wildfire	364	27	36	17	45	67	12	**64%**	**64%**
Regen. Harvest	20	320	138	11	15	17	47	**56%**	**56%**
Mod. Thin.	3	115	335	30	27	6	52	**59%**	**61%**
Light Thin.	7	25	56	277	31	61	111	**49%**	
Other	19	36	61	60	25	18	349	**61%**	
Broad. Burn.	22	15	37	17	442	23	12	**78%**	**78%**
Insect Activity	25	13	23	42	32	414	19	**73%**	**73%**

3.4 Post-processing

Several post-processing steps were completed to enhance data usability and to reduce prediction errors in the final product. The post-processing steps included (1) simplifying modeled categories, (2) adding in known wildfire areas, (3) converting annual raster products to polygons with one disturbance or treatment class per polygon, (4) removing areas labeled with broadcast burning within regeneration harvest or thinning treatments, (5) removing treatments or other disturbances within post-fire areas.

The first post-processing step was to combine the moderate thinning, light thinning, and other categories into a single class, "thinning." This was done to reduce errors as it was noted that these categories were often mis-classified as each other (Table 4). These categories, in addition to regeneration harvest, are not strictly separable. Initial modeling was done on the higher resolution classes in the hopes that the model would be able to differentiate more classes. After noting the issues with higher error in these classes, we decided to either combine the classes or produce a model of the simpler classes. The simpler 5-class model was less accurate, so we combine the classes during post-processing.

Next, we added in wildfire areas using annual mosaics of burn severity produced by the DNR FRD. This was done to improve detection accuracies of known wildfires, since LCMS does not always detect the full fire perimeters, and often misses areas affected by low-severity wildfire.

The third post-processing step, converting raster products to polygons with a single change class per polygon, was done to produce more usable and realistic results. Polygons were created at the request of data users. Additionally, the pixel-level predictions often meant that multiple disturbance types (e.g., wildfire, thinning, and insect activity) would occur within a single landscape patch in the same year. To fix this unrealistic scenario, we located patches of disturbance within each annual raster using the "get_patches" function from *landscapemetrics* (Hesselbarth et al. 2019), considering all 8 surrounding pixels as neighbors. Any patches below a specified size threshold for each disturbance class were removed, thus removing single pixel and very small change locations. For all disturbance types other than insect activity, a threshold patch size of 5 acres was used. Insect activity can occur over much smaller areas, so a threshold patch size of 1 acre was used for that disturbance type. Next, each identified patch was limited to a single disturbance type. The patch disturbance type was determined as the disturbance with the most pixels in the patch (e.g., if 70% of the patch pixels were wildfire, then all pixels within the patch were changed to wildfire).

Fourth, we found and removed potential pile burning locations. These locations were noted to have low prediction certainty when manually examining the raw model output rasters. To fix the issue, we found all areas of broadcast burning in the raw model output rasters that also overlapped thinning or regeneration harvest patches in the simplified rasters (following the first and second post-processing steps). All broadcast burning locations included in these overlap areas were saved separately but removed from the final results.

Finally, it was also noted through manual examination that areas labeled as insect activity and active management in the two years following a wildfire were often actually post-fire mortality. Therefore, we removed any disturbance or management polygons within wildfire polygons that occurred within two years of the fire.

The final change detection product accuracy was assessed in the same way as the original raw model predictions. The updated confusion matrix is shown in Table 5. Overall accuracy for the final results was 86%.

Table 5. Final class-level accuracy following post-processing on the change detection mapping product.

	Wildfire	**Regen. Harvest**	**Thinning**	**Broad. Burn.**	**Insect Act.**	**Accuracy**
Wildfire	1094	0	3	123	21	**88%**
Regen. Harvest	2	681	152	0	8	**81%**
Thinning	1	277	2443	63	114	**84%**
Broad. Burn.	0	17	37	689	26	**90%**
Insect Act.	1	7	40	10	438	**88%**

We also assessed how well final mapped change locations matched known disturbance locations to get at detection accuracy. Exact detection accuracy could not be assessed for this analysis because we lack a true “truth” dataset with all disturbance and active management activity across eastern Washington. To get at this number as best as possible, we sampled locations within known disturbance polygons between 2017 and 2021. 2,000 points were sampled within each of the final five disturbance classes to assess our ability to map those polygons. These sample locations were not included in the model training or validation steps. At each of the resulting 10,000 sample locations, we determined if a change was labeled in our final change detection product. About 80% of the sampled locations had changes labeled. Within each class, wildfire was detected 97% of the time, regeneration harvest 86% of the time, thinning

85% of the time, broadcast burning 78% of the time, and insect activity only 52% of the time. This gives us some indication that we are missing some locations in the change dataset, but again is not a true detection accuracy. Many polygons do not have changes in every pixel within the polygon, and the training dataset is missing a number of treatment and disturbance locations. Additionally, mapping insect activity is a known challenge in remotely sensed change mapping. The DNR FRD has an ongoing contract to improve insect mapping capabilities (see the main 2024 Monitoring Report). All of this said, we are confident that we are capturing the most severe changes across the landscape. In combination with the Forest Health Treatment database, the change detection product should greatly improve our ability to assess changes in forest conditions across the 20-Year Plan area.

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Appendix B. DAP-Based Forest Structural Change

1. Overview

Digital Aerial Photogrammetry (DAP) data consist of point clouds that can be used in the same way as lidar data. While DAP data tend to be less accurate than lidar data, it is substantially cheaper than lidar to collect, and the stereo imagery used to produce the data is available every two years. This makes DAP a critical tool for monitoring across large landscapes where wall-to-wall structure information is needed on a regular basis. Here, we describe our DAP-based modeling approach to assess changes to forest structure in areas where change was detected by the combination of the change detection product (see Appendix A) and Forest Health Treatment (FHT) database.

Like the change detection attribution model, we used Random Forest classification models to predict tree size and canopy cover across eastern Washington. Structure classes were created with the lidar structure class definitions**,** combining tree size and canopy cover.

2. DAP Processing

Currently, DNR photogrammetry staff produce DAP data from NAIP stereo imagery approximately every two years, as imagery is available. The last two cycles (2019 and 2021) of NAIP imagery have been incomplete, necessitating two years of data collection to get wall-to-wall coverage across Washington. Therefore, 2019 data include 2019 and 2020 imagery, and 2021 data include both 2021 and 2022 imagery.

The derivation of structure metrics from DAP is somewhat complicated by multiple sources of errors in the DAP data. Tree shadows can reduce the accuracy of the derived point clouds, and this error changes based on the time of year and time of day of each flight. As such, DAP has higher year-to-year variability in values (i.e., lower precision) than lidar because flights take place on different dates and at different times across flight years. DAP also tends to reduce tree heights in open canopies and canopy cover saturates at ~80% canopy cover (Kane et al., in prep). DNR FRD scientists and collaborators at the University of Washington (UW) are currently working to prepare a scientific paper on DAP accuracy and precision relative to lidar data and to outline methods for assessing the capabilities of DAP for use in long-term monitoring projects (Kane et al., in prep).

To minimize any DAP errors in the data used for structure change analysis, DNR staff and contractors manually investigated DAP-derived canopy height and top surface data for obvious anomalies. Areas where potential errors were found were re-processed by DNR photogrammetry staff to attempt to remove the errors. In most cases, this was successful, however, there were some errors remaining in the data (see section 2.1).

Once point clouds were as clean as possible given the manual error inspections and re-processing, forest structure metrics were estimated using the program FUSION (McGaughey, 2009). All FUSION grid metrics were calculated, using a minimum height cutoff of 6 feet and a maximum height of 350 feet. Grid metrics were created at 66ft resolution for all years where DAP data were available.

Error identification

DNR FRD funded a contract with researchers at the UW to build a tool that detects and labels remaining errors so that the areas are flagged as unreliable. The tool, built in R (R Core Team, 2023), identifies potential errors using other DAP years and thresholds of change between years. Pixels are flagged if there was no change labeled in change detection or the FHT database, but a total change of 15% or more between the current DAP year and the average over all DAP years. Potential DAP errors are stored as rasters for each DAP year.

3. QMD models

Model response variable

The structure class definitions used in the 20-Year Plan lidar-based Landscape Evaluations require an estimate of tree size at the pixel scale, in this case quadratic mean diameter of the top 25th percentile trees by height (QMD_{25}). This variable must be collected in the field and so we used a plot database including plots between 2013 and 2018 developed through a contract with UW researchers. The plot database included DNR Remotely Sensed – Forest Resource Inventory System (RS-FRIS) plots, USFS Region 6 biometric lidar plots, and several other smaller field plot collections from both DNR and UW (Rogers et al. 2021). Additional RS-FRIS plots collected between 2018 and 2023 were added to the plot database for this modeling effort.

We calculated QMD_{25} for each plot based on tree lists. We then also summarized QMD_{25} into size classes based on those required for DNR structure classes. For this analysis, our three size classes were small: $QMD_{25} < 10$”, medium: $QMD_{25} \geq 10$” and < 20”, and large: $QMD_{25} \geq 20$”.

Plots with changes as detected in the change detection of FHT database were removed from the analysis. The final plot set included 257 plots with a small size class designation, 872 plots with medium size class, and 463 plots with a large size class. Plots for each class were distributed across eastern Washington.

Model predictor data

Variables considered as predictors for the Random Forest models of tree size included DAP metrics, actual evapotranspiration (AET), climatic water deficit (deficit), two separate estimates of water holding capacity (WHC), topographic wetness index (TWI), short-wave radiation (SWR), snow water equivalent (SWE), elevation, slope, aspect, potential vegetation group (PVG), ecoregion, and DNR region. DAP cloud metrics were summarized for each plot using FUSION (McGaughey, 2009) using the DAP year closest to the plot measurement year. Climate variables (AET, deficit, WHC, TWI, SWR, SWE) are described in more detail in the DNR FRD data dictionary. Topographic variables (elevation, slope, aspect) were derived from digital elevation model produced by aggregating the USGS NED digital elevation model to 90m resolution. Potential vegetation group differentiates between dry, moist, and cold forests and is described in more detail in the DNR FRD data dictionary. Finally, ecoregions were provided by DNR scientists. All variables other than DAP metrics were extracted at their native resolutions to plot locations from DNR layers using the function “exact_extract” from the R package *exactextractr (*Baston, 2021). If a plot overlapped more than one pixel of a predictor raster, the mean value of all overlapping pixels was calculated, weighted by the fraction of pixel covered by the plot.

Modeling

The Random Forest model predicting size class (Table 2) was fit using the *randomForest* package (Liaw and Wiener, 2002) in R (R Core Team, 2023). To ensure an even sample from each size class, the training sample was a random subset of each class with 70% of the number of plots in the class with the fewest plots. The resulting training sample had 180 plots for each class. Validation data used to fine-tune the model consisted of another 20% of the number of plots in the class with the fewest plots (51 plots per class). The testing dataset to determine final model accuracy consisted of the remaining plots (By size class, small: 26, medium: 641, large: 232). Training, validation, and testing samples did not include any overlapping plots.

To reach the final Random Forest size class model, we followed a two-step procedure to determine predictor variables and model hyperparameters. For predictor variables, models were fit and determined the variable importance. The variable with the lowest importance was dropped from the model and the model re-fit. We repeated this procedure, comparing overall accuracies between models based on the validation set until the drop in accuracy exceeded 4%. This threshold was chosen to maximize accuracy while minimizing predictor variables. We set out to minimize predictor variables so that models stayed as consistent as possible and were relatively fast and easy to update (minimal need to update predictor variables). The second procedure for determining the best model was to test different numbers of trees in the model as well as minimum node sizes required for splitting the data. The options with the highest accuracy were chosen for the final model. The final model had 8 predictors (Table 1), 7 of which were DAP metrics (Figure 1). The final hyperparameters were 500 trees and a minimum node size of 2.

Table 1. Predictor variables included in the final size class model. The first 7 variables are DAP metrics.

Predictor Variable Abbreviation	Predictor Variable Full Name
ht_p90	90th percentile height
ht_p95	95th percentile height
ht_p80	80th percentile height
ht_p99	99th percentile height
ht_variance	Variance in height
ht_aad	Mean absolute deviation in height
first_cover_abovexpxx	Canopy cover above 6’
swr	Short wave radiation

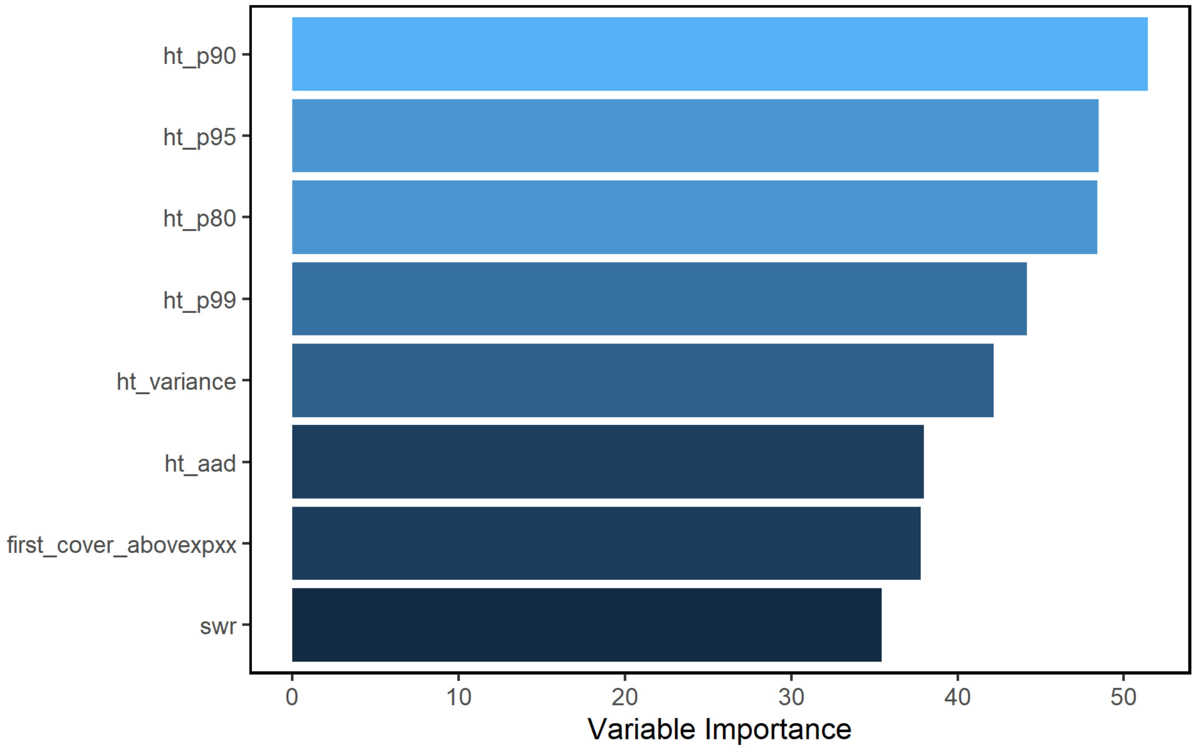

Figure 1. Variable importance of predictors used in the DAP-based size class model. Predictor variable descriptions are found in Table 1. Variable importance is the mean decrease in Gini score. A higher value indicates higher variable importance.

The resulting model accuracy was determined by combining the validation and testing datasets and predicting over those plots. Overall accuracy for the size class model was 69%. Class-level accuracies are shown in Table 2.

Table 2. Confusion matrix showing class-levels accuracies for the size class model.

	Small (<10")	**Medium (10-20")**	**Large (>20")**	**Accuracy**
Small (<10")	56	106	15	32%
Medium (10-20")	15	444	44	88%
Large (≥20")	6	142	224	60%

Post-processing

Several issues were identified with the initial size class model results. Primary issues were erroneous values in known DAP error pixels, variability in predicted values between DAP years in areas where no change was detected, an overprediction of large trees in later DAP years. We implemented several post-processing steps to improve prediction results. For all post-processing steps, incomplete years were combined to create complete eastern Washington rasters. So, 2019 data are 2019 merged with 2020, and 2021 data are 2021 and 2022 data. The later year's data took priority when merging.

The first step in post-processing was to fix areas with known DAP errors. For this, we either removed the pixel or filled in with the following or previous DAP year's predictions. The decision for which value to change error areas to was based on the presence of change and errors in the previous and following years. We first determined all pixels for a given year that had errors and did not experience change that year. For these pixels, we assigned the next year's value if there was no future change or future errors. Pixels with either future change or future error, but neither previous change nor error, were assigned the previous year's value. All other pixels were assigned NA.

The second post-processing step was to stabilize changes between DAP years. We identified areas where the structure class increased by more than one class in a single year, or a change of one class was not sustained for two or more years, or where the size class increased but the average increase in height for the period of size class increase was higher than 3 feet per year. In these areas, size class was chosen based on model probabilities. The size class of the year with the highest prediction probability was assigned to both the current and following DAP years.

Similarly, for decreases in size class, we identified areas where the structure class decreased but no change was detected. If the decline was in an area where no change was labeled, but was sustained for two or more years, the value was not changed. In areas where the change was not sustained, we chose the size class for based on model probabilities. The size class of the year with the highest prediction probability was assigned to both the current and following DAP years.

The final post-processing step was minimizing over-prediction of the large tree size class. We noticed that this class tended to be over-represented on the maps through visual inspection of the results, and that this was particularly true in later DAP years. These years were less represented in the plot database, and this error will hopefully be addressed in the future through an increased field training dataset for the model. This year, we compared the size class model results with those from a separate model of large and potential large trees ("large tree model"). The large tree model was created with similar methods and training data, but the classes differed slightly. However, the large tree classes (trees ≥ 20" QMD_{25}) were the same for both models.

