Evaluation of potential habitat breaks (PHBs) for use in delineating the upstream extent of fish habitat in forested landscapes in Washington State

Study Design prepared for the Washington Forest Practices Board

(Revised from PHB Science Panel Draft 2019)

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Preface

In 2018, the Potential Habitat Break (PHB) Science Panel convened by The Forest Practices Board (FPB or Board) developed a study design (PHB Science Panel 2019) to validate potential habitat breaks (PHBs). The study design (PHB Science Panel 2019) was reviewed and approved by Independent Scientific Peer Review (ISPR), however there were varying levels of comments and criticisms from all caucuses participating in the Forest Practices Adaptive Management Program (AMP) to particular aspects of the study design and the review process. In 2019, the Forest Practices Board remanded the project to the Department of Natural Resources' adaptive management science program, tasking the Cooperative Monitoring, Evaluation and Research (CMER) committee with revising the study design following CMER's protocols and standards (referenced in Forest Practices Board Manual Section 22). CMER assigned the study design revision to the Instream Science Advisory Group (ISAG). This revised study design was developed by a project team formed within ISAG. This document was adapted from the PHB Science Panel draft (2019) and includes substantial excerpts from this previous version.

Summary

The upstream extent of both fish distribution and fish habitat in forested watersheds is influenced by many factors including channel gradient, channel size, channel condition, nutrients, flow, barriers to migration, history of anthropogenic and natural disturbance, and/or fish abundance. Potential habitat breaks (PHBs) are defined as permanent, distinct, and measurable in-channel physical characteristics that limit the upstream extent of fish distributions. PHBs would be used in a Fish Habitat Assessment Methodology (FHAM), currently under development. The Washington Forest Practices Board has proposed three sets of criteria to be considered in determining PHBs between fish (Type F) and non-fish bearing (Type N) waters across the state. These criteria are based upon data that can be collected during a single Washington Department of Natural Resources (DNR) protocol electrofishing survey and include channel gradient, bankfull width, and both vertical and non-vertical non-deformable natural obstacles to upstream migration. Detailed information is needed on the uppermost fish location and associated habitat in small streams across Washington State to evaluate which physical criteria best define the end of fish (EOF) habitat (the uppermost stream segments that are actually or potentially could be inhabited by fish at any time of the year based on habitat accessibility and suitability). Some data on habitat conditions at uppermost detected fish

locations are available (e.g., from existing water type modification forms [WTMFs] submitted to DNR), but these data were found to be insufficient to determine PHBs that defined uppermost detected fish locations and associated habitat.

The purpose of this study is to develop criteria to characterize PHBs as accurately as possible and to evaluate the utility and accuracy of PHB criteria selected by the Board for use in the Fish Habitat Assessment methodology (FHAM) as part of a water typing rule. The study is designed to assess combinations of gradient, channel width, barriers to migration, and other physical habitat and geomorphic conditions associated with uppermost detected fish locations. Study findings will 1) inform which Board-identified PHB criteria most accurately identify the upstream extent of fish habitat in an objective and repeatable manner as applied in the FHAM; 2) evaluate whether an alternative set or combination of empirically derived criteria more accurately achieves this goal; and 3) provide insight into how uppermost detected fish points and associated stream characteristics may vary across geography, seasons, and years.

The study will be conducted across two sampling seasons (spring and fall/winter) in each of three years at 350 sites statewide; 160 in Eastern and 190 in Western Washington. Uppermost detected fish locations will be determined during each season at each site following modified DNR protocols for electrofishing surveys. Once the uppermost fish is located during each sampling event, the uppermost detected fish location will be flagged, GPS coordinates will be recorded, and a longitudinal profile habitat survey will be conducted to characterize habitat and geomorphic conditions 660 ft (200 meters) downstream and 660 ft upstream of the uppermost detected fish location. To evaluate seasonal changes in the location of the uppermost detected fish, the sites that can be accessed in the fall/winter season will be visited with an augmented serially alternating panel design. One quarter of the sites will be assigned to the fixed panel and will be surveyed every fall/winter, and the remainder will be allocated to three alternating panels. One of the three alternating panels will be surveyed each year, and the sample is augmented by the fixed panel of sites such that every accessible site will be surveyed at least once during the fall/winter. If an uppermost detected fish location changes during any subsequent survey, additional longitudinal profile survey data will be collected to ensure that there are channel data 660 ft above and 660 ft below uppermost detected fish locations for all seasons and years. Data will be analyzed using a suite of statistical methods (e.g., random forest, classification, and regression) to determine the combinations of gradient, channel width, and other geomorphic features associated with the uppermost detected fish locations across all seasons and years at each site, which will define PHBs and EOF habitat, and whether these vary across Eastern and Western Washington. Finally, a suite of PHB performance analyses will be used to evaluate the effectiveness of Board-proposed or other empirically derived PHB criteria resulting from this study in determining the regulatory break between fish (Type F) and non-fish bearing (Type N) waters.

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List of Acronyms

AMP	Adaptive Management Program
BFW	Bankfull Width
CMER	Cooperative Monitoring, Evaluation & Research Committee
DNR	Washington State Department of Natural Resources
DPC	Default Physical Characteristics
eDNA	Environmental DNA
EOF	End of Fish (Last detected fish following a Protocol Survey)
EOFH	End of Fish Habitat
F/N Break	Regulatory break between fish and non-fish bearing waters
FHAM	Fish Habitat Assessment Method
FPB, or "Board"	Washington State Forest Practices Board
GIS	Geographic Information System
HCP	Habitat Conservation Plan
ISPR	Independent Scientific Peer Review
NVO	Non-vertical obstacle
PHB	Potential Habitat Break(s)
TFW	Timber, Fish & Wildlife
Type F	Fish Bearing Streams
Type N	Non-Fish Bearing Streams
WTM	Water Type Modification
WTMF	Water Type Modification Form

Introduction

In Washington State, forest practices are regulated by the Forest Practices Act (RCW 76.09) established by the legislature, with rules established by the Washington Forest Practices Board (Board). The goals of the rules include protecting public resources (water quality, fish, and wildlife) and maintaining an economically viable timber industry. Rules pertaining to aquatic and riparian habitats are specifically included in the Forest Practices Habitat Conservation Plan (HCP), which provides coverage for approximately 9.3 million acres of forestland in Washington (6.1 million acres west of the Cascade Crest and 3.2 million acres in eastern Washington). Specific timber harvest and road prescriptions (rules) are applied to waters used by fish to protect fish and their habitats.

The Board is responsible for rulemaking and overseeing the implementation of forest practice rules. The evaluation of the effectiveness of these rules is administered by the Adaptive Management Program of the Washington Department of Natural Resources. Water typing is an important part of applying contemporary forest practice rules since prescriptions in riparian areas are based in part on whether streams are or potentially could be used by fish. Streams identified as having fish habitat are classified as Type F waters, defined in the water typing rule (WAC 222-16-030), and have specific riparian buffer prescriptions and fish passage requirements. Fish habitat is defined in WAC 222-16-010 as "…habitat, which is used by fish at any life stage at any time of the year including potential habitat likely to be used by fish, which could be recovered by restoration or management and includes off-channel habitat." Currently, an interim rule allows for the delineation of Type F waters through the use of either default physical characteristics (WAC 222-16-031) or a protocol electrofishing survey. DNR provides a map showing stream segments of modeled fish habitat. The Forest Practice Rules require forest landowners to verify, in the field, the type of any regulated waters identified within proposed harvest areas prior to submitting a forest practices application/notification. Landowners may use the default physical criteria or the results from protocol survey electrofishing to identify the regulatory Type F/N break. Landowners are encouraged to submit a Water Type Modification Form (WTMF) to the DNR to make permanent changes to the water type maps. Thousands of WTMFs have been submitted to DNR to modify water types and modify the location of the break between Type F and Type N waters.

The Board is currently in the process of establishing a permanent water typing rule. Ultimately, the rule must be implementable, repeatable, and enforceable by practitioners and regulators involved in the water typing system. An important part of the permanent rule will be guidance on a specific protocol to determine the regulatory break between Type F and Type N waters. The Board is considering the use of a fish habitat assessment method that incorporates known fish use with PHBs to identify the upstream extent of fish habitat. The Board recommended that PHBs be based on permanent physical channel characteristics such as gradient, stream size, and/or the presence of non-deformable vertical and non-vertical natural obstacles as potential barriers to upstream fish movement (WA Forest Practices Board 2017).

Study Purpose

The purpose of this study is to develop criteria for accurately identifying PHBs and to evaluate the utility of PHB criteria for use in the Fish Habitat Assessment Methodology (FHAM) as part of a water typing rule. The study is designed to assess which combinations of gradient, channel width, barriers to migration, and other physical habitat and geomorphic conditions are associated with uppermost detected fish locations. This will 1) inform which Board-identified PHB criteria most accurately identify the upstream extent of fish habitat in an objective and repeatable manner as applied in the FHAM and 2) evaluate whether an alternative set or combination of empirically derived criteria more accurately achieves this goal (CMER 2020). Additionally, this study is intended to provide insight into how uppermost detected fish points, upstream extent of fish habitat based on FHAM, and PHBs proposed by the Washington Forest Practice Board may vary across geography, seasons, and years. The Board is expected to use the study findings to inform which PHB criteria to use in FHAM.

It is important to note that this study is not intended to evaluate the current water typing system or the FHAM; nor is it intended to describe how the regulatory Type F/N break should be determined. PHBs are defined in FHAM as permanent, distinct, and measurable changes to in-channel physical characteristics. Other factors such as temperature, flow, water quality, population dynamics, anthropogenic and natural disturbance, and biological interactions are important covariates that might influence the distribution of fishes but do not affect PHBs. Therefore, they are not being evaluated in this study.

Project Research Questions

The following project-specific research questions were developed to address key uncertainties and provide information needed to evaluate the performance of the PHB criteria provided by the Washington Forest Practices Board and empirically derived alternatives. They also address certain aspects of the CMER Workplan Rule Group critical questions listed in Appendix A.

UPSTREAM-MOST FISH LOCATIONS

1. **How do the locations of the last (uppermost) detected fish vary interannually?**
2. **How do the locations of the last (uppermost) detected fish vary seasonally?**
3. **How do the locations of last (uppermost) detected fish vary geographically across the state of Washington?**

HABITAT ASSOCIATED WITH UPSTREAM-MOST FISH LOCATIONS

4. **How do the physical channel and basin characteristics (e.g., bankfull width; average gradient, basin size) associated with the identified end (upstream extent) of fish habitat vary geographically across the state of Washington?**
5. **Where the location of the last (uppermost) detected fish changes (seasonally or interannually), how does that influence which PHB would be associated with the F/N break and how frequently does that occur?**
6. **How do the physical channel features at the locations initially identified as PHBs change over the course of the study?**
7. **How often do similar features appear to limit upstream fish distributions in some contexts but not others (e.g., further into the headwaters vs. downstream; different flow levels)?**

PHB PERFORMANCE ANALYSES

8. **Which combinations of physical channel features and basin characteristics (for example, gradient, channel width, barriers to migration) best identify the end of fish habitat relative to the location of the last (uppermost) detected fish?**
9. **Can protocols used to describe PHBs be consistently applied among survey crews and be expected to provide similar results in practice?**
10. **How well do the PHB criteria provided by the Washington Forest Practices Board accurately identify the EOF habitat when applied in the Fish Habitat Assessment Methodology (FHAM)?**

Approach

We will use data from electrofishing and physical habitat channel surveys in a spatially balanced sample of 350 streams across Eastern and Western Washington to address the project research questions above and to evaluate proposed criteria to be used as potential habitat breaks in the FHAM. We will conduct multiple surveys over a three-year period to document seasonal and interannual changes in fish distribution and to maximize the likelihood of identifying the upper extent of fish use in each stream. This will allow us to address questions about seasonal and interannual changes in uppermost fish location, and to evaluate proposed criteria to be used as potential habitat breaks in the FHAM. We will identify PHBs associated with the upper extent of fish habitat using a suite of physical channel attributes and basin characteristics. Three sets of PHB classification criteria proposed by the Board will be assessed and an independent set of criteria will be developed with statistical tools for classification.

Background (*adapted from PHB Science Panel 2019*)

Over the past 20 years, protocol electrofishing surveys have been conducted under WAC 222-16-031 with guidance provided by Board Manual Section 13 to determine the upper extent of Type F waters. These surveys often incorporate additional stream length upstream of the uppermost detected fish to include habitat “likely to be used by fish” (defined in WAC 222-16-010). Throughout Washington, the uppermost fish[1] detected during protocol electrofishing surveys is most often a salmonid, and in around 90% of cases the uppermost fish is a cutthroat trout (*Oncorhynchus clarki*) (D. Collins, Washington Department of Natural Resources, unpublished data; Fransen et al. 2006). Other salmonid species that have been documented at uppermost fish locations on water type modification forms across Washington include rainbow trout (*O. mykiss*), brook trout (*Salvelinus fontinalis* - an introduced non-native that has become established in many Washington streams), and (rarely) bull trout (*S. confluentus*). In headwater reaches that are accessible to anadromous fishes, coho salmon (*O. kisutch*) juveniles have been reported on occasion as the uppermost fish. Of the non-salmonid species documented at uppermost fish sites on WTMFs in western Washington, sculpins (*Cottus* spp.) were most

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[1] WAC 222-16-010: "Fish" means for purposes of these rules, species of the vertebrate taxonomic groups of Cephalospidomorphi [lampreys] and Osteichthyes [bony fish].

prevalent, followed by brook lamprey (*Lampetra* spp.), and less commonly dace (*Rhinichthys* spp.), three-spine stickleback (*Gasterosteus aculeatus*), and Olympic mudminnow (*Novumbra hubbsi*). The only non- salmonid uppermost fish species recorded in east-side Washington streams were sculpins.

Many factors can limit the distribution of fishes including barriers to migration, stream gradient, flow, and channel size. Understanding the current science on how these factors influence fish distribution is important when discussing how they can be used to most accurately define the upstream limits of fish habitat in forested streams of Washington State.

Obstacles to Migration

Natural stream habitat breaks that might obstruct or completely block upstream fish movement to apparently suitable habitat include: vertical drops, cascades, bedrock sheets, and/or chutes (Hawkins et al. 1993; Figure 1).

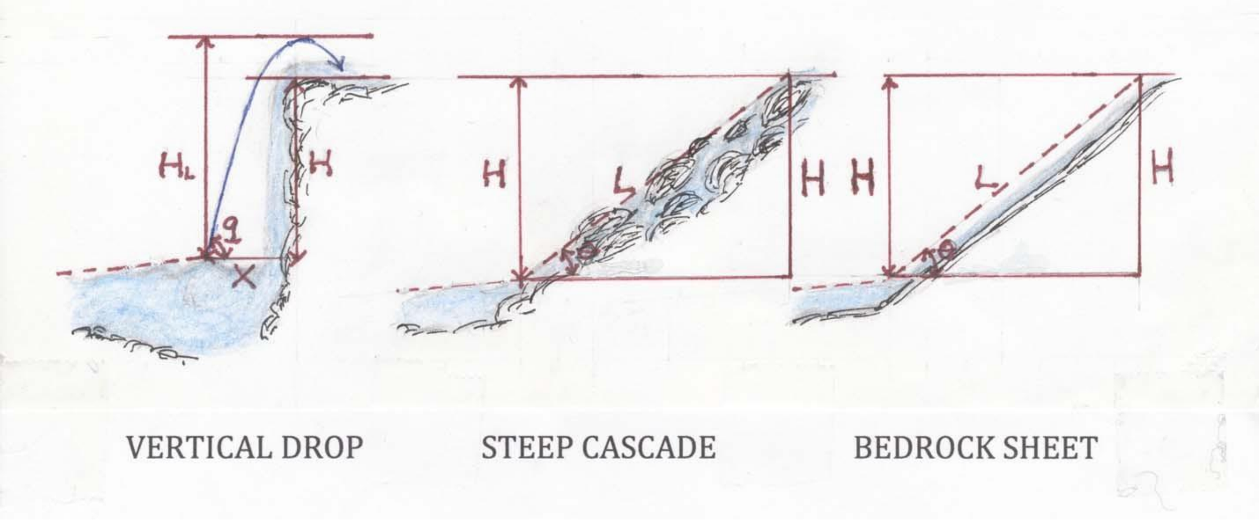

Figure 1. Three types of features that could pose obstacles or barriers to upstream movement of headwater fishes. (PHB Science Panel 2019)

The ability of fishes to pass such obstacles is associated with the interactions between their swimming and leaping abilities, environmental factors such as flow and temperature and the dimensions of the obstacles. The swimming ability of fishes is typically described in terms of cruising, prolonged, and burst speeds, which are measured in units of body lengths per second

(Watts 1974; Beamish 1978; Webb 1984; Bell 1991; Hammer 1995). Body form also affects swimming ability, with more fusiform body shapes being advantageous for stronger burst speeds in fishes such as cutthroat and rainbow trout (Bisson et al. 1988; Hawkins and Quinn 1996) in comparison to some other fishes, such as sculpin (*Cottus* spp.), commonly found at EOF locations. Cruising speed is the speed a fish can sustain essentially indefinitely without fatigue or stress, usually 2–4 body lengths per second. Cruising speed is used during normal migration or movements through gentle currents or low gradient reaches. Prolonged speed (also called sustained speed) is the speed a fish can maintain for a period of several minutes to less than an hour before fatiguing, typically 4–7 body lengths per second. Prolonged swimming speed is used when a fish is confronted with more robust currents or moderate gradients. Burst speed is the speed a fish can maintain for only a few seconds without fatigue, typically 8–12 body lengths per second. Fish typically accelerate to burst speed when necessary to ascend short, swift, steep sections of streams; to leap obstacles; and/or to avoid predators.

When leaping obstacles, fish come out of the water at burst velocity and move in a parabolic trajectory (Powers and Orsborn 1985). Relationships for the height attained in the leap, and the horizontal distance traversed to the point of maximum height are often used to assess barriers. Depth at the point of takeoff is important for enabling fish to reach burst velocity. Stuart (1962) found water depth of at least 1.25 times the height of an obstacle to be required for successful upstream barrier passage. More recently, however, Kondratieff and Myrick (2006) reported that small brook trout (size range 100-150 mm) could jump vertical waterfalls as high as 4.7 times their body length from plunge pools only 0.78 times the obstacle height, and larger brook trout (size ranges 150-200 mm and 200 mm+) could jump waterfalls with heights 3 to 4 times their body length if the plunge pool depth was at least 0.54 times the obstacle height.

To successfully ascend 4.7 body lengths in height, a back-calculation from the Powers and Orsborn (1985) trajectory equation yields a burst speed of 22 body lengths per second (11.7 feet per second) for the 100-150 mm body-length brook trout reported by Kondratieff and Myrick (2006). If it is assumed that other salmonids (e.g., cutthroat, rainbow trout or coho salmon) could perform as well as brook trout in the size range typically found at uppermost fish locations in Washington (Sedell et al. 1982; Fransen et al. 1998; Liquori 2000; Latterell et al. 2003; Peterson et al. 2013), then a burst speed of 22 body lengths per second (11.7 feet per second) would allow the largest fishes in the size range typical of headwater-dwelling salmonids (6.3 in, 160 mm) to leap a vertical obstacle 2.6 feet high, whereas a vertical obstacle of 3 feet high would be impassable.

When leaping is not required, fishes may ascend steep cascades and other high-velocity habitat units (Hawkins et al. 1993) by seeking pockets of slow water interspersed in areas with turbulent flow (e.g., boundary layers near rocks or logs). For example, Bisson et al. (1988) reported the average water velocity was only 24.8 ± 3.2 cm/s (0.8 ft/s) in shallow (10.0 ± 1.4 cm; 4 inches) cascade habitat units of small western Washington streams. It is possible that fish may ascend streams during periods of elevated flow by moving along the channel margins where water velocities are reduced relative to mid-stream and small falls and boulder cascades are partially or completely submerged.

Although studies examining fish migration through potential non-vertical obstacles are rare, some studies have examined brook trout movement through steep cascades and reported fish ascending cascades of more than 20% gradient (Moore et al. 1985; Adams et al. 2000; Björkelid 2005). For example, Adams et al. (2000) reported that adult brook trout ascended cascades with slopes of 13% that extended for more than 67 m, and 22% for more than 14 m as well as adult brook trout ascending a waterfall 1.2m high. Similarly, Björkelid (2005) reported invasive brook trout colonizing 18 headwater streams in Sweden and found they ascended stream segments with slopes of 22% (measured with a clinometer) and 31% (measured with GIS).

Gradient

In Washington streams, fish (not necessarily the uppermost fish) have been observed in headwater segments with overall slopes as steep as 31% (S. Conroy, formerly Washington Trout [now Wild Fish Conservancy], unpublished data), 35% (J. Silver, Hoh Indian Tribe, unpublished data; D. Collins, Washington Department of Natural Resources, unpublished data), and in reach gradients of 25% and steeper in Oregon streams (C. Andrus, Oregon Department of Forestry, unpublished data; Connolly and Hall 1999). This range of channel steepness is consistent with other observations in western North America (e.g., Leathe 1985; Fausch 1989; Ziller 1992; Kruse et al. 1997; Watson and Hillman 1997; Dunham et al. 1999; Hastings et al. 2005; Bryant et al. 2004, 2007) and Europe (Huet 1959). In the “trout zones” of European rivers (headwaters), brown trout (*Salmo trutta*) predominate and reach gradients may be 10 to 25% or steeper (Huet 1959; Watson 1993). In Washington, it is important to note that fish presence in streams steeper than 15% accounted for only 10% of reported occurrences in forested streams (Cole et al. 2006; J. T. Light, Plum Creek Timber, unpublished data). Kondolf et al. (1991) reported that often the water surface slopes where fish occur in step-pool habitats have much lower local gradients than the overall reach gradient and may range from only 0.4 to 4%, even where overall reach gradients may be as high as 35% (Figure 2). These observations indicate that in some cases fish habitat in headwater streams can extend into the types of steep step-pool and cascade reaches described by Montgomery and Buffington (1993).

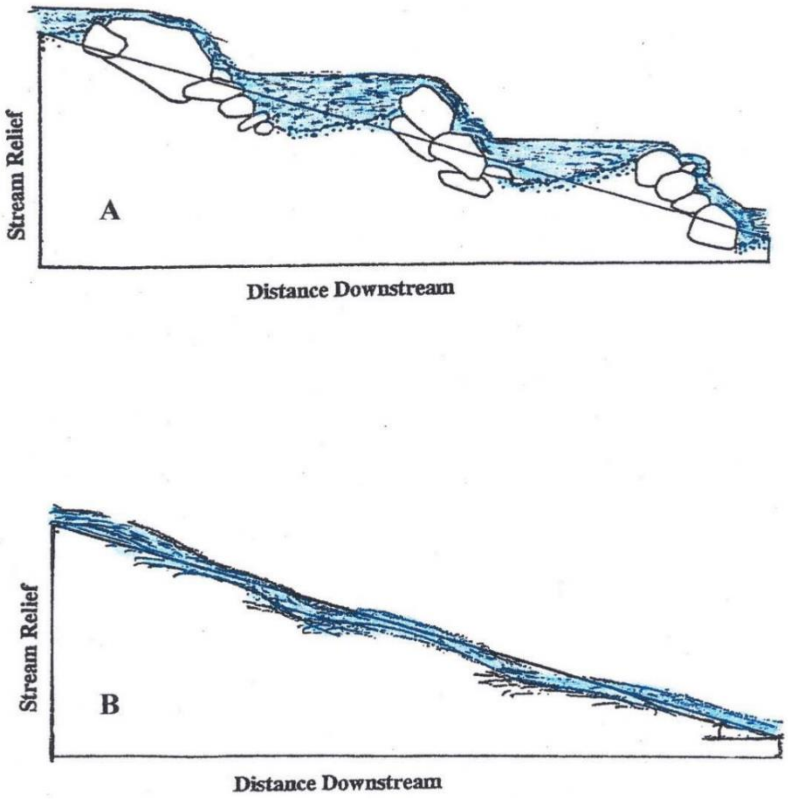

Figure 2. Two very different profiles of a headwater reach with the same overall reach gradient. Illustration (A) demonstrates how roughening elements create local gradients that are lower than the overall reach gradient, while reaches without such features (B) do not. (PHB Science Panel 2019)

Flow and Channel Size

Bankfull width (BFW) has been found to reflect the stage of discharge at which a stream does its habitat-building work (Andrews 1980; Leopold 1994; Rosgen 1996). Studies have shown that BFW is correlated with drainage area and varies with climate, geology, and topography of the basin (Castro and Jackson 2001). For example, Beechie and Imaki (2014) developed an equation for BFW for Columbia Basin streams based on annual precipitation and catchment (drainage) area. Although that equation was developed for larger streams, the PHB Science Panel (2019) tested it using empirical BFW data from multiple smaller streams across Washington State and found that it accurately predicted BFW in headwater streams. However, Castro and Jackson (2001) found that while BFW and drainage area relationships worked well in areas of similar lithology/geology and precipitation regimes to those for which they were developed, they were less useful in the Pacific coastal areas of western Washington where the geology and precipitation patterns are highly variable. Researchers continue to work on developing accurate and usable relationship models for highly variable headwater streams, which may become useful as more precise information and mapping of lithology, topography, and precipitation becomes available.

Because of the perceived relationship between channel width and discharge, BFW is often used as a surrogate for stream discharge (area, depth, and velocity), which is often important for determining the uppermost fish and upstream extent of fish habitat (Harvey 1993). Fransen et al. (1998) estimated mean annual flow rates at the upstream extent of fish distribution for 79 streams in the western Cascade foothills and Willapa Hills in Washington and found that 90% of these streams had mean annual flows of ~3.5 cfs or less at the upper boundary of fish presence; 80% had mean annual flows of ~2 cfs or less at the upper boundary; 65% had mean annual flows of ~1 cfs or less at the upper boundary; and approximately 25% of the sites had mean annual flows of 0.5 cfs or less at the upper boundary (Figure 3).

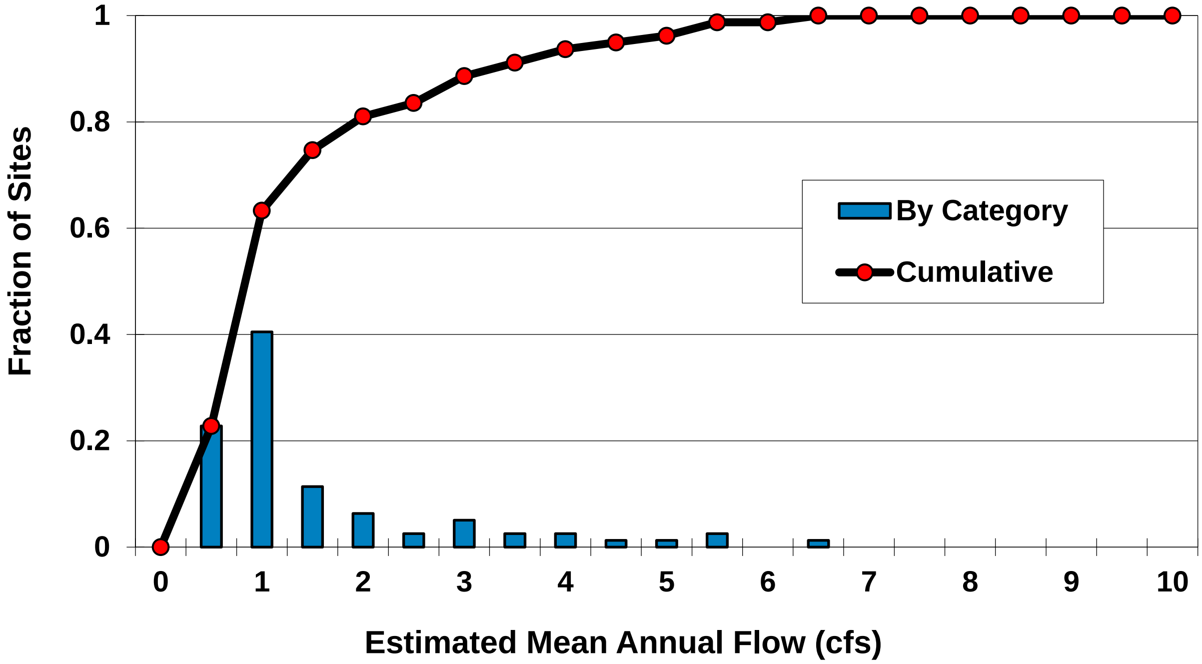

Figure 3. Estimated mean annual flows at uppermost fish locations in 79 streams in the Cascade foothills and Willapa Hills of western Washington (from Fransen et al. 1998)

Food Availability

Many studies, particularly in Pacific Northwest streams, have demonstrated strong food limitations for fish inhabiting (using) small streams (Warren et al. 1964; Mason 1976; Naiman and Sedell 1980; Bisson and Bilby 1998). Headwater segments are often characterized by closed forest canopies, requiring primary energy sources from allochthonous inputs of coarse particulate organic matter (CPOM). Shredder organisms occur in these reaches and feed on this CPOM. These aquatic organisms, along with any terrestrial invertebrates that fall into the stream, comprise the food base for trout and other predators (Vannote et al. 1980; Hawkins and Sedell 1981; Triska et al. 1982; Wipfli 1997). The total production of macroinvertebrate organisms is substantially lower in small headwater stream reaches than in the larger, lower-gradient reaches further downstream (Northcote and Hartmann 1988; Haggerty et al. 2004). As a result, resident fishes in small headwater stream reaches tend to be small bodied, which limits their ability to negotiate obstacles to upstream movement and migration.

Fish Habitat Assessment Method (FHAM)

Water typing surveyors have used professional judgment to estimate “habitat likely to be used by fish” when proposing regulatory fish bearing/non-fish bearing (F/N) water type breaks. Stream segments that are accessible to fish and exhibit the same characteristics as those of fish-bearing reaches are typically assumed to be fish habitat, whether or not fish are present at the time of a survey. Surveyors have assessed barriers and measurable changes in stream size and/or gradient to estimate the EOF habitat (Cupp 2002; Cole et al. 2006). Although research is somewhat limited, the upstream extent of fish distribution in forest lands appears to be strongly influenced by stream size, channel gradient, and access to suitable habitat (Fransen et al. 2006; PHB Science Panel 2018). In response to these findings, the Board embraced the concept of a Fish Habitat Assessment Methodology developed by a diverse group of AMP technical stakeholders intended to be repeatable, implementable, and enforceable (WA Forest Practices Board 2018; WA DNR 2019). The FHAM will utilize PHBs that reflect a measurable change in the physical stream characteristics at or upstream from a detected fish point, above which a protocol electrofishing survey would be undertaken (Figure 4). The first PHB located at or upstream from the uppermost detected fish would serve as the end of fish habitat (F/N Break) when no fish are detected above this PHB.

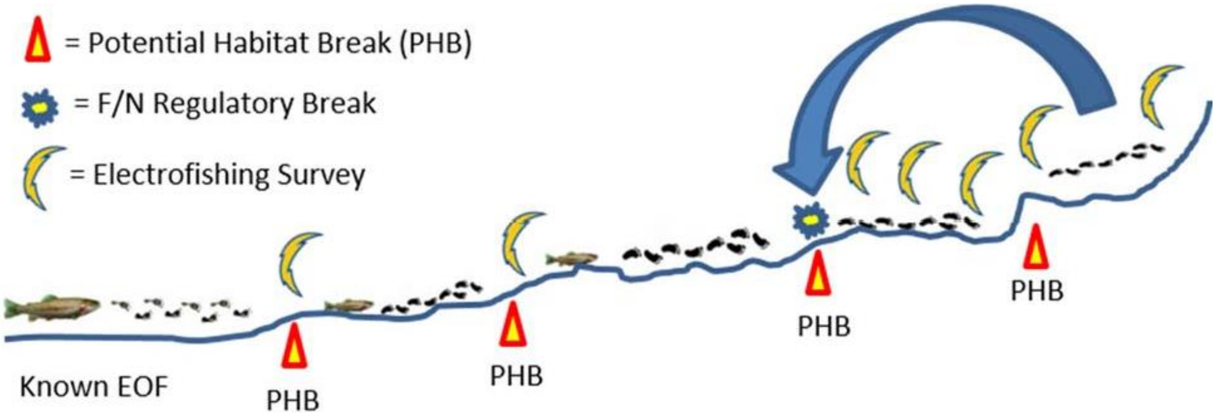

Figure 4. Example of how the PHB criteria and Fish Habitat Assessment Methodology (FHAM) will be applied in the field. The first step is to identify the uppermost detected fish location. Once the point is identified, the survey team would begin to measure bankfull width, gradient, and barrier (obstacle) criteria while moving upstream. Once a point in the stream meeting one of the PHB criterion (gradient, barrier, change in channel width) is identified, the survey team would apply a fish survey (e.g., electrofishing) upstream of the PHB to determine if fish are present upstream. If sampling yields no fish ¼ mile upstream, then the F/N break would occur at the location where the survey commenced (see arrow in the figure). If fish are encountered above any PHB, the process of measuring and moving upstream would repeat until fish are not encountered. (PHB Science Panel 2019)

Per FHAM, PHBs are based on stream size, gradient, and access to fish habitat. The PHB Science Panel reviewed the available science and data on PHBs and provided recommendations to the Board for specific PHB criteria for eastern and western Washington (PHB Science Panel 2018). The Panel considered a variety of potential PHB criteria, including the physical attributes of a stream channel, water quality and quantity parameters, and other factors that might contribute to measurable habitat breaks. These attributes were evaluated for the ability to simply, objectively, accurately and repeatably measure them in the field, as well as the amount and relevance of existing scientific literature pertaining to each. The Panel concluded that it was possible to identify PHBs based on stream size, channel gradient, and natural non-deformable obstacles. These three attributes satisfied the objectives of simplicity, objectivity, accuracy, ease of measurement, and repeatability that can be consistently identified in the field and can be incorporated into a practical survey protocol. The Board then selected three combinations of stakeholder-proposed PHB criteria for these attributes at their 14 February 2018 meeting (WA FPB 2018) and instructed the PHB Science Panel to develop a field study to evaluate the performance of these proposals (Table 1). It was important to the Board to determine which of the proposed criteria most reliably identify PHBs in eastern and western Washington. The Board also instructed the Science Panel to stratify sampling by ecoregion and to examine crew variability in identifying PHBs, especially evaluating aspects of field measurement practicality and repeatability (WA FPB August 2017). This study is designed to evaluate which Board-identified PHB criteria most accurately identify the upstream extent of fish habitat and to determine whether an alternative set or combination of empirically derived criteria more accurately achieves this goal (CMER 2020).

Table 1. Three combinations of barrier (obstacle), gradient, and width PHBs selected for evaluation by the Washington Forest Practices Board during their February 2018 meeting. Descriptions are abbreviated for readability from WA Forest Practices Board 2018. Criteria may be revised by the Forest Practices Board before project is implemented.

