EASTSIDE TIMBER HABITAT EVALUATION PROJECT (ETHEP)

Evaluation of Frameworks for Applying Riparian Harvest Rules Along Type S and Type F Streams in Eastern Washington Based on FPHCP Objectives and Performance Targets: Final Report

Prepared by:

October 2025

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Executive Summary

This report presents results from Phases I and II of the Eastside Timber Habitat Evaluation Project (ETHEP). The purpose of ETHEP was to develop alternative framework(s) to the current Timber Habitat Type (THT) framework for applying riparian harvest rules along Type S (i.e., shorelines of the state) and Type F (i.e., fish-bearing) streams in eastern Washington based on the five riparian functions defined in the Forest Practices rules (WAC 222-16-010), along with the functional objectives and performance targets (Schedule L-1, Appendix N) of the Forest Practices Habitat Conservation Plan (FPHCP) (FPHCP, 2005). ETHEP was performed and conducted under the authority and guidance of the Cooperative Monitoring Evaluation and Research (CMER) Committee. ETHEP was accomplished in two Phases. Phase I involved the appraisal of publicly available datasets and then the development of alternative framework(s) based on the best available data. Phase II involved collecting field data to evaluate the performance of the alternative framework(s) developed in Phase I.

As a part of Phase I, ~~four~~ alternative frameworks were chosen or developed from the best available data. Each alternative framework employed a different method to discriminate forest type categories derived from the Washington State Department of Natural Resources' (WA DNR) 20-year Forest Health Plan (20yFHP map). Some alternative frameworks discriminate forest vegetation cover at a relatively fine resolution (e.g., species and/or species groups), and others aggregate the finer resolutions into broader ecological groupings (e.g., DRY, MOIST, and COLD forest communities). They included:

1. The 20yFHP map – providing an independent mapped alternative to the THT framework at both the fine (6-category) and coarse (3-category) levels of resolution of forest type categories.
2. Machine Learning Map (BRT~~ML Map~~BRT Map) – Fine- and coarse-resolution forest type categories derived from the 20yFHP map and predicted from independent environmental variables.
3. ~~Elevation-based Framework – Coarse-level resolution categories aggregated from the 20yFHP map, discriminated by elevation zones within each ecoregion.~~
4. ~~Precipitation-based Framework - Coarse-level resolution categories aggregated from the 20yFHP map, discriminated by mean annual precipitation zones within each ecoregion (defined in methods).~~

In Phase II, each alternative framework was evaluated for its accuracy and usefulness relative to the THT. Accuracy was assessed using error matrices that compared the framework-based classification of forest type categories to classifications based on the collection and analysis of detailed forest cover and site characteristics observed in the field at 88 sites randomly selected along Type S and F streams in eastern Washington, as regulated by Washington Forest Practice Rules. Usefulness was qualitatively assessed based on the framework's relationship between forest type categories and riparian function (evaluated in Step 2 of Phase II). Specifically, the final framework will contain the most parsimonious groupings of forest type categories as they relate to their expected functional relationships.

The alternative framework showing the greatest improvement over the THT framework was the 20yFHP map at the coarse resolution of forest type categories. Three forest type categories were delineated—DRY, MOIST, and COLD—which are comparable to the three THT categories—Ponderosa Pine, Mixed Conifer, and High Elevation, respectively—in terms of their riparian function. The mapping of the distribution of these 20yFHP map coarse forest type categories, however, was substantially improved relative to the THT equivalents.

The 20yFHP map showed error percentages of 19%, 22%, and 50% for the DRY, MOIST, and COLD forest type categories, respectively, with an overall error rate of **22%** when evaluated with the observed field site classifications. The ~~ML Map~~BRT Map framework showed error percentages of 21%, 41%, and 50% for the DRY, MOIST, and COLD forest type categories, respectively, and an overall error rate of **30%**. The THT framework yielded error percentages of 34%, 25%, and 75% for the crosswalk 20yFHP map forest type categories, corresponding to DRY = Ponderosa Pine, MOIST = Mixed Conifer, and COLD = High Elevation, respectively, with an overall error rate of **33%** when evaluated against the observed field site classifications.

~~The elevation- and precipitation-based frameworks had varying aggregations of forest type categories (e.g., low elevation zones predict a ponderosa pine or dry mixed conifer type) depending on the ecoregion. aggregations for these frameworks did not always follow the DRY, MOIST, COLD categories. For example, the spruce-fir category (COLD) aggregated with the moist mixed conifer (MOIST) category in the East Cascades. This was because the thresholds for each forest type category, as well as their aggregation or separation, were determined through statistical analysis of their distinct distributions. The elevation-based framework exhibited error percentages of **17%, 33%, 32%, and 30%** for each of the four ecoregions Blue Mountains, East Cascades, Columbia Plateau, and Northeast (Okanogan and Canadian Rocky Mountains combined), respectively. The precipitation-based framework exhibited error rates of **53%, 57%, 29%, and 14%** across those same ecoregions. These results were mixed when compared to the THT framework performance (33%, 39%, 35%, 28% for each of the four ecoregions, respectively).~~

In summary, the~~ three~~ alternative framework~~s~~ we developed (~~ML Map~~BRT Map)~~, elevation-based, and precipitation-based)~~ performed as well or better than the THT, but did not perform as well as the 20yFHP map, based on our accuracy assessment in Step 2 of Phase II. The ~~ML Map~~BRT Map framework fine variant (6-categories) did not discriminate dry and moist forest type categories very well, and the coarse variant (3-category), while performing better than the THT framework, did not perform as well as the 20yFHP map (Appendix III Confusion matrices). ~~The Elevation- and Precipitation-based frameworks, both derived from the 20yFHP map, had poorer accuracy than the ML Map framework; nevertheless, they still showed improvement over~~

the THT framework in some ecoregions. However, the frameworks using elevation or precipitation breaks tended to aggregate fine forest type categories with widely varying riparian function (based on our results of modeled stand development over time); thus, neither framework was as useful as the 20yFHP map or the current THT framework.

We identified several pertinent future directions, including improving the ML MapBRT Map through additional field data collection and independent verification of the 20yFHP map. The ML MapBRT Map was trained on millions of data points, using the 20yFHP map as the dependent variable and environmental variables as independent variables. Although we attempted to calibrate the ML MapBRT Map with collected field data, the relatively small sample size compared to the much larger training sample siz, the relatively small sample size compared to the much larger training sample did not improve the map's accuracy. (Appendix II). We considered supplementing our field data with a pre-existing, publicly available dataset of stand-level field data (Eastern Washington Riparian Assessment Project; from the Eastern Washington Riparian Assessment Project (EWRAP). However, the site locations were not evenly distributed throughout the conditions we identified as important factors for predicting forest type categories. Further, the methods used for data collection in EWRAP (e.g., 240 ft transects) meant the transects crossed multiple conditions at several locations. Finally, the field protocols of EWRAP collected site factors (e.g., slope, aspect, elevation) at a coarser resolution than what was used for our field protocols. Thus, we ultimately decided that the EWRAP data had a limited scope of inference for our assessment analysis. Thus, the ML MapBRT Map framework has the potential for improvement with the collection of more field data. Furthermore, to the best of our knowledge, WA DNR has not conducted an accuracy assessment of the mapped 20yFHP map forest type categories. Since this analysis treated the 20yFHP mapped forest types as "truth" (the dependent variable), we recommend a more robust evaluation of its accuracy.

Introduction

This report presents results from Phases I and II of the Eastside Timber Habitat Evaluation Project (ETHEP). ETHEP is seeking to develop framework(s) for applying riparian harvest rules along Type S (i.e., fish-bearing streams that are also classified as shorelines of the state) and Type F (fish-bearing) streams in eastern Washington that are based on the Forest Practices Habitat Conservation Plan (FPHCP 2005) objectives and performance targets. The project was conducted under the authority and guidance of the Scientific Advisory Group Eastside (SAGE), a subgroup of the Cooperative Monitoring, Evaluation, and Research (CMER) Committee, and it addresses Eastside Type F Riparian Rule Tool Program research needs presented in the 2025-2027 Biennium CMER Work Plan. This report describes the implementation of the *Study Design to Evaluate Frameworks for Applying Riparian Harvest Rules Along Type S and Type F Streams in Eastern Washington Based on FPHCP Objectives and Performance Targets* (Spei et al. 2023).

Background

Washington's current Forest Practices Rules in eastern Washington use a Timber Habitat Type (THT) system to determine the application of riparian rule prescriptions along Type S and Type F streams (WAC 222-30-022). This system defines THTs according to three elevation zones: <2500 feet (nominally, "Ponderosa Pine"), 2500-5000 feet ("Mixed Conifer"), and >5000 feet ("High Elevation"). The riparian harvest rules specify different leave tree requirements for each THT. For instance, thinning of the riparian management zone within Mixed Conifer (2500 – 5000 feet) habitat type requires a higher minimum basal area (70 – 110 square feet per acre, depending on site index) compared to the Ponderosa Pine (< 2500 feet; 60 square feet per acre regardless of site index) habitat type. Other rules for preferred species and tree distributions are further described in the WAC 222-30-022. Though developed prior to the FP~~C~~HCP, the THT system reflects that potential riparian function—a metric by which to gauge restoration and maintenance of riparian habitat (and FP~~C~~HCP objective)—differs among forest stands as represented by these nominal forest type categories.

While the current application of THTs relies on elevation alone to reflect the dominant riparian forest vegetation, a previous CMER study indicated that elevation zones alone do not fully identify differences in riparian forest vegetation. Phase II of the Eastern Washington Riparian Assessment Project (EWRAP; Schuett-Hames, 2015) determined the reclassification of potential late successional or climax species for 103 riparian sites in eastern Washington using the classification criteria established by Cooper et al. (1991) and Kovalchik and Clausnitzer (2004). They found that the distribution of riparian forest vegetation does not necessarily align with the predominant species suggested by the THTs. Ceder et al. (2020) evaluated the effectiveness of the Forest Practice Rules using the same EWRAP data set. They found there was considerable overlap in riparian vegetation conditions among THTs, which also supports the premise that elevation is likely not a reliable surrogate in determining dominant forest vegetation~~stand type~~, and thus in determining the silvicultural prescriptions necessary to support riparian functions.

The shortcoming of using elevation alone is acknowledged elsewhere in the literature. Franklin and Dyrness (1973) cautioned that the use of a zonal classification scheme (e.g., THTs) should consider several caveats regarding riparian zones:

> "Zones may occur as sequential belts on mountain slopes, but more often they interfinger, with each attaining its lower elevational limits in valleys and its highest limits on ridges; as a consequence, the zones along the slopes of a narrow valley can be reversed from their otherwise altitudinal relationship."

Similarly, in an analysis of landscapes of northern Idaho and eastern Washington, Daubenmire (1980) concluded that microclimates controlled by topographic features allow vegetation characteristic of subalpine environments to descend locally to very low altitudes, and vice versa (Figure 1). Overall, though it seems reasonable to identify three coarse vegetation types—Ponderosa Pine, Mixed Conifer, and High Elevation—among which riparian functions would reasonably be expected to differ, the use of elevation alone does not entirely describe the differences in riparian vegetation found across eastern Washington.

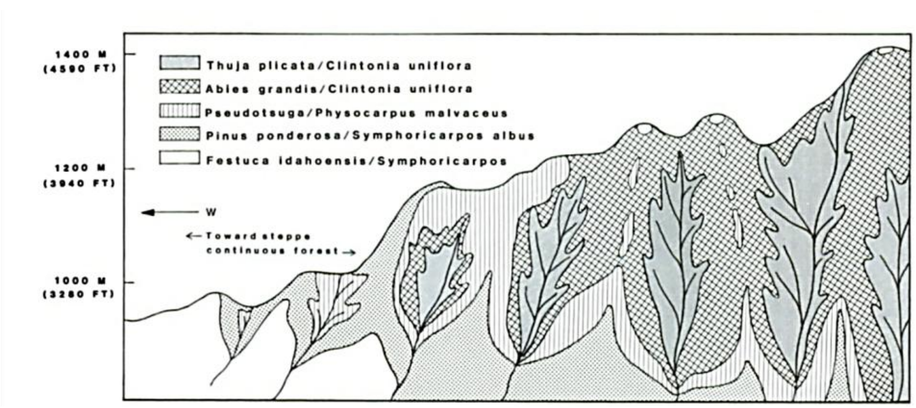

Figure 1. Diagrammatic representation of habitat type and topography relationships on a southern facing slope of the Palouse Range in Eastern Washington. Taken from Daubenmire 1980. The vegetation groups listed in order from top to bottom: Thuja plicata/Clintonia uniflora, Abies grandis/Clintonia uniflora, Pseudotsuga/Physocarpus malvaceus, Pinus ponderosa/Symphoricarpos albus, Fastuca idahoensis/symphoricarpos.

Purpose

The purpose of ETHEP was to develop alternative frameworks (to the THT system) for applying riparian harvest rules along Type S and Type F streams in eastern Washington based on the functional objectives and performance targets (Schedule L-1, Appendix N) of the Forest Practices Habitat Conservation Plan (FPHCP, 2005). The five "key" riparian forest functions specified in the FPHCP include "large woody debris recruitment, sediment filtration, stream bank stability, shade, litterfall and nutrients, in addition to other processes important to riparian and aquatic systems." For this study, a framework is generally defined as a system that can be used to inform and guide management prescriptions that support the goals and objectives of the FPHCP (the current THT system is one example). Such alternative framework(s) could improve on the current THT system.

Objectives

ETHEP was guided by a scoping document approved by SAGE, CMER, and the Timber Fish and Wildlife Policy Committee (Policy) (2021). The scoping document identified two objectives:

1. Develop a framework for applying riparian harvest rules in eastern Washington based on the FPHCP functional objectives and performance targets (Schedule L-1, Appendix N).

2. Test the framework(s) for characterizing eastside riparian forests using data collected in the field.

From these objectives, ETHEP sought to answer four critical questions, also outlined in the scoping document:

Objective 1:

1. What type and quality of data are needed to accurately characterize and differentiate riparian stands, their development in eastern Washington, and their associated riparian functions?

2. Do existing datasets (alone or in combination) provide the necessary information to accurately characterize and differentiate riparian stands, their development, and associated riparian functions?

3. If existing datasets do not provide the necessary information to differentiate riparian stands, their development, and associated riparian functions, how can this additional information be acquired and utilized?

Objective 2:

4. Does the framework accurately characterize riparian forests in the field based on characteristics important for meeting FPHCP functional objectives and performance targets?

The study design (Spei et al. 2023) laid out procedures and methods for addressing these questions in two phases (Figure 2). Phase I addressed Objective 1 and involved three steps that provided information for answering the first three critical questions. Phase II addressed Objective 2 and involved two steps that provided information for answering the fourth critical question.

Step 1 of Phase I entailed a desktop analysis of publicly available datasets that evaluated their ability to characterize site, vegetation, and landscape features. Step 2 of Phase I involved the development of alternative classification frameworks, based on data deemed useful in Step 1, using multiple classification methods. Step 3 of Phase I sought to assess and refine alternative classification frameworks using simulation modeling. Step 1 of Phase II entailed field data collection to assess alternative classification frameworks developed in Phase I and to fill data gaps (e.g., data to support simulation modeling). Step 2 of Phase II entailed validating the frameworks developed in Phase I and refining those alternative classification frameworks.

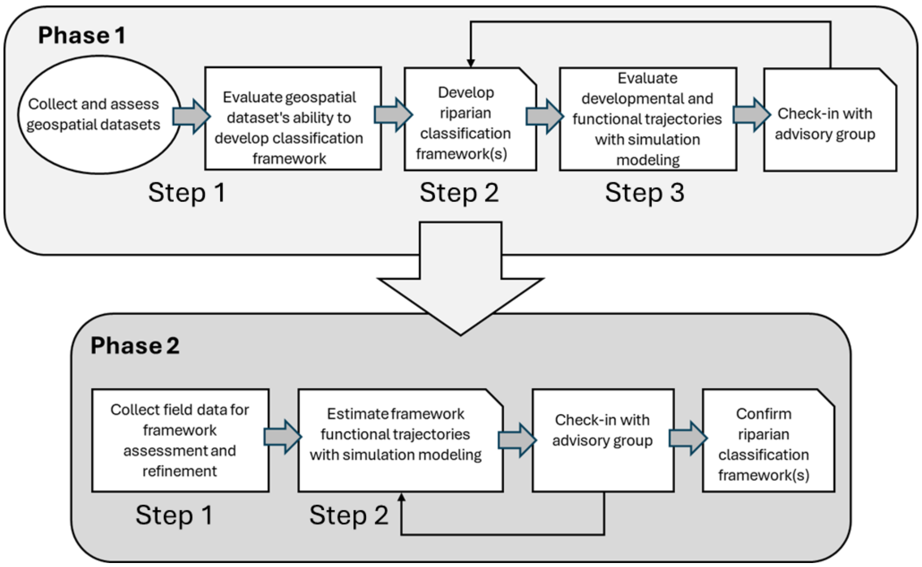

Figure 2. Flow chart representation of each Phase and Step of the proposed study design from Spei et al. 2023.

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Study area

Existing data sets were used to derive a geospatial data layer representing riparian areas along streams classified as Type F or Type S by the WA DNR Hydrography Watercourses Forest Practices Regulation stream layer (hereafter referred to as the WA DNR Hydro layer). This includes both Private Lands and State Lands that are subject to the WA DNR Forest Practice Application Process. Type F and Type S streams were extracted from the publicly available WA DNR Hydro layer. The extracted streams were clipped to exclude reaches within federal and tribal lands as mapped in the parcel ownership data layer retrieved from the WA DNR website. Finally, the layer was further clipped to include only reaches along forested landscapes as mapped in the LANDFIRE, LEMMA, and 20-year Forest Health Plan datasets (described in Phase I, Step 1). The LANDFIRE, LEMMA, and 20-year Forest Health Plan datasets contain predictive maps with expected vegetation types (LANDFIRE), modeled individual tree species coverage (LEMMA), and expected forest types (20- year Forest Health Plan datasets).

The resulting study area covers approximately 4,500 miles of Type F and Type S stream length across Bailey's five ecoregions (Table 1; Figure 3). Over three-fifths of the study area occurs in the Okanogan Highlands and East Cascades; the Columbia Plateau and the Canadian Rockies each contain about 15%; and less than 5% occurs in the Blue Mountains. Nearly all the study areas occur within the Ponderosa Pine and Mixed Conifer THTs, split about 60/40 between the two types, respectively. The High Elevation category contains only approximately 0.01% of FPA managed stream length.

Table 1. Estimated stream lengths (mi) for each THT category within each of the five Bailey's ecoregions on lands potentially subjected to timber harvest rules defined in the Forest Practices Act (FPA) based on the WA DNR Hydro layer. Stream length was estimated by clipping the WA DNR Hydro layer by Bailey's ecoregion and then by THT regulatory zone (based on elevation). The resulting length of each section was calculated in ArcGIS Pro.

Timber Habitat Type (THT)	Okanogan	East Cascades	Columbia Plateau	Canadian Rockies	Blue Mountains	Total
Ponderosa Pine	913	641	574	317	66	2,511
Mixed Conifer	619	571	224	383	145	1,942
High Elevation	34	17	0	1	0	51
Total	1,566	1,228	798	701	211	4,504

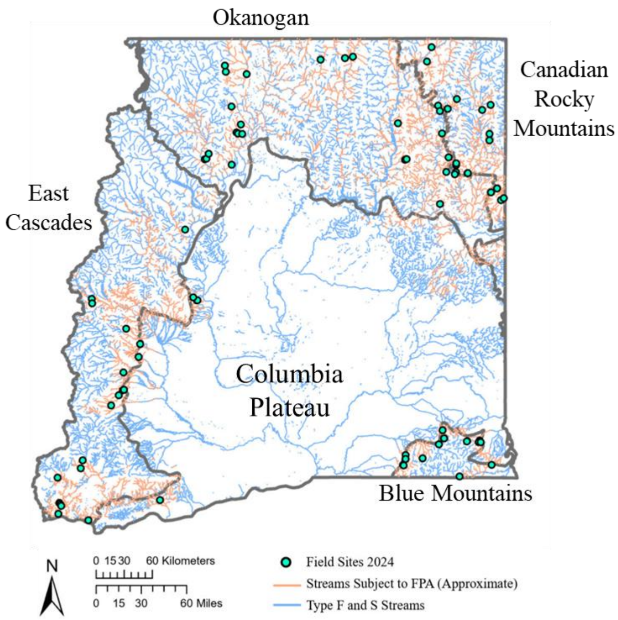

Figure 3. Study Area. Study sites were selected from lands subject to the Washington State Forest Practices Rules defined by the FPHCP; FPA includes riparian forest stands along Type S and Type F streams (fish-bearing) in eastern Washington (east of the Cascade Crest) that have the potential to be harvested under WAC-222-30-022. Sampling sites, shown in blue, were selected from Bailey's Ecoregions: East Cascades, Okanogan, Canadian Rocky Mountains, Columbia Plateau, and Blue Mountains ecoregions. Streams colored in blue represent all mapped Type F and S streams in eastern Washington. Streams colored orange represent all streams within the study area (i.e., streams with adjacent forested areas that have the potential to be harvested under WAC-222-30-022) Streams colored orange represent Type F and S streams within the study area with adjacent forested areas that have the potential to be harvested under WAC-222-30-022.

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Phase I

Step 1: Appraisal of Available Datasets

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Available Datasets

We evaluated 12 geospatial datasets that contained tree species and/or productivity information:

- Forest Inventory and Analysis BIGMAP Tree Species Aboveground Forest Biomass (FIA BIGMAP). FIA's cloud-based national scale modeling, mapping, and analysis environment for US forests produced by the USDA Forest Service. FIA uses an annualized sample of over 350,000 plots distributed across the United Stateslandscape to provide information on the status and trends of the Nation's forest resources. (Last updated 2019, Datasets not listed in the ETHEP study design)

- Ecological Classification of Native Wetland and Riparian Vegetation of Washington (ECNW). (Rocchio and Crawford, Washington Natural Heritage Program, *in progress*). Developed by NatureServe to provide a mid-scale ecological classification for uplands and wetlands, which is useful for conservation and environmental planning. Ecological Systems represent recurring groups of terrestrial plant communities found in similar climatic and physical environments and are influenced by similar dynamic ecological processes, such as fire or flooding, share similar substrates, and/or environmental gradients. (Last updated 2024)

- Ecological Systems of Washington (ESW) Produced by NatureServe and the Washington Natural Heritage Program (Rocchio and Crawford 2015). Terrestrial ecological systems concepts form the basis for three map products from the inter-agency Landfire effort: 1) Existing Vegetation Type (EVT); i.e., the current location of vegetative components of each terrestrial ecological system is mapped in that layer. 2) Environmental Site Potential (ESP) is a spatial model of environments that constrain the possible locations where a given ecological system could occur, without including natural disturbance regime as a factor. 3) Biophysical Settings (BpS) provides another spatial model depicting the probable location of each ecological system type, assuming the inclusion of natural disturbance regimes as a factor. (Last updated 2019)

- Forest Biomass geospatial dataset (USDA Forest Service). A spatially explicit dataset of aboveground live forest biomass made from ground measured inventory plots for the conterminous U.S., Alaska and Puerto Rico. The plot data are from the USDA Forest Service Forest Inventory and Analysis (FIA) program. To scale these plot data to maps, models were developed relating field-measured response variables to plot attributes serving as the predictor variables. Among the predictor layers used were digital elevation models (DEM) and DEM derivatives; Moderate Resolution Spectroradiometer (MODIS) multi-date composites, vegetation indices and vegetation continuous fields; class summaries from the 1992 National Land Cover Dataset (NLCD); various ecologic zones; and summarized Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate data. (Last updated 2018)

- Individual Tree Species Parameter Maps (ITSP) (USDA Forest Service). The Individual Tree Species Parameter Maps were developed to support the National Insect and Disease Risk Map (NIDRM). Basal area and stand density index are mapped for each individual tree species. The parameter products are based on 30-meter Landsat satellite data, climate, terrain, and soil predictor layers and ground samples from the USFS Forest Inventory and Analysis plot data. (Last update 2012)

- Landscape Ecology, Modeling, Mapping, and Analysis (LEMMA) dataset produced by the USDA Forest Service, Pacific Northwest Research Station, and the Department of Forest Ecosystems and Society at Oregon State University (OSU) (e.g., Ohmann and Spies 1998, Ohmann et al. 2011). The gradient nearest neighbor (GNN) was used to develop quantitative maps of forest vegetation based on imputations of numerous attributes (e.g., species, density, basal area, canopy cover, height, diameter) collected by the Forest Inventory and Analysis data program. (Last updated 2017)

- Maps of Specific Forest Plant Species and Climate Profile Predictions (MSFP) (USDA Forest Service). Contains three generations of climate surface models developed using 1961 to 1990 climate normals—access to ancillary datasets used in modeling. Models contain predictions for species range changes based on multiple emission scenarios. (Last updated 2024)

- Maximum Stand Density Index models (MSDIM) developed by the University of Idaho (UofI) Intermountain Forestry Cooperative (Kimsey et al. 2019). In these models, the maximum stand density index was fit with stochastic frontier regression using stand density (trees per hectare) as the dependent variable, quadratic mean diameter (QMD) as the independent variable, and site factors (e.g., soil, topography, climate) as covariates. Provides access to multiple climate, soil, and topographic variables. (Last updated 2025)

- Modeled Potential Vegetation Zones (MPVZ) of Washington and Oregon and Modeled Plant Association Groups (MPAG) of Washington and Oregon were produced by the USDA Forest Service and hosted by Ecoshare, the Interagency Clearinghouse for Ecological Information. The site includes analytical tools, publications, data sets, code sets, GIS data/maps, digital imagery, and educational opportunities and materials. (Last updated 2010)

- ~~Public data for the 20-year Forest Health Strategic Plan (20yFHP): Eastern Washington~~Public data for the 20-year Forest Health Strategic Plan (20yFHP): Eastern Washington (Washington Department of Natural Resources); https://bit.ly/ForestHealthData. Landscape evaluations conducted for priority planning areas across central and eastern Washington. Access to 1) Key information for each planning area, including landscape evaluation summaries, presentation slides, and datasets. 2) Maps and spatial data covering eastern Washington. 3) Data documentation and methods. 4) Reports and documents related to each planning area and the 20-year plan. (Last updated 2023)

- Site Potential Tree Height Public (MapServer) (wa.gov) Statewide riparian site potential tree height map produced for priority habitats and species by the Washington State Department of Fish and Wildlife (WDFW). (Date of last update unknown)

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- [TreeMap, a tree-level model of conterminous US forests circa 2014 produced by imputation of FIA plot data | Scientific Data (nature.com)](). Continuous raster of tree cover produced by the USDA Forest Service. The values associated with the raster contain unique identifiers of Forest Inventory Analysis (FIA) plots. Plots are identified in a supplemental table containing codes for individual tree species within each plot. (Last updated 2014)

Acronyms listed in parentheses define the source of each dataset. Oregon State University (OSU), United States Department of Agriculture (USDA), University of Idaho (UofI), United States Forest Service (USFS).