To fix the over-representation of large trees, we identified pixels where only one model predicted the large tree size class. If either prediction probability was ≥60% for the large tree class for that pixel, both model results were changed to the large tree size class. Otherwise, both model results were changed to the medium (or potential large tree) size class. The 60% cutoff was chosen based on visual inspection of the prediction and probability maps. In the future, we plan to identify the cutoff using more quantitative methods.

Following the three post-processing steps, we determined the model accuracy again using the same methods as we did for the initial model, except that we used all available plot data and split results by year. Overall accuracy ranged from 59-63%, with the highest accuracy for 2021, and the lowest for 2017. The combined confusion matrix is in Table 3. The final results are more balanced in terms of class-level accuracies, but it's clear that the small class in particular remains harder to predict. This is potentially because these plots may have considerable understory tree presence, which DAP will often miss because it does not penetrate the canopy.

Table 3. Confusion matrix for all post-processed results 2015-2022 compared to the full plot database.

	Small (<10")	Medium (10-20")	Large (>20")	Accuracy
Small (<10")	659	843	213	38%
Medium (10-20")	212	2,032	534	73%
Large (≥20")	60	494	1,024	65%

We also compared validated post-processed raster results against available stand exam data. We summarized the predictions to the stand level by assigning the most common class to the entire stand. The overall accuracy at the stand level ranged from 69% in 2021 to 78% in 2017.

4. Canopy cover models

Model response variable

The second variable used in creating forest structure classes for the 20-Year Plan is canopy cover. We used lidar-derived canopy cover data as the response variable for this model. We matched lidar and DAP data based on years and then gathered a spatial sample of pixels to be used for modeling. The spatial sample was chosen to minimize the chances of autocorrelation in the modeling dataset.

To choose the dataset, we first split the continuous canopy cover values into ten bins: 0-10%, 10-20%, 20-30%, and so on until 100% canopy cover. We chose to split canopy cover into ten bins to maximize utility for other modeling purposes with various canopy cover splits, as well as to maximize model accuracy. We had initially tested several models with different response variables, including continuous canopy cover, four canopy cover classes, and three canopy cover classes. The ten class models always outperformed the others. After assigning categories to the lidar data, we chose a stratified sample of 50,000 pixels, with 5,000 pixels in each canopy cover bin. Finally, we selected 16,076 pixels of the 50,000 random sample that were a minimum of 1km apart. Spatial sampling was done with the *spatialEco* (Evans, 2020) package in R (R Core Team, 2023). The 1km distance was determined by fitting a semivariogram to the lidar canopy cover data using the package *gstat* (Pebesma, 2004; Gräler, Pebesma, & Heuvelink, 2016).

Pixels with changes as detected in the change detection or forest health treatment database were removed from the analysis. The final sampled pixel set had between 1,144 and 2,227 pixels in each canopy cover bin.

Model predictor data

Variables considered as predictors for the Random Forest models of canopy cover included DAP metrics, actual evapotranspiration (AET), climatic water deficit (deficit), two separate estimates of water holding capacity (WHC), topographic wetness index (TWI), short-wave radiation (SWR), snow water equivalent (SWE), elevation, slope, aspect, potential vegetation group (PVG), ecoregion, and DNR region. DAP cloud metrics were summarized for each plot using FUSION (McGaughey, 2009) using the DAP year closest to the plot measurement year. Climate variables (AET, deficit, WHC, TWI, SWR, SWE) are described in more detail in the DNR FRD data dictionary. Topographic variables (elevation, slope, aspect) were derived from digital elevation model produced by aggregating the USGS NED digital elevation model to 90m resolution. Potential vegetation group differentiates between dry, moist, and cold forests and is described in more detail in the DNR FRD data dictionary. Finally, ecoregions were provided by DNR scientists. All variables other than DAP metrics were reprojected to the DAP rasters using the *terra* package in R (Hijmans, 2023).

Modeling

The Random Forest model predicting canopy cover class (Table 5) was fit using the *randomForest* package (Liaw and Wiener, 2002) in R (R Core Team, 2023). To ensure an even sample from each size class, the training sample was a random subset of each class with about 70% of the number of pixels in the class with the fewest pixels. The resulting training sample had 800 pixels for each class. Validation data used to fine-tune the model consisted of another 17% of the number of plots in the class with the fewest plots (200 pixels per class). The testing dataset to determine final model accuracy consisted of the remaining 13% (144 pixels per class).

To reach the final Random Forest size class model, we followed a two-step procedure to determine predictor variables and model hyperparameters. For predictor variables, models were fit and determined the variable importance. The variable with the lowest importance was dropped from the model and the model re-fit. We repeated this procedure, comparing overall accuracies between models based on the validation set until the drop in accuracy exceeded 3%. This threshold was chosen to maximize accuracy while minimizing predictor variables. We set out to minimize predictor variables so that models stayed as consistent as possible and were relatively fast and easy to update (minimal need to update predictor variables). The second procedure for determining the best model was to test different numbers of trees in the model as well as minimum node sizes required for splitting the data. The options with the highest accuracy were chosen for the final model. The final model had 5 predictors (Table 4, Figure 2), 2 of which were DAP metrics. The final hyperparameters were 500 trees and a minimum node size of 2.

Table 4. Predictor variables included in the final canopy cover class model. The first 2 variables are DAP metrics.

Predictor Variable Abbreviation	Predictor Variable Full Name
all_cover_abovexpxx	Canopy cover above 6’
ht_p99	99^{th} percentile height
swe	Snow-water equivalent
def	Climatic water deficit
whc	Water-holding capacity

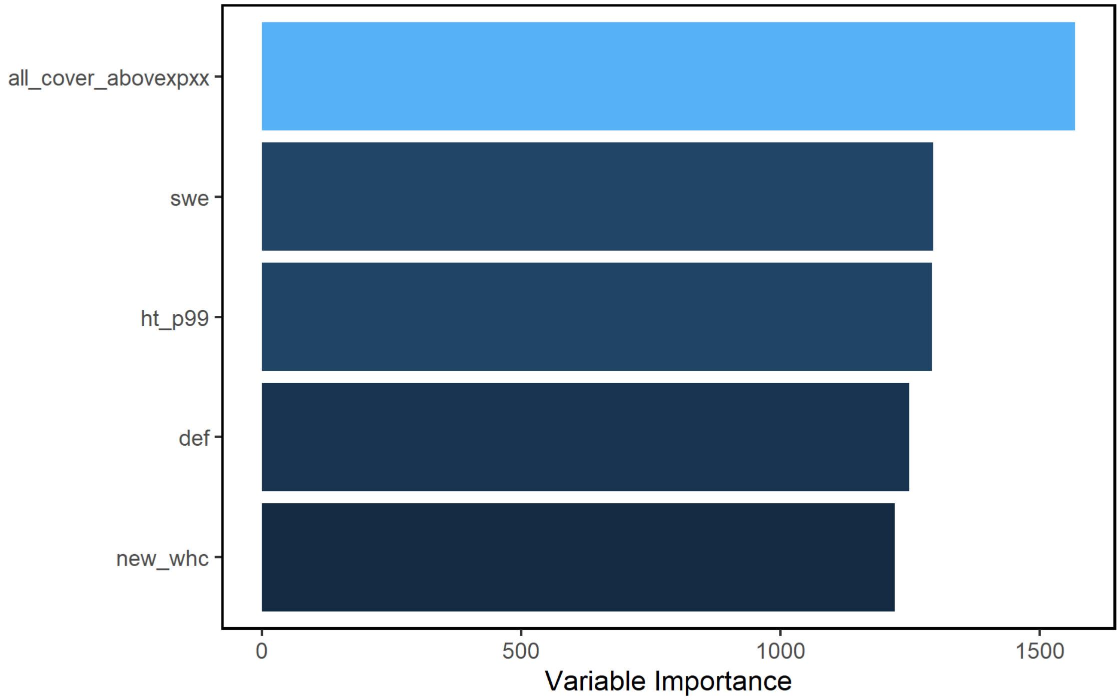

Figure 2. Variable importance of predictors used in the DAP-based canopy cover class model. Predictor variable descriptions are found in Table 4. Variable importance is the mean decrease in Gini score. A higher value indicates higher variable importance.

The resulting model accuracy was determined by combining the validation and testing datasets and predicting over those plots. Overall accuracy for the 10-class canopy cover class model was 49%. However, for the structure class analysis we were interested in canopy cover binned into four classes: 0-10%, 10-40%, 40-60%, and ≥60%. We summarized the model predictions into those bins and found an overall accuracy of 83%. These class-level accuracies are shown in Table 5.

Table 5. Confusion matrix showing class-levels accuracies for the canopy cover class model.

	<10%	**10-40%**	**40-60%**	**≥60%**	**Accuracy**
<10%	813	53	1	0	94%
10-40%	197	875	54	8	77%
40-60%	11	84	284	47	67%
≥60%	6	15	51	582	89%

Post-processing

Several issues were identified with the initial canopy cover class model results. Identified issues were erroneous values in known DAP error pixels and variability in predicted values between DAP years in areas where no change was detected. We implemented two post-processing steps to improve prediction results. For all post-processing steps, incomplete years were combined to create complete eastern Washington rasters. So, 2019 data are 2019 merged with 2020, and 2021 data are 2021 and 2022 data. The later year's data took priority when merging.

The first step in post-processing was to fix areas with known DAP errors. For this, we either removed the pixel or filled in with the following or previous DAP year's predictions. The decision for which value to change error areas to was based on the presence of change and errors in the previous and following years. We first determined all pixels for a given year that had errors and did not experience change that year. For these pixels, we assigned the next year's value if there was no future change or future errors. Pixels with either future change or future error, but neither previous change nor error, were assigned the previous year's value. All other pixels were assigned NA.

The second post-processing step was to stabilize changes between DAP years. We identified areas where the canopy cover class increased by more than one class in a single year. In these areas, cover class was chosen based on model probabilities. The cover class of the year with the highest prediction probability was assigned to both the current and following DAP years.

Similarly, for decreases in canopy cover class, we identified areas where the cover class decreased but no change was detected. If the decline was in an area where no change was labeled, but was sustained for two or more years, the value was not changed. In areas where the change was not sustained, we chose the cover class based on model probabilities. The cover class of the year with the highest prediction probability was assigned to both the current and following DAP years.

Finally, we determined the model accuracy again using the same methods as we did for the initial model, except that we used all available sampled data and split results by year. Overall accuracy ranged from 79-83%, with the lowest accuracy for 2021, and the highest for 2017 and 2019. The combined confusion matrix is in Table 6.

Table 6. Confusion matrix for all post-processed results 2015-2022 compared to the full plot database.

	<10%	**10-40%**	**40-60%**	**≥60%**	**Accuracy**
<10%	3,905	1,444	281	502	64%
10-40%	601	11,049	1,366	493	82%
40-60%	27	1,005	6,392	1,245	74%
≥60%	13	230	1,113	16,064	92%

5. Creating structure classes

We combined the post-processed results of both the size and canopy cover class models to create structure classes. There are eight structure classes used for the monitoring report. Definitions and example photos of these classes can be found in the DNR 20-Year Plan Structure Class Definitions document. A table of the crosswalk to get these eight structure classes in in Table 7.

Table 7. The eight structure classes used in the 20-Year Plan and 2024 monitoring report, with their associated size and canopy cover classes.

Structure Class	Size Class	Canopy Cover Class
Small Open	<10"	<10% OR 10-40%
Small Closed		40-60% OR ≥60%
Medium Open	10-20"	10-40%
Medium Moderate		40-60%
Medium Closed		≥60%
Large Open	≥20"	10-40%
Large Moderate		40-60%
Large Closed		≥60%

To create the structure classes used for the 2024 monitoring report, we did not want to use 2015 data in comparison to 2021 data due to remaining concerns about over-predicting large trees in 2021. As such, we chose to use the 2015 structure class data as the baseline. For the 2021 structure class data used in the report, we used the 2015 baseline data and filled in changed areas, mapped using both change detection and forest health treatment database products, with the 2021 structure class results. This is a conservative approach that only accounts for forest loss, not growth. As we continue to improve forest structure models, we will revisit whether this methodological choice should be changed.

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Appendix C. Change detection and forest health treatment database categories

Treatments are defined in the monitoring report based on how they are identified as follows:

- **Change Detection Treatments (Table 1):** Changes to vegetation identified by satellite change detection from any treatment regardless of landowner objective. Regeneration, thinning, and broadcast burning treatments are distinguished from wildfires and insect activity.
- **Forest Health Treatment Database Treatments (Table 2):** Any modification of vegetation in a forest that has a forest health objective, although the treatment may have other objectives. These treatments are reported to DNR by partner landowners.
- **Combined Treatment Database and Change Detection**: In the combined treatment layer, treatments are any management activity to modify vegetation in a forest regardless of landowner objective.

Table 1. Change detection categories and training data sources. Change detection is a modeled product, so the sources refer to those used to train the model, not those used as the final product. See Appendix A for more details on more specifics on the data included in each change detection category.

Change Detection Category	Model Training Data Source(s)
Wildfire	DNR Large Fires database
Insect Activity	Forest Service Aerial Survey Polygons, filtered to major insect and disease agents and polygons with ≥10 trees per acre affected
Regeneration Harvest **Thinning** **Broadcast Burning**	• DNR Forest Health treatment database • DNR Forest Practices harvest data • DNR State Lands completed treatments database

Table 2: See next page

Table 2. Descriptions of treatment categories used in the 2024 monitoring report ("Monitoring Report Category") and the corresponding forest health treatment database categories ("Detailed Treatment Activity Category").

Monitoring Report Category	Detailed Treatment Activity Category	Description
Regeneration Harvest	Regeneration Treatment	Treatments where the majority of the overstory is cut and removed from the site. The amount and pattern of tree retention can range from very little (clear cuts) to considerable (variable retention harvest or irregular shelterwood). Regeneration of new cohorts of trees is generally a goal of the treatment. Other treatment types include seed tree harvest, overstory removal, patch-cuts.
Thinning	Commercial Thin	Thinning or intermediate treatment where logs are removed from site and sold to a wood processing facility or utilized for other purposes. Net revenue may be positive or negative. Included treatments where trees are chipped, and chips/biomass is removed from site.
	Non-commercial thin	Thinning where cut trees are left on site. Trees may be dropped, lopped, scattered, and/or piled, but not removed from the site. May be pre-commercial thinning of young stands with small trees, understory thinning of small trees in older forests, ladder fuel treatments, or cutting of larger trees that are left on site.
Pile Burning	Rx Fire - Pile burning	Burning of hand and machine piles, within the unit and in landings.
Broadcast Burning	Rx Fire - Broadcast Burn	Prescribe fire where most of the area is burned for fuel reduction purposes and/or site preparation objectives.
Fuels Re-arrangement	Fuels re-arrangement	Treatments where surface fuels (woody or herbaceous material) or other fuels (branches, very small trees, activity fuels) are hand or machine piled, chipped, masticated, yarded, and/or pruned.
Other	Rx Fire - Planned but burned in Wildfire	Prescribed fire treatments that were intentionally planned and ready for implementation but were burned/implemented in a wildfire event. This does not include low or moderately burned areas that were not part of a planned Rx fire prior to the wildfire.
	Herbaceous Veg Control	Treatments to control herbaceous or other non-tree vegetation for tree release, invasives/weed control, or other objectives. May be chemical or mechanical.
	Tree establishment	Planting of trees, as well as site prep or other activities related to establishing a new cohort of planted or naturally seeded trees. Does not include vegetation control treatments after trees are planted.
	Other - Unknown	Treatments not directly related to forest health goals such as permanent land clearing, wildlife habitat improvement, leave tree protection, rangeland treatments. Also includes treatments where the intent or type of treatment activities are not known.

Appendix D:
Tillicum Creek Restoration Thinning
Monitoring report (2023)

Primary objectives	Treatment date	Monitoring date
Increase resistance to crown fire and drought mortality.	Spring - Summer 2022	Summer - Fall 2022

Project objectives

1) Decrease risk of severe wildfire and increase drought and disease resistance by restoring forest structure and composition that is more characteristic of frequent fire forests in the East Cascades.
2) Enhance wildlife habitat for a broader array of species by providing spatial heterogeneity and reducing forest density to encourage growth of large trees.

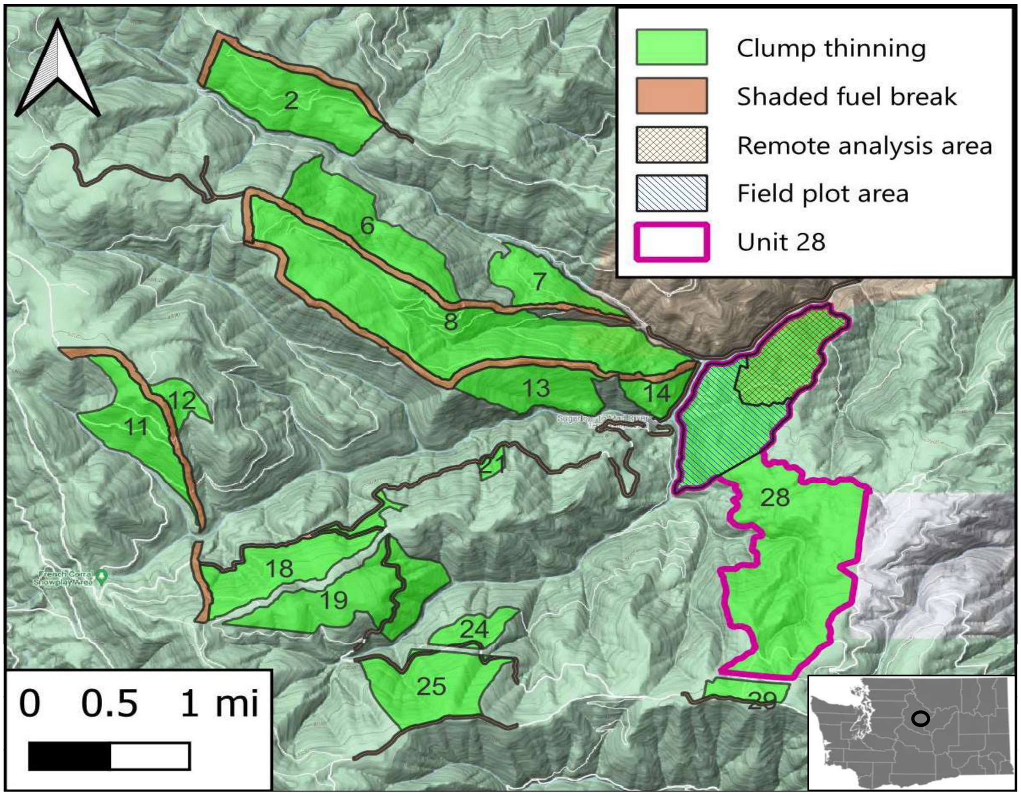

Figure 1. Local topography, roads, and unit boundaries. Analyses were restricted to locations with pre- and post-treatment data (hatched areas).