Type/	Description of Criteria
Criteria Set 1	
Width	2 ft BFW threshold (upstream BFW ≤2ft)
Gradient	Gradient increase of ≥10%
Vertical Obstacle	Obstacle height ≥3ft
Non-Vert Obstacle	Obstacle gradient ≥20%, AND elevation difference is ≥ 1x upstream BFW
Criteria Set 2	
Width	2 ft BFW threshold (upstream BFW ≤2ft)
Gradient	Gradient increase of ≥5%
Vertical Obstacle	Obstacle height ≥3ft AND ≥ 1x upstream BFW
Non-Vert Obstacle	Obstacle gradient ≥30%, AND elevation difference is > 2x upstream BFW
Criteria Set 3	
Width	20% BFW decrease (up- to downstream BFW ratio at tributary junctions ≤.8)
Gradient	Gradient increase of ≥5%
Vertical Obstacle	Obstacle height ≥3ft
Non-Vert Obstacle	Obstacle gradient ≥20%, AND elevation difference is ≥ upstream BFW

Methods

Survey Design

Sampling Frame and Study Sites

Current F/N break points on the DNR Forest Practices water type map will serve as the sampling frame for this study. The target population is defined as the set of all F/N break points on streams on Forests and Fish (FFR) lands in Washington. A sampling frame that matches the target population as closely as possible is needed for unbiased inference. Fish/non-fish stream type break points extracted from the current DNR water type GIS map layer (DNR Forest Practices hydro, watercourses (“wchydro"); https://data-wadnr.opendata.arcgis.com/datasets/wadnr::dnr-hydrography-watercourses-forest-practices-regulation/about) represent an accessible source of possible study sites. Some of these points are based on field surveys that were concurred (survey-based) through the WTM review process while others are modeled points obtained from a logistic regression model that predicts F/N points based on basin area, upstream and downstream gradients, elevation, and precipitation (Conrad et al. 2003; Duke, 2005). The hybrid approach using both modeled and concurred F/N break points as the sampling frame incorporates existing information while allowing a broad scope of inference.

The study design will incorporate spatially balanced sampling. A spatially balanced sample provides a sample that is geographically diverse, which generally means outcomes exhibit less spatial correlation across units (Olsen et al. 2015). When outcomes are less correlated, outcomes are more spatially independent of one another, thus increasing effective sample sizes. Several types of spatially balanced sampling exist, including two-dimensional systematic (or grid) samples, balanced acceptance sampling (BAS; Robertson et al. 2013), Halton iterative partitioning (HIP; Robertson et al. 2018), and generalized random tessellation stratification (GRTS; Stevens and Olsen 2003, 2004). Because the R package used to draw BAS & HIP samples is currently not maintained on the CRAN server for R packages, the GRTS package maintained by the EPA, spsurvey (Dumelle et al. 2022), will be used to draw the spatially balanced sample to ensure best practices for security protocols and package functionality by using a currently-maintained R package.

The spatially balanced sample of F/N points will be stratified by region (eastern or western Washington)[2]. The western region of Washington consists of about one-third of the state's area but has twice the stream density. Given the differences in stream distribution across the state and the different sources of frame error in each region, east-west stratification will be applied to ensure that spatial balance is maintained within each region.

Previous iterations of this study design incorporated ecoregion as a stratification variable. Ecoregions reflect broad ecological patterns occurring on the landscape. In general, each ecoregion has a distinctive composition and pattern of plant and animal species distribution. Abiotic factors, such as climate, landform, soil, and hydrology are important in the development of ecosystems and thus help define ecoregions. The Washington State Natural Heritage Program modified ecoregions defined by the US EPA into Level III ecoregions specific to Washington, each of which is described at http://www.landscope.org/washington/natural_geography/ecoregions (Figure 5). While it is possible that there is something about ecoregions, particularly precipitation patterns, that might cause differences in the barriers to fish movement, there is no strong reason to restrain the analysis of results to that factor at the expense of our ability to investigate other, potentially more important factors. We agree that there are likely to be differences among ecoregions in where the fish and barriers to movement occur on the landscape but identifying those spatial patterns of occurrence is not the purpose of the PHB study.

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[2] We considered other finer scale stratification (e.g., geology, channel type, elevation, valley confinement), but these were not logistically feasible and would greatly increase the sample size, cost and time needed to complete the study. The Washington Forest Practices Board also instructed the PHB Science Panel to develop a study plan that specifically included stratification by ecoregion.

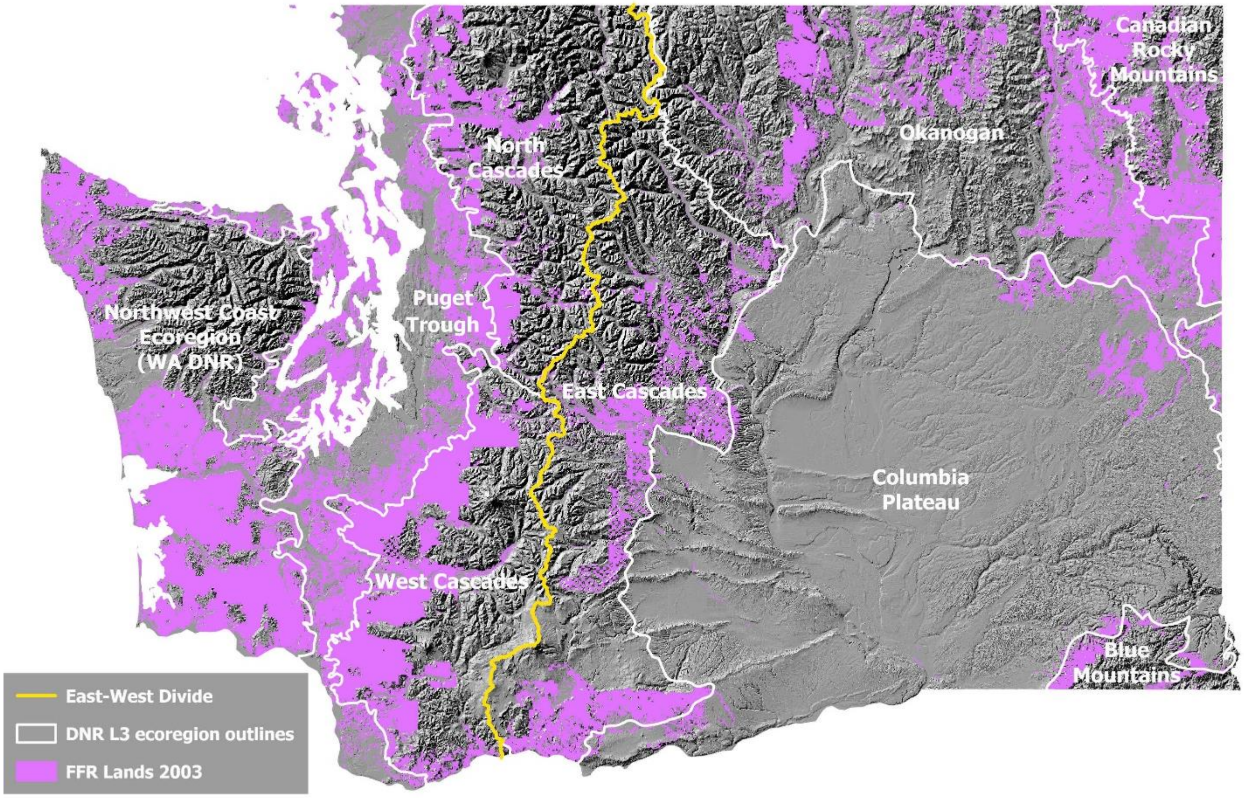

Figure 5. Washington Natural Heritage Program Level III ecoregions with Lands subject to the Forests and Fish (FFR) forest practices rules designated in purple. Note the general absence of FFR lands in the Columbia Plateau ecoregion. FFR lands mapped as of 2003. Ecoregion data downloaded from https://data-wadnr.opendata.arcgis.com/datasets/wadnr::ecoregions-of-the-pacific-northwest/explore?location=46.585091%2C-118.050200%2C6.03 in 2022.

In this design, we do not propose the use of *a priori* stratification by ecoregion. A priori stratification would be advisable for this study to model PHBs by ecoregion, to attain a desired level of precision for each ecoregion, for administrative convenience, or to apply different survey methodologies by ecoregion (Cochran 1977). However, none of these considerations apply in this sampling design. We expect sampling effort to be allocated proportionally to the relative area of ecoregions due to the implicit probability-proportional-to-size sampling obtained from spatially balanced sampling. However, smaller ecoregions, such as the Blue Mountains ecoregion, may receive fewer sampling points due to its smaller area and remote location. "Islands" of sampling frame that are not contiguous can affect overall spatial balance

(Don Stevens, personal communication), in which case a priori stratification might be necessary. When the sampling frame is available, the allocation of sites will be examined for test sample draws to determine if adequate sample sizes within each ecoregion are obtainable.

Sampling effort will be apportioned among mapped terminal or lateral F/N break point types (Figure 6) with post-hoc stratification. This approach is useful when the point types are not known for each site before the survey, so no sampling frame is available to identify each subpopulation for *a priori* stratification. Survey crews will record the point type at the time of the survey and, when the desired sample size for a point type is satisfied, survey data from this point type will not be collected at subsequent points of this type. Because the point type is not known a priori so cannot be included as a survey design variable for stratification, employing this technique will require adherence to the spatially balanced ordered list of sites to ensure that the obtained sample of sites within each point type is also spatially balanced. The point type should be recorded for each site so that inclusion probabilities for each site may be calculated prior to analysis for any design-based summaries such as means and totals (Larsen et al. 2008, section 2.4). This apportionment will only occur during the initial site surveys. If a site changes from lateral to a terminal over the course of the study, we will not add any study sites to accommodate that change.

Based on an analysis of observed variability in channel gradient and width upstream of uppermost detected fish points from previous CMER studies and existing water type modification forms (Appendix B), we propose to determine the location of uppermost detectable fish at 160 sites in forested watersheds in eastern Washington and 190 sites in forested watersheds in western Washington[3]. Habitat characteristics (gradient, channel width, obstacles) will be measured using a longitudinal stream channel profile survey 660 ft (200 m) above and 660 ft below the uppermost detected fish. The uppermost detected fish locations will be determined during each sampling event via electrofishing surveys. The corresponding habitat surveys surrounding the located uppermost fish point are expected to provide the data necessary to evaluate differences among PHB criteria across the state and within the eastern

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[3] The recommended sample size includes sites in addition to the minimum number calculated to meet the specified statistical requirements. This allows for site attrition over life of the project.

and western Washington regions. Data collected with consistent methods and crews might have lower variability than the data we used to estimate sample size.

We will sample a small subset of sites across east/west regions concurrent with the site selection year/process (during 'Year-0') in order to field test our methods without causing a delay to project implementation.

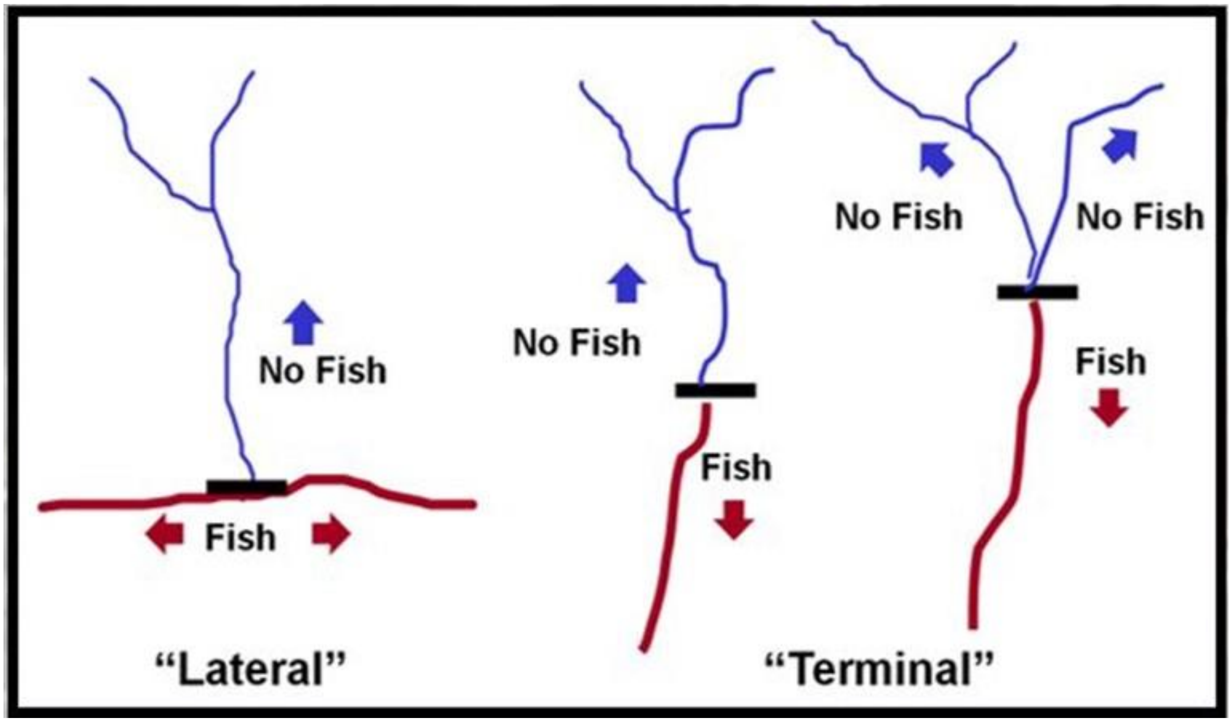

Figure 6. Schematic diagram of lateral versus terminal upstream limits of fish occurrence within streams. The black bar(s) indicate the location of the uppermost fish (Fransen et al. 2006).

Site Identification

The DNR Hydro Watercourses hydrography data layer contains stream channel locations across the state. Stream lines are kept as segments with properties of each segment stored as attributes. Segments are divided at intersections with other stream segments and any place where their recorded properties change (e.g. - fish use/non-fish use). The points at which this classification changes from fish (Type F) to non-fish (Type N) will be extracted from this hydro layer. The properties of the fish use segment below the break will be retained with those data points and stored in the new point layer. The attributes (properties) of interest for this study include the criteria for fish use determination, such as whether it was a segment modeled as likely fish habitat, a concurred point from a water type modification form, or a legacy determination. Another attribute is whether that determination was based on biological information (fish observation or electroshocking findings) or on physical habitat assessment. Such information will be important for locating the optimum survey starting location but will not be used for the purposes of selecting sample streams.

The F/N break points are intersected with the East/West Washington polygons to assign them an East/West attribute. Points will also be intersected with the DNR Ecoregions polygon layer to assign them an Ecoregion attribute. However, that attribute will be used as a covariate in post-hoc analyses rather than as a stratification variable unless test sampling indicates otherwise. The point layer will be subjected to the GRTS spatial randomization procedure, which will assign a sequence number to each point. The points to be inspected for this study will be selected from each side of the state in the sequence assigned. As points are discarded according to our rejection criteria (below), the next sequential point will be added to the sample population. In this way, spatial balance and random validity should be maintained.

In practice, batches of points will be selected and assessed for suitability, access permission, and field crew accessibility to facilitate the sample set delineation prior to field surveys. These batches will ensure that more points (streams) are ready to be sampled (and even perhaps initially sampled) than are actually needed in case selected points are rejected during the first study season. GRTS sample locations will be obtained from the sample draw in a GRTS design file. Surveys that maintain the order of sites in the GRTS design file are spatially balanced relative to the sampling frame from which the sample was drawn. Any sequential subset of sites in the GRTS ordering is a spatially balanced subset of sites. Note that spatial balance does not require that sites are *visited* in the order of the design file, but the sequential list of sites should be fully enumerated by the end of the survey season with no skipped sites. This allows field crews to visit the sites in an efficient manner while maintaining overall spatial balance of the sample within any given year. For each site in the GRTS design file that is considered for surveys, notes on any frame error or reasons for nonresponse will be recorded so that inclusion probabilities for each site can be accurately calculated.

The F/N break point will identify the stream to be sampled, not necessarily the sample starting point. The starting points will be the uppermost known fish location for that stream based on any available information that can be obtained about that stream. The GIS layer contains some information, such as the typing basis. Other information may be obtained from landowners, tribal entities that monitor that stream area, and other local experts. In the case of tributary streams that have no reliable fish observations, the electrofishing survey will start at the confluence of the subject stream with the known fish-bearing mainstem stream. The initial survey will determine lateral versus terminal status of the selected tributary for site allocation purposes during site selection.

Site Rejection Criteria

Some potential study sites will be excluded from the sample population due to unforeseen circumstances. During the site selection and field validation task, study sites may be dropped as follows:

- Sites where the uppermost detected fish is associated with a man-made barrier;
- Streams showing evidence of recent (e.g., within five years) debris flows through the subject stream;
- Sites where we cannot obtain landowner permission for the full survey length;
- Sites that are not safely accessible by field crews;
- Other reasons determined by project team.

In every case that a site is excluded from the sample, the reasons will be thoroughly documented. Site rejection decisions will be approved by project managers and are not the sole responsibility of field crews.

Temporal Revisit Design

Field surveys (electrofishing and habitat data collection) will be conducted during the spring/early summer and the late fall/early winter sampling periods (seasons). These two sample periods were chosen because they represent the most likely time periods for fish to be found at their uppermost point in the stream network, and therefore should be adequate to evaluate seasonal differences in the upper extent of fish use. While summer sampling may be beneficial to compare seasons, due to the low flows typical of summer, it is unlikely that fish would move higher into the system in that season (Cole and Lemke, 2006).

All sites will be surveyed every year during spring/early summer (current protocol electrofishing survey window of March 1 to July 15) for three years to examine inter-annual changes in uppermost detected fish locations. To evaluate seasonal changes in the location of the uppermost detected fish, the sites that can be safely accessed in the fall/winter season will also be visited with an augmented serially-alternating panel design. One quarter of the sites will be assigned to the fixed panel and will be surveyed every fall/winter, and the remainder of sites will be allocated to three alternating panels. One of three alternating panels will be surveyed each year, with the sample augmented by the fixed panel to connect the sample across years and seasons. The fixed panel will consist of the full count of sites from Table 2, while the alternating panel counts will vary depending on site accessibility. The survey timing within both sampling periods will be determined through consultation with regional experts to optimize the timing based on local hydrology, fish life history, and potential for site access, and resurvey timing will be consistent (within two weeks of the original survey date) across years.

Table 2. Overall sampling schedule and number of sample sites by calendar year and season 2024 to 2026. All sites will be sampled in spring to early summer (March 1 to July 15) with the seasonal fixed and alternating panel being resampled in fall to early winter high flow period (dates determined through consultation with regional experts). A pilot study sampling 15 sites in eastern and 12 sites in western Washington was completed in September of 2018 (Roni et al. 2018).

Sampling Event	Pilot year (2018)	Year 1 (2024)	Year 2 (2025)	Year 3 (2026)
Spring to early summer		160 eastern Washington 190 western Washington	160 eastern Washington 190 western Washington	160 eastern Washington 190 western Washington
Late Fall/Winter Fixed Panel Sampled All Years (same sites)	27 to test methods	40 E WA 48 W WA	40 E WA 48 W WA	40 E WA 48 W WA
Late Fall/Winter Alternating panel, Sampled Only in Single Season		40 E WA 48 W WA	40 E WA 47 W WA	40 E WA 47 W WA
Reporting	Pilot study report	Annual report	Annual Report	Final Report

Data Collection

Protocol Electrofishing and Habitat Surveys

Electrofishing and habitat survey will provide a robust data set to inform the PHB and associated analyses. Electrofishing surveys will be conducted to determine the location of the uppermost fish at each survey event. Surveys at all study sites over three years will maximize the probability of locating the upstream extent of fish habitat by incorporating both temporal and spatial variability in fish movement due to physical (e.g., stream flow) and biological (population dynamics) factors.

An intensive longitudinal thalweg and water surface profile survey (Roni et al. 2018) will be conducted up- and downstream of the uppermost fish points following the electrofishing surveys. The channel survey data will be used to partition the study reach into variable-length stream segments that are scaled to lengths of homogeneous habitat attributes within the long-channel profile. The length of segments will be based on changes in gradient and channel width that are associated with inflection points and/or changes in habitat features (e.g., vertical and non-vertical obstacle). Vertical and near-vertical obstacles will be captured as individual segments, as such features will have some segment length associated with them.

Prior to sampling a site, the project team will review existing information from any available sources on access, previous location of uppermost detected fish and habitat data, and obtain landowner permission for access and sampling. In determining the upstream extent of fish distribution, multiple upstream segments may be available for survey. When this situation occurs, the selected surveyed segment will be the mainstem channel, defined as the stream segment with the largest contributing basin area upstream from a tributary junction (should have largest bankfull width, most flow, etc.). Where basin area upstream from a junction appears approximately equal, rely on additional on-site metrics such as bankfull width and/or flow to determine upstream direction of survey. Stream segments not included in the hydrolayer may be encountered when moving upstream. These stream segments will be included in the survey process in accordance with the above criteria.

Field crews will use modified DNR protocol electrofishing surveys with the intensity consistent with methods being developed for FHAM to determine uppermost detected fish (Figure 7a) and surveys will only be conducted when sampling conditions are suitable (avoiding periods of extreme high/low flow or temperature, elevated turbidity, etc.). Water temperature (to the nearest 0.1 °C), conductivity (microsiemens), and electrofishing setting (e.g., voltage, frequency, pulse width) will be recorded at the beginning of each electrofishing survey. The GPS coordinates of each uppermost detected fish location will be recorded, and the location will be flagged and monumented with a marker including the survey date on an adjacent tree. The fish species and approximate sizes will be recorded. Electrofishing surveys will continue from the uppermost detected fish point upstream to at least the end of default physical fish criteria (end DPC point). In the event the uppermost detected fish is found at the end of DPC, electrofishing will continue 660 feet (upstream) to align with the extent of the detailed habitat surveys. We will also record electrofishing survey time (shock seconds). In addition, coarse scale habitat data will be collected on the full extent of the stream sampled during the e-fishing survey. These data will include channel gradient, bankfull width, wetted width and confinement within unequal length segments of relatively uniform habitat character.

An intensive longitudinal thalweg and water surface profile survey (Roni et al. 2018) will be used to assess key habitat attributes (i.e., gradient, bankfull and wetted width, water depth, substrate size composition, and height of channel steps) below and above the uppermost detected fish (Figure 7b). A previous study of variability on the upper limits of fish distribution in headwater streams suggested that over 90% of the interannual variation in the uppermost detected fish location occurred within 200 m (Cole et al. 2006). Therefore, we will use a distance of 660 feet (200 m) below and 660 feet above the uppermost detected fish as our intensive habitat survey reach. The crew will measure 660 feet (horizontal distance) downstream from the uppermost detected fish point to determine the beginning point for the intensive stream habitat survey.

The intensive habitat survey involves surveying the streambed elevation along the deepest portion of the stream (the thalweg), yielding a two-dimensional longitudinal profile of streambed elevations. This has been shown to be a reliable and consistent method for measuring change in stream morphology and fish habitat independent of flow (Mossop and Bradford 2006). We will also be recording water surface heights because surface levels are what are important to fish with regard to obstacle heights. Survey measurements will be taken every ten feet, and at any significant inflection points in topography or planform to be sure we capture all changes in thalweg topography and gradient. A laser range finder mounted on a monopod and a target on a second monopod will be used to collect distance and elevation data. All data will be entered into a computer tablet in the field. Measurements and observations at each point will include horizontal distance and slope between survey points, water depths, wetted widths, bankfull width, dominant substrate (e.g., sand, gravel, cobble), large wood, habitat feature type (e.g., pool, riffle, cascade), and general characterization of flow and water conditions. Water surface elevation will be calculated after the survey from the bed elevation plus the measured water depth. For steps and potential migration barriers, the crew will record whether the step is formed by wood, bedrock, or another substrate. The presence of wood is particularly important because wood-formed barriers and obstacles are considered deformable and therefore are not PHBs. Crews will also note whether flow is continuous or intermittent, the presence of beaver dams, groundwater inputs, and any other unusual features (e.g., tunneled or sub-surface flow) that could influence fish distribution. Because sites will generally be in small, constrained streams that are unlikely to change significantly throughout the sampling year, it is likely that the habitat survey data for each stream will only need to be collected once each year with the spring sampling effort. The survey will be repeated annually to ensure we have a complete survey 660 feet above and 660 feet below the uppermost detected fish found during each sampling event (Figure 7c). During each survey, fixed elevation benchmarks will be placed at the bottom, middle (uppermost fish point) and top of the intensive habitat survey reach to facilitate the coherence of repeat surveys. A similar protocol based on Mossop and Bradford (2006) has been used to survey barrier removal projects on small streams throughout the Columbia River Basin (Clark et al. 2019, 2020).

Evaluations of various regional stream habitat survey protocols have demonstrated that with *well-trained* field crews, measurement error is small relative to naturally occurring variability amongst sites (Kershner et al. 2002; Roper et al. 2002; Whitacre et al. 2007, Archer et al. 2004).

Therefore, all crews will participate in a three to five-day training course each year prior to initiation of spring sampling to ensure consistency among crews in determining uppermost detected fish locations, surveying habitat characteristics (long-profiles), and data collection. Training should incorporate identifying potential sources of variation in measurement that can result from dense vegetation, identification of features, and clarity of protocols (Roper et al. 2010). In addition, mid-season check-in/corrections will be conducted with each crew to prevent sampling drift (this process will be outlined in the Quality Assurance Plan). Moreover, to quantify variability among crews in conducting longitudinal surveys, we propose that 10% of all sites sampled each spring should be resampled during the same year and season by other crews every year. Since variation in stream flow during subsequent surveys should not affect the longitudinal bed profile, we don’t expect flow changes to contribute to variability observed among crews in these resurveys.

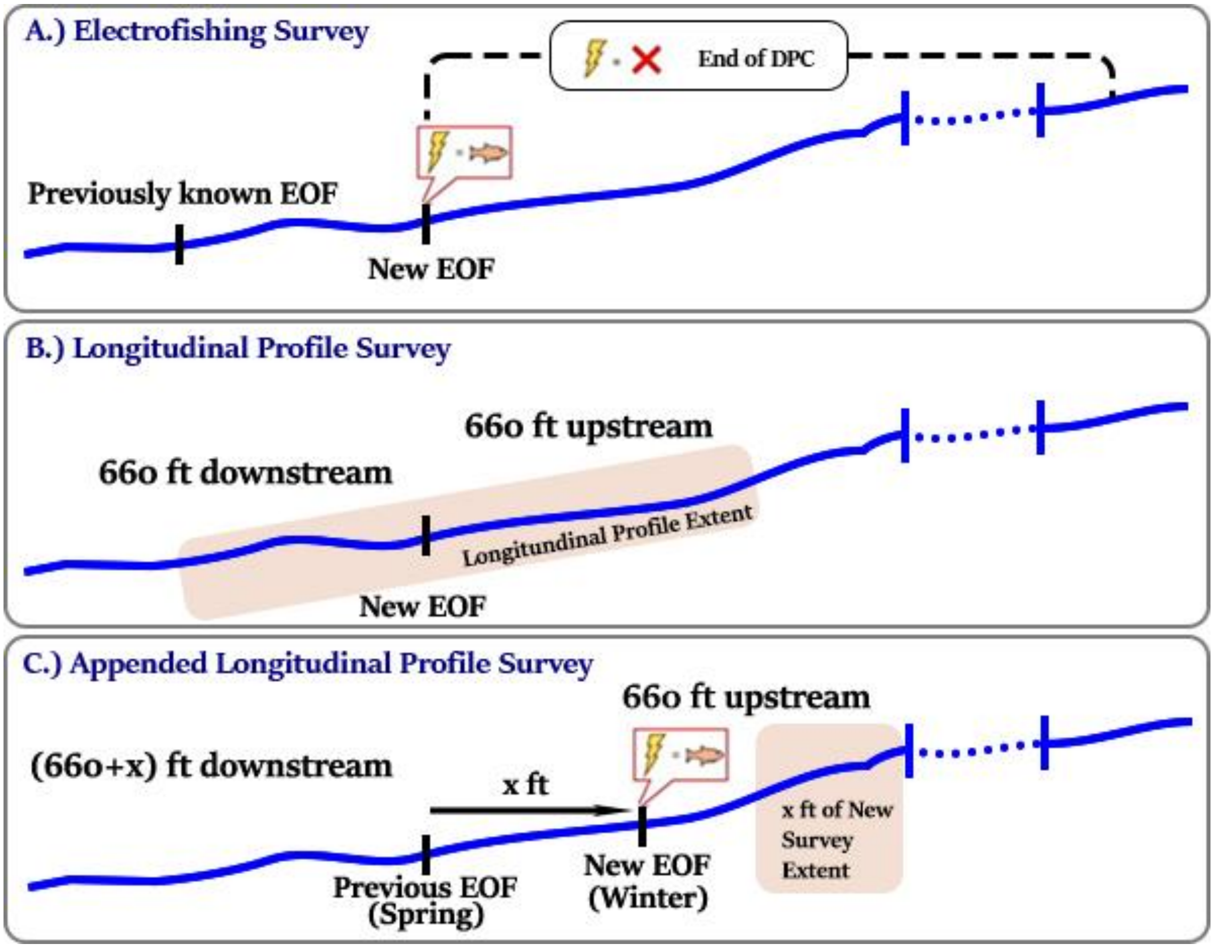

Figure 7. Components of field surveys demonstrating: (A) the extent of the protocol electrofishing survey to determine uppermost detected fish (EOF) point, (B) the range of the initial longitudinal profile habitat survey associated with the initial EOF point, and (C) an example of how the longitudinal profile survey would be appended if follow up protocol electrofishing surveys identify a new EOF point (adapted from PHB Science Panel 2019).

Reach- and Basin-Scale Explanatory Variables Derived from Office and Remote Sources

We will also collect data on several other factors that are thought to play a role in uppermost detected fish point and identification of PHBs from sources other than field data. These include: elevation, aspect, drainage area, distance-from-divide[4], valley width, annual precipitation, channel type[5], riparian stand condition[6], whether uppermost detected fish and PHB is at a mid-

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[4] Palmquist (2005) found distance-from-divide to be less variable and more reliably calculated than basin area

[5] Montgomery & Buffington, 1993

[6] Watershed Analysis categories, WA DNR 1997

channel point (mainstem or terminal) or confluence (tributary or lateral tributary), dominant drainage area geologic competence category[7], stream order, and whether a stream is accessible to anadromous fish or only resident fish. Many of these variables will be derived from existing GIS data layers. Drainage area, distance-from-divide, and valley width are important because they, combined with annual precipitation, are related to flow and stream size. The local geology around the stream determines whether stream substrate tends to consist of hard, resistant, larger particles or friable, fine-grained substrates, which have been shown to influence fish distribution (Gresswell et al. 2006; Torgersen et al. 2008).

Data Preparation

Physical attribute and fish presence data will be organized by site and variable-length segment as laid out in Appendix F. To prepare data for analysis, the stream profile will be divided into variable-length homogeneous segments, and each segment will be populated with a suite of segment-scale physical attributes and fish presence or absence. Variable-length segments will also be populated with associated basin-scale attributes that will be derived from GIS. Other basin-scale characteristics will be included for each site. Measures such as gradient and channel width can be used to form threshold variables and cumulative metrics (e.g., gradient and width expressed over multiple segments) that can be assessed as predictors of PHBs. Data sets will be developed for each sampling event to assess changes in distribution over time.

Data Analyses

Data Exploration, Summary Statistics, and Initial Tests

After data preparation is complete, initial data exploration will include graphical examination of habitat metrics for segments within a site and segment means of physical characteristics for each site (Figure 8). Distributions of physical attributes for variable-length segments at a site can be compared for segments with and without fish by and across sites. The length of segments will be based on changes in gradient and channel width that are associated with inflection points and/or specific habitat features (e.g., vertical [falls] and non-vertical obstacles

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[7] Competent/Incompetent, per McIntyre et al. 2009

[steep cascades]). Criteria for classifying variable-length segments and obstacles will be derived during post-hoc data analysis using linear regression methods similar to those described by Tompalski et al. (2017). All statistical analysis described here presume the use of the R statistical programming language (R Core Team 2021).

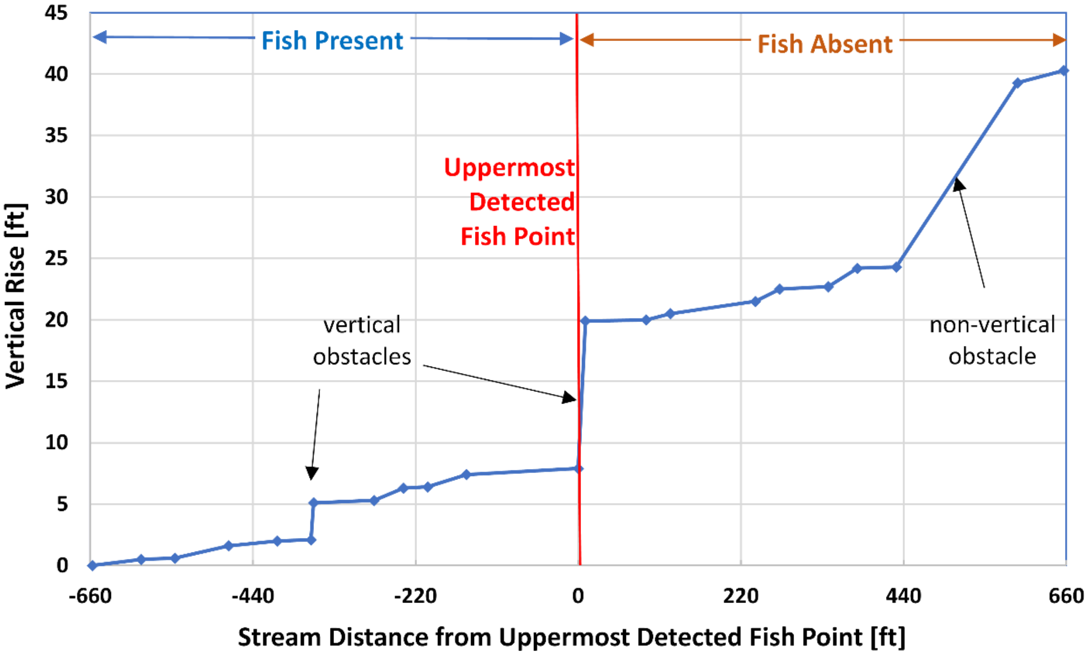

Figure 8. Schematic of channel long-profile survey showing variable-length segments (i.e., distance between inflection points) and associated vertical and non-vertical obstacles.

Examining Uppermost Detected Fish Locations

Research questions related to uppermost detected fish locations will address interannual (Research Question #1), seasonal (Research Question #2), and spatial (Research Question #3) dynamics. For sites in the fixed and alternating panels that are revisited over time, physical attributes at each site may be summarized by year and by season (spring or fall/winter). Stream profile plots (Figure 7) will be developed to compare uppermost detected fish points across seasons and years.

To examine spatial patterns, physical attributes at each site will be summarized by region (east or west), ecoregion, or other spatial classifications, and maps of attributes will be developed to visually assess spatial patterns in distribution. Summaries may also be examined by point type (lateral or terminal). For the subset of streams visited in the panel design, distances between the lowest and highest uppermost detected fish locations will be computed for each stream and mapped to examine spatial distributions of movements over time. Mapping the spatial distribution of movements over time will contribute to adequate determination of PHBs based on probability of observed fish movement.

