Assessing the Status and Trends of Spring Chinook Habitat in the Upper Grande Ronde River and Catherine Creek: Annual Report 2019

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Executive Summary

Background and Objectives

The Columbia River Inter-Tribal Fish Commission is conducting a research, monitoring, and evaluation study designed to determine the effectiveness of aggregate restoration actions in improving freshwater habitat conditions and viability of ESA-listed spring Chinook Salmon (*Oncorhynchus tshawytscha*) populations. A critical uncertainty for fisheries managers in the Columbia Basin is whether freshwater habitat restoration actions will improve basin-wide habitat quantity/quality and thereby salmon productivity to a level sufficient to offset human-caused survival impairments elsewhere in the life cycle. Geographically, this project is focused on the upper Grande Ronde River and Catherine Creek basins (tributaries of the Snake River in the Columbia River basin), but with applications and testing of models also occurring in other Columbia River tributaries.

The objectives of this project are to: 1) Assess current status and trends in fish habitat characteristics considered to be key ecological concerns for viability of spring Chinook Salmon populations; 2) Evaluate effectiveness of aggregate stream restoration actions aimed at improving key ecological concerns; and 3) Develop a life cycle model to link biotic responses of spring Chinook Salmon populations to projected changes in stream habitat conditions.

We have categorized our work towards these objectives into the following project components:

- Component 1: Habitat and biotic assessments,
- Component 2: Riverscape analyses, and
- Component 3: Fish-habitat modeling.

These individual components are linked together conceptually in an overall cycle of research, monitoring, and evaluation, with analyses feeding into an adaptive management framework (Figure 1).

Figure 1. CRITFC's cycle of research, monitoring, and evaluation providing the basis for decision-making in an adaptive management framework.

Progress and Key Findings

Component 1: Habitat and Biotic Assessments

Development of a tributary habitat assessment protocol

- Addressing the need for an updated regional monitoring approach that incorporates remotely-sensed data collection, we developed a new protocol (Appendix A) that is a product of other well-established and widely used methodologies for assessing the availability and changes to salmon habitat within the Columbia River Basin and additionally addresses emerging restoration strategies such as increased emphasis on floodplain reconnection.
- The combined lessons learned from our testing of this initial protocol conducted at discrete stream reaches in NE Oregon subbasins in 2018, along with efforts and feedback from collaborators in the basin helped inform this new version of the protocol that utilizes unmanned aerial vehicles.
- Implementation of this protocol throughout the Columbia River Basin would substantially increase efficiency, spatial coverage, reproducibility, and reduce costs in comparison to historic ground-based stream habitat surveys.

Assessing the potential of utilizing unmanned aerial vehicles for physical stream habitat surveys

- To test the feasibility of integrating remotely sensed data collection into monitoring we completed a comparative analysis of several channel unit and site level metrics using ground-based validation data and those derived from imagery collected with a UAV.
- Using several common metrics relevant to predicting fish density we analyzed the strength of the relationships between the two data collection methods, finding metrics derived from imagery were sensitive to both geomorphic conditions and canopy densities.
- In general, imagery error increased with both gradient and canopy density, but metrics relating to the quantity of available instream habitat (total area and volume) showed the strongest relationships ($R^2 = 0.99$ and $R^2 = 0.96$ respectively) to ground-based validation data.

Reanalysis of snorkel survey calibration methods

- We re-analyzed the snorkel survey calibration method used by our group, based on concerns with the statistical methodology that was previously used to obtain the correction factors.
- The model we developed uses the data in a more raw format and assesses the importance, magnitude, and direction of various covariate effects on snorkel survey detection efficiency directly using a Bayesian hierarchical model that more fully captures the uncertainty in all data sources used by the model.
- Important variables were species (Chinook more efficiently counted than *O. mykiss*), large wood density (decreases efficiency but only if the density is very high), visibility (increases efficiency but only if it is very good), depth, and habitat type. We found that depth increases detection efficiency in non-pool habitats but decreases it in pool habitats and that Chinook salmon are counted more easily than *O. mykiss*.
- When the revised calibration method was applied to historical snorkel data, the density estimates were reasonably similar to those obtained using the previous approach, but estimates for juvenile Chinook Salmon generally decreased because findings suggested efficiency is higher than previously thought.

Component 2: Riverscape Analyses

Spatial patterns and drivers of juvenile Chinook Salmon size and growth

- Chinook Salmon parr size, density, and growth rates were quantified at the network scale in the upper Grande Ronde River and Catherine Creek.
- In July, both basins exhibited clear size gradients with larger parr at downstream sites and decreasing size with distance upstream. In addition, parr were larger in Catherine Creek compared to upper Grande Ronde.
- Modeling of emergence timing indicated earlier fry emergence at downstream sites compared to upstream sites, and earlier emergence in Catherine Creek compared to upper

Grande Ronde, which suggests that emergence timing was a main contributor to observed size patterns in July.

- Summer growth rates exhibited the opposite trend as size, with increasing mass-standardized growth rates with distance upstream in both basins.
- Spatial patterns of densities revealed that in upper Grande Ronde, parr were concentrated high in the watershed, where size was smaller, but in Catherine Creek, high densities were observed lower in the watershed.

Indicators of food availability for Columbia basin salmonids using broadly available data

- We tested the utility of broadly available benthic macroinvertebrate data as a rapid indicator of food web integrity and food availability to salmonids.
- A model of drift propensity using benthic macroinvertebrate data was validated using paired benthic-drift sampling. Groups of invertebrate taxa categorized as high, medium, and low drift propensity based on life history characteristics tended to drift at frequencies in accordance with *a priori* groupings.
- Standard benthic macroinvertebrate metrics (IBIs, sensitive taxa, etc.) related to environmental conditions (climate, land use, and intrinsic factors) better than novel food web and drift propensity metrics.
- A food availability metric based on drift propensity was correlated with juvenile Chinook Salmon density, but only after habitat quality—as measured by pool frequencies meeting an expected threshold for natural streams—was taken into account.
- Preliminary results indicated the food availability metric was significantly correlated with the total energy content of aquatic and emergent-aquatic prey items in juvenile Chinook Salmon diets, but not with fish growth rates or production.

National Water Model streamflow analysis

- We analyzed simulated streamflow data from the National Oceanic and Atmospheric Administration (NOAA) National Water Model (NWM) Reanalysis dataset spanning 26 years (January 1993 – December 2018) to assess its reliability as environmental inputs to ongoing salmon life cycle models and other fish-habitat models in the Grande Ronde River basin.
- Predicted streamflows were compared with observed flow data from five streamflow gauging stations located in key Chinook Salmon spawning, rearing, and migration areas.
- In general, the NWM Reanalysis dataset was good at predicting spatial variability in streamflow across sites, but was less reliable at capturing temporal variability within sites.
- Metrics describing average flow magnitude over long time periods (i.e., mean annual flow, mean summer flow) tended to have the highest precision (R^2 across all sites = 0.96 and 0.97 respectively), metrics related to flow timing (center of flow mass) had moderate precision (R^2 across all sites = 0.70), and the metric related to flow duration (days below the 25th percentile flow) had the lowest precision (R^2 across all sites = 0.28).

Component 3: Fish-Habitat Modeling

Update on Life Cycle Model

- We made significant advances in a collaboration (CRITFC, NOAA, ODFW) in the development of a revised life cycle model for Grande Ronde basin spring Chinook Salmon populations.
- The revised modeling approach is intended to improve on previous life cycle model efforts by bringing all available biological data and key habitat and environmental data into a single state-space framework.
- Although a state-space model exists (as initially developed by NOAA), our collaboration is intended to improve it by bringing in more information sources and specifying the linkage between habitat/environmental conditions and fish population dynamics more explicitly.
- The output from this model is expected to inform simulation analyses that seek to evaluate the likelihood of different population outcomes under various climate and habitat restoration scenarios.

Adaptive Management

Progress on an Adaptive Management Framework

- As a response to an Independent Scientific Review Panel (ISRP) recommendation for our project, we embarked on two pathways towards the goal of increasing the use of adaptive management in the Columbia River Basin: (a) a needs assessment workshop and manuscript documenting our progress and setbacks towards a comprehensive approach to habitat restoration in the Columbia basin and (b) involvement in a multi-agency workgroup developing a 5- and 20-year adaptive management plan for the Grande Ronde basin.
- We organized a multi-agency adaptive management workgroup with Grande Ronde basin partners to describe the background and overall goals of an adaptive management program. A draft manuscript (Appendix C) was developed and submitted to *Fisheries* based on the responses to a 2-day workshop with partners focused in increasing the use of adaptive management.
- Building on lessons learned from our collaborative review of the Grande Ronde basin habitat restoration program (i.e., *Fisheries* manuscript; response to Rieman et al. (2015)), we have begun the process of developing a formal adaptive management plan to guide future salmon habitat restoration actions.

Conclusions

In 2019 we made significant advances towards understanding limiting factors and cumulative impacts of tributary habitat restoration on salmon populations in the Grande Ronde River subbasin, and by extension to the broader Columbia River basin. Our team continued testing and finalized a draft habitat protocol characterizing key tributary habitat conditions in a rapid yet robust manner, taking advantage of emerging remote sensing technology. We reevaluated statistical extrapolation of snorkel counts to fish abundance at the reach level, a critical variable in estimating tributary

habitat capacity and assessing empirical fish-habitat relationships. Patterns and drivers of juvenile Chinook Salmon size, density, and growth rates were evaluated in a field study with fry emergence timing coming out as a strong driving factor, providing insights regarding restoration strategies that would equate to increased smolt survival and leading to hypotheses for future research. Rapid indicators of salmon food availability based on broadly available benthic macroinvertebrate data were developed and were related to juvenile Chinook Salmon distribution after accounting for habitat quality, and were additionally associated with diet content. Recent data from NOAA's National Water Model (NWM) Reanalysis were assessed for reliability as a potential input to our forthcoming life cycle model (LCM) for Chinook Salmon. We made significant advances in our collaboration with NOAA and ODFW in the development of a revised LCM for Grande Ronde basin spring Chinook Salmon populations. These involved efforts to include all available biological data and hey habitat and environmental data in a single state-space framework, developing an explicit link between habitat/environmental conditions and fish population dynamics, and planning for forthcoming simulation analysis under various climate and habitat restoration scenarios. Finally, we increased our engagement with Grande Ronde basin partners (in particular Grande Ronde Model Watershed) to articulate and formalize an adaptive management plan for the subbasin. This included 1) organizing a multi-agency workgroup and drafting a manuscript focused on goals and overall vision of an adaptive management framework and 2) assisting with the development of a 5- and 20-year adaptive management plan for the Grande Ronde basin. Overall, our team's activities in 2019—in collaboration with several tribal, federal, state, and local partners—represented important advances towards project objectives.

Introduction

The Columbia River Inter-Tribal Fish Commission is conducting a research, monitoring, and evaluation study designed to determine the effectiveness of aggregate restoration actions in improving freshwater habitat conditions and viability of ESA-listed spring Chinook Salmon populations. A critical uncertainty for fisheries managers in the Columbia Basin is whether freshwater habitat restoration actions will improve basin-wide habitat quantity/quality and thereby salmon productivity to a level sufficient to offset human-caused survival impairments elsewhere in the life cycle. Geographically, this project is focused on the upper Grande Ronde River and Catherine Creek watersheds (tributaries of the Snake River in the Columbia River basin), but with applications and testing of models occurring in other Columbia River tributaries.

Many studies in recent years have examined the current condition of fish habitat in Columbia River subbasins. Some of the most common impediments to survival of salmon include high water temperatures, increased concentrations of fine sediment in spawning gravel, loss of riparian vegetation, channelization and diminished channel and floodplain complexity, loss of large wood in the channel, loss of large pools for adult fish holding and juvenile rearing, and depletion of summertime streamflow. We refer to these as *ecological concerns* (formerly known as *limiting factors*). More recent studies have additionally identified food webs (e.g., nutrient limitation, primary productivity, or prey availability) as ecological concerns for salmonids (Naiman et al. 2012). Climate change presents and additional threat, as it can lead to changes in the timing of runoff from snowmelt, increased summer air and water temperatures, and change in the seasonal distribution of precipitation (Mantua et al. 2010, Beechie et al. 2013).

Habitat restoration in the upper Grande Ronde River and Catherine Creek basins is being conducted by agencies including the U.S. Forest Service, Confederated Tribes of the Umatilla Indian Reservation (CTUIR), Oregon Department of Fish and Wildlife (ODFW), Union Soil and Water Conservation District (USWCD), Grande Ronde Model Watershed (GRMW), and U.S. Bureau of Reclamation (USBR). However, it remains unclear how these collective restoration actions affect salmon habitat quality and quantity in the freshwater tributary life stages, let alone how they impact salmon populations in the context of the complete life cycle. Fish-habitat relationships are inherently complex as they are influenced by interactions among intrinsic watershed factors (e.g., geology, valley form, flood regime) and anthropogenic factors (e.g., land use, climate change, restoration). These in turn affect ecological conditions and ultimately drive changes in fish abundance and productivity. This project incorporates several of these interacting factors in a holistic analytical framework.

The objectives of this project are to: 1) Assess current status and trends in fish habitat characteristics considered to be key ecological concerns for viability of spring Chinook Salmon populations; 2) Evaluate effectiveness of aggregate stream restoration actions aimed at improving these ecological concerns; and 3) Develop a life cycle model to link biotic responses of spring

Chinook Salmon populations to projected changes in stream habitat conditions that may result from restoration and climate change.

We have categorized our work towards these objectives into the following project components:

- Component 1: Habitat and biotic assessments,
- Component 2: Riverscape analyses, and
- Component 3: Fish-habitat modeling.

These individual components are linked together conceptually in an overall sequence of research, monitoring, and evaluation, with analyses feeding into an adaptive management framework (Figure 2).

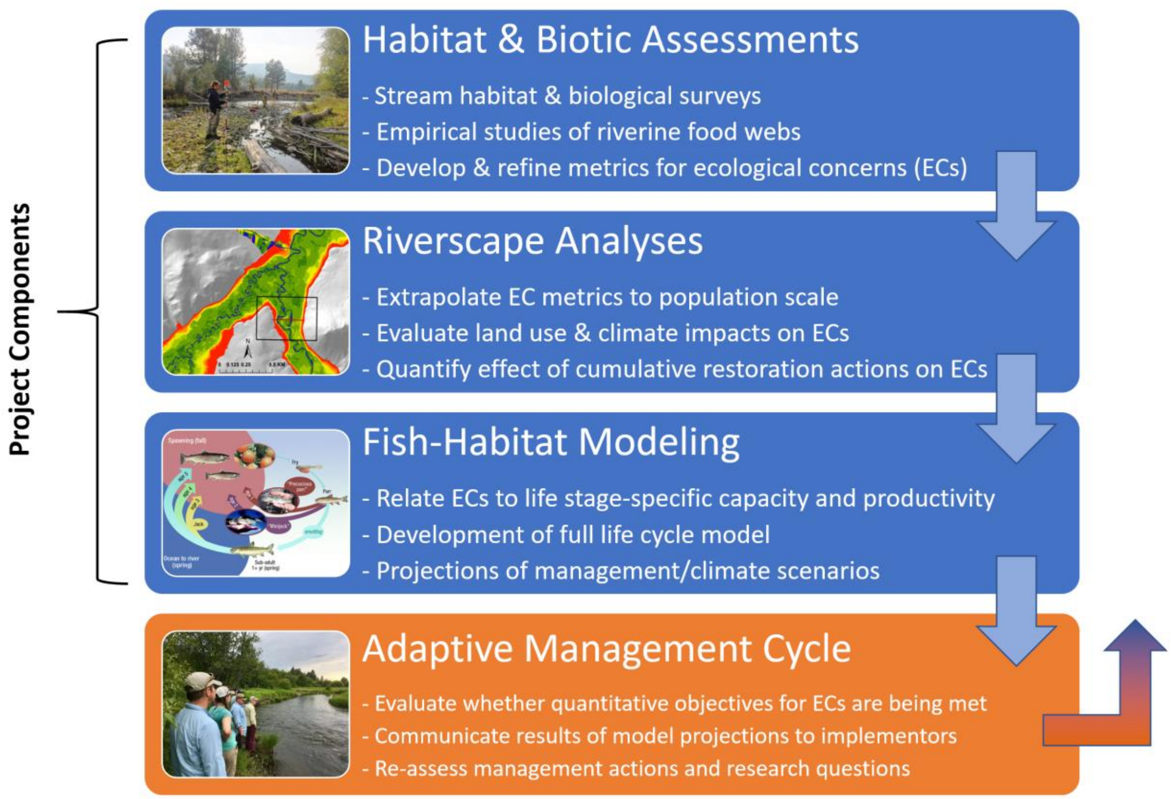

Figure 2. CRITFC's cycle of research, monitoring, and evaluation providing the basis for decision-making in an adaptive management framework.

Component 1: Habitat and biotic assessments—This component of our work involves collecting raw data from field surveys and remote sensing required to develop metrics for ecological concerns including habitat quality and quantity, site-specific estimates of fish capacity and productivity, and condition of salmonid prey resources. Since 2010, CRITFC has monitored fish habitat conditions in the upper Grande Ronde River and Catherine Creek (impacted basins) and the Minam River (a wilderness reference system). We initiated our own habitat protocol in 2010, but in 2011 we were

encouraged by Bonneville Power Administration (BPA) staff to adopt the Columbia Habitat Monitoring Program (CHaMP) stream habitat assessment survey. Data collected under these programs provided the basis for describing status and trends of key ecological concerns for Chinook Salmon in the study basins. In 2017, BPA commissioned a review of CHaMP which revealed several potential problems concerning both the collection of measurements and extrapolation of metrics. In response, our project initiated a revised habitat protocol in 2018 that includes a pared-down list of metrics identified as having minimal observer bias and is intended to provide comparison with metrics collected using emerging technologies, including unmanned aerial vehicles (UAVs) in collaboration with Bureau of Indian Affairs (BIA). Measurements of physical habitat are paired with estimates of fish abundance derived from snorkel surveys and collection of drift and benthic macroinvertebrates. Additional work includes development and maintenance of an inter-agency stream temperature database in the upper Grande Ronde River, Catherine Creek, and Minam River watersheds.

Component 2: Riverscape analyses—This component of our work involves extrapolating metrics for ecological concerns across stream networks and to the watershed/population scale using statistically rigorous approaches (e.g., GRTS-based averages or spatial stream-network [SSN] models). Additionally, we evaluate linkages among habitat conditions, land use, and climate conditions to understand watershed-scale processes affecting spatial and temporal trends in ecological conditions and investigate which management or policy scenarios will have the greatest impact. Quantifying the effects of cumulative restoration efforts in the subbasins is another aspect of this work, and includes developing a comprehensive restoration database for generating standardized metrics of restoration intensity. The above endeavors work towards assessing current patterns and trends of habitat quality and quantity that can be measured against historical or reference baselines.

Recovery of salmonid populations within the Columbia Basin may require an integrated approach involving management actions that consider food webs in addition to physical habitat availability (Naiman et al. 2012). To better understand the role of food webs in salmon recovery, we conducted a series of studies examining spatial patterns in nutrient concentrations and stream metabolism (Kaylor et al. 2019), carcass additions and the role of nutrient limitation and food availability on juvenile salmonid growth (Kaylor et al. 2020), and spatial patterns and drivers of juvenile Chinook Salmon size and growth (Kaylor et al. *in* prep; See Chapter 2.1). We additionally analyzed relationships among food web indicators derived from benthic macroinvertebrates, land use, climate conditions, and instream habitat conditions (See Chapter 2.2). Collectively, efforts to assess salmonid food webs provide insight into the factors limiting juvenile salmonid productivity (e.g., prey availability), actions that can be taken to increase productivity (e.g. carcass additions and nutrient supplementation), and where in these basins targeted restoration efforts may have the greatest impact on increasing juvenile salmonid productivity given the biophysical characteristics of these stream networks.

Component 3: Fish-habitat modeling—This component draws from the above data and analyses to relate ecological concerns to life stage-specific capacity or productivity, develop and apply a full spring Chinook Salmon life cycle model, and project the outcomes of alternative management and climate change scenarios. Life stage-specific models have thus far emphasized relationships between water temperature, instream habitat conditions, and abundance of rearing fish (parr); these models are then used to project anticipated changes to habitat capacity based on alternative riparian management and climate change. The life cycle model is a tool to simulate fish population trends in relation to projected habitat conditions, and to examine the relative benefits of habitat improvements on fish population recovery potential, accounting for out-of-basin impacts such as survival of out-migrating smolts at dams or mortality in the ocean phase. The fundamental basis of the model is that intrinsic watershed factors (such as geology, climate, or valley morphology) interact with human actions (such as forest harvest, cattle grazing, or stream restoration) to affect processes that drive known ecological concerns (e.g., flow, temperature, pool area, etc.), and therefore fish survival via both density-dependent and density-independent processes.

Adaptive management framework—CRITFC plays an important but limited role in the adaptive management framework for the Grande Ronde subbasin. Our project is involved in collection of data, development of models, and hypothesis testing regarding the types of cumulative management activities likely to be most effective for restoring fish populations. Local agencies (e.g., CTUIR, ODFW, USFS, SWCD, USBR) play a larger role in implementing restoration projects and conducting site-scale action effectiveness monitoring of individual restoration projects. CRITFC communicates results of model projections to local managers who re-assess the efficacy of management actions. CRITFC is currently working towards a clarified vision of adaptive management with Grande Ronde Model Watershed and its cooperating agencies.

Study Area

This study is occurring in the Grande Ronde River and its tributaries, which originates in the Blue Mountains of NE Oregon and flows 334 km to its confluence with Snake River near the town of Rogersburg, Washington (Figure 3). Focal study watersheds include the upper Grande Ronde River upstream of the town of La Grande, Catherine Creek, and to a lesser extent, the Minam River, which drain areas of approximately 1,896, 1,051, and 618 km^2, respectively.

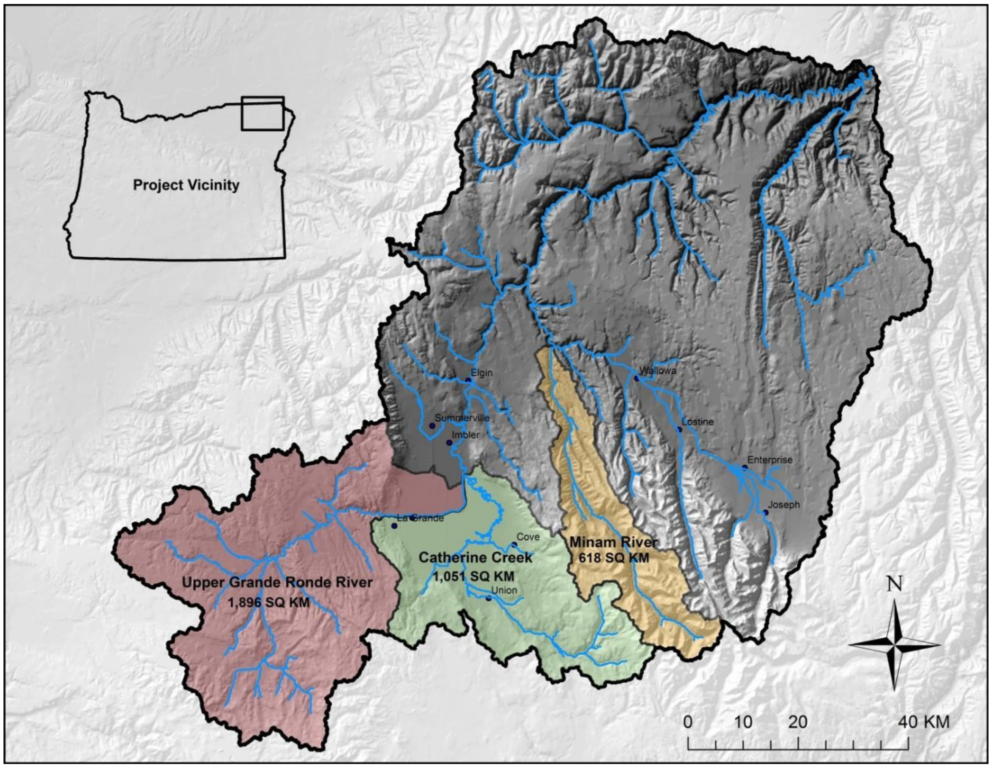

Figure 3. Study area in the Grande Ronde River basin, NE Oregon. Focal watersheds include the upper Grande Ronde River, Catherine Creek, and Minam River. The upper Grande Ronde and Catherine Creek are the basins with significantly impacted habitat that is undergoing restoration in various locations. The Minam River basin is the local reference basin that has far less current evidence of human impact.