Monitoring highlights

- **406 acres** were assessed via field plots and **174 acres** were assessed via LiDAR and drone-based data.
- **Density targets were achieved** at the high end of the 90 to 120 trees per acre target range
- **Trees primarily <8″ diameter** were removed to achieve density targets
- **Species composition was shifted towards ponderosa pine**. Ponderosa pine increased from 19 to 47% of all trees and from 38 to 61% of trees >8″ diameter.
- **Mean canopy cover was reduced** by 20% in trees >6′ tall. Areas of >75% canopy cover decreased from 51% to 11%, areas of between 35% and 65% canopy cover increased from 21% to 43%, and areas of <25% canopy cover increased from 15% to 25%.
- **A patchy and more open pattern of forest cover was created**. Gaps of all sizes increased and further work should characterize gaps by shape as well as size. Trees were concentrated in 16+ tree clumps. More attention should be paid to implementation of spatial variability in addition to TPA targets to add more dispersed trees and smaller clumps.

Project area and background

The Tillicum Creek restoration project is located on the east slopes of the Cascade Mountains, 12 miles west of the town of Entiat, WA (**Figure 1**). The project is on the Entiat Ranger District of the Okanogan-Wenatchee National Forest and resulted from a proposed action in 2022 to reduce fuels and enhance forest function across 7,500 acres of young forest. Forest treatments were implemented in 2022 and 2023 on 4,012 acres of which 406 were covered by pre- and post-treatment plots and 174 were flown with a drone to assess post-treatment structure using photogrammetry.

The forest in Tillicum is ~87% dry mixed conifer, dominated by Douglas-fir and ponderosa pine, while 13% is moist-mixed conifer above ~4,500′ elevation and dominated by Douglas-fir, grand fir, and lodgepole pine. Before treatment, the forest had a mean of 377±50 trees per acre (TPA) >4′ diameter at breast height (DBH). Trees per acre ranged from 50 to 1,400. Some trees were as large as 35″ DBH, while the forest had an 11″ quadratic mean diameter (QMD). This TPA is generally higher and QMD lower than dry-type natural reference forest stands that have TPA <60, basal area per acre (BAA) between 40 and 90 ft^2 ac^{-1}, and QMD ~16″ (Churchill et al., 2013).

The state of the forest is the result of past management including timber harvest, salvage logging, excessive road building, sheep grazing, and wildfire.

The forest conditions were over-represented by closed-canopy small trees, thus were providing suboptimal spatial heterogeneity to moderate fire behavior, provide habitat and disease resistance, or to ensure a diverse range of tree ages. There were also many redundant road systems that increased maintenance costs and impaired riparian function.

Management strategy and targets

The strategy consisted of three actions to address the above concerns, including thinning, road improvement and decommissioning, and riparian rehabilitation. This report will focus on tree thinning to reduce fuels, improve stand resistance to fire and insects, and improve wildlife habitat. The general strategy was to treat most of the area with **clumped-thinning** while interspersing **shaded fuel breaks** consisting of evenly dispersed larger trees along roads and ridges as points from which fire behavior could be controlled. In addition, leave trees were pruned to reduce ladder fuels (**Table 1**).

Data collection and analysis methods

This report focuses solely on two sub sections of the northern portion of unit 28. The first was 406 acres encompassing plots taken pre- and post-treatment. The second was 174 acres representing overlap between pre- and post-treatment LiDAR and drone-based photogrammetry (see map on front page). These areas included the clumped thinning treatment but not the shaded fuel break treatment.

The following data were used for analysis:

- *Pre-treatment plot data:* US Forest Service stand exam plot data (*N* = 9) with variables summarized per-acre. These were collected with different plot radii for different DBH classes, then trees in the tree list were duplicated as necessary to attain area-based summaries. Variables for each tree included DBH, height, species, and per-acre-equivalent tree count. Trees had to be 4.5′ tall to be measured. These plots were in different locations than post-treatment plots.
- *Post-treatment plot data:* Two data sets: **1)** Plot-level compliance data (*N* = 138) with TPA of all trees >1′ tall from 0.2 acre fixed-radius plots.

Table 1. General strategy showing actions common to both types of actions (above) and individual actions (below). This table shows the prescription for the whole treatment area for context. The remainder of this report focuses on the clumped thinning treatments within unit 28. DBH = diameter at breast height, TPA = trees per acre.

Prescription	
<u>*All areas*</u> • Preferentially retain more fire-resistant species in the following order: Ponderosa pine > Douglas-fir > Engelman spruce > Abies species > lodgepole pine	• Leave all hardwoods and uncommon conifers • Remove trees within 30′ of trees >20″ DBH • Follow with burning to reduce fuels created by treatment and pruning to reduce ladder fuels • Follow with noxious weed control as needed
<u>*Clumped thinning units*</u> (~3,497 ac) • Create a matrix of small clumps in open terrain • Only take trees <8″ DBH • Lower TPA to ~100 • Prune lower limbs on 50% of trees >8′ tall	<u>*Shaded fuel breaks*</u> (~515 ac) • Create an evenly-dispersed low-density forest • Strategically place along roads and ridges • Only take trees <10″ DBH • Lower TPA to ~50 • Prune lower limbs on 100% of trees > 8′ tall

These were installed by WA DNR Federal Lands Program compliance foresters during treatment administration in 2022. **2)** Variable-radius monitoring plot data (Basal Area Factor = 10, *N* = 16) in which species, DBH, and height were collected. These were installed by Resilient Forestry LLC staff in 2022.

- <u>*Pre-treatment LiDAR data:*</u> Publicly available LiDAR data from 2020 included a digital elevation model (DEM) and canopy height model (CHM)
- <u>*Post-treatment Drone data:*</u> DNR-acquired drone photogrammetry from 2022 included a CHM.

<u>*Plot data*</u>

Metrics from plots were standardized across all datasets to obtain TPA. For post treatment TPA, compliance data (*N* = 138) were used to supplement variable radius plot data. These were then summarized by species within plots, for all trees, for those <8″ DBH, and for those ≥8″ DBH. Quadratic mean diameter (QMD) was calculated per plot and diameter class. Plots without trees in certain diameter classes (e.g., >8″) were not included in the mean QMD calculation across plots. The mean and 95% confidence interval (CI) of TPA and QMD based on the Student's-T distribution were used as comparison statistics in MS Excel.

<u>*Remote data*</u>

Analysis of LiDAR and drone-based data were the same and are summarized together below. Before the drone-based CHM could be used it had to be corrected for systematic bias. This is documented in another report, but briefly the bias in heights where canopy was absent was interpolated across the whole area and applied to the drone-based CHM (see companion report on CHM correction). While this CHM was sufficient for metrics such as spatial pattern, canopy cover, and tree locations, it was less accurate for heights and height-derived metrics such as predicted DBH.

Canopy cover was defined as any vegetation >6′ by thresholding the CHMs. To understand variability, the percent canopy cover was summarized in 66x66′ cells and plotted against percent of analysis area.

Analyses counting trees from remote data required tree segmentation from CHMs. First, the 2x2′ resolution CHMs were smoothed by the mean of 3x3 pixel moving window using the "terra" package in R.

A tree segmentation algorithm ("taos_fast" function of the "spatern" package in R) was used to extract overstory tree locations and heights. Segmentation was implemented for canopy >6′ tall using a circular search window size of 11 pixels (22′).

Segmented tree heights were used to back-calculate tree diameter and basal area based on a height-to-diameter regression from field data ($DBH = 0.09347 \times height^{1.19338}$, adjusted $R^2 = 0.69$, $N = 1056$). Tree counts and basal area were then summed in 66′x66′ (0.1 acre) raster cells. These raster cells were used to assess variability across the analysis region using the mean and 95% CI.

Spatial patterns of gaps and tree clumping were assessed using segmented tree patterns. Gap and clumping patterns were detected using nearest-neighbor algorithms and limiting distances via the "spatern" package in R (**Appendix A**).

Core gap area was defined as regions <6′ tall at least 15′ from a tree, then the core area was expanded by 10′. Gaps <0.1 acre were removed from the analysis. Gaps were delineated if the gap area was connected by at least one side of a pixel, which resulted in good gap coverage but also a lot of connectivity of complex gap shapes (**Figure 2**).

Tree clumps were defined based on a 20′-limiting distance between trees using the "tree_clump" function of the "spatern" package in R. These were then summarized into the proportion of all trees >6′ tall within clump size classes of 1, 2-4, 5-9, 10-15, and >16 trees per clump.

To compare remote drone and plot data methods, pre and post treatment density was estimated above and below a diameter threshold of 8″ for the CHMs and non-compliance plot data. Diameters for remote datasets were predicted from height using the above-mentioned regression. The difference between the estimate for all trees and those in different categories were then compared.

Figure 1. Example of gap delineation overlaying a CHM and segmented trees in 1.8-acres of unit 28. Tree height is shown with the brown-to-green color ramp while gaps are in greyscale. Gaps can be large and convoluted (left) when areas are connected narrow regions.

We also compared post-treatment CHM-segmented trees and a subsample of compliance plot data that fell within the CHM area ($N = 64$). The TPA and 95% CI of compliance data was compared to the TPA estimated from segmented trees with three different height thresholds (0, 1, and 6′). Last, the mean and 95% CI of TPA within 66x66′ pixels were compared to mean TPA from compliance plot data.

Monitoring Questions and Results

Overlapping pre- and post-treatment field and remote datasets only included the clumped thinning treatment. Targets from the treatment prescription were used to assess how close treatments came to management objectives (**Table 2**).

Monitoring questions and results

Q1: How did forest density change following treatment?

Table 2. Questions, metrics and targets, and summarized results and conclusions for the analyses in this report

Question	Metrics and Targets	Pre	Post	Interpretation
Q1 How did forest density change following treatment?	TPA[1] 109 (90-120 range) Analysis of plots over 406 ac All (*N* = 10 pre, 154 post*) ≥8″ (*N* = 10 pre, 16 post) <8″ (*N* = 10 pre, 16 post)	All: 610 ± 368 ≥8″: 65 ± 48 <8″: 545 ± 383	All: 119 ± 10* ≥8″: 78 ± 23 <8″: 90 ± 61	TPA decreased substantially and is now in the upper range of target TPA. TPA of larger trees was not different.
Q2 How did tree size change?	Increase in mean diameter (QMD[2]) from plot data	All: 6.3 ± 2.4 ≥8″: 10.6 ± 1.5 <8″: 4.2 ± 1.3	All: 10.2 ± 2.0 ≥8″: 12.1 ± 2.1 <8″: 7.7 ± 1.1	Mean diameter increased likely because of QMD increases in <8″ trees
	Change in height distribution based on remote data, with a shift towards larger trees	**Figure 3**, Median ht: 34′, ≤20 ft: 45 TPA 40′ - 60: 44 TPA	**Figure 3**, Median ht: 31′, ≤20 ft: 28 TPA 40′ - 60′: 22 TPA	Median tree height and TPA of nearly all heights decreased, more so ≤20′ tall and from 40 to 60′ tall. Errors in CHM heights may have compromised results (see text).
Q3 Was composition shifted to more fire-resistant trees?	Shift to more PP, and DF from ES, GF, and LP. Increase % hardwoods, pines, larch, and Cedar, if present.	All PP 19% DF 81% ≥ 8″ PP 38% DF 62%	All PP 47% DF 53% ≥ 8″ PP 61% DF 39%	Composition was shifted to more fire resistance ponderosa pine from Douglas fir in larger trees and overall. No other species were present in plots
Q4 Was a heterogeneous forest structure with clumps and gaps created?	Percent cover shift to less area in higher cover classes from more area in lower cover classes	**Figure 4**, Cover%: Area% ≤25%: 15% 35%-65%: 21% ≥75%: 51%	**Figure 4**, Cover%: Area% ≤25%: 25% 35%-65%: 43% ≥75%: 11%	Total cover was reduced ~20% and the distribution shifted from strongly skewed towards high cover to unimodal around 40% cover
	Gap size distribution shift to more gaps in all classes, including some large gaps	**Figure 5**, Gap size:Area % 0.1-0.5ac: 4.0% 0.5-2ac: 0.9% 2+ac: 1.3%	**Figure 5**, Gap size:Area % 0.1-0.5ac: 8.2% 0.5-2ac: 8.6% 2+ac: 8.8%	Gaps increased across all gap sizes, especially in medium and large sized gaps
	Tree clumping distribution shift from larger clumps to smaller clumps	**Table 3**, TPC[3]: % of trees 16+: 89% 5-9: 3% 2-4: 4%	**Table 3** TPC[3]: % of trees 16+: 65% 5-9: 10% 2-4: 12%	More trees were in smaller clumps, but the larger clumps need to be broken further into smaller ones to represent historical conditions
Q5 How does stand density using remote vs. plot-based metrics compare?	Compare the estimated TPA of plots to remote estimates in similar height and diameter classes	**Table 4**, plot – remote All: 472 TPA ≥8″: 20 TPA <8″: 452 TPA	**Table 4**, plot – remote All: 26 TPA ≥8″: 56 TPA <8″: 19 TPA	Remote data under-detected smaller trees when there were many small trees and generally under-detected all trees. 16% fewer TPA were detected >1′ tall.
[1]TPA = trees per acre >0.1″ DBH [3]TPC = trees per clump		[2]QMD = quadratic mean diameter (in)= sqrt(sum(diameters)/number of trees) *TPA of all trees post-treatment used compliance plots (*N* = 138) plus variable-radius plots (*N* = 16).		

Figure 2. Representative aerial pre-treatment conditions (left), post treatment conditions (right) for Tillicum Unit 28.

Figure 4. Representative terrestrial pre-treatment conditions (top), post treatment conditions (bottom) for Tillicum Unit 28.

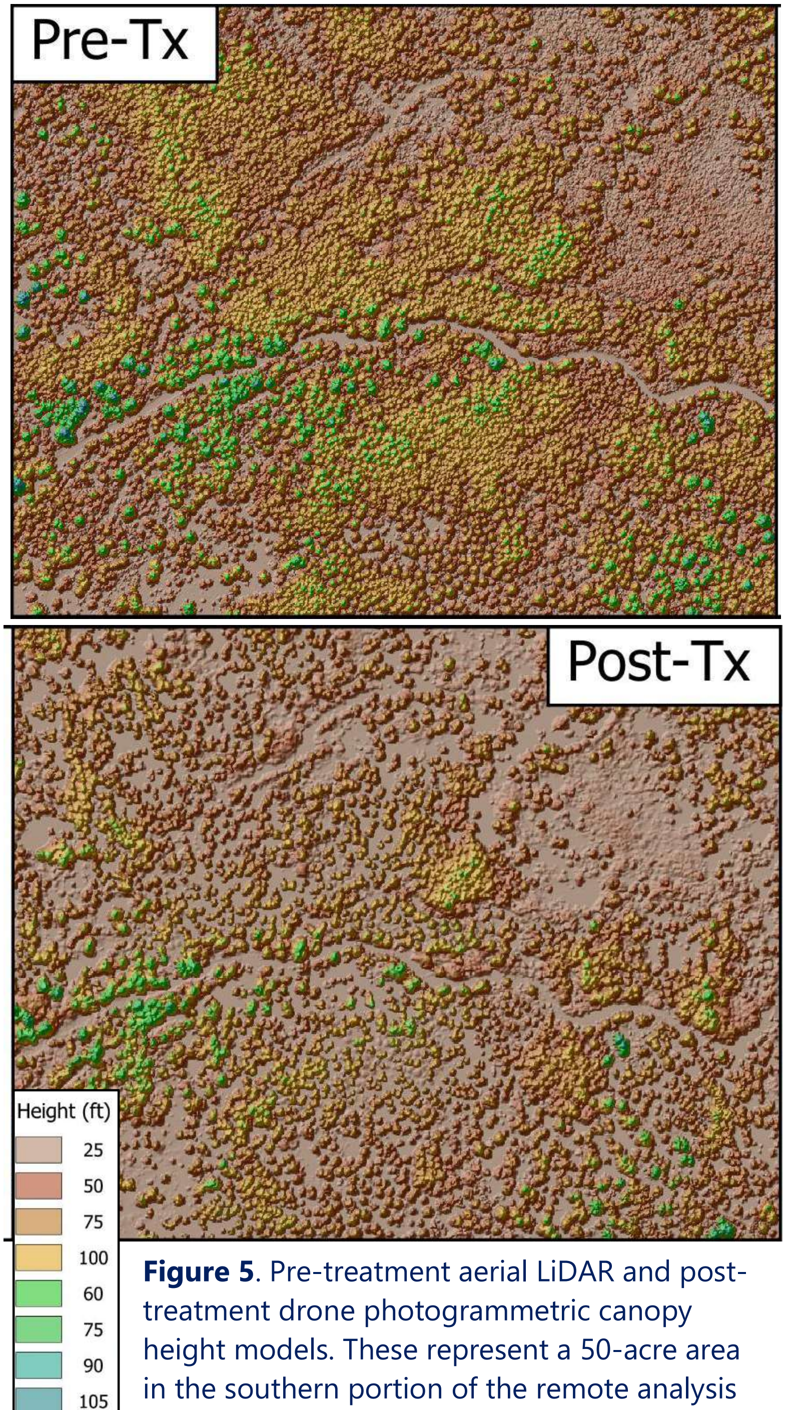

Figure 5. Pre-treatment aerial LiDAR and post-treatment drone photogrammetric canopy height models. These represent a 50-acre area in the southern portion of the remote analysis area in the cover page map.