Examining Habitat Associated with Uppermost Detected Fish Locations

Spatial patterns in physical channel and basin characteristics (e.g., bankfull width; average gradient, basin size) associated with the identified upstream extent of fish habitat will be examined to determine how these metrics vary geographically across the state of Washington (Research Question #4). Maps and histograms of physical channel and basin characteristics will be used to assess distributional patterns in attributes associated with the uppermost detected fish. Summaries of physical channel and basin characteristics (mean, median, standard deviation, range) will be calculated by spatial categories such as region (e.g., eastern versus western Washington) and ecoregion. Generalized linear mixed models (GLMM ; McCullagh and Nelder 2019, Bolker et al. 2009) of physical channel and basin characteristic metrics, as response variables, will incorporate fixed effects for region, ecoregion, point type (terminal and lateral), and other spatial factors. Random effects reflecting spatial structure (e.g., segments within streams) will be incorporated to account for correlation. Surveys will identify the uppermost detected fish point during each sample period at each study site, and the first PHB encountered upstream from that point. Characteristics of these PHBs will be used to determine how survey timing might influence which PHB would be associated with the proposed F/N break and how frequently the PHB might be identified differently (Research Question #5). Distributions of continuous habitat metrics (e.g., gradient, channel width) will be compared with boxplots or violin plots for sites where fish have moved above PHBs compared to sites where fish did not. These graphical summaries will be used to identify factors associated with fish movement by year and season. The probability that the uppermost PHB at a site is consistently selected during different survey occasions will be modeled as a function of season, spatial factors, point type, and physical channel and basin characteristics to determine what factors influence repeatability of identifying a PHB.

Physical changes in features originally identified as PHBs over time (Research Question #6) will also be assessed. For each measured physical characteristic, a GLMM will be applied to examine effects of time to estimate trends or changes over the course of the study. An examination of how similar features appear to limit upstream fish distributions in some contexts but not others (Research Question #7) will be conducted to examine any potential interactions among physical characteristics (e.g., headwaters vs. downstream; different flow levels). These relationships will be assessed in GLMMs with significance tests of the interaction effects.

PHB Performance Analyses

The primary goal of this project is to identify PHBs associated with EOF habitat using a suite of physical channel attributes and basin characteristics (Research Questions #7 and #8). A subset of physical channel attributes and basin characteristics will be identified as predictors to develop PHB criteria using classification methods described below. The performance of these developed PHB criteria and three sets of classification criteria proposed by the Board will be evaluated. We first describe how random forests (Cutler et al. 2007, Trigal and Degerman 2015) and interaction forest (Hornung and Boulesteix 2022) will be used to identify a subset of PHB predictors that will be used in a classification and regression tree (CART; Breiman et al. 1984) model to obtain thresholds for identifying PHBs. Then we describe the methods used to compare the performance of each set of PHBs to inform the final selection of PHB criteria. Random forest modeling will apply the *randomForest* package (Liaw and Wiener 2002), interaction forest will utilize the *diversityForest* package (Hornung 2022) and generalized linear mixed modeling will be conducted with the *glmmTMB* package (Brooks et al. 2017). CART modeling and visualization will utilize the *rpart* package (Thernau and Atkinson 2022).

PHB Classification Methods

Given the complexity of identifying PHBs due to the variability in stream characteristics across space and time and fish movement across obstacles, the classification of alternative PHBs will incorporate: 1) Random forest modeling to determine variables important for separating fish bearing segment from non-fish bearing; 2) Interaction forest models to identify characteristics that in combination create PHBs; 3) an evaluation of variables related to probability of fish movement using binomial GLMM; and 4) CART models to identify the thresholds for PHBs based on the random forest and interaction forest outputs and the evaluation of probability of fish movement.

Random forest (RF) methodology is a nonparametric approach used for classification and prediction and can identify important predictor variables among a large suite of possible covariates even when those covariates are highly correlated (Cutler et al. 2007, Kubosova et al. 2010). Random forest can also bin continuous data into discrete categories as part of the analysis, as opposed to assigning arbitrary bins *a priori*. Cutler et al. (2007) found that random forests had high classification accuracy compared to classification trees, generalized linear models (logistic regression), and linear discriminant analysis. Random forest classification has been used to classify salmonid habitat in Alaska (Romey and Martin 2021), fish assemblage presence in stream segments in coastal Australia (Rose et al. 2016), and in macroinvertebrate habitat in the Czech Republic (Kubosova et al. 2010). Random forest methods have been extended to boosted random forests (Ko et al. 2015, Mishina et al. 2015) which features more memory-efficient calculations. When classification covariates are impacted by spatial and/or temporal correlation, binary mixed model forest (Speiser et al. 2019) or generalized mixed effects random forest (Fontana et al. 2021, Seibold et al. 2019) can account for these sources of correlation.

Random forest classification of fish use will be used to determine which segment-level, cumulative (e.g., metrics such as gradient and width expressed over multiple segments), and basin-scale characteristics are important variables for PHB establishment. Separate random forest classification models may be applied to eastern and western sites and for lateral and terminal points to identify influential variables independently in each system. The data will be split into training and testing data sets to assess the performance of the random forest classification. A random forest model will be developed from the training data set and then applied to the test data set to assess classification. Classification performance metrics will include sensitivity (proportion of presences correctly classified), specificity (proportion of absences correctly classified), kappa (a measure of agreement computed across presences and absences, Cohen 1960), and the area under the receiver operating characteristic curve (Fawcett 2006). The final model will be applied to the entire sample of uppermost detected fish points at each site to obtain habitat variables related to the PHB associated with those points. Sites with PHBs formed by vertical and non-vertical obstacles (e.g., waterfalls and cascades) can also be analyzed separately from sites with width- and gradient-related PHBs so that random forest models accurately reflect each type of PHB and more nuanced habitat relationships are not missed. Vertical step height will be included as a segment-scale attribute. Alternatively, a single model incorporating waterfall height (where height is zero if no waterfall is present) may provide the basis for threshold definitions across all streams. Interaction random forest modeling will be used to identify more complex relationships between habitat covariates relative to PHBs. The covariates identified in the random forest and interaction forest models will be used in the CART model to identify thresholds for PHB criteria. See the pilot data analysis summary (Appendix C) for more information.

The probability of fish movement will be evaluated through a binomial GLMM based on whether the uppermost detected fish location changed across surveys at a particular site. The purpose is to identify weaker or stronger PHBs. After all data have been collected over the three-year study, uppermost detected fish points identified during all surveys at all locations will be categorized into two sets of PHBs: those that fish were and were not observed to move beyond in an upstream direction over the course of the study. Physical channel and basin characteristics will be calculated at the segment level and cumulatively across segments both upstream and downstream of the uppermost detected fish point. A binomial GLMM will be applied to the segment-level indicator that no fish was detected at or above the segment at a particular survey occasion to model the probability that no movement occurs upstream of the PHB, and a stream level random effect will be incorporated to account for the nesting of segments within a stream. The model of the probability that fish do not move above a PHB may contain classification and continuous covariates that describe physical habitat attributes (e.g., channel bankfull width, gradient) or explain seasonal movement, including the season, region (east/west), ecoregion, and point type (lateral/terminal). Random effects for space and time will ensure that standard errors for fixed effects estimates are not underestimated due to correlation. Variance components may also incorporate habitat categories for which variance heterogeneity in seasonal movement is observed (e.g., low vs high elevation). This model will be used to assess the reliability of the PHBs identified by the CART model. A PHB that is surpassed more often could be considered a weaker PHB, whereas a PHB that is surpassed less frequently could be deemed a strong PHB.

CART models are a type of decision tree machine learning model that can identify variables of importance, can accommodate unequal spatial sampling, and classify based on continuous and categorical predictors (Morgan 2014, Loh 2011). We propose incorporating CART models because, unlike random forest classification models, CART models return thresholds used at splits in a decision tree. While, random forest models will likely have higher prediction accuracy, they are not ideal for establishing thresholds. A random forest contains many individual decision trees (a forest) to deal with the uncertainty that results from a single decision tree (Maroco et al. 2011). CART models will be built for several combinations of variables (e.g., variables identified by random forest, interaction forest, or the FPB) to determine which combination of variables produces the highest prediction accuracy and enables comparison of model performance based on sensitivity, specificity, and Matthews Correlation Coefficient (MCC). MCC is a statistical representation of all four confusion matrix categories (true positives, true negatives, false positives, and false negatives) that is a reliable and holistic indicator of model performance (Chicco and Jurman 2020). A visual decision tree will be presented for each model to identify potential thresholds for variables in the model. We plan to compare the existing Board criteria and alternatives by comparing the accuracy, sensitivity, specificity, and MCC between models. These metrics will enable us to investigate trade-offs between model accuracy and complexity for establishing putative thresholds. The model can also be tuned based on the false negative cost to influence the model's emphasis for sensitivity or specificity. Additionally, CART models may be built from data combined across years or may be developed from data specific to a single year and then applied to a subsequent year to evaluate classification accuracy.

Crew-variability testing conducted within this study will provide insight into our ability to identify the same PHBs using data collected by different survey crews when implementing FHAM in the field in the future (Research Question #9). Data from the subset of streams surveyed multiple times by different survey crews will be used to assess crew variability in measuring the physical stream characteristics that would be used to identify PHBs. Physical characteristics measured at the same streams by different survey crews will be modeled to identify attributes that are more susceptible to survey crew variability. Distances between PHBs identified at the same stream based on data collected by different crews will be modeled as a function of spatial characteristics such as region and ecoregion to determine if spatial factors influence crew variability.

Performance Evaluation of Board-Accepted PHB Criteria

The three sets of classification criteria proposed by the Washington Forest Practices Board (Research Question #10) will be assessed in three different ways. The first method will be to compare frequencies that the various criteria occur above and below the uppermost detected fish. The performance of each type of PHB variable (i.e. – gradient, obstacle characteristic, channel width) and criterion within the three proposed criteria sets will be assessed individually and then in combination with the others. The second will be to create a confusion matrix and MCC for the Board criteria, as compared to the alternative PHBs determined by the CART models. The third method will use CART analysis including only the physical habitat variables utilized in the Board criteria. The resulting critical values, or thresholds, identified by the CART model will be compared to the values in each criteria set established by the Board.

For each set of Board criteria, distance between the PHB and the uppermost detected fish will be examined as a measure of PHB prediction performance. The mean, median, standard deviation, and range of the set of distances for each set of Board criteria will be calculated and compared to the distances obtained with PHB criteria from the CART analysis. The distances between a PHB and the uppermost detected fish will be modeled with GLMMs as a function of covariates, and the associated covariates identified in the model will be used in the random forest and CART models to identify new PHBs. The distribution of distances between a PHB and the uppermost detected fish will also be compared for the alternative PHB criteria from the

CART models to the Board Criteria. The proposed analysis methods are summarized by research question in Table 3.

Following the first year of data collection we will perform a demonstration analysis to verify desired outputs and analytical approaches described here within.

Analysis of Pilot Study Data

Data from a 2018 pilot PHB study (Roni et al. 2018) that used similar habitat data collection methods as those proposed in this current design were analyzed to demonstrate available analysis tools to identify habitat attributes associated with the uppermost detected fish (Appendix C). Random forest models, interaction forest models, and CART models were applied to habitat covariates obtained from the pilot data to identify important habitat covariates associated with the uppermost detected fish. Additionally, random forest methodology was used to assess the Forest Practices Board-proposed PHB criteria. Covariates identified by random forest and interaction forest models were used in CART models to identify PHB criteria. Accuracy, sensitivity, specificity, and Matthews correlation coefficient (MCC; Chicco and Jurman 2020) were used to assess performance. The pilot study data set does not include temporal replication and therefore could not inform inference on seasonal and/or annual fish movement.

Table 3. Proposed data analysis methods by Research Question.

Research Question	Question	Proposed Methods	Data Sets
1	How do the locations of the last (uppermost) detected fish vary interannually?	Stream profile plots, summaries of physical channel and basin characteristics by year, summaries/models of distances between lowest and highest uppermost detected fish points across seasons by year	All data excluding crew variability data and error distance surveys
2	How do the locations of the last (uppermost) detected fish vary seasonally?	Stream profile plots, summaries of physical channel and basin characteristics by season, summaries/models of distances between lowest and highest uppermost detected fish points between seasons within years	Yearly data excluding crew variability data and error distance surveys

Research Question	Question	Proposed Methods	Data Sets
3	How do the locations of last (uppermost) detected fish vary geographically across the state of Washington?	Stream profile plots, maps of distances between lowest and highest uppermost detected fish points within streams among all survey occasions.	Stream and PHB attributes associated with uppermost detected fish points for each site
4	How do the physical channel and basin characteristics (e.g., bankfull width; average gradient, basin size) associated with the identified end (upstream extent) of fish habitat vary geographically across the state of Washington?	Maps of physical channel and basin characteristics associated with the identified end (upstream extent) of fish habitat, summaries of physical channel and basin characteristics associated with the identified end (upstream extent) of fish habitat for spatial categories such as region and ecoregion, models of physical channel and basin characteristics metrics with fixed effects for region, ecoregion, and other spatial factors.	Stream and PHB attributes associated with uppermost detected fish points for each site
5	Where the location of the last (uppermost) detected fish changes (seasonally or interannually), how does that influence which PHB would be associated with the F/N break and how frequently does that occur?	For each visit to a stream, determine the PHB corresponding to the uppermost detected fish for that visit then model the indicator of whether or not a fish was observed upstream of each PHB as a function of physical channel and basin characteristics to assess the probability that a PHB remains the "PHB of rule".	All data excluding crew variability data and error distance surveys
6	How do the physical channel features at the locations initially identified as PHBs change over the course of the study?	For the subset of PHBs visited at least twice, model changes each physical characteristic as linear trends, seasonal effects, and/or nonlinear effects. Include site random effects to examine spatial patterns in physical channel feature variation. Note that changes in physical characteristics can be related to crew effects.	The subset of PHBs visited at least twice

Research Question	Question	Proposed Methods	Data Sets
7	How often do similar features appear to limit upstream fish distributions in some contexts but not others (e.g., further into the headwaters vs. downstream; different flow levels)?	Assess interactions between physical characteristics in GLMM of distances between uppermost detected fish locations and PHB	Stream and PHB attributes associated with uppermost detected fish points for each site
8	Which combinations of physical channel features and basin characteristics (for example, gradient, channel width, barriers to migration) best identify the end (upstream extent) of fish habitat relative to the location of the last (uppermost) detected fish?	CART models informed by random forest, interaction forest, Board criteria, and covariates from a GLMM of distances between the uppermost detected fish and PHB defined from Board criteria. Assess segment-level performance of CART model thresholds with confusion matrices; measures of sensitivity, specificity, MCC, and classification accuracy. Assess stream-level performance of CART model thresholds by comparing the mean, median, range, and SD of distances between the uppermost detected fish and PHB across all streams and select PHB criteria that minimize those metrics.	Stream and PHB attributes associated with uppermost detected fish points for each site will be used to develop a potential alternative to the FPB-selected criteria sets, but all uppermost detected fish points would be used for the probability of movement test of PHB strength
9	Can protocols used to describe PHBs be consistently applied among survey crews and be expected to provide similar results in practice?	Physical characteristics measured in repeated surveys by different crews at the same sites will be used to identify PHBs. Models of PHB consistency relative to the uppermost PHB will be used to estimate the probability that crews identify the same PHB. Physical characteristics will be modeled to identify attributes that are more susceptible to measurement error among survey crews.	Crew variability data

Research Question	Question	Proposed Methods	Data Sets
10	How well do the PHB criteria provided by the Washington Forest Practices Board accurately identify the EOF (upstream extent of fish) habitat when applied in the Fish Habitat Assessment Methodology (FHAM)?	Assess segment-level performance with confusion matrices; measures of sensitivity, specificity, MCC, and classification accuracy. Assess stream-level performance by comparing the mean, median, range, and SD of distances between the uppermost detected fish and PHB.	Stream and PHB attributes associated with uppermost detected fish points for each site

Potential Challenges

Although the methods we propose have been widely used to quantify habitat conditions and identify the location of uppermost detected fish, there are some potential challenges. These include location of sites that meet selection criteria, access to initially identified sites, and access to these sites throughout the two seasons and three years. It is possible that we may not have access to selected sample sites due to issues with land ownership, landowner willingness to permit access, or problems with the road networks. Thus, if a site is not suitable due to access or for other reasons a different site (the next consecutive site number from the initial random selection) would be used to replace the non-suitable site, and the reasons the site is excluded will be documented. This study is targeted at identifying the features and channel characteristics that limit the upstream extent of fish distribution, which should not be strongly dependent on particular land uses or ownership types. Therefore, results should have broad applicability despite any site selection biases that may occur. A more challenging scenario would be if accessibility changes between or among seasons and years. For example, forest fires, heavy early or late snow, or road failures could affect repeat surveys at a site. In such cases, we would continue to sample sites during other seasons and years when possible. The recommended sample size includes sites in addition to the minimum number calculated to meet the specified statistical requirements. This allows for some site attrition over life of the project.

An additional challenge with study implementation will be largely financial and could result from underestimating or overestimating the amount of time and cost needed to adequately sample sites initially and repeatedly. Similarly, we need to ensure that the data collected will allow us to answer the PHB study questions. To proactively assess these critical uncertainties, a pilot (feasibility) study was conducted in August of 2018 to test and refine protocols, and estimate the time needed to conduct a survey and collect data at a site (Roni et al. 2018). The pilot study included conducting longitudinal thalweg profile surveys upstream and downstream of known uppermost detected fish points at 27 sites on private, state, and federal forestlands in western and eastern Washington. The analysis of longitudinal survey data from the pilot study demonstrated that PHBs based on gradient, BFW, and obstacles being examined by the Board could be easily determined from the survey data. The field surveys helped identify several modifications to the initial proposed protocol that are needed to assure the proposed and other potential PHBs can be easily identified (e.g., spacing of the survey points, habitat types, minimum habitat length, and substrate categories). It also provided important information on time needed to conduct surveys, which we have incorporated into the study plan and estimated cost to conduct the full validation study.

This study does not address long-term changes in small streams that may render them unsuitable for fish occupancy, or conversely, may render previously unsuitable streams habitable for fish. At any point in time, some headwater streams are not used by fish during any season of the year due to a blockage, to invasion, or to unfavorable physical conditions (e.g., gradient) in the channel itself. Factors that determine whether small streams can be used by fish are typically related to disturbances such as exceptionally high discharge, landslides, debris flows, and windstorms. Such episodic disturbances are erratic and can be widely spaced in time (decades to centuries), but their overall effect in drainage systems is to create a mosaic of streams suitable for fish occupancy that changes over long intervals (often hundreds of years) in response to local disturbance regimes (Kershner et al. 2018; Penaluna et al. 2018). An important implication of the notion that the potential use of small tributaries by fish can change over time is that while some stream segments are not now occupied by fish, there is no guarantee that they may not become suitable in the future, or that those which are currently habitable will always remain so. This study, however, does not address the expansion and contraction of fish habitat over long time intervals, because the sample time is limited to three years and the methods cannot predict with certainty where and in what form large disturbances capable of transforming a stream segment's ability to support fish will occur.

Expected Results and Additional Studies

Highly precise measurements of stream channel conditions both upstream and downstream of uppermost detected fish locations will provide a nearly continuous dataset of physical stream characteristics within the surveyed area. Thus, we will be able to objectively identify the physical stream characteristics most closely associated with uppermost detected fish. These data will be used to test the different PHB criteria under consideration by the Board in 2018, and also to identify alternative physical stream characteristics that may function as PHBs. We expect that the study will assess the performance of proposed and/or identify alternative PHB criteria for gradient, channel width, and obstacles that are most frequently associated with the furthest upstream of all uppermost detected fish points found at each stream across the time period of the study. Seasonal and inter-annual sampling will allow us to examine the variation of uppermost detected fish locations across years and seasons, which will help identify PHBs that are consistently associated with the upstream extent of fish habitat across years, seasons, and flow conditions regardless of where fish are found on any given day. Because we will be using some sites for which a WTMF already exists and the location of the uppermost detected fish was potentially identified, examining longer-term inter-annual variation in the uppermost detected fish may be possible for a subset of sites where uppermost detected fish has been previously identified and monumented. In addition, study sites could be revisited in the future to look at longer-term changes in uppermost detected fish locations, if desired.

Ultimately, the analysis will provide the distances (upstream and downstream) from uppermost detected fish to the different proposed PHB criteria, if and how that differs among years and seasons, whether one set of criteria performs better in terms of consistently identifying EOF habitat across seasons and years, and whether different PHB criteria should be applied for different regions or should be stratified by other factors. While the focus of the study is to test the three different sets of PHB criteria being considered for adoption by the board, we expect that the analyses will help identify other criteria that might more consistently be associated with the uppermost detected fish and therefore better indicate upstream extent of fish habitat when integrated with FHAM.

The results should also help inform the protocols for measuring gradient, bankfull width, and obstacles in the field to minimize variability among field crews and assure consistent identification of PHBs. Focus should be placed on specific protocols used to consistently and accurately identify and measure physical stream characteristics, including gradient, bankfull width, obstacles, and any other criteria that may be used to identify PHBs in this study.

We will also examine seasonal and inter-annual changes in uppermost detected fish locations in headwater streams across the state. While this would potentially lay the groundwork for continued monitoring of long-term variability in the upstream extent of fish distribution, it is not designed as a long-term study on such variability. Depending on results, we may recommend that sites continue to be periodically revisited in the future to examine this longer-term variability. It is possible that a 3-year study period may not capture a sufficiently broad range of hydrological conditions associated with shifts in climatic cycles (e.g., El-Nino/La-Nina) to allow for the estimation of the best "average" upon which a PHB boundary can be determined. This can only be assessed once the 3-years of sampling have been completed.

DPC Study Integration

The electrofishing and habitat surveys for each PHB study stream will extend up to or beyond the end of current DPCs. Therefore, the PHBs study will yield a data set that can be analyzed regarding the frequency with which fish are found up to the limits of current DPCs, including how this varies between seasons, years, and geography. The coarse-scale data collected during the electrofishing survey will also provide channel profiles and other data for the reaches between EOF/H and end of current DPC that can be analyzed for possible explanations as to what habitat attributes and/or features are limiting fish distributions for those sites where fish use does not extend to end of current DPCs. These data will include channel gradient, bankfull width, wetted width and confinement within unequal length segments of relatively uniform habitat character. The results might suggest appropriate metrics for vertical and non-vertical obstacles that could be used in conjunction with width and gradient to add an element of accessibility to the DPCs, thereby improving their accuracy and utility. In particular, this would reduce the degree to which the current DPCs, when used on their own in the absence of a protocol survey, predict fish use where there are no fish, and are not likely to ever be.

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Washington State Forest Practices Board 2018. Minutes and meeting materials from February 2018 Forest Practices Board meeting. https://www.dnr.wa.gov/publications/bc_fb_mtgminutes_20180213_14.pdf, https://www.dnr.wa.gov/publications/bc_fpb_mtg_packet_20180213.pdf?p3kh5ut FPB meeting minutes Feb 2018: "Berge reiterated that a PHB is not necessarily the Type F/N break, but rather the first point of potential unfavorable habitat and the starting point for a protocol survey."

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Appendix A. CMER Workplan and prior science panel study questions

CMER Workplan Water Typing Rule Group Critical Questions

The following are the critical questions of the water typing rule group program this study will address:

CQ 1. How can the line demarcating fish- and non-fish habitat waters be accurately identified?

CQ 2. To what extent does the current water typing survey window capture seasonal and annual variability in fish distribution considering potential geographic differences?

CQ 3. How do different fish species use seasonal habitats (timing, frequency, duration)?

CQ 4. How does the upstream extent of fish use at individual sites vary seasonally and annually?

CQ 5. How does the delineation of the upstream extent of fish habitat change seasonally?

Science Panel Document Study Questions

- Do the PHB criteria provided by the Washington Forest Practices Board accurately capture the EOF habitat when applied in the Fish Habitat Assessment Methodology (FHAM)?
- Based on data collected, what is the most accurate combination of metrics for determining PHB by region or ecoregion?
- Are there differences in PHB criteria by Environmental Protection Agency (EPA) Level III ecoregion, eastern vs western Washington, or some other geographic or landscape strata?
- Are there additional variables (e.g., geology, drainage area, valley width, land use, channel type, and stand age) that could improve the accuracy of existing criteria?
- What is the influence of season/timing of survey on PHB identification?

- What is the typical inter-annual variability in last detected fish and PHBs?
- Can protocols used to describe PHB be consistently applied among survey crews and be expected to provide similar results in practice?
- Answering these questions requires identifying the last detected fish and surveying habitat above and below these points in a random representative sample of streams across the state.

Appendix B. Sample Size Estimation Memo of Jan 4, 2022

ENVIRONMENTAL & STATISTICAL CONSULTANTS
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MEMO

To: Instream Science Advisory Group
From: Leigh Ann Starcevich (WEST, Inc.)
Date: January 4, 2022
Re: Sample size approximation from Eastern WA and Western WA data

The Instream Science Advisory Group (ISAG) is developing a sampling design for surveys of potential habitat breaks (PHB) for fish use. A sample size approximation is needed to ensure that the data collected to assess criteria defined by the Washington Forest Practices Board (Board) for the Fish Habitat Assessment methodology (FHAM) yield useful covariates for PHB modeling. Cooperative Monitoring, Evaluation, and Research (CMER) data from eastern Washington surveys conducted in 2001, 2002, and 2005 were provided by Chris Mendoza. Stream habitat data associated with uppermost detected fish points from concurred water type modification forms for surveys conducted in western Washington between 2016 and 2020 were provided by Weyerhaeuser. These data were used to approximate sample sizes needed to estimate means of PHB model covariates with desired levels of precision and accuracy.

Eastern Washington Data

The eastern Washington data were collected in 2001 by Terrapin Environmental (Cupp 2002) and in 2002 and 2005 by ABR, Inc. Environmental Research & Services (Cole and Lemke 2003, 2006). Channel characteristic metrics included mean channel widths and means gradients for reaches extending up to 100m above and 100m below the last fish point obtained in the 2001 survey. Data for barriers were collected but inconsistencies in how barriers were classified and recorded prevented sample size evaluation specific to barriers. For surveys conducted after 2001, the last fish distance relative to the 2001 last fish was provided. A metric for the maximum change in distance from the 2001 last fish point was calculated for each site. Using the 2001 point as baseline, the range of distances where the last fish was observed during subsequent surveys was calculated and used to inform the sample size approximation.

Data screening was used to limit the data set to a subset of locations with natural habitat breaks. Unscreened data sets included sites where large woody debris jams were found, no surface flow occurred for at least 100m, and surveys were conducted past July 15. The screened data sets eliminated many of these sites. Sites where fish passage was limited by culverts were removed from all data sets. About 46% of the unscreened points were classified as lateral points.

Western Washington Data

Water type modification form data from western Washington were collected between 2016 and 2021 and included gradient and bankfull width metrics for stream segments upstream and downstream of the last fish point. For many lateral points, only the upstream measurements were provided because the point was located on a river mainstem. At these points, data on gradient and bankfull width metrics downstream of the confluence were not always collected, so these points are omitted for sample size calculations based on the downstream metrics. About 70% of the points were classified as lateral points.

Sample Size Approximation

Estimated means of channel characteristic metrics and change in last fish locations among years were used as the basis for the sample size approximation. Let z reflect the quantile of a standard normal random variable for a given Type I error rate (α). For $\alpha = 0.10$ we have that $z = 1.645$. Let d be the maximum absolute error (i.e. confidence interval half-width), let r be the relative precision of the estimate, and let γ be the coefficient of variation (CV). The coefficient of variation is a standardized measure of precision calculated as the standard deviation (SD) of the outcome divided by the mean of the outcome (Thompson 2002). The sample size approximation formula below is applied with the mean and standard deviation for each outcome of interest. The sample size needed to obtain an estimate that is within 100*r% of the true mean with probability 1 - α was calculated. In other words, the confidence interval half-width of the mean should be 100*r% of the true mean. The sample size to accomplish this goal is based on a normal approximation and calculated as:

$$n = \frac{z^2\gamma^2}{r^2}.$$

For each outcome of interest from the eastern Washington data sets, the coefficient of variation was computed from the mean and standard deviation of the screened (Tables 1 through 3) and unscreened (Tables 4 through 6) data, and sample sizes were approximated for relative precision values of 0.10, 0.15, 0.20, and 0.30. Variation was slightly higher in the unscreened data set, resulting in slightly larger sample sizes. For the eastern data, the coefficients of variation were higher for terminal points than for lateral points for the upstream reach gradient, reach gradient difference, and maximum change in distance (Tables 2 and 3, Tables 5 and 6). The coefficients of variation were higher for lateral points than for terminal points for downstream reach gradient and downstream bankfull width.

Similar results were observed for the western Washington data. For estimation of mean channel metrics across point types, coefficients of variation ranged from 0.69 to 0.79 for reach gradient metrics and for the bankfull width above the point. However, bankfull width measured below the last fish point was less precise than in the eastern Washington data set with a CV of 1.28 (Table 7). The precision for the gradient difference was similar to that observed for the eastern Washington data with coefficients of variation near or above one. For the western data, the coefficients of variation were higher for terminal points than for lateral points for the reach gradient difference (Tables 8 and 9). The coefficients of variation were higher for lateral points than for terminal points for reach gradient metrics and the downstream bankfull width. The higher variability in these metrics suggest larger sample sizes are needed for precise estimation of means. While mean estimation of channel characteristics is not the ultimate inferential goal, we assume that samples large enough to provide information on the range of values for each of the potential PHB modeling covariates will yield a useful data set for modeling.

The maximum change in distance from the eastern data was highly variable and generated large sample sizes for levels of desired precision. The difference in reach gradient exhibited high variability across both the eastern and western data sets, and sample sizes needed for precise mean estimation are large. To obtain relative precision of 0.15, the required sample size is nearly double that calculated for relative precision of 0.20. Note that the sum of the sample sizes calculated for lateral and terminal points generally exceeds the sample size calculated from data pooled across point types. This indicates that overall sample sizes may need to be larger than indicated by the pooled analysis to achieve the same level of precision for means of channel characteristics for lateral and terminal points.

Table 1: Estimates of means, standard deviations, and coefficients of variation from *screened eastern WA data pooled across point types* with sample size approximations for four levels of relative precision.

Outcome	**n**	**Est. Mean**	**SD**	**CV**	***r* = 0.10**	***r* = 0.15**	***r* = 0.20**	***r* = 0.30**
Reach gradient (%) above LF point	193	21.56	13.98	0.65	114	50	28	13
Reach gradient (%) below LF point	161	10.31	6.73	0.65	115	51	29	13
Reach gradient difference (%)	161	9.96	11.19	1.12	341	152	85	38
Bankfull width (m) above LF point	197	2.14	1.41	0.66	117	52	29	13
Bankfull width (m) below LF point	174	1.84	1.35	0.74	146	65	37	16
Maximum change in distance (m)	121	73.26	186.34	2.54	1751	778	438	195

Table 2: Estimates of means, standard deviations, and coefficients of variation from *screened eastern WA data at lateral point types* with sample size approximations for four levels of relative precision.

Outcome	**n**	**Est. Mean**	**SD**	**CV**	***r* = 0.10**	***r* = 0.15**	***r* = 0.20**	***r* = 0.30**
Reach gradient (%) above LF point	67	24.03	12.36	0.52	72	32	18	8
Reach gradient (%) below LF point	53	8.30	9.25	1.11	336	149	84	37
Reach gradient difference (%)	53	18.30	10.77	0.59	94	42	23	10
Bankfull width (m) above LF point	74	1.42	0.79	0.55	83	37	21	9
Bankfull width (m) below LF point	64	0.83	0.74	0.89	214	95	53	24
Maximum change in distance (m)	13	72.12	72.49	1.01	273	121	68	30

Table 3: Estimates of means, standard deviations, and coefficients of variation from *screened eastern WA data at terminal point types* with sample size approximations for four levels of relative precision.

Outcome	**n**	**Est. Mean**	**SD**	**CV**	***r* = 0.10**	***r* = 0.15**	***r* = 0.20**	***r* = 0.30**
Reach gradient (%) above LF point	126	20.25	14.64	0.72	141	63	35	16
Reach gradient (%) below LF point	108	11.30	4.81	0.43	49	22	12	5
Reach gradient difference (%)	108	5.87	8.92	1.52	624	277	156	69
Bankfull width (m) above LF point	123	2.57	1.52	0.59	95	42	24	11
Bankfull width (m) below LF point	110	2.43	1.28	0.53	75	34	19	8
Maximum change in distance (m)	108	73.40	195.84	2.67	1926	856	481	214

Table 4: Estimates of means, standard deviations, and coefficients of variation from *unscreened eastern WA data pooled across point types* with sample size approximations for four levels of relative precision (recommended eastern WA sample size in bold).

Outcome	n	Est. Mean	SD	CV	*r* = 0.10	*r* = 0.15	*r* = 0.20	*r* = 0.30
Reach gradient (%) above LF point	268	18.73	13.30	0.71	136	61	34	15
Reach gradient (%) below LF point	227	9.72	6.42	0.66	118	52	29	13
Reach gradient difference	227	8.13	10.23	1.26	428	190	107	48
Bankfull width (m) above LF point	282	2.02	1.47	0.73	**143**	63	36	16
Bankfull width (m)below LF point	264	1.59	1.30	0.81	179	79	45	20
Maximum change in distance (m)	153	74.21	172.56	2.33	1463	650	366	163

Table 5: Estimates of means, standard deviations, and coefficients of variation from *unscreened eastern WA data at lateral point types* with sample size approximations for four levels of relative precision.

Outcome	n	Est. Mean	SD	CV	*r* = 0.10	*r* = 0.15	*r* = 0.20	*r* = 0.30
Reach gradient (%) above LF point	104	19.65	12.76	0.65	114	51	29	13
Reach gradient (%) below LF point	83	7.90	8.22	1.04	293	130	73	33
Reach gradient difference (%)	83	13.65	10.92	0.80	173	77	43	19
Bankfull width (m) above LF point	129	1.38	0.81	0.59	93	41	23	10
Bankfull width (m) below LF point	116	0.72	0.71	0.98	261	116	65	29
Maximum change in distance (m)	14	67.89	71.42	1.05	299	133	75	33

Table 6: Estimates of means, standard deviations, and coefficients of variation from *unscreened eastern WA data at terminal point types* with sample size approximations for four levels of relative precision.

Outcome	n	Est. Mean	SD	CV	*r* = 0.10	*r* = 0.15	*r* = 0.20	*r* = 0.30
Reach gradient (%) above LF point	164	18.15	13.64	0.75	153	68	38	17
Reach gradient (%) below LF point	144	10.77	4.83	0.45	55	24	14	6
Reach gradient difference (%)	144	4.94	8.31	1.68	765	340	191	85
Bankfull width (m) above LF point	153	2.55	1.67	0.65	115	51	29	13
Bankfull width (m) below LF point	148	2.28	1.24	0.55	80	36	20	9
Maximum change in distance (m)	139	74.85	179.75	2.40	1561	694	390	173

Table 7: Estimates of means, standard deviations, and coefficients of variation from *western Washington WTMF data pooled across point types* with sample size approximations for four levels of relative precision (recommended western WA sample size in bold).

Outcome	n	Est. Mean	SD	CV	*r* = 0.10	*r* = 0.15	*r* = 0.20	*r* = 0.30
Reach gradient (%) above LF point	1982	17.59	13.97	0.79	**171**	76	43	19
Reach gradient (%) below LF point	1512	5.96	4.13	0.69	130	58	32	14
Reach gradient difference (%)	1505	10.79	13.39	1.24	416	185	104	46
Bankfull width above LF point	1900	1.00	0.76	0.76	157	70	39	17
Bankfull width below LF point	1502	4.18	5.79	1.38	518	230	130	58

Table 8: Estimates of means, standard deviations, and coefficients of variation from *western Washington WTMF data at lateral point types* with sample size approximations for four levels of relative precision.