Of these geospatial datasets, we asked three questions:

1. Does the dataset differentiate between riparian and upland forest types?
2. Does the data set cover lands managed under FPA (Forest Practice Act)~~ ~~?
3. Does the data set offer adequate resolution (i.e., mapped pixel resolution 40 m or finer, size distinguishes a regulatory buffer zone)?

In the study design, we also proposed ~~to use~~using available stand-level data in simulation modeling (e.g., FVS, SHADE.xls). This involves evaluating not only distinctions in dominant riparian forest vegetation but also evaluating distinctions in associated riparian function (e.g., shade, large wood recruitment).~~ to evaluate whether forest type categories develop and maintain their distinction over time and to evaluate relationships between stand development and riparian function (e.g., shade, LW). This exercise was separate from the geospatial dataset appraisal described above.~~ These data were appraised for their potential to be used in Step 3 of Phase I: the refinement of the preliminary classification frameworks (developed in Step 2, Phase I), using simulation modeling. We evaluated five stand-level datasets for this purpose:

- PacFish/InFish Biological Opinion Monitoring Program (PIBO MP; USFS)
- Forest Inventory and Analysis (FIA)
- Landscape Fire and Resource Management Planning Tools (LANDFIRE) (USDA)
- Eastern Washington Riparian Assessment Project (EWRAP) Phase 1 (Bonoff et al. 2008)
- Forest Resource Information System (FRIS; WA DNR)*

*Datasets not originally listed in the experimental design.

On these, we considered four questions:

1. Does the dataset differentiate between riparian and upland forest stands?
2. Does the data set cover lands managed under FPA?
3. Does the data set offer adequate resolution (i.e., define characteristics at a scale within the regulatory zone: 75-130 feet)?
4. Does the dataset support use in simulators (e.g., Forest Vegetation Simulator, Shade.xls)?

These questions are derived from ~~ask and answer~~ the first two Critical Questions—briefly, what type of data are needed to characterize riparian stands, and do existing datasets fulfill this need? These questions were developed explicitly from the attributes identified in the study plan as important for classification development (Spei et al., 2023). They include coverage, scale/resolution, and types of data needed (e.g., topography, climate, soil characteristics, and vegetation descriptions).

Data Suitability

Of the 12 geospatial vegetation datasets we evaluated, only one—the 20-year Forest Health Strategic Plan: Eastern Washington (20yFHP map) dataset from the Washington State Department of Natural Resources (WA DNR) —answered in the affirmative for all three questions (Table 2). In this data set, forest type mapping was conducted at several levels of aggregation. The other datasets fell short for various reasons. Several datasets—LEMMA, TreeMap, and ITSP—provided detailed depictions of stocking by species at the pixel level from which we considered the possibility of deriving forest type categories; however, they provided either limited coverage of the study area / or were too coarse (i.e., >40 m resolution) for our application. Nevertheless, they show general agreement among each other where coverage within the study area overlapped (Table 2). ESW, MPVZ, and BigMap mapped forest types, but classifications were not specific enough to be of practical use; ECNW and LANDFIRE mapped riparian areas only generally; MSFP mapped forest types but provided no coverage at all within the study area; and the remaining datasets provided ancillary data for classification. The MSDIM dataset did not contain useful vegetation cover.

We chose to move forward with the 20yFHP map not only as an alternative framework itself but also to use to explore additional alternative framework development (Phase I, Step 2). We chose to move forward with the 20yFHP map to explore alternative framework development (Phase I, Step 2). The 20yFHP map was the only dataset that contained delineated using forest types at multiple scales, that had complete coverage of the study area, andarea, and was mapped at a resolution within which riparian areas could be distinguished (30 m x 30 m). The 20yFHP map vegetation type layers were constructed using two versions of Potential Vegetation Type (PVT) data from the Integrated Landscape Assessment Project (ILAP) for forested areas (BurcsuHalofsky et al. 2014). The current version of the 20yFHP map PVTs includes an update of different plant association groups from Henderson ("Henderson's update"; WA DNR 2020). Especially relevant to our objectives, this map includes an updated forest mask that identifies forested areas and their vegetation types in FPA managed areas identified as "non-forest" or "no data" in the federal datasets we appraised and investigated (Table 2). Further, while riparian forests are not specifically delineated or designated as "riparian forests," the 30 m x 30 m resolution is a fine enough resolution that shows expected riparian forest types (e.g., western redcedar). Indeed, the mapped forest categories show variation that follows riparian areas with differences and transitions into different forest types with increasing distance from the stream (see Figure S6).An added benefit of using the 20yFHP map is it is currently in use for forest health assessment and management by the WA DNR forest managers in eastern Washington.

The specific methods used for generating forest type predictions (i.e., PVTs), delineations, and groupings in the 20yFHP are, however, unclear. The methods are described in BurcsuHalofsky et al. (2014) as "dynamic", utilizing a combination of modeling systems as well as "expert opinion" where data wasere lacking. We were also unable to find any formal evaluations or accuracy assessments of the 20yFHP map. Thus, framework development from the 20yFHP data will first require investigation into how these groups distribute across the study area and their relationship

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Of the stand-level datasets, none answered in the affirmative for all four questions (Table 2). Three of the five datasets provided some coverage of FPA-managed lands—EWRAP, FRIS, and FIA (Table 2). Each provides detailed tree information that could be used to discern forest type categories and to inform simulators. However, none provided comprehensive coverage of FPA-managed lands. Because of the limited sample size, EWRAP did not cover the range of elevation, moisture, and temperature regimes encountered on FPA-managed lands cover all conditions covered by the Step 2 frameworks. Similarly, the FRIS dataset, though of similar data quality, where it was collected, only covered DNR lands and did not cover all riparian conditions covered by the Step 2 frameworks. And, though the FIA dataset was of similar quality as EWRAP and FRIS, exact plot locations are not publicly availabledegraded, and we could not discern plots in riparian areas nor FPA management. The remaining stand datasets—LANDFIRE and PIBO—were located on federal lands and, therefore, are unrepresentative. .

Table 2. Answers to the four screening questions used to gauge the suitability of each geospatial and stand-level dataset in forest habitat mapping and framework building. Areas highlighted in green indicate that the criteria for inclusion were met.

Geospatial Datasets

Source	Q1. Forest types mapped	Q2. % Study area covered	Q3. Resolution
20-year Forest Health Strategic Plan Eastern Washington (20yFHP map; version February 2023)	Forest types mapped: Dominant conifer species; species groups; and relative moisture and temperature categories (i.e., DRY, MOIST, COLD). Riparian areas are not explicitly delineated.	100	30 m
BIGMAP	Forest types mapped: Continental species groups. Limited to lands classified as forests by the federal database. Riparian areas not delineated.	50	30 m
Ecological Classification of Native Wetland and Riparian Vegetation of Washington (ECNW)	Forest types are not mapped in the study area.	100	Large polygons
Ecological Systems of Washington (ESW)	Forest types mapped: Plant association groups. Riparian areas are not explicitly delineated	100	30 m
Forest Biomass Geospatial Dataset (Forest Biomass)	Forest types are not mapped. This data set depicts modeled projections of forest biomass	50	250 m
Individual Tree Species Parameter Maps (ITSP)	Forest types are not mapped. However, basal area per acre by tree species is calculated for each pixel permitting forest typing. Riparian areas not explicitly delineated.	100	240 m
Landscape Ecology, Modeling, Mapping, and Analysis (LEMMA)	Forest types mapped: Predominant species/groups; however, basal area per acre by tree species is calculated for each pixel permitting forest typing. Limited to lands classified as forests. Riparian areas are not explicitly delineated	50	30 m

Landscape Fire and Resource Management Planning Tools (LANDFIRE)	Upland forest types mapped: Existing vegetation type; and Biophysical Settings Riparian areas are explicitly classified but only categorized into one broad 'Riparian' class (i.e., **riparian forest types not mapped**)	100	30 m
Maps of Specific Forest Plant Species and Climate Profile Predictions (MSFP)	Forest types not mapped in the study area	0	1 km
Maximum Stand Density Index Models (MSDIM)	Forest types are not mapped. Instead, this tool is used for mapping maximum stand density index for individual tree and species groups.	100	30 m
Modeled Potential Natural Vegetation Zones of Washington and Oregon (MPVZ)	Forest types mapped: Modeled potential natural vegetation zones. Riparian areas are not explicitly delineated.	100	90 m
Site Potential Tree Height Maps	Forest types are not mapped. This data set depicts modeled expected height of several common tree species at 200 years of growth.	100	Large polygons
TreeMap	Forest types mapped: Predominant species/groups; however, basal area per acre by tree species is calculated for each pixel permitting forest typing. Predominantly limited to federal lands. Riparian areas are not explicitly delineated	50	30 m

Stand Level Datasets

Source	Q1. Stand data collected	Q2. Study area covered	Q3. Resolution	Q4. Ancillary Data
EWRAP	Tree species, size, condition, cover, and location measured along a 240 ft transect perpendicular from the stream bank. Tree lists can inform FVS. Study designed to assess riparian stands, however, transects can include uplands. Breaks interpreted using tree locations and site data.	102 transects	Variable width transect	Yes. Site-specific characteristics (elevation, slope, aspect, topographic position)
FIA	Tree species, size, and condition measured on variable radius plots. Tree lists can inform FVS. Locations degraded so cannot select plots within specified distance of the stream.	Unknown	Variable radius plot	Yes. Site-specific characteristics (elevation, slope, aspect, topographic position)
FRIS	Tree species, size, and condition measured on variable radius plots. Tree lists can inform FVS. GPS locations permit selecting plots within a specified distance of mapped streams.	DNR lands only	Variable radius plot	Yes. Site-specific characteristics (elevation, slope, aspect)
LANDFIRE	Tree species, size, and condition measured on variable radius plots. Tree lists can inform FVS. Locations degraded, so cannot select plots within specified distance of the stream.	Federal lands only	Fixed plots	Yes. PRISSM climate data; SSURGO soils data; POLARIS soils data; Elevation, slope, aspect, Topographic position
PIBO	Cover class of vascular vegetation > 5 pct cover by species in each of two layers--lower and upper	Federal lands only	Strip transect	Yes. Site-specific characteristics (elevation, slope, aspect, topographic position)

Step 2: Framework Development

Procedural Overview

~~In this step, we developed alternative frameworks from the available data screened in Step 1. This framework development entailed several incremental components. First, we assembled and clipped vegetation data and ancillary data (physiography, climate, soil, topography) from the 20yFHP map and MSDIM datasets for our study area.~~ In this step, we attempted to develop an alternative framework, in addition to the 20yFHP map, by developing a predictive model of the distribution of forest type categories in the 20yFHP data set based on environmental factors (e.g., physiography, climate, soil, topography). We used the MSDIM dataset, evaluated in Step 1, to quantify these environmental factors. MSDIM contains several unique data layers (e.g., heatload, solar radiation at the soil layer) useful as independent variables. Heatload is the interaction term of solar radiation x Degree Days between 10-40 ºC. In attempting to develop such an alternative framework, we would also be testing the hypothesis that the 20yFHP forest type categories are meaningfully distributed along environmental gradients. Next, we conducted a reconnaissance survey of riparian forest stands across the study area to observe common species assemblages and compared these to the forest types listed in the 20yFHP map. Following that, we used ~~machine learning~~Boosted Regression Tree analysis (BRT) to identify the most important factors (e.g., physiography) determining the distribution of forest types along the study area as mapped in the 20yFHP map. From these identified factors~~this, we generated~~ a map was generated of expected forest types (dependent variable) based on the variation and interaction of these factors (independent variables). Variable importance results from ~~Machine learning~~BRT were corroborated with ~~by two other approaches,~~ non-metric dimensional scaling (NMDS) performed on a subset of the data ~~and principal component analysis (PCA)~~ (methods and results ~~for these approaches~~ are described in Appendix I ~~Appendix III~~). After identifying the important factors relevant to dominant tree species, including ILAP zone (ecoregion), precipitation, and elevation, we sought to identify thresholds, or break point values, for the important factors above and below which forest types mapped in the 20yFHP map were distributed. With this approach, we developed two alternative frameworks.

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Data Extraction

For data extraction from the 20yFHP map, we first applied a 120 m buffer surrounding either side (240 m total) of the prepared WA DNR Hydrography Watercourses Forest Practices Regulation stream layer clipped to the study area (Figure 4). We chose a 120 m buffer as a sum of 75 m (240 ft), the length of the EWRAP transect sampling design + 12.2 m to account for the national mapping standard inaccuracy + 26 m to account for the greatest discrepancy between lines in the WA DNR stream layer and the USGS hydrography stream layer. This equaled 107.2 m, which we rounded up to 120 m to fit 12-10 m pixels (resolution of the digital elevation model; DEM) on either side of the stream (Figure 5). We converted the buffer to a polygon that covered approximately 671.7 sq mi (173,969.5 ha). We then generated a 10 x 10 m point grid over the study area polygon for data extraction. This resulted in 47,089,718 points, which were used for ~~machine learning~~BRT. A subset of these data was also employed in ~~(PCA) and~~ (NMDS) to corroborate these results (Appendix I~~Appendix III~~).

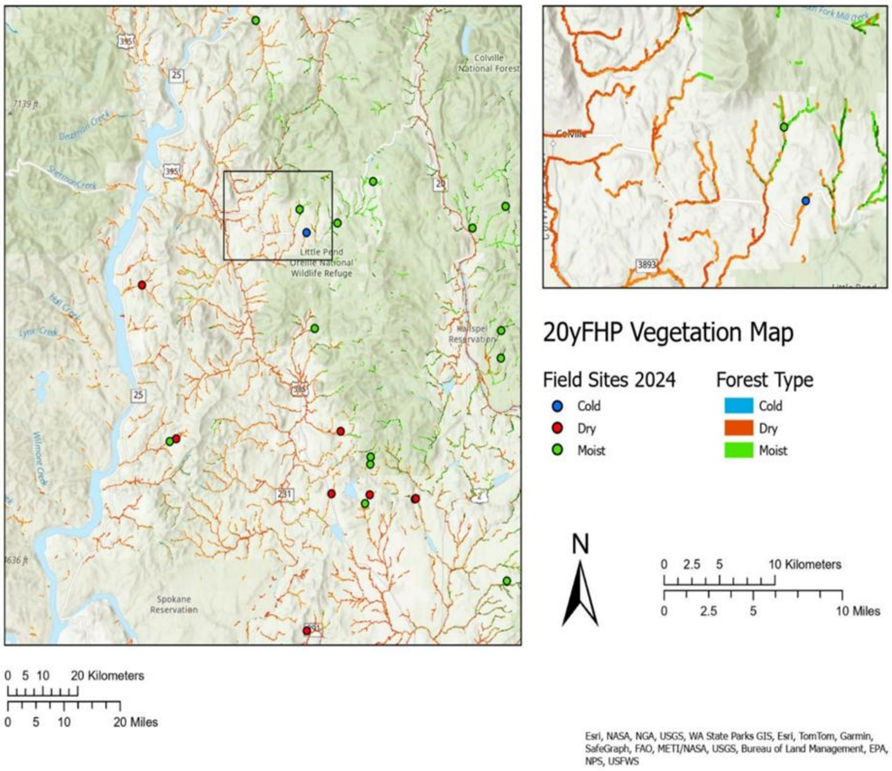

Figure 4. Map of forest types defined by the 20-year Forest Health Plan (6-category) within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset) following field-data collection at these points (described in Phase II). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

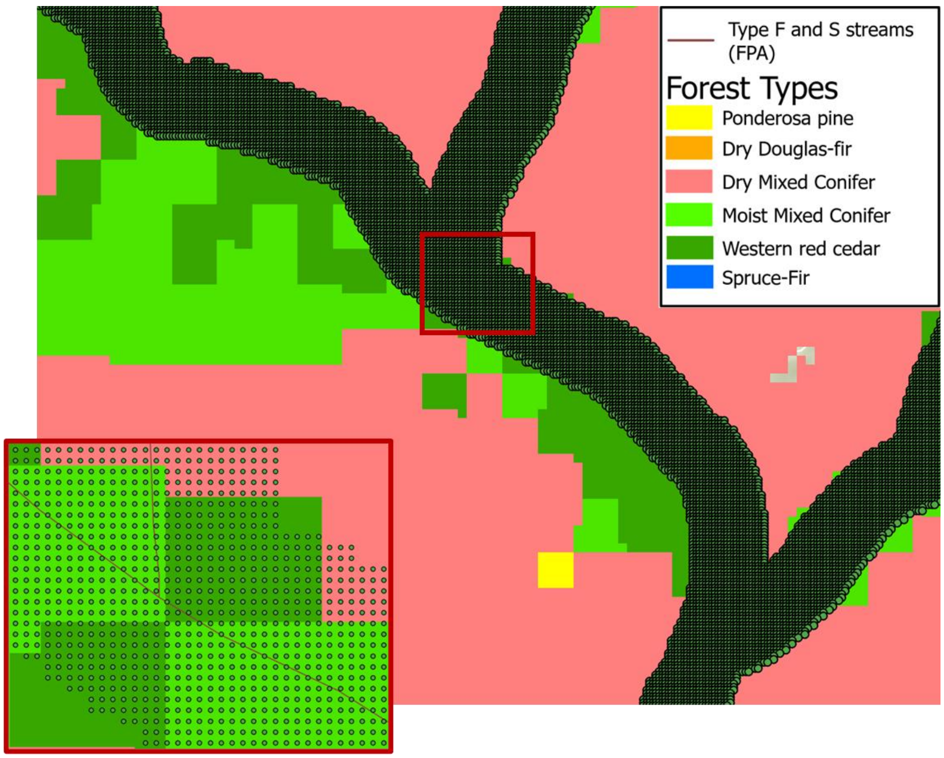

Figure 5. Screenshot of the 10 x 10-meter point grid used to extract vegetation cover data (20yFHP map), physiographic data (20yFHP map, MSDIM). The point grid was developed within a 120 m buffer on either side of the WA DNR Hydrography Watercourses shapefile. The full buffer point grid was used to extract 47,089,718 data points (containing all available vegetation, physiography, and soil attributes) for the ~~machine learning~~BRT and predictive modeling approach.

Field Reconnaissance

In June of 2023, we conducted field reconnaissance across the study area as accessible. Field reconnaissance is the first step in the Multi-factor Classification and Habitat Typing Approaches (Layser 1974; Pfister & Arno 1980; Barnes et al. 1982). This step was done to give the researchers an understanding of the variety of communities present in the study area~~,~~ and their relative frequency. Generally, this entails driving along the study area (Forested Type F and S streams on FPA managed lands) and recording areas of continuous vegetation associations that are of a considerable size (e.g., > 1000 m of stream length). The team leader drove along as many reaches as accessible by road, covering as much of the study area as possible. The team leader noted visible transitions of homogenous vegetation communities, topographic, and edaphic features. The team made frequent stops in areas of continuous communities (based on feature homogeneity and vegetation) and collected data on soil, topography, and species composition and coverage. Specifically, areas with distinct and continuous dominant timber species (e.g., Douglas-fir) or forest type communities (e.g., moist forest: western redcedar and western hemlock) that were accompanied by relatively continuous site features (e.g., aspect, slope, soil type). Sites were deemed appropriate for data collection if they 1) had a continuous vegetation association (i.e., not an ecotone or transitional zone of two or more vegetation associations); this criteria is a part of the traditional ecosystem classification approaches (Pfister & Arno 1980; Barnes et al. 1982) in that they identify forest type categories that are of considerable size, are repeatable across the landscape, and will thus, most likely provide similar function throughout, 2) did not show evidence of recent disturbance (e.g., freshly cut stumps, logging roads, recent burn scars); this criteria minimizes the possibility that the stand is in a novel stage of development or is deviated from a "natural" condition, and 3) contained a vegetation structure that reflected a mature forest (e.g., in stem-exclusion phase or older); this criteria is specific too the purpose of our framework which will only be applied to forest stands that have the potential to be harvested for timber. These three criteria were important for grouping forest categories based on our framework objectives (i.e., a framework that categorizes forest types with potential to be harvested for timber and are combined based on their likelihood of having similar functions, such as shade and LW recruitment).

From the data collected, ~~hypothesized~~ potential forest type categories were developed through interpretation of visual ordination (Figure S1). We used these hypothesized groups to cross-reference with the vegetation groups listed in the 20yFHP map: ponderosa pine (PP), dry Douglas-fir (DRY DF), western redcedar (WR), dry mixed conifer (DRY MXD), moist mixed conifer (MOIST MXD), and Engelmann spruce/silver fir (SF). The reconnaissance data was not used.

The reconnaissance survey yielded species cover data for 63 sites on a mixture of WA DNR trust lands and industrial timber lands (Inland Empire Paper, Manulife). We attempted to type each site based on species compositions using~~. We found associations similar to the~~ riparian forest series listed by Kovalchik and Clausnitzer (2004): western redcedar/western hemlock; grand fir/Douglas-fir; Douglas-fir; lodgepole pine/Engelmann spruce. Overall, the reconnaissance survey gave us additional confidence that the six categories listed in the 20YFHP map were appropriately classified and represented commonly found (i.e., repeatable forest type categories of considerable size). Because the reconnaissance data was collected based on ease of accessibility (e.g., accessible by road), it was not used for any tests of statistical significance; it was only used for hypothesis development and cross-referencing with available data.~~.~~

Boosted Regression Tree (BRT)~~Machine Learning~~

Boosted Regression Tree (BRT)~~Machine learning~~ was used to identify the most important input variables (e.g., physiography) for predicting categorical output variables (i.e., six forest type categories as mapped by the 20yFHP map). Because the methods employed for the construction of the 20yFHP map are unclear (see Data Suitability section), we sought to gain a better understanding of how the listed forest types are distributed across the study area based on their relationships with physiographic variables. We used this analysis as further validation of the 20yFHP forest groups to increase our confidence in the dataset and thus, its use as a potential framework. During this exploration, the BRT also generated a new predictive map that was trained on these data points extracted from the 20yFHP map. These points extracted and used for training fell solely within riparian corridors and adjacent uplands. This newly generated predictive map (BRT map) was a byproduct of our exploration and was also investigated as a potential alternative framework.

We used a Gradient Boosting Machine (GBM) algorithm from H20-3, an open source, in-memory, distributed, fast, and scalable machine learning and predictive analytics platform. Boosted regression trees (BRT) can handle different types of predictors (categorical or continuous data) and accommodate missing data. BRT models are complex, but they can be summarized to give ecological insight and provide a predictive performance that is superior to most traditional modeling approaches (Elith et al., 2008). The BRT is also appropriate for developing predictive maps of species distributions across environmental gradients when applying an auto-logistic modeling approach to account for -spatial autocorrelation by calculating the auto-covariates on spatial autocorrelation in residuals (Crase et al., 2012).

The BRT~~Machine learning approach~~ was conducted on 36,425,967 unique points derived from the prepared dataset of 47,089,718 points. Points with the same values for all dependent and independent variables were~~are~~ removed.~~ to avoid pseudo-replication.~~ We combined categorical ecoregions (aka ILAP zones) and continuous variables (physiographic data) for the ~~machine learning~~BRT exercise to compare their relative strength at predicting riparian forest~~ vegetation~~ type. The model was trained on 95% of the points to determine how soil, climate, and topographic factors vary across different forest type categories. Then, it predicted which category each remaining 5% of the original data should be defined in based on the values of these factors. The result of the prediction generates an error matrix to estimate the expected accuracy of the newly produced classification model. Once produced, the model must be validated with field data collected along a gradient of the most important ecological factors identified in the model for predicting riparian forest~~ cover~~ type (Phase II). After the initial validation of the model with site specific field data, the model was further calibrated by increasing the weight of the field data compared to the modeled data in Phase 2. To align with species assemblages we encountered during our field reconnaissance in the summer of 2023 and determined from ordination (Appendix I~~I~~), ~~(Appendix III), ~~riparian forest~~ vegetation~~ types mapped in the 20yFHP map were collapsed into six forest type categories (Table 3): ponderosa pine (PP), dry Douglas-fir (DRY DF), western redcedar (WR), dry mixed conifer (DRY MXD), moist mixed conifer (MOIST MXD), and spruce-fir (SF).

Table 3. Table of forest type categories developed from pre-existing forest type categories defined in the 20yFHP map and used in the machine learningBRT approach as the dependent variable.