<u>Targets</u>— Decrease TPA to between 90 and 120 by removing <8″-DBH trees.

<u>Results</u>— The plot data showed that the treatment decreased TPA approximately 5-fold and that this decrease came from trees <8″ DBH (**Table 2**).

<u>Discussion</u>— The treatment decreased forest density towards the high end of the target TPA range. We were confident in the plot-based estimate (119±10) because *N* = 154 (compliance plus monitoring plots). **Figures 3, 4 and 5** provides a visual representation of the stand change. It remains unclear whether ≥8″-DBH TPA changed much because there were so few plots in which DBH was measured and plots were in different locations post-treatment than pre-treatment. Smaller trees clearly decreased despite the small number of plots because the reduction of 455 TPA was outside of the 383 TPA confidence interval (**Table 2**).

Q2: How did tree size change?

For this question we used QMD change from plot measurements and the height distribution change from remote data.

<u>Targets</u>— Increased QMD in <8″-DBH trees and similar QMD in ≥8″-DBH trees. Lower numbers of trees in shorter height classes and similar numbers of trees in taller height classes.

<u>Results</u>— Plot data indicated an increase in QMD across all trees that was not detectible in ≥8″-DBH trees but was in <8″-DBH trees (**Table 2**). Remote data showed a decrease in most height classes, with the highest proportional decreases ≥45′ tall and <10′ tall (**Figure 6**). The largest absolute decreases were in <10′-tall trees and in 40 to 60′-tall trees (**Figure 6**).

<u>Discussion</u>— Because the QMD was detected across all trees and not for trees ≥8″ DBH, we can assume the decrease was due mostly to the reduction of smaller trees.

The change in the height distribution based on remote data were harder to interpret. As mentioned above, a height-correction was applied to the drone-based data. We cannot eliminate the possibility that the reduction of taller trees in **Figure 6** is an artifact of this correction. It should be a research priority to determine the source of the systematic errors encountered in the drone CHM and a suitable correction process (see companion CHM report).

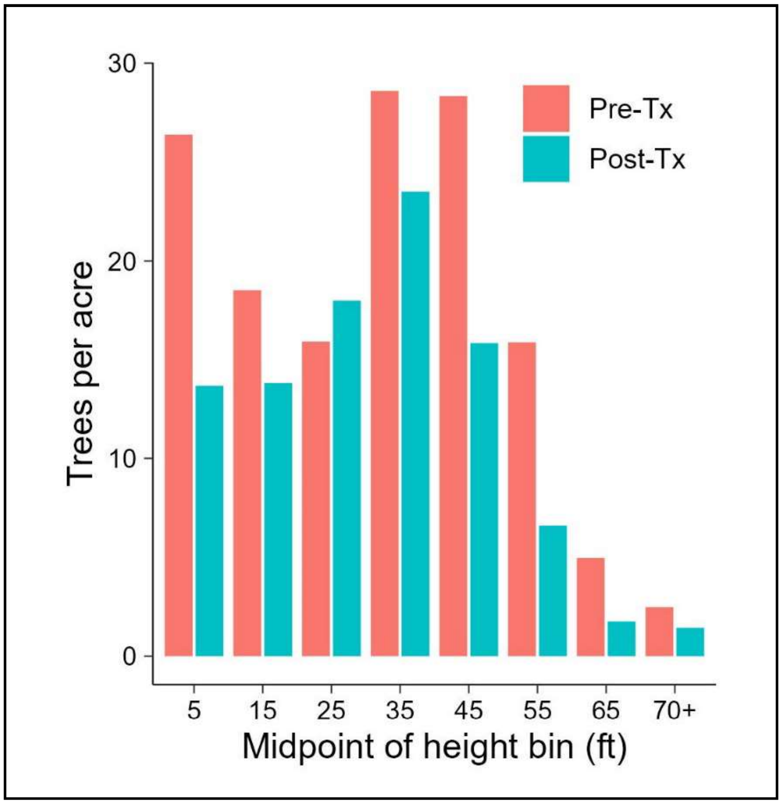

Figure 6. Height of segmented trees were counted in 0.1-acre cells to estimate TPA in height bins.

Q3; Was composition shifted to more fire-resistant trees?

Targets— Increased ponderosa pine relative to Douglas-fir and both species relative to others. If present, increased proportions of larch, pines, hardwoods, and cedar.

Results— Only ponderosa pine and Douglas-fir occurred in the plots. The composition was shifted favorably with Douglas fir decreasing from ~80% to ~50% composition. In ≥8"-DBH trees, the Douglas fir was less abundant initially (62%) and was further decreased to 39% (**Table 2**).

Discussion— The relative reduction of Douglas fir was probably a robust finding given that tree counts in each plot was relatively high before and after treatment. The finding of a reduction in ≥8"-DBH Douglas fir was less robust because they occurred less frequently, however, both the pre- and post-treatment plots employed larger radii for larger tree sizes, which partially mitigated this problem. Paired locations pre- and post- treatment would eliminate any ambiguity.

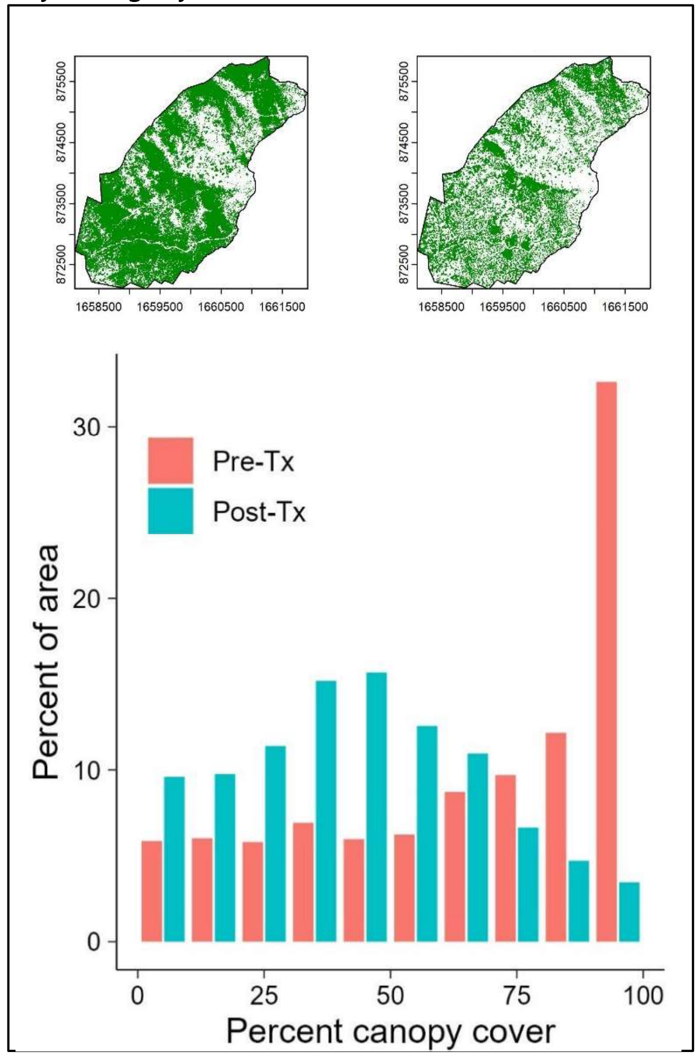

Figure 7. Canopy cover in upper panels pre- (left) and post-treatment (right) within the remote sensing project area boundary (see map on cover page). Percent cover pre- and post-treatment is based on binned summaries of canopy cover within 0.1-acre cells (bottom).

Q4 Was a heterogeneous forest structure with clumps and gaps created?

We examined this question by analyzing percent cover, gap distributions, and tree clumping patterns.

Targets— There were no specific targets for this other than to decrease cover, create more gaps of varying size, and to create a clumped rather than dispersed tree arrangement. Ideally, clumping would fall withing ranges of reference stands from similar forest types.

Results— The mean canopy cover change over any given 0.1 acre was -23±1% and ranged from a 0 to 80% reduction. Forest with ≤25% cover increased from 15% to 25% of the project area, forest with 35% to 65% cover increased from 21% to 43% of the project area, and forest with ≥75% cover decreased from 51%% to 11%. The distribution of canopy cover was shifted from highly skewed towards high cover to more unimodal cover with the most area having 35 to 55% cover (**Figure 6**).

Area in small gaps approximately doubled while area in medium and large gaps increased 5- to 8-fold (**Figure 7**). The sum of all delineated gaps ≥0.1 acre increased from 6 to 26% of the analysis area.

While the number of trees in the largest clumps decreased 24%, they still contained 65% of detected trees (**Table 3**). Clumping did not reach that of any reference stands, but came within 1% of the minimum 11% of trees in 5-to-9-tree clumps. The remaining clump tree counts needed to contain between 3 and 26% more of the total trees to resemble minimum reference stand clumping patterns (**Table 3**).

Discussion— Estimates of canopy cover and gaps from remote data did not suffer from the same drawbacks as estimated TPA and BA because they relied more on one height cutoff than on segmented trees with accurate height estimates. The analysis of

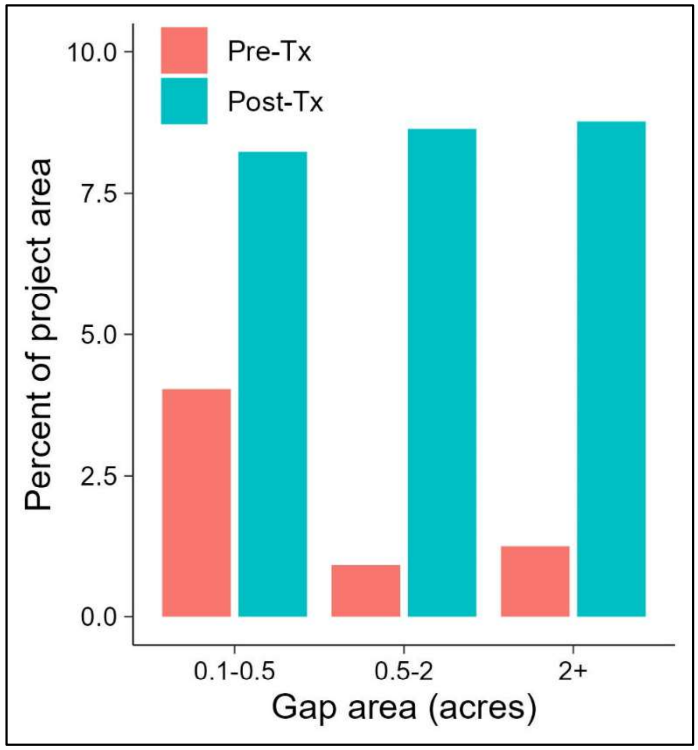

Figure 8. Gaps classified into size categories and summarized as percent of project area pre- and post-treatment.

canopy cover and gaps showed an ~20% change toward more open conditions.

The even distribution of gap sizes could be misleading without knowledge of the shape of the gaps (**Figure 5**). Many of what might be called small gaps were subsumed into larger gaps because of narrow connections between them. A future analysis of gap distribution may benefit from a 3x3 matrix of gap size and gap shape complexity. Such a measure of complexity could be as simple as the perimeter to area ratio.

Table 3. Clumping distribution of reference stands (Churchill et al., 2013) of various density compared to Tillicum pre- and post-treatment. Values in each clump count class are percent of total trees.

Sites	TPA	Trees per clump				
		1	2-4	5-9	10-15	16+
Reference – High	40-60+	0.22	0.38	0.24	0.10	0.06
Reference – Medium	24-40	0.30	0.42	0.11	0.17	-
Reference – Low	15-25	0.45	0.43	0.12	-	-
Pre-Tx	138	0.02	0.04	0.03	0.02	0.89
Post-Tx	93	0.06	0.12	0.10	0.07	0.65

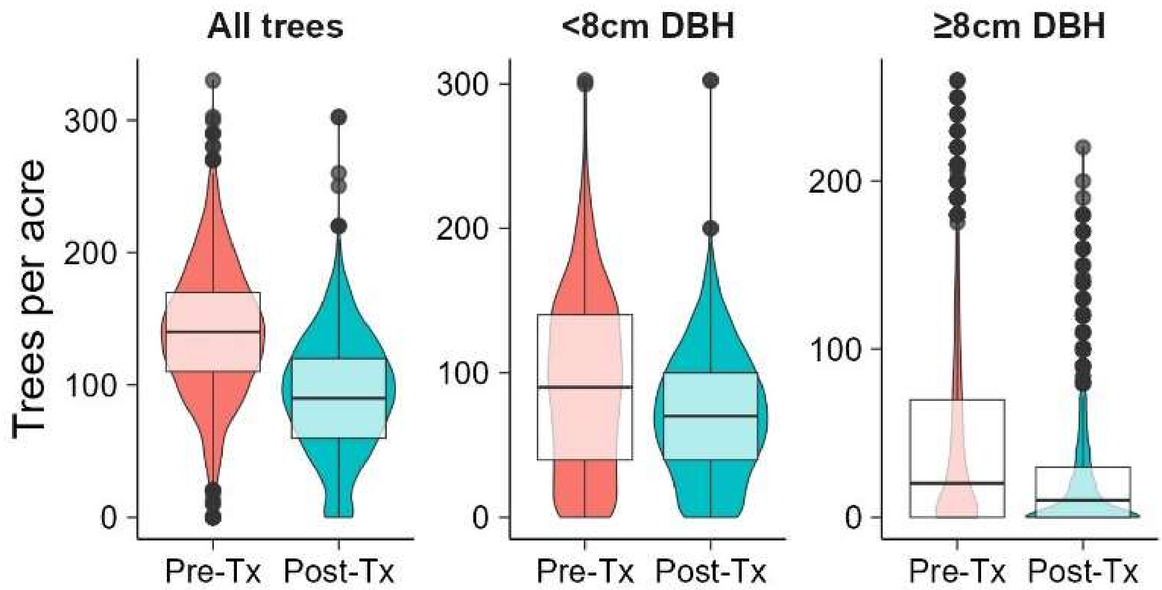

Figure 8. Segmented trees were summarized in 0.1-acre cells to estimate TPA from remote datasets.

There were not nearly as many trees in small clumps as needed. This analysis is likely sensitive to the height cutoff used to segment trees from the CHM in comparison to the minimum diameters measured in the reference stands they were compared against. A future analysis could seek an optimal solution by testing which diameter cutoffs (or better yet, height) in reference stands produce the most concordant clumping distributions with various height cutoffs applied to remote data.

Another reason the clumping patterns were not reached could be because the 8″ DBH limit on tree removal may have limited options. Was it possible to create the clumped pattern under this constraint while also reaching the TPA target? A *post hoc* look at the data showed the mean TPA of >8″-DBH trees was 73. Therefore, the TPA target could have been met, but it is unclear if these trees were arranged in a dispersed vs. clumped pattern. If the former, it may have been difficult to create the clumping desired without removing them.

Q5: How does stand density using remote- versus plot-based methods compare?

Results— Compared to plots with DBH measurements (N = 10 pre and 16 post), remote data showed 77% and 22% fewer trees >6′ tall of any diameter, 31% and 72% fewer trees ≥8″-DBH, and 83% and 21% fewer trees <8″-DBH per acre pre- vs post-treatment, respectively (**Table 2**).

Compliance plots within the boundary of the drone-based data (N = 64) had a mean TPA nearly ~50% larger than that of drone-based data when no height cutoff was used. The compliance data had a minimum height cutoff of 1′ tall. When filtering the drone-based data to ≥1′ or to ≥6′, the drone-based estimate was 85 to 87% of the plot-based estimate (**Table 4**).

Discussion—The relationship between remote and plot-level data changed pre and post treatment from drastically under-detecting small trees pre-treatment to under-detecting larger trees more than smaller trees post-treatment. This may have been because there simply were not many small trees to detect post treatment.

The results or pre- vs post-treatment remote to field data comparisons were confounded by at least four

Table 4. Comparison of estimated TPA from compliance data (*N* = 64). Segmented trees were summarized for 0.1-acre raster cells (*N* = 1,845), and as a full census. Remote datasets are shown with 0′, 1′, and 6′ height cutoffs.