Outcome	n	Est. Mean	SD	CV	*r* = 0.10	*r* = 0.15	*r* = 0.20	*r* = 0.30
Reach gradient (%) above LF point	1393	19.65	15.45	0.79	167	74	42	19
Reach gradient (%) below LF point	921	4.23	2.81	0.66	119	53	30	13
Reach gradient difference (%)	916	15.13	14.86	0.98	261	116	65	29
Bankfull width (m) above LF point	1318	0.81	0.54	0.67	121	54	30	13
Bankfull width (m) below LF point	913	5.90	6.86	1.16	367	163	92	41

Table 9: Estimates of means, standard deviations, and coefficients of variation from *western Washington WTMF data at terminal point types* with sample size approximations for four levels of relative precision.

Outcome	n	Est. Mean	SD	CV	*r* = 0.10	*r* = 0.15	*r* = 0.20	*r* = 0.30
Reach gradient (%) above LF point	589	12.71	7.60	0.60	97	43	24	11
Reach gradient (%) below LF point	591	8.65	4.41	0.51	70	31	18	8
Reach gradient difference (%)	589	4.06	6.34	1.56	661	294	165	73
Bankfull width (m) above LF point	582	1.44	0.98	0.68	125	55	31	14
Bankfull width (m) below LF point	589	1.53	0.92	0.61	99	44	25	11

Initial results from the sample size approximation (Tables 1 through 9) suggested to the ISAG subgroup that upstream metrics provided a robust basis for sample size approximation. Upstream gradient and bankfull width metrics were consistently measured and are ecologically meaningful for both point types, were available for both eastern and western WA data, and were the most precise among the channel characteristics examined. Furthermore, the subgroup also decided to use the unscreened data for sample size approximations based on eastern WA data because the metrics were slightly more variable in this data set and provide more conservative sample sizes.

To obtain an overall statewide sample size that accounted for variation across the state, the unscreened eastern data and the western data were pooled. Coefficients of variation for estimates of means of both upstream metrics were computed to generate statewide sample sizes across both point types (Table 10), for lateral points (Table 11), and for terminal points (Table 12). From this analysis, a conservative statewide minimal sample size of surveyed sites to provide relative precision of 0.10 is obtained from the upstream bankfull width approximation of 190 sites (Table 10). Assuming that the proportion of sites classified as lateral points is similar to the proportion observed in the eastern WA data set (46%) and western WA data set (70%), we can expect roughly 87 to 133 lateral sites and 57 to 103 terminal sites from this sample of 190 sites. These sample sizes within each point type should be sufficient to obtain means of the two upstream metrics with at least 0.15 relative precision (Tables 11 and 12).

Table 10: Estimates of means, standard deviations, and coefficients of variation from *pooled eastern and western Washington data at all point types* with sample size approximations for four levels of relative precision.

Outcome	**n**	**Est. Mean**	**SD**	**CV**	***r* = 0.10**	***r* = 0.15**	***r* = 0.20**	***r* = 0.30**
Reach gradient (%) above LF point	2250	17.73	13.89	0.78	166	74	42	18
Bankfull width (m) above LF point	2182	1.13	0.95	0.84	190	84	47	21

Table 11: Estimates of means, standard deviations, and coefficients of variation from *pooled eastern and western Washington data at lateral point types* with sample size approximations for four levels of relative precision.

Outcome	**n**	**Est. Mean**	**SD**	**CV**	***r* = 0.10**	***r* = 0.15**	***r* = 0.20**	***r* = 0.30**
Reach gradient (%) above LF point	1497	19.65	15.28	0.78	164	73	41	18
Bankfull width (m) above LF point	1447	0.86	0.59	0.69	129	57	32	14

Table 12: Estimates of means, standard deviations, and coefficients of variation from *pooled eastern and western Washington data at terminal point types* with sample size approximations for four levels of relative precision.

Outcome	**n**	**Est. Mean**	**SD**	**CV**	***r* = 0.10**	***r* = 0.15**	***r* = 0.20**	***r* = 0.30**
Reach gradient (%) above LF point	753	13.90	9.52	0.69	127	56	32	14
Bankfull width (m) above LF point	735	1.67	1.24	0.74	149	66	37	17

This analysis provides guidance for establishing the sample size of sites for PHB surveys in eastern and western Washington. If the data sets that were provided are not representative of the larger population of PHBs in Washington, then variation may be underestimated causing approximated sample sizes to be lower than needed for the desired precision. The unscreened CMER data were used for the sample size approximation because they provided more conservative sample sizes than when the screened data were used. However, this application does not imply a preference for the unscreened data set relative to other analyses. Differences in site selection for eastern and western Washington data sets were not considered when pooling the data, but the combined data set provided an index of statewide variability that was not available otherwise. While the ultimate goal of this project is to identify criteria with which to identify PHBs, ensuring that the data collected on potential PHB criteria represent the range of conditions in the population will provide a robust basis for PHB modeling when three years of data are available.

Sampling Design Recommendations

Probabilistic selection of the sampling locations from the sampling frame is recommended to avoid selection bias and to provide a basis for inference to the larger population of interest (Lohr 2009). For ecological surveys, spatially-balanced sampling approaches provide methods to obtain probabilistic samples across large areas without risking selection of clustered points that are correlated and provide duplicate information. Several methods for selecting spatially-balanced samples are available and include generalized random tessellation stratified (GRTS) sampling (Stevens and Olsen 2003, 2004), balanced acceptance sampling (BAS; Robertson et al. 2013), and Halton iterative partitioning (HIP, Robertson et al. 2018). Data from samples selected with spatially-balanced sampling can be analyzed with design-based tools available in the *spsurvey* package (Dumelle et al. 2022). All three of the sampling techniques can be implemented in the *SDraw* package (McDonald and McDonald 2020). However, since the *SDraw* package is currently not maintained on the CRAN website (as of 12/6/21 and since 11/16/21), drawing GRTS samples with the *spsurvey* package is recommended to ensure that best practices for security protocols and package functionality are maintained.

The sampling design for the PHB surveys will incorporate *a priori* geographic stratification by region (east or west WA) so that spatial balance is obtained for each region. Additionally, sampling effort will be apportioned among point types (terminal or lateral points) with “soft stratification” (Larsen et al. 2008, section 2). This approach is useful when the point types are not known for each site before the survey so no sampling frame is available to identify each subpopulation for a priori stratification. Survey crews will record the point type at the time of the survey and, when the desired sample size for a point type is satisfied, survey data from this point type will not be collected at subsequent points of this type. Because the point type is not known a priori so cannot be included as a survey design variable for stratification, employing this technique will require adherence to the spatially-balanced ordered list of sites to ensure that the obtained sample of sites within each point type is also spatially balanced. The point type should be recorded for each site so that inclusion probabilities for each site may be calculated prior to analysis for any design-based summaries such as means and totals (Larsen et al. 2008, section 2.4).

Based on the sample size approximation for data pooled across region, the total sample size should be no less than 190 sites (Table 10) to obtain relation precision of 0.10 for the statewide estimates of mean channel characteristics. ISAG members expressed a desire to obtain estimates of means for channel characteristics with geographic stratum-level relative precision of 0.10. For the two metrics of interest (reach gradient above LF point and bankfull width above LF point), obtaining the more conservative sample size for each region is recommended. Therefore, the eastern WA sample should consist of 143 sites (Table 4) and the western WA sample should consist of 171 sites (Table 7) for a total of 314 sites across the state.

Given the ISAG statement that there are roughly five times more lateral points than terminal points, I examined methods to allocate sampling effort among the two point types. Proportional allocation of effort will favor lateral points since they exist more frequently throughout the landscape. Optimal allocation accounts for the relative precision of lateral and terminal points but is still influenced by the larger relative frequency of lateral points as compared to terminal points. The final sample sizes were based on reach gradient above LF point in eastern WA and bankfull width above LF point in eastern WA. The precision in the means for these two sets of estimates were similar between lateral and terminal point types. Therefore, I recommend an equal allocation of sampling effort among the two point types. Based on the sample size approximation of lateral and terminal points for eastern and western WA (Tables 5, 6, 8, and 9), equal allocation of effort between the two point types should still provide channel characteristic means with relative precision between 0.10 and 0.15.

Note that the suggested sample sizes are the numbers of sites where data are successfully collected. To account for inaccessible sites and sites that do not meet the definition of the target population (such as in reaches with no water), a larger sample of sites (perhaps three to five times larger than the desired sample size) should be drawn to successfully collect data at the desired number of sites. There is no penalty for selecting a much larger sample than needed, but the final set of surveyed sites should consist of a contiguous set of sites from the spatially-balanced randomized list of locations to avoid any sort of systematic or geographic bias in the sample locations caused by surveying a disproportionate number of sites in one area. For each site visited, notes on any frame error or nonresponse error should be recorded so that inclusion probabilities for each site can be accurately calculated. For model-based analysis approaches, incorporating design variables such as *a priori* and soft stratification variables such as region and point type (lateral or terminal) may account for the sampling design without directly incorporating inclusion probabilities.

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Appendix C. Random Forest Modeling Report

Identifying Potential Habitat Breaks in Washington Streams Using Random Forest Modeling

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OBJECTIVES

The Washington Department of Natural Resources (WA DNR) is developing a survey protocol to identify physical characteristics associated with fish habitat breaks in Washington streams. In addition to developing criteria for identifying potential habitat breaks (PHBs), the Instream Scientific Advisory Group (ISAG) would like to evaluate criteria proposed by the Washington Forest Practices Board (FPB or Board). The goal of this analysis is to characterize the features associated with the end of fish occurrence in each stream. The goals of this pilot data analysis are to demonstrate methods for identifying PHBs and assessing FPB criteria. ISAG provided pilot data from streams in eastern and western Washington to facilitate an example analysis to identify the end of fish in each stream.

This pilot data analysis demonstrates several tools available for characterizing the end of fish based on stream segments classified as fish bearing (fish) or non-fish bearing (no fish). The end of fish is where electrofishing has identified the last fish segment, all waters upstream are thus non-fish bearing segments. The space between the sampling segment at the end of fish and the subsequent segment contains the potential habitat barrier, either as a segment level variable or a cumulative variable. A random forest analysis (Cutler et al. 2007) was applied to segment-level stream data to model fish presence as a function of habitat feature metrics. Random forest modeling generates a predictive model that can be accurately applied to novel datasets. Additionally, interaction forest models were applied to accommodate multivariate comparisons of habitat covariates that may exhibit relatively strong interactions. Random forest models were developed with R statistical software (2022) packages to evaluate the Board criteria that included binary categorical variables of stream characteristics, including gradient, width, obstacles, and other physical stream characteristics that affect or limit fish dispersal further upstream. For this objective, we trained a separate random forest model for each of three FPB-proposed PHB groups identifying criteria options for PHBs based on barrier, gradient, and width criteria, and a model for all seven unique criteria combined.

Random forest methodology does not explicitly identify the location of the end of fish nor exact thresholds, but stream metrics that are cumulative over multiple segments above or below a given segment can be used to explain habitat relationships with fish distribution at a broader scale rather than only at the segment scale. Additionally, Classification and Regression Tree (CART) models were developed based on the results of the random forest and interaction forest analyses and Board criteria to establish thresholds representing potential habitat barriers.

METHODS

Pilot Data and Covariates

The pilot data set used for analysis included measurements from 2,313 stream segments representing 32 stream reaches across 11 basins, spanning western and eastern Washington and five ecoregions (Eastern: Canadian Rocky Mountains, East Cascades; Western: Northwest Coast Ecoregion [under the purview of WA DNR], Puget Trough, and West Cascades). Stream segments are defined as the stretch of stream between two survey stations, which are located at inflection points in the topography of the stream thalweg (Roni et al. 2018). Segment-level habitat metrics were provided for the random forest analysis. To expand the scale of habitat metrics for the predictive models, several covariates used in the analysis aggregate data from continuous groups of segments either upstream or downstream of the segment of interest. Examples include the maximum gradient upstream of a particular segment and the average sustained gradient of the 20 segments upstream from the segment of interest. We assessed the correlation between variables to eliminate covariate combinations that were highly correlated and redundant (Table 1) to avoid bias in variance importance metrics (Strobl et al. 2007, 2008), but retained all variables when not included in the same model. Individual stream segments were classified as fish bearing (Fish) or non-fish bearing (No-fish). The point at which the last fish was detected is the end of fish (EOF).

Table 1. Details of which stream characteristics were correlated (>0.6). All characteristics were retained in this demonstration analysis to help determine which variables may be important for data collection.

Variable 1	Variable 2	Correlation
Eff.Step.Ht.m	Eff.Step.Ht.BFW	0.88
Eff.Grad	DelEff.Grad.Dn	0.72
Avg.Sus.Grad.Up	Del.Sus.Grad.UpDn	0.70
Avg.Sus.Grad.Dn	Max.Dn.Grad	0.65
Max.Dn.Grad	Max.Dn.Step.BFW10	0.63
Max.Up.Grad	Max.Up.Step.BFW10	0.63

Avg= average; BFW = bankfull width; BFW10 = ?; DelEff = change in effective; Dn = downstream; Eff = effective; Grad = gradient; Ht = height; m = meter; Step = Segment step:Sus = sustained; Up = upstream

Random Forest Models

Random forest classification models can predict binary outcomes such as stream segments with fish or without fish, can accommodate both continuous and categorical (including binary) covariates, and are useful in identifying important covariates from covariates sets with substantial interactions (Cutler et al. 2007). Random forest does not explicitly identify the end of fish based on habitat characteristics, but provides a method for identifying variables that describe the binary state of a stream segment that does or does not contain fish. Here the random forest model is applied to determine variables of interest for use in the CART models and assess variation in variables of importance across the state of Washington.

Using a random forest model requires training and testing (validation) before applying the model to novel data sets. We trained a number of models and evaluated model performance to provide accurate prediction at different spatial scales. In this process, we used the full data set across Washington and split the data into east and west subsets to determine how transferrable the model might be across the entire state. For the first approach, we trained the model on a random subset of 80% of all stream segments across the Washington State dataset. The remaining segments were used for validation. This statewide *Full Random* model was compared to a model that was trained on all streams but one, which is referred to as *Full Random Leave One Out (LOO*) approach. The segments from the “left out” stream were used for model validation. We also compared the *Full Random* model performance to a model that incorporated geographic west/east as a predictor variable (*Full Random WE Predictor*). We performed the same routine for both the western (*Western Random and Western Random* LOO) and eastern (*Eastern Random* and *Eastern Random LOO*) regions in Washington. All models initially included categorical variables for streambed substrate and habitat unit type.

Random forest models cannot accommodate missing values in covariates. The *randomForest* package (Liaw and Wiener 2002) can impute these values based on the mean of other correlated covariates; however, this is not appropriate for this data set. Values were missing for the upstream gradient of the last segment along the stream and for step-related covariates where no step was observed. In order to include the last segment of each stream, the gradient was set to zero. This corresponded to the trajectory of most streams, and several segments had several zero values prior to the last segment. Missing values for step-related covariates were also set to zero following the logic that a stream missing a step has a step height of zero. The *Full Random* model includes these covariates, whereas the *Full Random Reduced Covariates* model excludes the variables with missing values. This comparison may help in determining the suite of variables important for future data collection. All eastern and western models included the same covariates as the *Full Random* model because the *Full Random* model performed better than the *Full Random Reduced Covariates* model (Table 2).

Table 2. Tuning parameters obtained from package *caret*. Model performance evaluated with validation testing.

	mtry	Maxnodes	Number of Trees	AUC	Accuracy (PCC)	Sensitivity	Specificity	Kappa
Full Random Reduced Covariates	10	26	250	0.87	85.53%	0.92	0.82	0.69
Full Random	11	29	250	0.93	93.52%	0.91	0.96	0.87
Full Random (WE Predictor)	7	29	350	0.90	89.41%	0.91	0.88	0.78
Full Random (LOO)	12	24	250	0.86	82.14%	0.73	1.00	0.65
Eastern Random	6	24	250	0.93	92.83%	0.91	0.94	0.86
Eastern Random (LOO)	12	25	250	0.69	61.19%	0.8	0.58	0.20
Western Random	11	15	250	0.93	92.92%	0.91	0.94	0.85
Western Random (LOO)	5	19	250	0.86	86.08%	0.73	1.00	0.72

AUC = area under the curve; kappa = a measure of agreement between predicted presences and absences; LOO = Leave One Out; Maxnodes = maximum number of nodes; mtry = optimum number of covariates; PCC = proportion of presence correctly classified; sensitivity = proportion of presence correctly classified; specificity = the proportion of absence correctly classified

Each model was built and tuned to maximize accuracy using the R package *caret* (Kuhn 2008) and trained and validated using *randomForest* (Liaw and Wiener 2002). We determined the optimum number of covariates allowed at each node (*mtry*), the number of trees, and the maximum number of nodes (*max nodes*) by comparing the accuracy of the model with varying values of *mtry, number of trees,* and *max nodes*. Parameters were tuned for each data subset described in the previous section.

For final model evaluation and comparison, we reported the area under the curve (AUC) to compare model performance, accuracy (overall percentage correctly classified), sensitivity (proportion of presence correctly classified), specificity (the proportion of absence correctly classified), and kappa (a measure of agreement between predicted presences and absences). Variables deemed important by random forest are displayed graphically along with partial dependency plots for all continuous variables. To further validate the variables deemed important in *randomForest*, we used the package *Boruta* as a secondary way to characterize important variables for each model (Kursa and Rudnicki 2010). To increase the utility of this demonstration, an appendix of box plots and violin plots were produced to qualitatively visualize potential criteria cutoffs for variables deemed important by random forest analyses (see Appendix A).

Interaction Forest Models

The random forest approach described above does not explicitly account for interactions between covariates that can influence categorical outcomes (Hornung and Boulesteix 2022). To investigate how interactions between stream features effect the predictive capacity of the model, we fit an interaction forest model using the *Full Random* training data set. We used the R package *diversityForest* (Hornung 2022) to train an interaction forest and R package *iml* (Molnar et al. 2018) to visualize interactions between covariates. The package *diversityForest* uses bivariate splitting to model quantitative and qualitative interaction effects. The effect importance measure (EIM) is produced to rank variable pairs with respect to their predictive importance. The pairs with the highest EIM are displayed through contour plots and cross section plots based on a 2-dimensional LOESS fit. Additionally, graphical output for the overall strength of interactions for all pairs was produced using the *iml* package in R. Overall interaction strength is calculated using Friedman's H-statistic (Friedman and Popescu 2008). The H-statistic quantifies the share of variance that is explained by the interaction and represents the strength, but not the direction, of the interaction.

Evaluating Forest Practice Board proposed Potential Habitat Break Criteria

To evaluate the FPB-proposed PHB criteria for end of fish habitat designation (Table 3), we used the pilot data to compare observed fish presence to predicted fish presence for four sets of criteria. The FPB criteria options A, B, and C consist of seven unique criteria overall. Each of the seven unique criteria was calculated from the pilot data as a binary indicator that the criterion was met. The FPB criteria options A, B, and C were based on the specific combinations of test criteria within each Fish Habitat Assessment Methodology (FHAM) Rule Option as outlined in Table 3. Additionally, a fourth criteria set that included all seven unique test criteria was examined. Each of the four criteria sets was used to predict fish presence and the results were compared to the observed fish data. A confusion matrix of results, AUC, accuracy, sensitivity, and specificity are reported for each of the criteria sets. See Appendix B for covariate definitions used in the assessment of FPB criteria.

Table 3. List of draft Fish Habitat Assessment Methodology rule criteria (presented Washington Department of Natural Resources 2019) translated to metrics/variable names used for pilot analysis. The Forest Practices Board (FPB) Manual definition of bankfull width (BFW) as that for 10 times average BFW is used throughout unless specified otherwise. See Appendix B for variable definitions.

FHAM PHB Option	FHAM Draft Rule Line#	Criterion Type	FHAM Criterion Description	Criterion Description Translated to Pilot Data Variables	Test Criterion #
A	3-a-i	Gradient	Sustained gradient increase >= 5%; sustained = over 20*BFW	(AvgSusGradUpstrm-AvgSusGradDnstrm) >= 0.05	1
A	3-a-ii	Width	Bankfull width <= 2 feet (ft), sustained over 20*BFW	BFW_Up20_ft <= 2.0	2
A	3-a-iii-A	Obstacle	Vertical obstacle height >= BFW AND >= 3 ft	EffectiveGrad_pct > 150% AND EffectiveStepHeight_m >= (3*.3048) AND EffectiveStepHeight_BFW >=1.0	3
A	3-a-iii-B	Obstacle	Non-vertical step >= 30% AND elevation increase > 2*BFW	EffectiveGrad_pct >= 0.3 AND EffectiveStepHeight_BFW > 2.0	4
B	3-a	Gradient	Gradient >10%, sustained over 20 * BFW	AvgSusGradUpstrm > 10%	5
B	3-b (same as A 3-a-ii)	Width	Bankfull width <= 2 ft, sustained over 20*BFW	*See above*	
B	3-c-i (same as A 3-a-iii-A)	Obstacle	Vertical obstacle height >= BFW AND >= 3 ft	*See above*	
B	3-c-ii	Obstacle	Non-vertical step >= 20% gradient AND elevation increase >= upstream BFW	EffectiveGrad_pct >= 0.2 AND EffectiveStepHeight_m > BFW_Up10_m	6
C	3-i (same as A 3-a-i)	Gradient	Sustained gradient increase >= 5%; sustained for >= 20 * BFW	*See above*	
C	3-ii	Width	[Downstream to Upstream] BFW decrease >20%, sustained over 20 * BFW (at tributary junctions)	(BFW_Up20_m/BFW_Dn10_m) < 0.8	7

Table 3. List of draft Fish Habitat Assessment Methodology rule criteria (presented Washington Department of Natural Resources 2019) translated to metrics/variable names used for pilot analysis. The Forest Practices Board (FPB) Manual definition of bankfull width (BFW) as that for 10 times average BFW is used throughout unless specified otherwise. See Appendix B for variable definitions.

FHAM PHB Option	FHAM Draft Rule Line#	Criterion Type	FHAM Criterion Description	Criterion Description Translated to Pilot Data Variables	Test Criterion #
C	3-iii-A (same as A 3-a-iii-A)	Obstacle	Vertical obstacle height >= BFW AND > 3 feet	*See above*	
C	3-iii-B (same as B 3-c-ii)	Obstacle	Non-vertical step >= 20% gradient, and elevation increase >= upstream BFW	*See above*	
A, B, C		Tributary Jctn	Tributary junctions must meet one of the other PHB criteria	*none*	

*(4) For purposes of this section:

(a) “Permanent Natural Obstacle” means a natural, non-deformable obstacle that completely blocks upstream fish movement. “Permanent natural obstacles” include vertical drops, steep cascades, bedrock sheets and bedrock chutes. A permanent natural obstacle excludes large woody debris and sedimentary deposits.

(b) “Potential Habitat Break” means a permanent, distinct and measurable change to in-stream physical characteristics. PHBs are typically associated with underlying geomorphic conditions and may consist of natural obstacles that physically prevent fish access to upstream reaches or a distinct measurable change in channel, bankfull width or a combination of the two.

BFW = bankfull width; FHAM = Fish Habitat Assessment Methodology; Jctn = junction; PHB = Potential Habitat Break; pct = Percent; Upstrm = Upstream.

As a more robust comparison, we trained and tested four separate random forest models using the *Full Random* training approach and validation datasets described above and in Table 3. For each of the four criteria sets the original dataset was altered to contain the fish/no-fish classification column and a binary feature column; one column for each of the criteria within each set as outlined in Table 3. The *Boruta* package was used to validate variable importance. The model AUC, accuracy, sensitivity, specificity, and kappa are reported to evaluate model performance.

CART Analysis to Determine Thresholds Representing Potential Habitat Breaks

Classification and regression tree analysis (CART) was performed using the *rpart* package (Thernau and Atkinson 2022) in program R on the *Full Random* data set. A CART model was built for several combinations of variables to determine which set produces the highest prediction accuracy and enables comparison of model performance based on sensitivity, specificity, and Matthews Correlation Coefficient (MCC). Sensitivity represents the proportion of positive cases (fish) correctly classified whereas specificity represents the proportion of negative cases (no-fish) correctly classified. MCC is a statistical representation of all four confusion matrix categories (true positives, true negatives, false positives, and false negatives) that is a reliable and holistic indicator of model performance (Chicco and Jurman 2020). The data were split into a training and testing data set to assess the performance of CART models and produce a confusion matrix, prediction accuracy, sensitivity, specificity, and MCC. Additionally, a visual decision tree was generated for each model to identify potential thresholds for variables used at each node or decision point (Figure 1). The decision trees presented in this analysis includes a root node where a decision is made on a single variable forming a split and separate branches. Each subsequent node is a decision node where additional splits form new branches. The final node is the leaf node that is predicted on the outcome variable of interest. If a threshold at a split is true to the right branch the output is a "no fish" classification, if the threshold to the left represents "fish" classification. The classification rate (number of cases divided by total cases in that split) will be displayed below each leaf node.

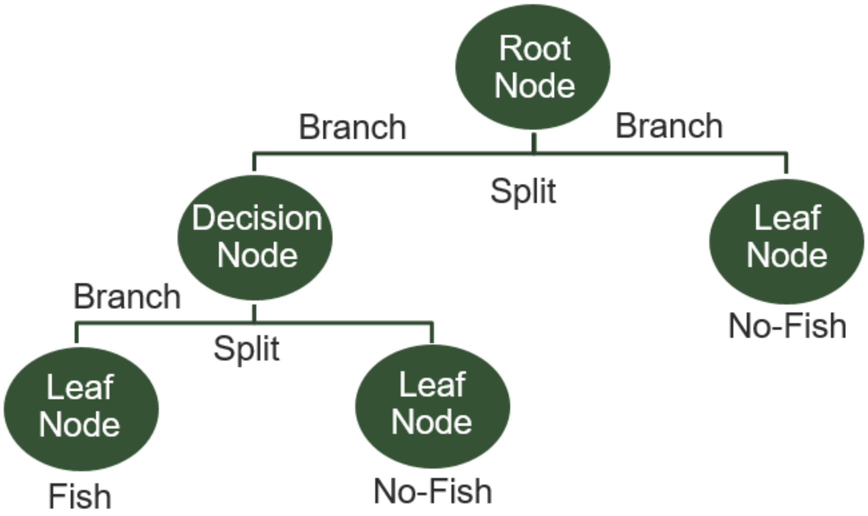


Figure 1. Example labeled diagram for CART model decision tree output. Classification rates are not displayed but will be located below each leaf node.

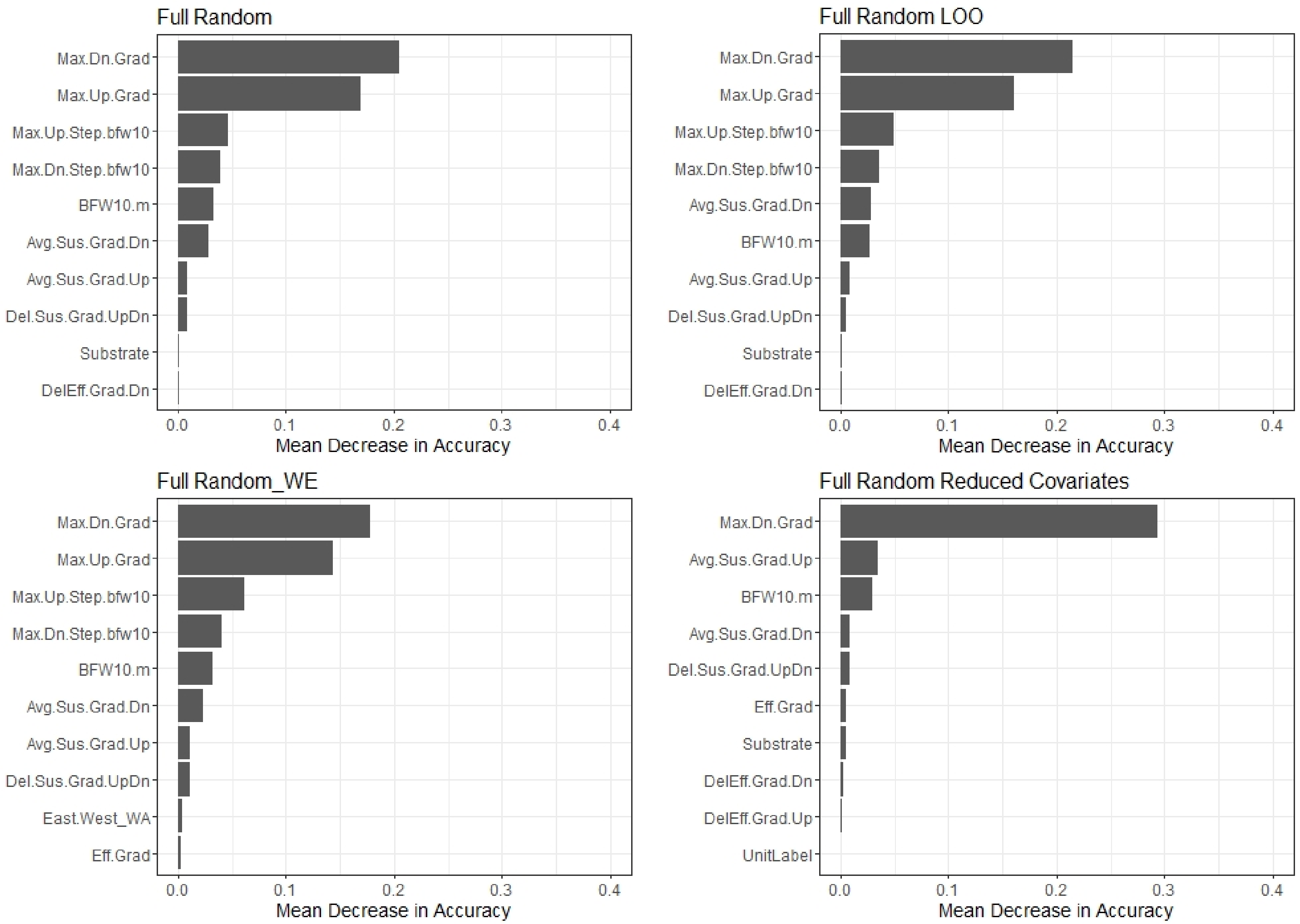
The CART models were informed by the random forest and interaction forest models and the criteria previously established by the Board. The CART model with the highest accuracy was manually pruned for improved clarity and utility by reducing the output to two and three splits. By comparing the accuracy, sensitivity, specificity, and MCC of the top model and the pruned models we can investigate trade-offs between model accuracy and complexity for establishing putative thresholds.

RESULTS

Random Forest Models

Of the eight random forest models, the full random model was most accurate (Table 2). The *Full Random* model including step covariates exhibited an accuracy of 93.52%, whereas the *Full Random* model without step covariates demonstrated 85.53% accuracy. The random sampling of stream segments as opposed to the leave one-out approach of an entire stream performed better for all data set groupings. The difference between the accuracy of the *Western Random*, (92.92%), and the *Western Random LOO*, (86.08%) was 6.84%. The difference in accuracy between *Full Random,* (93.52%) and the *Full Random LOO* (82.14%), was 11.38%. However, the greatest difference in accuracy, 31.64%, occurred between the *Eastern Random* (92.83%), and the *Eastern Random LOO* (61.19%). The *Full Random WE Predictor* model exhibited an accuracy of 89.41%, which was higher than the *Full Random LOO* accuracy of 82.14% but lower than the *Full Random* (93.52%). Tuning parameters between model iterations appears to be an important procedure for these data as the *mtry*, *max nodes*, and *number of trees* values differed across models at the same spatial scale and across spatial scales (Table 2).

Across almost all model iterations, the maximum upstream gradient (Max.Up.Grad) and maximum downstream gradient (Max.Dn.Grad) exhibited the top two highest variable importance scores (Figure 2). However, the maximum upstream step bankfull width (Max.Up.Step.BFW10) was the most important variable for the *Western Random* model. Gradient and step-related characteristics exhibited the highest variable importance scores across all models. Substrate and UnitLabel exhibited small importance scores for all models. Violin plots and box plots in Appendix A provide a qualitative assessment for possible test criteria to define end of fish for several of these important variables. For example, the average values for maximum downstream gradient for fish segments is lower than the average at the end of fish segment and the segment just above the end of fish. The analysis using the *Boruta* package concluded that almost all variables were deemed important for each model iteration (Figure 3), and importance values followed a similar pattern as that reported by the *randomForest* output (Figure 3). Unit type (UnitLabel) for *Western Random LOO* was deemed tentatively important and unimportant for the *Western Random* model (Figure 3d). Effective step height in meters (Eff.StepHt.m) and effective step height at bankfull width (Eff.StepHt.BFW) for the *Eastern Random* models were deemed tentatively important (Figure 3c). The partial dependency plots (Figure 4) demonstrate the importance of maximum downstream gradient, maximum upstream gradient, and bankfull width at predicting fish presence at a segment.