The topography of the upper portion of the subbasin (i.e., upstream of the Wallowa River confluence) is characterized by rugged mountains in the headwater areas and a broad, low gradient valley between the Blue and Wallowa Mountains. Peaks in the Wallowa Mountains reach a maximum elevation of 2,999 m and provide the source of many of the Grande Ronde's tributaries including Catherine Creek, the Minam River and the Wallowa River. The Blue Mountains reach elevations of 2,347 m and are the source of the Grande Ronde River, Wenaha River, and other tributaries. Due to the lower elevation of the Blue Mountains, snow melt generally occurs earlier in these tributaries, often resulting in very low flows during summer.

Surface geology of the Grande Ronde subbasin is dominated by rocks of the Columbia River Basalt group, with some older granitic intrusives and volcanics with associated sedimentary deposits present in the headwater areas of the upper Grande Ronde and Catherine Creek. The climate is characterized by cold, moist winters and warm, dry summers with mean daily air temperatures near La Grande averaging -0.42°C in January and 21°C in July. Average annual precipitation ranges from 36 cm in the valleys to 152 cm in the mountains, with most of the precipitation in the mountains falling as winter snow.

The vegetation community at lower elevations is dominated by grasslands consisting of Idaho fescue/bluebunch wheatgrass (*Festuca idahoensis-Agropyron spicatum*) and bluebunch wheatgrass-Sandberg's bluegrass (*Agropyron spicatum-Poa sandbergii*) (Nowak 2004). As elevation increases, the grasslands transition to shrub/scrub plants, and eventually to coniferous forests in the mountains. Forest species consist of low elevation Ponderosa pine (*Pinus ponderosa*) and lodgepole pine (*Pinus contorta*) associations grading into Douglas-fir (*Pseudotsuga menziesii*), grand fir (*Abies grandis*), subalpine fir (*Abies lasiocarpa*), and mountain hemlock (*Tsuga mertensiana*) associations at higher elevations. Riparian vegetation is dominated by black cottonwood (*Populus trichocarpa*) and willow (*Salix* spp.), black hawthorn (*Crataegus douglasii*), mountain alder (*Alnus incana*), and mountain maple (*Acer glabrum*).

Approximately 49% of the land in the Grande Ronde basin is publicly owned, of which about 97% is managed by the US Forest Service. The remaining public land is managed by the Bureau of Land Management and the States of Oregon and Washington. With the exceptions of the Eagle Cap and Wenaha-Tucannon Wilderness Areas, the National Forests are managed for multiple use including timber production, livestock grazing, and recreation. Private property comprises the remaining 51% of the land in the basin and is located primarily in lower elevation valleys and along rivers. A large proportion of the private property is used for agriculture including crop production, livestock grazing, and forestry. Only 0.1% of the land in the Grande Ronde Basin is currently owned by the tribes, although the tribes retain fishing and hunting access rights at all usual and accustomed locations as afforded under the treaties of 1855 and 1863.

Spring Chinook Salmon populations in these basins were listed as threatened under the Endangered Species Act in 1992. Population declines over the past century were due in part to overharvest, hydropower impacts, and degraded habitat conditions resulting from intensive anthropogenic disturbances including timber harvest, cattle grazing, levee and road construction, stream diversions for irrigation, and removal of beaver populations (*Castor canadensis*). Specifically, stream temperature, streamflow, fine sediment, habitat diversity, and quantity of key habitats such as large pools, have been identified as key ecological concerns for recovery of Chinook Salmon populations in these basins.

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Project Components

1. Habitat and Biotic Assessments

1.1 Development of a tributary habitat assessment protocol

***Note**: A draft of the protocol introduced in this section is available in Appendix A – "Draft Tributary Habitat Assessment Protocol".*

Introduction

Physical stream habitat surveys are used to monitor the quantity, quality, and changes to fish habitat. Across the Columbia River Basin (CRB), data obtained from these surveys aid in evaluating the effectiveness of aggregate restoration actions in improving freshwater habitat conditions and viability of ESA-listed fish species at the population, major population group (MPG), and evolutionarily significant unit (ESU) scales. Implementing regional habitat monitoring with the goal of assessing status and trends of tributary habitat for anadromous species has proven to be methodologically challenging. More specifically, the accuracy and resolution of data needed to answer broad questions of status and trends in salmon-bearing tributary habitats during any one life stage necessitates data collection at small spatial scales (e.g., meso-habitat; pool, riffle, etc.), where the intensity of sampling restricts large spatial coverage.

The Columbia Habitat Monitoring Program (CHaMP) was the collaborative product of numerous agencies, designed as a spatially balanced intensive monitoring program conducted at randomly selected representative reaches ($10^2 – 10^3$ m) throughout the CRB. CHaMP was designed as a long-term monitoring program to collect fine scale data that could be extrapolated to unsampled areas. After seven years (2011-2017) of intensive data collection to determine habitat status and trends within sampled watersheds through the CRB, CHaMP was cut two years prior to reaching the originally proposed nine-year panel which would have allowed for statistically valid trend analysis. Addressing the need for a new coordinated regional strategy for tributary habitat status and trend monitoring, this document describes the development of a new monitoring protocol.

Moving forward while acknowledging the criticisms of previous monitoring approaches used in the basin (Rosgen et al. 2018; Roper et al. 2010), our primary objectives include: 1) develop a rapid yet robust protocol for monitoring status trends of tributary habitat conditions and assess restoration effectiveness relevant to salmonid recovery, 2) integrate new technology in the form of remote sensing technology, where feasible, to increase efficiency and spatial scale of data collection; and 3) ensure compatibility with key metrics from previously implemented habitat assessment protocols.

Habitat Survey Methods

While much is known about fish populations at microhabitat and basin scales, in this protocol we seek to address the gap in understanding at intermediate scales (e.g., $10^3 – 10^5$ m; Fausch et al. 2002). This protocol is designed to provide a more comprehensive and continuous riverscape perspective of the status and trends in fish habitat by ultimately merging datasets from multiple spatial scales. The major components of this protocol are split into ground and aerial-based methods. The ground-based methods are a fusion of two widely used and accepted protocols that are currently used (Aquatic Inventories Project [AIP]; Moore et al 2019) or were historically used (CHaMP 2016) within the CRB. To increase efficiency, improve reproducibility, and address the need for data collection at intermediate spatial scales, we reduced the frequency and total measures of habitat collected by ground crews. Measures of habitat quantity and quality retained in this protocol are quantifiable, requiring little if any visual estimation, and intended to be robust enough to provide meaningful comparisons against preexisting and future complimentary datasets.

The aerial-based portion of the protocol utilizes an unmanned aerial vehicle (UAV, or more commonly referred to as, drone). Drones have become ubiquitous in monitoring throughout a range of disciplines within the CRB. The most common application of drones in monitoring to date is the collection of true color imagery. Automated flight plans, increased safety features, and post-processing software allow restoration practitioners, videographers, and biologists to collect imagery, derive meaningful fish habitat data through image post-processing, and relay their findings on a level easily understood by the general public and policy makers. However, drones equipped with advanced sensors (e.g., multispectral, light detection and ranging (LiDAR), etc.) allow for more quantitative approaches of assessing habitat and monitoring restoration effectiveness. Of specific interest to fish habitat surveys, drones are a relatively inexpensive technology that can reduce the time and effort spent collecting ground-based data, while yielding imagery that is data rich enough to allow for further processing and discovery as new information in this field continues to grow. Furthermore, operating a drone and collecting imagery is a relatively unbiased method of collecting data that is not prone to the same subjectivity and transcription errors of ground-based measures. Drones are used in this protocol to collect imagery from multiple viewing angles (i.e., nadir and off-nadir), which together can be used to reconstruct continuous orthorectified mosaics of the stream channel and immediate floodplain in which multiple measures of channel dimensions, canopy height, and vegetation indices can be derived.

This protocol provides a flexible framework for assessment of fish habitat conditions across a range of spatial scales from geomorphic channel unit (i.e., pool, fast turbulent, fast non-turbulent), to reach, segment, or whole network/watershed scales. Ground-based data is collected at the channel unit scale (i.e., the finest grain of resolution), but can be easily aggregated to larger scales depending on the goals of the monitoring program. At a minimum, channel unit data will be summarized at the reach scale for calculation of common habitat metrics (e.g., pool frequency, large wood frequency, side channel area, etc.) and analysis of fish-habitat relationships. While the

specific methods used to roll-up data to larger spatial scales are beyond the scope of this field protocol, we emphasize that aggregation methods should account for differences in natural channel morphology (i.e., slope, discharge, sediment supply, valley confinement; Montgomery and Buffington 1997; Beechie and Imaki 2014).

The approach outlined in this protocol is hierarchical, where the location of data collection will depend on the desired scale of inference. For example, if the goal is to quantify habitat conditions within a single stream segment or small watershed (1 – 50 km), then it is feasible to conduct a spatially continuous census of all available habitat during a single year. Organizations may also choose to collect census data covering different portions of a watershed over a number of years and then merge the data together. If the desired scale of inference is too extensive to census (i.e., large watershed, Major Population Group (MPG), or Evolutionarily Significant Unit (ESU)), then a randomized sampling design is recommended in which a subsample of the total population is randomly sampled to produce an estimate of average habitat conditions. A good choice for this approach is the Generalized Random Tessellation Stratified (GRTS) design (Stevens and Olsen 2004), which provides a spatially balanced sample across a stream network and has been widely used for aquatic habitat monitoring in the Pacific Northwest (CHaMP 2016; Moore et al. 2019). Ideally, sample locations would be drawn from the Columbia River basin-wide master sample to facilitate integration of survey data across multiple monitoring programs (Larsen et al. 2008).

Existing Implementation Challenges

Perhaps the largest impediment to the adoption of a regional protocol that uses drones is the uncertainty in legislation, funding, and potential of these new and emerging remote sensing platforms. And while it is clear that UAVs are being widely used, the development of standardized methods for integrating their use into monitoring have not yet been established. Furthermore, the diversity of subbasins throughout the CRB and range of limiting factors for imagery acquisition (i.e., dense canopy, high gradient reaches, climate/weather) necessitates the collection of additional imagery or use of advanced sensors which will both increase processing time and complexity of subsequent data analysis to derive meaningful metrics. However, based on our initial testing, coupling ground-based data collection with aerial mapping represents a cost-effective, repeatable approach to conducting surveys of tributary habitat throughout the CRB.

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1.2 Assessing the potential of utilizing unmanned aerial vehicles for physical stream habitat surveys

__Note__: Complete details of the overall study design, post-processing methods, and cursory analysis, along with the protocol used to collect the data presented in this document can be found in White et al. 2019 ("Evaluation of Habitat Protocol Using Remote Sensing" and Appendix A, respectively therein).

Introduction

Advances in the development of high-resolution surveying technologies have substantially increased the ability to map riverine topography with high accuracy and precision. Unmanned aerial vehicles (UAVs) represent one solution capable of quantifying habitat at resolutions useful for exploring fish-habitat linkages (e.g., meso-habitat; pool, riffle, etc.) and over continuous spatial scales (Tamminga et al. 2015). These emerging technologies provide opportunities to improve the accuracy and precision of fish habitat metrics at larger spatial extents than previously available with solely on-the-ground observations. Here we provide an update on progress towards assessing the performance and capabilities of UAVs for stream habitat surveys by comparing ground-based measurements of physical stream fish habitat to those derived from imagery collected with a UAV.

The impetus for this work was primarily: 1) Testing the feasibility of incorporating drones into monitoring methods to increase efficiency, reduce costs, and produce repeatable and accurate measures of habitat; 2) Addressing a knowledge gap in the literature concerning a lack of replication in studies using drones and environmental limitations; and 3) Fulfilling a need to continue collecting stream habitat data to characterize the status and trends in fish habitat and restoration effectiveness throughout the Columbia River Basin (CRB).

While many studies have demonstrated the capabilities of UAVs and post-processing methods to obtain bathymetry and characterize in-stream habitat, we are unaware of any other studies that have examined their application across varying riparian canopy and along gradients of stream geomorphology. To evaluate how a UAV would perform in a variety of settings, we selected thirteen stream reaches that represented the greatest diversity of geomorphic and riparian conditions encountered by salmonids in the study area located in two NE Oregon watersheds (Catherine Creek and the upper Grande Ronde River; Figure 4; Table 1). Reaches were chosen based on four criteria: 1) area of accumulated upstream watershed (i.e., small or large), 2) the combination of river confinement and gradient (i.e., constrained or unconstrained), 3) riparian canopy density (i.e., sparse, medium, or dense; Table 2), and 4) part of historical monitoring using the Columbia Habitat Monitoring Program protocol (CHaMP 2016).

Methods

During the summer of 2018, ground-based and aerial surveys were conducted to characterize physical habitat conditions. The ground-based portion of data collection was based loosely on the CHaMP protocol; retaining measures of habitat quantity and quality only if they were quantifiable, required little to no visual estimation, repeatable, and provided the option for reanalysis of preexisting datasets collected by CHaMP. The ground-based portion of this study consisted of multiday surveys with a minimum crew size of three persons, where highly precise and accurate topographic data of the streambed and floodplain were collected with a total station or real time kinematic (RTK) GPS in addition to measures of in-stream habitat. Aerial surveys consisted of a minimum of one UAV and one Federal Aviation Administration (FAA) certified pilot, and additional crew members serving as visual observers. The resulting data from each of these independent surveys were post-processed and key measures relating to the quantity and quality of available fish habitat were calculated.

Results and Discussion

We found UAV remote sensing methods overall showed good agreement to traditional ground-based total station surveys of topography (Figure 5). Of the six direct comparisons made between ground and imagery derived measures of habitat summarized across all channel units at each of the thirteen reaches, the strongest relationships were observed between total wetted area (R^2 = 0.99; Figure 5A) and total wetted volume (R^2 = 0.96; Figure 5E). Conversely, metrics relating to channel bathymetry showed much lower agreement between aerial and ground-based measurements. Measures of thalweg exit depth derived from imagery were able to account for 54% (Figure 5C) of the variation in ground-based stream topography measurements, whereas maximum depth only 27% (Figure 5B) and residual depth 2% (Figure 5D). Some of the unexplained variation in these comparisons of depth measurements was attributed to the channel unit type, canopy density, presence of shadows, or geomorphology. Canopy density and geomorphic type were included as covariates in a general linear model to account for additional sources of error associated with measures of depth. These additional covariates increased the amount of explained variance in thalweg exit depth, maximum depth, and residual depth by 4, 33, and 70 % respectively.

In addition to measures of habitat dimensions, the agreement of large wood counts between measurement techniques was also tested. Though pieces of wood meeting our minimum criteria for counting (15 cm in diameter and 3 m in length) were easily visible in imagery collected with the drone, we found a large difference between the pieces identified and counted on the ground compared to those that were visible from the air, with fewer wood pieces counted using the UAV approach (R^2 = 0.66, MD = 27; Figure 5F). This observed discrepancy may partially be attributed to large wood structures spanning the channel that were both overlapping and partially sunken (e.g., into the bank, bedform, or underwater), which restricted our ability to identify qualifying pieces meeting our length and diameter requirements. Nevertheless, we believe the UAV shows promise for quantifying surface area of LWD within the channel as opposed to LWD count (see

‘wood jam area’ in Beechie et al. 2017), and that this metric may be more relevant to fish use because it reflects only the portions of wood in the wetted channel where fish reside.

Obtaining stream habitat data representative of all habitat conditions expected to be encountered by fish has been difficult to achieve from ground-based habitat surveys or other remote sensing methods alone. We assessed the quality of UAV derived data in comparison to those collected using ground-based methods and demonstrated the effects of geomorphology and canopy density on commonly computed habitat metrics. Overall, we found water surface roughness/turbulence, shadows, overlapping sections, and riparian vegetation (grasses, trees) to have a large effect on accuracy and precision of many of the measures derived from UAV imagery. Though previously untested outside of individually selected stream reaches with ideal conditions, these results indicate that coupling ground-based data collection with high-resolution aerial photography using a UAV would provide the spatio-temporal resolution needed to investigate many common fish-habitat linkages.

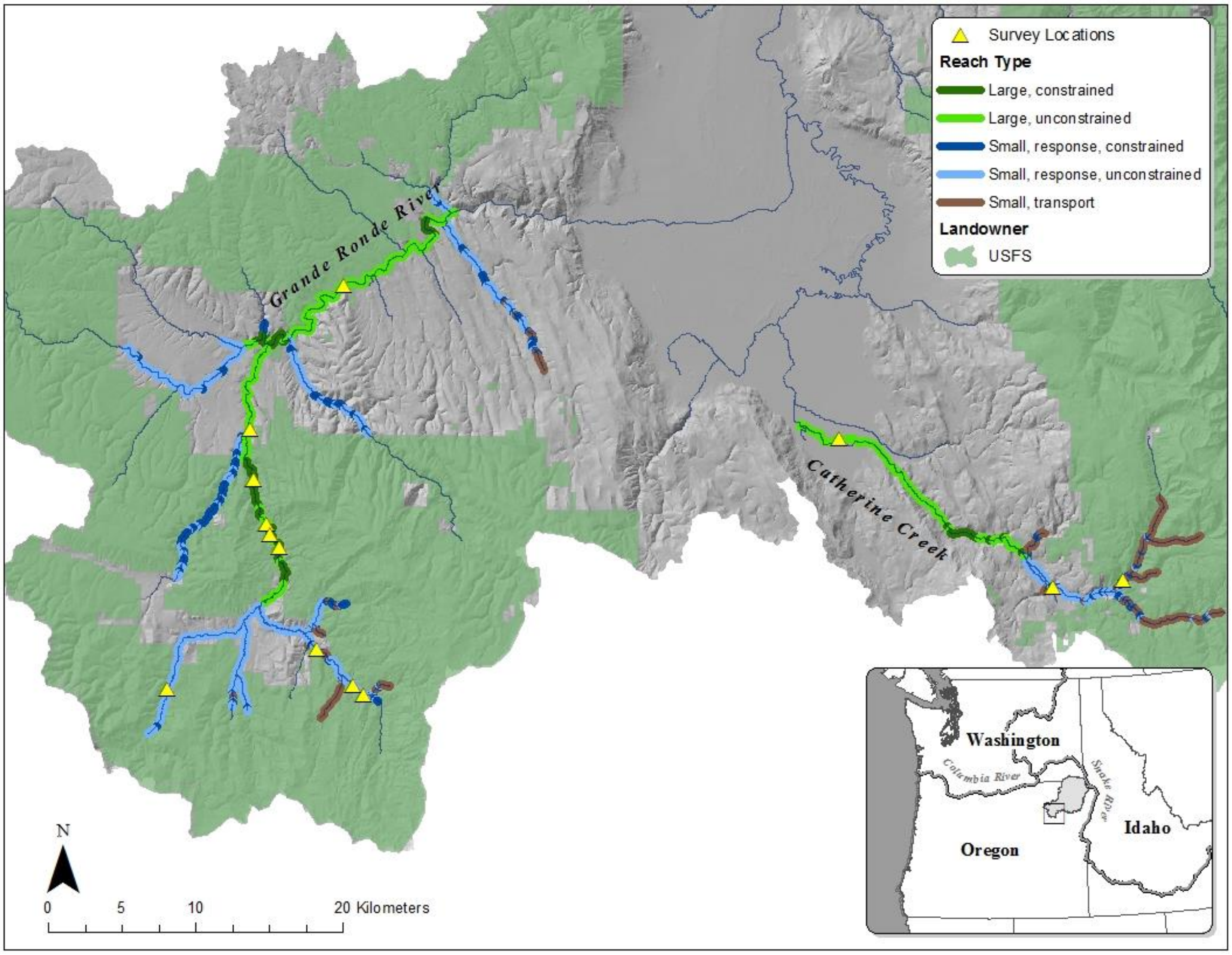

Figure 4. Sampling locations (n=13) with their associated stream reach classifications within the upper Grande Ronde River and Catherine Creek basins in Eastern Oregon.

Table 1. Sampling locations (n=13) and associated characteristics within the upper Grande Ronde (UGR) and Catherine Creek (CC) Watersheds in Eastern Oregon.

Reaches	Watershed Name	Watershed Size	River Confinement	Riparian Canopy Density	Elevation (m)	Gradient (%)
CBW05583-138666	CC	Small	Constrained	Dense	1178	2.66
CBW05583-456106	CC	Small	Constrained	Medium	1044	1.11
CBW05583-099818	UGR	Small	Unconstrained	Medium	1359	0.58
CBW05583-280042	UGR	Small	Unconstrained	Sparse	1372	0.62
CBW05583-335162	UGR	Small	Unconstrained	Sparse	1334	0.86
CBW05583-468458	UGR	Small	Unconstrained	Dense	1306	2.49
CBW05583-321338	UGR	Large	Constrained	Sparse	1169	2.82
CBW05583-370490	UGR	Large	Constrained	Medium	1189	0.85
CBW05583-486202	UGR	Large	Constrained	Dense	1303	1.71
CBW05583-031546	UGR	Large	Unconstrained	Medium	1077	0.74
CBW05583-071770	UGR	Large	Unconstrained	Sparse	942	0.44
CBW05583-235322	UGR	Large	Unconstrained	Sparse	1154	0.92
CBW05583-430250	CC	Large	Unconstrained	Dense	847	0.69

Table 2. Thresholds of riparian canopy density by stream channel constraint type.

	Canopy density values (%)		
Reach type	**Sparse***	**Medium†**	**Dense+**
Constrained	15.8 – 30.4	35.9 – 42.8	44.9 – 53.1
Unconstrained	9.6 – 22.4	25.7 – 38.5	45.8 – 65.7
Quantile range:	* 5^{th}-25^{th}	† 35^{th}-65^{th}	+ 75^{th}-95^{th}

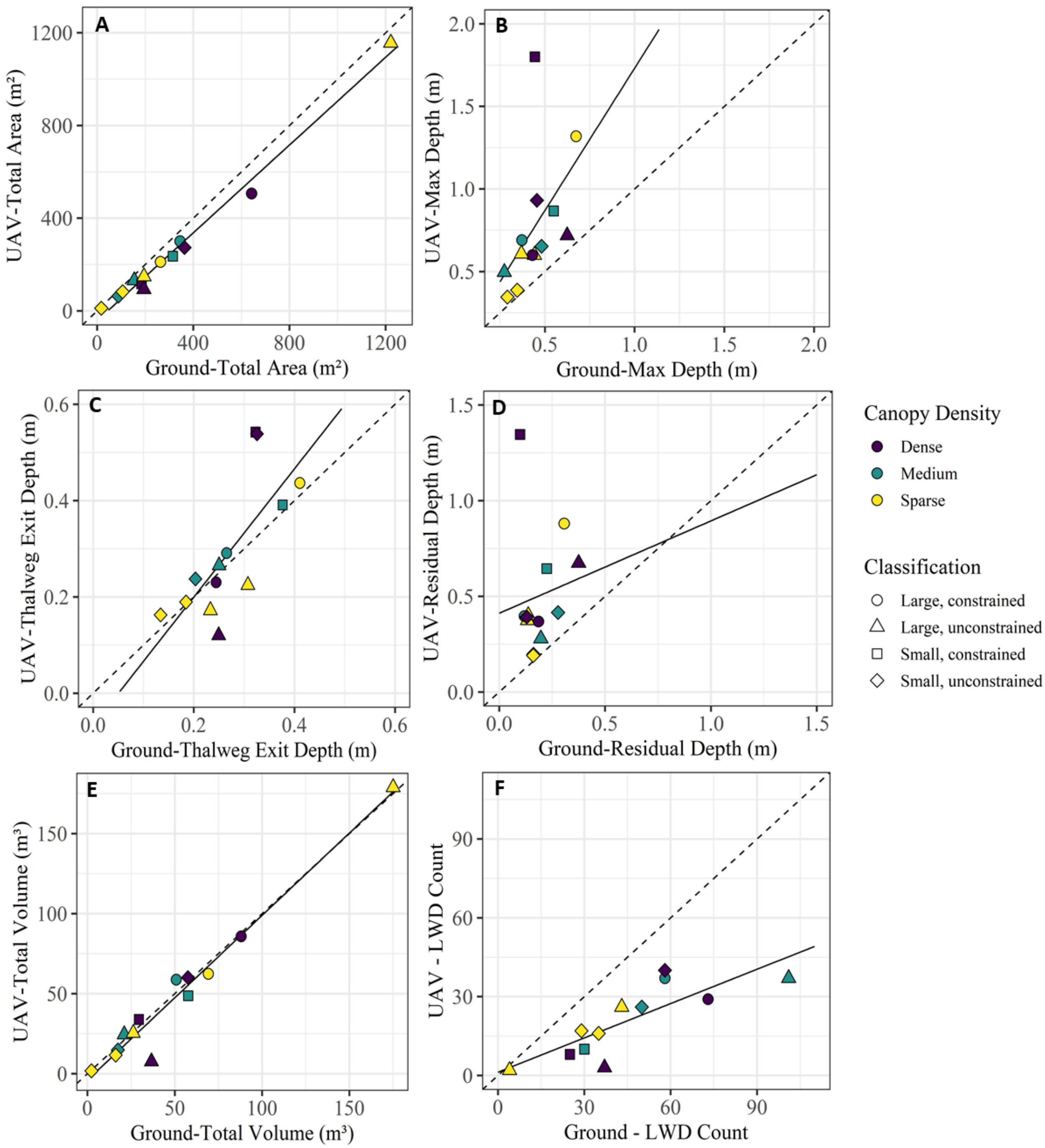

Figure 5. Relationships between ground-based and UAV-based metrics summarized by stream reach: A) mean total wetted area (m²), B) mean maximum depth (m), C) mean thalweg exit depth (m), D) mean residual depth (m), E) mean total wetted volume (m³), and F) sum of large wood counts. The solid line represents the regression line, while the dashed line is the 1:1 equality line.