Dataset	Min ht (ft)	TPA
Compliance data	1	109 ± 17.0
Drone raster summary	0	153 ± 4.2
Drone TOA census	0	156
Drone raster summary	1	91 ± 1.6
Drone TOA census	1	93
Drone raster summary	6	93± 2.0
Drone TAO census	6	95

sources of error. **1)** the drone-based CHM was height-corrected prior to analysis to eliminate systematic topographic bias (see companion CHM report), and this may have resulted in inaccurate heights from which the 8″-DBH cutoff was derived. **2)** Remote data were not optimal for detecting small trees that may have been obscured by lager trees, especially in the dense pre-treatment forest. **3)** The segmentation algorithm used a search window to find local maxima from the CHM. If many small trees were closer together than this window size they were missed. This issue can be remedied in future projects by using a variably-sized search window, which would require a subset of crown spread and height measurements to calibrate. **4)** The small number of plots reduces our confidence in the comparisons. If these sources of error can be reduce, we can more accurately assess the relative abilities of LiDAR, drone, and field data to quantify tree density.

When using the compliance data, we were able to increase the sample size (*N* = 64), but were only able to compare them to the post-treatment drone-based data. We assume these plots reflected actual TPA and served as an error check on the drone-based methods. Using a drone to estimate tree density appeared sensitive to below a 1′ threshold and reasonable above 1′ for this region (**Table 4**). Without a cutoff, the segmentation algorithm was identifying local maxima that were not trees, while above 1′ tall, it was missing trees. We can assume the trees missing from remote data were smaller, thus sampling plots using a larger height threshold than 1′ would likely yield more similar results to drone-based data.

For basic descriptions of density, remote data were close enough to plot data that they could be used as a relative measure of treatment effects on TPA. A future mini study could be performed to determine which height thresholds of plot and remote data yield the most similar results.

Conclusions

The project objectives were: **1)** to decrease risk of severe wildfire and increase drought and disease resistance by restoring forest structure and composition more characteristic of frequent fire forests in the East Cascades, and **2)** to enhance wildlife habitat for a broader array of species by providing spatial heterogeneity and reducing forest density to encourage growth of large trees.

It is not possible to know whether these functional properties of the forest have changed solely from this implementation monitoring effort without direct measurements of fuels, mortality, tree growth, and wildlife monitoring. However, given the structural conditions encountered post-treatment, the following observations are reasonable to assume.

- The lower TPA, percent cover, and larger gap areas have reduced canopy fuel loading and the possibility of carrying a crown fire. Simultaneously, the lower evaporative demand of the lower density forest has freed resources for the remaining trees to resist drought in disease.
- The focus on removing small trees has likely reduced ladder fuels that could allow a fire to reach the canopy. However, the density of small trees still appears high enough to ensure future canopy recruitment.
- The lower TPA and increased gap areas have also freed growing space to allow trees to differentiate and some will eventually become larger than the untreated forest. These trees, the new gaps with the ability to grow more shrubs and herbs in the understory, and remaining patched of dense trees will provide habitat and forage for larger and more diverse populations of wildlife.

A few lessons were learned during the making of this report that can aid future efforts. First, remote datasets are much better for detecting heights and crown dimensions than for measuring DBH. To better calibrate the tree segmentation and metrics that rely on it, measurements of height and crown radius should be taken for trees of a variety of tree heights during plot work. These data would allow us to use a variably-size search window for detecting treetops based on the CHM height to radius relationship. Plots with height data would also allow us to better compare TPA based on segmentation of a CHM to that from plots by allowing us to filter the data on the common metric of height.

Key results:

- Density targets were met at the higher end of retention targets.
- Small trees were preferentially removed, but plot-based and remote dataset show conflicting evidence about large tree removal.
- Composition was shifted towards ponderosa pine from Douglas-fir to a nearly equal split with no other species occurring in the plots
- QMD increased more for small trees than large trees, indicating the smallest trees were preferentially removed.
- Changes in the tree height distribution could not be ruled out as artifacts of data correction steps taken pre-analysis. These should be investigated further to create trustworthy data workflows.
- Stand density estimated using remote data is slightly lower than plot installations so it is better thought of as a relative density measure.
- Canopy cover was reduced 20% and the most common cover classes were near 40%.
- Gap area increased 2- to 8-fold and occupied ~8% of area across each gap size. Further work should focus on the shape and area of gaps because many small gaps were linked into convoluted larger gaps.
- Tree clumps were concentrated in large clump tree counts even after treatment. These should be broken into smaller clumps, possibly by removing some >8” DBH trees if necessary.

Second, remote data make delineating gaps easy relative to field-based groundwork. Because readily describing gaps is newly available, we do not yet have standard methods for describing gap structure. There is some back and forth when finetuning the parameters of gap delineation and some best practices should be researched and implemented. Among these are rules governing connectivity between gaps, minimum gap size, and buffer distance from edge trees for an area to be considered a gap. This is an imperfect process and is often guided visually to balance omitting gaps versus having too many gaps connected by into complex sinuous shapes. Furthermore, the gap distribution should probably be parsed into size as well as shape characteristics as these are likely to have an effect of their functional characteristics. For example, a narrow gap with large area will be more shaded than a round gap is smaller area.

Last, a common issue in monitoring projects is that pre- and post-treatment sample sizes are typically small and sometimes use different methods. A concerted effort should be made to locate plots pre- and post-treatment in the same place. This will allow for reliable analyses of small sample sizes but also require some creative geolocation so plots centers can be found after a logging operation.

Reference

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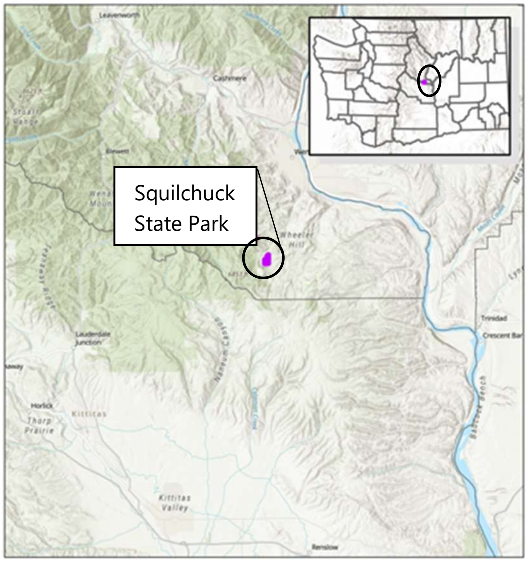
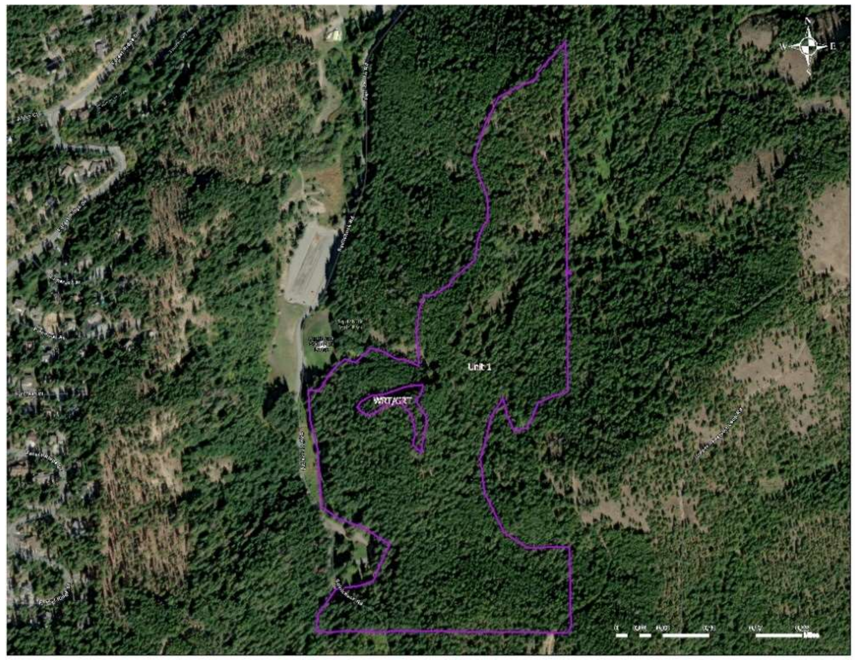
Appendix E:
Squilchuck State Park near Wenatchee, WA
Treatment Monitoring (2023)

Total acres	Landowner	Treatment date	Monitoring date
67	WA State Parks & Recreation	November 2022-March 2023	August 2023





Above: Squilchuck State Park location in WA state, purple polygon and circled in black. **Right:** Satellite imagery of park and purple outline of project area.

Project goals

- Reduce overall tree stocking throughout the unit to increase residual tree vigor.
- Thin from below to favor leaving larger trees and a higher average diameter.
- Shift species composition to favor ponderosa pine and western larch.
- Protect sensitive natural and cultural resources including: old growth trees, legacy trees, fire scarred stumps, rare plants and animals, and historic park infrastructure.
- Increase spatial diversity and mimic historic stand structure by creating clumps, gaps and skips throughout the unit in the park.
- Create a fire-adapted forest structure with lower density to resist severe disturbances.
- Maintain scenic, recreational values, and habitat values.

Project highlights

- Plot level data showed trees per acre (TPA) reduced from 280 to 119 and basal area per acre (BA) from 198 to 100 ft^{2}.
- Roughly 10% of the proportion of Douglas-fir shifted to ponderosa pine, however Douglas-fir was still 38% of the trees.
- The treatment reduced ladder and canopy fuels. Surface fuels after logging were generally low.

Project area and background

The project area, Squilchuck State Park, is a mountainous region located in central Washington, near Mission Ridge and south of Wenatchee. The 249 acre park sits between 3,200'-4,000' elevation and is within the Squilchuck Creek watershed, which flows into the Columbia River. Squilchuck State Park is a parcel of publicly owned land, surrounded by private land all around, including a neighborhood of homes west of the park. A large, contiguous area of the Okanogan-Wenatchee National Forest is nearby the park, to the west, with a checkerboard of private, WA Dept. of Fish and Wildfire and WA Dept. of Natural Resources managed land to the east and south of the park.

Squilchuck State Park is currently a hiking, trail running and mountain biking destination park, serving the locals of Wenatchee and attracting mountain bikers from across the state. The park was slated to be closed during the economic and budget crisis in 2009, but with the help of local community support and The Evergreen Mountain Bike Alliance, the park was saved. Trails continue to be built and maintained in the park.

In fall, 2022, 67 acres of the forest in the park were thinned as part of a forest health project. The forest primarily consisted of Douglas-fir and ponderosa pine, with some grand fir, western larch and a mix of hardwood shrubs in riparian and wet areas, and was heavily overstocked with consistent canopy closure. The age range of the trees was not determined, but sizes ranged from 6"-36" DBH (diameter at breast height), with the average DBH among trees in the treatment area ranging from 12"-18". Average tree heights were between 65'-90.'

Forests in this area were historically lower density and park like. Pre-treatment basal area in the park ranged from 80-220 sq ft/acre and treatment target was 60-80 sq ft/acre (Figure 1). Also historically, few smaller trees may have been isolated in clumps due to frequent fires that killed most of them and left surviving larger trees. Dense areas of forest were typically in relatively moist locations. Ingrowth of the small shade-tolerant tree species have led to dense stands with vertically continuous fuels from the ground to canopy which can increase the severity of wildfire in this forest.

Figure 1. Before (upper) and after (lower) images of forest health thinning project in Squilchuck State Park. Images by John Marshall.

The land footprint of Squilchuck State Park was once part of a fire-adapted ecosystem with very different forest structure and disturbance dynamics (Figure 2). The overstocked, or crowded forests, cause increased drought stress, which can contribute to higher levels of insect and disease damage and mortality within the park. With the increasing severity of wildfires across the west, the proximity of homes and structures to forests, the highly departed ecosystem structure and disturbance dynamics from historical conditions, and the high recreational value of this park, WA State Parks decided to lead a forest health project that would address many of these risks and concerns and set the forest on a more resilient trajectory.

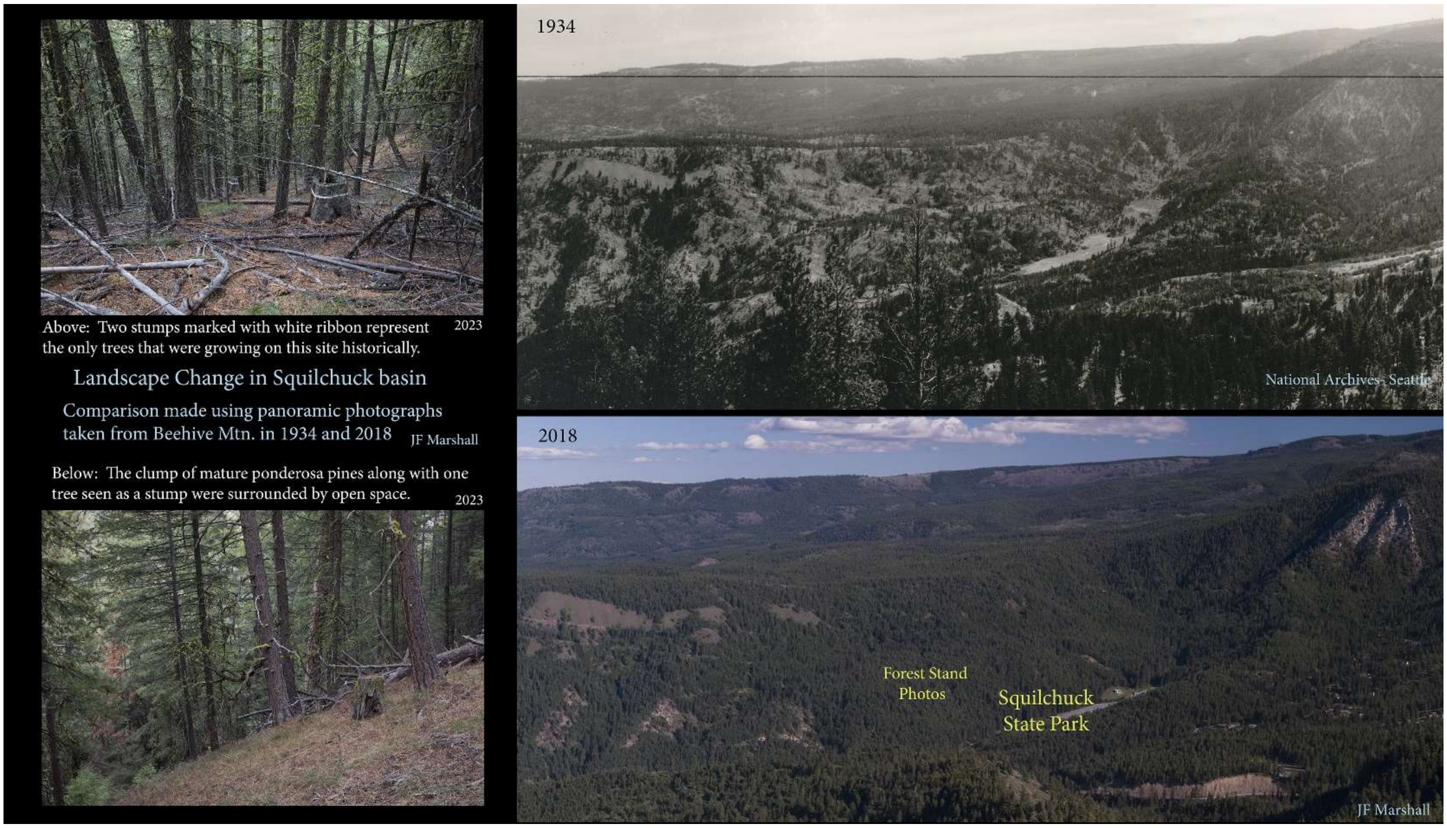


Figure 2. Historic and current Squilchuck SP and surrounding landscape forest conditions. Images by John Marshall.

Table 1. Prescription details paraphrased from contractor documentation of draft harvest prescription and WA State Parks.

Prescription	
Create a resilient stand that can meet the needs of future generations: Retain legacy trees >20" DBH ponderosa pine and > 22" Douglas-fir, western larch of any size unless diseased, and restore spatial patterns found in frequent-fire regimes consisting of individual trees, clumps, and openings. **Maintain recreation**: Clumps of 2-5 or 6-10 trees will be left in areas of more unique topography, such as forested wetlands, rocky bluff areas and near mountain bike structures. **Maintain habitat values**: Create high, 10'-15' off the ground, habitat snags when the base of the tree is heavily defected.	**Reduce disease**: Create gaps of 0.1-0.25 acres every 2-4 acres, ideally focused on areas where there are defected or diseased trees. **Reduce overstocking to improve leave tree and understory growth**: Preferentially remove trees in the 6" to 20"-DBH range and leave trees in the 20"+DBH range. Thin from below (cut smallest diameter first), favoring the retention of western larch, ponderosa pine and Douglas-fir over lodgepole pine and grand fir on the entire treatment unit. Thin to target basal area of 60-80 square feet per acre and 40-60 trees per acre.

Methods

Plot-based data were used to evaluate management outcomes. Pre-treatment plot data were from 37 variable radius (BAF 20) timber cruise and DBH count plots. Post-thinning treatment plot data were from 12 fixed-radius (10^{th} acre) plots and included plot, vegetation and disturbance data, as well as tree species and DBH data. These data were collected using the WDNR's Treatment Level Monitoring Protocol and entered into a Survey123 based AGOL data platform.

Because pre and post-treatment plot data were limited and not aligned at the onset of the project, we only used them for analyzing the change of trees per acre, basal area, DBH and species composition. Other data were collected post-thinning regarding fuels and other vegetation composition, but not included in this monitoring report.

Monitoring Questions & Results

This monitoring report is designed around specific questions. Some questions were based on targets from the treatment prescription (Table 1) while others were assessed based on a general description (Table 2, includes results).

Table 2. Results and specific targets to evaluate treatment implementation. PP – Ponderosa pine, WL – Western larch.