Full Random

Full Random LOO

Full Random_WE

Full Random Reduced Covariates

Figure 2a. **Variable importance from random forest models using the *Full Random, Full Random Leave One Out (LOO), Full Random West/East (WE),* and *Full Random Reduced Covariates* data sets. Visualized using package vip (Greenwell and Boehmke 2020). Mean Decrease in Accuracy represents how much accuracy the model loses without the inclusion of that variable.**

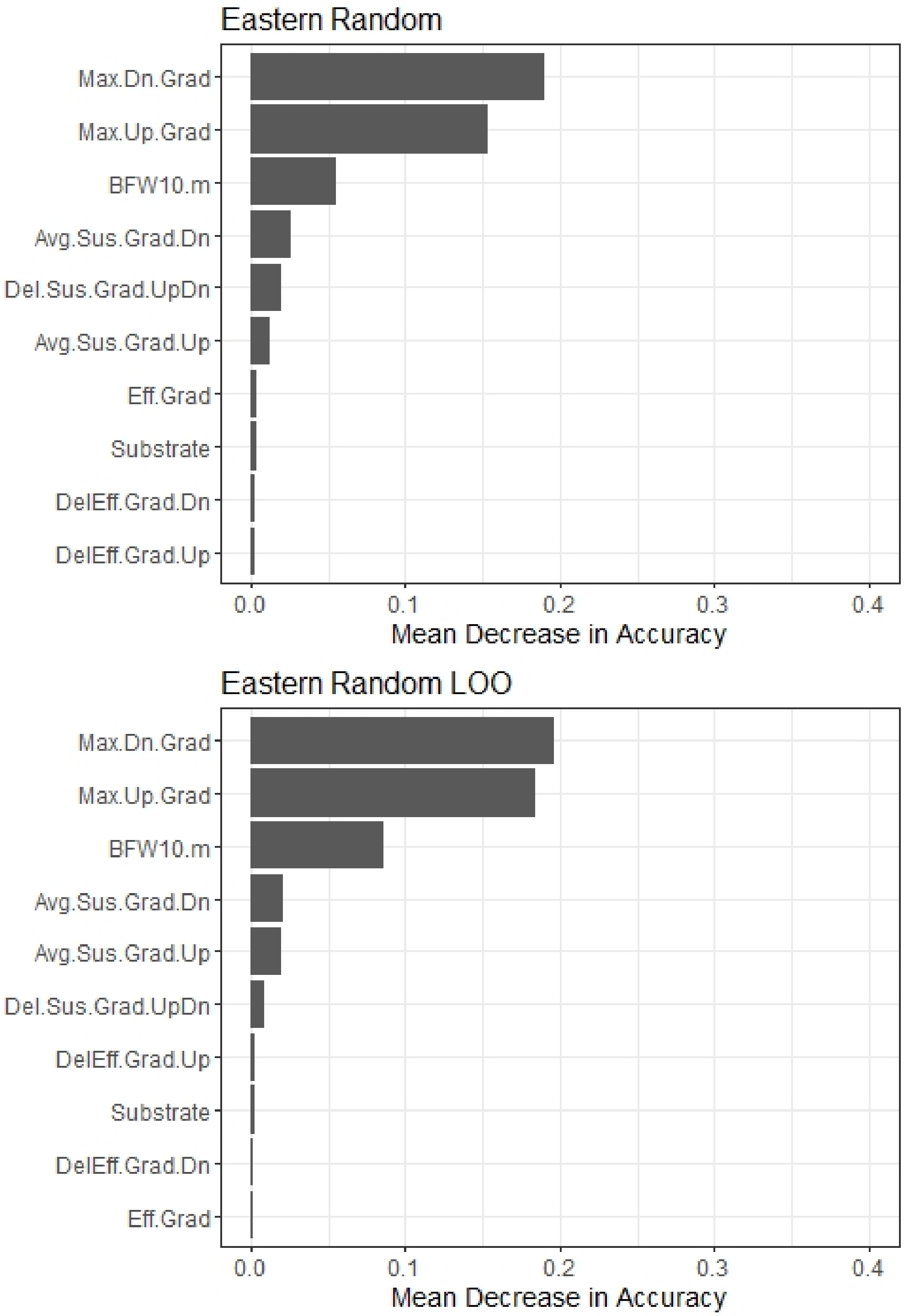


Figure 2b. **Variable importance (mean decrease in accuracy if the variable is removed) from random forest models using the *Eastern Random* and *Eastern Random Leave One Out (LOO)* data sets. Visualized using package vip (Greenwell and Boehmke 2020).**

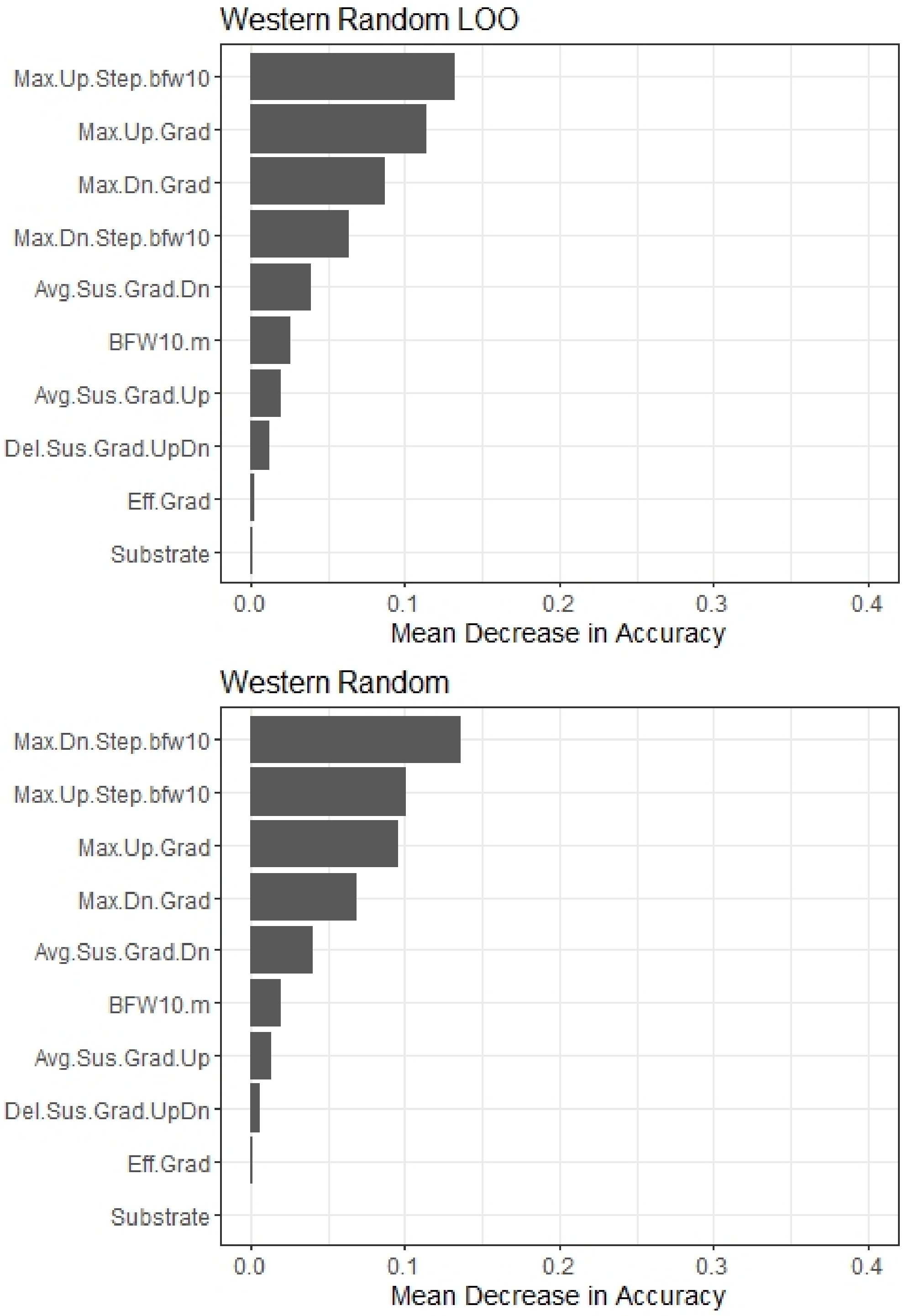


Figure 2c. **Variable importance (mean decrease in accuracy if the variable is removed) from random forest models using the *Western Random* and *Western Random Leave One Out (LOO)* data sets. Visualized using package vip (Greenwell and Boehmke 2020).**

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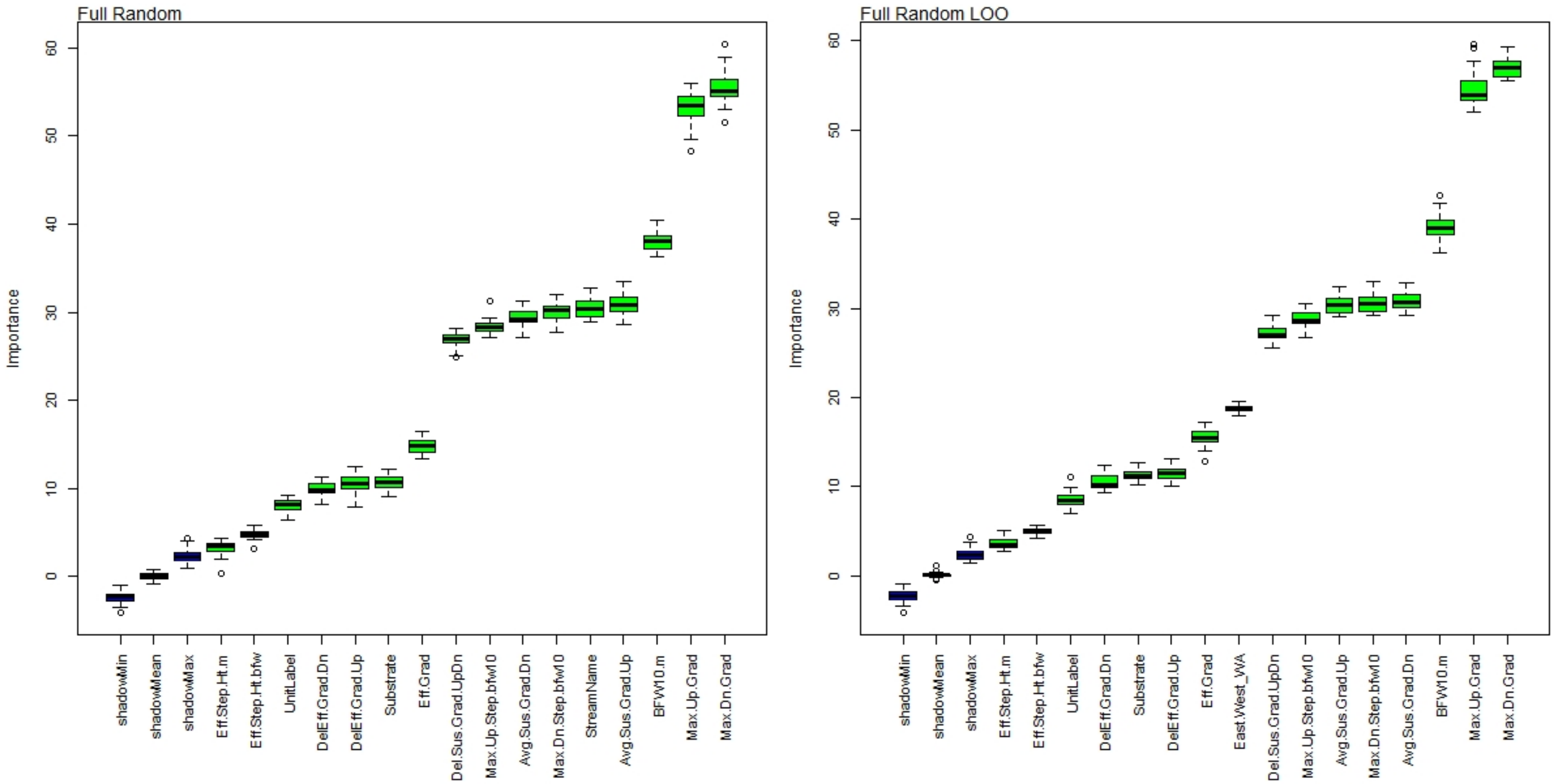

Figure 3a. **Confirming variable importance with *Boruta* package using the *Full Random* and the *Full Random Leave One Out* data sets. Features in green were deemed important by *Boruta,* yellow are tentatively important, red are unimportant, and blue are called shadow features from *Boruta.* Shadow features are shuffled copies of all features to add randomness to the *Boruta* algorithm.**

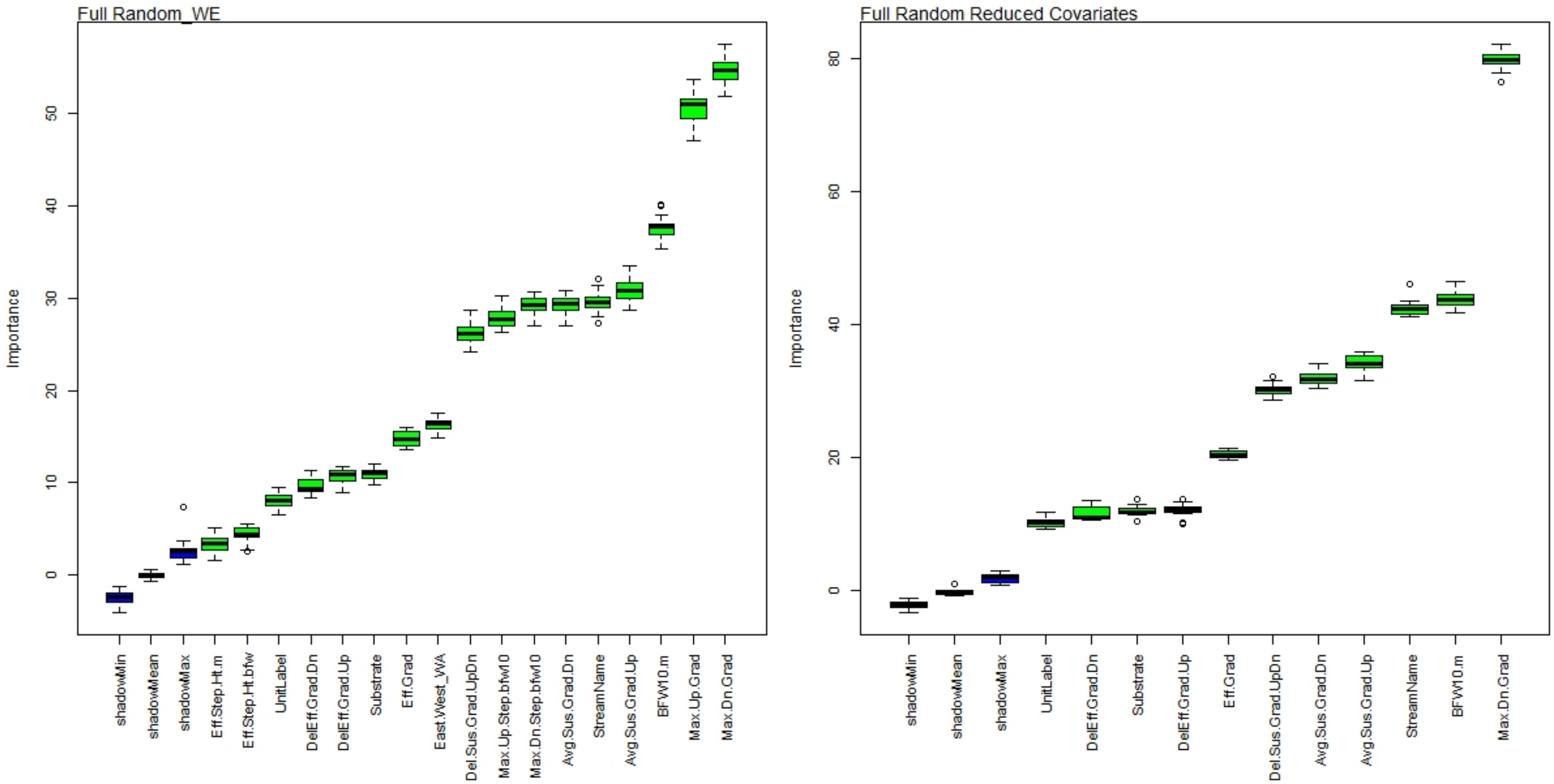

Figure 3b. **Confirming variable importance with *Boruta* package using the *Full Random West/East (WE),* and the *Full Random Reduced Covariates* data sets. Features in green were deemed important by *Boruta,* yellow are tentatively important, red are unimportant, and blue are called shadow features from *Boruta.* Shadow features are shuffled copies of all features to add randomness to the *Boruta* algorithm.**

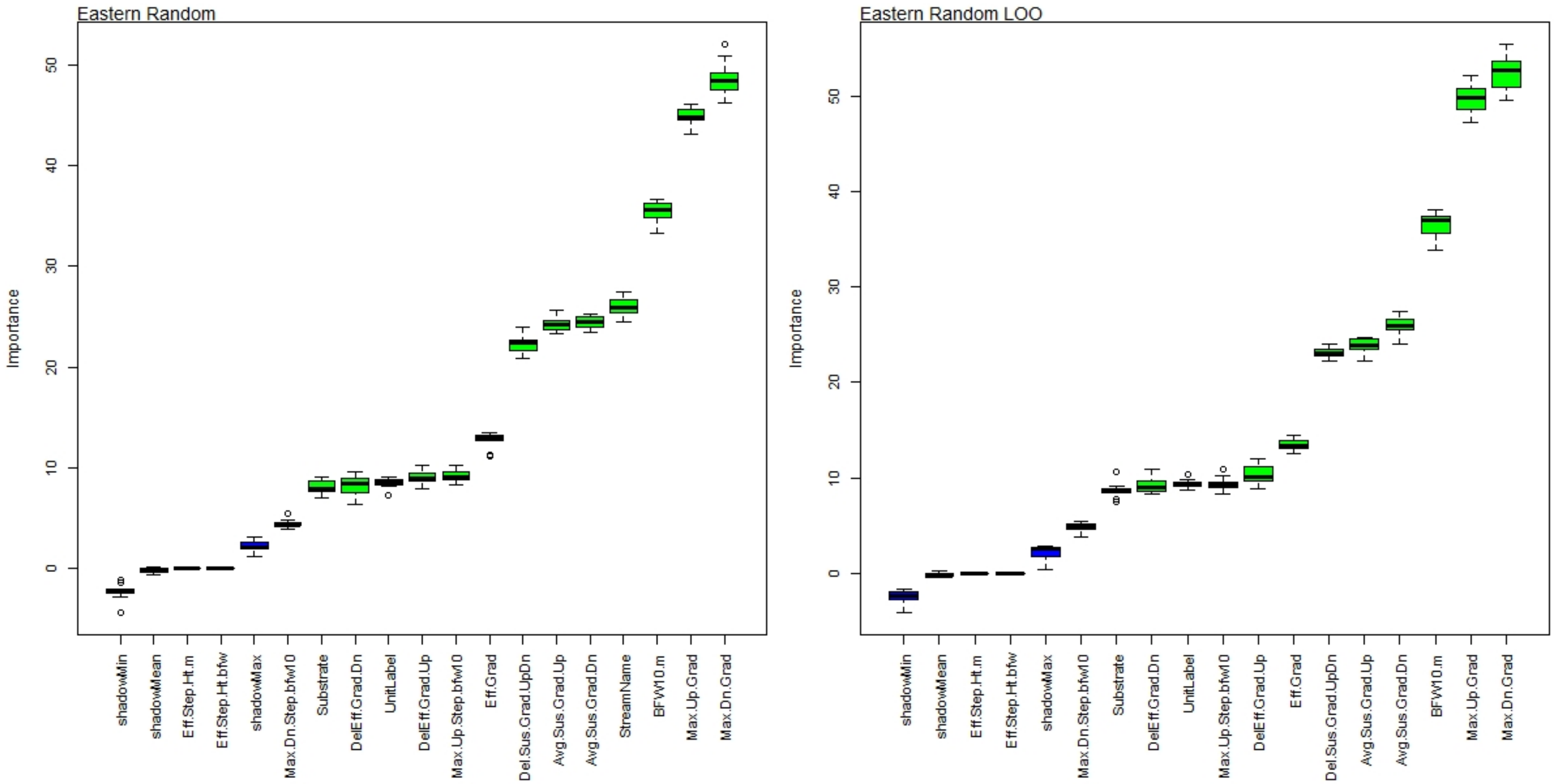

Figure 3c. **Confirming variable importance with *Boruta* package using the *Eastern Random* and *Eastern Random Leave One Out* data sets. Features in green were deemed important by *Boruta,* yellow are tentatively important, red are unimportant, and blue are called shadow features from *Boruta.* Shadow features are shuffled copies of all features to add randomness to the *Boruta* algorithm.**

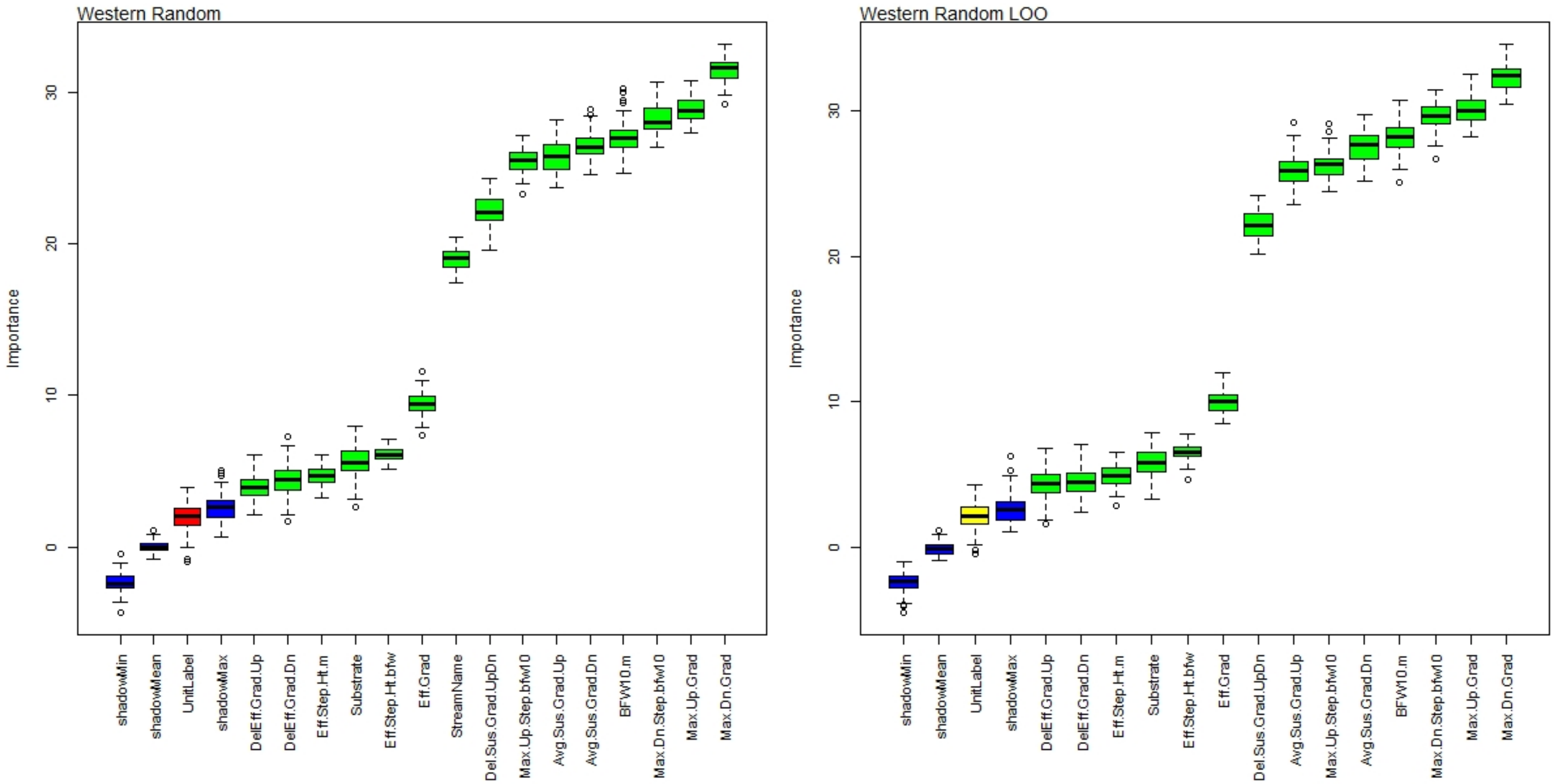

Figure 3d. **Confirming variable importance with *Boruta* package using the *Western Random* and *Western Random Leave One Out* data sets. Features in green were deemed important by *Boruta,* yellow are tentatively important, red are unimportant, and blue are called shadow features from *Boruta.* Shadow features are shuffled copies of all features to add randomness to the *Boruta* algorithm.**

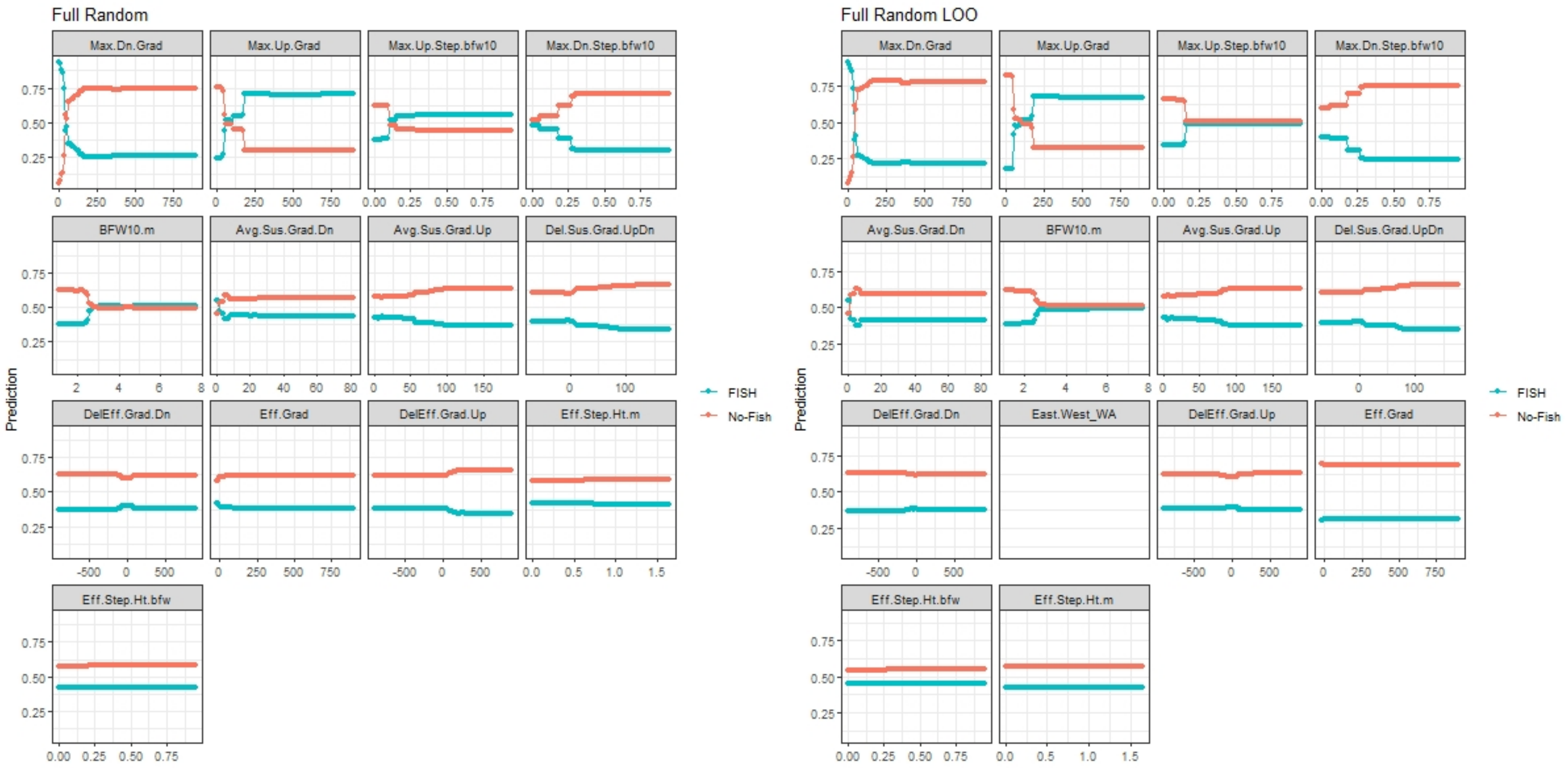

Figure 4a. **Partial dependency plots in order of importance to the random forest model for *Full Random* and *Full Random Leave One Out (LOO)*. The y-axis represents the probability of prediction into a particular class based on the value (x axis) for that particular feature. X-axis labels are in the gray text box above each graph. Substrate and unit are not displayed. *Full Random West/East Predictor* model output is not displayed because it follows the same pattern as the *Full Random* model.**

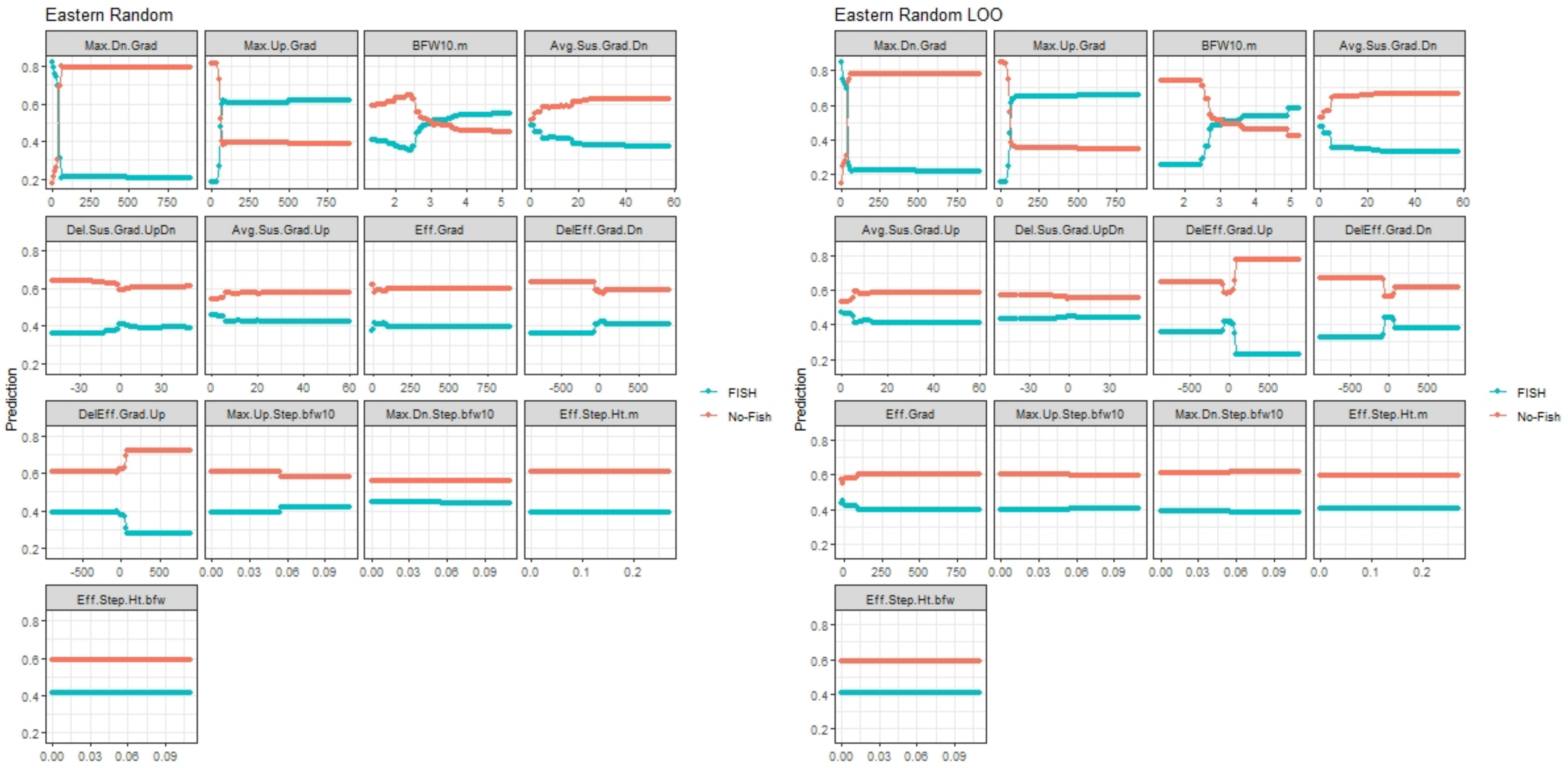

Figure 4b. **Partial dependency plots in order of importance to the random forest model for *Eastern Random* and *Eastern Random Leave One Out (LOO)*. The y-axis represents the probability of prediction into a particular class based on the values (x-axis) for that particular feature. X-axis labels are in the gray text box above each graph. Substrate and unit are not displayed.**

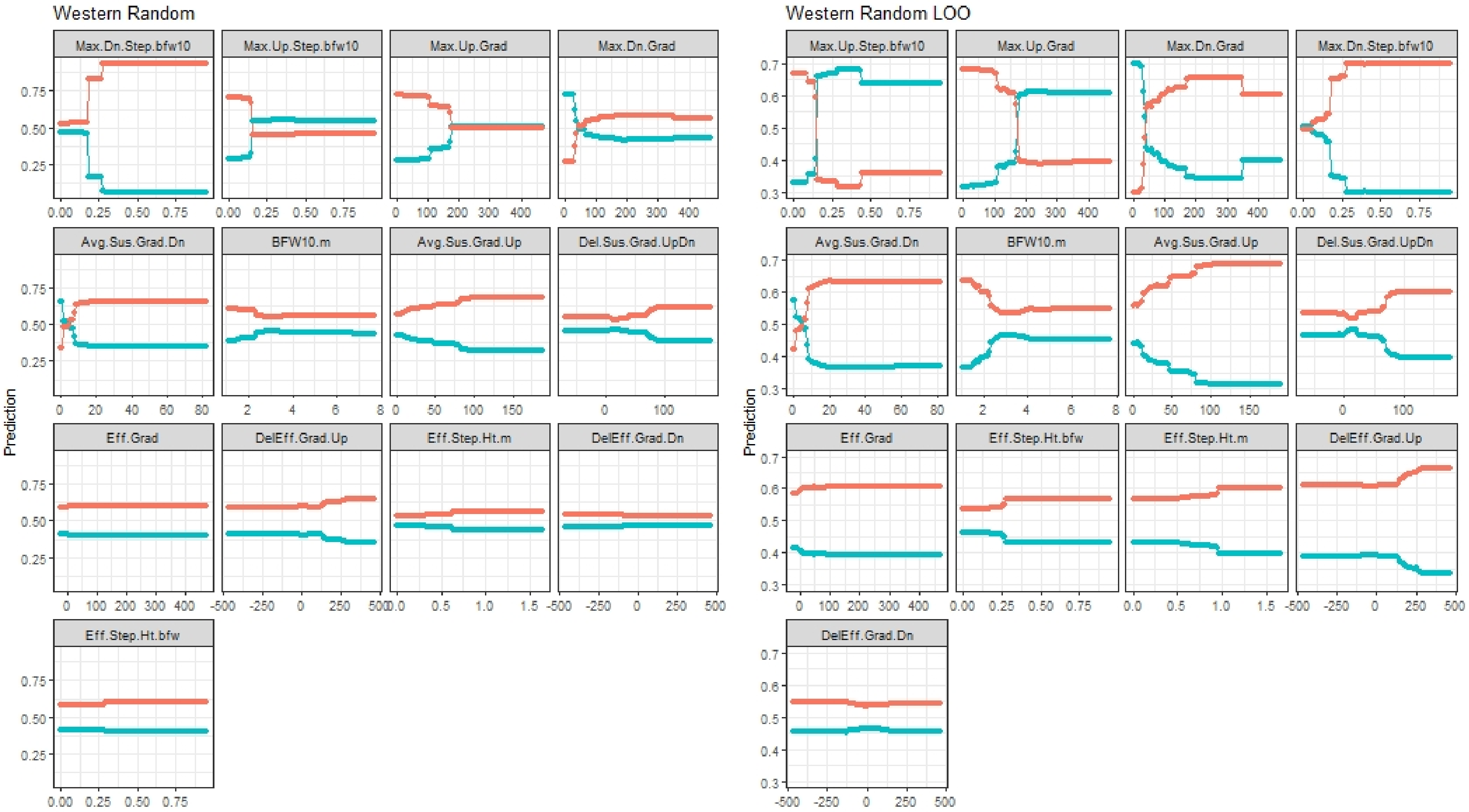

Figure 4c. Partial dependency plots in order of importance to the random forest model for ***Western Random*** and ***Western Random Leave One Out (LOO)***. The y-axis represents the probability of prediction into a particular class based on the values (x-axis) for that particular feature. X-axis labels are in the gray text box above each graph. Substrate and unit are not displayed.

Interaction Forest Models

Using the pilot dataset, the interaction forest model produced a more accurate prediction (97.17%) than the random forest model, (89.63%; Table 4). The accuracy was primarily a function of higher specificity with the interaction forest model as compared to the random forest model which demonstrated higher sensitivity. This result would imply that the random forest model was more adept at identifying physical characteristics associated with the segments below a PHB while the interaction forest identified features associated with segments above the PHB. The pairwise interaction strength for the five covariate pairs with the highest EIM (Table 5) are displayed as contour maps (Figure 5). The contour maps display the probability of predicting fish presence given particular pairwise relationships. For example, a segment where the maximum upstream gradient is greater than 200% and the maximum downstream step (bankfull widths) is lower than 0.38m has a high (90-100%) probability of being classified as containing fish. Additionally, the logistic regression test for interaction effects between pairs of covariates demonstrates that segments with a maximum downstream gradient greater than 71% and a low maximum upstream step bankfull width has a low probability of being classified as containing fish (Figure 5). The highest effect importance measure for maximum upstream gradient and maximum downstream step (bankfull width) was 0.007 (Table 5; Figure 5). While effective gradient had an overall low interaction strength, near zero (Figure 6), the interaction between effective gradient and maximum downstream gradient was one of the highest at 0.005 (Table 5). Maximum downstream gradient, maximum upstream gradient, maximum step bankfull width, bankfull width (BFW10.m), and the average sustained upstream gradient had the highest overall interaction strengths of all covariates (Figure 6).