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1.3 Reanalysis of snorkel survey calibration methods

***Note**: much of the detail (methods and results) on this work is contained in a draft manuscript (Appendix B, this document).*

Background

Snorkel surveys are a widely used method of assessing the abundance and distribution of juvenile salmonids in the freshwater component of their life cycle. Counts obtained from these surveys index the density of fish by species and/or size classes, which can then inform fine-scale patterns of fish-habitat associations unavailable from other larger-scale monitoring methods alone (e.g., rotary screw traps). Further, because the observer never handles the fish, these surveys are more rapid and less intrusive than other survey methods (e.g., backpack electrofishing or piscicide applications) making them well-suited for larger scale monitoring of the abundance and distribution of threatened and endangered salmonids.

However, given the difficult nature of counting many small and mobile organisms in flowing water, the counts are also subject to substantial observation errors. We presume the most prevalent error made when conducting snorkel surveys is failing to see some of the fish present, i.e., the concept of partial detectability (Kellner and Swihart 2014). If left unaccounted for, partial detection will always result in counts that are biased low relative to the true abundance. Coupled with the fact that detection efficiency (or equivalently, probability) can be a complex function of habitat conditions (e.g., in-stream obstructions) that may co-vary with abundance, we believe partial detection is the most important source of error to model and correct for.

Previous efforts directed at quantifying detection efficiency in snorkel surveys have relied on paired estimates of total juvenile salmonid abundance (via mark-recapture or multi-pass depletion estimators) and snorkel counts (e.g., Hillman et al. 1992; Hankin and Reeves 1988; Thurow et al. 2006). A statistical relationship is then obtained that attempts to explain the variability in abundance from a given snorkel count using covariates (i.e., habitat conditions). The estimated relationship can be used as a means to correct future snorkel counts for partial detectability to place them on the scale of population abundance.

Such a study was conducted in the Grande Ronde Basin by the Oregon Department of Fish and Wildlife (ODFW) and CRITFC during the summers of 2012 and 2015 in which paired mark-recapture estimates and snorkel surveys were conducted in the same channel units (Jonasson et al. 2016; McCullough et al. 2016, Appendix F therein). The statistical relationship predicted the natural logarithm (log) abundance from the log snorkel count and one other explanatory covariate (stream size). When converted to the natural scale, this relationship implied a curvilinear

relationship between snorkel counts and abundance, with the scale dependent on stream size (Figure 6a). This method has been used to correct snorkel counts conducted by both ODFW and CRITFC since the conclusion of that study.

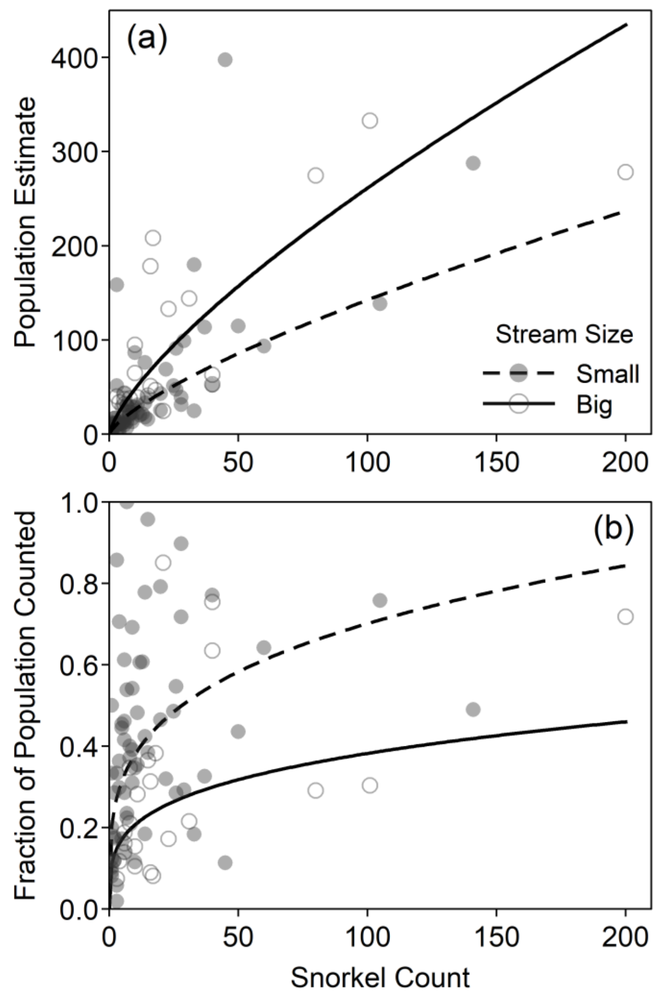

Figure 6. (a) Relationship between mark-recapture estimates of total juvenile salmonid abundance (*y*-axis) and the snorkel count (*x*-axis), reproduced from Jonasson et al. (2016). Each point represents a channel unit visit; point and line types denote the size of stream each sample was taken in. (b) The implied relationship between snorkel survey detection efficiency and snorkel counts from the relationship shown in (a). Note that the detection efficiency is assumed to be a function of the count in this approach.

Motivation for reanalysis

Although the model shown in Figure 6a (hereafter referred to as the "log-log regression" approach) was obtained using reasonably valid and logical statistical procedures, there are still reasons why it is non-ideal from a statistical standpoint.

(1) *Imperfectly measured response variable*—The regression methodology assumes that log abundance is known without error – this is severely violated by using mark-recapture estimates as they can have substantial statistical uncertainty even when model assumptions are perfectly satisfied.

(2) *Possibility of pseudoreplication*—Observations were collected at the channel unit level with some replicates at the site level – these channel units may share some features that render them more similar to units that are close by rather than units farther away. The log-log approach that was applied did not account for this possibility of spatial similarity.

(3) *Lack of useful predictive covariates*—Although other covariates were assessed for predictive power (year and type [fast vs. slow water]) they were not selected by the variable selection approach used. The large amount of variability left unexplained in Figure 6a indicates that more factors influence snorkel detection efficiency that should be investigated.

(4) *Equal detection of all salmonids*—The model was fitted to total juvenile salmonid abundance, which assumes that all species are equally detectable, however, anecdotal evidence suggests that some species are more difficult to see than others.

(5) *Detection varies with the count*—Most importantly, the log-log approach assumes that the fraction of the population that was counted changes with the snorkel count (Figure 6b). Generally, population index counts such as snorkel counts are assumed to be proportional to the countable population (Kéry and Royle 2010) and variability in detection efficiency (i.e., catchability) is a result of other factors affecting the efficiency of the gear or method used to obtain the count. However, as shown in Figure 6b, the log-log regression approach assumes that the fraction of the population that is counted is a function of the snorkel count. For example, this method suggests that 21% of the population in a channel unit found in a small stream was counted if one fish was observed in the survey, but that 38% of the population was seen if 10 fish were counted. This assumption has the largest implications at small counts (as shown in Figure 6b), which is also where most snorkel survey counts occur.

As a result of these potential issues with the currently applied log-log regression approach, we believe that it could possibly lead to large errors when applied to out-of-sample cases (i.e., when snorkel counts are available but not mark-recapture data). Thus, we performed a reanalysis of snorkel survey correction factors. Namely, we recast the analytical framework to view the counting of fish via snorkel survey as a binomial process, in which each fish in a channel unit vulnerable to being counted is detected with constant probability. This approach enabled direct modeling of the effects of local conditions on snorkel detection efficiency, and more sophisticated statistical approaches allowed better accounting of uncertainty and more nuanced selection of important covariates.

Methods

Complete details of the analytical methods (equations, likelihoods, and assumptions), are presented in Appendix B of this document and the details of field sampling are presented in Jonasson et al. 2016; rather than belabor the reader with complete descriptions, we have chosen instead to summarize these aspects here and invite interested readers to examine the draft manuscript in Appendix B.

Data collection

A wide variety of habitat types in the upper Grande Ronde River and Catherine Creek were included in the 2012 and 2015 data sets. Habitats were classified according to a hierarchical channel unit classification system using the Columbia Habitat Monitoring Program protocol (CHaMP 2016). These channel unit delineations provided the spatial scale at which snorkeling was conducted using the protocol of White et al. (2012). Mark-recapture data were collected at the same scale as snorkel surveys and as a two-pass design using backpack electrofishing for capture and fin clips for marking (block nets were used to aid in meeting the population closure assumption). Juvenile Chinook Salmon (*Oncorhynchus tshawytscha*) and steelhead/rainbow trout (*O. mykiss*) were the target species. A total of 105 observations (unique species by channel unit visit combination) with adequate data were available which included 82 unique channel units (34 and 48 in 2012 and 2015, respectively) across 40 unique sites; 29 of the observations were of Chinook Salmon and 76 were of *O. mykiss*.

Associated with these count and abundance data were additional covariates intended to describe fish behavior and local habitat conditions that we hypothesized would have a meaningful and measurable effect on snorkel detection efficiency. These covariates included: unit type (pool versus non-pool), average unit depth (m), density of large wood (none, low, high), snorkeler-determined quality of visibility (poor, average, good), and species of observation (Chinook Salmon vs. *O. mykiss*).

Estimation of detection efficiency relationships

Our goal was to describe how snorkel detection efficiency for each observation varied as a function of covariates. Because snorkel detection efficiency is a fraction (count/abundance), a straightforward method for analysis is logistic regression, where the count is the number of successes in a binomial experiment, abundance is the number of trials, and detection efficiency is the probability of success in each trial. However, abundance is not known perfectly and so cannot be used in this exact context. Rather, we constructed a hierarchical model that treated abundance by species at each channel unit as a free parameter, which acknowledges uncertainty. Essentially, the species-specific abundance in each sampled channel unit is seen as a latent (i.e., a true but only ever partially or imperfectly observed) state that is sampled by two independent sources of information: mark-recapture data and snorkel data. Snorkel detection efficiency is predicted by

covariates specific to each channel unit via a logit-linear model. Variable selection and multi-model inference was conducted using the notion of "indicator variable selection" (Hooten and Hobbs 2015; Kuo and Mallick 1998) wherein an additional set of parameters were estimated that toggled the effect of each covariate on or off and when summarized represent the probability each covariate should be included in a predictive model. We chose to employ the Bayesian inferential framework (implemented with JAGS; Plummer 2003) because, even in the absence of prior information, it is useful for hierarchical modeling, propagating estimated uncertainty and parameter correlations to derived quantities, and variable selection using direct and transparently interpretable probabilistic output.

In addition to the analysis of Grande Ronde data, we conducted a simulation study intended to investigate the reliability of this hierarchical model (see Appendix B for more details regarding the methods and results of this analysis). In short, we found that the hierarchical model we developed can return reasonably accurate and precise estimates of detection efficiency and abundance, is more robust than a method that does not acknowledge mark-recapture uncertainty, and is reasonably robust to some violations in assumptions.

Correction of snorkel counts

The majority of snorkel data we have collected do not have paired mark-recapture information, requiring that we apply the estimated snorkel detection efficiency relationships to correct the counts for partial detection. The basic approach is to divide the count by the predicted detection efficiency (fraction of population counted) – this provides an estimate of how many fish would have been counted had all fish been seen in the surveyed area. Two additional expansions were necessary to obtain total abundance at the site-level: not every sampled channel unit is surveyed entirely (i.e. some units are partially surveyed) and not every channel unit at a site is surveyed. Following expansions that correct for these issues, site-level abundance estimates were then converted to densities (both by stream area and by stream length). The same procedure had previously been done for the density estimates obtained via the log-log regression approach, and the revised estimates were compared to the old estimates to investigate the impact that applying the revision had on our density estimates of Chinook Salmon and *O. mykiss* juveniles in the Grande Ronde Basin.

Results

Our hierarchical model identified patterns in the data that strongly suggested snorkel survey detection efficiency varied as a function of the covariates included in the analysis. We found strong evidence that snorkel survey detection varied by unit type, and that the effect of depth varied depending on whether or not a channel unit was a pool (Figure 7). The species effect was strongly positive, indicating that Chinook Salmon were more efficiently counted than *O. mykiss* (Figure 7). The coefficients associated with these covariates all had parameter inclusion probabilities of 1 (i.e.,

they were included in every model assessed by the fitting algorithm). Visibility was only important to account for if the snorkeler determined it was "good" ("VIS3" in Figure 7). Poor visibility ("VIS1") had a low probability of inclusion and small effect size, indicating units placed in this category had similar detection efficiencies as average visibility units. Likewise, units with low large wood density ("LWD2" in Figure 7) behaved similarly to units with no large wood, but the presence of high wood density ("LWD3") had a pronounced negative effect on snorkel survey detection efficiency.

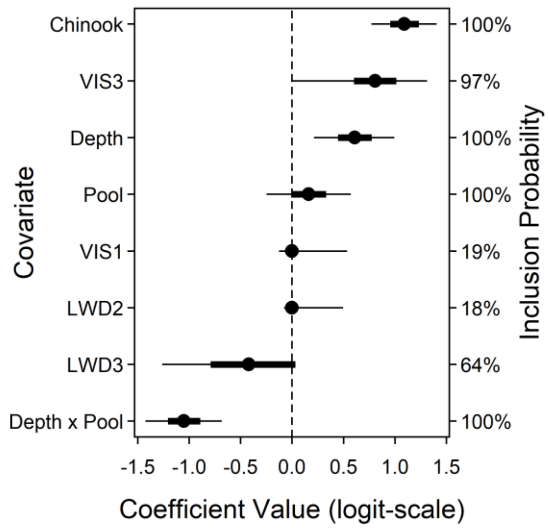

Figure 7. Model-averaged coefficient estimates from the Grande Ronde application of the hierarchical snorkel detection efficiency model. Positive coefficient values indicate that covariate increases snorkel detection efficiency; points represent posterior medians, thick bars represent the central 50% credible limits and the thin bars represent 95% credible limits. All covariates are binary except for depth and its interaction with unit type; depth values were scaled and centered prior to the analysis. Also shown along the right axis are the posterior probabilities that each covariate should be included in a predictive model (referred to as "parameter inclusion probabilities" in the text).

The predicted detection efficiency based on these effects, as well as the distribution of observations, are shown in Figure 8. Clearly, most observations occurred in channel units with no large wood present and with average visibility. Some wood by visibility combinations had few or no observations, which prevented the investigation of interactions between these variables, as well as by species interactions with the other variables. However, there was relatively good contrast in the range of average depths available within each unit type, allowing the estimation of the interaction between these two covariates. As seen in Figure 8, this interaction was estimated such that increasing depth had a positive effect on detection efficiency in non-pool units, but a negative effect in pool units. As suggested by the direction and magnitude of the effects in Figure 8, the detection efficiency curves were higher for Chinook Salmon than for *O. mykiss* and there was little difference between no wood and low wood and between poor visibility and average visibility. The

scatter of the points around the fixed-effect curves in Figure 8 is a result of a random site effect, the standard deviation of these effects was estimated to be quite large (1.22; 95% credible limits 0.9-1.64).

Model fit to the data was good, with the exception of several recapture events being under-predicted (Appendix B, Figure 1b therein). Nonetheless, the observed values fell within the 95% posterior predictive intervals in 95% of the data points for recapture data and in 97% of snorkel data points, indicating good model adequacy for the data. In general, model-estimated abundance was similar to abundance obtained by applying an external Chapman (1951) estimator (Appendix B, Figure 2 therein) – discrepancies in these two estimates are due to the hierarchical model having to explain sampling variability in both the mark-recapture and snorkel survey sampling.

In comparing the revised density estimates to those obtained via the log-log regression approach, we found that the estimates were not identical. In terms of qualitative inferences, the two approaches yielded generally similar results: densities that were high using the log-log approach were also generally high using the hierarchical model approach (Figure 9). However, from a quantitative standpoint, the scale of the densities changed to some degree. Revised Chinook Salmon densities were lower on average compared with the log-log regression estimates (22% and 29%; median percent decrease for length- and area-based density estimates, respectively) due to the finding that a larger fraction of the Chinook Salmon population is counted (the log-log regression pooled fish of all species). Conversely, *O. mykiss* density estimates increased for the opposite reason following revision (60% and 41%; median percent increase for length- and area-based density estimates, respectively).

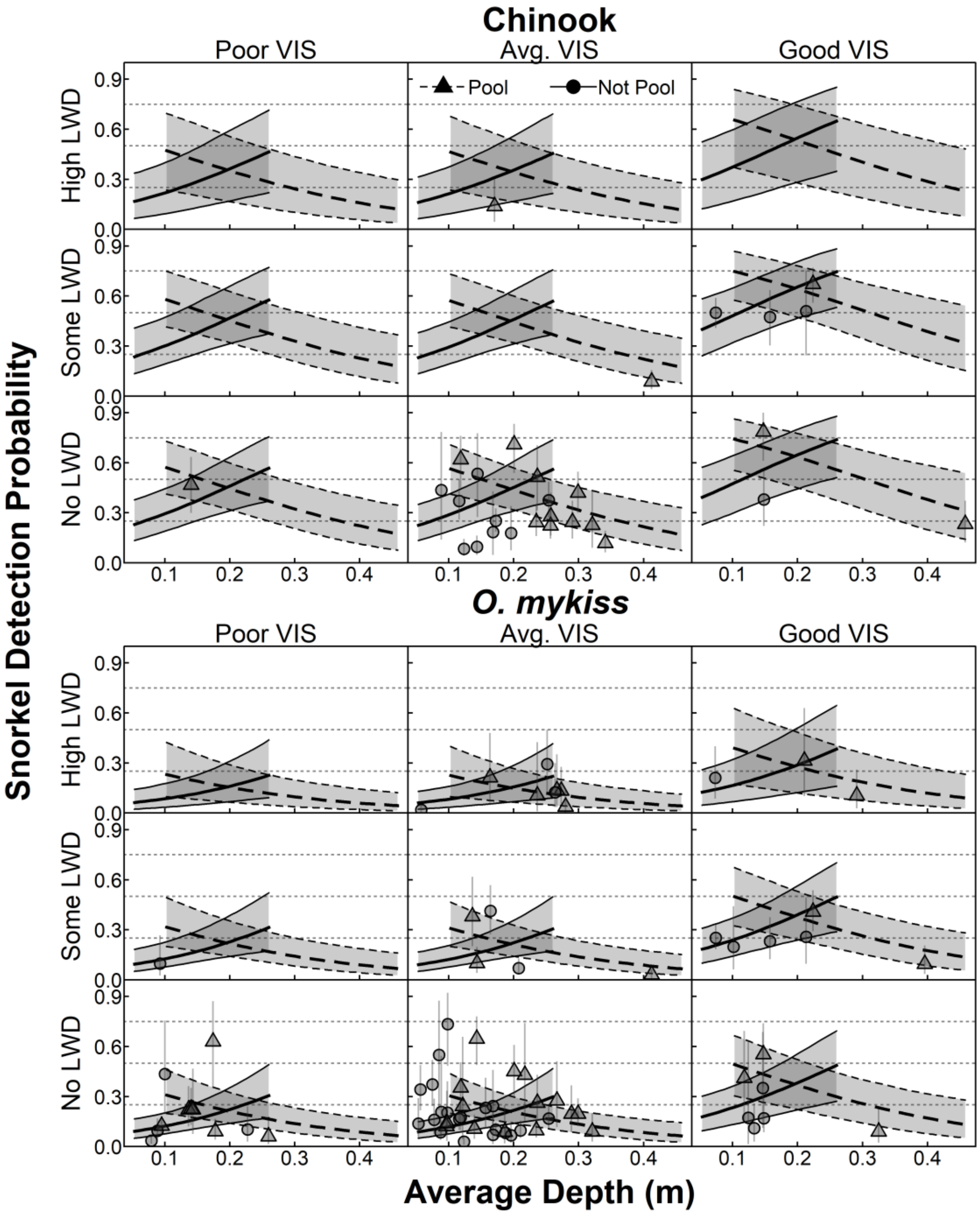

Figure 8. Response of snorkel survey detection probability to average depth and several other covariates for two salmonid species in the Grande Ronde Basin in northeastern Oregon. Each panel shows a unique combination of large wood density (LWD; rows) and snorkeler-determined visibility (VIS; columns) grouped by species (axes extent equal for all panels). Curves and points display the model-averaged posterior median fixed-effect relationship and observation-specific detection probability, respectively, for non-pool (solid lines; circles) and pool units (dashed lines; triangles). Grey bands and error bars denote 95% equal-tailed credible intervals.

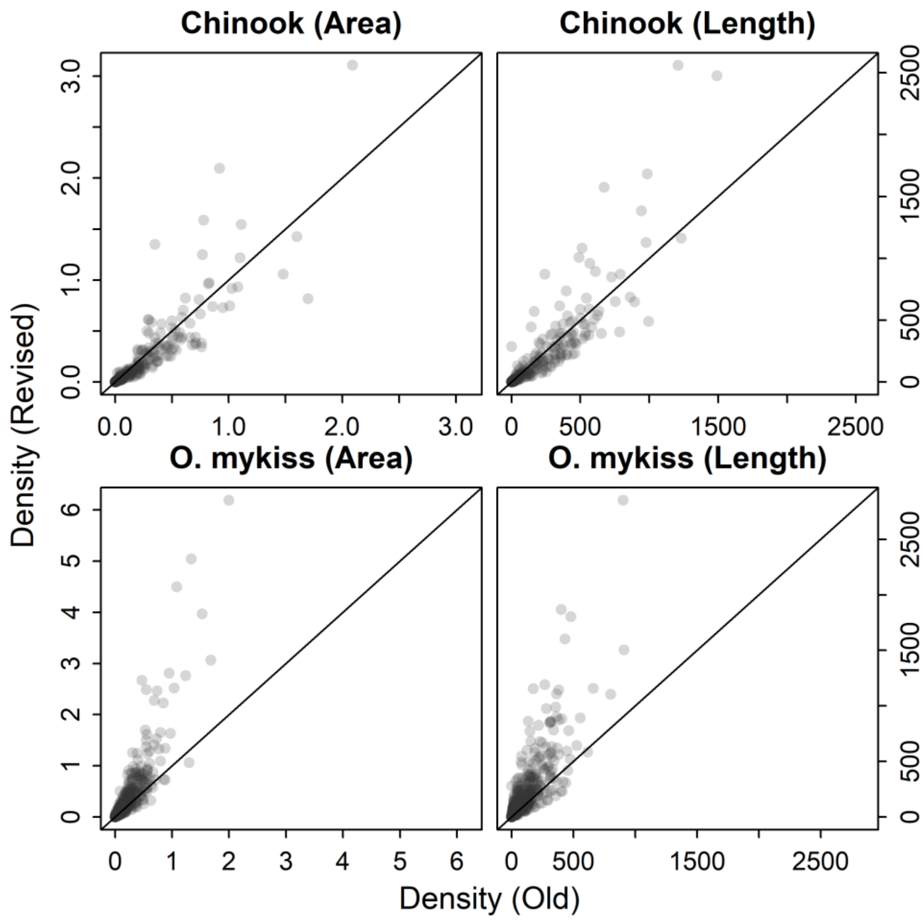

Figure 9. Comparison of site-specific density estimates (corrected for non-snorkeled channel units) obtained via the hierarchical model ("revised" estimates; y-axes) and the log-log regression approach ("old" estimates; x-axes). Diagonal lines represent the 1:1 equality line. Density units are number of fish per square meter for area-based estimates and number of fish per 100 meters of wetted channel for length-based estimates.

Discussion and future directions

We conclude we have developed a modeling framework that adequately addresses the concerns we had with the initial log-log regression approach. Not only is the model more defensible from a statistical standpoint, it is able to quantify important patterns that arise from mechanistic observational processes (e.g., large wood density impedes the view of the snorkeler, depth has opposite effects in pools vs. non-pools, etc.) that will be useful in prediction. For these reasons, we are moving forward to adopt the hierarchical modeling approach for our snorkel program, even though density predictions from it and the log-log approach were generally similar. This finding of similarity is important because it indicates that any previous inferences made from snorkel data corrected using the log-log approach were likely not vastly erroneous and that if we performed the same analyses using the revised estimates we would likely come to a similar conclusion. We are

looking forward to seeing the draft manuscript in Appendix B through to publication, as well as designing future studies directed at obtaining better estimates of detection efficiency through the application of this hierarchical modeling approach.