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20yFHP Categories	ML Categories
Dry Douglas-Fir	Dry Douglas-fir (DRY DF)
Dry Mixed Conifer	Dry Mixed Conifer (DRY MXD)
NRM Mixed Conifer*	Dry Mixed Conifer (DRY MXD)
Moist Mixed Conifer	Moist Mixed Conifer (MOIST MXD)
Mountain Hemlock	Moist Mixed Conifer (MOIST MXD)
Pacific Silver Fir	Moist Mixed Conifer (MOIST MXD)
Herbland	Non-Forest (NF)
Shrubland	Non-Forest (NF)
Ponderosa Pine	Ponderosa Pine (PP)
Subalpine - Spruce	Spruce-Fir (SF)
Subalpine Parklands	Spruce-Fir (SF)
Subalpine Fir	Spruce-Fir (SF)
Western Redcedar	Western Redcedar (WR)

In assessing the most important factors for predicting riparian forest type categories, we used the ancillary data available in the 20yFHP map (Table 4). We also sourced discovered during our evaluation of the geospatial datasets in Phase I Step 1 that the MSDIM dataset contained several unique data layers (e.g., heatload, solar radiation at the soil layer) from the MSDIM dataset.useful as independent variables. Finally, we sourced other ancillary datasets such as the digital elevation model (DEM) from the United States Geological Survey (USGS).

Table 4. List of independent variables, their source, and description, that were used in ordination and machine learningBRT to evaluate their relative contribution in predicting the dependent variable (i.e., forest type categories).

Variables	*Source*	*Description*
Actual Evapotranspiration (AET)	20yFHP map	Sourced originally from PRISM. Continuous variable
Ash Prescription	MSDIM	Categorical variables: Soil type and presence of ash (e.g., Sedimentary, Andisol, Ash influence)
Aspect	Calculated from DEM	Continuous variable: converted to Sine(Aspect) and Cosine(Aspect)
Available Water Supply (AWS)	MSDIM	Volume of plant available water that the soil can store in a designated layer based on all map unit components
Depth to Restrictive layer (DEP2RES)	MSDIM	Continuous variable: Soil depth to non-permeable/hydrophobic layer
Digital Elevation Model (DEM)	USGS	Continuous variable: 3DEP DEM 10 m resolution

Heatload	MSDIM	Continuous variable: Calculated from the interaction between solar radiation and degree days between 10 -40 degrees Celsius in ArcGIS Pro
HillShade (HILLS)	Calculated from DEM	Continuous variable: Shade produced by local topography
Latitude	Calculated in ArcGIS Pro	Continuous variable
Mean Annual Precipitation (MAP)	20yFHP map	Sourced originally from PRISM. Continuous variable
Normalized Difference Vegetation Index (NDVI)	USGS	Continuous variable: calculated from USGS Landsat imagery
Slope	Calculated from DEM	Continuous variable
Solar Radiation (Solar)	MSDIM	Continuous variable: calculated in ArcGIS Pro from multiple physiographic variables
Mean Annual Temperature (Tave)	20yFHP map	Sourced originally from PRISM. Continuous variable: From 30-year normals 1980 -2010
Maximum Annual Temperature (Tmax)	20yFHP map	Sourced originally from PRISM. Continuous variable: From 30-year normals 1980 -2011
Maximum Summer temperature (Tmax_sm)	20yFHP map	Sourced originally from PRISM. Continuous variable: From 30-year normals 1980 -2012
Maximum Winter Temperature (Tmax_wt)	20yFHP map	Sourced originally from PRISM. Continuous variable: From 30-year normals 1980 -2013
Minimum Annual Temperature (Tmin)	20yFHP map	Sourced originally from PRISM. Continuous variable: From 30-year normals 1980 -2014
Topographic Position Index (TPI)	Calculated from DEM	Continuous variable: From 30-year normals 1980 -2015
Point Distance to Stream (DTS)	Calculated in ArcGIS Pro	linear distance from a randomly sampled point to the closest stream
Bailey's Ecoregions	USGS	Categorical variable: Delineation of study area by ecoregions defined by Baileys
Integrated Landscape Assessment Project (ILAP) Zone	20yFHP map	Categorical variable: Delineation of study area by ecoregions defined by ILAP and used in the 20yFHP map

The results of the model showed that nearly ~~>~~80% of the variation in the 20yFHP map forest type categories could be predicted using the 10 most important independent variables listed in Table 5. ~~These results indicated that the 20yFHP map forest type categories are informed by ecological gradients.~~ The model identified that the most important variables in predicting forest cover type categories were those associated with ~~ecoregion, temperature, and moisture. Specifically,~~ the Integrated Landscape Assessment Project (ILAP) zone (an ecoregion delineation used in the 20yFHP map, modified from Bailey's ecoregions to combine the

Okanogan and Canadian Rocky mountains), maximum summer temperature, actual evapotranspiration, Normalized Difference Vegetation Index (NDVI), maximum winter temperature, mean annual precipitation (MAP), and elevation. Using these variables, we generated a map of the study area that predicted what forest type categories would most likely occur under the combination of conditions (Figure 6 below and Figure M3, Appendix II). We interpreted these results as confirmation that the 20yFHP map forest type distributions follow a temperature and moisture gradient. This increased our confidence in the utility of the 20yFHP map as an alternative framework.

The side-by-side comparison of the THT and 20yFHP map (Figure 6) shows how the details of the 20yFHP map forest type categories better reflect not only coarse differences in upland forest type categories but also finer-scale moisture and temperature influences that better represent interfingering of forest type categories as depicted in Figure 1~~are more nuanced and follow streams and rivers identifying MOIST/DRY types (Figure 6)~~. The ~~ML Map~~BRT Map, developed from machine learning investigation of the 20yFHP map, builds on the 20yFHP map and attempts to refine the classifications based on the input factors (independent variables) used to learn from the 20yFHP map forest groups and redefine them based on those predictions. The ~~ML Map~~BRT Map shows an even finer resolution~~more nuanced classification of~~ forest type separations ~~categories~~ along streams (note that aspect appears to influence typing more strongly than in the 20yFHP map). However, because the model learned from the 20yFHP map, the error already associated with the 20yFHP map has been ~~folded in and~~ potentially compounded during the modeling process. Thus, we assume that the ~~ML Map~~BRT Map's ~~modeled~~model predictions may have overpredicted the effect of the leading independent variables on the dependent variable (forest type categories). We attempted to rectify the compounding of error by calibrating with field data, but the relatively small sample size across a large error had little impact (discussed further in Phase II, Step 2).

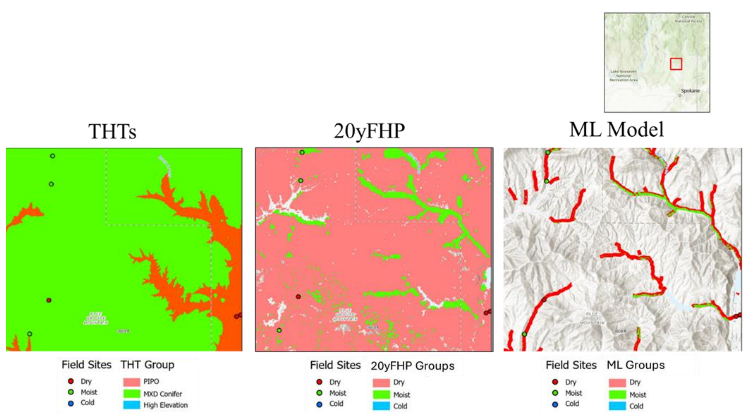

Figure 6. Zoomed in display of mapped regulatory zones of the THT for side-by-side comparison with forest type categories (coarse) mapped by the 20yFHP map, and the predictive

forest type category map (coarse) developed during the ~~machine learning~~BRT assessment of the 20yFHP map forest type categories.

Moving forward, we dropped AET and NDVI for further consideration in our experimental design field validation sampling effort (Phase II)~~framework development~~. While AET and NDVI also showed relatively high importance, these factors were not appropriate for framework development given their high annual variability and ephemeral nature (i.e., they are calculated across varying timescales from factors that are themselves variable and thus less stable than other factors considered). Consequently, we chose to move forward with the remaining ILAP zone ecoregions, temperature, precipitation, and elevation factors for framework ~~development~~assessment.

Table 5. List of the top ten independent variables based on their relative importance in predicting the six forest cover type categories used in ~~machine learning~~BRT. The percentage column shows the percentage of the variation in the dependent variable distribution that could be explained by the variable. ILAP zone shows the highest percentage (higher than Bailey's ecoregion) and was chosen as the first factor for delineation for frameworks #1 and #2. While AET and NDVI also showed relatively high importance, these factors were not appropriate for framework development given their high annual variability and ephemeral nature. We chose temperature, precipitation, and elevation as the factors for single-factor framework development (Appendix IV).

Variables	*Relative Importance*	*Scaled Importance*	*Percentage*
ILAP Zone	2.02E+06	1	21.70%
Maximum summer temperature	9.37E+05	0.463543	10.06%
Actual Evapotranspiration (AET)	7.38E+05	0.365275	7.93%
Normalized Difference Vegetation Index (NDVI)	6.94E+05	0.343481	7.45%
Bailey's Ecoregions	6.48E+05	0.320631	6.96%
Maximum Winter Temperature	6.24E+05	0.308966	6.71%
Mean Annual Precipitation	4.22E+05	0.208962	4.53%
Elevation	4.04E+05	0.199903	4.34%
Minimum Annual Temperature	3.96E+05	0.195998	4.25%
Mean Annual Temperature	3.45E+05	0.17065	3.70%

To corroborate the results of the ~~machine learning~~BRT ~~approach~~approach, we also applied an ~~PCA and~~ NMDS analysis on a random subsample of the points extracted from the study area (~15,000) as part of the Multifactor Classification and Habitat ~~typing~~ Typing Approaches. The results of ~~PCA~~ NMDS showed agreement with the ~~machine learning approach~~BRT that the temperature, precipitation, and elevation factors were most important (Appendix I~~Appendix III~~).

~~Discrimination of Forest Type Categories~~

~~After the most important factors for predicting forest type categories were identified and the original forest type categories from the 20yFHP map were deemed to be accurate from the analyses described above, we used histogram analysis to estimate under what conditions (e.g., elevation, annual precipitation) each forest type category was most commonly found. That is,~~

thresholds, or break points, above and below which forest type categories were distributed. Within each ILAP zone, we visually inspected the distribution of forest type categories across either precipitation or elevation gradients to identify the values where one or more forest type categories transition to a different forest type category. For example, as the mean annual precipitation increases on the x-axis, forest type categories that favor drier types (e.g., dry Douglas-fir, ponderosa pine) become less frequent and moister types more frequent (e.g., moist mixed conifer, western redcedar). The resulting breaks constituted the first two alternative frameworks to the Timber Habitat Type (THT) framework: one for elevation and one for precipitation.

To test significant differences among resulting groups in a framework, we used either an Analysis of Variance (ANOVA) if key assumptions were satisfied (e.g., normality, equality of variances) or the Kruskal-Wallis rank sum test if key assumptions were not met. We then applied a Tukey's test for pairwise comparison. This analysis gave us empirical evidence and objective reasoning for splitting or combining categories. In order to evaluate the significance of separation among forest type categories, we chose a minimum 65% probability (i.e., more likely to be statistically different than a 1:1 probability) of predicting forest type categories for each predictor variable before combining categories (Zar & Zar, 2014).

Given the foregoing, several independent variables consistently showed strong relationships with the distribution of forest type categories throughout the study area: ILAP zone, mean annual precipitation, and elevation. From this finding, we developed alternative frameworks, delineating the forest type categories of the 20yFHP map based on meaningful thresholds, or breaks, above and below which forest type categories tended to associate themselves (Figure 7). We used the ILAP zone as the first level of delineation because it was ranked as the variable with the highest importance in the machine learning approach (Table 5). For each ILAP zone, we then determined thresholds – one for mean annual precipitation and one for elevation – above and below which forest type categories tended to associate themselves. We attempted to separate the forest groups based on temperature thresholds as well, but the distributions all peaked in a narrow range of temperatures (1-2 degrees Celsius), making it difficult to separate groups with confidence. The resulting two alternative classification frameworks (one for elevation and one for precipitation) from this analysis are shown in Figures 8 and 9. The expected error of each category was created based on the percentage of points that fell within the ranges defined by the histogram analysis.

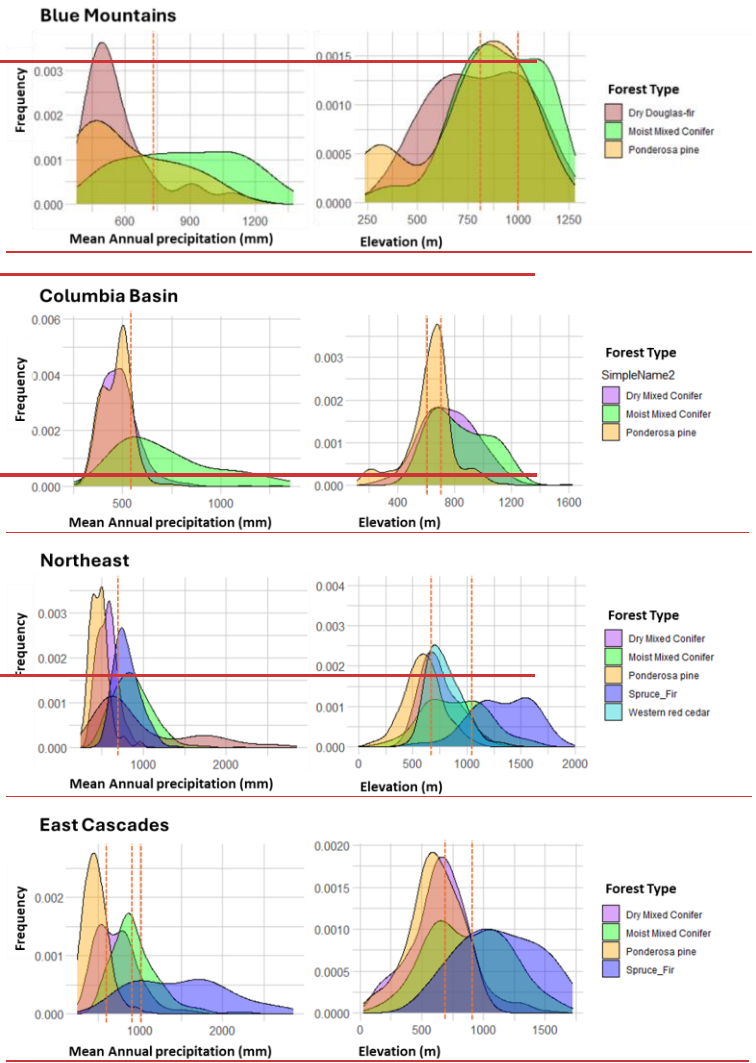

Figure 7. Frequency distributions of each 20yFHP map forest type category by mean annual precipitation (mm) and elevation (m) for each ILAP zone (Blue Mountains, Columbia Basin, East Cascades, and Northeast). From here, breakpoints for the distribution of forest type categories along elevation and precipitation gradients were developed based on visual inspection of the histograms. Red dashed lines indicate values that separate forest groups. Note: the x- and y-axis scales are not standardized across figures to increase visibility of the forest type category distributions within each ecoregion.

Expected Covertypes Based on Precipitation Gradient

A. Blue Mountains
  a. Mean annual precipitation
    i. < 745 mm……………………...Dry Douglas-fir, Ponderosa Pine (20.7%)
    ii. >745 mm ……………………..…..……..…Moist Mixed Conifer (34.7%)
B. East Cascades
  a. Mean annual precipitation
    i. < 600 mm ………..……………………..………...……Ponderosa Pine (15.0%)
    ii. 500 – 1000 mm ……………………………...…Dry Mixed Conifer (32.5%)
    iii. >800 mm ……….………………………………Moist Mixed Conifer (27.1%)
    iv. >1000 ……………………………………………………Spruce/Fir (24.7%)
C. Columbia Basin
  a. Mean annual precipitation
    i. <550 mm……...………………Dry Mixed Conifer; Ponderosa Pine (15.2%)
    ii. >550 mm………………………….………Moist Mixed Conifer (32.5%)
D. Northeast (Okanogan and Canadian Rocky Mountains)
  a. Mean annual precipitation
    i. < 700 mm………..…Spruce-Fir; Ponderosa Pine; Dry Mixed Conifer (19.3%)
    ii. >700 mm…………..……Western Red Cedar; Moist Mixed Conifer (24.2%)

Figure 8. Preliminary framework for predicting forest type categories based on their expected distributions along a precipitation gradient within each ILAP zone. The value shown in parentheses represents the estimated expected error for each group. Expected error was calculated as the percentage of points of each group that fell outside of the chosen threshold.

Expected Covertypes Based on Elevational Gradient

A. Blue Mountains
  a. Elevation
    i. < 1000 m…………………..…..Dry Douglas-fir; Ponderosa Pine (24.7%)
    ii. >800 ……………………..……………..…….Moist Mixed Conifer (31.5%)
B. East Cascades
  a. Elevation
    i. < 800 m …..…..……………...……Ponderosa Pine, Dry Mixed Conifer (24.3%)
    ii. > 700 m…………………………………………..………..Moist Mixed (31.1%)
    iii. >900 m……………………………………………...….Spruce/Fir (27.6%)
C. Columbia Basin
  a. Elevation
    i. <725 m ………..………………………………………Ponderosa Pine (16.4%)
    ii. >600 m ………………….………………Dry/Moist Mixed Conifer (15.6%)
D. Northeast (Okanogan and Canadian Rocky Mountains)
  a. Elevation
    i. < 700 m..Ponderosa Pine (27.0%)
    ii. 600 -1100 m …...Dry/Moist Mixed Conifer; Western redcedar (28.0 %)
    iii. > 1050 m...Spruce/Fir (15.2%)

Figure 9. Preliminary framework for predicting forest type categories based on their expected distributions along an elevation gradient within each ILAP zone. The value shown in parentheses represents the estimated expected error for each group. Expected error was calculated as the percentage of points of each group that fell outside of the chosen threshold.

Conclusions

All modeling efforts and statistical analyses yielded consistent results (detailed in Appendix I Appendix III), indicating that forest type categories derived from the 20yFHP map are consistent and repeatable components that tend to distribute across the study area based, most commonly, on factors that quantify temperature and moisture (e.g., actual evapotranspiration, mean annual precipitation, heatload, seasonal maximum and minimum temperatures). Indeed, the species groups inherently identify forest type categories that are expected to follow a dry to moist and warm to cold distribution. Drier forest type categories (e.g., ponderosa pine) tend to associate with lower mean annual precipitation and/or elevations, and moister (e.g., moist mixed conifer) and colder (e.g., spruce-fir) forest type categories at higher precipitation and/or elevation levels. These results were not surprising and are consistent with the relationships described in Daubenmire (1980) and Franklin and Dyrness (1973).

In Phase 1, as a byproduct of our exploration of the 20yFHP map, the model generated a predictive map (BRT Map) with an estimated classification error ranging between 5.5% and 19.7%. Considering the evidence that the 20yFHP forest types are distributed based on environmental factors, and the mixture of methods used to construct the 20yFHP, the development of the BRT map was experimental. While it was trained on the existing 20yFHP forest groups, it only used data extracted from the riparian corridors in the study area and immediately adjacent uplands. We saw this as an opportunity to test another potential alternative framework (the BRT map).

In Phase 1, we developed three alternative frameworks to the THT system: 1) A machine learning map (ML Map), 2) a precipitation-based framework within ILAP zones, and 3) an elevation-based framework within ILAP zones. Overall, the estimated classification error in the ML Map ranged between 5.5% and 19.7%. The estimated error rates for the precipitation-based and elevation-based frameworks ranged between 15.0% and 34.7%, and 15.2% and 31.5%, respectively.

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Step 3: Framework Refinement with Simulation Modeling using Existing Field Data

Our study design (Spei et al., 2023) proposed using existing field data to refine and validate, through simulation modeling, the preliminary frameworks developed in Phase I, Step 2, based on the relationships between forest type categories and riparian function (e.g., large wood recruitment, shade). However, our results from Phase I, Step 1 showed that the available field data were insufficient for this analysis. For example, the EWRAP data did not cover all conditions described by the preliminary frameworks (Phase I, Step 2). Similarly, the FRIS dataset did not cover all the riparian conditions defined by the preliminary frameworks. Furthermore, the FRIS dataset only covered DNR trust lands and did not contain important riparian zone characteristics necessary for modeling (e.g., distance to stream for each stem). Thus, we did not initiate Phase I, Step 3, due to a lack of sufficient data. We presented these findings to SAGE on June 11, 2024, and received approval to initiate Phase II of the study.

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Phase II

Step 1: Field Data Collection

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Field data were collected to assess the alternative classification frameworks developed in Phase I, to refine the frameworks, and to use in modeling riparian function.

In eastern Washington, riparian management zones (RMZs) vary in width depending on 1) the width of the stream at bank full width (BFW), and 2) site class, grouped into 5 ~~classes depending~~classes depending on site index, which quantifies a site's timber growing capacity (WAC 222-30-022). Streams with a bank full width (BFW) less than or equal to 15 feet are assigned an RMZ width between 75 and 130 feet, depending on site class. Streams with a BFW greater than 15 feet are assigned an RMZ width between 100 and 130 feet, depending on site class. Our proposed frameworks were developed as a tool for applying harvest rules in eastern Washington (objective 1). Thus, our field data used to test these proposed frameworks should be collected at regular intervals, describing features and vegetation within these RMZs at a minimum. However, our available geospatial data lacked the necessary information to determine the expected RMZ width at any given location. Therefore, we chose a sampling design that would cover the maximum possible RMZ width (130 feet) with a 30-foot extension (160 feet total) to compensate for any inaccuracies in the geospatial datasets. The 160-foot sampling distance was applied to the site selection, and field data collection protocols described below.

Site Selection Methods

Our site selection was implemented along an ecological gradient intended to capture the variation of conditions (independent variables: elevation, precipitation, temperature, and ecoregion) and their relationship to forest type categories (dependent variable). The population of sampling locations was defined as those 36,425,967 unique sampling points used in ~~machine learning~~BRT (Phase I) that fell within 50 m of a Type F or Type S stream identified by the WA DNR Hydrography Watercourses layer. A 50 m buffer width (~164 feet) was chosen to encompass (capture) the maximum width of all possible regulatory riparian buffers in eastern Washington under the current Forest Practices rules, across all water types, plus a 25% "cushion" beyond that to compensate for any potential inaccuracies in identifying the high-water mark. A total of 14,888 points were in this sampling population. From this, a total of 90 sites were randomly selected across a range of ecoregions, mean annual precipitation, elevation, and heatload (interaction term of solar radiation x Degree Days between 10-40 ºC). We chose heatload because it localizes temperature to the topographic factors of aspect slope, and sun azimuth through the use of solar radiation.

The sample population was first stratified by Bailey's Ecoregions (Bailey 1998), which were also used in the 20yFHP map (Canadian Rocky Mountains, Okanogan, East Cascades, Columbia Plateau, and Blue Mountains). Then, we used an orthogonal sampling approach to select points within each Bailey ecoregion randomly. Orthogonal sampling is an experimental design that ensures representative sampling across multiple dimensions by minimizing correlation between sample points. In each ecoregion, we used an orthogonal sampling matrix consisting of 3 levels each of mean annual precipitation and heatload, across two elevation bands, to randomly select sites for field visits. This resulted in 18 unique combinations within each ecoregion (2 elevation x 3 precipitation x 3 heatload) for a total of 90 site types across the entire study area (18 x 5 ecoregions). This method creates 90 unique site types for field-data collection (i.e., no replication). This sampling design captured the range of variability observed across independent variable datasets (site factors) associated with forest type categories (dependent variable) across the study area. This selection process is appropriate for calibration and assessment of the ~~ML Map~~BRT Map and ensures objective coverage of all forest type categories developed for the precipitation-based and elevation-based frameworks. We selected a set of five points within each strata, with the intention of sampling the first point chosen, but with four alternative points of identical conditions. Alternative points were used if, in the field, the first point selected was highly disturbed (e.g., freshly cut stumps or road construction, evidence of recent burning such as fire scars and ash) or inaccessible (e.g., gated roads that passed through privately owned parcels, decommissioned roads not labelled in available maps, roads rendered impassable from recent disturbance such as flooding, fire, or large tree blow-down)~~.~~. This orthogonal sampling design stratified landscapes based on an input variable's mean and +/- 1 standard deviation, which has been shown to be useful for the development, refinement, and validation of forest type landscape prediction models (Olea, 1980; Hemingway and Kimsey, 2020).

Field Methods

We modified the protocols developed by Mason, Bruce, and Girard (MB&G 2006), which were developed for the EWRAP Study (Schuett-Hames, 2015), to collect data at each sampling location on large and small trees, canopy closure, and in-channel large wood percent cover during the Summer and Fall of 2024. The basic plot configuration used a variable horizontal line sampling transect with a Basal Area Factor (BAF) of 20 for snags (standing dead trees) and live trees ≥ 3.0" diameter at breast height (DBH), and fixed area subplots (10~~5~~ x 5~~10~~ ft) for smaller trees established at each 10-foot mark (i.e. at the 0', 10', 20', ….,150' marks) along the central axis and extending out perpendicularly on either side by 2.5 feet (i.e. the 10' x 5' plot is centered on the central axis). Sampling transects were oriented perpendicular to the stream bank and extended 160 ft from the estimated bank-full width (BFW) or high-water mark. Sites that showed evidence of recent management (e.g., logging immediately beyond riparian buffer, evidence of dramatic changes in age class, logging road construction) or disturbance (e.g., fire) were avoided, and an alternative site location was sampled. The species, DBH, total height, height to crown, status (live/dead), health (presence of damage agents), and distance to BFW were recorded for all large trees ≥ 3.0" DBH. Large trees were identified as "in" by a person walking the transect line looking in both directions with a relascope (Spiegel Relaskop(R)). Small trees (< 3.0" DBH) were tallied within each 10~~5~~ x 5~~10~~ ft fixed area subplot and grouped by species and diameter class. Diameter classes for small trees included four categories (0 = seedlings <3.5 feet tall, 1 = trees 0.1- 1 in DBH, 2 = trees 1.1 – 2 in DBH, and 3 = trees 2.1 – 2.9 in DBH). Site characteristics such as slope, aspect, BFW, Rosgen valley, and stream type (Rosgen 1996) were recorded. Photographs of the stream and site were taken from multiple vantage points. Sketches of the valley shape with notations of natural or anthropogenic disturbance (e.g., abandoned logging roads, cut stumps) or topographic changes (e.g., terracing) and where they were located along the transect were also recorded for each site. Horizontal line sampling has been described by Ducey et al (2002).