Table 4. Comparison between the full random sample using random forest and interaction forest. Interaction forest performed marginally better.

Model Type	Number of Trees	AUC	Accuracy (PCC)	Sensitivity	Specificity	Kappa
Random Forest†	300	0.90	89.63%	0.94	0.87	0.79
Interaction Forest	300	0.94	94.17%	0.90	0.98	0.88

†Random forest model tuning parameters and performance metrics using the *Random Full* data set with substrate and unit features removed.

AUC = area under the curve; kappa =a measure of agreement between predicted presences and absences; PCC = proportion of presence correctly classified; sensitivity = proportion of presence correctly classified; specificity = the proportion of absence correctly classified

Table 5. Effect importance measure (EIM) values for the interaction between variable pairs (A and B).

Variable A	Variable B	EIM
Max.Up.Grad	Max.Dn.Step.BFW10	0.007
Max.Dn.Grad	Max.Up.Step.BFW10	0.005
Eff.Grad	Max.Dn.Grad	0.005
Max.Up.Grad	Max.Up.Step.BFW10	0.004
Avg.Sus.Grad.Up	Max.Dn.Grad	0.004

Avg= average; BFW = bankfull width; BFW10 = BFW for 5 segments below, the current segment, and four segments above; DelEff = Change in effective; Dn = downstream; Eff = effective; Grad = gradient; Ht = height; m = meter; Step = ?:Sus = sustained; Up = upstream

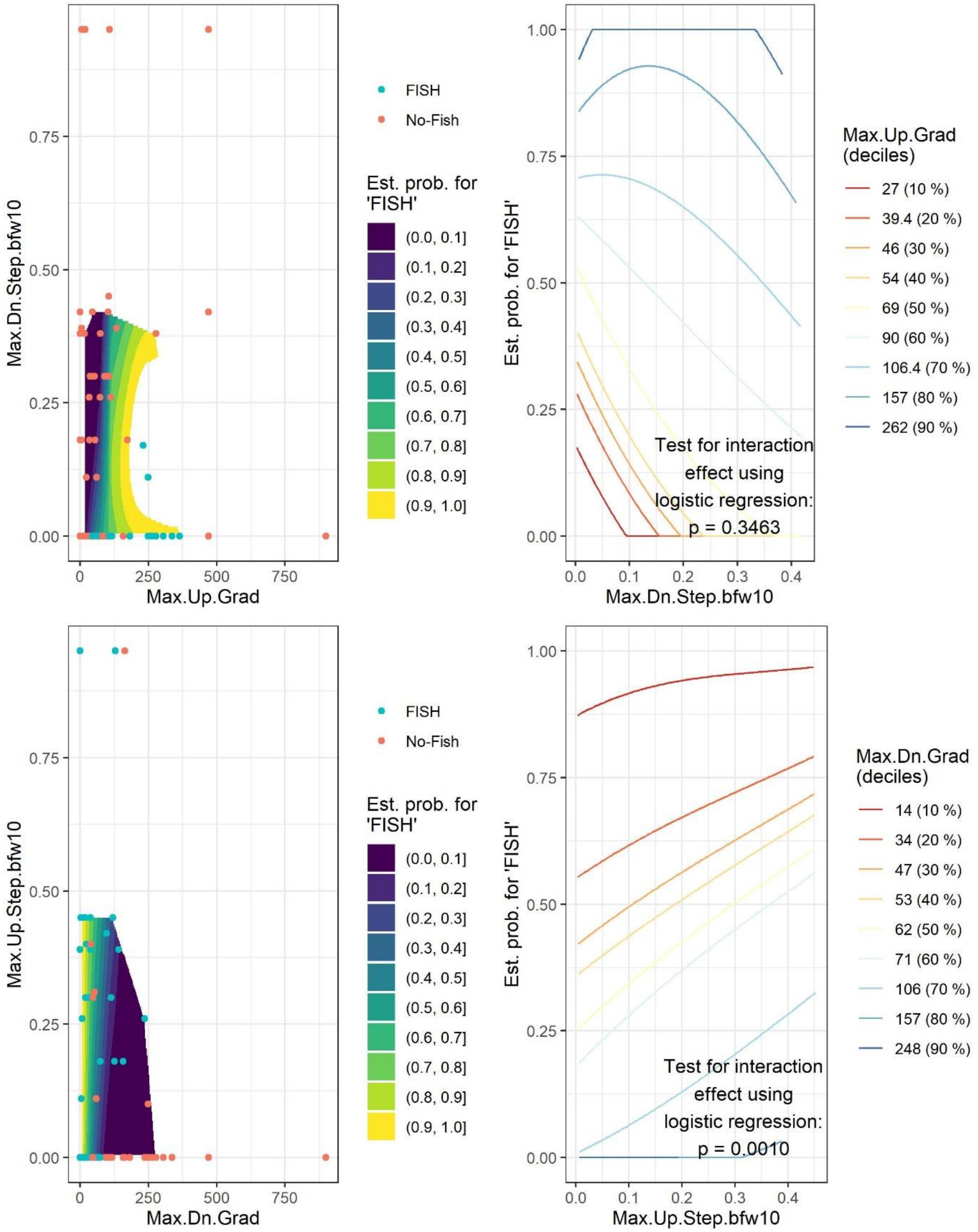

Figure 5. **Interaction contour and cross section plots for pairs of variables with the highest effect importance measure values. P-values on each cross-section plot are overly optimistic according to the *diversityForest* manual. Since both predictors are continuous and the outcome is categorical, *diversityForest* employs a 2-dimensional LOESS regression. The color gradient in the contour plot ranges from purple at 0 (no-fish) to yellow at 1 (fish).**

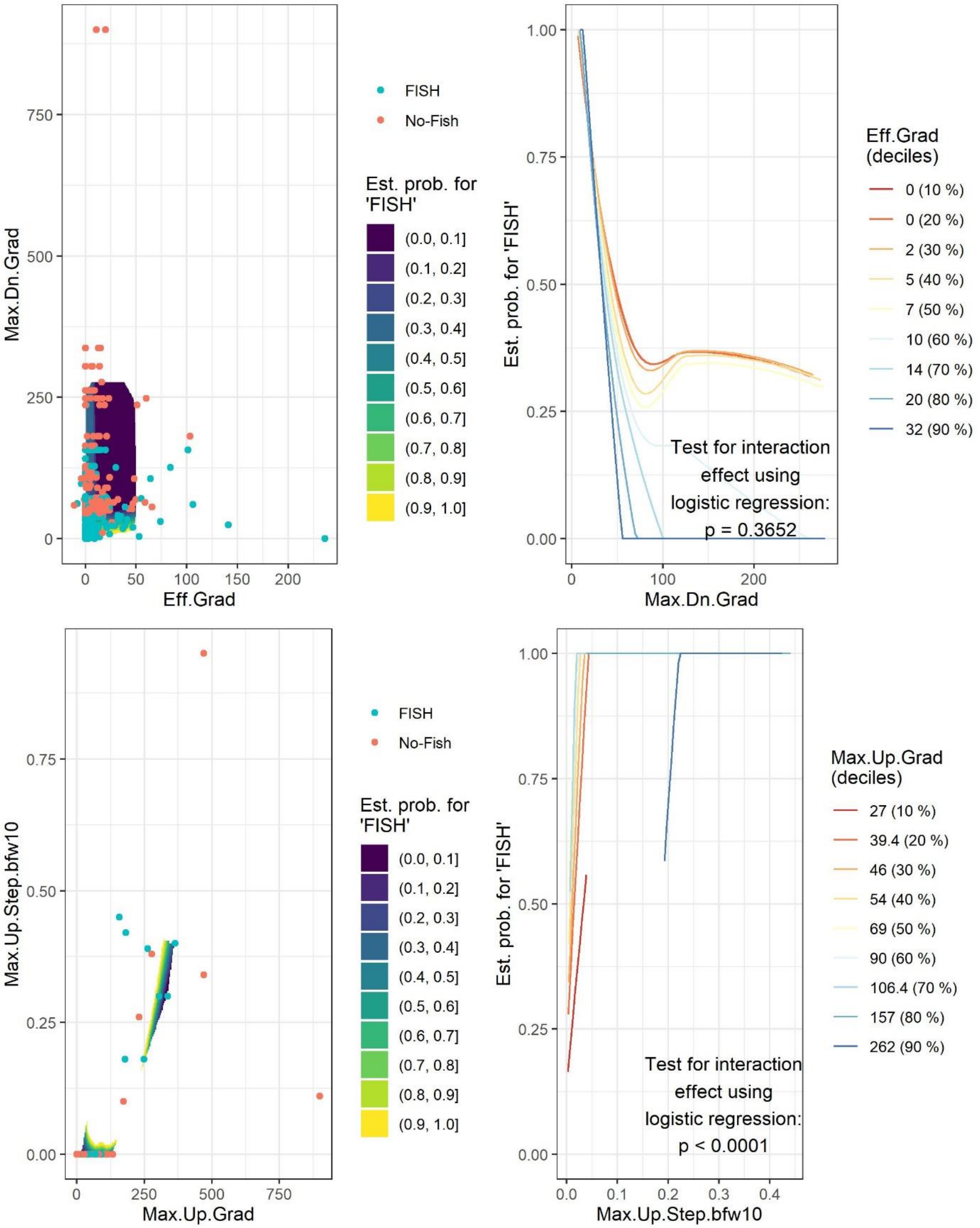

Figure 5. **(*continued*) Interaction contour and cross section plots for pairs of variables with the highest effect importance measure values. P-values on each cross-section plot are overly optimistic according to the *diversityForest* manual. Since both predictors are continuous and the outcome is categorical, *diversityForest* employs a 2-dimensional LOESS regression. The color gradient in the contour plot ranges from purple at 0 (no-fish) to yellow at 1 (fish).**

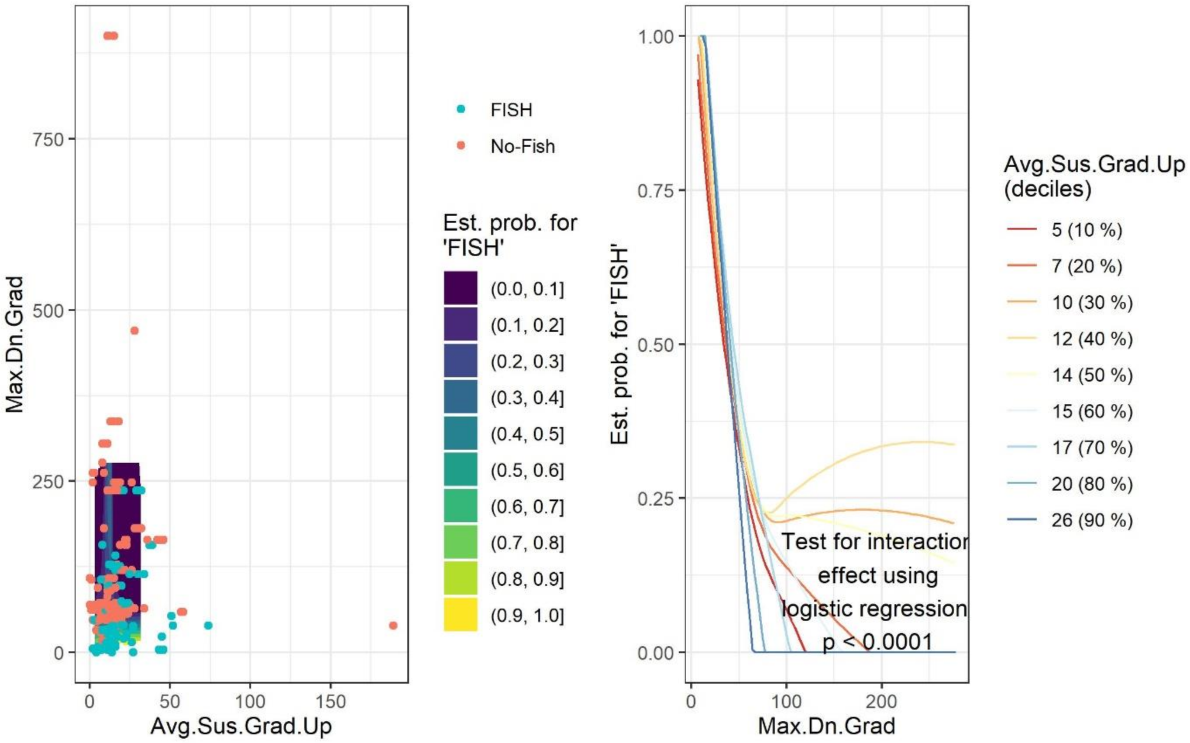

Figure 5. (***continued***) **Interaction contour and cross section plots for pairs of variables with the highest EIM values. P-values on each cross-section plot are overly optimistic according to the *diversityForest* manual. Since both predictors are continuous and the outcome is categorical, *diversityForest* employs a 2-dimensional LOESS regression. The color gradient in the contour plot ranges from purple at 0 (no -fish) to yellow at 1 (fish).**

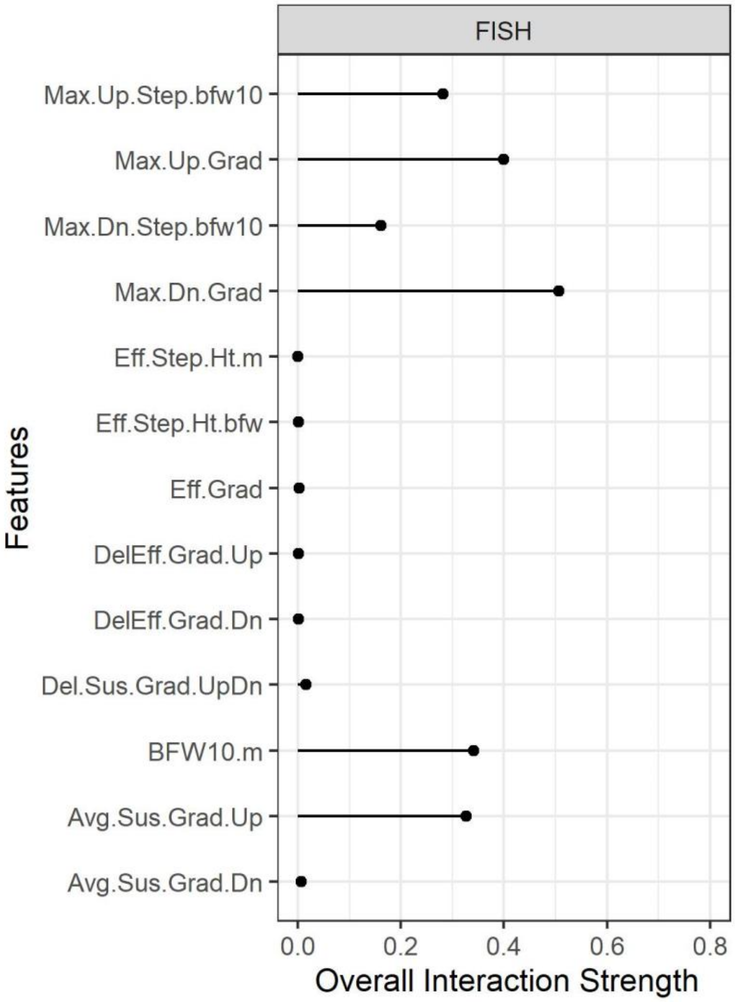

Figure 6. **Overall interaction strength using package *iml* for each stream characteristic.**

Evaluating Forest Practice Board proposed Potential Habitat Break Criteria

Four criteria sets were examined related to the FPB criteria: options A, B, and C and the combined set of unique criteria used in the All Criteria model. Because no stream segments in the pilot data set met TestCriterion2 or TestCriterion3, these criteria were not included in the evaluations of options A, B, or C. Similarly, the random forest model for All Criteria combined contained only the five criteria that were met by any segments in the pilot data set (TestCriterion1, TestCriterion4, TestCriterion5, TestCriterion6, and TestCriterion7).

Predicting fish presence using the four criteria sets resulted in low accuracy, sensitivity, specificity, and kappa parameters (Table 6). This was most notable for Option B that exhibited an accuracy of 48.36%. The confusion matrices in Table 7 display the comparisons of observed fish presence versus. The fish presence based on FPB criteria. This result seems largely driven by the large number of false negative results (observed = fish; prediction = no-fish) for Option A, and false positives (observed = no-fish, prediction = fish) for All Criteria and Option B. Option C had nearly equal numbers of false negatives and false positives. Evaluating the FPB criteria using random forest models resulted in low accuracies and poor model performance (Table 8).

Table 6. Prediction evaluation of the four criteria compared to observed fish presence.

	AUC	Accuracy (PCC)	Sensitivity	Specificity	Kappa
All Criteria*	0.54	49.28%	0.84	0.24	0.07
Option A	0.60	62.52%	0.40	0.79	0.20
Option B	0.52	48.36%	0.74	0.29	0.03
Option C	0.59	59.8%	0.52	0.65	0.18

* Includes only TestCriterion1, TestCriterion4, TestCriterion5, TestCriterion6, and TestCriterion7 because no stream segments met the condition for TestCriterion2 or TestCriterion3.

AUC = area under the curve; kappa = a measure of agreement between predicted presences and absences; PCC = proportion of presence correctly classified; sensitivity = proportion of presence correctly classified; specificity = the proportion of absence correctly classified

Table 7. Confusion matrices for each of the four criteria sets and the observed data.

		Observed	
All Criteria*		**Fish**	**No-Fish**
Prediction	Fish	811	997
	No-Fish	160	313
		Observed	
Option A		**Fish**	**No-Fish**
Prediction	Fish	391	275
	No-Fish	580	1,035
		Observed	
Option B		**Fish**	**No-Fish**
Prediction	Fish	721	928
	No-Fish	250	382
		Observed	
Option C		**Fish**	**No-Fish**
Prediction	Fish	509	455
	No-Fish	462	855

* Includes only TestCriterion1, TestCriterion4, TestCriterion5, TestCriterion6, and TestCriterion7 because no stream segments met the condition for TestCriterion2 or TestCriterion3.

Table 8. **Parameters from model tuning in *caret* and model performance from validation testing for TestCriterion1, TestCriterion2, and TestCriterion3.**

	mtry	Maxnodes	Number of Trees	AUC	Accuracy (PCC)	Sensitivity	Specificity	Kappa
All Criteria*	5	5	250	0.58	59.73%	0.53	0.62	0.13
Option A	1	5	250	0.64	64.77%	0.61	0.66	0.24
Option B	1	5	250	NA	57.77%	NA	0.58	0
Option C	2	5	250	0.62	62.14%	0.62	0.62	0.21

* Includes only TestCriterion1, TestCriterion4, TestCriterion5, TestCriterion6, and TestCriterion7 because no stream segments met the condition for TestCriterion2 or TestCriterion3.

AUC = area under the curve; kappa = a measure of agreement between predicted presences and absences; Maxnodes = maximum number of nodes; mtry = optimum number of covariates; PCC = proportion of presence correctly classified; sensitivity = proportion of presence correctly classified; specificity = the proportion of absence correctly classified

Variables of importance differed little between each for each criteria set. TestCriterion1, the barrier cutoff of 20%, was the most useful predictor for the models for All Criteria, Option A, and Option C (Figure 7). TestCriterion5 and TestCriterion6, followed by the gradient of 10%, exhibited low variable importance in the All Criteria and Option C models (Figure 7), but was deemed unimportant for the Option B model by the *Boruta* algorithm (Figures 7 and 8). Similarly, TestCriterion7 was deemed important in the All Criteria model by random forest and *Boruta*, but unimportant for the Option C model (Figures 7 and 8).

TestCriterion1 relates to sustained stream gradient and parallels the results from the random forest *Full Random* model (Figure 2) where variables related to gradient were deemed most important and the interaction forest model (Figure 6) where gradient variables had strongest interaction strength. TestCriterion5 is also related to gradient but did not emerge as strong of a predictor as TestCriterion1. TestCriterion6 relates to obstacles and step heights and was found most important when paired with TestCriterion1 (Figure 8). This finding is corroborated in both the random forest models and the interaction forest model. Step-related variables were consistently in the top five most important variables (Figures 2–4), and the strongest interaction strength existed between gradient-related variables and step variables (Figure 5). More specifically, the interaction strengths were strongest for maximum upstream or downstream gradient variables and the bankfull width at the step. Width changes are encapsulated in TestCriterion7, and the width criteria were deemed important for the All Criteria model.

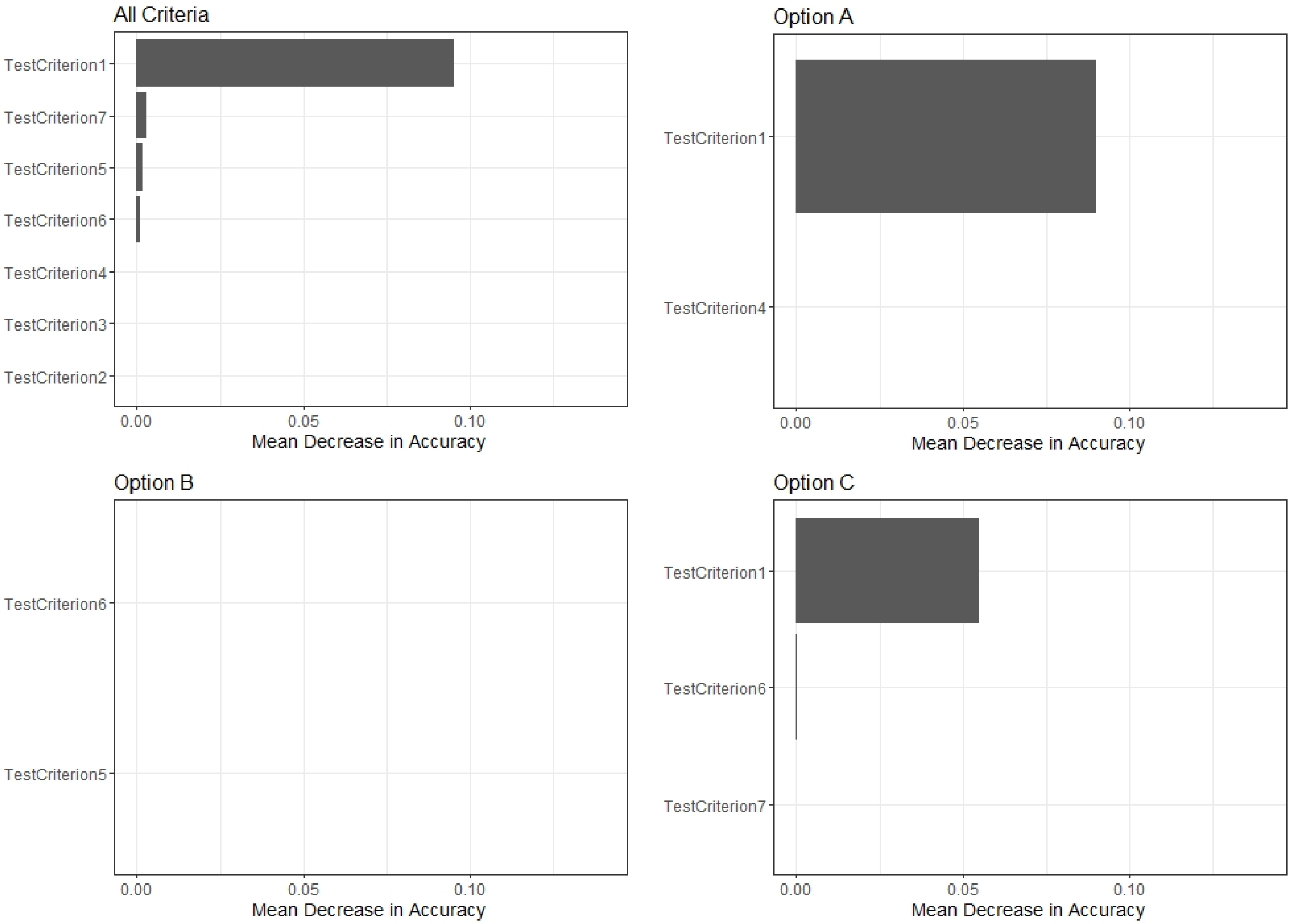

Figure 7. Variable importance from random forest models for criteria sets based on options from the Washington Forest Practices Board outlined in Table 3. Visualized using package vip (Greenwell and Boehmke 2020).

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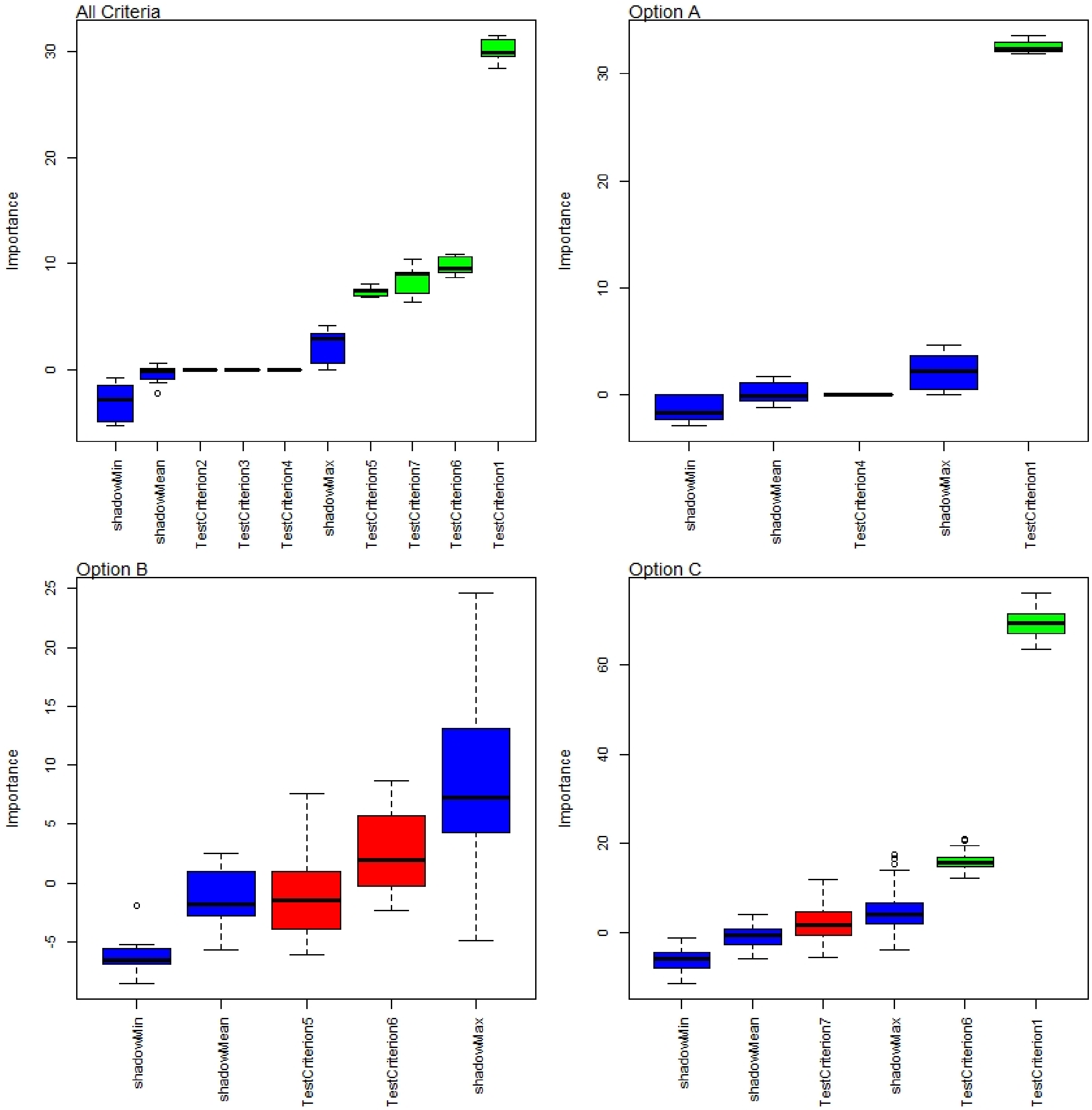


Figure 8. Variable importance validation using *Boruta*. Variable importance is displayed for each criterion described by the Washington Forest Practices Board in Table 3. Features in green were deemed important by *Boruta,* yellow are tentatively important, red are unimportant, and blue are called shadow features from *Boruta.* Shadow features are shuffled copies of all features to add randomness to the *Boruta* algorithm.

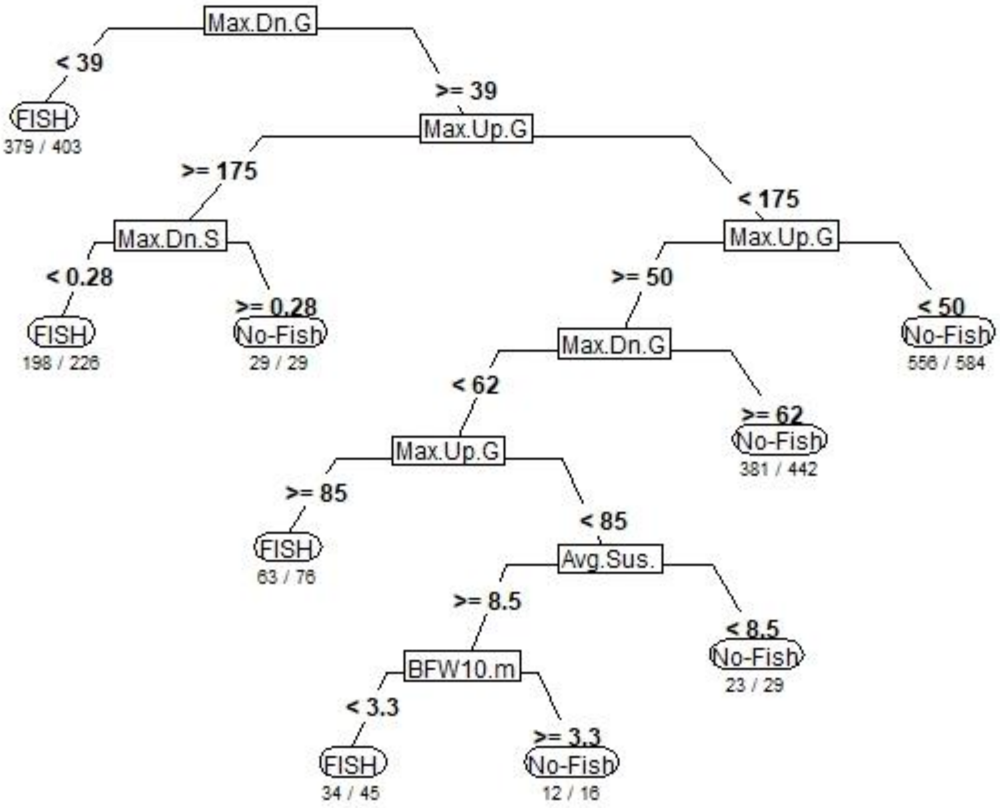
CART Analysis to Determine Thresholds Representing Potential Habitat Breaks

The CART model derived from the random forest analysis included the six most important variables (Figure 2; Table 9) and the CART model derived from the interaction forest analysis included the top three interaction pairs (Table 5; Table 9).

Table 9. **CART model summaries. The basis for the variables included in the CART models and comparison metrics are included in the table.**

Informed CART Model	Variables Included	Prediction Accuracy	Sensitivity	Specificity	MCC
Random Forest	BFW10.m Avg.Sus.Grad.Dn Max.Dn.Grad Max.Up.Grad Max.Dn.Step.bfw10 Max.Up.Step.bfw10	90.06% [86.97-92.63%]	0.84	0.95	0.80
Interaction Forest (Pairs)	Eff.Step.Ht.m/Eff.Step.Ht.bfw Eff.Grad/Del.Eff.Grad.Dn Avg.Sus.Grad.Up/Del.Sus.Grad.UpDn	67.82% [63.35-72.06%]	0.43	0.86	0.32
Board Criteria	Avg.Sus.Grad.Up Avg.Sus.Grad.Dn BFW10.m Eff.Grad Eff.Step.Ht.m Eff.Step.Ht.bfw	71.27% [66.92-75.36%]	0.52	0.86	0.40
Random Forest 3 splits	BFW10.m Avg.Sus.Grad.Dn Max.Dn.Grad Max.Up.Grad Max.Dn.Step.bfw10 Max.Up.Step.bfw10	89.2% [86.01-91.88%]	0.80	0.96	0.78
Random Forest 2 splits	BFW10.m Avg.Sus.Grad.Dn Max.Dn.Grad Max.Up.Grad Max.Dn.Step.bfw10 Max.Up.Step.bfw10	88.34% [85.06-91.12%]	0.80	0.94	0.76

The CART model informed by the random forest analyses produced an accuracy of 90.06% (Table 9). The high accuracy is mostly due to the correct classification of no-fish stream segments (specificity = 0.95), and limited by the correct classification of fish bearing segments predicted as non-fish (sensitivity = 0.84). All six of the included variables were deemed important by the CART model (Table 10). The overall classification capacity of the model, as represented by MCC, is relatively high at 0.80. The root node splits at a maximum downstream gradient of 39%; segments with a maximum downstream gradient less than 39 were split into a final leaf node classified as fish (Figure 9). Segments with a maximum downstream gradient greater than 39% were further split at a decision node for maximum upstream gradient of 175%. Segments with a maximum upstream gradient greater than or equal to 175% were further split by Max.Dn.Step.bfw.10 of 0.28 m. Overall there are eight splits in this decision tree representing putative thresholds for PHBs if the thresholds are considered relative to the root node and the decision nodes above each leaf. For example, if a segment has less than an average sustained gradient of 8.5% it should only be used as a threshold if the decision nodes above it are considered, including a maximum upstream gradient of less than 85%, maximum downstream gradient of less than 62%, maximum upstream gradient of greater than or equal to 50%, but less than 175%, and a maximum downstream gradient of 39%. A decision tree of this length, while more accurate, may be impractical for application in the field and a pruned model may be more beneficial.



Variable Name	Variable Abbreviation
Max.Dn.Grad	Max.Dn.G
Max.Up.Grad	Max.Up.G
Max.Up.Step.bfw10	Max.up.S
Avg.Sus.Grad.Dn	Avg.Sus.
Max.Dn.Step.BFW10	Max.Dn.S
BFW10.m	BFW10.m

Figure 9. Decision tree for the CART model informed by the most influential variables in the random forest analysis.