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2. Riverscape Analyses

2.1 Spatial patterns and drivers of juvenile Chinook Salmon size and growth

Abstract

The size achieved by juvenile salmon in freshwater has important consequences for survival through multiple life stages. However, little is known about the biophysical processes that govern spatial patterns of size within stream networks. In the summer of 2019, we quantified Chinook Salmon (*Oncorhynchus tshawytscha*) parr size in early and late summer at 53 sites in two NE Oregon tributaries and estimated growth rates during this interval. In addition, we combined spawning surveys and annual temperature data to estimate emergence timing as a function of watershed position. To determine how size patterns related to spatial patterns in parr density, we estimated parr density at 59 sites and then predicted densities throughout both basins using statistical stream-network (SSN) models.

Both basins exhibited clear size gradients in July with larger parr downstream and decreasing size with distance upstream. Parr were much larger in Catherine Creek compared to upper Grande Ronde. Estimates of emergence timing indicated that spatiotemporal patterns in emergence contributed to observed spatial patterns in parr size. In both basins, estimated emergence at the farthest downstream site was approximately one month earlier than the farthest upstream site. Between basins, fry emergence in Catherine Creek was approximately one month earlier than in upper Grande Ronde. Summer parr growth rates exhibited the opposite trend as parr size with increasing mass-standardized growth rates with distance upstream in both basins. This resulted in partially reduced parr size gradients in September compared to July. The top-ranked SSN model explained 67% of the variance in parr densities using fixed-effect habitat covariates (wood density, percent pool area, and redd proximity) along with autocovariance functions. Spatial patterns of densities revealed that in upper Grande Ronde, parr were concentrated high in the watershed, where size was smaller, but in Catherine Creek, high parr densities were observed lower in the watershed. Collectively these results suggest that downstream sections evaluated in this study have the potential to promote larger parr, but that the phenology of growth is different; summer growth rates are lower, but earlier emergence and high spring growth rates allowed these parr to achieve large size. Therefore, restoration efforts targeting areas lower in the network may produce larger individuals, potentially increasing survival through freshwater rearing and other life stages. Directly quantifying parr survival rates throughout these networks will provide increased understanding of where restoration efforts may be most impactful in achieving recovery goals.

Introduction

Pacific salmon are some of the most valued species in the Pacific Northwest due to their cultural, subsistence, recreational, and economic importance. However, human activities over the last

century including over-harvest, hydropower operations, and habitat degradation have led to stark declines in returning adult salmon and steelhead within the Columbia River Basin, resulting in the listing of some of these stocks under the Endangered Species Act (Nehlsen et al. 1991). Recovery of these stocks will benefit from studies identifying factors limiting productivity and survival rates. In the freshwater rearing stage, in which management efforts to improve habitat conditions are most often applied, the size achieved by juvenile (parr) salmon is linked with survival rates during summer and winter rearing and emigration (Quinn and Peterson 1996, Zabel and Achord 2004, Ebersole et al. 2006). Parr size, in turn, is related to individual growth rates and duration of growth. Rearing habitats within stream networks reflect a mosaic of biophysical factors affecting growth, yet little is known about spatial patterns in size and growth within stream networks (but see Ebersole et al. 2006). Determining spatial patterns in parr size and the biophysical factors regulating size may assist in directing restoration efforts towards habitats in greatest need of increased parr productivity and survival.

Factors influencing growth and size are expected to vary spatially within a stream network (Figure 10). Perhaps most notably, temperature typically increases with distance downstream in rivers lacking substantial groundwater inputs. Increasing temperatures may yield greater growth rates when food is abundant (Falke et al. 2020), but may reduce growth rates at high temperatures or when prey consumption is low (Beauchamp 2009). Spatial patterns in thermal regimes may also shape emergence timing within a stream network, resulting in gradients of emergence phenology and potential (mis)matches with prey availability. Prey availability may also vary throughout a stream network (Wipfli and Baxter 2010), with studies indicating increasing invertebrate abundance with distance downstream (Li et al. 1994, Tait et al. 1994). However, consumption reflects the availability of prey relative to the demand of inter- and intra-specific competitors. The density of juvenile salmon, as well as species with similar feeding niches, may be related to physical habitat quality and biotic interactions that vary throughout a stream network. Juvenile Chinook Salmon (*Oncorhynchus tshawytscha*) typically prefer deep, slow moving pools and cool temperatures (Everest and Chapman 1972, Richter and Kolmes 2005), but the distribution of juvenile salmon parr is also related to proximity to spawning locations, as movement following emergence is often limited (Einum et al. 2008, Teichert et al. 2011). Sampling at the network scale may elucidate how these factors collectively shape patterns of juvenile salmon size and growth (Fausch et al. 2002).

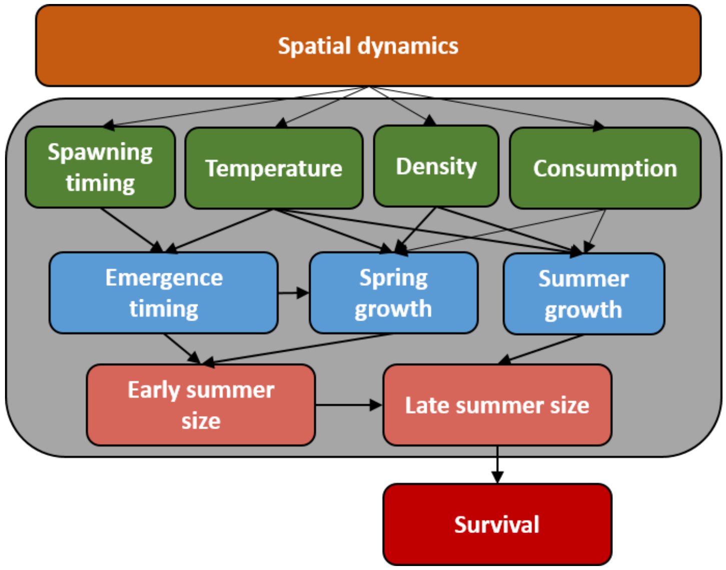

Figure 10. Conceptual diagram of the biophysical factors shaping Chinook Salmon parr size and survival. Direction of arrows indicates direction of hypothesized influence of one factor on another.

In this study, we evaluated Chinook Salmon parr size, growth rates, and density at the network-scale in two NE Oregon tributaries where Spring Chinook Salmon are listed as threatened under the Endangered Species Act. In addition, we estimated emergence timing within each basin to determine whether spatial patterns in emergence existed and shaped spatial patterns in size. Disentangling the complex factors influencing growth and size within a network may provide managers with information to guide restoration efforts yielding greater production and survival. Furthermore, the analysis framework can be applied more broadly to other Columbia River subbasins.

Methods

Study area

The study was conducted in two tributaries of the Grande Ronde River in northeast Oregon: the upper Grande Ronde River (UGR) and Catherine Creek (CC). The Grande Ronde River flows north from its headwaters in the Blue Mountains to its confluence with the Snake River. The UGR subbasin originates in the Blue Mountains and drains 1896 km^2, while the CC subbasin originates in the Wallowa Mountains and drains 1051 km^2. The region is characterized by cold winters in which the majority of precipitation falls as snow, and hot, dry summers with little precipitation. Consequently, annual streamflow is dominated by snowmelt with peak flows occurring in the spring. Flows decrease in early summer resulting in low base flow and warm water temperature during the remaining summer months.

Size and growth

We quantified Chinook Salmon parr size and growth rates at 53 sites in the summer of 2019: 27 sites in CC and 26 sites in UGR. Sites were selected to be spatially distributed throughout core rearing range of Chinook Salmon in each basin and also spanned a wide range in thermal regimes and physical habitat (Figure 11). Each site was sampled in July and then again in September, approximately eight weeks later. Growth during this interval represents summer low-flow growth, which is a critical period in the relatively short time juvenile Chinook Salmon in the Columbia River basin spend in freshwater (~1 year).

We captured parr using snorkel-herding methods in which one or two snorkelers located and then herded parr into a seine net (Tattam et al. 2017). To ensure we were representing parr from various habitats, we captured parr from a length approximately 15x the bankfull width of each site. Captured parr were anesthetized with AQUI-S 20E (AQUI-S, Lower Hutt, New Zealand), measured (fork length; nearest mm), and weighed (nearest 0.1 g). If we captured more than 50 parr, we randomly selected and measured 50 parr to reduce the number of handled fish.

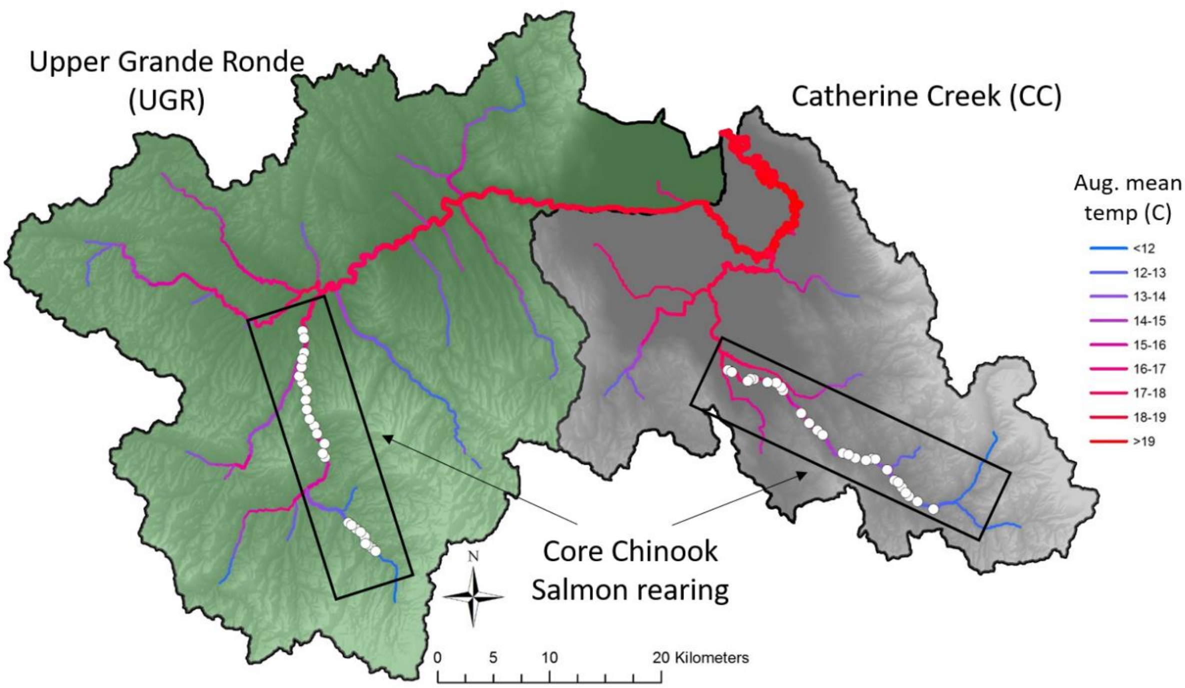

Figure 11. Map of sites sampled for size and growth in the summer of 2019 within the core rearing extent of Chinook Salmon in Catherine Creek (27 sites) and upper Grande Ronde (26 sites). Mean August temperature was derived from the NorWeST stream temperature model for the years 2006-2015 (Isaak et al. 2017).

We used changes in mean size between sampling events to estimate growth rates at each site. To compare growth rates among sites, we needed to account for the effect of size, as growth potential is inherently linked to fish size (i.e., growth potential is higher for smaller fish; Beauchamp 2009). We therefore used mass-standardized growth rates (MSGR), in which growth is scaled as a function of the allometric mass exponent (Ostrovsky 1995), allowing for comparison of growth rates of individuals regardless of their size. MSGR is scaled to the specific growth rate of a 1 g fish and represents the percent growth per day:

Equation 1:

$$MSGR\ (\%/d) = \frac{W_{t1}^{b} - W_{t0}^{b}}{b * d} * 100,$$

where W_{t1} is the mean weight of parr during the second sampling event, W_{t0} is the mean weight of parr during the first sampling event, d is the duration of the growth interval (i.e., number of days), and b is the allometric mass exponent for Chinook Salmon (0.338; Perry et al. 2015). We used bootstrap methods to estimate uncertainty of MSGR for each site. This entailed randomly resampling the weights of individual parr from each site with replacement to obtain different plausible values of W_{t1} and W_{t0} based on our sample, from which we were able to obtain 95% confidence intervals of MSGR.

Quantifying cohort growth rates using changes in mean size is a commonly utilized method, but may be subject to error stemming from size-specific mortality and movement (Einum and Nislow 2005). To evaluate potential bias in cohort growth rates compared to measured individual growth rates, we marked and recaptured individual parr at a subset of sites in coordination with the Oregon Department of Fish and Wildlife (ODFW). In CC, we tagged approximately 1900 Chinook spread over 13 sites and in UGR we tagged 1000 Chinook spread over 8 sites. Chinook Salmon were tagged in late July in CC, but owing to small mean size of parr in UGR and the need to consistently tag parr at the same time as previous years (as per ODFW protocol), tagging in UGR did not occur until late August. Parr > 55 mm were injected with a 12 mm passive-integrated transponder (PIT) tag. We calculated cohort growth rates (e.g. using changes in mean size) and individual growth rates (e.g. PIT-tagged recaptures) from tagging until late September to validate that the cohort method appropriately characterized growth rates.

Emergence timing analysis

We estimated Chinook Salmon fry emergence at four locations within each subbasin (Figure 12). These sites were selected to represent the geographic range of sites sampled for size and growth in summer 2019 and were within the known range of Chinook Salmon spawning distributions. In addition, these sites had temperature data from the onset of spawning in August of 2018 through the summer of 2019.

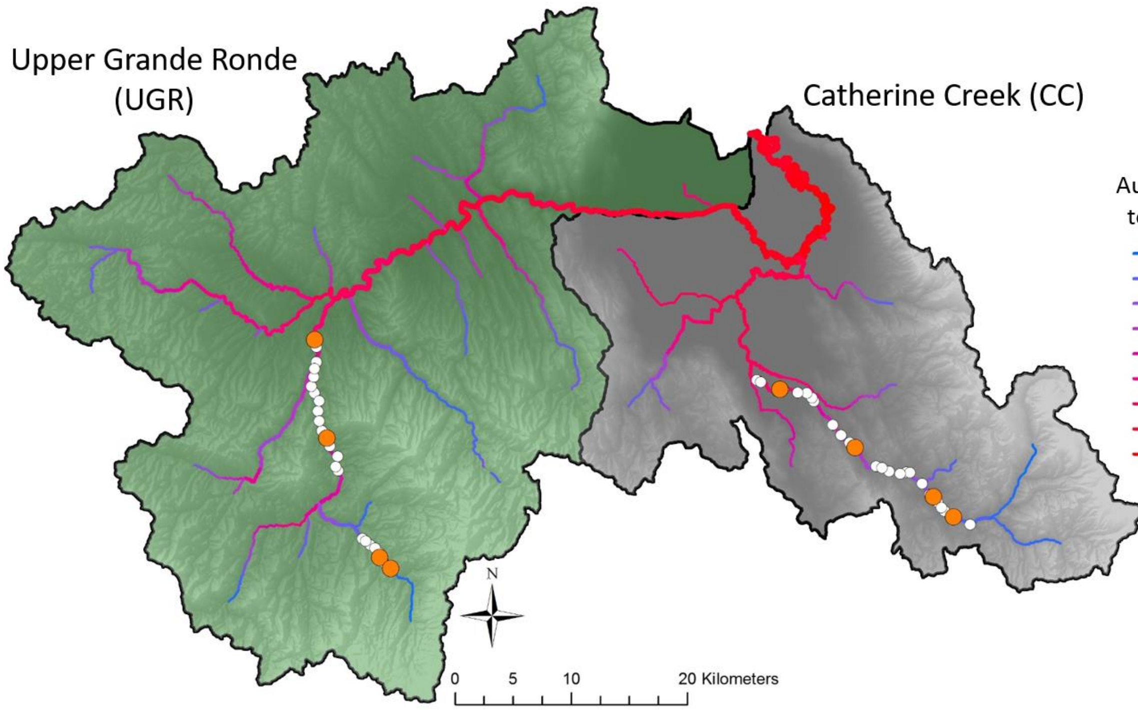

Figure 12. Locations of sites where Chinook Salmon emergence timing was estimated (orange circles) within the distribution of sites sampled from size and growth (open circles).

Emergence timing was modeled as a function of spawning date, accumulated thermal units (ATUs), and mean incubation temperature (Beacham and Murray 1990). Spawning date ranges from 2018 were obtained from redd surveys conducted by ODFW. Weekly redd surveys were conducted throughout each basin and the date and spatial location of each new redd was recorded. For each site, we used a spawning window based on the observed timing of new redds near that site to account for temporal variation in spawning. For each successive day from the initial spawning date, we calculated ATUs and mean temperature to that day. We used the following equation (equation 4 in Beacham and Murray 1990) to determine when ATUs exceeded the threshold required for emergence given a mean incubation temperature:

Equation 2

$$ATUs\ at\ emergence = T * \ e^{10.404+(-2.042*(\ln(T+7.575)))}$$

where T is the mean temperature from spawning to that date. When ATUs exceeded those based on this equation, we assumed the onset of emergence (Beacham and Murray 1990). We calculated this for the range of observed spawning dates to obtain a reasonable emergence window representing variability in spawn timing.

We used the estimated dates of emergence to further estimate spring MSGR from emergence to the first sampling event in July. We assumed that Chinook Salmon fry size at emergence was 0.5

g (Beacham and Murray 1990). Lastly, we estimated consumption rates as a proportion of the theoretical consumption rates that would yield maximum growth given the thermal regime (i.e., a bioenergetic p-value). The resulting p-value can be used to infer the degree of food limitation among sites and during different time periods. Using size at emergence, size at the first capture event, and temperature over this interval, we used the Wisconsin Bioenergetics Model (Hanson et al. 1997) to estimate p. We estimated p during spring and summer for each site where emergence was estimated.

Snorkel and habitat surveys

We conducted coupled snorkel and habitat surveys at 59 sites to develop relationships between habitat attributes and Chinook Salmon density, and then predict densities at the network scale using these relationships. In addition, we expected density to explain variation in growth rates due to density-dependent influences on prey consumption (Figure 10). Sites were selected prior to summer sampling to encompass the geographic extent of Chinook Salmon parr rearing and to encompass a wide range in temperature and habitat attributes. Although site selection was not random, spatial stream-network (SSN) models were used to analyze data (see below) and the assumption of independence among sites is relaxed due to modeling of autocorrelation among sites (Isaak et al. 2014).

At each site, the length of snorkel surveys was approximately 15 times the bankfull width of that site. The reach was delineated into habitat units based on geomorphic distinctions (e.g., pools, riffles, runs). Depending on the width of the stream and habitat unit, one or two snorkelers were used. For each unit, we progressively worked upstream and counted all salmonids by species. When two snorkelers were used, we communicated to reduce double counting. All pools and runs were snorkeled. Because Chinook Salmon parr typically exhibit lower densities in riffles, we sampled every other riffle. When a site was dominated by riffle habitat, we sampled at least 50% of this habitat. We summed the amount of riffle habitat snorkeled and the total amount of riffle habitat and then extrapolated counts based on the percentage of riffle area snorkeled. After a habitat unit was snorkeled, habitat characteristics were measured. For each unit, we measured length (parallel to flowing water) and width at 3 transects located at approximately 25%, 50%, and 75% of the unit length. At each transect we additionally measured depth (nearest 0.1 m) at 5 locations. The number of wood pieces greater than 3.0 m in length and 15 cm in diameter that were within the bankfull channel of each unit were visually estimated.

To estimate parr densities from snorkel counts, we applied a correction for partial detection that was specific to the habitat conditions present at each snorkeling event, as informed by a Bayesian hierarchical model fitted to paired mark-recapture and snorkel data (Appendix B; Jonasson et al. 2016).

SSN modeling of Chinook Salmon Density

We used spatial stream-network (SSN) models to evaluate relationships between habitat covariates and parr density and to predict densities at unsampled locations throughout the Chinook Salmon rearing extent of CC and UGR. SSN models incorporate spatial autocorrelation among sites, and when sites are non-independent – typical of stream networks – SSN models improve parameter estimation and prediction at unsampled locations (Isaak et al. 2014).

SSN models have been previously applied to fish density data (Isaak et al. 2017a), but our analysis takes a more mechanistic approach to predicting fish densities using habitat covariates. Covariates used to predict the response variable need to be available at sampled and unsampled sites throughout a stream network. Because of these large spatial scales and the logistic constraints of obtaining empirical covariates for each unsampled location, geospatially-derived fixed-effect covariates (e.g. watershed area, elevation, stream order) are commonly used in SSN models. These models may still be accurate in predicting the response variable at unsampled locations due to incorporation of autocorrelation, but inference into the mechanisms driving spatial relationships is often lost (e.g., habitat relationships). We were able to maintain mechanistic covariates using continuously measured habitat at the network scale from the ODFW Aquatic Inventories (AQI) Project (Moore et al. 2017). Methodology for AQI habitat measurements is comparable to our 2019 habitat sampling.

AQI surveys of the mainstems of CC and UGR were conducted at multiple time periods starting in the 1990s. For each stream section, we used the most recent survey data (2010 for the mainstem CC; 2018 for the North and South Fork CC; 2015 for UGR) as this best represents current habitat. Some stream sections were not sampled in the most recent round of AQI surveys due to changes in access and ongoing restoration projects. Data collected in 1991 was used for the unsampled area of UGR, as this was the only data available. Land-use practices of this area have not changed over this time interval and no restoration has occurred. In the unsampled area of CC, extensive restoration projects have been implemented since the last AQI surveys, and these data no longer represent current habitat. We therefore used the average habitat metrics measured in 2019 from four sites within this section to fill in unsampled locations in which similar restoration occurred.

In order to predict parr densities at unsampled locations, we needed to first delineate prediction sites that matched the length and habitat covariates of sites sampled in 2019. We combined 100 m segments from the NetMap stream layer (Benda et al. 2007) to create segments that were approximately 15 times the bankfull width (i.e., prediction segment lengths increased with distance downstream). These longer sections reduce the influence of single habitat units and better represent the habitat characteristics of a given stream section. We then overlaid these segments and the AQI habitat unit layer in ArcGIS (v 10.7.1). The AQI data represents individual habitat units. For each segment, we quantified the proportion of each AQI habitat unit within a segment. For example, if a pool was entirely within a single segment, it would have proportion of 1; if 60% of a long riffle unit length was in one segment and 40% was in another, it would have a proportion of 0.6 and 0.4

in each segment, respectively. For each segment, we then calculated habitat metrics including percent pool area, number of pools per 100 m, number of wood pieces per 100 m, and gradient.

Prior to SSN model formation, spatial data were formatted and processed using the STARs package (v 2.0.7; Peterson and Ver Hoef 2014) in ArcGIS. Each observation (i.e., sites sampled in 2019) and prediction segment was converted to a point feature. The observation and prediction point layers were snapped to a National Stream Internet (NSI) layer (https://www.fs.fed.us/rm/boise/AWAE/projects/NationalStreamInternet/NSI_network.html), which has already been preconditioned so that all stream segments are flow-oriented towards a single drainage point. Spatial processing to produce an SSN object followed procedures outlined in Ver Hoef et al. (2014).

We used the following approach to fit models and select the best approximating model structure predicting Chinook Salmon parr densities. First, we narrowed a list of potential fixed-effect covariates based on relationships between single factors and the response variable, and from previous studies in these basins that found support for habitat variables explaining Chinook Salmon densities (Justice et al. 2017, White et al. 2018). This narrowed list included four fixed-effect covariates (Table 3): redd counts within 2 km upstream of a site from the previous year (2018); number of wood pieces per 100 m, percent pool area within a reach, and mean August temperature from the NorWeST temperature model (Isaak et al. 2017b). In addition, to account for a potential non-linear relationship between temperature and density (Isaak and Hubert 2004), we added August temperature squared as a quadratic term. We fitted a global model with these four fixed-effects with all three covariance structures (tail-up, tail-down, and Euclidian) separately. Model residuals indicated heteroscedasticity and several observations with high leverage which was corrected when we applied a square-root transformation. Next, we formulated a set of models with the same fixed-effect covariates but all combinations of covariance structures to determine the best covariance structure given the data. Euclidian covariance alone was the best approximating model, as assessed using AIC (Burnham and Anderson 2004). We then formulated a set of candidate models with all combinations of fixed-effect covariates and EU covariance structure (15 total models). The model with the lowest AIC was selected to predict parr densities at unsampled locations.

Table 3. Habitat covariates used to predict Chinook Salmon parr density.