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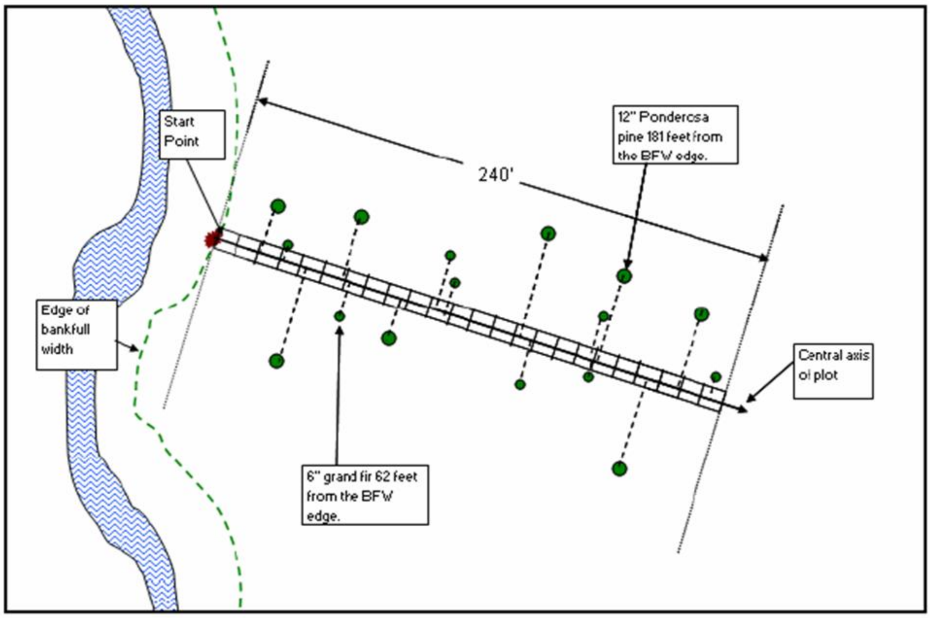

Figure 7. General sample plot layout showing start point, central axis, 24 subplots each 10' x 5', and trees and snags tallied using horizontal line sampling (taken from MB & G, 2006). For purposes of ETHEP, the transect was reduced to a maximum length of 160' (~50 m) to describe only vegetation within the designated RMZ. This also resulted in only 16-10 x 5 foot subplots instead of 24.

Results

We were able to obtain access and successfully sample 88 of the 90 sites. One site in the Columbia Plateau (lower elevation, highest heatload, highest precipitation), and one site in the Blue Mountains (higher elevation, highest heatload, and highest precipitation) could not be sampled because they (primary and alternate sites) were only within the boundaries of small privately owned land parcels, and owners could not be contacted for access permission. Of the 88 sites sampled, the relative frequencies of the moist mixed conifer (28%), ponderosa pine (28%), and dry mixed conifer (27%) types were nearly equal (Figure 8~~10~~). The methods used for forest typing followed methods described in the 20yFHP (explained in more detail in the Accuracy Assessment section). The western redcedar (WR; 6%), dry Douglas-fir (5%), and spruce-fir (5%) occurred much less frequently. Field sites occurred most frequently on WA DNR trust lands (55%), less frequently on parcels owned and managed by Washington State agencies (Department of Fish & Wildlife, Department of Parks & Recreation; 24%), and parcels owned and managed by industrial forestry companies (Inland Empire Paper company, Manulife, Stimson, Bennet; 22%) (Figure 9~~11~~). These ownership distributions of random site selection

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Formatted: Font: (Default) Times New Roman, Bold were commensurate with the distribution of our study area when accounting for the inaccessibility of privately owned parcels (Table 6). Across all sites, the most common dominant conifers based on basal area per acre were Douglas-fir (43% of sites) and ponderosa pine (28% of sites) (Figure 10~~2~~).

Table 6. Estimated number of acres of RMZ by ownership across the study area based on a contiguous 75-foot buffer for comparison. We used a 75-foot buffer (the smallest regulatory buffer) to be conservative.

	Industrial	DNR	Other State	Private
Length (miles) of Type F and S streams estimated by the WA DNR Hydro layer	1,288.1	1,463.6	669.7	1082.9

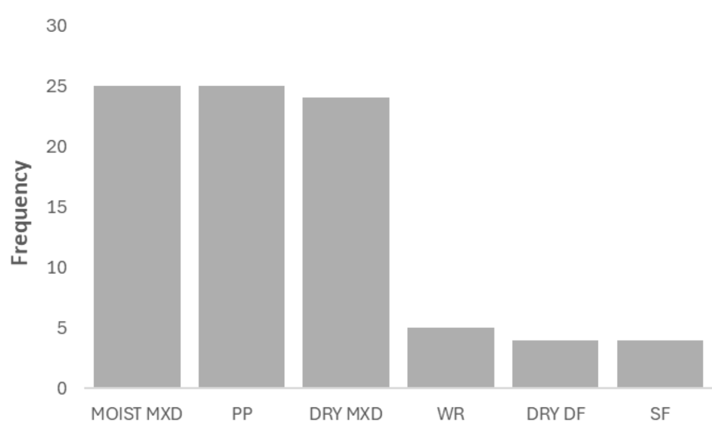

Figure 8. Frequency distribution of forest type categories found at 88 field sites across eastern Washington. PP = ponderosa pine, WR = western redcedar, SF = spruce-fir.

~~**Figure 10.** Frequency distribution of forest type categories found at 88 field sites across eastern Washington. PP = ponderosa pine, WR = western redcedar, SF = spruce-fir.~~

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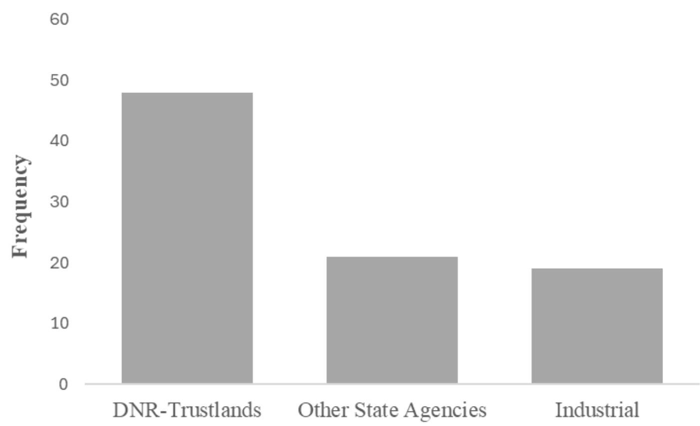

Figure 9. Frequency of ownership across 88 field sites. Other state agencies include the Department of Fish and Wildlife and the Washington State Parks and Recreation Commission. Industrial land included owners Inland Empire Paper, Manulife, Stimson, and Bennet Lumber.

Figure 11. Frequency of ownership across 88 field sites. Other state agencies include the Department of Fish and Wildlife and the Washington State Parks and Recreation Commission. Industrial land included owners Inland Empire Paper, Manulife, Stimson, and Bennet Lumber.

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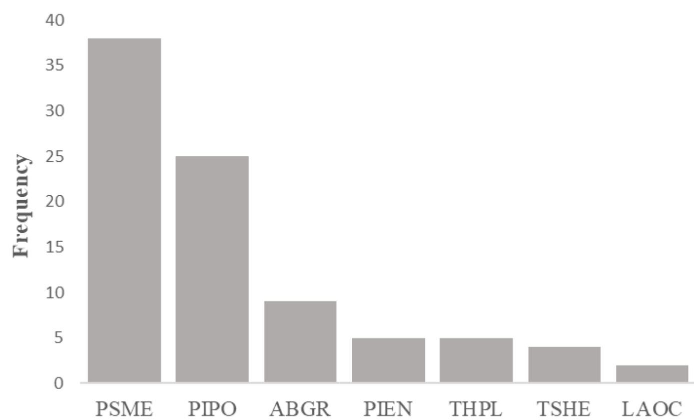

Figure 10. Frequency of dominant conifer species across 88 field sites based on basal area per acre. PSME = Douglas-fir, PIPO = ponderosa pine, ABGR = grand fir, PIEN = Englemann spruce, THPL = western redcedar, TSHE = western hemlock, LAOC = western larch.

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~~**Figure 12.** Frequency of dominant conifer species across 88 field sites based on basal area per acre. PSME = Douglas-fir, PIPO = ponderosa pine, ABGR = grand fir, PIEN = Englemann spruce, THPL = western redcedar, TSHE = western hemlock, LAOC = western larch.~~

Step 2: Validation and Refinement

Procedural Overview

Field data were used to assess the accuracy of the three alternative classification frameworks developed in Phase I and to model riparian functions of shade and LWD potential. We performed an accuracy assessment by producing error matrices showing the frequency of errors associated with the field classified forest type categories when compared to those mapped by the 20yFHP map itself and those predicted by the ~~ML Map~~BRT Map. We also produced error matrices for the THT classifications to compare the performance of the alternative frameworks. Simulation modeling (FVS) was used to compare estimates for LW recruitment potential and effective shade after 50 years of growth, at 10-year time steps, to assess similarities and differences in riparian function among the forest type categories over time. Error matrices and results of modeling were then considered during calibration of the ~~ML Map~~BRT Map and/or to inform the framework refinement.

Accuracy Assessment

We categorized each field site into one of the framework categories (moist mixed conifer, dry mixed conifer, etc.) using methods employed by the 20yFHP map (WA DNR 2020) and informed by data collected in Step 1. This approach identifies forest type categories based on (1) current dominant species coverage using relative dominance (total basal area of a species/total basal area of all species), (2) interpretation of stand-level data, including physiography (e.g., aspect, valley morphology), groundcover (e.g., noted presence of indicator species such as *Gymnocarpium dryopteris, Alnus spp., Thuja plicata, Tsuga heterophylla)*~~, and~~ photos, and (3) historical fire return interval and fire severity. Specifically, we used field data to derive species composition and stand structure (e.g., dominance by trees per acre). We supplemented this data with interpretation of stand-level photographs and sketches of valley topography, species groupings, and distribution. Finally, we also cross-referenced this information with fire regime information retrieved from LANDFIRE.

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We removed five sites from the Blue Mountains ecoregion because they were dominated by non-conifer species (e.g., quaking aspen, cottonwood), and considered non-forest based on a <10% canopy cover. Thus, 83 sites were used for validation and ecological modeling. ~~Error matrices for the two alternative frameworks developed in Phase I show a variation in error rates depending on the factor (elevation, precipitation) or the ILAP zone used (Figures 13 and 14). The framework for precipitation in the East Cascades showed the highest overall error, while the framework for elevation showed the lowest overall error.~~ The results of the ~~ML Map~~BRT Map showed relatively~~the~~ high~~est~~ overall error, with individual forest type category errors ranging from 15-75~~96~~% (Figures 11~~3~~ and 12~~4~~). Because of these high error rates, we considered investigating the effect of distance to stream in forest type category delineation. For example, some sites showed a moist forest type category (e.g., western redcedar dominant) within the first 20-50 feet of the stream, which rapidly transitioned to dry forest type categories (e.g., ponderosa pine dominant) beyond 30-50 feet from the stream bank. Thus, we also conducted typing along the core buffer zone (0-30 ft from BFW) and within the outer zone (31-160 ft) from BFW, reflecting regulatory buffer zones. Results are shown in Figures S3, S4,~~5~~ and S5~~6,~~ in Appendix I ~~Appendix III~~.

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To better understand the ability of the 20yFHP map to be used in the machine learning model (ML MapBRT Map), we evaluated the accuracy of the ML MapBRT Map predictions (Figure 115) as well as the accuracy of forest type categories as mapped by the 20yFHP map dataset (Figure 126). Error rates in the ML MapBRT Map predictions ranged from 175-7596% depending on the forest type category, with PP having the highest error and DRY MXD having the lowest (Figure 115). Error rates in the 20yFHP map vegetation map ranged from 21-75% with PP and DRY DF (dry Douglas-fir) having the highest error, and DRY MXD (dry mixed conifer) having the lowest (Figure 126).

		Predicted with Machine LearningBRT							
		PP	DRY MXD	DRY DF	MOIST MXD	WR	SF	Forest Type	%Error
Observed	PP	51	1115	02	45	00	00	PP	75%96%
	DRY MXD	00	2017	00	43	00	00	DRY MXD	17%15%
	DRY DF	11	00	11	21	00	00	DRY DF	75%67%
	MOIST MXD	00	1013	00	1012	54	00	MOIST MXD	60%59%
	WR	00	43	00	00	22	00	WR	67%60%
	SF	00	11	00	11	00	22	SF	50%50%
								Overall	52%58%

Figure 11. Error matrix describing the percent error for each forest type category predicted by the BRT Map when compared to field site forest type category (Observed).

Figure 15. Error matrix describing the percent error for each forest type category predicted by the ML Map when compared to field site forest type category (Observed).

	Predicted by 20yFHP Map							
	PP	DRY MXD	DRY DF	MOIST MXD	WR	SF	Forest Type	%Error

Observed	PP	5	11	0	4	0	0		PP	75%
	DRY MXD	0	19	0	4	0	1		DRY MXD	21%
	DRY DF	2	0	1	1	0	0		DRY DF	75%
	MOIST MXD	0	5	0	14	6	0		MOIST MXD	44%
	WR	0	2	0	1	3	0		WR	50%
	SF	0	1	0	1	0	2		SF	50%
									Overall	47%

Figure 12. Error matrix describing the percent error for each forest type category predicted by the 20yFHP map when compared to observed field site forest type categories.

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~~**Figure 16.** Error matrix describing the percent error for each forest type category predicted by the 20yFHP map when compared to observed field site forest type categories.~~

We also investigated the relationships between the field-observed forest type categories and physiographic characteristics. This approach produces evidence of the strength of these relationships, the relative importance of each factor in driving forest stand development, and the level of overlap and separation between groups (i.e., forest type categories). To investigate these relationships and patterns of riparian forest type distribution across the study area, we performed non-metric multidimensional scaling (NMDS) with the 83 field sites using the metaMDS package in R. The species matrix included the basal area by species of all trees present within a site that was relativized to a value between 0 and 1. The dimensionality of the NMDS was determined with a scree plot of stress vs. the number of dimensions and the lowest number of dimensions with stress less than 2.0 (e.g., stress values 0-0.5 = excellent, 0.5-1.0 =fair, 1.0 = 2.0 = fair; > 2.0 = poor; as values approach a value of 2 less reliance should be placed on the details of the plot), following criteria suggested by McCune and Grace (2002). The goodness-of-fit of the model with the chosen number of dimensions was cross-referenced with a stress plot of the residuals. We applied a Bray-Curtis dissimilarity to measure ecological distance based on species abundances. We overlaid environmental vectors to visualize their correlations with forest types using the envfit function in R's vegan package. Finally, we used the ordiplot, orditorp, and ordiellipse functions in R's vegan package to visualize patterns of site groupings in ordination space by field identified forest types (e.g., PP, DRY DF, WR, etc.).

Results from the ~~non-metric dimensional scaling (~~NMDS~~) ordination~~ of the 83 field sites with six ~~fine-scale~~ categories show distinct groupings of the ponderosa pine (PP) and spruce-fir (SF) categories (Figure 13~~7~~). Separation of the western redcedar (WR), moist mixed conifer (MOIST MXD), dry mixed conifer (DRY MXD), and dry Douglas-fir (DRY DF) is less distinct. The WR category appears to be a specific condition of the MOIST MXD, and the DRY DF category appears to be a specific condition of the DRY MXD category. While there is much overlap between the DRY MXD and MOIST MXD categories, they correlate with different factors. The MOIST MXD category ellipsoid shows stretching along the axes that correlate with all direct and indirect moisture factors, MAP (mean annual precipitation), AWS (available water supply), AET (actual evapotranspiration), and NDVI (normalized difference vegetation index). The MOIST MXD group also shows correlations with site productivity factors such as total basal area (Total_BA), mean canopy cover over the stream (mean_CC), and the mean percent shade within the riparian area (SHD_meanPerc). The DRY MXD category stretches along the axes that correlate with all temperature factors and heatload. The SF category aggregates in the negative x- and y-coordinate values of the ordination plot, showing occurrence in areas with higher elevation and lower annual and seasonal temperature means relative to other forest type categories.

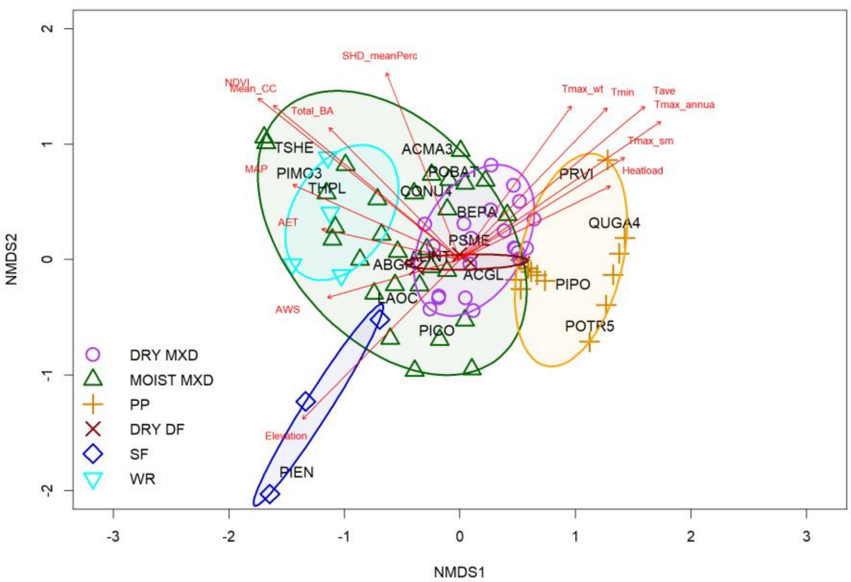

Figure 13. NMDS ordination of species basal area/acre for 83 timber sites with final stress = 0.1607668, observed with 2 dimensions (k = 2). Post-hoc ellipses encompass full coverage of forest type categories to show the overlap of forest type categories determined from the field data. They show distinct groupings of the ponderosa pine (PP) and SF forest type groups (Table 3). Separation of the western redcedar (WR), moist mixed conifer (MOIST MXD), dry mixed conifer (DRY MXD), and dry Douglas-fir (DRY DF) forest type categories is less distinct. The WR forest type category appears to be a specific condition of the MOIST MXD, and the DRY DF type appears to be a specific condition of the DRY MXD forest type category.

~~**Figure 17.** NMDS ordination of species basal area/acre for 83 timber sites. Post-hoc ellipses encompass full coverage of forest type categories to show the overlap of forest type categories determined from the field data. They show distinct groupings of the ponderosa pine (PP) and SF forest types groups (Table 3). Separation of the western redcedar (WR), moist mixed conifer~~

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(MOIST MXD), dry mixed conifer (DRY MXD), and dry Douglas-fir (DRY DF) forest type categories is less distinct. The WR forest type category appears to be a specific condition of the MOIST MXD, and the DRY DF type appears to be a specific condition of the DRY MXD forest type category.

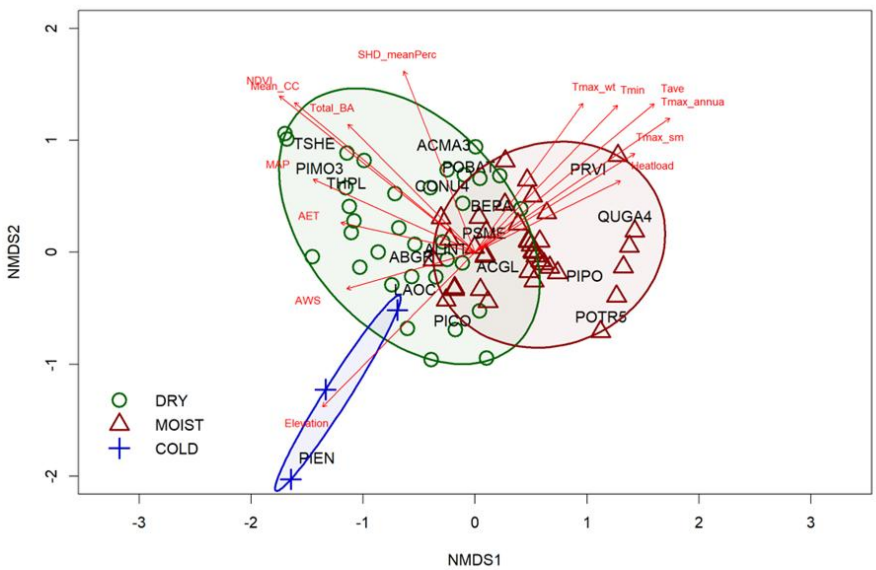

Figure 14. NMDS ordination of species basal area/acre for 83 timber sites with final stress = 0.1607668, observed with 2 dimensions (k = 2). Post-hoc ellipses encompass full coverage of coarsened forest type categories to show overlap of forest type categories derived from the field data. When the forest type categories derived from the field data are coarsened to three categories (DRY, MOIST, COLD), we see that separations and correlations are more apparent and visible than with the fine categories.

Figure 18. NMDS ordination of species basal area/acre for 83 timber sites. Post-hoc ellipses encompass full coverage of coarsened forest type categories to show overlap of forest type categories derived from the field data. When the forest type categories derived from the field data are coarsened to three categories (DRY, MOIST, COLD), we see that separations and correlations are more apparent and visible than with the fine categories.

These analyses suggested that an improved a more accurate framework could be constructed by coarsening the forest type categories into three groupings (DRY, MOIST, COLD) (Figure 148). While there is considerable overlap between the MOIST MXD and the DRY MXD groups, the DRY MXD group correlates more strongly with the temperature and heatload factors than the

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MOIST MXD. Further, the DRY MXD shows minimal correlation with MAP, AET, AWS, and NDVI, indicating they appear in areas of lower moisture availability. The overlap of MOIST MXD and DRY MXD types is potentially the result of unaccounted for local site factors (i.e., disturbance history)~~,~~ and likely due to a combination of factors, such as an interaction between such factors as aspect and slope. The WR group appears to be a ~~distinct~~ group that falls within a narrow range of site factors that correlate with the MOIST MXD group (e.g., MAP, AET). Similarly, the DRY DF group is completely encompassed by the DRY MXD group, showing it occurs within a narrower range of conditions. However, DRY DF's placement near the centroid shows it is itself as a group, variable, and not distinctly distributed in correlation with identifying factors. This could be due to a limited sample size, but it could also imply that it is not a distinct group and may be collapsed into the DRY MXD group altogether. Likewise, this option should be explored with the WR group, as well as its potential for collapse into the MOIST MXD category. These options are further explored in the modeling of riparian function sections.

We also considered evaluating forest type categories by regulatory zones (i.e., splitting the transect into core (≤30 ft) and non-core zones > 30 ft). Splitting the transect by regulatory zones did reduce variability in sites; however, it also caused groups to homogenize (i.e., there was less separation and distinction between groups), indicating that the variability within sites based on the full transect was useful for delineation (Figures S4, S5, and S6 in Appendix I~~Appendix III~~)

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Modeling Riparian Function (Shade and Large Wood Recruitment)

Overall, our results for ecological modeling of effective shade and large wood (LW) recruitment potential show compelling evidence ~~that~~ that the coarser groups (DRY, MOIST, COLD) exhibit greater separation and lower associated errors than the fine (~~six~~ six-category) forest groups (PP, DRY DF, DRY MXD, MOIST MXD, WR, SF). Over time, differences among fine forest type categories in riparian function, as measured by shade and LW, become indistinguishable within each coarse forest type category ~~In other words, the estimated functional responses for all drier forest type categories (PP, DRY DF, DRY MXD) and moister forest type categories (WR, MOIST MXD) showed convergence over time~~. These results corroborate ~~with~~ what was observed in the comparison of groups in the ordination results (Figures 13~~7~~ and 14~~8~~), that the coarse forest type categories based on (DRY, MOIST, COLD) may be more meaningful than the finer forest type categories.

Two riparian functions were modeled: LW recruitment potential and effective shade (ES). We compared estimates for LW recruitment potential and effective shade after 50 years of growth, at 10-year time steps. We chose a short 50-year timeline with 10-year timesteps because all stands sampled were mature stands (i.e., not regenerating stands), and the accuracy of stand development reduces beyond 30 years of growth and shows evidence of overprediction beyond 50 years of simulated growth even when calibrated with sufficient data (Bagdon et al. 2021; Swann et al. 2025). This step was developed only to compare the estimated riparian forest function over time by forest type category and is not intended to inform harvest prescriptions specifically. Stand development over this timeframe was simulated using Forest Vegetation Simulator (FVS) informed by the field data. Site and tree data were organized~~transformed~~ into FVS-ready formats for each specific variant used. Tree data were converted to trees per acre (TPA) using a modified version of the expansion factor for horizontal line sampling developed by Ducey et al. (2002) for all trees ≥3.0 in DBH. This method uses tree-specific expansion factors based on DBH, the basal area factor (BAF), and the length of the transect (160 ft). For seedlings (trees <3.0 in DBH), we used the subplot area (50 ft~~m~~^{2}) to calculate TPA. For seedlings, we used the midpoint of the diameter class to estimate DBH, and the midpoint of the plot was used to estimate seedling distance from the stream. Maximum stand density index (Max SDI) was estimated for each stand using the Forest Site Type Calculator tool developed and operated by the University of Idaho's Intermountain Forestry Cooperative (Kimsey et al., 2019). Max SDI is necessary when modeling stand growth and development in FVS. Without specifying the Max SDI of a stand, the growth rate and eventual plateau would not accurately reflect what would occur under the specified site conditions. The resulting data tables were developed in FVS-ready Excel sheets and used as the data source.