Question	Metrics & Targets	Pre Thinning	Post Thinning	Conclusion
What was the forest density and average basal area before and after treatment?	Change in Trees per Acre (average)	280.8	119.2	Reduced TPA and overall tree stocking.
	Change in Basal Area, square feet per acre (average)	196.8	100.1	Reduced basal area.
Did average DBH change to favor leaving larger trees?	Change in DBH (average) across all species, inches	11.3	12.8	The average DBH increased across the thinning area. 6.6% were legacy PP and 2.2% legacy DF.
Did species composition shift towards more PP and WL?	Increased proportion of PP and WL	**PP & WL:** 49.5% **Other species:** 50.5%	**PP & WL:** 60.4% **Other species:** 39.6%	The proportion of ponderosa pine and western larch increased, but the primary overstory species in the forest remain PP and DF.

Figure 3. Before (upper) and after (lower) images of forest health thinning project in Squilchuck State Park. Images by John Marshall.

Results and Management Implications

This forest health project in Squilchuck State Park successfully decreased trees per acre, basal area, increased the overall diameter of leave trees and shifted species composition. While thinning to the prescriptive target basal area of 60-80 square feet per acre and leaving 40-60 trees per acre in the park were not achieved, half of the basal area was removed (Figures 4 and 5).

Figure 4. Image showing the variation in structure left after the thinning project. Image by John Marshall.

Figure 5. Image showing thinned and unthinned areas of the project. Image by John Marshall.

The species composition and structure were shifted towards desired conditions during the forest health project (Figure 6). Overall, the project aesthetically looked good and made a significant impact on residual tree vigor and wildfire resilience.

Figure 6. Example of wildlife snag creation in foreground of image. These were created throughout the project area to maintain habitat values in the park.

Soil disturbance was present in some locations in the project area after the thinning. A native seed mix was spread in late winter, 2023, to help restore the native herbaceous species in those disturbed locations. In the future, additional areas with soil disturbance may benefit from invasive plant species monitoring and removal, as well as a broadcast burn across the area to reduce fuels remaining on the forest floor from the thinning operation.

In the future, additional plot-level data may be collected or drone base imagery analyzed to examine the spatial variability of the forest health thinning in Squilchuck State Park, as well as short and long-term impacts of this type of forest health treatment in a high recreation forested parks in eastern Washington.

Appendix F. Structure change in stream-adjacent forests

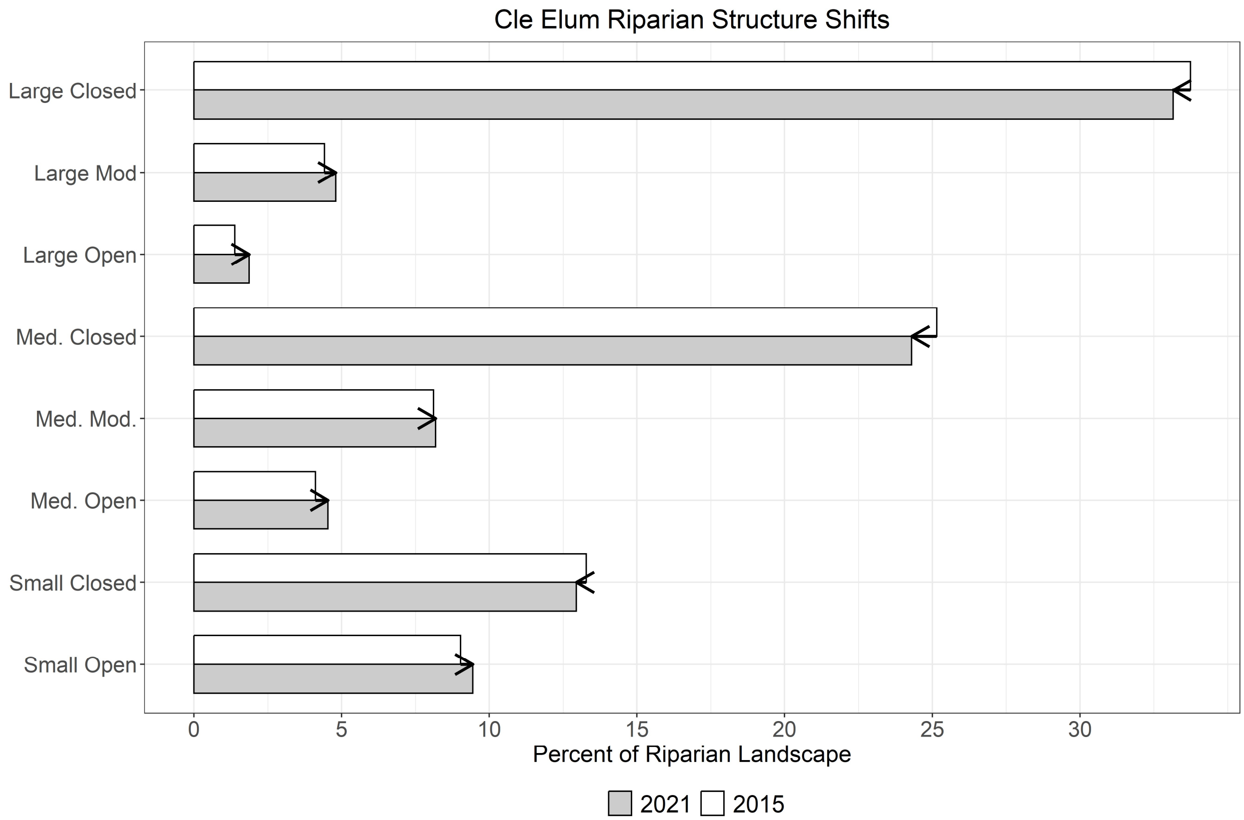


Figure 1. Proportion of stream-adjacent forests in the Cle Elum planning area covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars). This graph represents all vegetation types.

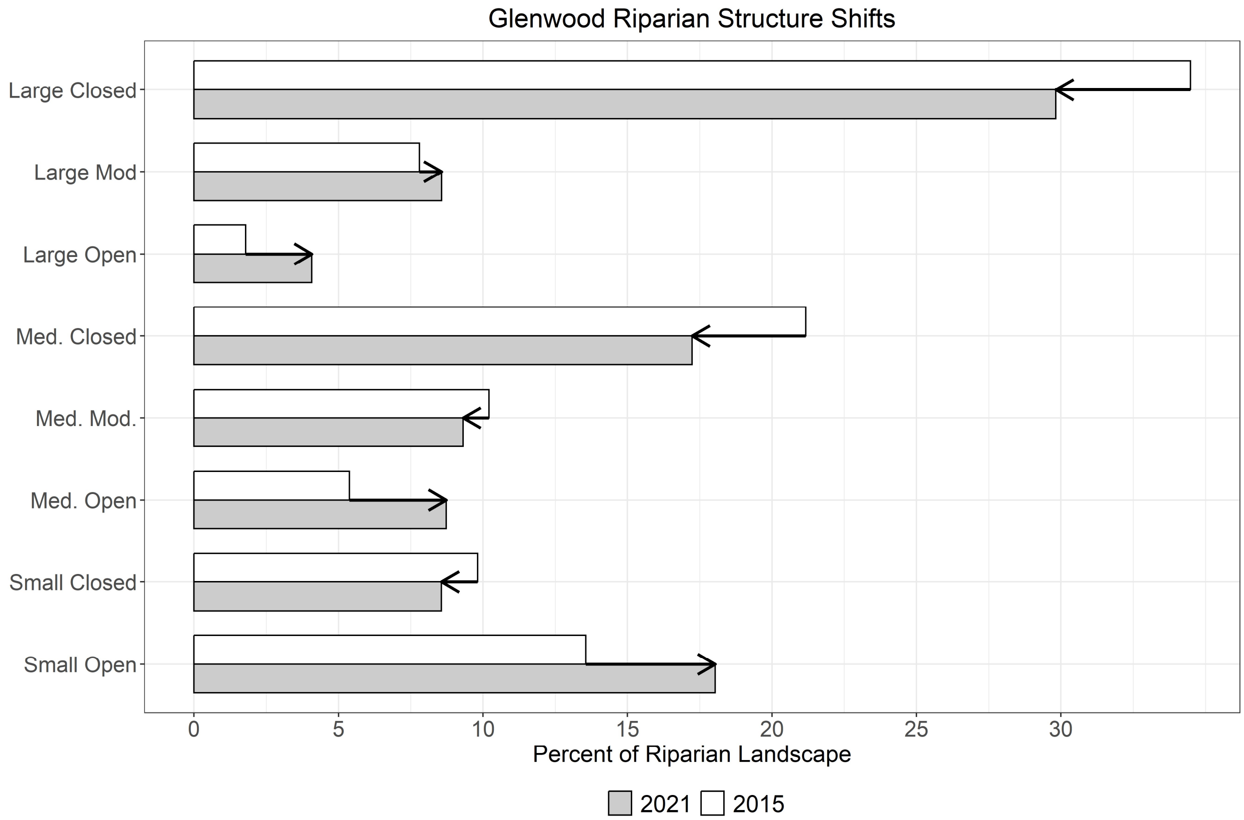


Figure 2. Proportion of stream-adjacent forests in the Glenwood planning area covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars). This graph represents all vegetation types.

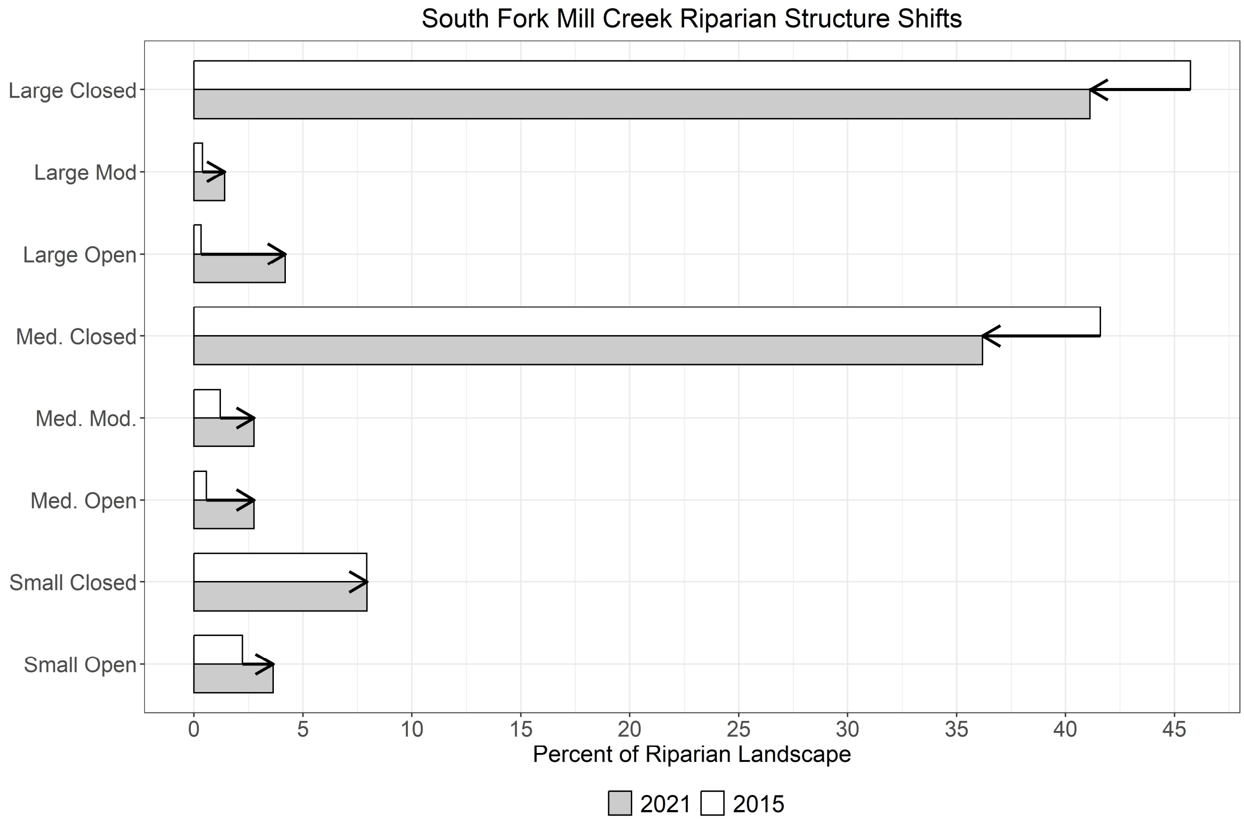


Figure 3. Proportion of stream-adjacent forests in the South Fork Mill Creek sub-watershed covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars). This graph represents all vegetation types.

Appendix G. Structure change departure in different forest types

Note: Structure change departure figures for forest types with less than 1000 acres in the planning area are not included here.

1. Cle Elum

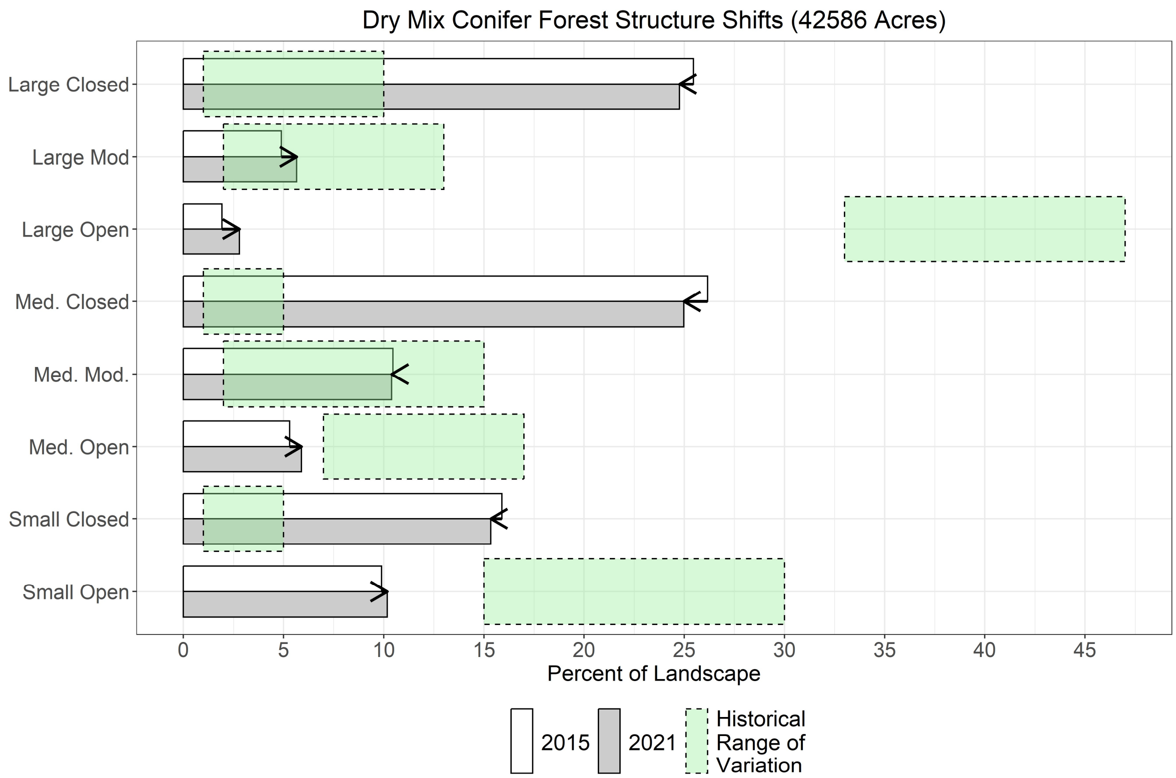


Figure 1. Proportion of dry mixed conifer forests covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the Cle Elum planning area (green shaded area). The total area covered by dry mixed conifer forests is shown in the figure title.

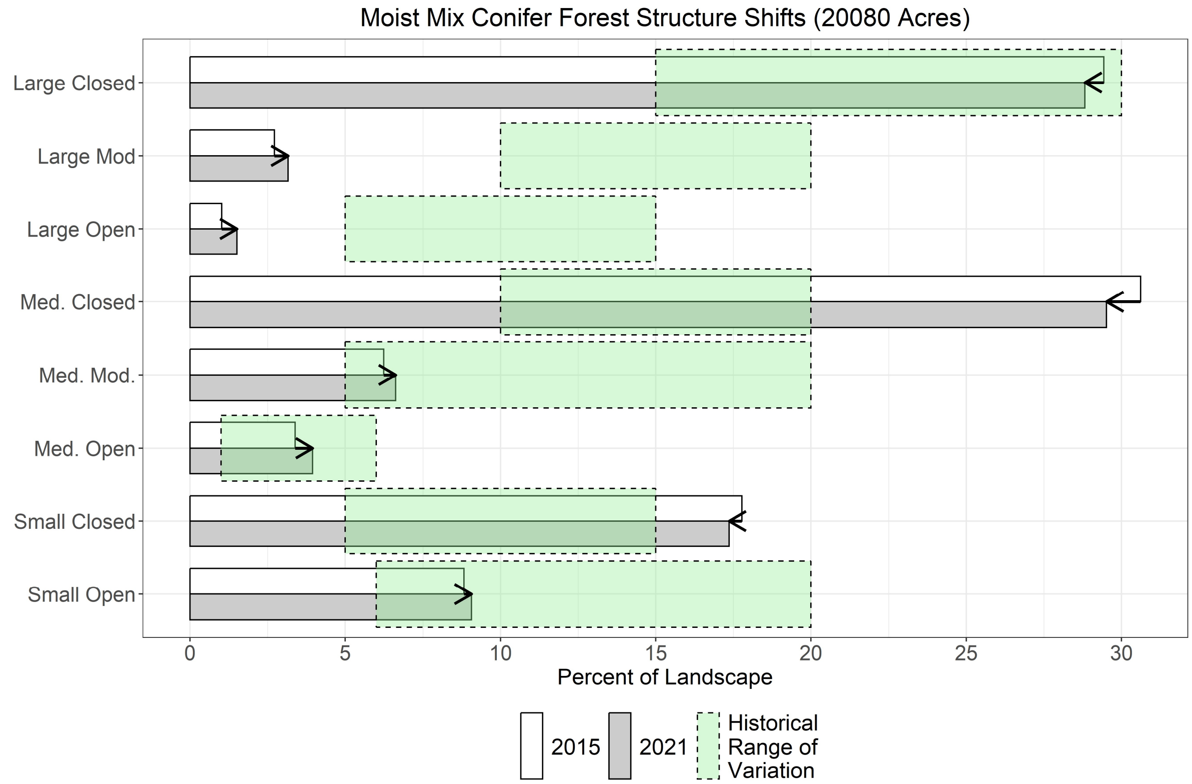


Figure 2. Proportion of moist mixed conifer forests covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the Cle Elum planning area (green shaded area). The total area covered by moist mixed conifer forests is shown in the figure title.