Variable	Source	Description
Redd count	2018 ODFW surveys	Number of redds within 2 km upstream of each segment (see Justice et al. 2017)
Wood count	2019 habitat surveys and AQI habitat surveys	Number of pieces of wood (> 3.0 m in length and 15 cm in diameter) per 100 m for each stream segment
Percent pool area	2019 habitat surveys and AQI habitat surveys	Sum of pool habitat area within a segment divided by total habitat area of all units, multiplied by 100.
August mean temperature	NorWeST stream temperature model	Mean August temperature for the years 2006-2015, derived from the NorWeST stream temperature model (Isaak et al. 2017)

Results

Size and growth

Chinook Salmon parr exhibited clear size gradients in each basin, with larger parr downstream and decreasing size with distance upstream (Figure 13). In July, parr at the five farthest downstream sites in CC were on average 2.4 times larger by weight (6.5 g) compared to parr at the five farthest upstream sites (2.4 g). For every increase in kilometer upstream, mean weight decreased by 0.19 g (0.16 - 0.22 g; $R^2 = 0.85$; $p < 0.001$). Similarly, in UGR, parr at the five farthest downstream sites were 3.0 times larger (2.8 g) than parr at the five farthest upstream sites (0.9 g), and mean weight decreased by 0.07 g for every increase in kilometer upstream (0.05-0.08 g; $R^2 = 0.83$; $p < 0.001$). CC parr were substantially larger than UGR parr in July when comparing sites with similar summer temperatures (August mean temperature).

By September, spatial patterns in CC were less apparent than in July. Parr downstream of river km 30 were larger (mean weight = 8.7 g) than parr upstream of river km 30 (mean weight = 6.1 g), but upstream of this point, size no longer decreased with upstream distance ($n = 18$; $R^2 = 0.02$; $p = 0.55$; Figure 13). In UGR, parr continued to exhibit decreasing size with distance upstream in September, with an estimated decrease in mean weight of 0.07 g for every kilometer upstream (0.05 – 0.09 g; $R^2 = 0.73$; $p < 0.001$). At the conclusion of the study, parr at the five farthest downstream sites in UGR were on average 4.6 g compared to 3.0 at the five farthest upstream sites.

Mass-standardized growth rates increased with distance upstream in both basins; however this relationship was stronger in CC (Figure 14). In CC, the linear relationship between upstream distance and MSGR was significant with an estimated increase in MSGR of 0.07 for every km upstream (0.052 – 0.088; $R^2 = 0.70$, $p < 0.001$). This relationship was also significant in UGR, but less variance was explained by distance upstream and the effect was lower with an estimated increase in MSGR of 0.026 for every km (0.008 – 0.044; $R^2 = 0.24$, $p = 0.007$). Because

temperature and river kilometer were highly correlated in each basin (R^2_{CC} = 0.98; R^2_{UGR} = 0.91), temperature was significantly negatively correlated with MSGR in CC (R^2 = 0.68; p < 0.001) and UGR (R^2 = 0.14; p = 0.035). In contrast to our expectations, parr density (log-transformed) explained little variation in MSGR and the relationships were not significant in CC (R^2 = 0.01, p = 0.32) or UGR (R^2 = 0.03, p = 0.21).

We found strong evidence for a positive relationship between cohort growth rates (using changes in mean size) and empirically derived individual growth rates from PIT-tagged parr with a slope near 1 (R^2 = 0.74, slope = 0.88; p < 0.001), indicating that cohort growth rates are an accurate method to characterize growth.

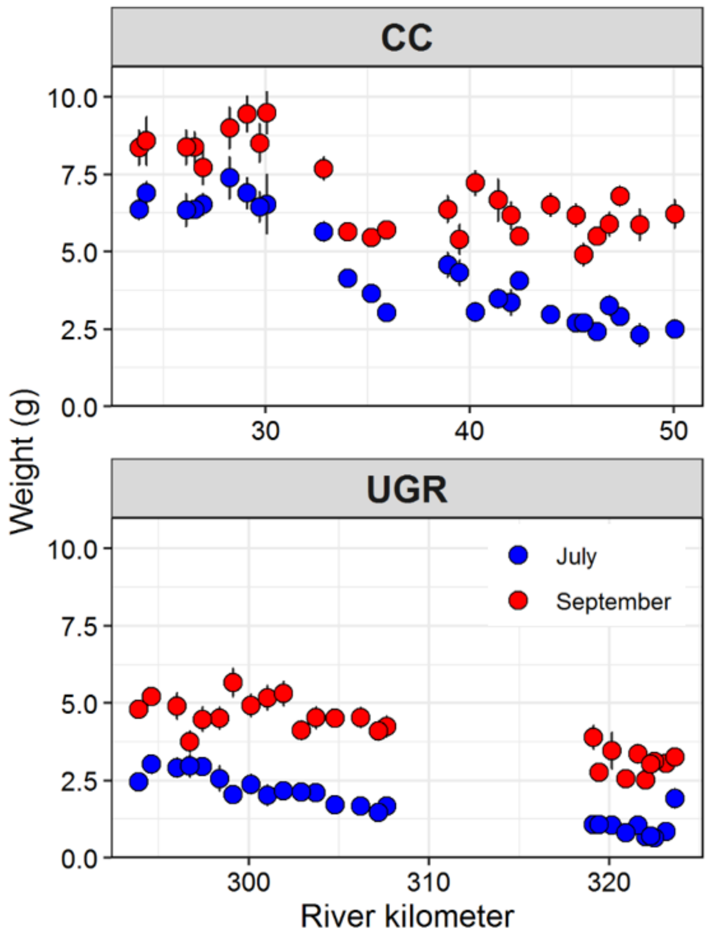

Figure 13. Mean weight and 95% confidence intervals of Chinook Salmon parr in July (blue circles) and September (red circles) in Catherine Creek (CC) and upper Grande Ronde (UGR). The large gap in sampling in UGR represents an inaccessible private property.

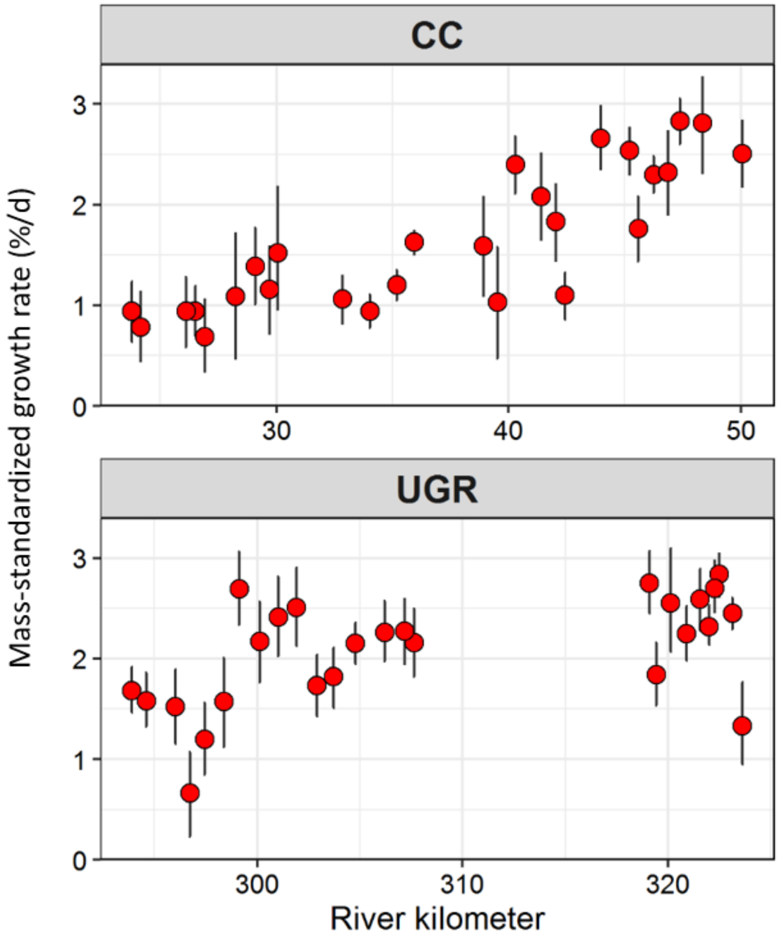

Figure 14. Summer mass-standardized growth rates (MSGR; %/d) of Chinook Salmon parr in Catherine Creek (CC) and upper Grande Ronde (UGR).

Emergence timing

Emergence timing varied with spatial position in both networks, even after accounting for later spawning in downstream sections of the network (Figure 15). In CC, emergence at the farthest downstream site (RKM 27) was expected to occur from late March to early May, whereas emergence at the farthest upstream site (RKM 49) was between early May and early June. Similarly, in UGR, emergence at the farthest downstream site (RKM 294) was estimated to be between early and late May, but between late May and late June at the farthest upstream site (RKM 324). This also reveals differences in emergence between basins, with estimated emergence being approximately one month earlier in CC compared to UGR.

MSGR was higher in spring compared to summer at downstream sites in each basin, but the difference between spring and summer MSGR decreased with distance upstream (Table 4). For

example, at the farthest downstream site in CC, growth rates were estimated to be 3-4.5 times greater in spring than in summer, but at the farthest upstream site, spring and summer growth rates were similar – a pattern that was also apparent in UGR. In contrast, bioenergetics p-values (the proportion of consumption that would yield theoretical maximum growth rate given the thermal regime) were consistently greater in spring compared to summer at all sites. Spring p-values in CC were higher (0.81 – 1.0) compared to UGR (0.63-0.81), but this was not the case for summer. We did not calculate spring growth rates and p-values for the farthest upstream site in UGR, as fry were very small in July indicating recent emergence.

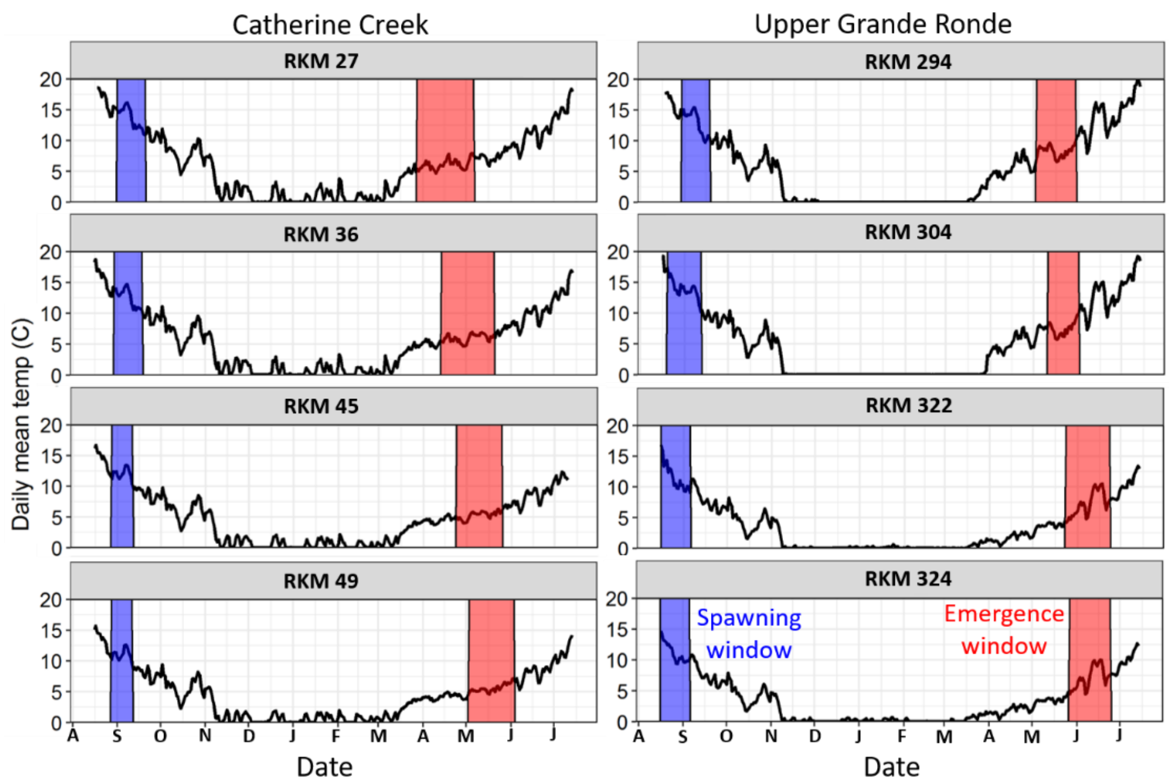

Figure 15. Estimated Chinook Salmon fry emergence timing (red bar) at four locations in Catherine Creek and upper Grande Ronde. The spawn date range (blue) was based on observed redds during 2018 surveys. The black line represents mean daily temperature over this period.

Table 4. Estimated emergence windows, spring and summer growth rates, and spring and summer p-values for four sites in CC and UGR.

Basin	River km	Emergence timing	Spring growth rate	Spring p-value	Summer growth rate	Summer p-value
CC	27	3/28-5/6	3.0-4.5	0.94-1.0	1.0	0.40
CC	36	4/14-5/20	2.3-3.5	0.81-0.84	1.0	0.36
CC	45	4/24-5/25	2.2-3.4	0.90-0.92	1.7	0.42
CC	49	5/3-6/3	2.1-3.3	0.85-0.88	2.8	0.55
UGR	294	5/3-5/30	2.8-4.5	0.70-0.81	1.7	0.44
UGR	304	5/11-6/1	2.8-4.2	0.70-0.74	1.8	0.44
UGR	322	5/24-6/23	1.0-2.7	0.63-0.81	2.3	0.49
UGR	324	5/27-6/24	NA	NA	1.3	0.43

Density

The best approximating model (lowest AIC) predicting Chinook Salmon parr density included wood density, redd count, and percent pool habitat as fixed effects with Euclidian autocovariance structure. Each of the fixed-effect covariates were significant (Table 5). Leave-one-out cross validation (LOOCV) indicated that this model explained 67% of the variation in parr density (Figure 16). The next best approximating model (ΔAICc = 2.03) included just percent pool habitat and redd count (Table 5). The third ranked model (ΔAICc = 2.59) included wood density, redd count, percent pool habitat, August temperature and August temperature squared.

Predicted density exhibited different spatial patterns in CC and UGR (Figure 17). In UGR, the highest densities were in the upper portion of the watershed, with 55% of total abundance concentrated in the upper 10 km of the 41 km in which densities were estimated. In CC, the highest observed and predicted densities were in middle sections of the stream, whereas the farthest upstream sections exhibited low densities. Prediction error increased with distance from sites sampled in 2019. This is especially apparent between river kilometer 307-318 in UGR in which we were not able to sample due a large tract of private land.

Table 5. Summary of top three models predicting Chinook Salmon parr density (fish/100 m). RMSPE indicates root mean-squared prediction error; LOOCV R^2 indicates the leave-one-out cross validation relationship between observed and model-predicted densities; and variance composition indicates the proportion of the explained variation by fixed-effects, spatial autocovariance functions, and the independent nugget component.

						Variance composition		
Model rank	ΔAIC	Fixed-effects	Fixed-effect *p*-value	RMSPE	LOOCV R^2	Fixed-effects	Spatial Autocorrelation	nugget
1	0	Redd count	0.005	4.942	0.67	0.51	0.37	0.12
		Wood count	0.023					
		Percent pool	<0.001					
2	2.03	Redd count	0.009	4.786	0.68	0.48	0.44	0.08
		Percent pool	<0.001					
3	2.59	Redd count	0.032	4.868	0.68	0.54	0.35	0.11
		Wood count	0.055					
		Percent pool	<0.001					
		Aug. temp	0.141					
		Aug. temp^2	0.155					

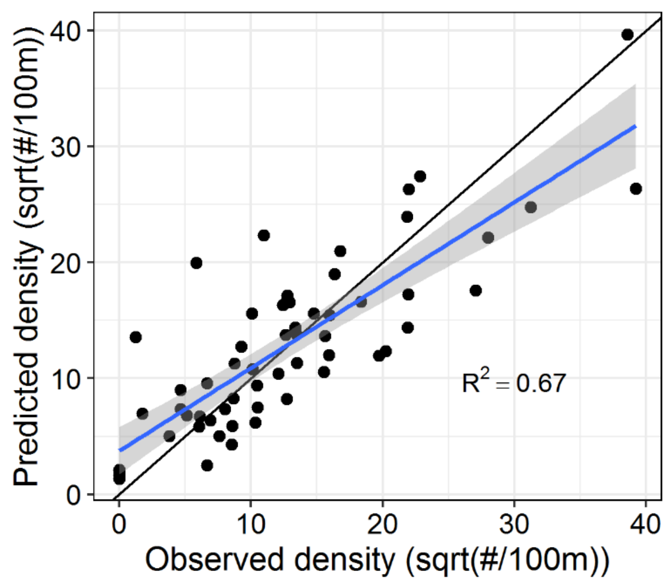

Figure 16. Relationship between observed parr densities and predicted parr densities through leave-one-out cross validation for the top ranked model. The solid black line represents a 1:1 relationship and the blue line is the fitted linear relationship.

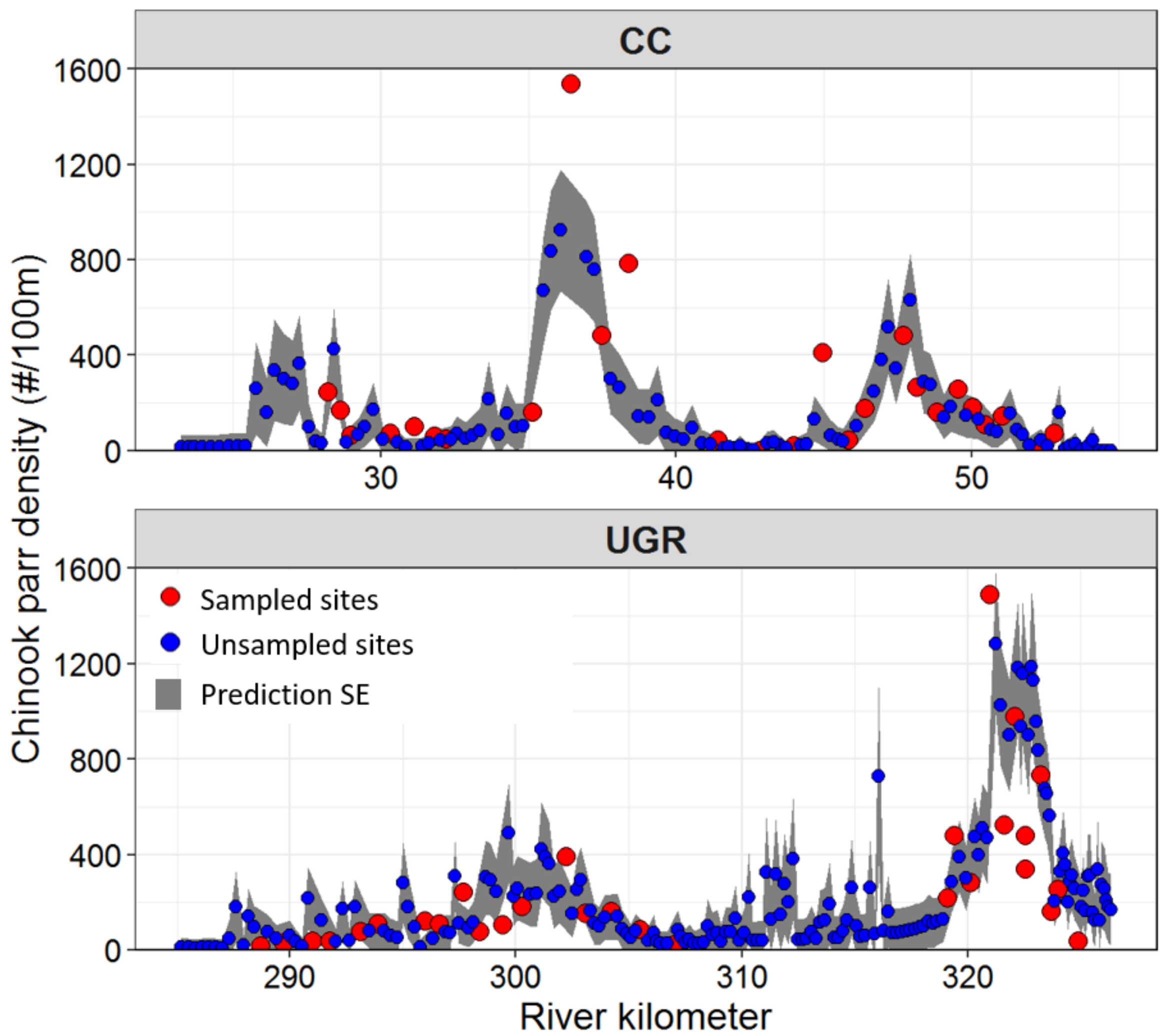

Figure 17. Observed (red circles) and predicted (blue circles) parr densities throughout CC (upper) and UGR (lower). The size of points for unsampled locations reflects the prediction standard error.

Discussion

Determining overall growth rates, abundance, and survival of a population is critical to understanding population dynamics and effectiveness of management efforts aimed at improving population viability. Moreover, understanding spatial patterns within a population and the processes that drive them may help target areas where restoration efforts can maximize population productivity. Our analysis of Chinook Salmon parr size, growth, and density at the network scale indicated clear spatial patterns within each network. Further, by quantifying factors expected to influence these metrics, we were able to provide insight into the biophysical processes regulating size, growth, and density within these stream networks.

A key finding from this study was the importance of emergence timing in shaping spatial patterns in Chinook Salmon parr within and among the two basins. In both CC and UGR, fry were estimated to emerge approximately a month earlier at the farthest downstream site compared to the farthest upstream site. These differences in emergence phenology clearly contributed to observed size gradients, with larger parr downstream and decreasing size with distance upstream. In addition, CC fry were estimated to emerge approximately one month earlier than UGR fry for a given position in the watershed, which likely explains why parr were larger in CC in July. It has been hypothesized that the timing of spawning has evolved to promote emergence during optimal conditions for growth and survival (Einum and Fleming 2000). Early emergence may lead to reduced growth and survival due to lack of prey and harsh environmental conditions, while late emergence may result in reduced growth and survival due to a shorter growing interval and potentially missed optimal foraging opportunities (Einum and Fleming 2000, Crozier et al. 2008). In Alaskan streams with contrasting thermal regimes (groundwater versus surface flow dominated), Coho Salmon (*O. kisutch*) spawned at different times among streams but emergence timing was synchronized, potentially to coincide with peak prey availability and growth potential (Campbell et al. 2019). In our streams, the timing of spawning varied as a function of watershed position, with later spawning occurring at locations farther downstream in the network; however, estimated emergence was not synchronized. One hypothesis is that in CC and UGR, optimal conditions to emerge may vary temporally as a function of watershed position. Downstream sites were consistently warmer than upstream sites in spring and earlier summer, potentially providing favorable growth conditions earlier. The phenology of invertebrate production and drift may also exhibit spatiotemporal patterns with peaks in prey availability occurring earlier downstream. Alternatively, environmental conditions such as summer water temperature may control when adults are able to spawn within a network, such that emergence timing reflects controls on spawn timing rather than evolutionary selection for optimal emergence timing (Beer and Anderson 2001).

Earlier emerging fry not only had a longer growth interval, but also exhibited higher spring growth rates compared to summer. This is especially apparent in CC, where growth rates at the farthest downstream site were 3-4.5 times greater in spring compared to summer. This highlights the importance of considering growth during seasons other than summer. Had we only evaluated growth rates in summer, we would have concluded these habitats were suboptimal; however, parr lower in the watershed exhibited growth near theoretical maximums during spring, while individuals farther upstream had not emerged yet due to effects of colder temperatures on incubation duration. Thus, tradeoffs may exist where sections of the stream network that are warmer in summer provide suboptimal conditions for summer growth but more optimal conditions in other seasons, thereby providing important habitats for juvenile salmon productivity at the population scale.

Contrary to our expectations, the density of parr at each site explained almost no variation in summer growth rates. This contrasts with a number of studies finding a negative effect of density on growth (Grant and Imre 2005, Lobon-Cervia 2007). Many of these studies focus on smaller

spatial scales but with greater temporal replication encompassing multiple years. Sites in our study covered approximately 30 kilometers of mainstem habitat in each subbasin, and biophysical factors scaling with watershed position may have been more important in shaping spatial patterns in growth at these scales. In addition, emergence-driven size gradients existed in both basins, and density-dependent effects on growth can be stronger for smaller, younger fish (Baerum et al. 2013). Smaller fish may also exhibit compensatory growth, potentially contributing to higher growth rates with distance upstream (Baerum et al. 2013). Spatial variation in parr size, temperature, habitat, and other biophysical factors may have dampened effects of density-dependence on growth at these spatial scales. In addition, the number of spawners in 2018 was among the lowest recorded in each basin and low densities of parr in 2019 may have weakened our ability to detect density-dependent effects on growth. Repeating this study over multiple years with varying parr densities may reveal different effects of density on summer growth rates.