FVS variants used were 1) Blue Mountains (Keyser & Dixon, 2008a) for sites in southeastern Washington; 2) East Cascades (Keyser & Dixon, 2008b) for all sites along the eastern Cascade Mountains, northcentral and portions of northeastern Washington; and 3) Inland Empire (Keyser, 2008) for all remaining sites in northeast Washington. The ~~dynamic computation (~~**COMPUTE**~~)~~ keyword was used to calculate the percent canopy cover (PCC). The PCC of each stand was needed to model effective shade in the Shade.xls model. Keywords used included: **NoTriple** to preserve stem counts, and **NumCycle** to specify 10-year output periods. We also selected outputs for periodic height and diameter growth. We ran each simulation with a no-management scenario to estimate stand development in the absence of anthropogenic disturbance. We chose a no-management scenario~~,~~ because we were seeking the potential function of forest type categories through undisturbed development (i.e., "natural conditions").

To estimate the LW recruitment potential for each stand, we used tree list outputs from FVS for each timestep containing data for DBH, total height, and distance to stream for each stem. This information was used to estimate LW recruitment potential via the equation *Ps* = cos-1 (d/Ht)/π, where *Ps* is the probability of a stem entering the stream, d = slope distance of stem to stream, and Ht is the height of the stem (Welty et al., 2002). A bias factor of 1.5 was applied to sites with a mean slope >30º (Teply et al., 2014~~07~~). Trees were only included in the equation if they had a DBH ≥5 in and a height that was at least 10 feet greater than their distance to the channel edge. This was done to increase the probability that wood entering the channel was of functional size (i.e., ≥4 inches in diameter at the smaller end, and ≥10 feet in length). This calculation was used to compare LW recruitment potential only and is not an estimate of changes in LW load potential over time. The resulting *Ps* value for each stem at each site was converted to a percentage. We counted potential pieces in 2 categories: those with a >25% potential of entering the stream and those with a >50% potential of entering the stream.

To estimate effective shade, we used the percent canopy cover (PCC) for each timestep for each sampling site~~tand~~. We used this information in Shade.xls (hereafter, SHADE) model (Washington State Department of Ecology, 2003). SHADE is an Excel/Visual Basic for Applications (VBA) program that uses topography and riparian vegetation characteristics (e.g., buffer width/height, PCC). We used the outputs for estimated PCC and tree heights from FVS at 10-year timesteps over the 50-year period. For buffer height, we used the mean height of the 20 tallest trees within 130 feet of the stream. The 20 tallest trees were used as an estimate of the average height of mature tree height of the species found at each site.~~ (WSDE 2007)~~ We assigned a 130-foot buffer width in the model because that is the widest regulatory buffer width assigned in the WAC 222-30-022. We deactivated the effect of topography and overhang to estimate the shade produced only by the trees. In the model, sites were grouped by latitude, with all sites in each group being within 1 degree of latitude of each other. The effective shade was estimated from sunrise to sunset for August 1, 2024, to 2074 in 10-year increments. We chose August 1 as the input date because it is the day when air temperatures tend~~s~~ to peak regionally and shade becomes most important. We averaged the overall hourly shade for August 1, for each period and for each forest type category at the fine (e.g., ponderosa pine, moist mixed conifer, etc.) and coarse (e.g., DRY, MOIST, COLD) scale.

The results of the LW potential recruitment model for pieces with a >25% probability of entering the stream show distinct separation of some groups, while others converge to similar values (Figure 15~~9~~ A). Specifically, the ponderosa pine group (PP), the dry mixed conifer group (DRY MXD), the moist mixed conifer group (MOIST MXD), and the SF group all show divergence over time, with the PP group having the lowest potential piece count values and the SF group having the highest. The dry Douglas-fir group (DRY DF) immediately converges with the DRY MXD group after the first time~~-~~ step and maintains similar values throughout the 50-year period. The western redcedar (WR) group appears to converge with the MOIST MXD group by the third time-step and maintains similar values. For the coarse categories (Figure 15~~9~~ B), the separations are more apparent and ~~consistent~~consistent, showing evidence of differences in riparian function. The COLD group has the highest variability based on the length of the standard error bars. The high variability of the COLD group is due to the low sample size (n = 4) compared to the other two groups. The low sample size in the COLD group is due to its relatively low frequency of occurrence in the study area (Table 1).

The results of the LW potential recruitment model for pieces with a >50% probability of entering the stream also show distinct groupings but with much higher variability (i.e., greater standard error) due to many sites having no stems meeting the 50% ~~with this~~ probability threshold (Figure 15~~9~~ C-D). The WR group, for example, shows a mean piece count probability 2-3 times greater than all other groups, but with a relatively large standard error. Neither the SF/COLD nor the DRY DF group had sites containing stems with a >50% chance of entering the stream~~ post-mortem~~.

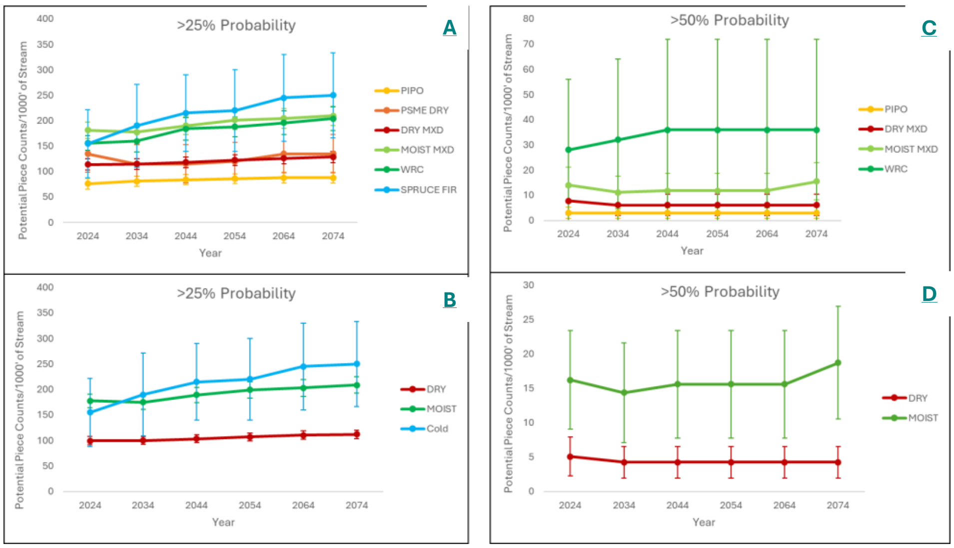

Figure 15 (A-D). Expected change in LW recruitment potential for piece counts per 1000 feet of stream. Piece counts were tallied if they had a >25% (A, B) or >50% (C, D) probability of entering the stream channel after mortality and averaged by forest type categories.

~~Figure 19 (A-D). Expected change in LW recruitment potential for piece counts per 1000 feet of stream. Piece counts were tallied if they had a >25% (A, B) or >50% (C, D) probability of entering the stream channel after mortality and averaged by forest type categories.~~

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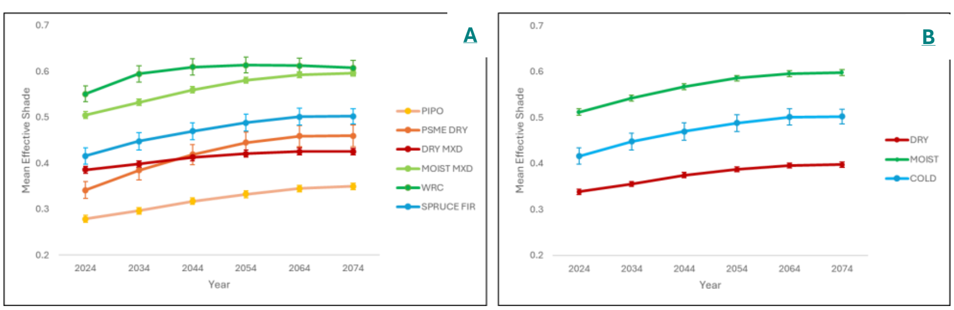

Figure 16 (A and B). Line graph showing the change in mean effective shade on August 1st, 2024 – 2074 (50 years) at 10-year timesteps for the fine (A) and coarse (B) forest type categories.

~~Figure 20 (A and B). Line graph showing the change in mean effective shade on August 1st, 2024 – 2074 (50 years) at 10-year timesteps for the fine (A) and coarse (B) forest type categories.~~

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The results from the effective shade estimates show similar trends ~~as~~ to the LW model. The graph shows distinct separation of some groups (Figure 16~~20~~ A), ~~that~~ which is more noticeable in the collapsed coarse groups (DRY, MOIST, COLD) (Figure 16~~20~~ B). The trend for the fine categories (PP, DRY DF, etc.) show PP as a distinct group, along with the SF group. The western redcedar (WR) group shows convergence with the MOIST MXD group, but only after 50 years of simulation. Further, our model does not account for the stochastic nature of mortality nor the susceptibility of different forest type categories to disturbances such as windthrow or fire. The convergence of the DRY DF group with the DRY MXD group within the first 30 years is likely more meaningful when considering function (i.e., while the forest types are different, the function provided is likely similar enough to combine for the framework). Taken together, the results of the LW model and the SHADE model show that the coarser groups (DRY, MOIST, COLD) exhibit greater separation and lower associated errors. This is also observed in the comparison of groups in the ordination results (Figures 13~~7~~ and 14~~8~~).

Refinement

Multiple lines of evidence showed that species distributions and assemblages (i.e., forest groups) followed several environmental gradients. From our analysis, we found evidence that the most influential factors (i.e., independent variables) in predicting forest type categories (i.e., dependent variable) were those describing temperature (e.g., mean annual temperature) and moisture gradients (e.g., mean annual precipitation), as well as elevation, which is negatively ~~spatially auto~~correlated with temperature (Table 5). We also found that ILAP zone was an important categorical variable for predicting forest type category. We produced two frameworks from these variables, but the classification error associated with these frameworks could be considerable (worse than a random assignment). Consequently, we explored one avenue of refinement suggested by the analyses: coarsening of the forest type categories to three ecologically distinct categories (DRY, MOIST, and COLD).

When the forest type categories are coarsened to the three categories, the classification error associated with the Phase I ~~ML Map~~BRT Map decreases~~,~~ enough to be comparable to classifications based on the elevation-based rules for the current three THT categories. Based on the 83 field sites, the classification error associated with both was about 30 percent (Tables 7 and 8). Overall, these coarse categories also appear to resolve much of the confusion we see when using the fine categories, especially around the overlap of the fine DRY and MOIST forest type categories we examined in Phase I.

Table 7. Confusion matrix shows the percentage error of the ~~ML Map~~BRT Map predictions when compared to the observed field site categories. The results show an overall slightly better performance than the THT framework. However, the MOIST forest type category was predicted with greater error than the THTs. Also, note the small sample size of the COLD group, the decreased error was only a result of 1 data point.

		Predicted: ~~ML Map~~BRT Map			
		DRY	MOIST	COLD	Error
Ob	DRY	37	10	0	**21%**

MOIST	12	19	1	**41%**
COLD	1	1	2	**50%**
Total Error				**30%**

Table 8. Confusion matrix shows the percentage error of the Timber Habitat Type (THT) framework when compared to the observed field site categories. +The THT categories for Ponderosa Pine, Mixed Conifer, and High Elevation were evaluated as DRY, MOIST, and COLD types, respectively.

		Predicted: THT			
		DRY+	MOIST+	COLD+	Error
Observed	DRY	31	16	0	**34%**
	MOIST	8	24	0	**25%**
	COLD	0	3	1	**75%**
	Total Error				**33%**

Despite this improvement, however, we recognized that the dependent variable (forest type categories) used in the ~~ML Map~~BRT Map was itself developed from an existing dataset, the 20yFHP map, which has its own inherent, unknown error. Comparing the coarse types from the 83 field sites to the coarse types mapped in the 20yFHP map (Table 9) gives an error of about 22%, which is enough to confound modeling. This is not surprising because developing a model from a pre-existing dataset with error (20yFHP map) usually results in amplification of the original dataset's error. Indeed, when compared to both the THT and Phase 1 ~~ML Map~~BRT Map (see tables above), we see that, at the fine scale, the 20yFHP map outperforms both in most ILAP zones.

This amplification of error can be overcome by calibrating the model with actual/observed field data to develop a more accurate final product. But this would require considerably more data than possible under the scope of this study. Aside from the inherent error associated with the dependent variables (forest type categories) modified from the 20yFHP map, there are also inherent errors associated with the independent variables (e.g., physiographic attributes).

Table 9. Confusion matrix shows the percentage error of the 20-year Forest health Plan mapped coarse forest type categories when compared to observed field forest type categories. The 20yFHP map outperforms the THT regulatory zones overall and in each category.

		Predicted: 20yFHP map			
		DRY	MOIST	COLD	Error
Observed	DRY	38	8	1	**19%**
	MOIST	7	25	0	**22%**
	COLD	1	1	2	**50%**
	Total Error				**22%**

Discussion

We evaluated a total of three~~five~~ frameworks, ~~thre~~one~~e of~~ of which we developed:~~ 1)~~ a Machine Learning map (~~ML Map~~BRT Map) that was created~~developed~~ after training on the dependent variables (forest type categories) found in the 20yFHP map with a collection of ancillary datasets (independent variables) of site factors, and later calibrated with field data.~~; 2) an elevation-based framework that was developed from the 20yFHP map forest types by creating breaks in elevational zones for forest type categories using histogram inspection and statistical analysis; 3) a precipitation-based framework that was developed from the 20yFHP map forest types by creating breaks in mean annual precipitation zones for forest type categories using histogram inspection and statistical analysis.~~ The other two frameworks we evaluated were: 1) the 20yFHP map, the base layer we used to develop our BRT map~~three frameworks~~; and 2) the currently used Timber Habitat Type (THT) elevation zones for forest type categories for comparison.

Overall, we discovered that the 20yFHP map was the best available framework for predicting meaningful riparian forest type categories within the study area (Appendix III~~Appendix I~~). We define "meaningful riparian forest type categories" as those types with species associations that give similar responses when evaluated by function (e.g., LW recruitment potential and shade). We also discovered that the evaluated functional responses were more distinct when the framework's forest type categories were collapsed ~~coarsened~~ from 6~~-~~ categories (PP, DRY DF, MOIST MXD, DRY MXD, WR, SF) to 3~~-~~ categories (DRY, MOIST, COLD). However, our observation of the convergence and divergence of each forest type category's functional response (i.e., estimated effective shade and LW recruitment potential at maturity) in the 6-category framework suggested that the PP group remained distinct (i.e., divergent) from the other two "DRY" forest type categories (DRY DF, DRY MXD; Figures 15~~9~~ A and C, and 16~~20~~ A). Ultimately, we interpret these results as evidence that a 4-category framework (PP, DRY MXD, MOIST MXD, COLD) may be ~~the~~ more~~most functionally~~ meaningful when considering function, especially differences in estimated effective shade. Our interpretation of each framework's performance is specifically discussed below.

The ~~Machine Learning Map (ML Map~~Boosted Regression Tree Map~~)~~

The ~~ML Map~~BRT Map was evaluated at two levels of forest type categories: 1) Fine, delineated into six categories (PP, DRY DF, MOIST MXD, DRY MXD, WR, SF), and coarse, delineated into three categories (DRY, MOIST, COLD). Evaluation of the fine-scale categories with 83 field sites (collected in Phase II) revealed error rates considerably higher than predicted (Appendix III~~Appendix II~~), ranging from 15% to 75~~96~~% with an overall error rate of 52~~6~~%. These error rates were reduced when evaluated by the coarse categories, ranging from 21% to 50%, with an overall error rate of 30%. This was a slight improvement in performance over the THT framework, which showed error rates ranging from 25% to 75% with an overall error rate of 33%. This comparison utilized a crosswalk that equated forest type categories from the ~~ML~~

~~Map~~BRT Map with THT categories: DRY with PP (low elevation; THT), MOIST with Mixed Conifer (mid-elevation), and COLD with High Elevation.

The benefit of the ~~ML Map~~BRT Map is that it was produced using a method that can be calibrated and updated over time as new data becomes ~~available and~~available, and is adept at capturing rapidly changing landscape features ~~on~~ in forest type category. The ~~ML Map~~BRT Map created for this report utilized tens of millions of data points (sourced in training and was then calibrated using 83 field data sites. We attempted to retrain and calibrate the model ~~improve performance~~ by increasing the weight of the 83 observed points (<0.01% of points) relative to the millions of geospatial data points ~~points during calibration and retraining~~. Calibration improved the model's performance (based on internal point prediction accuracy assessment); however, it could not be appropriately validated as it would require the collection of more field data, which was beyond the scope of our study.

Considering its utility, the ~~ML Map~~BRT Map at both fine and coarse scales provides a usable product for assessing riparian function. The forest groups are ecologically meaningful at both the fine and coarse scales, as substantiated by the FVS, LW, and Shade.xls modeling results. At a fine scale, the results of the riparian function modeling showed that the PP group and the SF groups maintained an average potential LW recruitment and effective shade over time, distinct from all other groups observed. Conversely, the DRY DF and DRY MXD groups converged over time for both riparian functions. Similarly, the WR group and the MOIST MXD group converged over time. Thus, a 4-category classification: PP, DRY MXD/DRY DF, MOIST MXD/WR, and SF may be a more accurate separation of forest type categories when considering ecological riparian function, based on our ~~ML Map~~BRT Map results.

The caveat of the ~~ML Map~~BRT Map is that the machine learning process used to create the ~~ML Map~~BRT Map was trained on modeled data, using the 20yFHP map forest groups as the dependent variable. This is not a traditional approach, and it is not recommended. The development of predictive species distribution models using tree-based learning (e.g., BRT) is best accomplished by training the model with large field verified or field collected historical datasets of species coverage that is then calibrated with more current or newly acquired species distribution data covering the study area (Liu et al. 2018). The model will then make predictions of species distributions across the area of interest that incorporates spatial and temporal variations. Unfortunately, no such datasets, historical or current, that contained riparian area specific species coverage data that spanned the study (FPA managed lands) could be found. D~~However, d~~uring our Phase I exploration of the data, the 20yFHP map was the only geospatial dataset that provided total coverage of the study area and contained relevant information on important timber species and forest type categories. Thus, our modeling approach was exploratory in nature, and the BRT map produced was essentially a byproduct of our investigation of the 20yFHP. We saw this as an opportunity to explore its utility as an alternative framework. We attempted this modeling step, anticipating having ~~an~~ the ability to conduct calibration and retraining with field data after the initiation of Phase II. However, as stated above, the field data sample size was proportionally minute compared to the geospatial training data (36,425,967 modeled points vs 83 field points). As a future direction, the model could be

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retrained with the field data and then calibrated with newly acquired, targeted field survey data. However, given the relatively large size of the study area along with its high variability in conditions, supplementation with high quality remotely sensed data would likely produce more accurate results (discussed further in the Future Directions section).

~~**The precipitation- and elevation-based frameworks**~~

~~The precipitation- and elevation-based frameworks were both developed directly from the 20yFHP map. Our exploratory analysis of the 20yFHP map using machine learning yielded results indicating that ecoregion (by ILAP zone), moisture, and temperature factors were the strongest predictors of vegetation groups. We corroborated these results with several other independent investigations (e.g., ordination) of the relationships between species coverage and site factors sourced from different datasets (e.g., reconnaissance field data and the LEMMA dataset; see Appendix II for results).~~

~~The elevation-based framework performed better than the precipitation-based framework in all ecoregions (by ILAP zones) except the Northeast (30.2% versus 13.9% error rate). In general, the elevation-based framework also performed as well or better than the THTs, depending on the ecoregion. The THT framework yielded an overall error rate of 33% when evaluated using our data collected from 83 field sites. The elevation-based framework exhibited overall error rates ranging from 16.7% to 33.3%, depending on the ecoregion. Thus, our elevation- and precipitation-based frameworks did not perform as well as predicted and do not show evidence of improvement over the THTs.~~

~~The potential utility of elevation- and precipitation-based frameworks varies across different ecoregions. During their development, the species groupings based on histogram analysis caused aggregations in some categories that had varied riparian function. For example, the SF category (COLD) aggregated with the MOIST MXD (MOIST) category in the East Cascades. This grouping of forest type categories is likely less ecologically meaningful than the THT categories or the coarse categories of the ML Map, as evidenced by the results of riparian function modeling; further supported by documented disturbance regimes, forest development and regeneration patterns of COLD forest species groups (e.g., Engelmann spruce, subalpine fir, lodgepole pine) versus MOIST forest species groups (e.g., western hemlock, grand fir, western larch) (Hanley, 2005). Thus, we cannot recommend these frameworks as improved alternatives to the current THT.~~

~~These single variable frameworks (precipitation or elevation), however, have some potential for improvement if the source from which they were developed were improved. Considering they were each designed based on the relationship of forest type categories in the 20yFHP map, and derived from a single factor (i.e., precipitation or elevation), their performance will likely never exceed that of the source (i.e., the 20yFHP map). However, considering utility, a framework that defines treatment by as few factors as possible would be the most useful. Our objective of producing a simple framework (single variable approach) with improved performance over the THTs was unsuccessful, however, our process of data exploration, forest type classification, and~~

~~framework development has yielded meaningful results that inform managers of the relationships between forest type categories and riparian function. Indeed, this work has led to the consideration of other existing alternatives to applying forest harvest rules (e.g., the 20yFHP map).~~

The 20yFHP map

Overall, the 20yFHP map was found to be the best-performing classification system for riparian forests along Type S and F streams we evaluated, based on our accuracy assessment using the 83 field sites. For the fine-scale, six-category framework, error rates ranged from 21% to 75% with an overall error rate of 47%, an improvement over the ~~ML Map~~BRT Map (error rate range: 15% to 75~~96~~%; overall: 52~~8~~%). The 20yFHP map's performance improved considerably when the fine-scale forest species groups (i.e., PP, DRY DF, DRY MXD, MOIST MXD, SF) collapsed into the coarse, three-category forest type categories (DRY, MOIST, COLD), with an error rates 19% (DRY), 22% (MOIST) and 50% (COLD) and an overall error rate of 22%. The 50% error rate, while high, was from the COLD group, which has very low representation (< 1%) in the study area compared to the other forest type categories, resulting in a low sample size (n = 4). Of all the frameworks, refinements, and available datasets assessed in this report - the current THT system~~, the elevation- and precipitation-based frameworks~~, the fine and coarsened ~~ML Map~~BRT Map, and the 20yFHP map (fine and coarse)—the coarse 20yFHP map exhibited the lowest error rates within all forest type categories and overall. This includes two single-factor frameworks that we also developed from the 20yFHP map (see Appendix IV). The single-factor frameworks were an experimental refinement of the 20yFHP map dataset to maximize forest management utility; however, they resulted in equal or lower accuracy than the current THT and have thus been removed from the report.

In addition to its performance during our evaluation, we recognize that the 20yFHP map is already in use as a management tool on WA State Forestlands managed under a different DNR HCP (1996) to "preserve and restore healthy forests in eastern Washington". It was developed for conducting landscape evaluations, based on the best available science on the ecology and management of fire-dependent landscapes, as well as quantitative assessments of wildfire risks, treatment prioritization, and climate change impacts and adaptation strategies (WA DNR 2020). Thus, the purpose of the 20yFHP map aligns with the DNR's privately managed FPHCP (2005) objectives, as one of its goals is to improve forest health and development in eastern Washington.

The 20yFHP map we evaluated and used for our framework development was developed and modified by WA DNR scientists using a combination of existing data sources, including local knowledge and photointerpretation. Furthermore, this project is currently operational and will continue to be updated and improved. We were, however, unable to find a record of any validation assessment~~. Thus, our assessment may be the first conducted~~. Thus, our interpretations of the 20yFHP map accuracy and utility are limited to the data collected for this study. A more robust evaluation of the accuracy of the 20yFHP map, clipped to the stream level, with targeted, randomly selected field surveys of the represented forest groups, could have value.

The main caveat to our study is the limited field sample size. We were able to gather high-quality field data at a total of 88 field sites representing approximately 4,400 feet of stream (0.83 stream miles) across the estimated 4,504 miles of stream within the study area. Further, because we needed to stratify our sampling by ecoregion, elevation, heatload, and precipitation to compensate for the full range of these conditions, each site represents a unique combination of these factors. Thus, we do not have replication for each combination of these important factors. However, it did provide replication within each forest type category, our dependent variable, especially when the categories were coarsened to three types. The sampling design used an orthogonal contrast of the most important predictor variables (elevation, precipitation, and heatload) to be used in our validation and calibration of the 20yFHP map. While each site is unique in its combined values of these three factors, it still inherently provided a ~~representative~~ sample size of each forest type category proportional to~~based on~~ its relative frequency of occurrence in the study area. We also fall short of recognized sampling guidelines for classification accuracy assessments. Congalton and Green (2019) suggest collecting a minimum of 50 samples per map class for maps less than 1 million acres in size and fewer than 12 classes for assessing the accuracy of remotely sensed maps (the base of the available geospatial maps evaluated) to achieve a 95% confidence level. However, according to the national standard for spatial data accuracy (NSSDA), twenty points per class is recommended to achieve a positional accuracy estimation with 11% variability (López and Gordo, 2008). Using the three classes (DRY, MOIST, COLD), we obtained samples from 47 DRY, 32 MOIST, and 4 COLD categories.

As with many studies, we were limited by the scope of the study, and unfortunately, we were unable to increase our sample size in time for the conclusion of this study. Regardless of these limitations, each alternative framework assessed~~developed (e.g., the preliminary frameworks for precipitation and elevation)~~, the predictive map generated with ~~machine learning~~BRT, and the 20yFHP map itself both ~~all~~ show similar or improved error rates compared to the current THT system for characterizing eastside riparian forests (Objective 2). The 20yFHP map showed the highest classification accuracy, especially when coarsened to three categories (DRY, MOIST, and COLD).