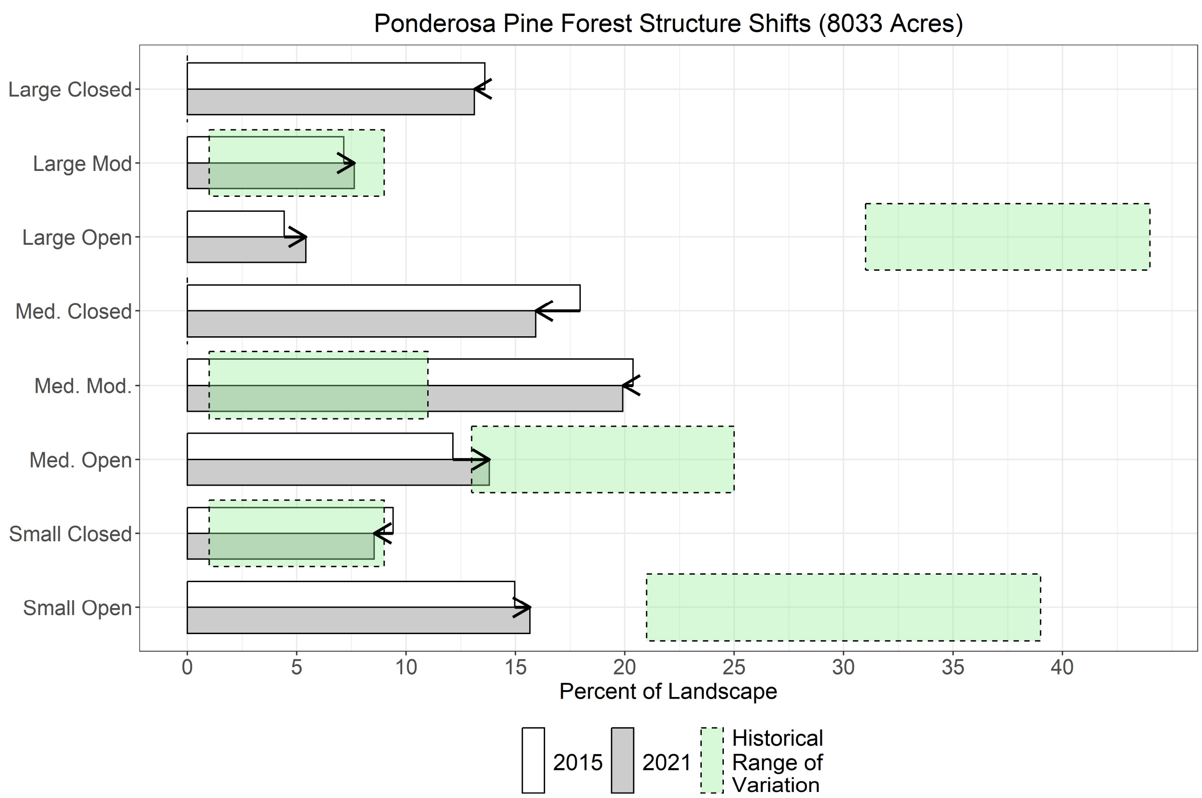


Figure 3. Proportion of Ponderosa Pine forests covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the Cle Elum planning area (green shaded area). The total area covered by Ponderosa Pine forests is shown in the figure title.

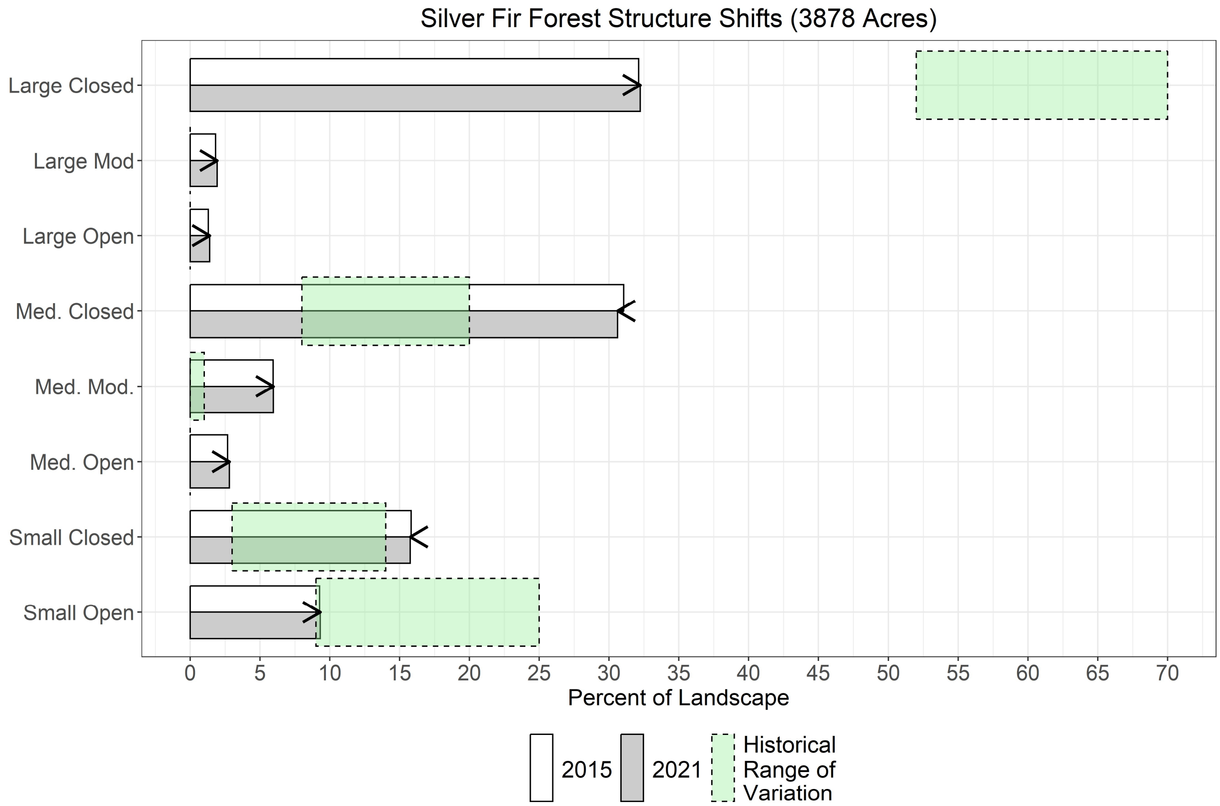


Figure 4. Proportion of Silver Fir forests covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the Cle Elum planning area (green shaded area). The total area covered by Silver Fir forests is shown in the figure title.

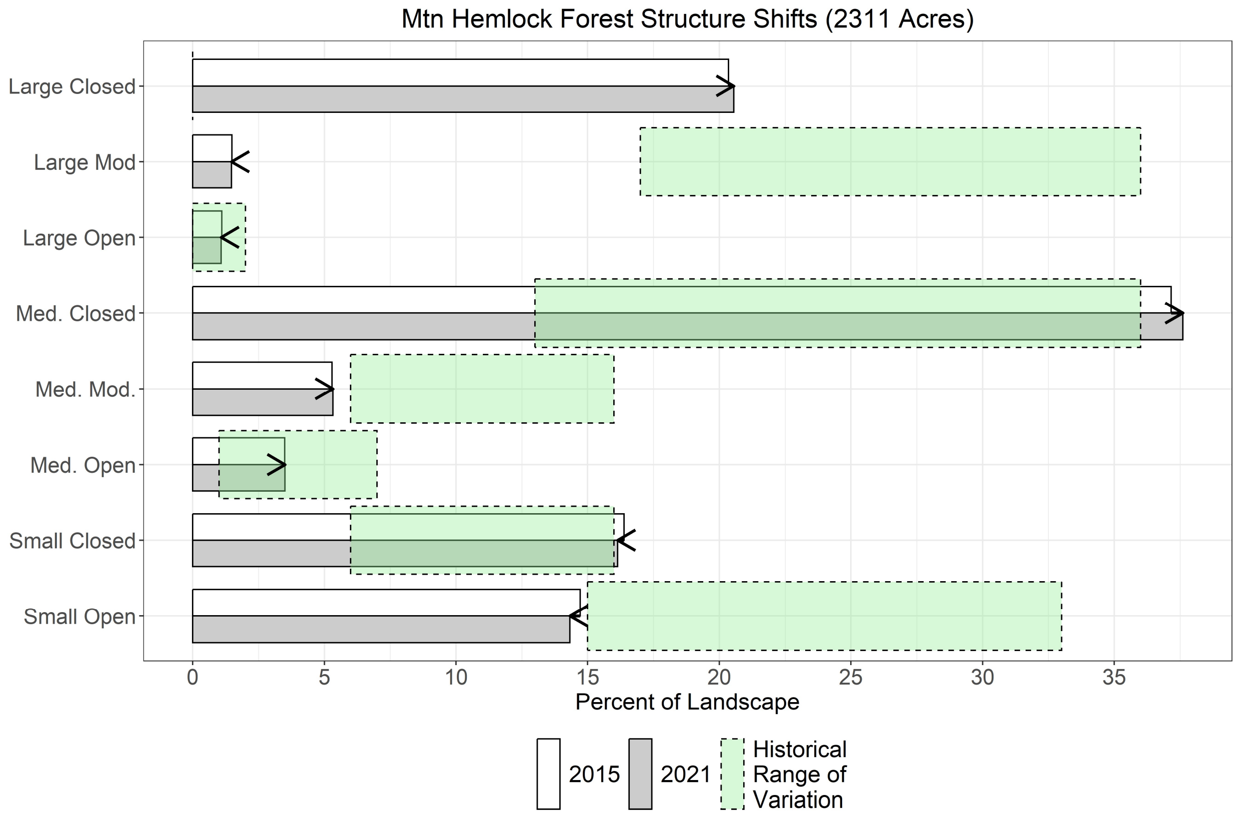


Figure 5. Proportion of Mountain Hemlock forests covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the Cle Elum planning area (green shaded area). The total area covered by Mountain Hemlock forests is shown in the figure title.

2. Glenwood

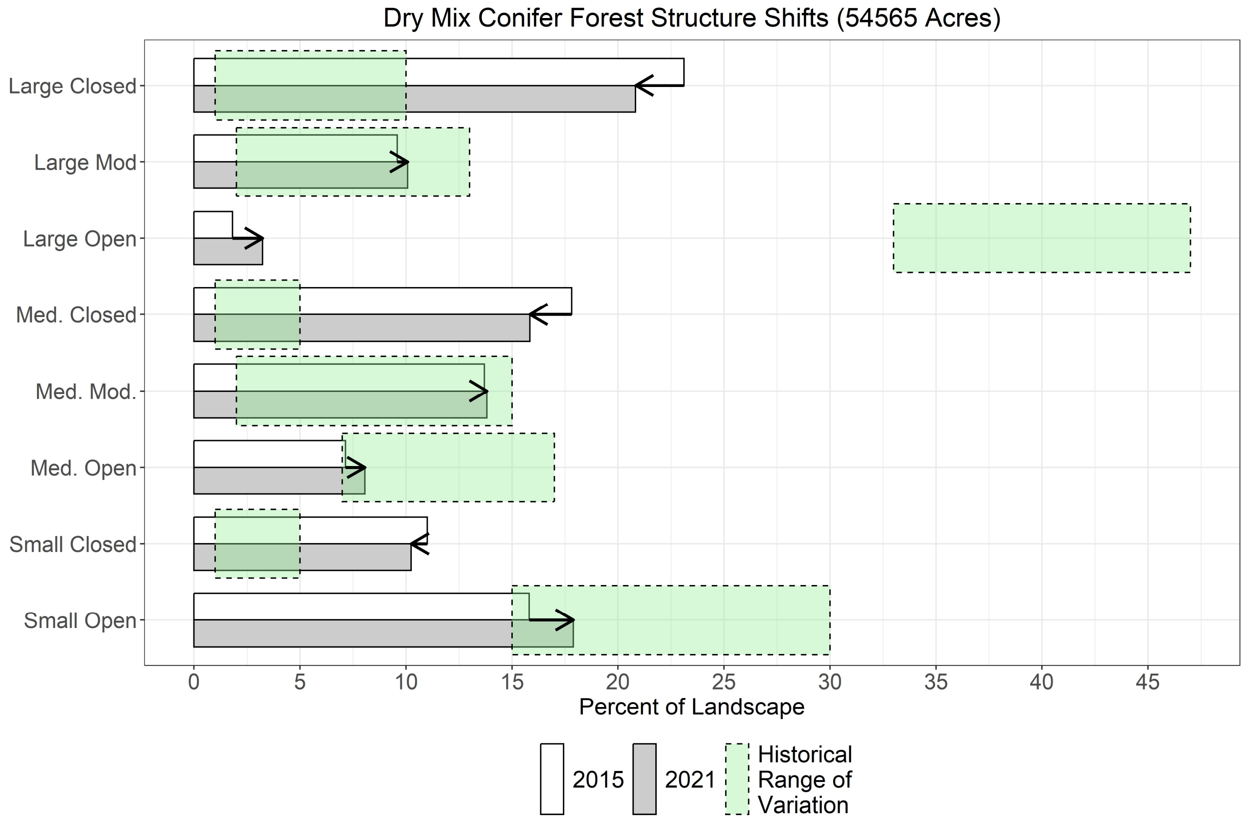


Figure 6. Proportion of dry mixed conifer forests covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the Glenwood planning area (green shaded area). The total area covered by dry mixed conifer forests is shown in the figure title.

Figure 7. Proportion of moist mixed conifer forests covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the Glenwood planning area (green shaded area). The total area covered by moist mixed conifer forests is shown in the figure title.

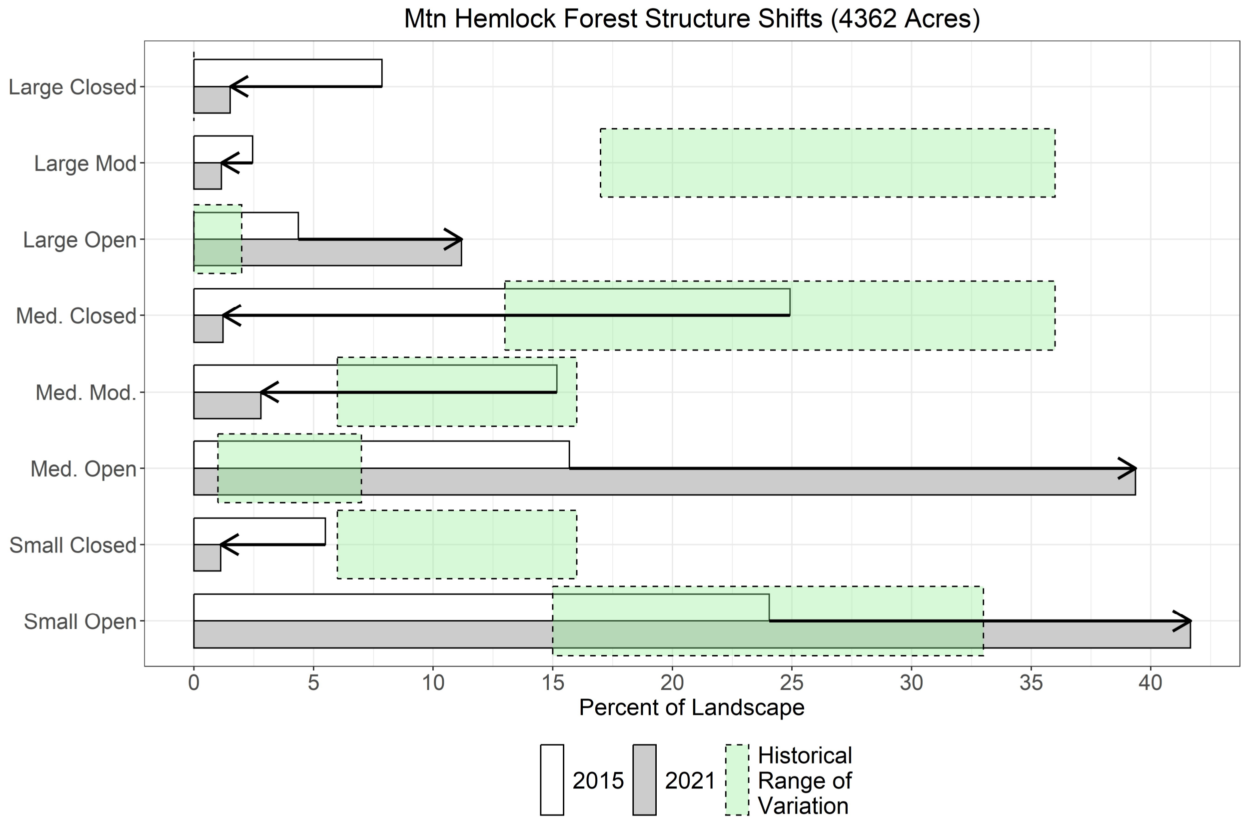


Figure 8. Proportion of Mountain Hemlock forests covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the Glenwood planning area (green shaded area). The total area covered by Mountain Hemlock forests is shown in the figure title.