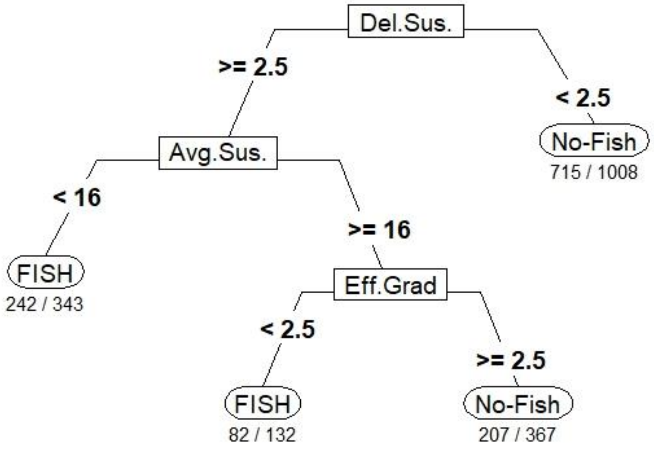
Table 10. Variable Importance for the Random Forest informed CART model.

Variable	Importance Value
Max.Dn.Grad	41
Max.Up.Grad	23
Max.Up.Step.bfw10	16
Avg.Sus.Grad.Dn	10
Max.Dn.Step.BFW10	5
BFW10.m	5

Table 11. Confusion Matrix for the Random Forest informed CART model.

	Reference	
Prediction	Fish	No-Fish
Fish	166	14
No-Fish	32	251

The CART model incorporating the three sets of variables with the highest interaction strength produced a substantially lower accuracy of 67.82% when compared to the random forest, 90.06% (Table 9). Although six variables were included in this model only three were deemed important, and the two most important variables (Del.Sus.Grad.UpDn/Avg.Sus.Grad.Up) were, surprisingly, not the two with the strongest interaction strength (Eff.Step.Ht.m/Eff.Step.Ht.bfw) (Table 12). The low sensitivity (0.43) for this model indicates that the correct classification of fish bearing segments was low. Only 83 out of 194 fish bearing segments were correctly classified (Table 13). The low sensitivity may have impacted the MCC score of 0.32 demonstrating an overall poor classification performance. However, the specificity was relatively high at 0.86, demonstrating that the non-fish bearing segments were classified correctly.



Variable Name	Variable Abbreviation
Del.Sus.Grad.UpDn	Del.Sus
Avg.Sus.Grad.Up	Avg.Sus
Eff.Grad	Eff.Grad

Figure 10. Decision tree for the CART model informed by the most influential variables in the interaction forest analyses.

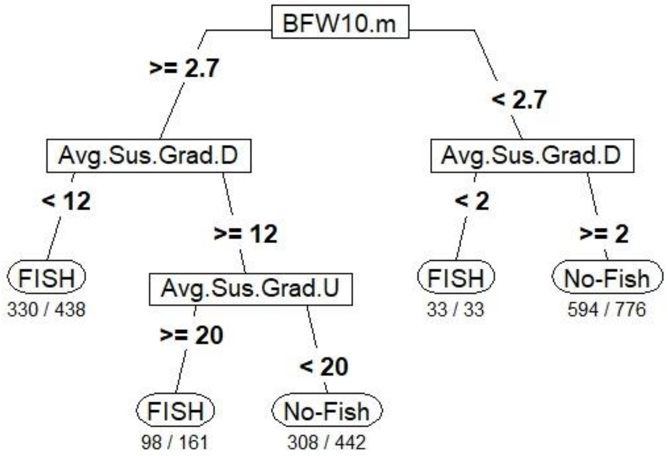
Table 12. Variable Importance for the Interaction Forest informed CART model.

Variable	Importance Value
Del.Sus.Grad.UpDn	56
Avg.Sus.Grad.Up	34
Eff.Grad	9

Table 13. Confusion Matrix for the Interaction Forest informed CART model.

	Reference	
Prediction	Fish	No-Fish
Fish	83	38
No-Fish	111	231

The CART model incorporating the variables used for the Board Criteria produced an accuracy, 71.27%, similar to that of the Interaction Forest, 67.82% (Table 9). Like the other models, the sensitivity was lower (0.52) indicating poor performance for classifying fish bearing segments correctly, but specificity was high (0.86). The root node splits for BFW10.m at 2.7 m (Figure 11). The subsequent decision nodes for those segments greater than or equal to 2.7 m BFW10.m are further split by an average sustained downstream gradient of 12% whereas those segments less than 2.7 m BFW10.m are split by an average sustained gradient of 2%. Four variables were deemed important including Avg.Sus.Grad.Dn, BFW10.m, Avg.Sus.Grad.Up, and Eff.Grad (Table 14), however, only the top three variables were influential enough to warrant a split in the decision tree (Figure 11).



Variable Name	Variable Abbreviation
BFW10.m	BFW10.m
Avg.Sus.Grad.Dn	Avg.Sus.Grad.D
Avg.Sus.Grad.Up	Avg.Sus.Grad.U

Figure 11. Decision tree for the CART model informed by the Board criteria.

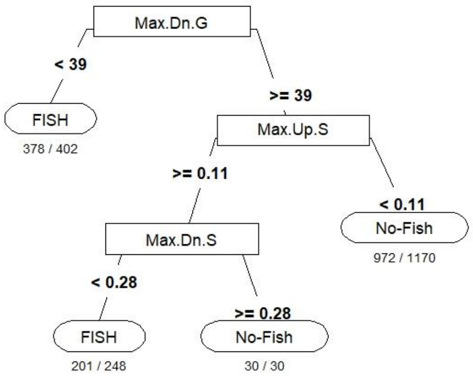
Table 14. Variable Importance for the Board criteria informed CART model.

Variable	Importance Value
Avg.Sus.Grad.Dn	44
BFW10.m	33
Avg.Sus.Grad.Up	19
Eff.Grad	4

Table 15. Confusion Matrix for the Board criteria informed CART model.

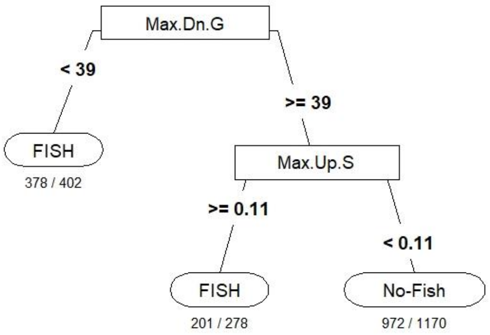
	Reference	
Prediction	Fish	No-Fish
Fish	100	39
No-Fish	94	230

Given the strong performance of the Random Forest informed CART model we wanted to test how well the model performed if pruned to three or two splits instead of allowing the CART model to select the optimal number of splits. The pruned models performed similarly to the full Random Forest informed CART model with accuracies of 88.34% for the two split and 89.2% for the three split models (Table 9). Additionally, the MCC scores remained similar to the overall model (0.8) with 0.78 for the three split and 0.76 for the two split. The two and three split models have the same sensitivity (0.8) but differ in specificity by the correct classification of four additional stream segments in the three split (Table 16) vs. the two split model (Table 17). The thresholds established in the Random Forest informed CART model are the same; only the number of splits (Figure 12 & 13) and, therefore, the distribution of segment classification has changed (Table 16 & 17).



Variable Name	Variable Abbreviation
Max.Dn.Grad	Max.Dn.G
Max.Up.Step.bfw10	Max.up.S
Max.Dn.Step.BFW10	Max.Dn.S

Figure 12. Decision tree for the CART model informed by the Random Forest model with only three splits.



Variable Name	Variable Abbreviation
Max.Dn.Grad	Max.Dn.G
Max.Up.Step.bfw10	Max.up.S

Figure 13. Decision tree for the CART model informed by the Random Forest model with only two splits.

Table 16. Confusion Matrix for the Random Forest informed CART model with only three splits.

	Reference	
Prediction	Fish	No-Fish
Fish	155	11
No-Fish	39	258

Table 17. Confusion Matrix for the Random Forest informed CART model with only two splits.

	Reference	
Prediction	Fish	No-Fish
Fish	155	15
No-Fish	39	254

DISCUSSION

In this example analysis with pilot data, we demonstrated that random forest models and interaction forest models can classify presence of fish on stream segments in Washington State with greater than 90% accuracy. More importantly, random forest and interaction forest enabled a multivariate analysis to determine which variables best described areas with fish and without fish, including stream gradient, steps or barrier height, bankfull width, and other characteristics. Interaction forests outperformed random forest models based on model accuracy, kappa, and specificity, and helped identify key parameters that in combination influence end of fish. These results correspond with findings from a comparison of random forest and interaction forest classification models on 220 different data sets (Hurnung and Boulesteix 2022). Given the lower accuracy of classifying eastern Washington stream segments, a larger sample in conjunction with an interaction forest approach may improve model performance in future analyses.

Applying a CART model to the variables identified in the random forest, interaction forest, and the board criteria demonstrated that thresholds for potential habitat breaks can be established using a decision tree with relatively high accuracy even when pruned. Notably, using the variables from the random forest model in a CART analysis resulted in an accuracy of 90.06% and accuracy was only reduced to 88.34% when the decision tree was pruned to only two splits. Including the variables, but not the thresholds, selected by the Board resulted in higher accuracies in the CART analysis 71.27% than applying the Board criteria to the available data set (48.36%-62.52%; Table 6). Across all CART models, root nodes included maximum downstream gradient, change in the sustained gradient, and bankfull width measurements. Decision nodes (below the root) included maximum downstream and upstream gradients, average sustained upstream and downstream gradient, effective gradient at the segment, and bank full width. Further investigation into the distribution of these thresholds on stream longitudinal profiles will be essential for their utility. The threshold values described at each split should not be extracted nor viewed in isolation from the previous nodes. Doing so may lead to misinterpretation when the same variable is used at different nodes on the same tree.

Evaluating the FPB criteria by comparing observed fish presence for sets of criteria with random forest models resulted in relatively low accuracies. Reducing a continuous habitat covariate to a binary indicator may reduce the predictive power of the random forest model if the cutoff point used to create the binary indicator is not closely associated with the end of fish. TestCriteria 2 and TestCriteria3 were not met by any segments in the pilot data set, but we anticipate that these criteria will be incorporated into future analyses. To more adequately evaluate the criteria following additional sampling, we recommend measuring all steps, not just those presumed to cause a barrier to reduce bias in the gradient and barrier parameters.

The random forest and interaction forest analyses demonstrated that certain stream features are useful predictors of fish versus non-fish habitat. Application of the random forest results to the CART analysis gets us closer to the ultimate objective of describing the inflection point or transition at the end of fish. Box and violin plots in Appendix A were added to qualitatively assess the stepwise progression from average fish habitat, habitat near end of fish, and habitat without fish. These plots in conjunction with the CART models provide an empirical basis for establishing criteria for habitat covariates.

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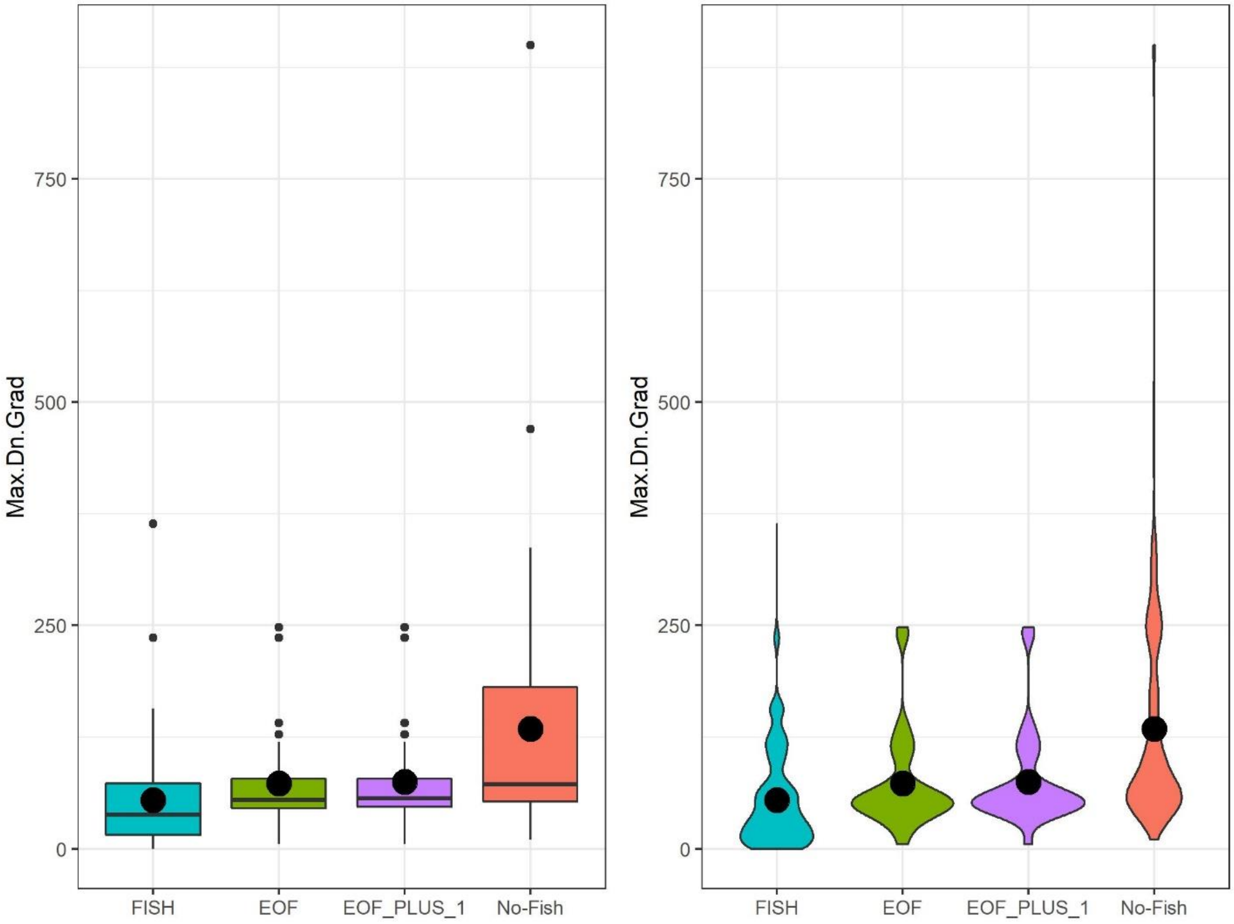
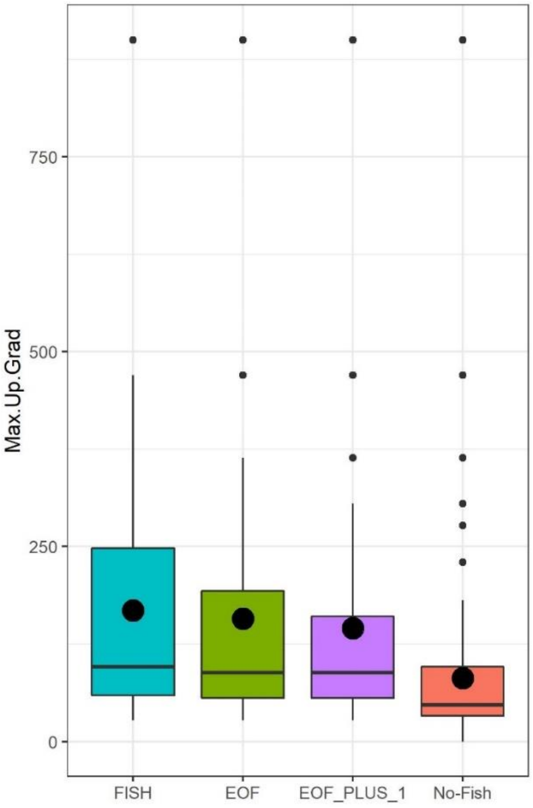
Appendix A. Additional Figures

Box and violin plots for the distribution of variables deemed important by the random forest analyses. The plots include stream segments designated as fish, end of fish (EOF), one segment above end of fish (EOF+1; EOF_Plus_1), and no-fish. Segments at EOF and EOF+1 were not double counted, and thus represent the average for a particular value at the potential habitat break. Figures are in the order of variable importance based on the *Full Random* model.

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750
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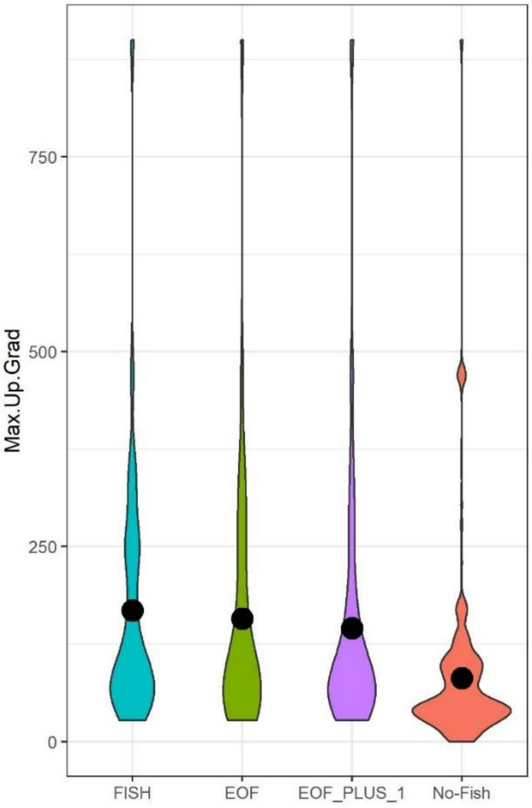
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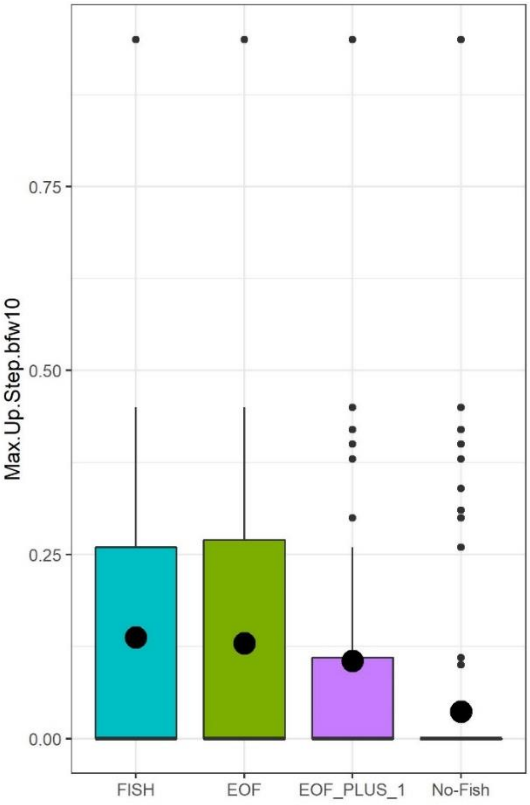
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0.50
0.75
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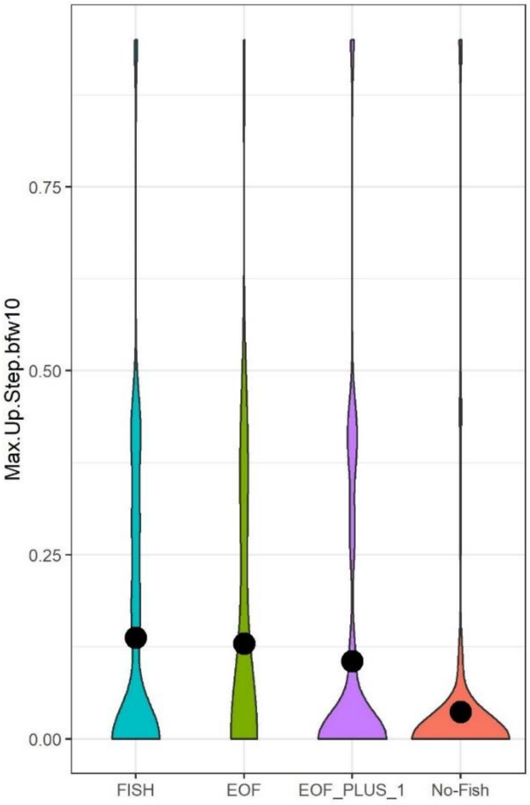
No-Fish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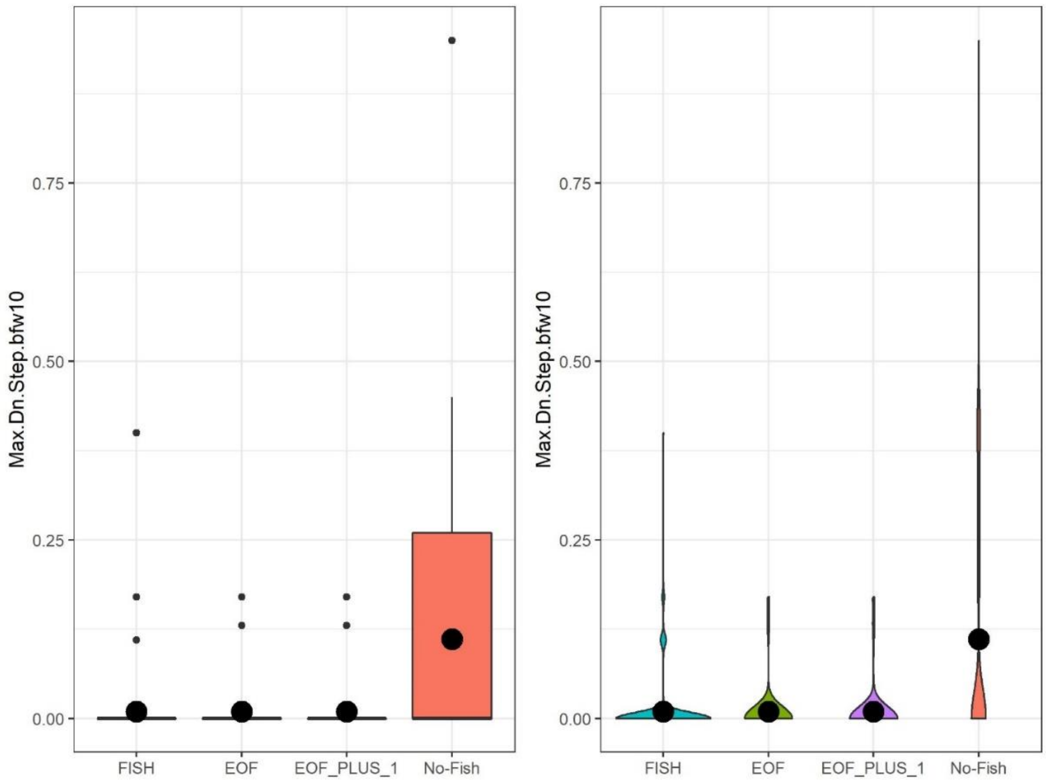
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0.50
0.75
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EOF
EOF_PLUS_1
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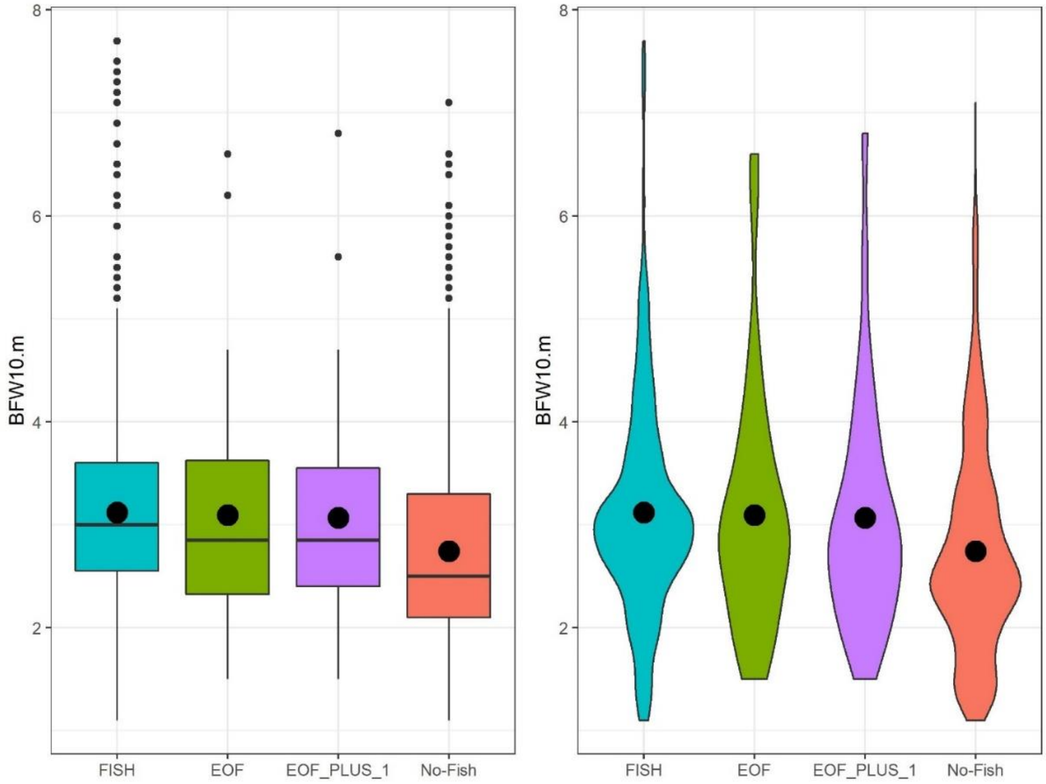
0.25
0.50
0.75
FISH
EOF
EOF_PLUS_1
No-Fish


BFW10.m
2
4
6
8
FISH
EOF
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No-Fish
BFW10.m
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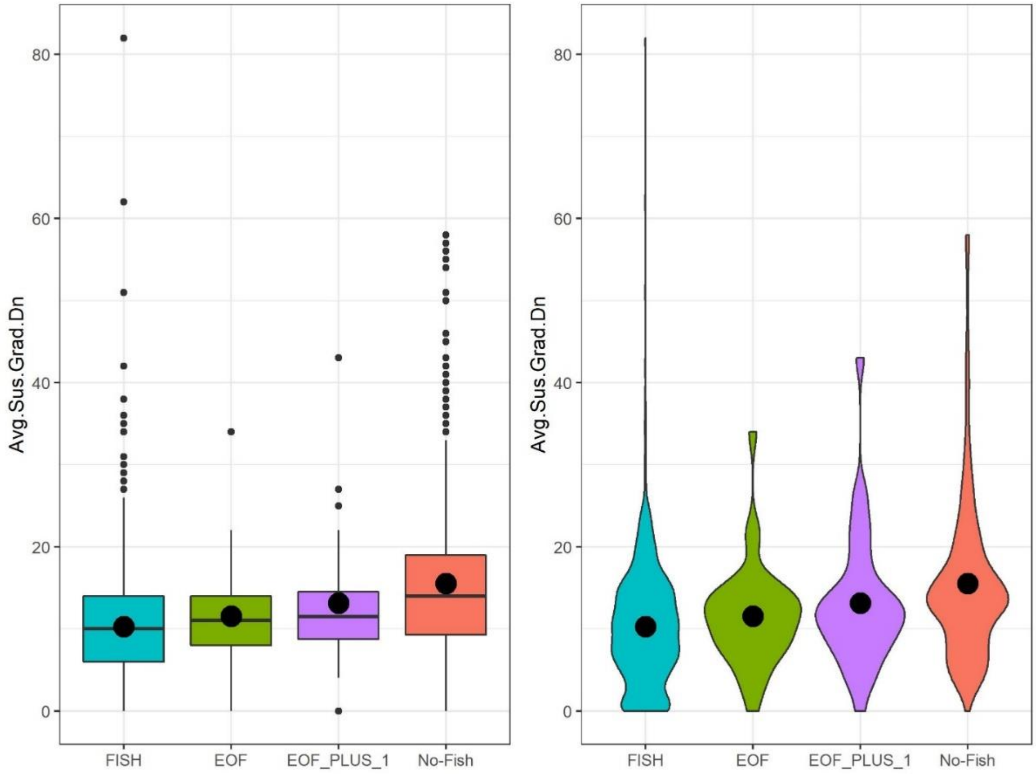
4
6
8
FISH
EOF
EOF_PLUS_1
No-Fish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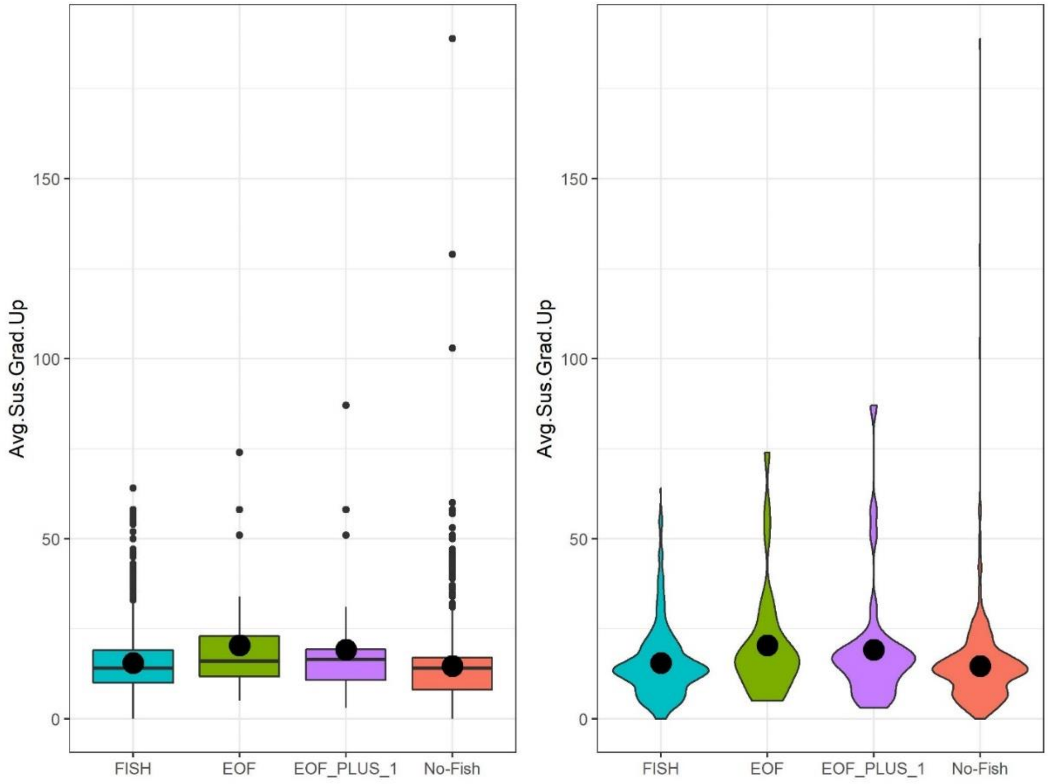
20
40
60
80
FISH
EOF
EOF_PLUS_1
No-Fish
Avg.Sus.Grad.Dn
0
20
40
60
80
FISH
EOF
EOF_PLUS_1
No-Fish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100
150
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50
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FISH
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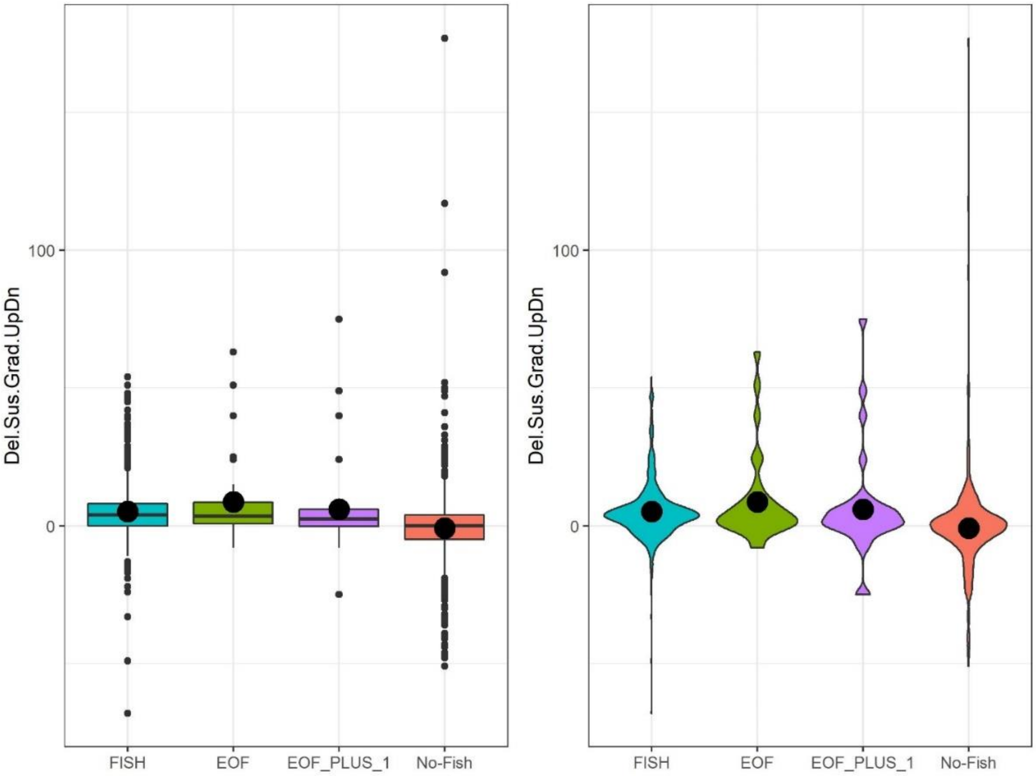
No-Fish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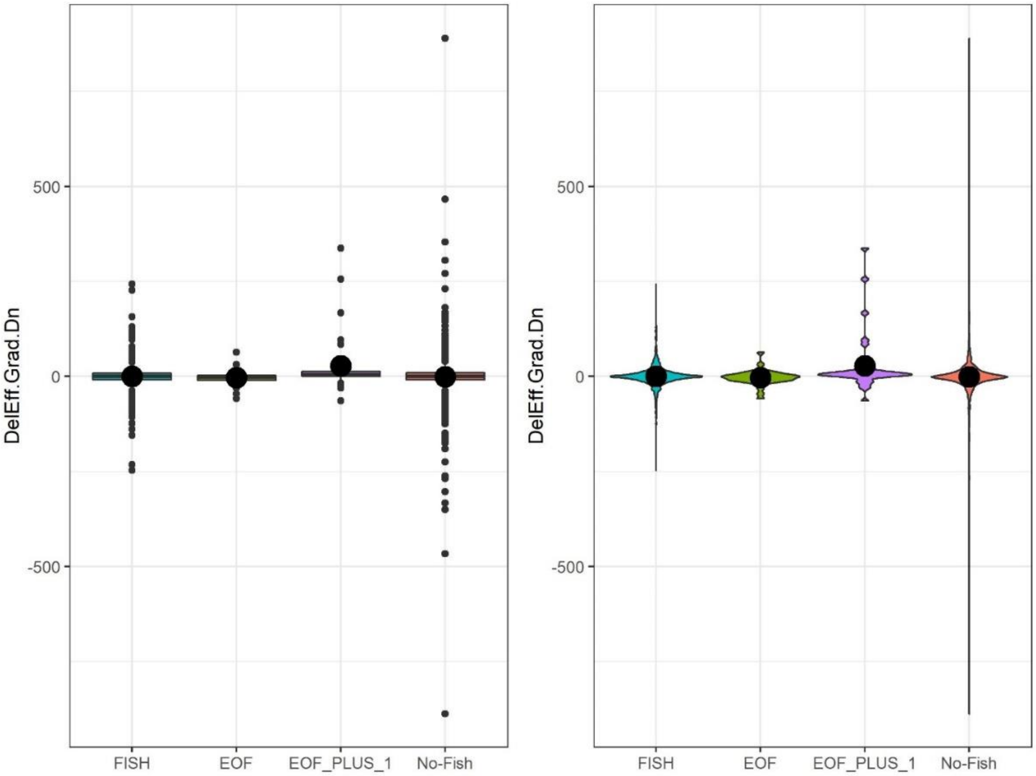
FISH
EOF
EOF_PLUS_1
No-Fish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500
0
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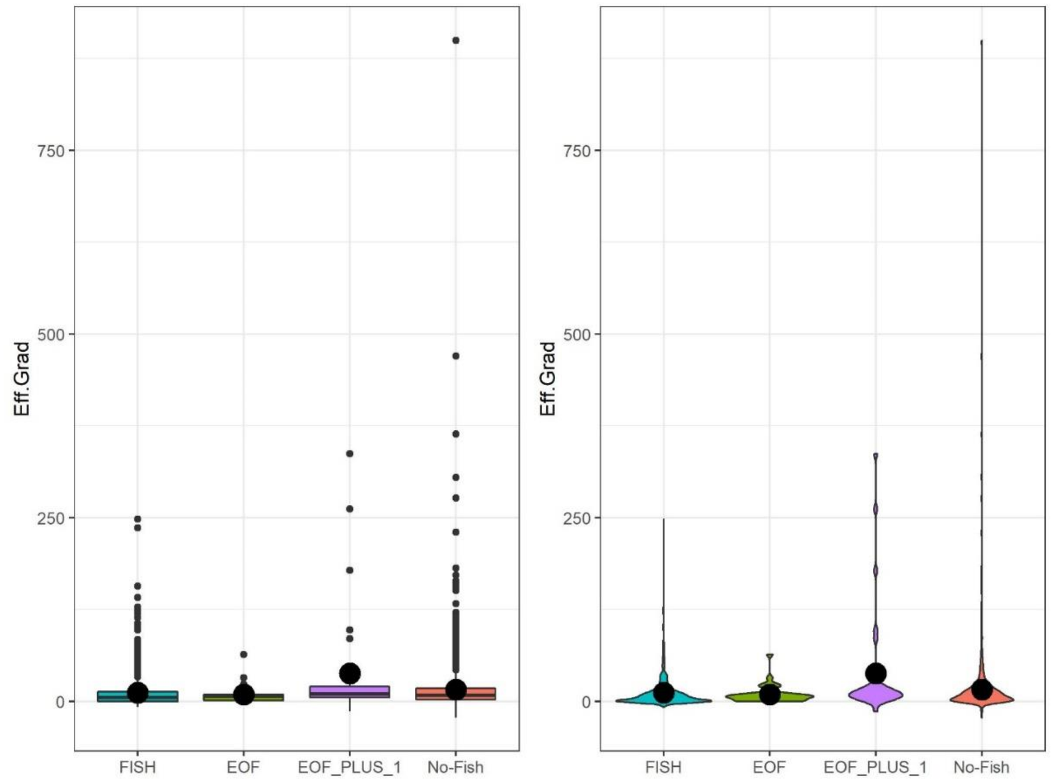
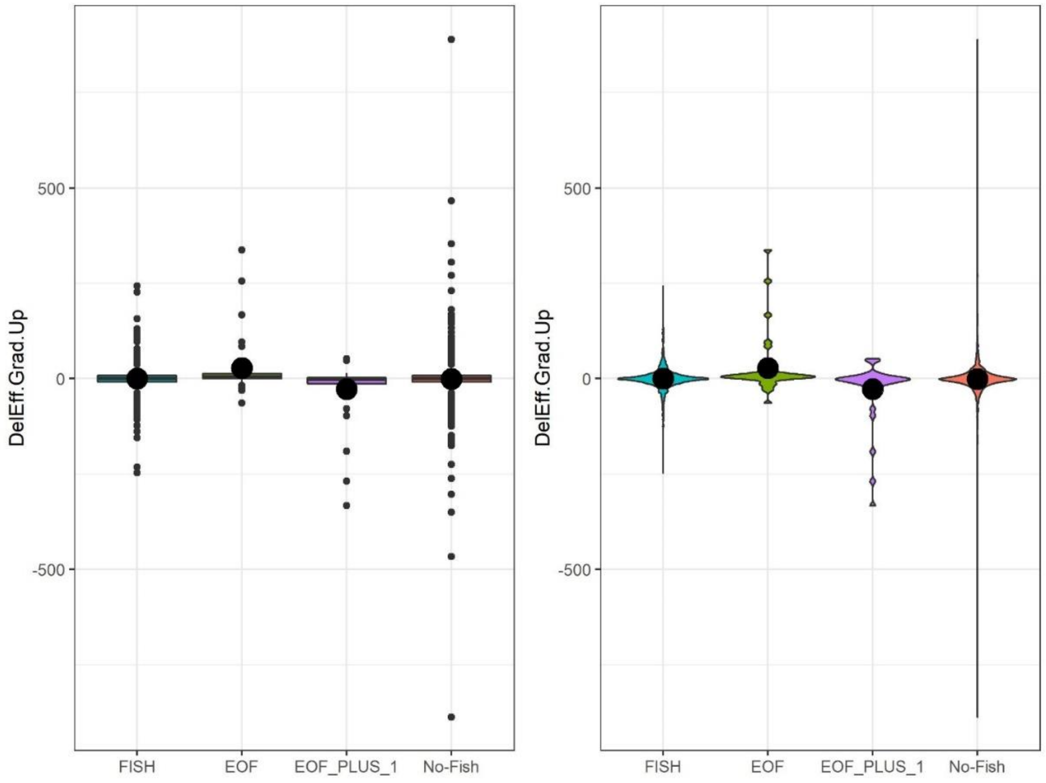
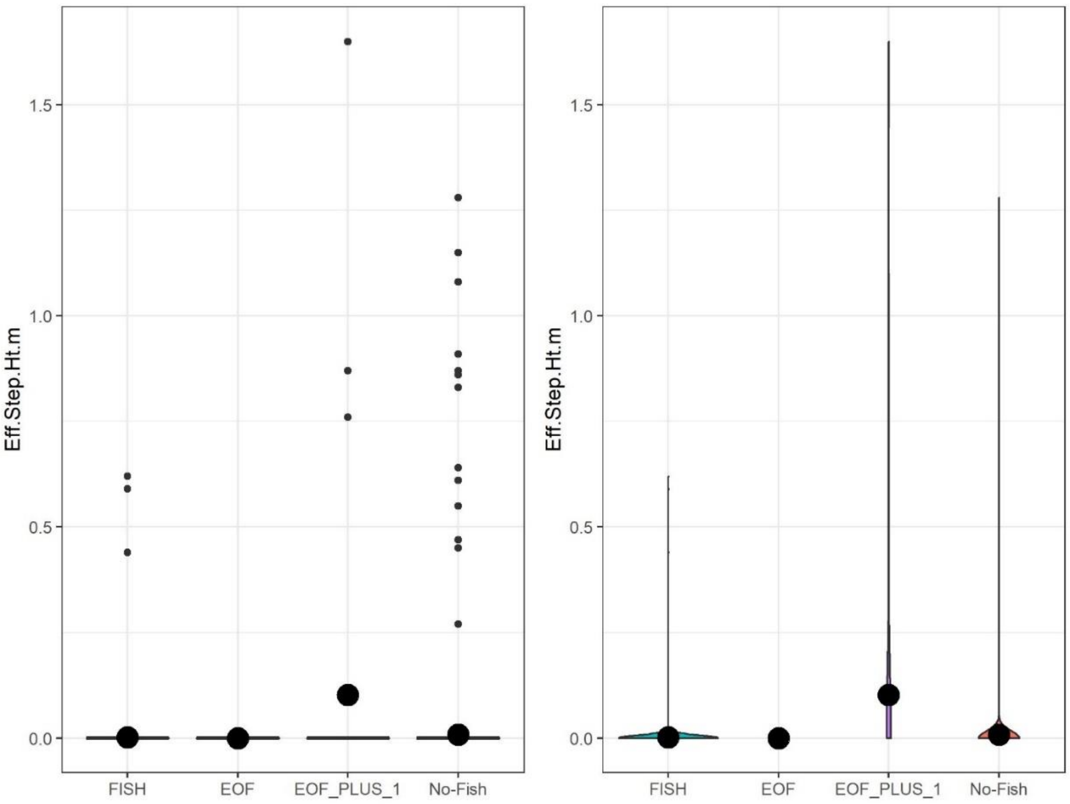
FISH
EOF
EOF_PLUS_1
No-Fish