Future Directions

In parallel with improvements to field-based training data, integrating high-resolution remote sensing datasets offers exciting opportunities to ~~to scale and~~ refine riparian classification. The widespread availability of NAIP imagery and LiDAR-derived products enables finer-grained analyses of vegetation structure, surface water presence, and topographic variation. These datasets are particularly useful for detecting subtle riparian boundaries, capturing canopy height differences, and even classifying tree species (Rusnák et al. 2022; Tatum & Wallin 2021). As these technologies continue to advance, they provide a scalable approach for applying detailed classification techniques across large and heterogeneous landscapes, especially in regions with limited field access.

Finally, if the 3-category or 6-category classification frameworks from the 20yFHP map (e.g., "DRY," "MOIST," and "COLD~~,~~") are to guide harvest regulations, further examination of their baseline riparian functions and vulnerabilities to harvest will be necessary. The 20yFHP map categories were originally developed to manage resilience to fire and insect disturbances in upland ecosystems. Riparian systems in eastern Washington, however, often reflect complex interactions between local microclimate and upslope disturbances (Biswas and Mallik 2010; Ruzicka et al. 2014). This complexity can result in ecological idiosyncrasies; for example, riparian corridors serving as critical cold-water refuges may occur within upland "DRY" climate zones. To partially address differences in functional capacity owing to different landscape classification frameworks, we applied shade modeling using Shade.xls alongside potential wood recruitment modeling via Climate-FVS. Building on this work, it may be useful to characterize additional ecological endpoints, such as stream temperature and projected fish habitat under climate change, and evaluate their distribution within both the default THT framework and each alternative framework (Isaak et al. 2017; Fuller et al. 2022). This analysis could help managers assess whether a three-category or six-category classification better balances riparian functions with harvest practices.

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Appendix I Supplemental Figures and Tables

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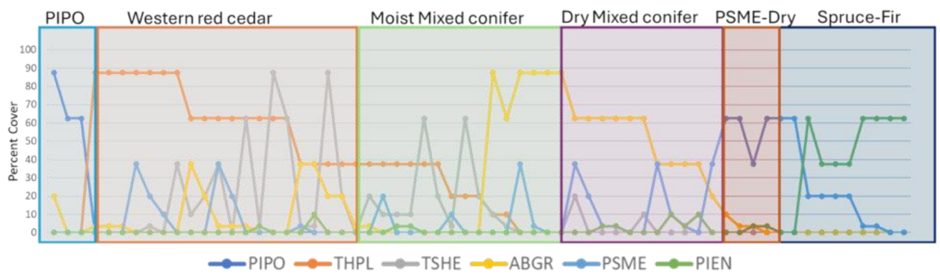


Figure S1. Visual ordination of vegetation cover data collected during field reconnaissance in the summer of 2023. Note that percent cover was based on the visual estimate of the percentage of plant canopy covering the sample plot. Thus, some plots with a multi-layered structure can have a total cover percentage of greater than 100%. Forest groups (colored boxes) were cross-referenced with those in the 20yFHP. The x-axis represents each site (63 total) sampled.

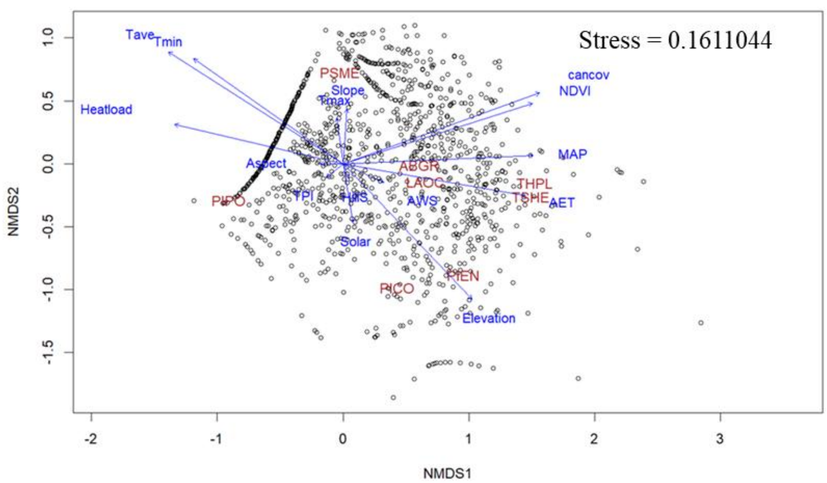


Figure S23. NMDS of 8,848 points extracted from the LEMMA dataset within the study area. The separation of species based on their relative frequency within each plot. The linear relationship of each independent factor with the distribution of each species.

The most significant factors correlating with the separations along the first axis (x: NMDS1) were mean annual precipitation (MAP; r2 0.99906, p <0.001) and heatload (r2 =-0.97366, p <0.001). Elevation, and all temperature factors were also significant (p <0.001) and showed the strongest relationship with species distributions along the first and second axes (y: NMDS2). Not surprisingly, species expected to occur on moister sites (e.g., western redcedar, western hemlock) clustered to the right of the centroid along with increasing MAP, while drier species (e.g., PIPO) were distributed further to the left of the centroid away from MAP and with increasing temperature values. Species expected to occur in colder habitats (Engelmann spruce, lodgepole pine) are distributed in the direction of increasing elevation and away from all temperature factors.

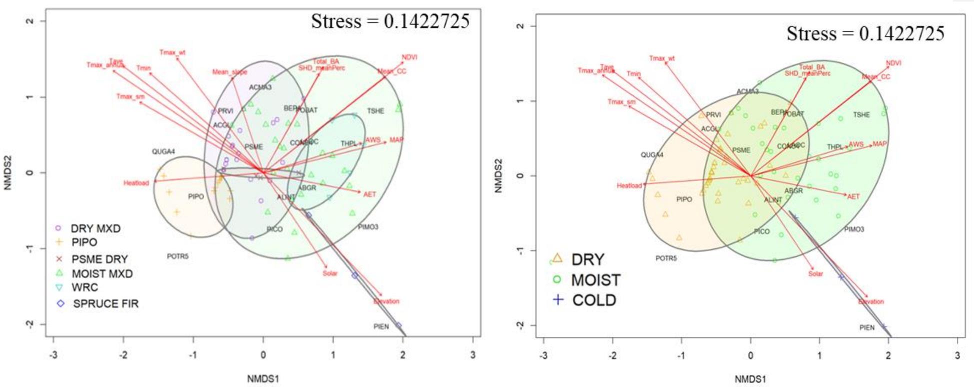
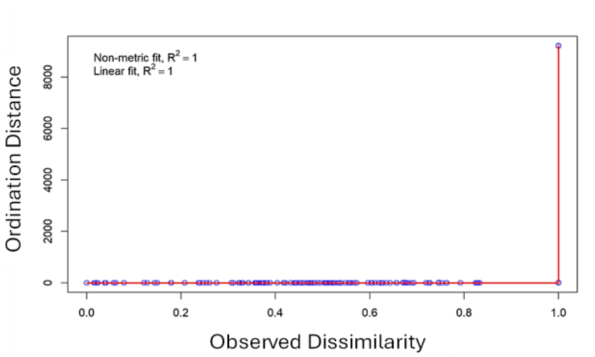


Figure S34, S45. NMDS ordination of species basal area/acre for the core zone (0-30’) of 83 timber sites. Post hoc ellipses encompass full coverage of fine categories (S4) and coarse categories (S5) to show overlap.

Results from the NMDS ordination of the outer zone species matrix showed similar distributions, groupings, and site factor correlations as the ordination results for the full transect but with slightly higher overlap. For example, while the PIPO group in the fine categories, and the DRY type in the coarse categories still show distinct separation, a larger portion of the PIPO (fine) and DRY (coarse) sites fall within other categories (e.g., MOIST) than in the full transect ordinations.



	DCA 1	DCA 2	DCA 3	DCA 4
Eigenvalues	1.000	0.8792	0.7779	0.6659
Additive Eigenvalues	1.000	0.8786	0.7775	0.5766
Decorana values	1.000	0.9301	0.7594	0.4577
Axis lengths	1.003	4.5820	5.1385	2.8552

Figure S56. Stressplot for NMDS ordination attempt on species basal area/acre for the inner zone (0-30 ft) for 83 timber sites, and table showing results of detrended correspondence analysis with 26 segments. Rescaling of axes with 4 iterations. Total inertia (scaled Chi-square): 8.1298. DCA1 axis length <2.7 = linear ordination is reasonable.

Our attempt to apply NMDS ordination to the species matrix of the core zone failed to produce results. The stress output and stressplot showed near zero stress, indicating that the species distributions across plots were following a linear distribution as opposed to a unimodal distribution. To check for linearity of the species distributions within the core zone, we applied a detrended correspondence analysis (DCA), and to investigate the variance associated with the species distributions, we applied a redundancy analysis (RDA). Results of the DCA show that the species distributions indeed follow a linear distribution and that using a linear ordination approach (e.g., principal component analysis; PCA) is reasonable. The PCA analysis did produce some interpretable results. However, the RDA showed that the variance between species groups was excessively high (6405). Thus, we could not confidently interpret the results of the PCA of the core zone.

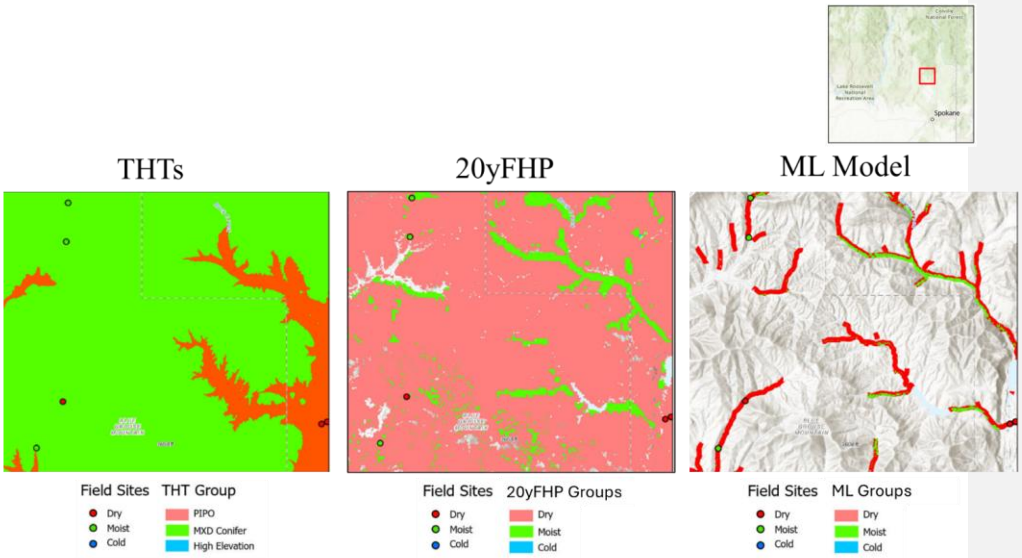


Figure S6. Zoomed in display of mapped regulatory zones of the THT for side-by-side comparison with forest types (coarse) mapped by the 20yFHP map, and the predictive forest type map (coarse) developed during the BRT assessment of the 20yFHP map forest types.

These figures show how the details of the 20yFHP map forest types are more devisive and follow streams and rivers identifying MOIST/DRY types. The BRT Map, developed from machine learning investigation of the 20yFHP map builds on the 20yFHP map and attempts to refine the classifications based on the input factors (independent variables) used to learn from the 20yFHP map forest groups and redefine them based on those predictions. The BRT Map shows an even finer resolution of forest type delineations along streams (note that aspect appears to influence typing more strongly than in the 20yFHP map). However, because the model learned from the 20yFHP map, the error already associated with the 20yFHP map has been folded in and compounded during the modeling process. We attempted to rectify the compounding of error by calibrating with field data, but the relatively small sample size across a large error had little impact.

Table S1 A-D. Results of Kruskal-Wallis analysis comparing the distributions of forest types across the spatial variations of mean annual precipitation (MAP), and elevation with post-hoc pairwise comparison (Dunn's test) significance.

	P-value	
A. Blue Mountains	Elevation	MAP
Moist Mixed Conifer-Dry Douglas-fir	< 0.01	< 0.01
Ponderosa pine-Dry Douglas-fir	0.654	0.644
Ponderosa pine-Moist Mixed Conifer	< 0.01	< 0.01

MAP by Forest Type
Kruskal-Wallis chi-squared = 131.38, df = 2, p-value < 2.2e-16
Elevation by Forest Type
Elevation Kruskal-Wallis chi-squared = 23.076, df = 2, p-value = 9.75e-06

	P-value	
B. East Cascades	Elevation	MAP
Moist Mixed Conifer-Dry Mixed Conifer	< 0.01	< 0.01
Ponderosa pine-Dry Mixed Conifer	0.0244	< 0.01
Spruce_Fir-Dry Mixed Conifer	< 0.01	< 0.01
Ponderosa pine-Moist Mixed Conifer	< 0.01	< 0.01
Spruce_Fir-Moist Mixed Conifer	< 0.01	< 0.01
Spruce_Fir-Ponderosa pine	< 0.01	< 0.01

MAP by Forest Type
Kruskal-Wallis chi-squared = 1056.1, df = 3, p-value < 2.2e-16
Elevation by Forest Type
Kruskal-Wallis chi-squared = 558.29, df = 3, p-value < 2.2e-16

	P-value	
C. Columbia Plateau	Elevation	MAP
Dry Mixed Conifer-Moist Mixed Conifer	< 0.01	< 0.01
Dry Mixed Conifer_Ponderosa pine	< 0.01	0.343
Moist Mixed Conifer Ponderosa pine	< 0.01	< 0.01

MAP by Forest Type
Kruskal-Wallis chi-squared = 265.82, df = 2, p-value < 2.2e-16
Elevation by Forest Type
Kruskal-Wallis chi-squared = 138.93, df = 2, p-value < 2.2e-16

	P-value	
D. Northeast	Elevation	MAP
Dry Mixed Conifer - Moist Mixed Conifer	0.0174	< 0.01
Dry Mixed Conifer - Ponderosa pine	< 0.01	0.023
Dry Mixed Conifer - Spruce_Fir	< 0.01	0.494
Dry Mixed Conifer - Western redcedar	0.0842	< 0.01
Moist Mixed Conifer - Ponderosa pine	< 0.01	< 0.01
Moist Mixed Conifer - Spruce_Fir	< 0.01	< 0.01
Moist Mixed Conifer - Western redcedar	0.0823	< 0.01
Ponderosa pine - Spruce_Fir	< 0.01	< 0.01
Ponderosa pine - Western redcedar	< 0.01	< 0.01
Spruce_Fir - Western redcedar	< 0.01	< 0.01

MAP by Forest Type
Kruskal-Wallis chi-squared = 3060.9, df = 4, p-value < 2.2e-16
Elevation by Forest Type
Kruskal-Wallis chi-squared = 1552, df = 4, p-value < 2.2e-16

Appendix II Maps

Figures SM1-SM6. Maps showing forest type categories for six frameworks: (1,2) the 20-year Forest Health Plan (20yFHP map) 3-category, and 6-category (3) the Precipitation-based framework, (4) Elevation-based framework, (5) BRT predictive map, and (6) the Timber Habitat Types (THTs). Note the larger map insets show only the Northeast region of eastern Washington. The relatively small area of the stream buffer makes it virtually invisible when at the study area's full extent.

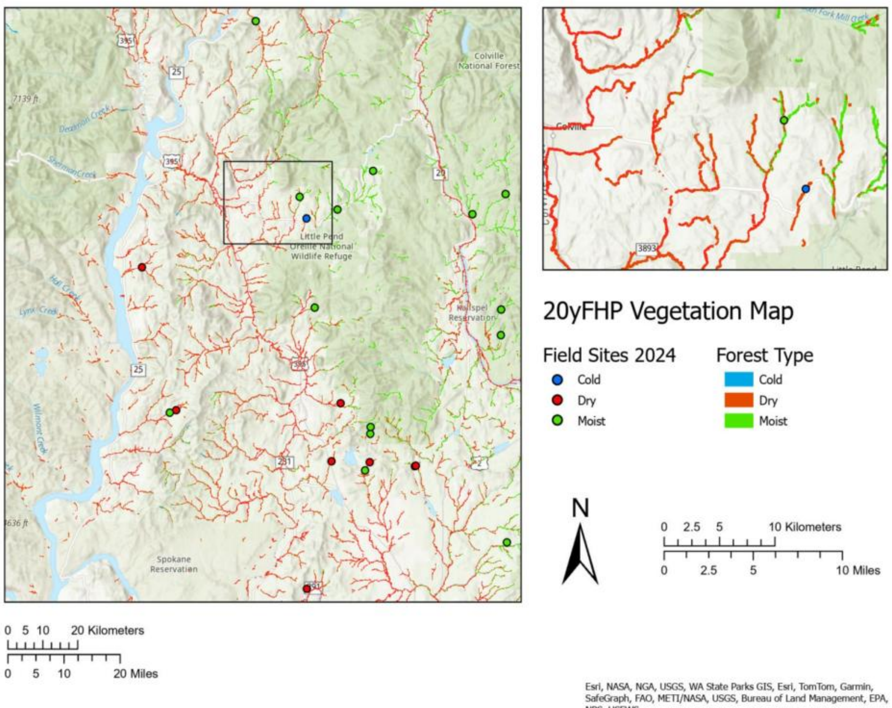


Figure SM1. Map of forest types defined by the 20-year Forest Health Plan (3-category) within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

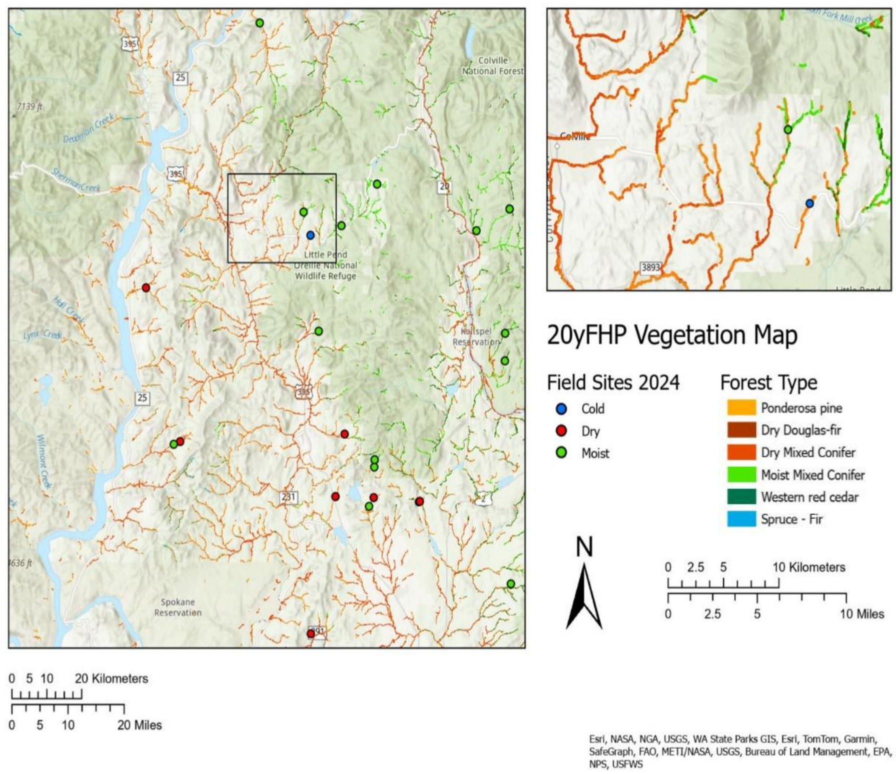


Figure SM2. Map of forest types defined by the 20-year Forest Health Plan (6-category) within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

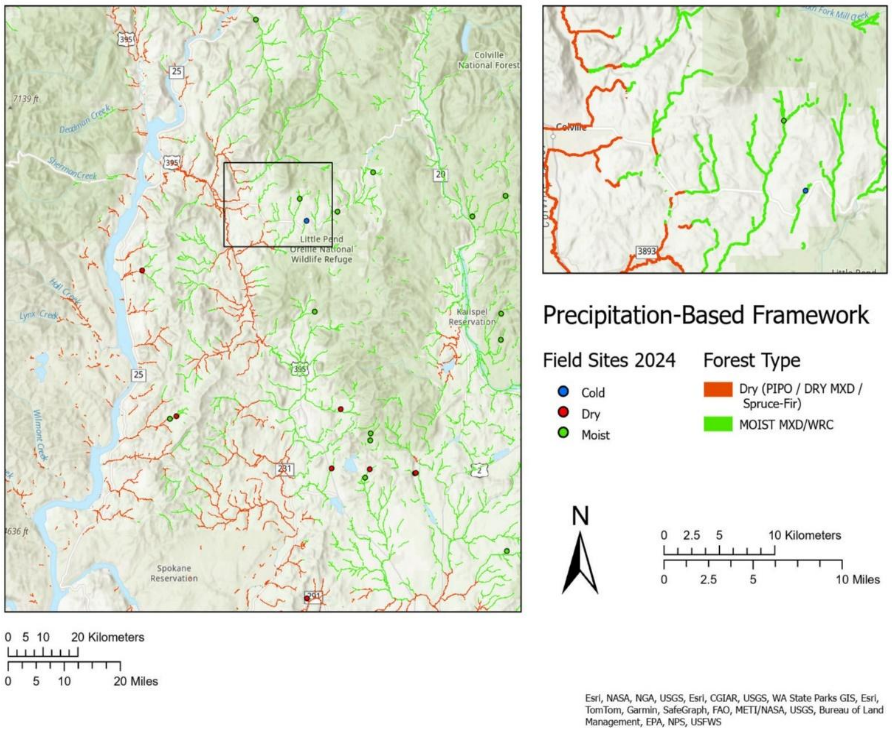


Figure SM3. Map of forest types defined by the Precipitation-based framework developed during Phase I, Step 2, within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

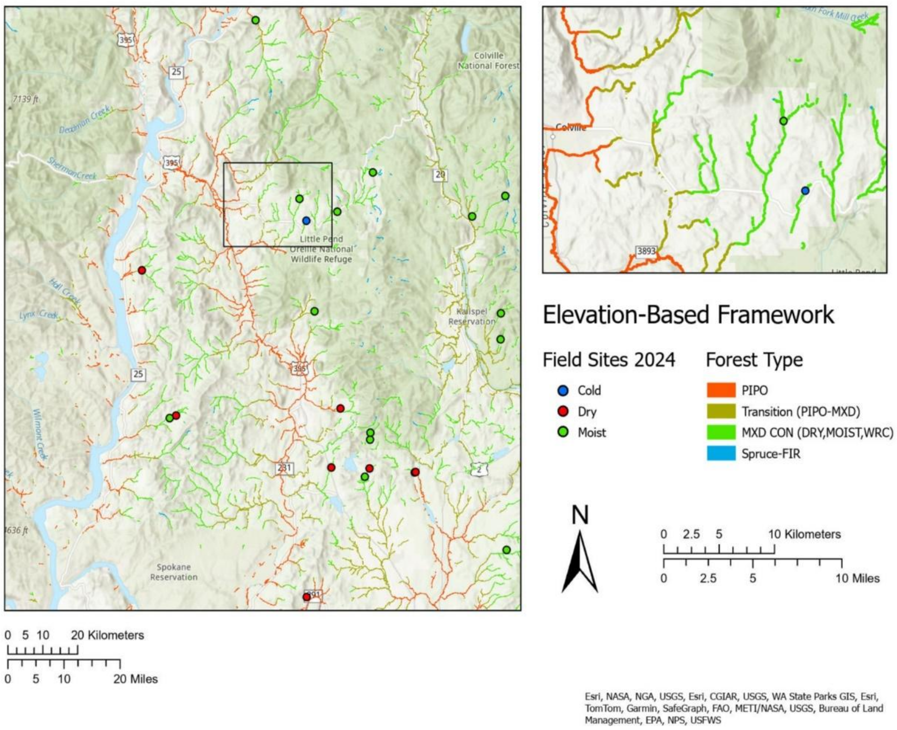


Figure SM4. Map of forest types defined by the Elevation-based framework, developed during Phase I, Step 2, within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

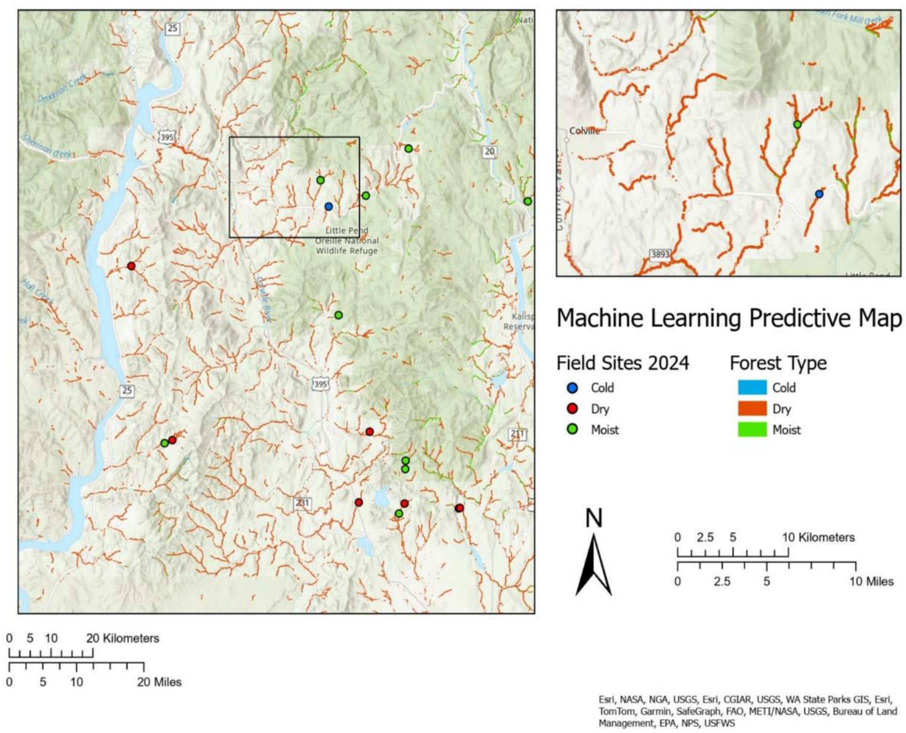


Figure SM5. Map of forest types defined by the Machine Learning predictive map developed during Phase I, Step 2, within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

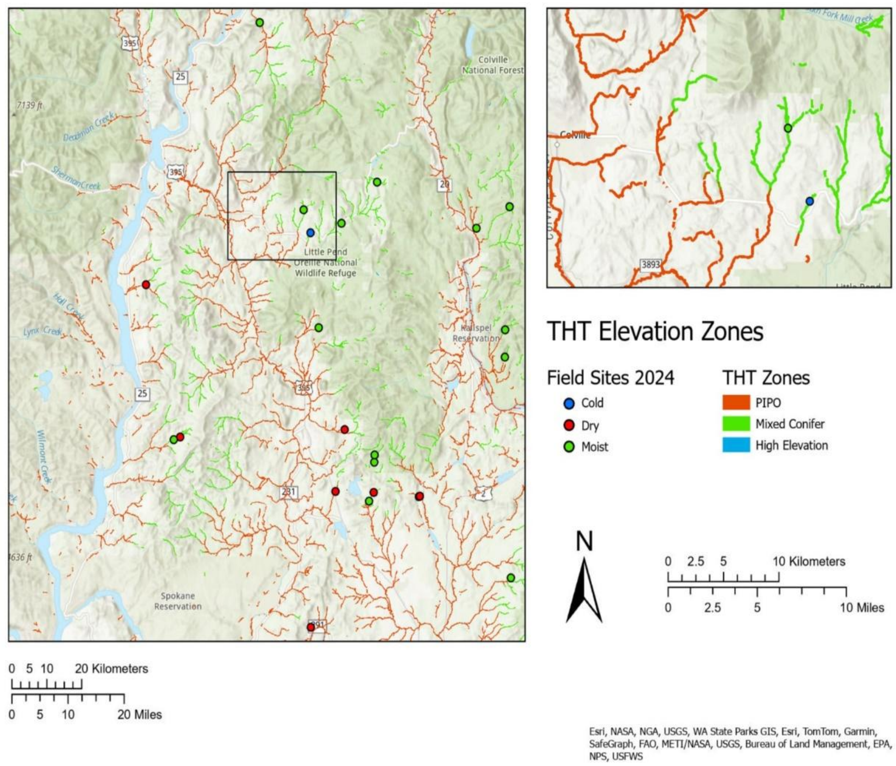


Figure SM6. Map of forest types defined by the Timber Habitat Type (THT) framework within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

Appendix III Confusion matrices

Table S1. Confusion matrices for accuracy assessments of observed riparian forest types from field data (PI method) vs. riparian forest types predicted by 4 frameworks: (1) the Timber Habitat Type (**THT**) framework, (2) the 20-year Forest Health Plan (**20yFHP map**), (3) model framework developed from 20yFHP map and calibrated with field data (~~Machine Learning~~BRT). Confusion matrices were developed for each ILAP zone to estimate performance. ^Five sites were removed from The Blue Mountains region due to non-conifer dominance. +DRY = PP, DRY MXD; MOIST = MOIST MXD, western redcedar; COLD = SF. *DRY = 0-2500 ft elevation, MOIST = 2501 – 5000 ft elevation, COLD = 5001+ ft elevation.