Spatial patterns of parr density differed between the two basins. In UGR, parr were concentrated in the upper portions of the watershed, where mean size was lowest. In contrast, parr density in the upper portions of CC was low, with a greater proportion of parr in the mid-sections. We believe these spatial patterns are largely driven by differences in longitudinal habitat profiles of the two basins. In CC, the upper portions are high gradient with little pool habitat, whereas the mid and lower sections are generally characterized by low gradient habitat with abundant, deep pools. In UGR, the upper portions are low-gradient with abundant pool habitat but the mid and lower sections generally have few pools. Habitat may also influence parr distributions through controls on adult spawning locations (Einum et al. 2008). Spatial patterns of redds generally reflected spatial patterns of parr density, and redds within two kilometers of a site was an important predictor of parr density. Therefore, observed densities may reflect habitat controls on adult spawning locations and rearing habitat quality. The number of redds in 2018 was very low compared to other years, and spatial patterns may differ in years with higher abundance. For example, the spatial distribution of juvenile salmon may contract to core areas in years of low adult spawning abundance, and expand when the number of spawners is greater (Flitcroft et al. 2014). Exploring interannual patterns in parr distribution may reveal core rearing areas and the habitat characteristics of these areas to aid in the prioritization of restoration actions.

Conclusions

The size achieved by juvenile salmon has important implications for survival through multiple life stages (Quinn and Peterson 1996, Zabel and Achord 2004, Ebersole et al. 2006, Connor and Tiffan 2012). Our results indicate that downstream portions of the network provided growth opportunities leading to larger parr compared to sites farther upstream. Summer growth rates at these downstream sections were lower compared to upstream sites and the large size these individuals achieved is attributed to earlier emergence and high spring growth rates. Thus, these habitats may be important to the overall production of parr in these basins, but the phenology of growth opportunities differs as a function of watershed position. In addition to effects of emergence timing

on size, variability in emergence timing may be an important aspect of population stability (Schindler et al. 2010). For example, in some years earlier emergence may be more favorable as it provides increased growth opportunities (Einum et al. 2008), while in other years, earlier emergence may result in reduced survival due to harsh environmental conditions (e.g. high flows). In this regard, focusing habitat restoration efforts on spreading the distribution of parr throughout potential rearing habitat may be effective in achieving long-term parr productivity.

Next steps

There are still several steps we need to take to finish analyzing data from this study. First, we will produce an SSN model predicting growth rates using factors such as parr density, temperature, and pool habitat, along with autocovariance functions. Accounting for non-independence of sites and other factors may result in different relationships between growth rates and density than those in this report. Second, we will determine whether parr size and position in the stream network influence emigration timing, emigration size, and survival. PIT-tagged parr captured at screw traps or detected at PIT-tag arrays within these basins and at Lower Granite Dam on the Snake River will be used for this analysis. We expect all 2019 tagged parr to emigrate out of the subbasins by early June 2020, and at that point, we will begin our analyses. At the conclusion of these analyses, we will submit the manuscript to a peer-reviewed journal.

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2.2 Indicators of food availability for Columbia basin salmonids using broadly available data

Summary

Many tribal, state, and federal programs routinely collect benthic macroinvertebrates (BMIs) as indicators of overall river health and water quality. These data have been under-utilized for describing the condition and resiliency of the food base for salmonids. Since 2015, the Columbia River Inter-Tribal Fish Commission (CRITFC) has been translating routinely collected aquatic macroinvertebrate data into metrics relevant to salmon food webs and aquatic ecosystems affected by habitat degradation, land use, and a changing climate. Objectives of this project are to 1) identify ongoing tribal field collection efforts of aquatic macroinvertebrates in salmon-bearing tributaries of the Columbia River basin; 2) coordinate field and laboratory procedures among participating tribal programs so that BMI, drift invertebrate, and fish diet data can be evaluated using common data standards and analytical procedures; 3) use the above data to refine and extend existing food availability and food web metrics developed previously by CRITFC; and 4) provide a statistical analysis framework relating food web metrics to climate-related variables as the basis for prioritizing climate change mitigation strategies in targeted areas. The following report documents progress made in 2019 relating alternative food availability metrics to fish abundance, diet, growth, and productivity.

Introduction

Aquatic macroinvertebrate communities are important ecological components of river ecosystems, provide a reliable index of river health, have intrinsic value, and support aquatic consumers including fish. However, they are experiencing unprecedented decline due to a variety of anthropogenic stressors including climate change (Domisch et al. 2011). Much of the science behind river basin management has focused on physical habitat conditions without an explicit link to biological interactions and food webs, which have been gaining evidence as vital components in river ecosystem management (White et al. 2014; Bellmore et al. 2017). Many regional fish habitat programs—including CRITFC and some of its member tribes—collect BMIs as part of ongoing fish habitat monitoring (Table 6), yet assessments of stream and river health are typically limited to biotic indices and multi-metric approaches (Li et al. 2010). Aquatic macroinvertebrates collected using standard protocols can be translated into indices relevant to the state of aquatic food webs including fish (Sullivan and White 2017). These food web metrics, based on invertebrate life history characteristics (Rader 1997; Esteban and Marchetti 2004) and descriptors of ecological network properties (Cohen et al. 2003; Gray et al. 2014), can shed light on how changes to invertebrate communities may impact river ecosystems and threatened salmon populations we are seeking to recover.

In this report, we summarize recent progress on (1) developing and validating alternative metrics from BMI data, (2) exploring relationships between alternative metrics and intrinsic watershed variables, land use, climate, and habitat variables, and (3) a preliminary analysis evaluating whether alternative metrics are indicative of fish distribution, diet, growth, and production.

Table 6. Macroinvertebrate protocols for selected fish-habitat programs in the Pacific Northwest.

Program	Abbreviation	Targeted riffle	Reach-wide	Multi-habitat	Drift
USFS-BLM Aquatic and Riparian Effectiveness Monitoring Program	AREMP	X			
California Department of Fish and Game	CDFG	X			
EPA Environmental Monitoring Assessment Program	EMAP	X	X		
National Aquatic Resource Surveys (developed from EMAP)	NARS		X		
Northwest Indian Fisheries Commission	NIFC				
Oregon Dept. Fish & Wildlife Aquatic Inventories Project	ODFW				
USFS-BLM Biological Opinion Effectiveness Monitoring Program	PIBO	X			
Upper Columbia Monitoring Strategy	UC	X			
Columbia Habitat Monitoring Program	CHaMP				X
BPA Action Effectiveness Monitoring	AEM	X		X	
BLM AIM-National Aquatic Monitoring Framework	AIM-NAMF	X	X		
USGS National Water-Quality Assessment	NAWQA	X			
Status and Trends Monitoring for Watershed Health and Salmon Recovery	WA	X			
Oregon Department of Environmental Quality	ODEQ	X			

Methods

Field and laboratory data collection

Aquatic macroinvertebrate, habitat, and fish distribution surveys were conducted by crews from CRITFC and Oregon Department of Fish and Wildlife (ODFW) at 162 sites in the upper Grande Ronde River, Catherine Creek, and Minam River of NE Oregon between 2011 and 2017 using a spatially balanced random survey design (Stevens and Olsen 2004). A portion of sites were surveyed every year while others were surveyed every three years, resulting in a total sample size of 471 surveys.

Using a standard regional protocol for targeted riffle samples (Hayslip 2007), BMI samples were obtained using either a D-framed kick net or a Hess sampler. Eight 1 ft^2 samples distributed in riffles throughout the reach were disturbed to dislodge benthic organisms from the substrate and combined to create one composite sample totaling 8 ft^2 (0.74 m^2) per site. Samples were filtered through a 500 μm sieve, preserved in 95% ethanol, and delivered to the lab for subsampling and taxonomic analysis. In addition to a multitude of standard indices typically derived from BMI data, we calculated novel metrics including descriptive indices of ecological networks (Cohen et al. 2003) and availability to food for salmonids based on life history characteristics, propensity to enter the water column, palatability to salmonids, and other characteristics (Rader 1997). Details of metric development are found in Sullivan and White (2017).

Drift samples of aquatic macroinvertebrates were collected concurrent to the habitat surveys (described below). Essentially, two adjacent drift nets with 500 μm mesh were placed at the downstream end of a riffle, immediately upstream of the habitat survey site. Drift nets sampled for 2 – 4 hrs during mid-day, with measurements of water depth (m) and velocity ($m \cdot s^{-1}$) of nets taken at the start and end of sampling, in addition to river discharge ($m^3 \cdot s^{-1}$) so that flux of invertebrates in nets could be extrapolated to the whole river. Drift samples were processed in the laboratory in an identical manner as BMIs.

Reach-scale habitat conditions (large wood abundance, pool frequency, substrate quality, river channel morphology, etc.) were assessed during summertime baseflow conditions using a standardized regional fish habitat protocol: the Columbia Habitat Monitoring Program (CHaMP 2016). Using CHaMP data, we calculated an additional metric—frequency of large pools ($\geq$ 0.8 m maximum depth and $\geq$ 20 m^2 surface area) per km of stream length—as a previous analysis revealed these habitats have been degraded in the Columbia River basin due to various land use practices (McIntosh et al. 2000). We used a threshold of 5.6 large pools $\cdot$ km^{-1} to define suitable habitat, as that value corresponded to the grand mean calculated by McIntosh et al. (2000) for streams minimally affected by human disturbance.

Juvenile Chinook Salmon (*Oncorhynchus tshawytscha*) and Rainbow Trout/steelhead (*O. mykiss*) were enumerated using snorkel counts (White et al. 2012) and expanded to abundance using a

species-specific correction factor from paired mark-recapture and snorkel survey data, in addition to habitat covariates expected to influence observability (Staton et al., in prep; Appendix B, this document). Salmonid abundance was expressed as linear density (fish · 100 m^{-1}) and aerial density (fish · m^{-2}) at the site level.

In 2019 at 16 survey sites in the upper Grande Ronde and Catherine Creek, juvenile Chinook Salmon were sampled for diet, growth, and production; these sites were a subset of a larger study that evaluated network-scale patterns of salmonid growth and production (Kaylor et al., in prep). At each site, 12 fish diets were obtained using non-lethal gastric lavage three times during summer (early and late August, early September). Energetic content of aquatic and emergent-aquatic prey (joules · g $fish^{-1}$) was calculated using information from Cummins and Wuycheck (1971). Mass-standardized growth rates were calculated for each site by evaluating change in mean fish size at the site from July to September. This method – using changes in mean size to estimate growth rates – was validated in comparison to individual growth rates of PIT-tagged juvenile Chinook Salmon quantified at 23 sites ($R^2 = 0.74$, slope = 0.88; $p < 0.001$; Kaylor et al., in prep). Fish production (g fish · day^{-1} · 100 m^{-1}) was calculated for the same time period by combining fish abundance (extrapolated from snorkel counts as per Staton et al., in prep; Appendix B, this document) with estimates of fish growth.

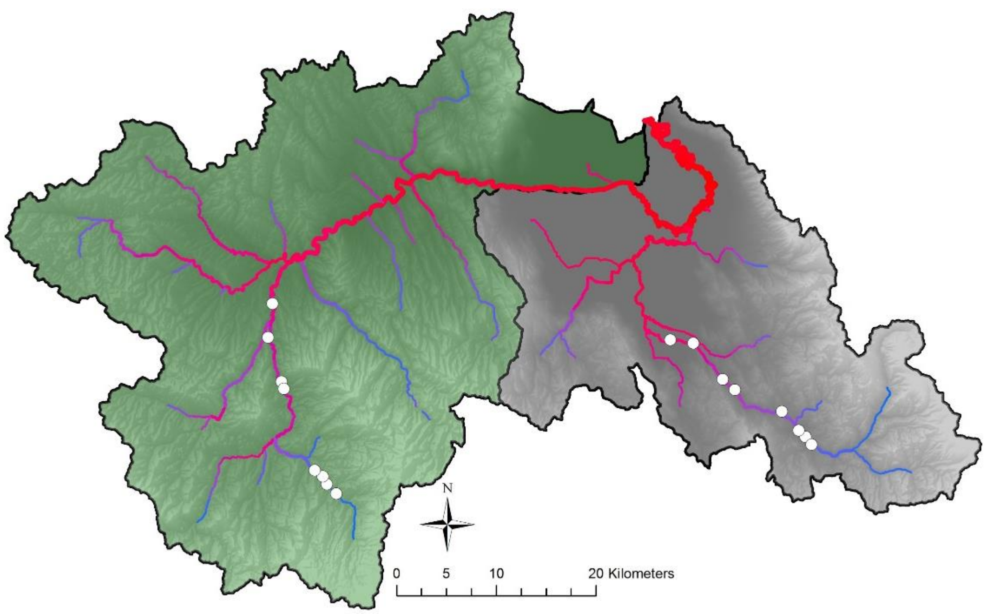

Figure 18. Locations of 16 sites in the upper Grande Ronde River (in green) and Catherine Creek (in grey) where juvenile Chinook Salmon diets, growth, and production were sampled in 2019 (from Kaylor et al., in prep).

Remotely sensed data collection

Intrinsic watershed variables are those typically unaffected by management actions yet can have a strong influence on fish distributions (Jackson et al. 2001). Variables including mean site elevation and gradient, cumulative watershed area, stream order, azimuth, etc. were calculated for each site using a geographic information system (GIS) and specialized computer software (NetMap 2019) that incorporated 10 m digital elevation models (DEMs) and high-resolution light detection and ranging (LiDAR) data from a fixed-wing aircraft where available.

Land use metrics included road density, forest loss, and cattle grazing intensity representing major anthropogenic disturbances occurring in the watershed. Road density and forest loss were derived from EPA's Stream-Catchment dataset (Hill et al. 2016). We additionally developed a cattle grazing intensity map across the project area incorporating cattle intrinsic potential based on distance to water, terrain slope, and land cover (Johnson et al. 2016) coupled with U.S. Forest Service data on permitted animal unit months (AUMs) in allotments, described in further detail in McCullough et al. (2016). For each category of land use, we derived land use metrics for the entire watershed upstream of each site, in the watershed within a 100 m buffer, within the local stream segment's catchment only, and within the local catchment and a 100 m buffer.

Climate variables included site-level estimates of summertime water temperature and annual and seasonal estimates of streamflow. Estimates of average August water temperature were derived from the Northwest Stream Temperature (NorWeST) database available for rivers across the western U.S. (Isaak et al. 2017). Streamflow metrics including center of flow timing, mean annual and summer flows, and frequency of winter floods were derived from the Western U.S. Hydroclimate Scenarios Project (Salathé et al. 2013).

Data analyses

<u>Validation of drift propensity</u>—We tested whether our assignment of benthic taxa drift propensity corresponded to frequency of taxa observed in the drift at each site. Drift propensity groups were assigned using hierarchical cluster analysis (Ward 1963) on the trait scores using a Euclidian distance measure. The dendrogram was trimmed at three guilds (low, medium and high drift propensity) to avoid overclasssification. Cluster analysis was performed in PC-ORD software (McCune and Mefford 2018). Taxa with low drift propensity, corresponding primarily to taxa occurring in depositional or hyporheic habitats, were excluded from subsequent calculations of site-level drift propensity scores as recommended by Rader (1997).

<u>Exploratory analysis of BMI metrics</u>—We used maximal information coefficients (*MIC*; Reshef et al. 2011) to explore links between standard and novel metrics derived from BMIs against land use, climate, habitat, intrinsic, and fish variables. *MIC* is analogous to Pearson correlation coefficients but accounts for linear, non-linear, and other complex associations between two variables. Because intrinsic, land use, and climate data were time invariant, we used data only from

the most recent visit to each site for *MIC* analysis. This resulted in 107 sites for comparisons between invertebrate metrics against habitat, intrinsic factors, land use, and climate, and 105 sites for the comparison of invertebrate metrics to fish metrics, as fish data were not available for two sites. Values of *MIC* were obtained using the 'minerva' package (Albanese et al. 2013) in R statistical software (R Core Team 2017).

Relating drift propensity to fish distribution—We used a mixed-effect zero-inflated negative binomial regression model (ZINB) to evaluate whether and to what degree a drift propensity metric (relative aquatic species composition, ASC_{Rel}) based on Rader's (1997) model could explain variability in juvenile Chinook Salmon distribution. The strictly positive and discrete nature of the response variable (fish·100m^{-1}) led us to believe that normal linear models would be inappropriate and that a generalized linear mixed-effect model was required. Relative to the Poisson (i.e., a default distribution for count data), the data were undoubtedly over-dispersed and it was apparent that the over-dispersion had two sources. First, an excessive amount of zero-valued fish densities were present in the data set (26% were zeros, median value of non-zero densities: 90.78) – this was true even after we included only records inside the range or season expected for Chinook Salmon in our study area. We excluded any site visits that were outside the historical Chinook Salmon extent, upstream of currently impassible barriers, or outside the window of summertime low flow conditions (Julian day 200 – 260) which left 237 records across 140 unique sites for analysis. The excessive zeros beyond what would be expected by a typical count distribution can be accommodated using a zero-inflated count distribution (Martin et al. 2005), which is a mixture of two stochastic processes. One process controls whether the expected value of the count is zero or non-zero, the other controls the expected value when the expectation is non-zero:

$$\omega_i \sim \text{Bernoulli}\ (\psi_i)$$

$$C_i \sim \text{f}(\omega_i \times \lambda_i)$$

where ω_i (a binary 0/1 variable) represents the habitat suitability for site visit i, ψ_i is the probability that site *i* had suitable habitat, C_i represents the observed counts that have expected value of λ_i in suitable conditions – f() is a probability mass function describing how C_i may vary randomly around λ_i. We hypothesized that the extra zero counts of Chinook Salmon in the dataset resulted from unsuitable habitat conditions and that food availability affects the scale of non-zero expected counts. Both ψ_i and λ_i can be modeled as functions of covariates to assess these relationships; our relationships had the form:

$$logit(\psi_i) = \gamma_0 + \gamma_1 pool_i,$$

$$log(\lambda_i) = \beta_0 + \beta_1 pool_i\ +\ \beta_2 ASC_i\ +\ \beta_3 pool_i ASC_i\ +\ \varepsilon_{j(i)},$$

where ASC_i represents the drift propensity score for site visit i (z-transformed prior to model fitting) and $pool_i$ represents binary habitat suitability based on pool frequency (a threshold of 5.6

large pools · km^{-1} was used; McIntosh et al. 2000). The coefficients γ_0 and γ_1 are parameters that govern how ψ_i responds to whether pool frequency was above or below the suitability threshold and β_0, β_1, β_2, and β_3 are coefficients controlling the response of λ_i to food availability and habitat type. Some sites were sampled repeatedly across years leading us to include a site-level random effect (ε_j) to mitigate for the possible effects of pseudo-replication; these effects were mean zero normal random variables with common variance of σ^2.

The second source of over-dispersion was in the non-zero counts: even these showed more variability, namely that there were infrequent but very large counts relative to the other data points, than would be expected under the Poisson distribution assumptions. To accommodate this source of extra variability, we employed the negative binomial distribution in place of the f() mass function above as it is a useful way to account for such large counts when the majority of the data are substantially lower in magnitude (Martin et al. 2005) by estimating an additional over-dispersion parameter (*r*, small values indicate high over-dispersion relative to a Poisson model). We fitted the ZINB using Bayesian inference implemented with JAGS (Plummer 2003). Prior distributions were selected to be minimally informative and initial values were generated as dispersed random deviates around estimates obtained from a simplified version of the model fitted with maximum likelihood methods. Convergence of the fitting algorithm was good and adequate for inference based on visual inspection of trace plots.

<u>Relating drift propensity to diet, growth, and production</u>—To evaluate whether drift propensity metrics (ASC_{Rel} and ASC_{TotAdj}) explained juvenile Chinook Salmon diet, growth, and production in the subset of 16 sites sampled in 2019, we employed simple linear regression using the 'base' package in R. Model assumptions were evaluated by inspecting residuals vs. fits, residuals vs. leverage, and normal Q-Q plots.

Results and Discussion

Validation of drift propensity

Although drift was highly variable as expected, median values of drift frequency according to cluster analysis groups revealed that taxa mostly conformed to expectations (Figure 19). In the high propensity group, families Chironomidae and Empididae and subfamily Orthocladiinae occurring in the benthic samples also occurred in the drift ≥ 70 percent of the time. Taxa from genera *Neoplasta*, *Maruina*, *Deuterophlebia*, *Hemerodromia*, and *Stictotarsus* were rarely (< 10%) found in the drift when present in the benthic samples although they clustered in the high propensity group. In the low propensity group, genera *Iswaeon*, *Argia*, *Agabus*, *Pacifastacus*, *Gyrinus*, and *Tropisternus* and subclass Hirudinea along with several other taxa conformed well to the model (< 20%), whereas taxa in families Tipulidae and Dytiscidae performed poorly (> 45%). The only other explicit test of the Rader's (1997) model that we are aware of was conducted in the Feather River in California (Esteban and Marchetti 2004). Authors of that study found that

Rader's model was correlated with stomach contents from fish diets but trait rankings did not correlate with abundance in the drift, suggesting that fish were further selecting certain taxa from the drift. While results of the present study are not unequivocal, we find more promise in the development of a drift propensity metric. Further analysis of individual taxa frequencies and their traits could help refine the drift propensity metrics.

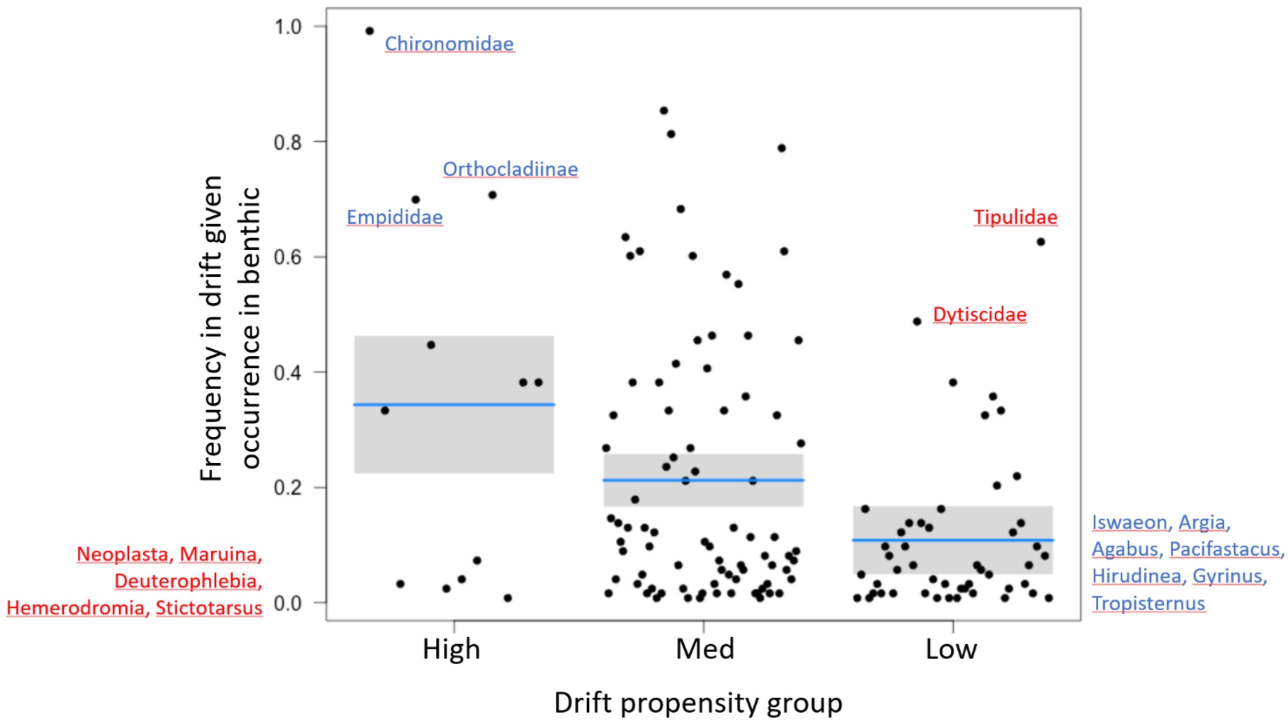

Figure 19. Frequency of invertebrate taxa occurring in the drift when present in the benthos. Taxa were grouped into high, medium, and low drift propensity groups based on cluster analysis of traits. Examples of exceptionally well- or poor-performing taxa are indicated in blue and red type, respectively. Low propensity taxa are excluded from ASC calculations.

Exploratory analysis of standard and novel BMI metrics

Exploratory analysis revealed that standard BMI indices were more responsive to climate, land use, and intrinsic variables (strongest *MIC* = 0.86, 0.67, and 0.58, respectively) than drift propensity or food web metrics (Table 7; Figure 20). Stronger relationships with standard BMI metrics were not surprising, since these metrics were originally developed to be responsive to environmental factors. All metrics derived from BMIs were most strongly associated with climate variables, followed in descending order by land use, intrinsic factors, habitat conditions, and fish distribution. All BMI metrics—standard, drift propensity, and food web—correlated poorly with fish distribution (strongest *MIC* = 0.40, 0.33, and 0.36, respectively). We expected stronger correlations between fish density and drift propensity scores, however, since those metrics were

specifically designed to describe food availability for salmonids (Rader 1997; Esteban and Marchetti 2004; Sullivan and White 2017). We conclude that standard BMI metrics are most appropriate for rapidly indicating climate, land use, and intrinsic conditions, and that relating drift propensity metrics with salmonid distribution would require more nuanced analyses incorporating habitat suitability.