Eff.Grad
750
500
250
0
FISH
EOF
EOF_PLUS_1
No-Fish
Eff.Grad
750
500
250
0
FISH
EOF
EOF_PLUS_1
No-Fish


DelEff.Grad.Up
500
0
-500
FISH
EOF
EOF_PLUS_1
No-Fish
DelEff.Grad.Up
500
0
-500
FISH
EOF
EOF_PLUS_1
No-Fish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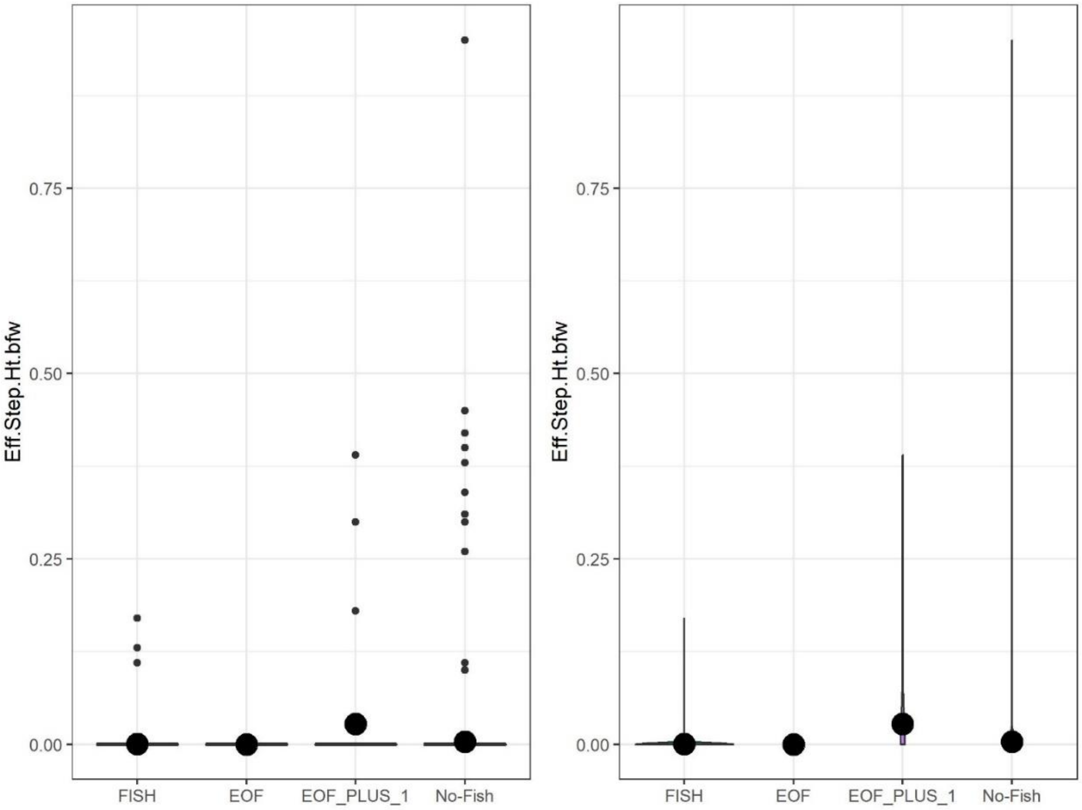
1.0
0.5
0.0
FISH
EOF
EOF_PLUS_1
No-Fish
Eff.Step.Ht.m
1.5
1.0
0.5
0.0
FISH
EOF
EOF_PLUS_1
No-Fish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No-Fish
Eff.Step.Ht.bfw
0.75
0.50
0.25
0.00
FISH
EOF
EOF_PLUS_1
No-Fish

Appendix B. Modeling Covariate Data Dictionary

2437

Variable	Definition
StreamName	copied main stream data to each tributary for separate evaluation, consistent with pilot study analysis.
Station	Survey station
DelDistance	Length of segment (m)
CumulativeDistance	Distance from start of survey (m)
Substrate	
Comments	
EOFpt	In methodology, be clear that this is the last segment WITH fish; EOF pt is at top of segment.
FISH/NO-FISH	fish are assumed to use all segments below the EOF station
Flow Condition	flowing/dry
UnitLabel	Unit type modified for use in PHB analysis Riffle/Pool/Step Step defined as >150% gradient based on pilot study. Step-Pool is when gradient is >8% and Substrate = Fines or Sand (not implemented) If Unit = Riffle but elevation change is <= 0, Unit was changed to Pool
EffectiveGrad_pct	Based on Effective Elevation Change, which sets pool elevations to the elevation of the tail-out (riffle or step downstream of pool) Add in functionality to figure out (presumed) head of pool and calculate gradient above that only? Subgroup decided 6/16/2022 not to bother for the purposes of this pilot, but real study must.

Variable	Definition
EffectiveStepHeight_m	Change in effective elevation (elevation - previous elevation or pool residual elevation) for a segment having gradient >=150%
EffectiveStepHeight_BFW	Change in effective elevation (elevation - previous elevation or pool residual elevation) for a segment having gradient >=150% reported in multiples of the BFW10 at each station (col BA)
DelEffectiveGradFromDnstrmSeg	Change in effective gradient from downstream segment
DelEffectiveGradToUpstrmSeg	Change in effective gradient to next segment upstream
BFW10_m	includes 10 stations, per WAC definition (as close as we can reasonably get); five stations below, the present station, and four stations above; bedrock units excluded from average calculation
AvgSusGradDnstrm	includes 20 segments downstream (19 stations below plus this one) stations, per WAC definition (as close as we can reasonably get)
AvgSusGradUpstrm	includes 20 segments upstream (20 stations above) stations, per WAC definition (as close as we can reasonably get)
MaxDnstrmGrad	Requires that data be ordered by StreamName and Station Maximum segment effective gradient downstream of each station

Variable	Definition
MaxUpstrmGrad	Requires that data be ordered by StreamName and Station Maximum segment gradient upstream of each station
MaxDnstrmStep_BFW10	The maximum step downstream of the present station, in multiples of BFW10
MaxUpstrmStep_BFW10	The maximum step upstream of the present station, in multiples of BFW10
BFW_Dn10	Average of the BFW for the 10 segments downstream of current station (m)
BFW_Up10_m	Average of the BFW of the 10 segments upstream of the current station (m)
BFW_Up20_m	Average of the BFWs for the 20 segments upstream of the current station (m)
BFW_Up20_ft	Average of the BFWs for the 20 segments upstream of the current station (ft)

Appendix D. Potential for a concurrent eDNA study

The original study design (PHB Science Panel 2019) included a proposed collaborative complementary study with the U.S. Forest service to compare environmental DNA (eDNA) and electrofishing to identify fish habitat. A separate pilot for that proposed complementary study was completed in 2020 (Penaluna 2020).

The project team explored ways to include further eDNA components into this study design. The team determined that the best option would be to recommend that an additional complementary study is developed by the Adaptive Management Program that utilizes the sample sites and the fish location data that are collected in this study. This companion study can further compare electrofishing and eDNA as methods for determining the location of the upper extent of fish use, as well as different methods for eDNA collection and analysis, and can take advantage of the lessons learned from the pilot study. Conducting a complementary study in conjunction with the PHB study might save time, money, and resources.

Appendix E. Budget

Budget estimate from DNR PM Anna Toledo as of February 18, 2022. Estimates are based on figures updated from the FY19 study design, expenditures from the FY19 pilot study, and existing contract budgets for similar work. These estimates may change based on revisions made during CMER, ISAG, and ISPR reviews.

Task	Expenditures FY17-FY21	FY22	FY23	FY24	FY25	FY26	FY27	FY28	FY29	Total
Study design, coordination, site reconnaissance, permitting, crew training		31,247	69,250	163,679	114,167	30,512	30,918	N/A	N/A	439,773
Field sampling – Spring/summer (350 sites)					723,697	723,433	737,901	N/A	N/A	2,185,031
Field sampling – Fall/winter (175 sites: fixed + alternating panels)					N/A	176,389	179,917	183,515	N/A	539,821
Crew variability (10% of sites – all crews)					57,944	55,028	56,129	25,505	N/A	194,606
Data collection equipment					183,600	27,540	27,540	27,540	N/A	266,220
Data analysis and reporting				12,485	39,202	67,832	69,189	94,796	61,229	344,733
Project Management				9,364	15,918	16,236	16,561	10,930	4,460	73,469
Total	**398,702**	**31,247**	**69,250**	**185,528**	**1,134,529**	**1,096,970**	**1,118,155**	**342,286**	**65,689**	**4,442,355**

Budget Comparison

Comparison of original study design and revised study design budgets. Original study design budget and tasks in grey.

Task	Original Study Design Totals	Revised Study Design Totals	Notes
Study design, coordination, site reconnaissance, permitting, crew training	421,900	439,773	Revised budget accounts for a 2% yearly increase for inflation/COLA throughout all line items, which was not accounted for in the original budget.
Field sampling – Spring (245 sites)	1,519,000		Total site visits (original): 529 Total site visits (revised): 525
Field sampling – Spring/summer (350 sites)		2,185,031	
Field sampling – Summer (82+60)	460,151		
Field sampling – Fall (82+60); pilot in FY 19	581,151		
Field sampling – Fall/winter (175 sites: fixed + alternating panels)		539,821	
Crew variability (10% of sites – all crews)	115,000	194,606	
Data collection equipment		266,220	Data collection equipment was not a separate line item in original budget.
eDNA sampling (82 sites 3 times)	50,000		eDNA recommended as a complementary study, removed from revised budget.
eDNA Lab Analysis and reporting	164,000		
Data analysis and reporting	180,163	344,733	Budget updated to reflect updated time estimate for analysis and reporting.
Project Management	72,669	73,469	
Total	3,564,034	4,442,355	

Appendix F. Data Tables and Attribute Descriptions

Table F-1. Site selection initial fish survey start point attributes – GIS-derived

Attribute	Source	Units	Description
SiteID	GIS		Identifier from DNR hydro layer
Stream Name	GIS		Local name
Stream Order	GIS		Strahler Stream Order #
Ecoregion	GIS		DNR Natural Heritage Level III [Northwest Coast, Puget Trough, North Cascades, West Cascades, East Cascades, Okanogan, Canadian Rocky Mountains, Blue Mountains]
Side of State	GIS		Location relative to cascade crest [East, West]
Latitude of currently mapped F/N break	GIS	dd	WGS1984
Longitude of currently mapped F/N break	GIS	dd	WGS1984
Elevation of currently mapped F/N break	GIS	m	
Currently mapped F/N break point type	GIS		Terminal or Lateral
Broad-scale land use class	GIS		Industrial timberland, USFS, small private timberland, conservation forest, residential, other forestry, other non-forest
30-year annual and seasonal normal precipitation	GIS	mm	PRISM model and data from neighborhood reference rain gauges
30-year annual and seasonal normal flows for one or more neighboring gauged streams	Calculated	cms	30-year or as close to that as possible; the point is to be able to place the survey year flow levels in the broader long-term flow context
Seasonal Sampling Scheme	Assigned		Fixed or alternating panel, and if alternating, which of (3) years
Optimal Spring Survey Timing	Assigned		Based on information provided by local/regional experts
Optimal Seasonal Survey Timing	Assigned		Based on information provided by local/regional experts

Table F-2. Site field attribute table

Attribute	**Source**	**Units**	**Description** (detail in Methods Manual)
SiteID	GIS		Identifier from DNR Hydro layer
Landscape Reference Point (LRP)	Field		Narrative description of a permanent topographic/physical feature used to help locate the FRPs and LFPs
LRP Latitude	Field	dd	Decimal degrees; WGS 1984
LRP Longitude	Field	dd	Decimal degrees; WGS 1984
Fixed Reference Point (FRP)	Field		Narrative description of FRP closest to initial LF point relative to permanent topographic/physical feature such as a confluence point with mainstem, tributary junction, etc.
FRP Latitude	Field	dd	Decimal degrees; WGS 1984
FRP Longitude	Field	dd	Decimal degrees; WGS 1984
FRP Elevation	Field	m	Will be baseline from which habitat surveys are conducted
Notes	Field		Any features significant at a site level

Table F-3. Uppermost fish survey data for each survey event; Uppermost fish point (EOF) will be baseline from which habitat surveys are conducted.

Attribute	**Source**	**Units**	**Description** (detail in Methods Manual)
SiteID	GIS		Identifier from DNR Hydro layer
SurveyID	Assigned		Which survey (year/season)
Date			
Weather Conditions	Field		sunny, rainy, snowy, cloudy
Air Temp	Field	C	
Field Crew			
Fish Survey Start Point	Field	dd, m	Lat, Long, Elev at fish survey start point
Fish Survey Start Water Temp	Field	C	
Stream Conductivity	Field	uS/cm	
Electrofisher Setting	Field		
Fish Survey End Point	Field	dd, m	Lat, Long, Elev at fish survey end point
Fish Survey End Water Temp	Field	C	
EOF Latitude	Field	dd	Decimal degrees; WGS 1984
EOF Longitude	Field	dd	Decimal degrees; WGS 1984
EOF Elevation_GPS	Field	m	NAD83

Attribute	**Source**	**Units**	**Description** (detail in Methods Manual)
EOF Stream Distance From Topographic Reference Point (RP)	Field	m	EOF point field-identifiable location relative to a permanent topographic or physical feature such as a confluence point with mainstem, tributary junction, etc., if feasible Also identify reference objects to help locate
EOF Date-Time	Field		YYYY-MM-DD-24-hour; Standard Time;
EOF WaterTemp	Field	C	To nearest 0.5 C
Upstream-Most Fish Species/Family	Field		When it can be determined (salmonid; sculpin (cottid); stickleback; mudminnow; etc)
Fish Size Category	Field	mm	<25mm, 25-75mm, 75-150mm, >150mm
EOF Point Type	Field		Terminal or Lateral
EOF Flow Status	Field		Flowing, Dry
EOF Habitat Unit Type	Field		Pool, Riffle, Step-Pool, Step (>=2' vertical)
EOF Measurement Point Type	Field		e.g. crest of tailout; bottom of pool; head of pool
Potential Reason (Feature) for Uppermost Fish	Field		If present and identifiable; eg – deformable obstacle/debris jam; dry channel; falls; other; etc
Vertical/Near-vertical Obstacle(s) present?	Field	Yes/No	
Lateral/Terminal Stream	Field		May vary based on uppermost fish location
EOF Riparian Stand Type (RB)	Field		Watershed Analysis methods
EOF Riparian Stand Type (LB)	Field		Watershed Analysis methods
Streamside Land Use Class at EOF	Field		Industrial timberland, USFS, small private timberland, conservation forest, agriculture, residential, other forestry, other non-forest
Notes	Field		Include potential explanatory features (CMZ, alluvial fan, debris flow, end of channel)
EOF Elevation_GIS	GIS	m	Lidar-based
EOF Drainage Area	GIS	km^2	
EOF Distance-From-Divide	GIS	m	
EOF Valley Aspect	GIS		Compass points [N, NE, E, SE, S, SW, W, NW]
EOF Valley Width	GIS	m	
EOF Valley Confinement	Calculated		Valley Width/Channel Width ratio
EOF Geologic Competence	GIS		Resistant or Erodible, based on classifications provided for Hard/Soft Rock Type N studies [Competent/Medium/Incompetent]

Attribute	**Source**	**Units**	**Description** (detail in Methods Manual)
Total Annual Precipitation for Current Hydrologic Year	nearby reference rain gauges	mm	from nearby reference rain gauges (see Table F-1)
Total Seasonal Precipitation for Survey Season	nearby reference rain gauges	mm	from nearby reference rain gauges
% of AnnualNormal Precipitation	Calculated	%	Total annual P for survey year/annual Normal
% of Seasonal Normal Precip	Calculated	%	Total seasonal P for survey season/seasonal Normal
Total Annual Streamflow for Current Hydrologic Year	nearby reference stream gauges	cms	from nearby reference stream gauges (see Table F-1)
Total Seasonal Streamflow for Survey Season	nearby reference stream gauges	cms	from nearby reference stream gauges (see Table F-1)
% of AnnualNormal Streamflow	Calculated	%	Total annual Q for survey year/annual Normal
% of Seasonal Normal Streamflow	Calculated	%	Total seasonal Q for survey season/seasonal Normal

Table F-4. Habitat survey site field attributes

Attribute	**Source**	**Units**	**Description**
SiteID	GIS		Identifier from DNR Hydro layer
SurveyID	Assigned		e.g., 2024-spring; 2025-fall, etc.; precise form of survey ID to be determined
Survey Date	Field		
Weather	Field		sunny, rainy, snowy, cloudy
Field Crew	Field		
Bottom of Survey (BOS) Latitude	Field, GPS	dd	WGS84
BOS Longitude	Field, GPS	dd	WGS84 (Negative dd for west)
BOS Elevation	Field, GPS	m	NAD83

Attribute	Source	Units	Description
Top of Survey (TOS) Latitude	Field, GPS	dd	WGS84
TOS Longitude	Field, GPS	dd	WGS84 (Negative dd for west)
TOS Elevation	Field, GPS	m	NAD83
Turnpoint Numbers and Locations	Assigned during survey		Turnpoints may be set on a Station, in which case the station can be identified as the location, or may be set outside of the channel thalweg, in which case the location relative to the previous turnpoint must be recorded.

Table F-5. Habitat Survey Channel Survey Station Measured Attributes

Attribute	Source	Units	Description
SiteID	GIS		Identifier from DNR Hydro layer
SurveyID			
Station Number	Assigned during survey		sequential numbering of survey stations from Bottom of Survey
Turnpoint Number	Assigned		Turnpoint ID (see Table F-4) from which station location is measured
Station Distance from Turnpoint	Measured	m	
Station Azimuth from Turnpoint	Measured	deg	
Station Elevation from Turnpoint	Measured	m	
Uppermost Fish Segment	Observation of Monument	LF	Observation of Uppermost Fish monument from Fish Survey occurs within measurement segment; not necessarily at the surveyed station if LF is monumented within a homogeneous segment
Water Depth	Measured	m	Instantaneous depth at station along thalweg (not BFD)
Channel Width	Measured	m	At bankfull elevation
Wetted Width	Measured	m	Water’s edge
Flow Status	Observation		Dry, Flowing
Dominant Substrate	Ocular estimate	Categ.	Categorical (e.g. sand, gravel, cobble, boulder, bedrock, silt/clay/fines, wood)
Habitat Unit Type	Ocular estimate	Categ.	Pool, Riffle, Step, Step-Pool, Obscured
Station Point Type	Ocular estimate	Categ.	e.g. crest of tailout; bottom of pool; head of pool (may be blank)

Attribute	Source	Units	Description
Obstacle Type	Ocular estimate	Categ.	Vertical/Non-Vertical
Step Forming Medium	Ocular estimate	Categ.	Categorical (e.g. wood (log, debris, roots), hardpan, boulder, bedrock)
Tributary Junction	Observation	1	Flag if present; place station at point
Vertical Step Height	Measured	m	Continuous variable with 0 as an allowable value

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2474 **Table F-6. Stream habitat survey segment calculated attributes**

Attribute	Source	Units	Description
SiteID			
SurveyID			
Station #			
Segment Length [m]	Calculated	m	Calculated distance from Station n-1 to Station n; segment data relate to the segment below the station (i.e., “stations” are the upstream point of the segment)
Distance from Bottom of Survey			Running total of segment lengths from BOS (BOS = Station 0)
Above, at, or Below Uppermost Fish Segment	Calculated	US/DS/LF	Calculated based on location of LF segment from Table F-5; required for calculation of other attributes
Fish Presence	Calculated	FISH/NO-FISH	Assigned to segments based on location relative to LF point; needed for random forest models
Bankfull Width 10 (=bfw10)	Calculated	m	Average of bankfull widths from 4 stations downstream, current station, and 5 stations upstream, in approximate conformance with Forest Practices rule
Average BFW for 10 * bfw10 upstream	Calculated	m	Average of bankfull widths for a distance of 10*bfw10 upstream Required to test for FPB criteria
Average BFW for 20 * bfw10 upstream	Calculated	m	Average of bankfull widths for a distance of 20*bfw10 upstream Required to test for FPB criteria
Average BFW for 10 * bfw10 downstream	Calculated	m	Average of bankfull widths for a distance of 10*bfw10 downstream Required to test for FPB criteria
Segment Thalweg Bed Rise (Vertical Distance)	Calculated	m	Vertical Distance from Beg to End of Segment; calculated as change in elevation from station n-1 to station n
Thalweg Bed Gradient	Calculated	%	Segment Thalweg Bed Elevation Change/Segment Length

Attribute	Source	Units	Description
Effective Elev	Calculated	m	Calculated for pools based on pool tailout elevation; that (residual pool) elevation is translated to the segment upstream of the pool to determine the "effective" bottom elevation of the next (n+1) stream segment, for the purpose of calculating "effective, fish-eye" gradient of the n+1 segment
Effective Segment Rise		m	elevation of segment end minus the Effective Elevation, if there is one; otherwise, equals segment thalweg bed rise
Effective Segment Gradient		%	Effective Segment Rise/Segment Length
Effective Gradient Change From Downstrm Segment			Effective Gradient change from n-1 to n
Effective Gradient Change To Upstrm Segment			Effective Gradient difference from n to n+1
Maximum Effective Gradient Downstream from EOF	Calculated	%	Calculated from segment data using effective gradients
Length of Max Dnstrm Gradient Feature	Calculated	m	Calculated from segment data using effective gradients
Max sustained5 gradient downstrm	Calculated		Max of the running Minimum gradient feature over 5 cw; using effective gradients
Sustained Gradient Downstream	Calculated	%	Minimum gradient feature over 20 cw downstream of station n (including segment n); using effective gradients
Maximum Gradient Upstream of EOF	Calculated	%	Calculated from segment data; using effective gradients
Length of Max upstrm Gradient	Calculated	m	Calculated from segment data
Max sustained5 gradient upstrm	Calculated		Max of the running Minimum gradient feature over 5 cw; using effective gradients
Sustained upstream gradient	Calculated	%	Minimum gradient feature over 20 cw upstream of station n; using effective gradients
Delta Sustained Gradient upstrm	Calculated	%	Sustained upstream gradient – Sustained downstream gradient
Maximum Step Height Upstream	Calculated	bfw10s	

Attribute	Source	Units	Description
Maximum Step Height Downstream	Calculated	bfw10s	
Pool Frequency Upstream of Segment	Calculated	pool count/ bfw10	Calculated over 20*bfw10 upstream of current station
Pool Spacing Upstream of Segment	Calculated	m	Calculated over 20*bfw10 upstream of current station
Pool Frequency Downstream of Segment	Calculated	pool count/ bfw10	Calculated over 20*bfw10 downstream of current station
Pool Spacing Downstream of Segment	Calculated	m	Calculated over 20*bfw10 downstream of current station

2475

2476 **Table F-7. Habitat survey attributes calculated for stream at each survey**

Attribute	Source	Units	Description
SiteID	GIS		Identifier from DNR Hydro layer
SurveyID			
LF Distance from BOS	Calculated	m	
LF Elevation_GIS	GIS	m	Lidar-based
LF Drainage Area	GIS	km^2	
LF Distance-From-Divide	GIS	m	
LF Valley Aspect	GIS		Compass points [N, NE, E, SE, S, SW, W, NW]
LF Valley Width	GIS	m	
LF Valley Confinement	Calculated		Valley Width/Channel Width ratio
LF Geologic Competence	GIS		Resistant or Erodible, based on classifications provided for Hard/Soft Rock Type N studies [Competent/Medium/Incompetent]
Total Annual Precipitation for Current Hydrologic Year	nearby reference rain gauges	mm	from nearby reference rain gauges (see Table F-1)
Total Seasonal Precipitation for Survey Season	nearby reference rain gauges	mm	from nearby reference rain gauges
% of AnnualNormal Precipitation	Calculated	%	Total annual P for survey year/annual Normal

Attribute	Source	Units	Description
% of Seasonal Normal Precip	Calculated	%	Total seasonal P for survey season/seasonal Normal
Total Annual Streamflow for Current Hydrologic Year	nearby reference stream gauges	cms	from nearby reference stream gauges (see Table F-1)
Total Seasonal Streamflow for Survey Season	nearby reference stream gauges	cms	from nearby reference stream gauges (see Table F-1)
% of AnnualNormal Streamflow	Calculated	%	Total annual Q for survey year/annual Normal
% of Seasonal Normal Streamflow	Calculated	%	Total seasonal Q for survey season/seasonal Normal
Habitat Unit Upstream of LF	Calculated		
Effective Gradient of Segment Upstream of LF	Calculated	%	
BFW of segment Upstream of LF	Calculated	m	
Delta Sustained Gradient upstrm of LF	Calculated	%	Sustained upstream gradient – Sustained downstream gradient
Maximum Gradient Downstream from LF	Calculated	%	Calculated from segment data
Length of Max Dnstrm Gradient Feature	Calculated	M	Calculated from segment data
Maximum Sustained Gradient Downstream from LF	Calculated	%	Defined based on 20 bfw (multiple versions)
Length of Max Sustained Dnstrm Gradient Feature	Calculated	Multiples of bfw (m)	Calculated from segment data
Max Gradient Change Downstream of LF	Calculated	%	Calculated from segment data
Maximum Gradient Upstream of LF	Calculated	%	Calculated from segment data
Length of Max upstrm Gradient	Calculated	m	Calculated from segment data

Attribute	Source	Units	Description
Max sustained upstream gradient	Calculated	%	Sustained for minimum of 20*bfw10 to be in line with PHB proposals
Length of Max sustained upstream gradient	Calculated	m, bfw10	Length of the above in meters and also in multiples of bfw10
Max Sustained Gradient Change upstrm of LF	Calculated	%	Calculated from segment data; each gradient sustained for 20* bfw10
Maximum Step Height Upstream of LF	Calculated	bfw10s	
Maximum Step Height Downstream of LF	Calculated	bfw10s	
Pool Frequency Upstream of Segment	Calculated	count/ bfw10	Calculated over 20*bfw10 upstream of current station
Pool Spacing Upstream of Segment	Calculated	m	Calculated over 20*bfw10 upstream of current station
Pool Frequency Downstream of Segment	Calculated	pool count/ bfw10	Calculated over 20*bfw10 downstream of current station
Pool Spacing Downstream of Segment	Calculated	m	Calculated over 20*bfw10 downstream of current station

Appendix G. Glossary

Concurred F/N Breaks: Supported by approved Water Type Modification Form

Cumulative Metrics (defined in the data tables): Those metrics averaged or calculated over greater than one measurement

Default Physical Criteria (DPC): Ranges of values for physical stream attributes presumed to represent fish use in the absence of protocol surveys

Distance-From-Divide: The distance from the watershed divide downstream along the flow path to the point of interest on the stream. Where there are tributaries upstream of the point of interest, the distance-from-divide is through the longest channel path.

Lateral (end of fish/end of habitat points): Sites where a stream without fish intersects a fish-bearing stream reach with fish both upstream and downstream of the junction with the fishless stream (Fransen et al 2006)

Legacy Water Type (from DNR Hydrolayer but not based on the model): See data dictionary (https://www.dnr.wa.gov/publications/fp_fpamt_wt_defn_viewingguide.pdf)

Region: East vs. west of the Cascade crest

Terminal (end of fish/end of habitat points): Sites where fish occurrence terminates within a continuous reach of stream or at the junction of two or more fishless streams (Fransen et al 2006)

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