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Blue Mountains

Predicted: **THT** (Observed)

	DRY*	MOIST*	COLD*	Error
DRY+	3	4	--	**57%**
MOIST+	0	5	--	**0%**
COLD+	--	--	--	**--**
Total				**33%**

Predicted: **20yFHP map** (Observed)

	DRY	MOIST	COLD	Error
DRY+	3	4	--	**57%**
MOIST+	0	5	--	**0%**
COLD+	--	--	--	**--**
Total				**33%**

Predicted: ~~Machine Learning~~BRT (Observed)

	DRY	MOIST	COLD	Error
DRY+	1	6	--	**86%**
MOIST+	1	4	--	**20%**
COLD+	--	--	--	**--**
Total				**58%**

F

Columbia Plateau

Predicted: **THT**

Observed		DRY*	MOIST*	COLD*	Error
	DRY+	11	4	--	**27%**
	MOIST+	2	0	--	**100%**
	COLD+	--	--	--	**--**
	Total				**35%**

Predicted: **20yFHP map**

Observed		DRY*	MOIST*	COLD*	Error
	DRY+	11	4	--	**27%**
	MOIST+	0	2	--	**0%**
	COLD+	--	--	--	**--**
	Total				**24%**

Predicted: **~~Machine Learning~~BRT**

Observed		DRY*	MOIST*	COLD*	Accuracy
	DRY+	12	3	--	**20%**
	MOIST+	0	2	--	**0%**
	COLD+	--	--	--	**--**
	Total				**18%**

East Cascades

Predicted: **THT**

Observe		DRY*	MOIST*	COLD*	Error
	DRY+	6	3	0	**33%**
	MOIST+	3	5	0	**37%**
	COLD+	0	1	0	**100%**
	Total				**39%**

Predicted: **20yFHP map**

Observe		DRY*	MOIST*	COLD*	Error
	DRY+	9	0	0	**0%**
	MOIST+	3	5	0	**37%**
	COLD+	0	1	0	**100%**
	Total				**22%**

Predicted: **~~Machine Learning~~BRT**

	DRY*	MOIST*	COLD*	Error

Observe					
	DRY+	8	1	0	**11%**
	MOIST+	3	5	0	**37%**
	COLD+	0	1	0	**100%**
	Total				**28%**

Northeast: Okanogan/Canadian Rockies

Predicted: **THT**

Observe		DRY*	MOIST*	COLD*	Error
	DRY+	11	5	0	**31%**
	MOIST+	3	14	0	**28%**
	COLD+	0	2	1	**66%**
	Total				**28%**

Predicted: **20yFHP map**

Observe		DRY*	MOIST*	COLD*	Accuracy
	DRY+	15	0	1	**6%**
	MOIST+	4	13	0	**24%**
	COLD+	1	0	2	**33%**
	Total				**17%**

Predicted: ~~**Machine Learning**~~**BRT**

Observe		DRY*	MOIST*	COLD*	Error
	DRY+	16	0	0	**0%**
	MOIST+	8	8	1	**53%**
	COLD+	1	0	2	**33%**
	Total				**28%**

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Appendix IV: Single-factor frameworks

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Alternative Framework Development

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In the interest of utility for forest managers, frameworks that categorize the study area based on a single factor are most easily applied. The THT is a single-factor framework based on elevation. The following is a report of our attempt to develop two different alternative frameworks that are informed by a single factor (one for precipitation, and one for elevation). These were developed by manipulating the forest type categories in the 20yFHP (identified as the most useful dataset in Phase I, Step1) into different groupings (collapsing) based on their relationships with precipitation or elevation. We expect there to be a reduction in accuracy compared to the 20yFHP, but with the trade off of increasing utility (i.e. usefulness by forest managers). The scoping document, SAGE, and CMER have not provided us with a minimum threshold of acceptable error. We instead compare the results of this experiment to the error values observed from the same field data for the THT framework.

After the most important factors for predicting forest type categories were identified in the BRT (Table 5),

We used histogram analysis to estimate under what conditions (e.g., elevation, annual precipitation) each forest type category was most commonly found. That is, thresholds, or break points, above and below which forest type categories were distributed. Within each ILAP zone, we visually inspected the distribution of forest type categories across either precipitation or elevation gradients to identify the values where one or more forest type categories transition to a different forest type category. For example, as the mean annual precipitation increases on the x-axis, forest type categories that favor drier types (e.g., dry Douglas-fir, ponderosa pine) become less frequent and moister types more frequent (e.g., moist mixed conifer, western redcedar). The resulting breaks constituted the first two alternative frameworks to the Timber Habitat Type (THT) framework: one for elevation and one for precipitation.

To test for differences in forest type distributions based on individual environmental factors for use in the single-factor frameworks, we used either an Analysis of Variance (ANOVA) if key assumptions were satisfied (e.g., normality, equality of variances) or the Kruskal-Wallis rank sum test (KW) if key assumptions were not met. We then applied a Tukey's test for pairwise comparison. We extracted the values for mean annual precipitation (MAP) and elevation for each point in the study area based on their designated forest type category. The comparison of mean values for MAP and elevation (ANOVA, KW) was used to explore differences in forest type category distributions based on these factors. We checked for homogeneity of variances using a Levene's test and distribution normality using a Shapiro-Wilkes test.

We tested the null hypotheses that the means of precipitation and elevation for each forest group, stratified by ILAP zone, were equal. Results that showed a significant difference in forest distributions based on their values for MAP or elevation reinforced our confidence in separations made from visual inspection of the histograms (Figure 7). All analysis and figures were conducted and constructed using R 4.2.0.This analysis gave us empirical evidence and objective reasoning for splitting or combining categories. In order to evaluate the significance of separation among forest type categories, we chose a minimum 65% probability (i.e., more likely to be statistically different than a 1:1 probability) of predicting forest type categories for each predictor variable before combining categories (Zar & Zar, 2014).

Given the foregoing, several independent variables consistently showed strong relationships with the distribution of forest type categories throughout the study area: ILAP zone, mean annual precipitation, and elevation. From this finding, we developed alternative frameworks, delineating the forest type categories of the 20yFHP map based on meaningful thresholds, or breaks, above and below which forest type categories tended to associate themselves (Figure 7). We used the ILAP zone as the first level of delineation because it was ranked as the variable with the highest importance in the machine learning approach (Table 5). For each ILAP zone, we then determined thresholds—one for mean annual precipitation and one for elevation—above and below which forest type categories tended to associate themselves. We attempted to separate the forest groups based on temperature thresholds as well, but the distributions all peaked in a narrow range of temperatures (1-2 degrees Celsius), making it difficult to separate groups with confidence. The resulting two alternative classification frameworks (one for elevation and one for precipitation) from this analysis are shown in Figures 8 and 9. The expected error of each category was created based on the percentage of points that fell within the ranges defined by the histogram analysis.

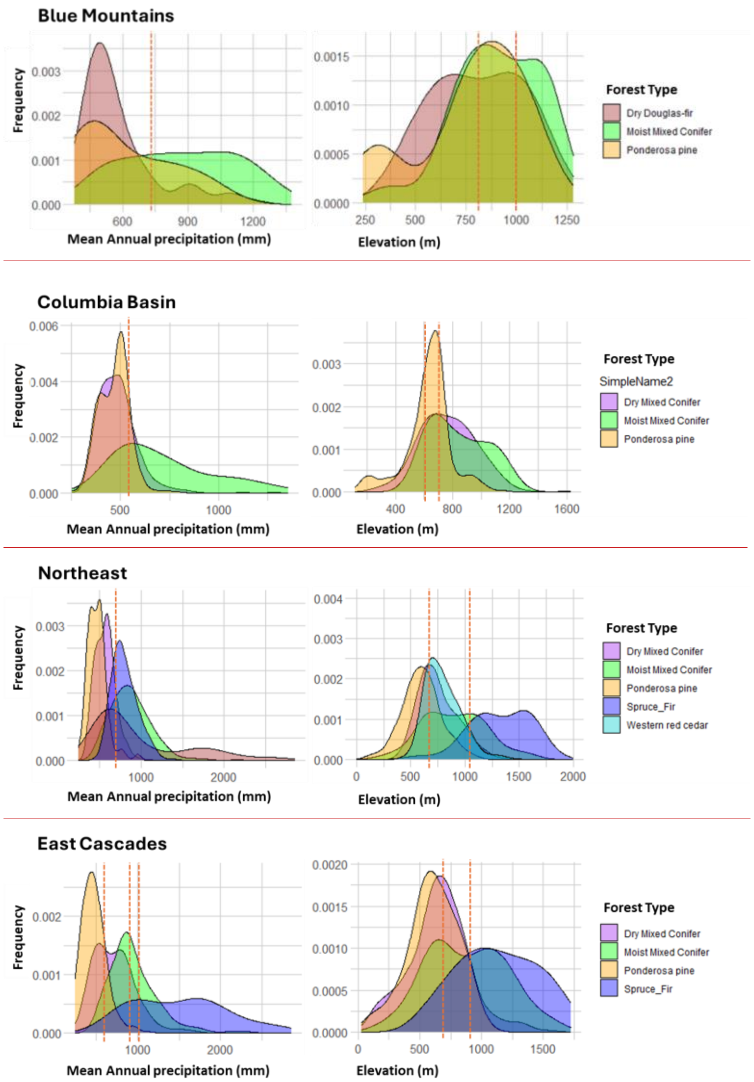

Figure S7. Frequency distributions of each 20yFHP map forest type category by mean annual precipitation (mm) and elevation (m) for each ILAP zone (Blue Mountains, Columbia Basin, East Cascades, and Northeast). From here, breakpoints for the distribution of forest type categories along elevation and precipitation gradients were developed based on visual inspection of the histograms. Red dashed lines indicate values that separate forest groups. Note: the x- and y-axis scales are not standardized across figures to increase visibility of the forest type category distributions within each ecoregion.

Expected Covertypes Based on Precipitation Gradient

A. Blue Mountains
   a. Mean annual precipitation
      i. < 745 mm……………………...Dry Douglas-fir, Ponderosa Pine (20.7%)
      ii. >745 mm ……………………..…..……..…Moist Mixed Conifer (34.7%)
B. East Cascades
   a. Mean annual precipitation
      i. < 600 mm ……….…………………..………..……Ponderosa Pine (15.0%)
      ii. 500 – 1000 mm ………………………………...…Dry Mixed Conifer (32.5%)
      iii. >800 mm ……….……………………………Moist Mixed Conifer (27.1%)
      iv. >1000 ……………………………………………………Spruce/Fir (24.7%)
C. Columbia Basin
   a. Mean annual precipitation
      i. <550 mm……..………………Dry Mixed Conifer; Ponderosa Pine (15.2%)
      ii. >550 mm……………………………….…………Moist Mixed Conifer (32.5%)
D. Northeast (Okanogan and Canadian Rocky Mountains)
   a. Mean annual precipitation
      i. < 700 mm……….…Spruce-Fir; Ponderosa Pine; Dry Mixed Conifer (19.3%)
      ii. >700 mm…………..……Western Red Cedar; Moist Mixed Conifer (24.2%)

Figure S8. Preliminary framework for predicting forest type categories based on their expected distributions along a precipitation gradient within each ILAP zone. The value shown in parentheses represents the estimated expected error for each group. Expected error was calculated as the percentage of points of each group that fell outside of the chosen threshold.

Expected Covertypes Based on Elevational Gradient

A. Blue Mountains
   a. Elevation
      i. < 1000 m…………………….…..Dry Douglas-fir; Ponderosa Pine (24.7%)
      ii. >800 ……………………..……………..…….Moist Mixed Conifer (31.5%)
B. East Cascades
   a. Elevation
      i. < 800 m …..….………………..……Ponderosa Pine, Dry Mixed Conifer (24.3%)
      ii. > 700 m…………………………………………..………..Moist Mixed (31.1%)
      iii. >900 m……………………………………………….….Spruce/Fir (27.6%)
C. Columbia Basin
   a. Elevation
      i. <725 m ………..……………………………………Ponderosa Pine (16.4%)
      ii. >600 m …………………….………………Dry/Moist Mixed Conifer (15.6%)
D. Northeast (Okanogan and Canadian Rocky Mountains)
   a. Elevation
      i. < 700 m..Ponderosa Pine (27.0%)
      ii. 600 -1100 m …...Dry/Moist Mixed Conifer; Western redcedar (28.0 %)
      iii. > 1050 m...Spruce/Fir (15.2%)

Figure S9. Preliminary framework for predicting forest type categories based on their expected distributions along an elevation gradient within each ILAP zone. The value shown in parentheses represents the estimated expected error for each group. Expected error was calculated as the percentage of points of each group that fell outside of the chosen threshold.

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Results

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Blue Mountains

			Predicted by Mean Annual Precipitation			
			PP/DRY DF	MOIST MXD	% Error	Rate
Observed	< 745 mm	PP/ DRY DF	2	5	71	5/7
	> 745 mm	MOIST MXD	3	2	60	3/5
	Total		5	7	52.9	8/12

East Cascades

			Predicted by Mean Annual Precipitation					
			PP	DRY MXD	MOIST MXD	SF	%Error	Rate
Observed	< 600 mm	PP	3	0	0	0	0	0/3
	500 - 1000 mm	DRY MXD	4	7	8	0	63.2	12/19
	> 800 mm	MOIST MXD	0	1	2	1	50	2/4
	>1000 mm	SF	0	0	3	1	75	3/4
	Total		7	8	13	2	56.7	17/30

Columbia Plateau

	Predicted by Mean Annual Precipitation			
	PP/DRY MXD	MOIST MXD	Error	Rate

Observed	< 550 mm	PP/ DRY MXD	11	4	29	5/16
	> 550 mm	MOIST MXD	0	2	0	0/1
	Total		11	6	29.4	5/17

Northeast

			Predicted by Mean Annual Precipitation			
			SF/ PIPO/ DRY MXD	WR/ MOIST MXD	%Error	Rate
Observed	<700 mm	SF/PP/DRY MXD	18	1	5	1/19
	>700 mm	WR/ MOIST MXD	4	13	24	4/17
	Total		22	14	13.9	5/36

Figure S10. Error matrices describing the percent error and error rate for each predicted forest type category by precipitation within each ILAP zone as defined and delineated in the Precipitation framework (Figure 8). The error rate and percentage are calculated based on the accuracy of each field site forest type category (observed) when compared to the forest type category predicted by the preliminary framework (predicted).

Blue Mountains

			Predicted by Elevation			
			PP/DRY DF	MOIST MXD	% Error	Rate
Observed	< 1000 m	PP/ DRY DF	10	3	23	3/13
	> 745 m	MOIST MXD	0	5	0	0/5
	Total		10	8	16.7	3/18

East Cascades

			Predicted by Elevation			
			PP/DRY MXD	MOIST MXD/SF	% Error	Rate
Observed	< 800 m	PP/ DRY MXD	12	7	40	7/19
	> 700 m	MOIST MXD/ SF	0	2	0	0/2
	Total		12	9	33.3	7/21

Columbia Plateau

			Predicted by Elevation			
			PP	DRY MXD/MOIST MXD	% Error	Rate

Observed	< 725 m	PP	6	3	33.3	3/9
	> 600 m	DRY MXD/ MOIST MXD	4	9	31	4/13
	Total	_	10	12	31.8	7/22

Northeast			Predicted by Elevation				
			PP	DRY MXD/MOIST MXD/WR	SF	% Error	Rate
Observed	< 700 m	PP	5	5	0	50	5/10
	600 - 1100 m	DRY MXD/ MOIST MXD	5	23	2	23	7/30
	> 1050 m	SF	0	1	2	33.3	1/3
	Total	_	10	29	4	30.2	13/43

Figure S11. Error matrices describing the percent error and error rate for each predicted forest type category by elevation within each ILAP zone as defined and delineated in the preliminary framework (Figure 9). The error rate and percentage are calculated based on the accuracy of each field site forest type category (observed) when compared to the forest type category predicted by the preliminary framework (predicted).

Conclusions: The precipitation- and elevation-based frameworks

The precipitation- and elevation-based frameworks were both developed directly from the 20yFHP map. Our exploratory analysis of the 20yFHP map using BRT yielded results indicating that ecoregion (by ILAP zone), moisture, and temperature factors were the strongest predictors of vegetation groups. We corroborated these results with several other independent investigations (e.g., ordination) of the relationships between species coverage and site factors sourced from different datasets (e.g., reconnaissance field data and the LEMMA dataset; see Appendix II for results).

The elevation-based framework performed better than the precipitation-based framework in all ecoregions (by ILAP zones) except the Northeast (30.2% versus 13.9% error rate). In general, the elevation-based framework also performed as well or better than the THTs, depending on the ecoregion. The THT framework yielded an overall error rate of 33% when evaluated using our data collected from 83 field sites. The elevation-based framework exhibited overall error rates ranging from 16.7% to 33.3%, depending on the ecoregion. Thus, our elevation- and precipitation-based frameworks did not perform as well as predicted and do not show evidence of improvement over the THTs.

The potential utility of elevation- and precipitation-based frameworks varies across different ecoregions. During their development, the species groupings based on histogram analysis caused aggregations in some categories that had varied riparian function. For example, the SF category (COLD) aggregated with the MOIST MXD (MOIST) category in the East Cascades. This grouping of forest type categories is likely less ecologically meaningful than the THT categories or the coarse categories of the BRT Map, as evidenced by the results of riparian function modeling; further supported by documented disturbance regimes, forest development and regeneration patterns of COLD forest species groups (e.g., Engelmann spruce, subalpine fir, lodgepole pine) versus MOIST forest species groups (e.g., western hemlock, grand fir, western larch) (Hanley, 2005). Thus, we cannot recommend these frameworks as improved alternatives to the current THT.

These single variable frameworks (precipitation or elevation), however, have some potential for improvement if the source from which they were developed were improved. Considering they were each designed based on the relationship of forest type categories in the 20yFHP map, and derived from a single factor (i.e., precipitation or elevation), their performance will likely never exceed that of the source (i.e., the 20yFHP map). However, considering utility, a framework that defines treatment by as few factors as possible would be the most useful. Our objective of producing a simple framework (single variable approach) with improved performance over the THTs was unsuccessful, however, our process of data exploration, forest type classification, and framework development has yielded meaningful results that inform managers of the relationships between forest type categories and riparian function. Indeed, this work has led to the consideration of other existing alternatives to applying forest harvest rules (e.g., the 20yFHP map).

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~~Appendix II Maps~~

~~**Figures SM1-SM6**. Maps showing forest type categories for six frameworks: (1,2) the 20-year Forest Health Plan (20yFHP map) 3-category, and 6-category (3) the Precipitation-based framework, (4) Elevation-based framework, (5) Machine Learning predictive map, and (6) the Timber Habitat Types (THTs). Note the larger map insets show only the Northeast region of eastern Washington. The relatively small area of the stream buffer makes it virtually invisible when at the study area's full extent.~~

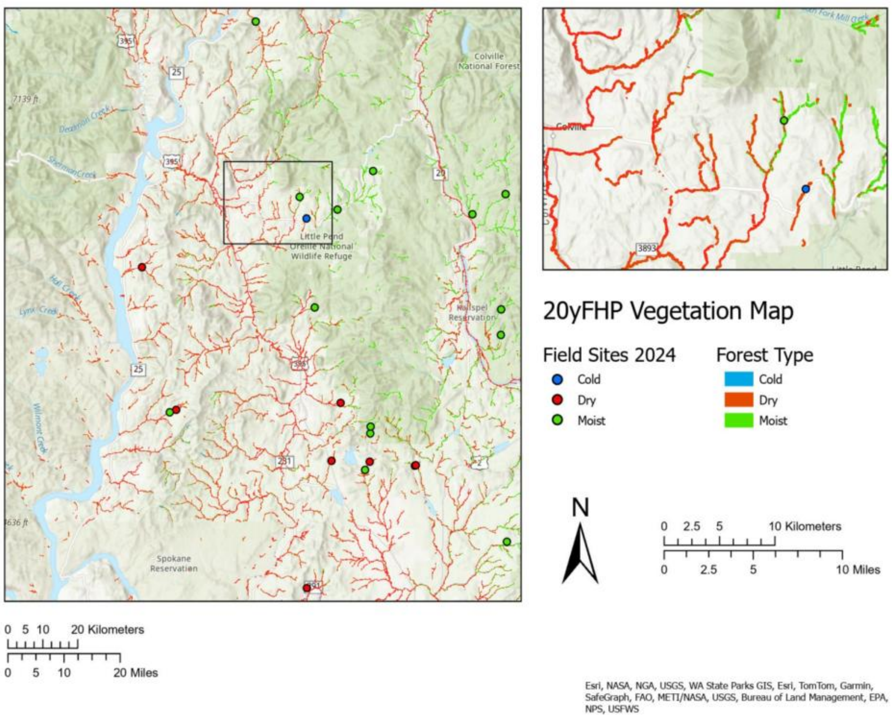

Figure SM1. Map of forest types defined by the 20-year Forest Health Plan (3-category) within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

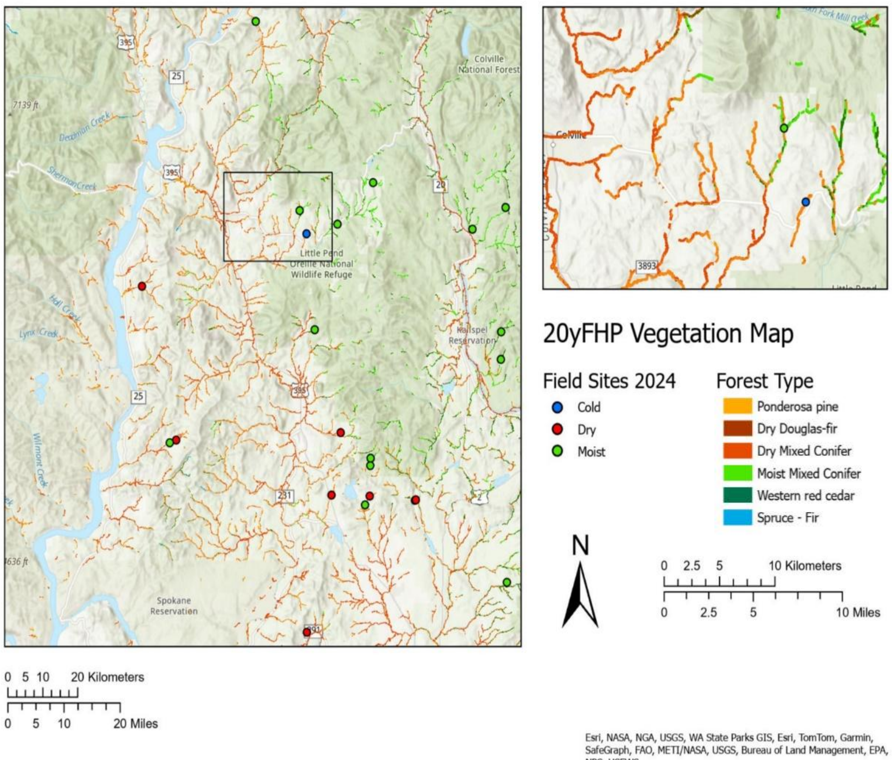

Figure SM2. Map of forest types defined by the 20-year Forest Health Plan (6-category) within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