Table 7. Maximal information coefficients (*MIC*) for relationships between standard benthic macroinvertebrate, food web, and drift propensity metrics and climate, intrinsic, land use, habitat, and fish distribution (juvenile Chinook and *O. mykiss*). Values of MIC closer to 1 indicate stronger linear or nonlinear relationships between two variables.

BMI category	BMI metric	Predictor category	Predictor metric	*MIC*
Standard	No. sensitive taxa	Climate	Mean Aug. water temperature	0.86
	No. sensitive taxa	Intrinsic	Mean site elevation	0.58
	No. sensitive taxa	Land use	Road density (watershed 100 m riparian buffer)	0.67
	Percent macrophyte herbivores	Habitat	Average bankfull width:depth ratio	0.40
	No. sensitive taxa	Fish	Median linear density juv. Chinook and *O. mykiss*	0.40
Foodweb	Proportion top level consumers	Climate	Mean Aug. water temperature	0.51
	Slope of log-abundance log-mass	Intrinsic	Modelled bankfull depth	0.41
	Proportion top level consumers	Land use	Cattle grazing intensity (watershed)	0.43
	Prey:predator ratio	Habitat	Mean large pool frequency	0.38
	Proportion trophically isolated taxa	Fish	Median linear density juv. Chinook	0.36
Drift propensity	ASC_{Rel}	Climate	Mean Aug. water temperature	0.51
	ASC_{SubTot}	Intrinsic	Modelled bankfull width	0.39
	ASC_{Rel}	Land use	Forest loss (watershed 100 m riparian buffer)	0.51
	ASC_{Rel}	Habitat	Percent area undercut	0.40
	ASC_{SubTot}	Fish	Median aerial density *O. mykiss*	0.33

	Climate	Land use	Intrinsic	Habitat	Fish
Standard BMI	**0.86**	**0.67**	**0.58**	**0.40**	**0.40**
Drift propensity	**0.51**	**0.51**	**0.39**	**0.40**	**0.33**
Foodweb structure	**0.51**	**0.43**	**0.41**	**0.38**	**0.36**

Figure 20. Maximal information coefficients (*MIC*) indicating strongest relationships between benthic macroinvertebrate (BMI) metrics and climate, land use, intrinsic, habitat, and fish variables. MIC values closer to 1 and darker shading indicate tighter linear or nonlinear relationships.

Food availability and habitat drivers of juvenile Chinook Salmon distribution

For this analysis, we focused on the drift propensity metric ASC_{Rel} because it indicates the proportional abundance of BMI taxa in a sample likely to be available as prey to salmonids, especially juvenile Chinook Salmon that rely on drift (Hayes et al. 2007). The distribution of ASC_{Rel} was heterogeneous throughout the study area (Figure 21). Values of ASC_{Rel} were notably highest in upper portions of the Minam River (reference watershed) and North and South Fork Catherine Creek; and lowest in the middle reaches of the mainstem upper Grande Ronde River and Meadow Creek. A general pattern of increasing ASC_{Rel} moving downstream to upstream was apparent, but with variability interspersed throughout the stream network indicating the downstream-upstream gradient did not explain all the variation.

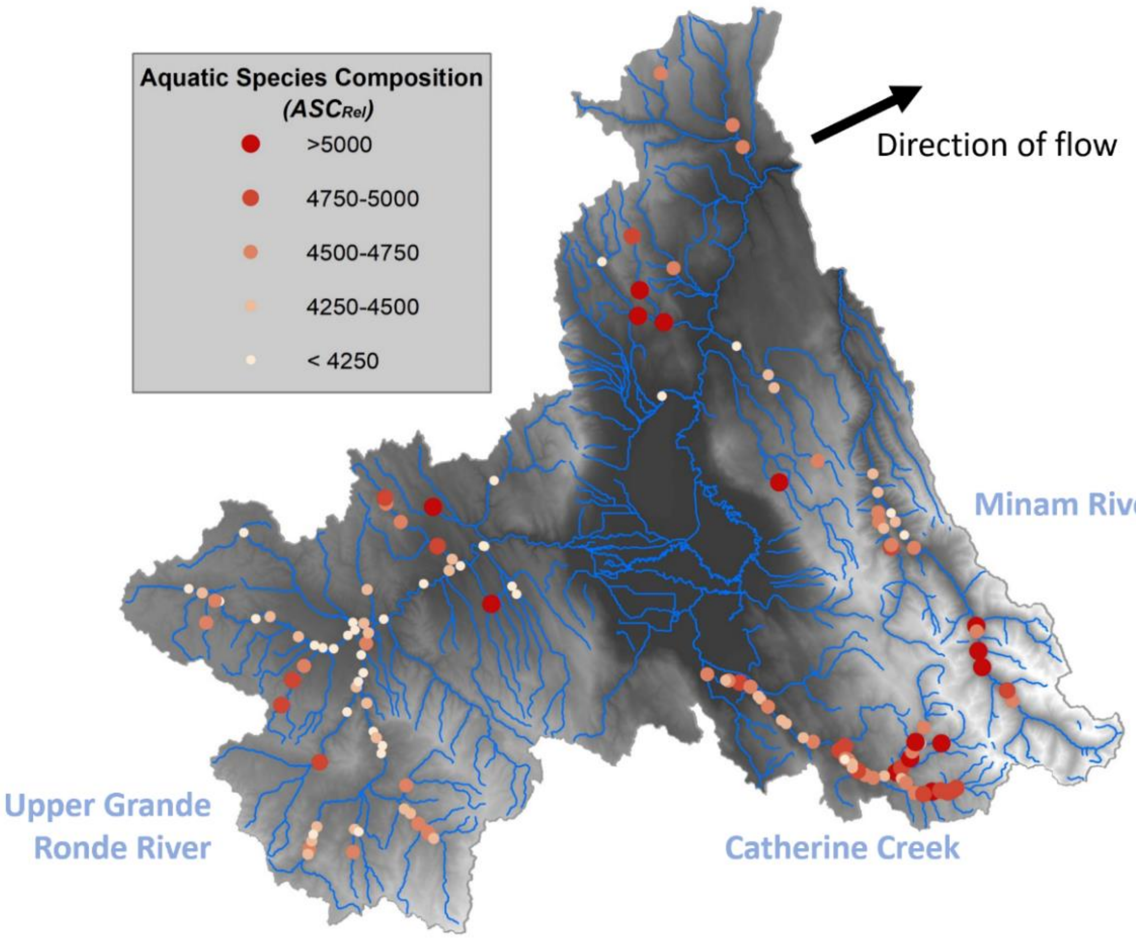

Figure 21. Distribution of drift propensity metric (ASC_{Rel}) values in upper Grande Ronde River, Catherine Creek, and Minam River. Increasing symbol size and shade indicate increasing ASC_{Rel} scores.

The ZINB model revealed that the probability of juvenile Chinook Salmon occurrence in each site (ψ_i) was highly dependent on the availability of large pools (Figure 22). For reaches within their historical range and where physical barriers did not prevent their occurrence, juvenile Chinook Salmon had a posterior median probability (1 - ψ_i) of 0.28 (0.20 – 0.35; 95% equal-tailed credible limits) of expected zero abundance when pool frequencies were below threshold historical values for public lands. Probability of expected zero abundance decreased to 0.04 (0.00 – 0.12) when pool frequencies exceeded this threshold value. Juvenile Chinook Salmon have previously been shown to exhibit a high affinity for large pool habitats (Mossop and Bradford 2006), but this association could also be caused by the affinity for large pools by adult spawning salmon (Torgersen et al. 1999) and fidelity of a portion of Chinook Salmon fry to emergence locations (Einem et al. 2008).

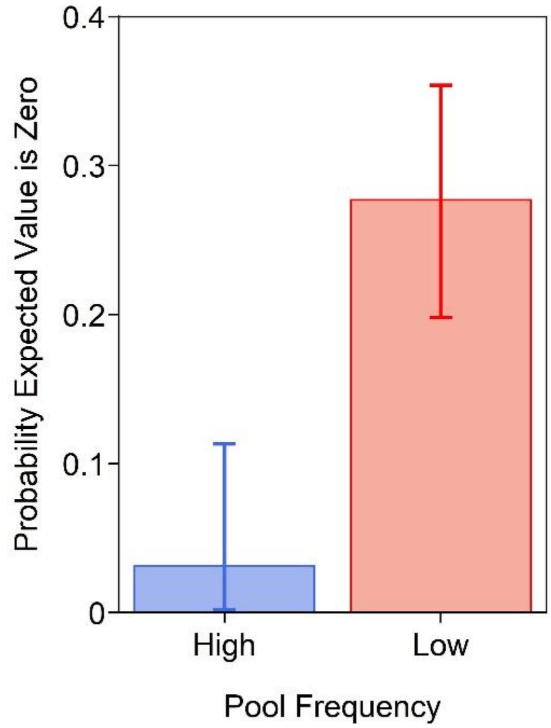

Figure 22. Probability of zero-value expected count of juvenile Chinook Salmon in high vs. low pool frequency habitats (0.04 and 0.28, respectively).

After accounting for pool habitat affecting the expected presence or absence of fish in a site visit, prey availability explained a portion of expected juvenile Chinook abundance (λ_i) (Figure 23). In low pool frequency habitats, a unit increase in food availability led to a barely detectable change in log fish abundance (β_2 = -0.02; -0.37 – 0.34) whereas in high pool frequency habitats, there was a positive yet highly uncertain trend of increasing log fish abundance with food availability ($\beta_2 + \beta_3$ = 0.35; -0.07 – 0.78). The negative binomial dispersion parameter (*r*) had a very small value (0.70; 0.49 – 0.94) which suggested a high amount of variability of the observations around the expected response, indicating there are other factors influencing fish distribution than pools and food availability. Posterior summaries of parameters directly estimated in the ZINB model are shown in Table 8.

Table 8. Posterior summaries of parameters directly estimated in the ZINB model.

		Posterior summaries		
Model component	Parameter	Median	2.50%	97.50%
Zero	γ_0	0.96	0.60	1.39
	γ_1	2.46	1.04	5.39
Count	β_0	4.65	4.21	5.02
	β_1	0.94	0.34	1.55
	β_2	-0.02	-0.36	0.34
	β_3	0.37	-0.19	0.93
	σ	0.98	0.36	1.52
	r	0.70	0.49	0.94

Several previous studies have documented food limitation of salmonids, including juvenile Chinook Salmon in this study area (Kaylor et al. 2019) and this is supported by bioenergetics studies of salmonids (Weber et al. 2014). However, few studies have incorporated the combined effects of physical habitat quality and food availability on salmonids (however see Jenkins and Keeley 2010; Bellmore et al. 2017). These findings point towards initiating restoration strategies that address both the physical conditions of sites and the capacity of river reaches to produce adequate prey to support salmonids.

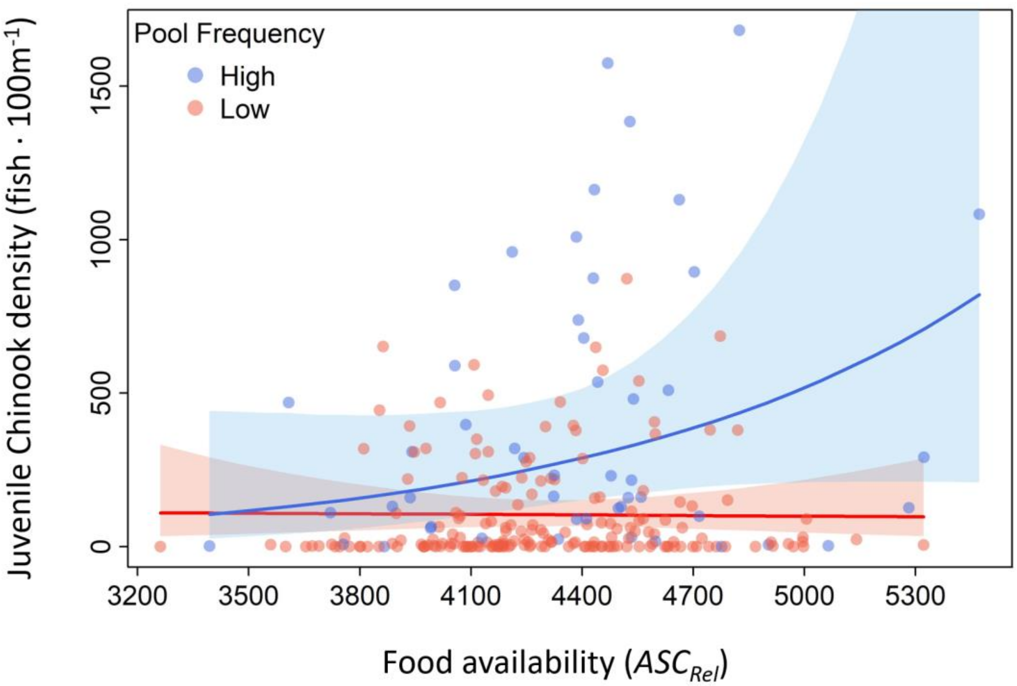

Figure 23. Juvenile Chinook Salmon density as a function of food availability in high vs. low pool frequency habitats.

Fish diets, growth, and production

Our preliminary analysis of 2019 data indicates mixed results regarding relationships between drift propensity (*ASC*) and juvenile Chinook Salmon diets, growth, and production in the upper Grande Ronde and Catherine Creek (Figure 24). Food availability (ASC_{Rel}) was significantly associated with fish diet (joules of aquatic and emergent-aquatic prey · g fish^{-1}) (p-value = 0.04, R^2 = 0.26) (Figure 24a), a finding corroborated by a test of Rader's (1997) model by Esteban and Marchetti (2004). Food availability (ASC_{TotAdj}) was not significantly associated with mass-standardized growth rate (p-value = 0.50, R^2 = 0.10) (Figure 24b). Food availability (ASC_{Rel}) was not significantly associated but showed a slight positive trend with fish production (g fish · day^{-1} · 100 m^{-1}) (p-value = 0.17, R^2 = 0.13) (Figure 24c). Further data collection in Lookingglass Creek (Grande Ronde basin), the mainstem and Middle Fork John Day River, Yankee Fork of the South Fork Salmon River, and the Priest River, ID is planned to extend and corroborate these findings.

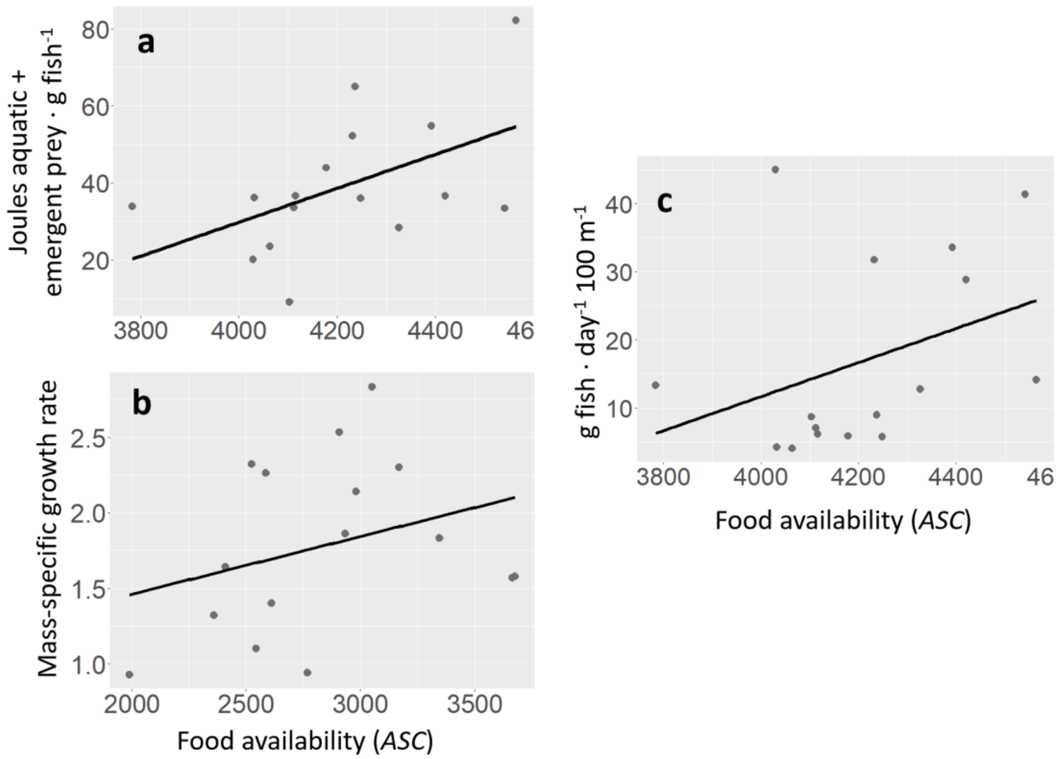

Figure 24. Relationships between drift propensity (ASC) and juvenile Chinook Salmon a) diet, b) growth rates, and c) production in the upper Grande Ronde and Catherine Creek, 2019.

Caveats and future directions

Caveats to this approach include our drift propensity metric does not incorporate the contribution of terrestrial invertebrates known to be important energetic components of salmonid diets (Wipfli and Baxter 2010). Another caveat is that our model does not incorporate water temperature into the interaction between food availability and fish distribution, which has been demonstrated empirically and through bioenergetic models (Weber et al. 2014).

These findings point towards additional tasks to increase the utility of our approach in the upper Grande Ronde River and other Columbia River subbasins:

- Refinement of ZINB model to include summer water temperature,
- Addition of model selection and/or variable inclusion probability analysis for ZINB model,
- Expansion of data collection, metric validation, and modeling into other Columbia River subbasins, thereby testing the generality of the approach.

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2.3 National Water Model streamflow analysis

We summarized simulated streamflow data from the National Oceanic and Atmospheric Administration (NOAA) National Water Model Reanalysis dataset to provide environmental inputs to ongoing salmon life cycle models and other fish-habitat models in the Grande Ronde River basin. This dataset contains output from a 26-year (January 1993 – December 2018) retrospective simulation using the NOAA National Water Model (NWM) version 2.0 (https://registry.opendata.aws/nwm-archive/). This simulation used precipitation and other meteorological data to predict hourly streamflow (m^3/s) at each stream segment in the 1:100K National Hydrography Dataset (NHDPlusV2; average segment length ≈ 1 km). The fine spatial and temporal scale of streamflow predictions provided by this retrospective dataset makes it particularly well-suited for use in salmon population models seeking to evaluate environmental drivers of spatial and temporal patterns in salmon productivity and capacity.

To assess the accuracy of the NWM simulated data, we compared predicted and observed streamflows from five gauging stations in the Grande Ronde River basin corresponding to key spawning, rearing, and migration areas for Endangered Species Act (ESA)-listed spring Chinook Salmon populations (Figure 25; Table 9). To avoid excessive computational time and processing capacity, the simulated hourly dataset was distilled down to a single measurement per day by extracting measurements from noon of each day (initial data summary courtesy of Morgan Bond, NOAA). Measured mean daily streamflow data were downloaded from the U.S. Geological Survey National Water Information System (https://waterdata.usgs.gov/nwis/sw) and the Oregon Water Resources Department (https://www.oregon.gov/OWRD/Pages/index.aspx).

At each gauging station and NWM prediction point, we calculated a set of six annual/seasonal streamflow metrics representing flow magnitude, timing, and duration for each water year from 1993 to 2018 (Table 10). Water years were defined as the period between October 1 and September 30, corresponding to the calendar year in which the period ended. The choice of streamflow metrics for this analysis was based one or both of the following criteria: 1) the metrics have a plausible effect on salmon productivity or capacity that we are interested in evaluating (i.e., *a priori* biological hypotheses), and/or 2) the metrics could be simulated forward in time using existing streamflow prediction models to evaluate potential climate change impacts on salmon populations. While not all six metrics met the second criteria, those that did (mean annual flow, mean summer flow, and center of flow mass) were consistent with the metrics described in the user guide for the Western US Stream Flow Metric Dataset (USFS 2015). Other metrics were based primarily on the work of Olden and Poff (2003) which provided a useful assessment of hydrologic indices with high explanatory power and limited redundancy.

Mean daily flows (m^3/s) in the Grande Ronde River and its tributaries typically peak during May and June and decline rapidly in mid June through July, reaching base flows by early August (Figure 26). The low flow period typically extends from August through February, followed by an

ascending hydrograph from March through May driven primarily by spring snowmelt. Streamflow in the lower elevation portions of the watershed (e.g., Grande Ronde at Troy) is more influenced by rainfall during the fall and winter months and earlier snowmelt in the spring, resulting in a hydrograph that is shifted earlier relative to higher elevation locations.

A comparison of observed (gauge data) and predicted (NWM simulated data) streamflow metrics indicated that, in general, the NWM Reanalysis dataset was good at predicting spatial variability in streamflow across sites, but was less reliable for capturing temporal variability within sites. The proportion of variation in annual/seasonal streamflow metrics explained by the NWM for all sites combined ranged from 0.28 to 0.97 (median $R^2 = 0.93$; Figure 27 and Figure 28). Metrics describing average flow magnitude over long time periods (i.e., mean annual flow, mean summer flow) tended to have the highest precision (R^2 across all sites = 0.96 and 0.97 respectively), metrics related to flow timing (center of flow mass) had moderate precision (R^2 across all sites = 0.70), and the metric related to flow duration (days below the 25th percentile flow) had the lowest precision (R^2 across all sites = 0.28). In addition, there was little evidence of systematic bias in the model predictions for most metrics (i.e., predictions tended to fall along the 1:1 line). Predicted mean summer flow was most accurate (least amount of bias) while days below the 25th percentile was least accurate.

Inter-annual variation in flow metrics explained by the NWM differed considerably across metrics and sites, with mean annual and mean summer flow having the highest within-site R^2 values among the metrics we evaluated (Figure 27). In particular, mean summer flow had the highest and most consistent predictive precision. Metrics intended to describe peaks and troughs in the hydrograph (i.e., max annual flow and 7-day low flow) tended to have higher variability across sites, with some sites having very poor precision ($R^2 < 0.10$) compared with other sites. For example, the NWM only explained approximately seven percent of the annual variation in max annual flow in the Lostine River ($R^2 = 0.075$) compared with an average R^2 of 0.44 for the other sites (Figure 27C). Relatively poor model accuracy for high and low flow metrics is not surprising given the difficulty of modeling extreme daily or weekly values across a long time series using globally available predictor variables. It's also likely that water withdrawals in the Lostine River and Catherine Creek, which are not accounted for in the NWM, resulted in a weaker model fit for these locations.

While model predictions of flow timing (center of flow mass) were less precise than those of flow magnitude, simulated flow timing was reasonably accurate and consistent across sites ($R^2 = 0.70$; Figure 28E) and could provide useful information for understanding spatial differences in biological processes such as migration timing, pre-spawn mortality, and fry dispersal. For example, portions of the stream network draining higher elevation, snowmelt dominated catchments or years with higher snowpack and/or cooler winter and spring air temperatures would tend to have later center of flow mass (Figure 29). These conditions would result in higher

streamflows during late spring and early summer when adult Chinook Salmon are migrating and holding prior to spawning and could therefore improve pre-spawn survival rates.

Overall, the NWM Reanalysis dataset provides accurate predictions of annual/seasonal flow magnitude (i.e., mean annual flow, mean summer flow) and moderately accurate estimates of peak flow timing (i.e., center of flow mass) at a fine spatial scale and across a long time series (1993-2018). However, predictions of annual maximum or minimum flows as well as low flow duration (i.e., days below the 25^{th} percentile) were inconsistent across sites are were generally not reliable. A similar example of a nationwide model that provides fine-scale predictions of streamflow includes the National Hydrography Dataset High Resolution data (NHDPlus HR; 1:24K scale), which includes estimates of mean annual flow averaged over the period from 1971-2000 for each flowline in the stream network. While these data are valuable for discerning broadscale spatial patterns in streamflow, they lack the temporal resolution needed to compute alternative flow metrics (e.g., mean summer flow, center of flow mass) or evaluate interannual flow variability. Streamflow gauging stations, on the other hand, provide very accurate measurements of temporal patterns in streamflow, but the data is limited to a relatively small number of sites within a watershed. The NWM Reanalysis dataset provides a unique combination of both high spatial and temporal resolution that makes it ideal for use in ecological models such as salmon life cycle models or water temperature models which seek to identify environmental factors driving spatial and temporal patterns stream biota and physical process.