3. South Fork Mill Creek

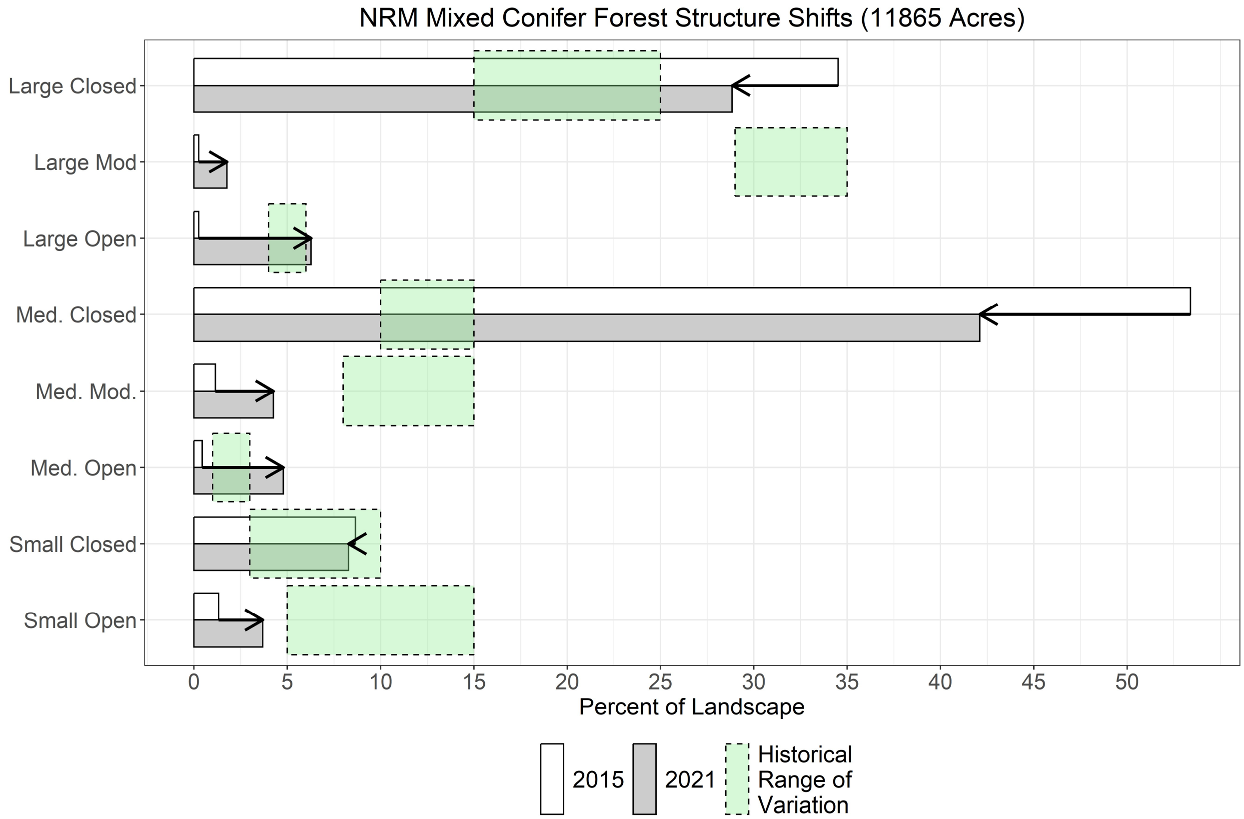


Figure 9. Proportion of Northern Rocky Mountain mixed conifer forests covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the South Fork Mill Creek sub-watershed (green shaded area). The total area covered by Northern Rocky Mountain mixed conifer forests is shown in the figure title.

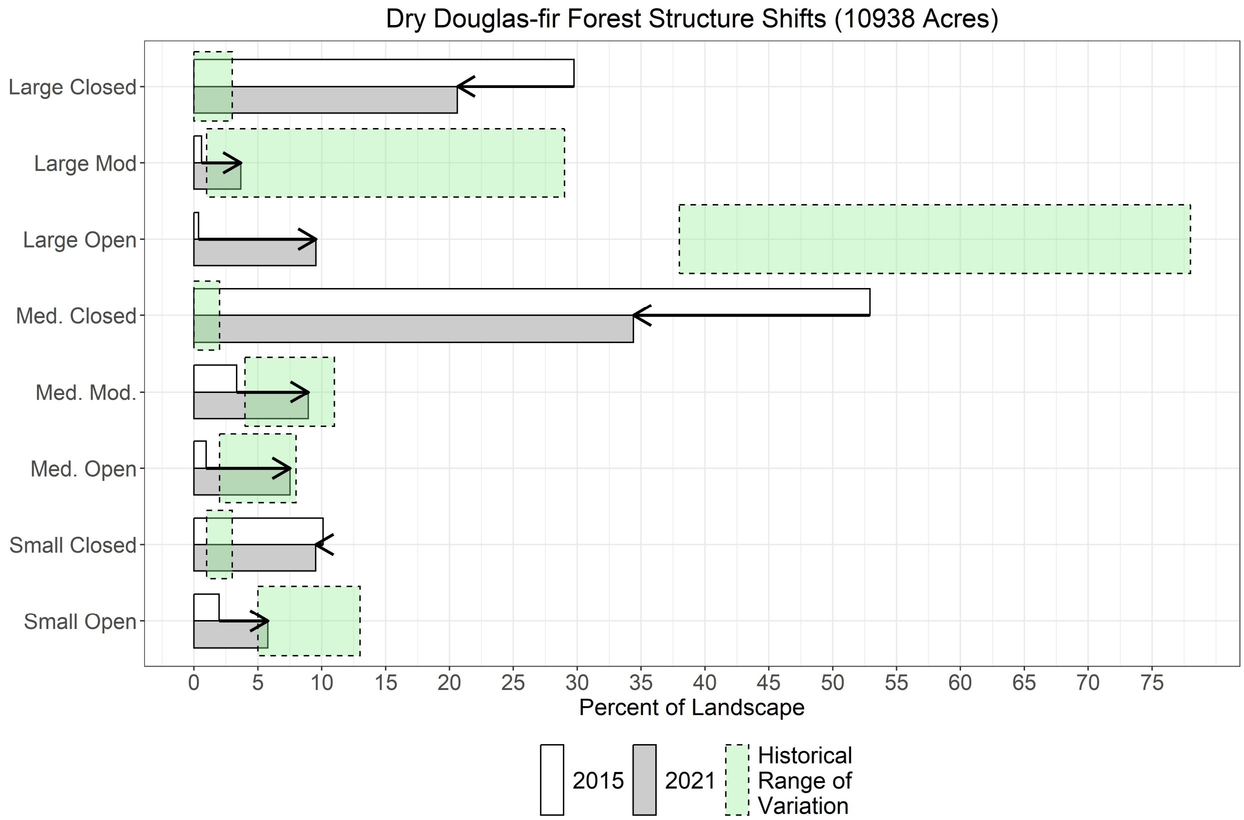


Figure 10. Proportion of dry Douglas-fir forests covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the South Fork Mill Creek sub-watershed (green shaded area). The total area covered by dry Douglas-fir forests is shown in the figure title.

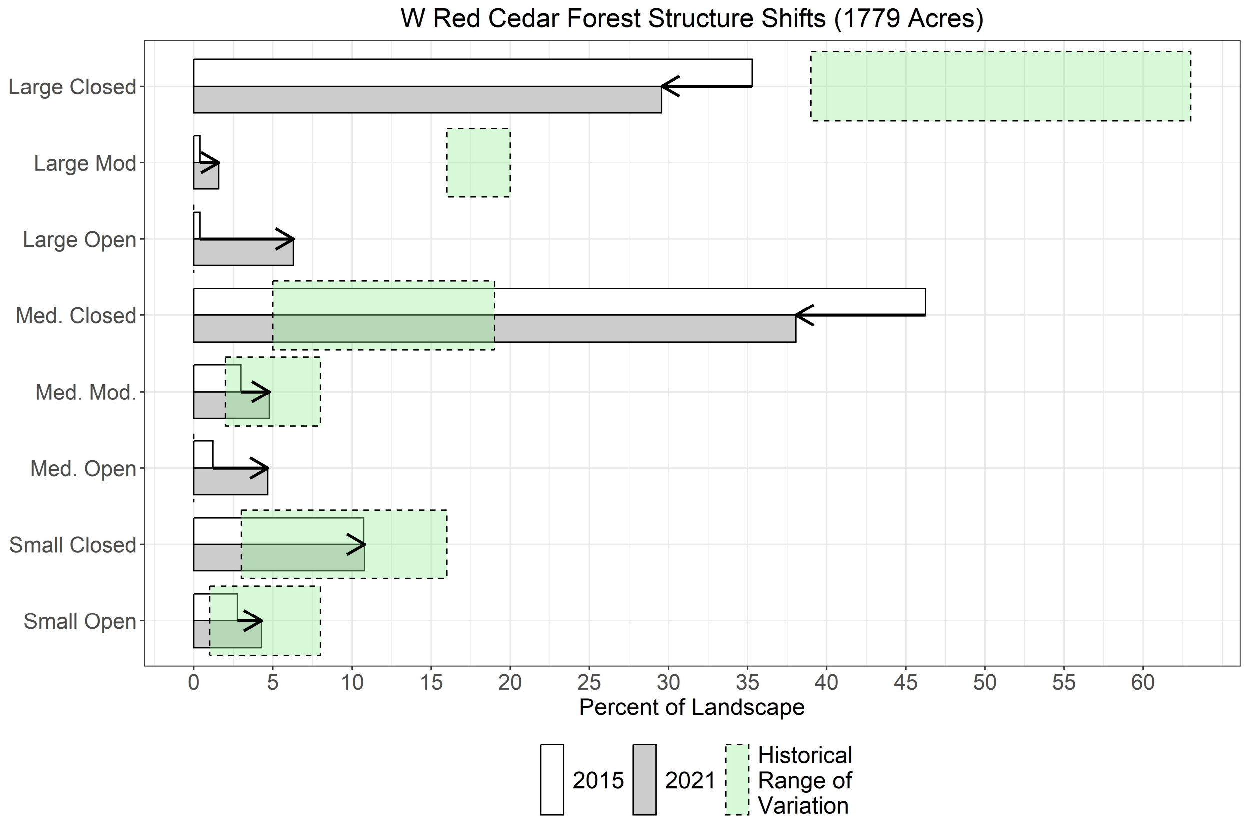


Figure 11. Proportion of Western Red Cedar forests covered by each of the forest structure classes in 2015 (white bars) and 2021 (gray bars), relative to the historical range of variation within the South Fork Mill Creek sub-watershed (green shaded area). The total area covered by Western Red Cedar forests is shown in the figure title.

Appendix H. List of DNR FRD completed and ongoing monitoring projects

Completed or ongoing projects with external partners related to monitoring within the DNR Forest Resilience Division (FRD). Projects with no budget amount listed did not require FRD funding.

<table>
<tr><th>Biennium</th><th>Topic</th><th>Project Lead</th><th>DNR-FRD Funding</th><th>Status and/or Outcome</th></tr>
<tr><td>2024-2025</td><td>Rapid Analysis of Fuel Treatment Effectiveness: Joint Fire Science Program</td><td>Alina Cansler (University of Montana)</td><td></td><td>Project is in early stages</td></tr>
<tr><td>2024-2025</td><td>3P: Design & simulation of treatment scenarios</td><td>Ana Barros (DNR)</td><td></td><td>Project is ongoing</td></tr>
<tr><td>2024-2025</td><td>Improvements in fire severity mapping</td><td>Susan Prichard (University of Washington)</td><td rowspan="2">$157,254</td><td rowspan="2">Project is in early stages</td></tr>
<tr><td>2024-2025</td><td>Drought vulnerability science workshop</td><td>Climate Impacts Group (USFS) & Climate Hub (University of Washington)</td></tr>
<tr><td>2024-2025 & 2022-2023</td><td>Species composition mapping</td><td>Jacob Strunk (USFS)</td><td>$85,000</td><td>Project nearing completion</td></tr>
<tr><td>2024-2025 & 2022-2023</td><td>Treatment monitoring of forest structure, large trees, and pattern using lidar and DAP</td><td>Miles LeFevre & Sean Jeronimo (Resilient Forestry)</td><td>$69,000</td><td>Project nearing completion</td></tr>
<tr><td>2024-2024</td><td>Analyze landscape change from treatments, disturbances, and growth with LiDAR and DAP on the Colville National Forest</td><td>Derek Churchill (DNR) & James Pass (USFS)</td><td></td><td>Project is in early stages</td></tr>
<tr><td>2022-2023</td><td>Social dimensions of 20-Year Plan: Stakeholder/Partner Assessment</td><td>Josh Petit (Socio-Eco Research Consultants)</td><td>$30,000</td><td>Final Report</td></tr>
<tr><td>2022-2023</td><td>Ecological silviculture in frequent fire forests</td><td>Derek Churchill (DNR) & Andrew Larson (University of Montana)</td><td></td><td>Book Chapter</td></tr>
<tr><td>2022-2023</td><td>Landscape effects of wildfire and treatments on snowpack and streamflow</td><td>Paul Hessburg (USFS) & Mark Wigmosta (PNNL)</td><td>$140,000</td><td>Final Report</td></tr>
<tr><td>2022-2023</td><td>Fuels treatment effectiveness in the 2021 Schneider Springs fire</td><td>Van Kane & Alina Cansler (University of Washington)</td><td>$93,580</td><td>Journal article in review</td></tr>
<tr><td>2022-2023</td><td>Improvements to FconstMTT to classify fire severity</td><td>Ana Barros (DNR) & Altura Solutions</td><td>$9,450</td><td>Data products</td></tr>
<tr><td>2022-2023</td><td>Update of WA hazard mapping</td><td>Ana Barros (DNR) & Pyrologix</td><td></td><td>Data products</td></tr>
<tr><td>2022-2023</td><td>Treatment monitoring analysis and report</td><td>Miles LeFevre (Resilient Forestry)</td><td>$39,000</td><td>Reports</td></tr>
<tr><td>2022-2023</td><td>Integrating fire refugia into landscape restoration</td><td>Meg Krawchuk (Oregon State University)</td><td>$30,000</td><td>Online toolbox</td></tr>
</table>

2022-2023	Role of fuel breaks in landscape restoration	Chuck Hersey (DNR)		DNR Report
2022-2023	Literature review of treatment impacts on carbon storage	Keala Hagmann (University of Washington)	$10,000	Final Report
2022-2023	Structure Class monitoring and plot database	Kevin Ceder (Woodland Creek Consulting)	$38,000	Results
2022-2023	Summary of North Central Washington fires and fuelbed emissions analysis	Susan Prichard (University of Washington)	$51,021	StoryMap
2022-2023 & 2020-2021	Comparing contemporary and historical rates of wildfire	Dan Donato (DNR)		Journal Article
2022-2023 & 2020-2021	Fire Generator WA – a spatiotemporal model of fire occurrence and spread – part 1	Ana Barros (DNR) & Haiganoush Preisler (USFS)	$32.100	Data products
2022-2023 & 2020-2021	Logging system and operational feasibility GIS tool	Sean Jeronimo (Resilient Forestry) & Kevin Ceder (Woodland Creek Consulting)	$65,000	Final Report
2022-2023 & 2020-2021	Forest conversion from climate change in the eastern Cascades	Garrett Meigs (DNR)		Journal Article
2022-2023 & 2020-2021	Insect disturbance mapping	Robert Kennedy (Oregon State University)	$70,000	Final Report
2022-2023 & 2020-2021	Effects of treatments on snowpack	Jessica Lundquist (University of Washington) & Susan Dickerson-Lange (Natural Systems Design)	$50,000	Journal Article Final Report
2020-2021	Wildfire transmission by ownership in WA	Ana Barros (DNR) & KingBird Software	$4,960	Data products
2020-2021	Focal wildlife species habitat classification and mapping	Bill Gaines (Washington Conservation Science Institute)	$27,900	Final Report
2020-2021	Forest structure mapping with Digital Aerial Photography	Van Kane (University of Washington)	$93,580	Journal Article in preparation
2020-2021	Fuels treatment longevity	Brian Harvey & Jon Bakker (University of Washington)	$188,000	Journal Article
2020-2021	Assessing restoration need in Eastern Washington	Brian Harvey & Jon Bakker (University of Washington)	$89,000	Journal Article
2020-2021	Mapping species composition	David Bell & Matt Gregory (USFS)	$55,433	Journal Article
2020-2021	Science basis for dry forest restoration and common misconceptions	Susan Prichard & Keala Hagmann (University of Washington)	$10,000	Journal Articles
2020-2021	Plot database and inventory mapping	Luke Rogers (University of Washington)	$143,373	Data Products
2020-2021	Drone monitoring of fuels	Sean Jeronimo (Resilient Forestry)	$38,000	Report
2020-2021	Northern Spotted Owl and Large tree closed forest sustainability	Dan Donato & Josh Halofsky (DNR)		Journal article in preparation
2020-2021 & 2018-2019	Postfire landscape management and treatments	Derek Churchill (DNR), Andrew Larson (University of Montana), & Paul Hessburg (USFS)		Journal Articles