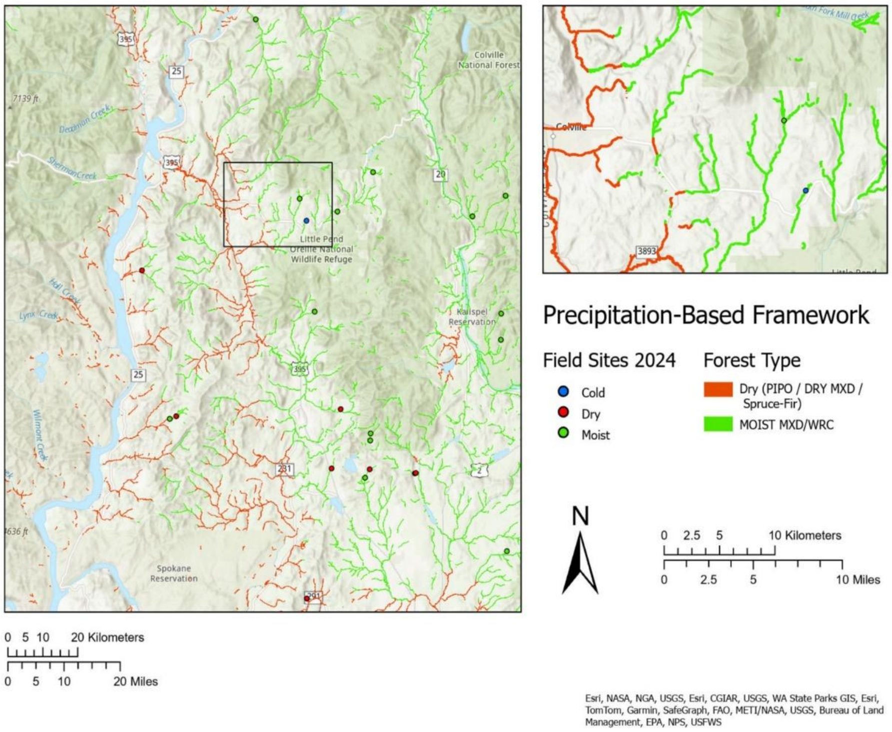

Figure SM3. Map of forest types defined by the Precipitation-based framework developed during Phase I, Step 2, within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

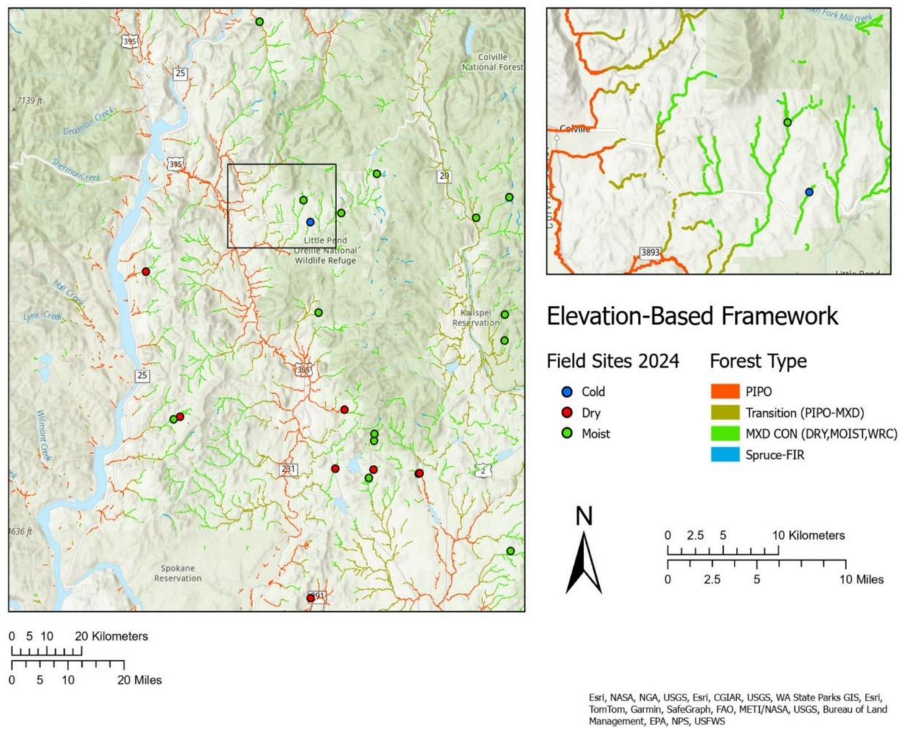

Figure SM4. Map of forest types defined by the Elevation-based framework, developed during Phase I, Step 2, within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

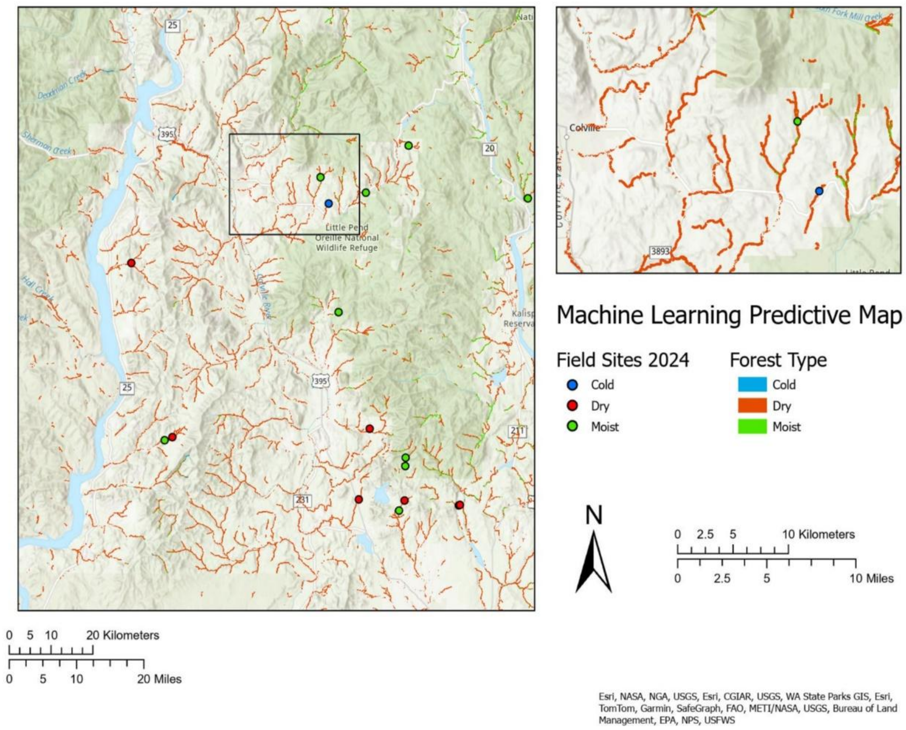

Figure SM5. Map of forest types defined by the Machine Learning predictive map developed during Phase I, Step 2, within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

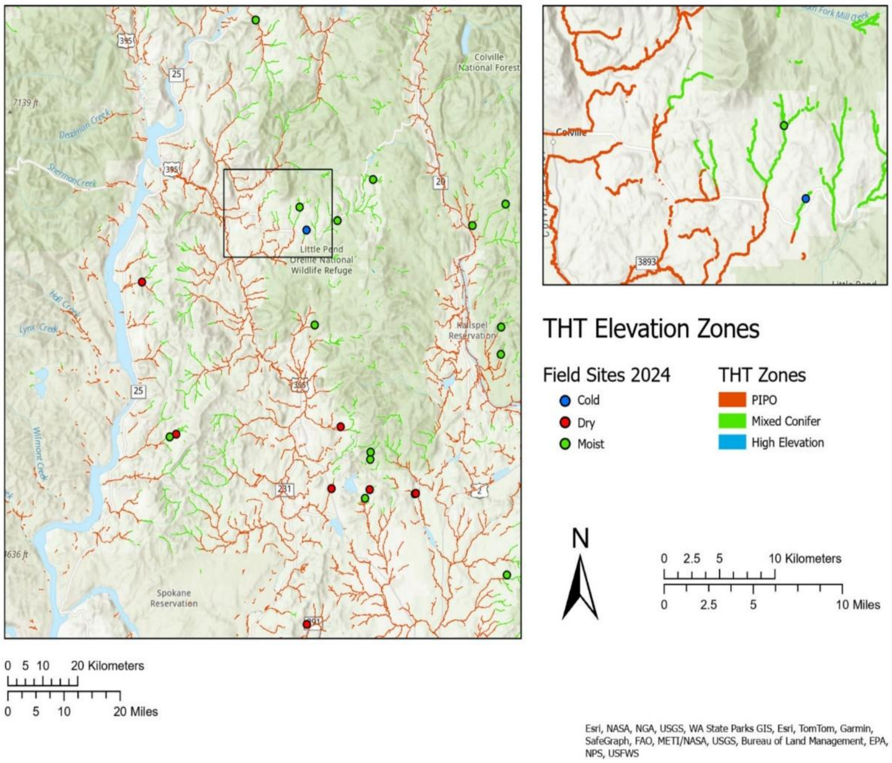

Figure SM6. Map of forest types defined by the Timber Habitat Type (THT) framework within 120 m of a Type F or Type S (fish-bearing) stream identified by the Washington State Department of Natural Resources Hydrology Layer. Field sites were identified as Cold, Dry, or Moist based on observed species composition, stand structure, and estimated fire return intervals (LANDFIRE dataset). The map shows the Northeastern area of Washington, centered on the Little Pend Oreille National Wildlife Refuge, to increase visibility of forest type variability.

~~Appendix III Supplemental Figures and Tables~~

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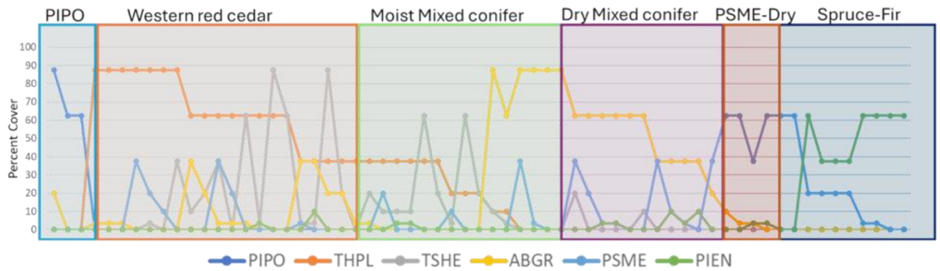


Figure S1. Visual ordination of vegetation cover data collected during field reconnaissance in the summer of 2023. Note that percent cover was based on the visual estimate of the percentage of plant canopy covering the sample plot. Thus, some plots with a multi-layered structure can have a total cover percentage of greater than 100%. Forest groups (colored boxes) were cross-referenced with those in the 20yFHP.

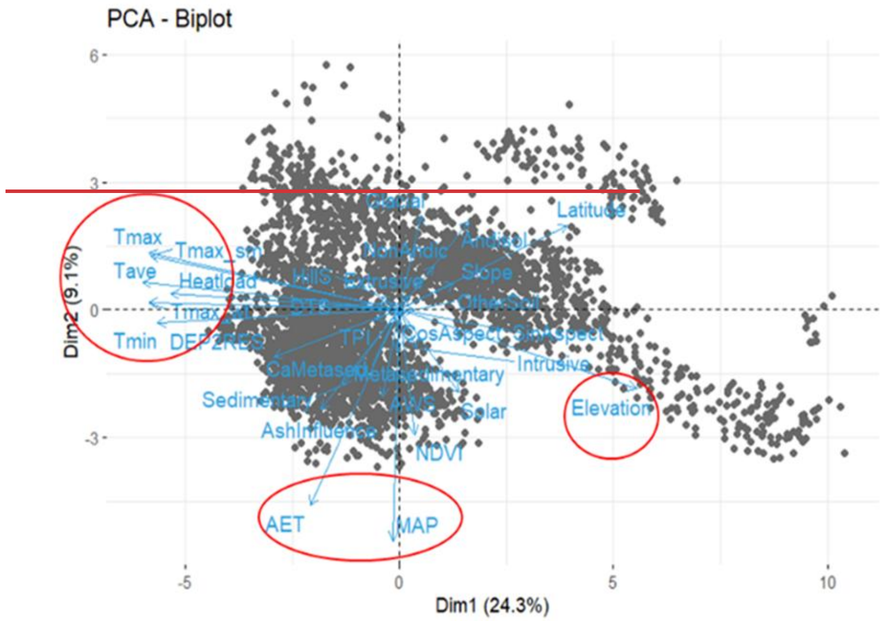


Figure S2. PCA biplot showing the distribution of 14,888 sampled points based on their similarity/dissimilarity in relative values of each independent variable. The longest vectors (surrounded by red circles) indicate the variables with that exhibit the highest variability across the study area. Variable abbreviations are listed in Table 3.

The Multifactor Classification Approach used Principal Component Analysis (PCA) to group data points based on similarities in 1) physiography, soil, and vegetation, 2) growth and yield (e.g., site index), 3) silvicultural potential (e.g., preferred species), and 4) susceptibility to damaging agents. Initial *a priori* classifications of units are made when different combinations of physiography-soil-vegetation (PSV) are identified. A unique PSV combination determined from spatial data sets is considered valid as a tentative classification if 1) they repeat throughout the landscape and are of sufficient size (e.g., > 1 ha), and 2) the hypothesized relationship of the PSV combination is valid in terms of ecological theory regarding plant-environment interactions and the physical ecosystem processes of soil and physiography (Spies & Barnes 1985). During the preliminary classification development process, physiography is given the most weight, followed by soil and then vegetation, as physiography is the most stable and vegetation is the least stable.

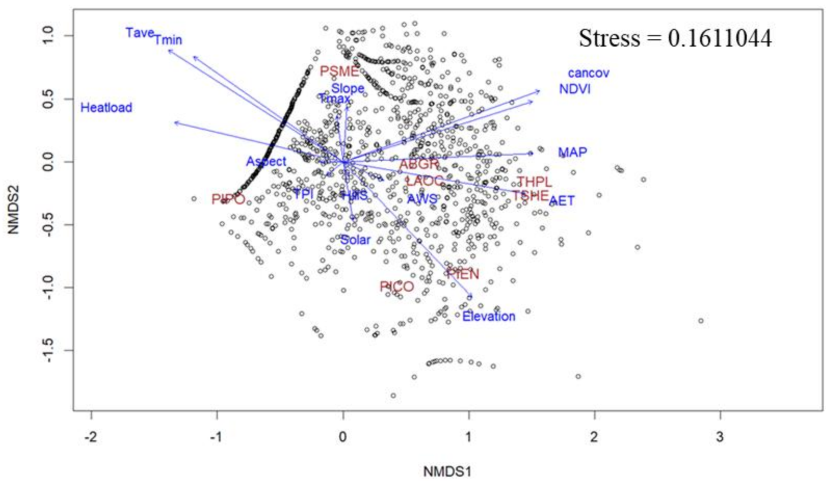


Figure S3. NMDS of 8,848 points extracted from the LEMMA dataset within the study area. The separation of species based on their relative frequency within each plot. The linear relationship of each independent factor with the distribution of each species.

The most significant factors correlating with the separations along the first axis (x: NMDS1) were mean annual precipitation (MAP; r2 0.99906, p <0.001) and heatload (r2 =-0.97366, p <0.001). Elevation, and all temperature factors were also significant (p <0.001) and showed the strongest relationship with species distributions along the first and second axes (y: NMDS2). Not surprisingly, species expected to occur on moister sites (e.g., western redcedar, western hemlock) clustered to the right of the centroid along with increasing MAP, while drier species (e.g., PIPO) were distributed further to the left of the centroid away from MAP and with increasing temperature values. Species expected to occur in colder habitats (Engelmann spruce, lodgepole pine) are distributed in the direction of increasing elevation and away from all temperature factors.

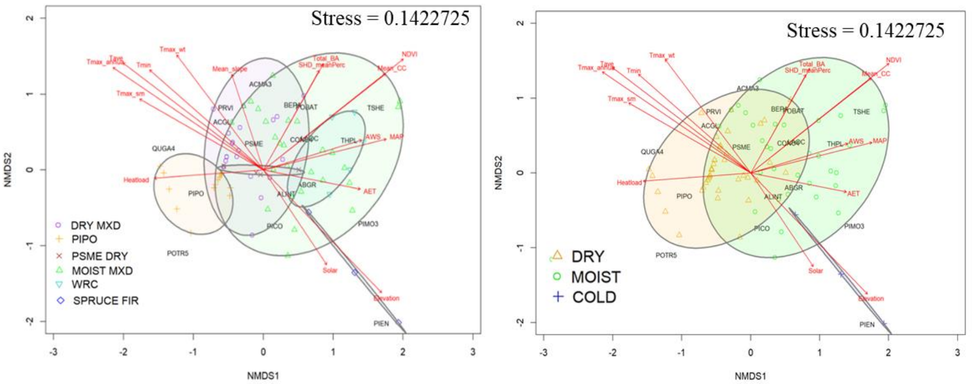
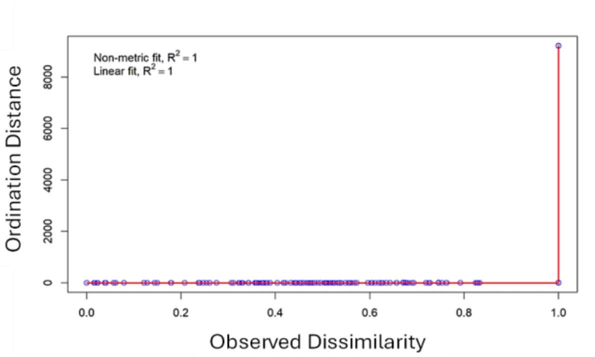


Figure S4, S5. NMDS ordination of species basal area/acre for the core zone (0-30') of 83 timber sites. Post hoc ellipses encompass full coverage of fine categories (S4) and coarse categories (S5) to show overlap.

Results from the NMDS ordination of the outer zone species matrix showed similar distributions, groupings, and site factor correlations as the ordination results for the full transect but with slightly higher overlap. For example, while the PIPO group in the fine categories, and the DRY type in the coarse categories still show distinct separation, a larger portion of the PIPO (fine) and DRY (coarse) sites fall within other categories (e.g., MOIST) than in the full transect ordinations.



	DCA 1	DCA 2	DCA 3	DCA 4
Eigenvalues	1.000	0.8792	0.7779	0.6659
Additive Eigenvalues	1.000	0.8786	0.7775	0.5766
Decorana values	1.000	0.9301	0.7594	0.4577
Axis lengths	1.003	4.5820	5.1385	2.8552

Figure S6. Stressplot for NMDS ordination attempt on species basal area/acre for the inner zone (0-30 ft) for 83 timber sites, and table showing results of detrended correspondence analysis with 26 segments. Rescaling of axes with 4 iterations. Total inertia (scaled Chi-square): 8.1298. DCA1 axis length <2.7 = linear ordination is reasonable.

Our attempt to apply NMDS ordination to the species matrix of the core zone failed to produce results. The stress output and stressplot showed near zero stress, indicating that the species distributions across plots were following a linear distribution as opposed to a unimodal distribution. To check for linearity of the species distributions within the core zone, we applied a detrended correspondence analysis (DCA), and to investigate the variance associated with the species distributions, we applied a redundancy analysis (RDA). Results of the DCA show that the species distributions indeed follow a linear distribution and that using a linear ordination approach (e.g., principal component analysis; PCA) is reasonable. The PCA analysis did produce some interpretable results. However, the RDA showed that the variance between species groups was excessively high (6405). Thus, we could not confidently interpret the results of the PCA of the core zone.

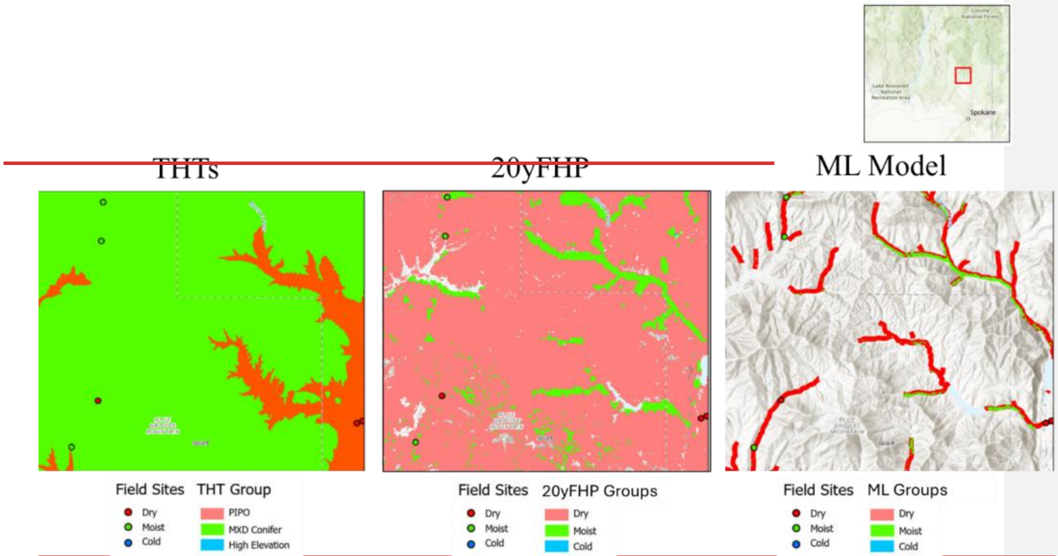


Figure S7. Zoomed in display of mapped regulatory zones of the THT for side-by-side comparison with forest types (coarse) mapped by the 20yFHP map, and the predictive forest type map (coarse) developed during the Machine Learning assessment of the 20yFHP map forest types.

These figures show how the details of the 20yFHP map forest types are more nuanced and follow streams and rivers identifying MOIST/DRY types. The ML Map, developed from machine learning investigation of the 20yFHP map builds on the 20yFHP map and attempts to refine the classifications based on the input factors (independent variables) used to learn from the 20yFHP map forest groups and redefine them based on those predictions. The ML Map shows an even more nuanced classification of forest types along streams (note that aspect appears to influence typing more strongly than in the 20yFHP map). However, because the model learned from the 20yFHP map, the error already associated with the 20yFHP map has been folded in and compounded during the modeling process. We attempted to rectify the compounding of error by calibrating with field data, but the relatively small sample size across a large error had little impact.

Table S1 A-D. Results of Kruskal-Wallis analysis comparing the distributions of forest types across the spatial variations of mean annual precipitation (MAP), and elevation with post-hoc pairwise comparison (Dunn's test) significance.

	P-value	
A. Blue Mountains	Elevation	MAP
Moist Mixed Conifer-Dry Douglas-fir	< 0.01	< 0.01
Ponderosa pine-Dry Douglas-fir	0.654	0.644
Ponderosa pine-Moist Mixed Conifer	< 0.01	< 0.01

MAP by Forest Type
Kruskal-Wallis chi-squared = 131.38, df = 2, p-value < 2.2e-16
Elevation by Forest Type
Elevation Kruskal-Wallis chi-squared = 23.076, df = 2, p-value = 9.75e-06

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	P-value	
B. East Cascades	Elevation	MAP
Moist Mixed Conifer-Dry Mixed Conifer	< 0.01	< 0.01
Ponderosa pine-Dry Mixed Conifer	0.0244	< 0.01
Spruce_Fir-Dry Mixed Conifer	< 0.01	< 0.01
Ponderosa pine-Moist Mixed Conifer	< 0.01	< 0.01
Spruce_Fir-Moist Mixed Conifer	< 0.01	< 0.01
Spruce_Fir-Ponderosa pine	< 0.01	< 0.01

MAP by Forest Type
Kruskal-Wallis chi-squared = 1056.1, df = 3, p-value < 2.2e-16
Elevation by Forest Type
Kruskal-Wallis chi-squared = 558.29, df = 3, p-value < 2.2e-16

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	P-value	
C. Columbia Plateau	Elevation	MAP
Dry Mixed Conifer-Moist Mixed Conifer	< 0.01	< 0.01
Dry Mixed Conifer- Ponderosa pine	< 0.01	0.343
Moist Mixed Conifer-Ponderosa pine	< 0.01	< 0.01

MAP by Forest Type
Kruskal-Wallis chi-squared = 265.82, df = 2, p-value < 2.2e-16
Elevation by Forest Type
Kruskal-Wallis chi-squared = 138.93, df = 2, p-value < 2.2e-16

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	P-value	
D. Northeast	Elevation	MAP
Dry Mixed Conifer - Moist Mixed Conifer	0.0174	< 0.01
Dry Mixed Conifer - Ponderosa pine	< 0.01	0.023
Dry Mixed Conifer - Spruce_Fir	< 0.01	0.494
Dry Mixed Conifer - Western redcedar	0.0842	< 0.01
Moist Mixed Conifer - Ponderosa pine	< 0.01	< 0.01
Moist Mixed Conifer - Spruce_Fir	< 0.01	< 0.01
Moist Mixed Conifer - Western redcedar	0.0823	< 0.01
Ponderosa pine - Spruce_Fir	< 0.01	< 0.01
Ponderosa pine - Western redcedar	< 0.01	< 0.01
Spruce_Fir - Western redcedar	< 0.01	< 0.01

MAP by Forest Type
Kruskal-Wallis chi-squared = 3060.9, df = 4, p-value < 2.2e-16
Elevation by Forest Type
Kruskal-Wallis chi-squared = 1552, df = 4, p-value < 2.2e-16

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