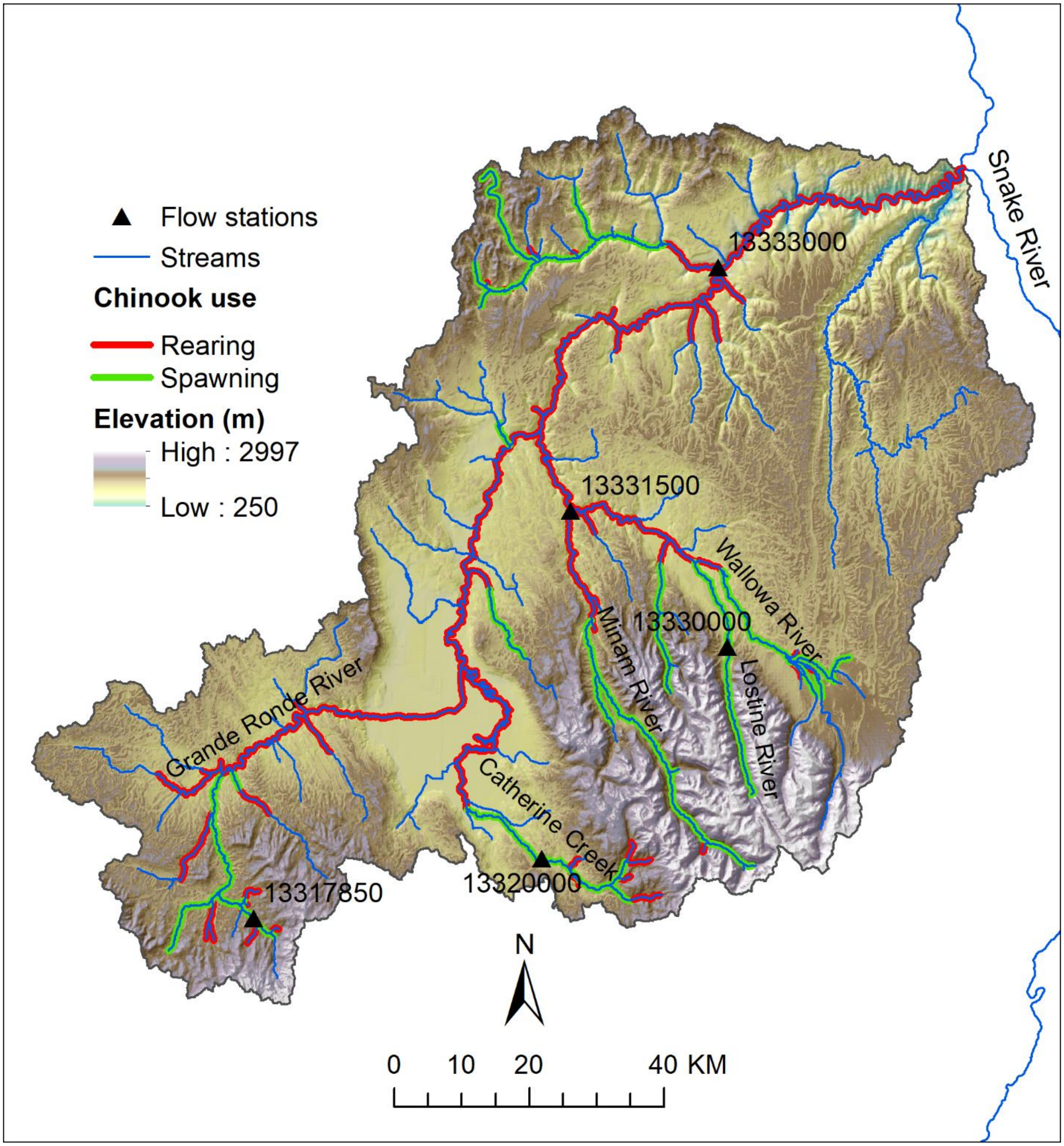

Figure 25. Streamflow gauging stations in the Grande Ronde River basin in NE Oregon used to compute flow metrics for water years 1992-2018.

Table 9. Streamflow gauging stations in the Grande Ronde basin used for analysis.

Station number	Station name	Stream name	Source	UTM easting	UTM northing	Drainage area (km²)	Years of record
13320000	Catherine Cr. nr Union, Or.	Catherine Creek	OWRD	439170	5000514	272	1911 - 2019
13317850	Grande Ronde R. bl Clear Cr, nr Starkey, Or.	Grande Ronde River	OWRD	396462	4991647	101	1992 - 2019
13333000	Grande Ronde R. at Troy, Or.	Grande Ronde River	USGS	465257	5088168	8482	1987 - 2019
13331500	Minam R. at Minam, Or.	Minam River	OWRD	443434	5052051	622	1912 - 2019
13330000	Lostine R. nr Lostine, Or.	Lostine River	OWRD	466651	5031849	184	1912 - 2019

Table 10. Summary of streamflow metrics computed from flow gauge data and the National Water Model (NWM) Reanalysis dataset.

Metric code	Metric name	Units	Metric definition	Source
MA	Mean annual flow	cubic meters per second (m^3/s)	Mean of all daily flow measurements within a water year (Oct 1 - Sep 30).	USFS (2015)
MS	Mean summer flow	cubic meters per second (m^3/s)	Mean of all daily flow measurements during summer (Jun 1 - Sep 30).	USFS (2015)
MaxA	Maximum annual flow	cubic meters per second (m^3/s)	Maximum daily flow measurement within a water year.	Olden and Poff (2003)
LF7D	Seven-day low flow	cubic meters per second (m^3/s)	Minimum of the seven-day running average of daily flow measurements during summer (Jun 1 - Sep 30). Data was limited to the summer period to avoid capturing winter low flows.	Modified from Olden and Poff (2003)
CFM	Center of flow mass	day of water year	Center of flow mass (i.e., center of timing) is the flow-weighted mean day of the water year given by the formula: $CFM = (flow_1 * 1 + flow_2 * 2 + \ldots + flow_i * i) / (flow_1 + flow_2 + \ldots + flow_i)$, where $flow_i$ is the flow (cms) on day i of the water year.	USFS (2015)
DBQP25	Days below 25th percentile	days	Sum of days within a water year where daily flow measurements were below the 25th percentile of daily flows for the period of record (1994-2018)[1].	Internal (CRITFC). Similar to low flood pulse count from Olden and Poff (2003)

[1]The 25th percentile was calculated beginning in 1994 because the data was incomplete for water year 1993 (i.e., data from October 1 – December 31, 1992 was not available in the NWM dataset).

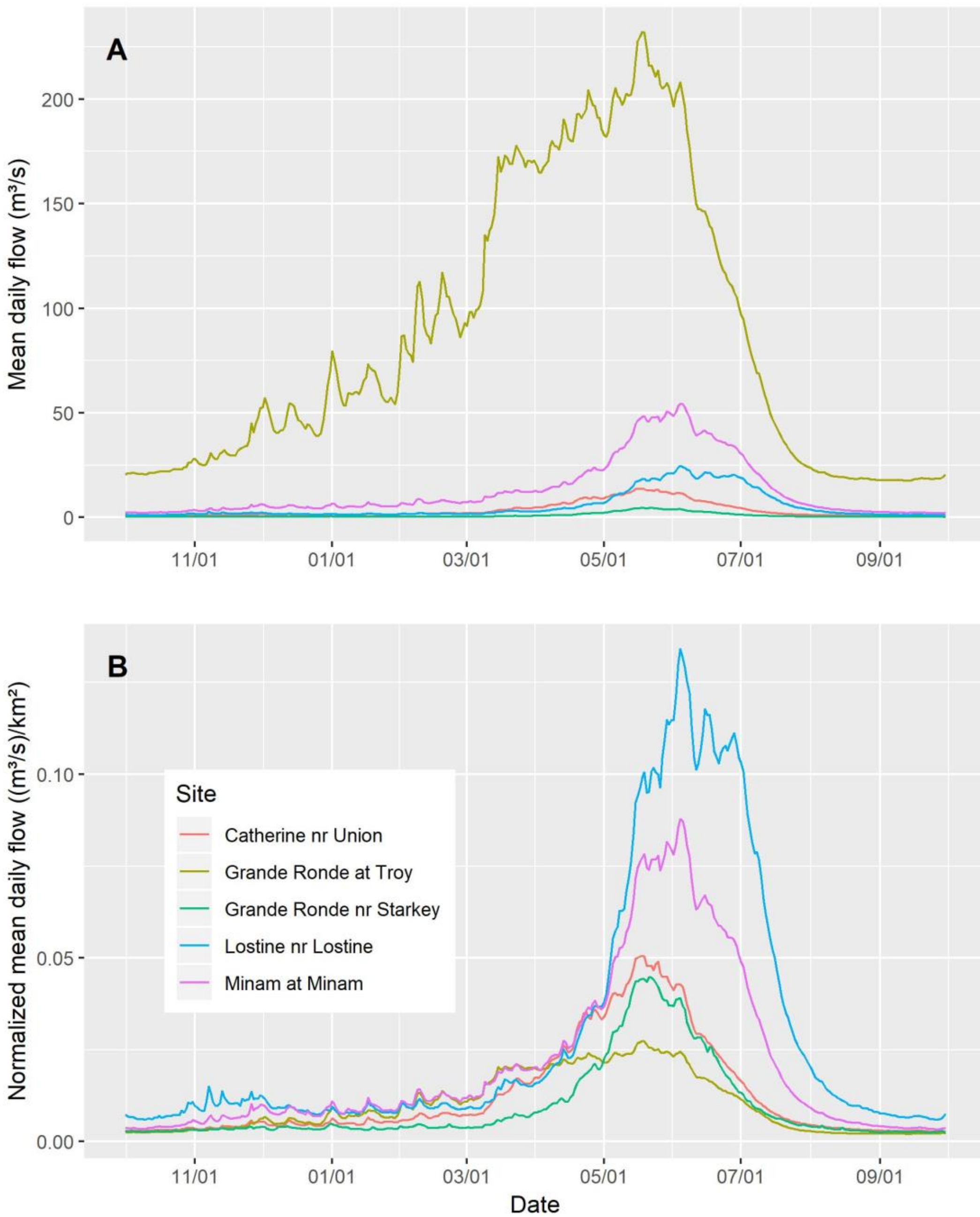

Figure 26. Mean daily flow (m^3/s) and normalized mean daily flow ($(m^3/s)/km^2$) at six streamflow gauging stations in the Grande Ronde River basin averaged over 26-year period of record (water years 1993-2018)

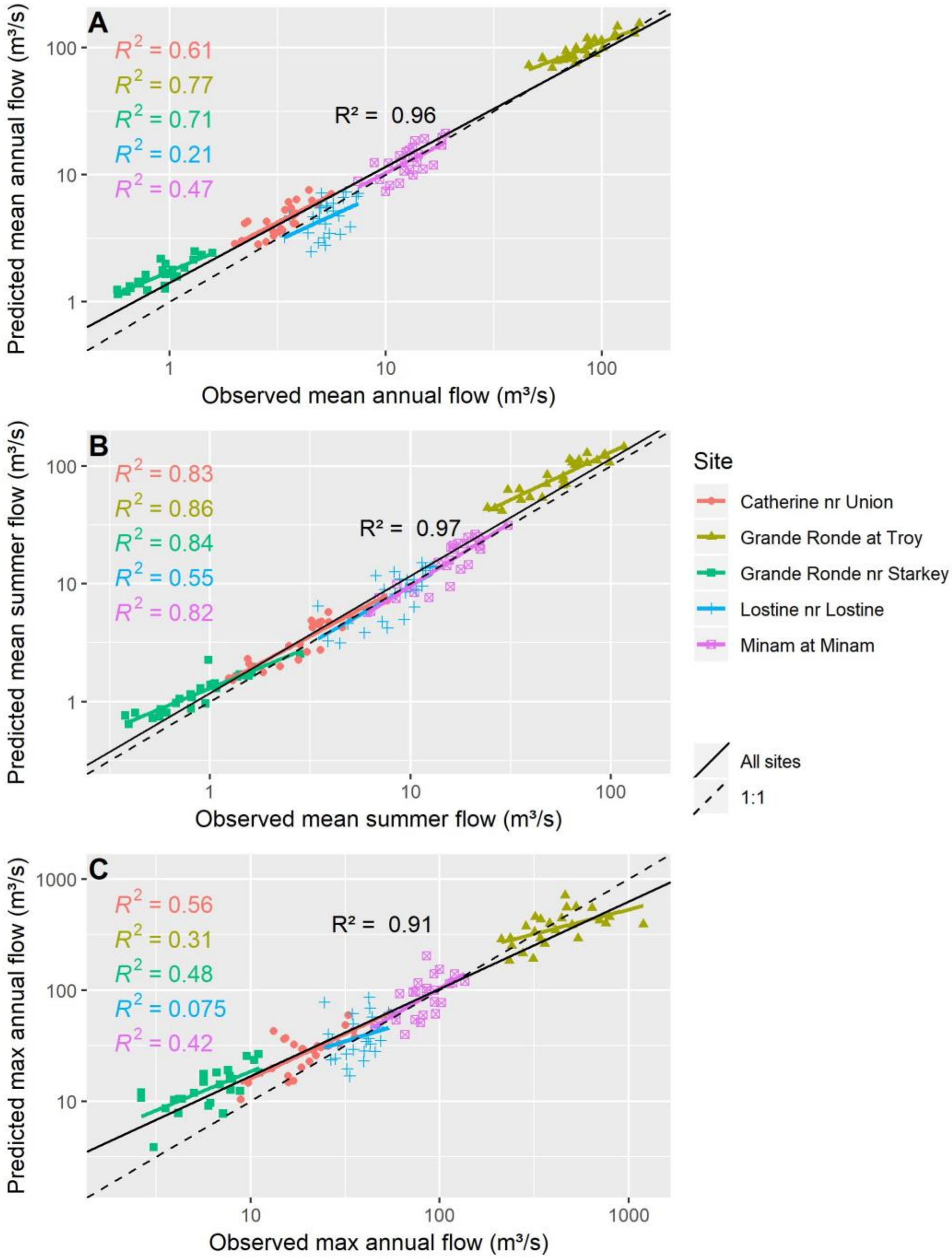

Figure 27. Relationships between observed (gauge data) and predicted (NWM data) streamflow metrics including A) mean annual flow (m³/s), B) mean summer flow (m³/s), and C) max annual flow (m³/s).

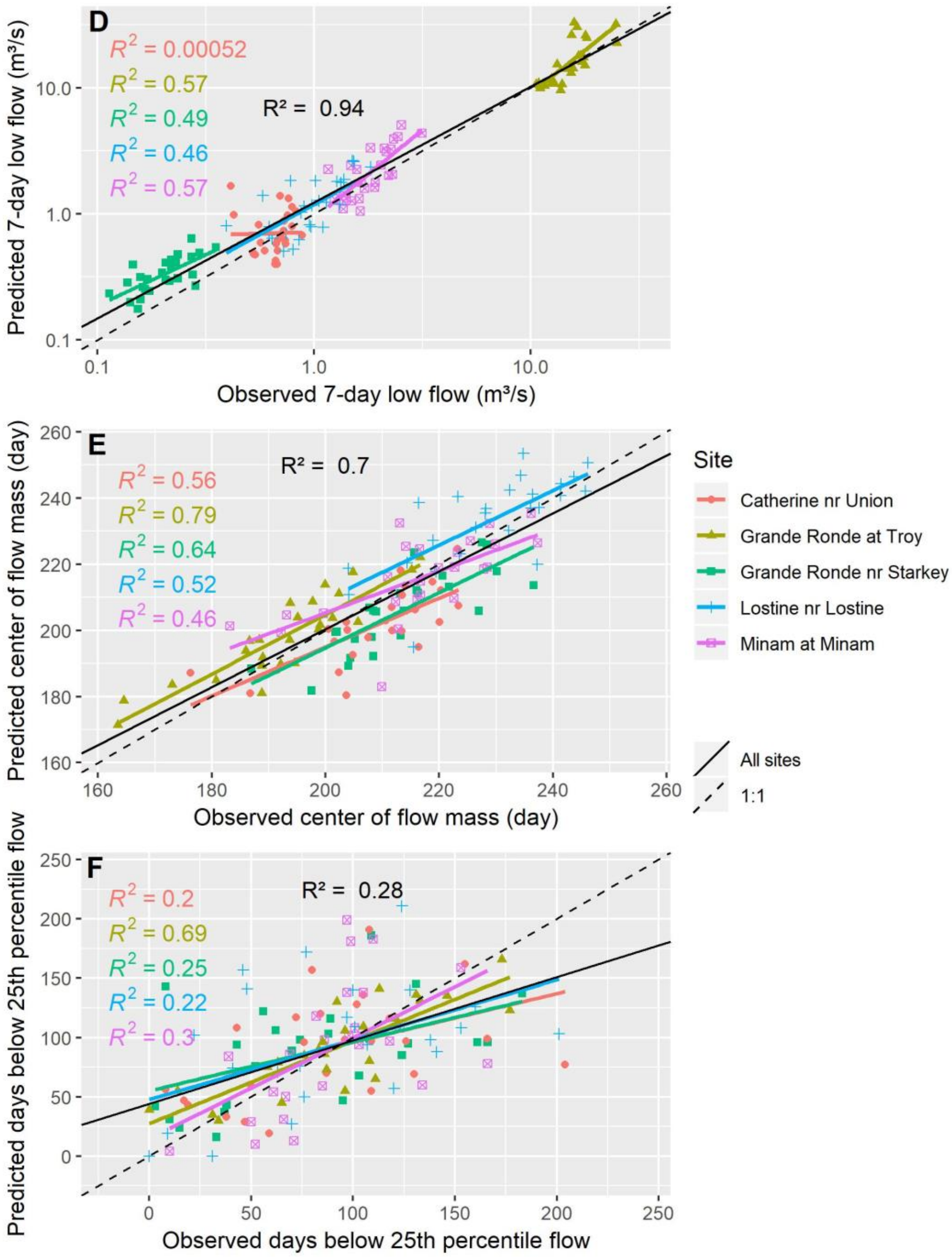

Figure 28. Relationships between observed (gauge data) and predicted (NWM data) streamflow metrics including D) 7-day low flow (m³/s), E) center of flow mass (day of water year), and F) days below the 25th percentile flow.

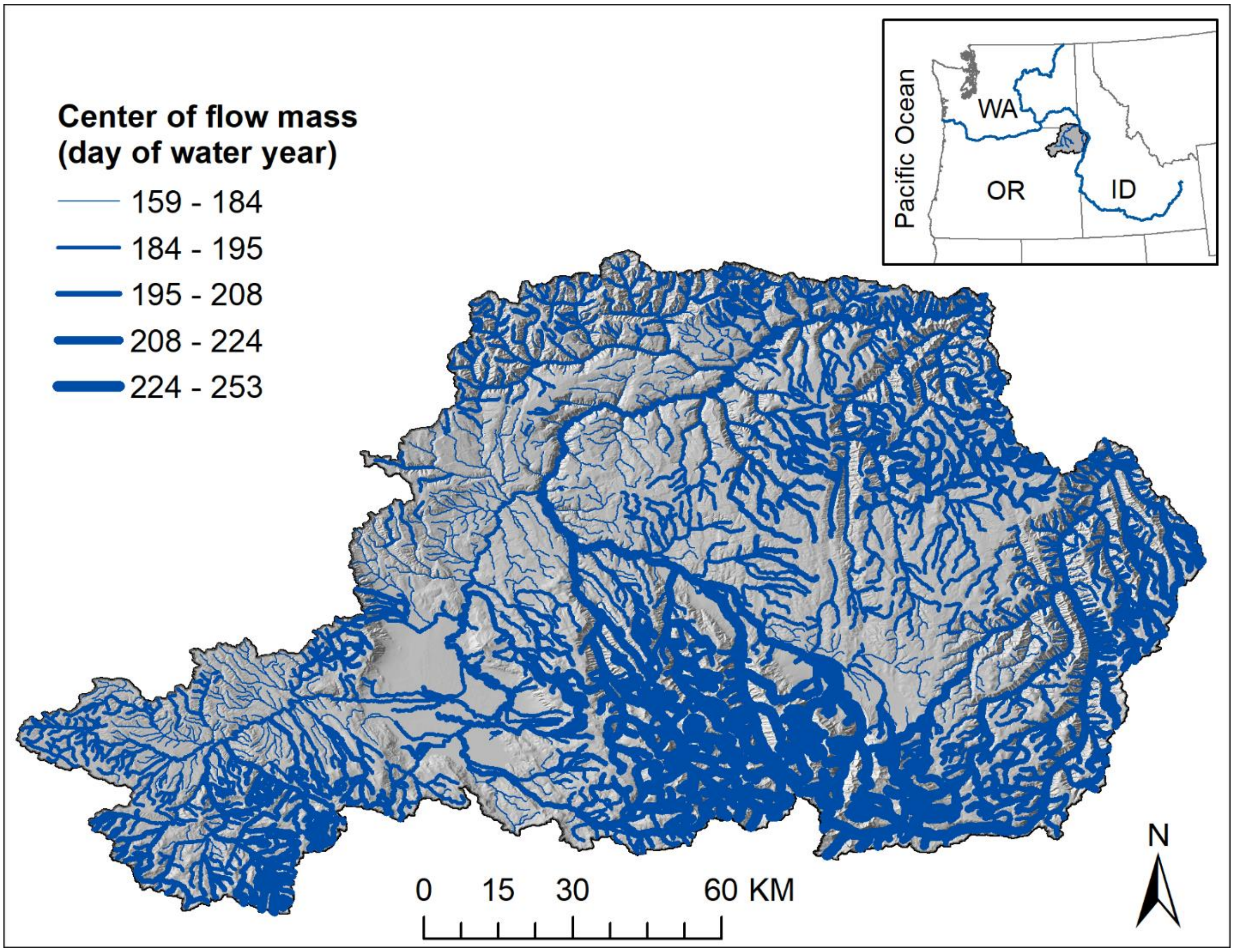

Figure 29. Center of flow mass (day of water year) predictions from the National Water Model reanalysis dataset averaged over the most recent 10 years (water years 2009-2018) in the Grande Ronde and Imnaha River basins in NE Oregon.

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3. Fish-Habitat Modeling

3.1 Update on Life Cycle Model

Background

In collaboration with NOAA staff (namely M. Liermann and R. Sharma) and ODFW staff (namely P. Gibson and T. Sedell), CRITFC is undergoing the development of a revised life cycle model framework for Grande Ronde basin spring Chinook Salmon. Several life cycle model efforts have been previously conducted. At a minimum, these include a model produced by NOAA (Cooney et al. 2017) and another by Eco Logical Research (Weber et al. 2018). The overall intent of both models was to assess the likely effectiveness of future management actions (habitat restoration, hatchery supplementation, etc.) in the face of changing climate conditions. Both models were stochastic simulation models: they sampled driving parameters (i.e., survival, capacity, and productivity terms) from distributions that were estimated from data (to the extent possible) and attempted to simulate the population dynamics forward under different scenarios.

These models set the stage for how spring Chinook Salmon population dynamics are understood in the Grande Ronde basin, but they have some potential weaknesses that we hope to address in a revised modeling framework. First, previous models have relied on piecemeal analyses that are conducted on each component of the life stage separately to inform estimates for a single life cycle simulation model. In the absence of a coherent framework to tie all data together, this is the only option. However, that approach makes it difficult or impossible to appropriately carry forward parameter uncertainty and correlations between parameters to simulation models. Second, the previous models analyzed the data from each of the subbasin populations independently of each other, preventing accounting for empirically derived covariation in their population dynamics in forward simulations. Accounting for this covariation will be important for realistic simulation scenarios, especially if performance metrics that describe the status of the aggregate Grande Ronde basin population are desired. Third, the linkage between future climate/restoration scenarios and salmon population dynamics used in these models was not as explicit as we believe it should be, given the critical role this aspect has for informing managers of the outlook for these populations.

The new model resulting from our collaborative efforts will contain two primary parts with two very different tasks. First, a unified state-space model, which in many ways has already been developed by NOAA as a third Grande Ronde Basin life cycle model, will be further refined to estimate the critical life stage-specific parameters necessary to describe the dynamics of the life cycle based on available data. For each of four subbasins within the Grande Ronde (upper Grande Ronde River, Catherine Creek, Minam River, and Lostine River), these data date back to at least 2000, with some subbasins having data collection in the early 1990s. Our task in applying this model will be to estimate parameters from the historical data and to provide a joint posterior distribution that quantifies knowledge, uncertainty, and correlations between parameters. We hope

to embed environmental relationships within the state-space model for the various survival terms to facilitate modeling the effects of future environmental conditions on population dynamics. The second part of the modeling framework will be a forward simulation model that samples from the joint posterior obtained from the state-space model. This model will be parameterized such that future restoration and climate scenarios can be more explicitly modeled, and by running many replicates (each representing a different draw from the joint posterior), we will be able to shed light on the likelihood of different future trajectories of the populations.

Current NOAA Life Cycle Model

Please note that this narrative represents our understanding of the model based on a version we have seen and discussions we have had with the initial state-space model developers. At the time of writing, it is possible that some minor aspects may have changed.

NOAA has put in an incredible amount of work so far to produce a state-space model, and this will be the basis of the state-space model in the revised framework. The model is fairly complex, but primarily because it models four populations simultaneously and includes several levels of parameter hierarchies. Thus, only a narrative description of the model will be included here; a full description (equations, diagrams, likelihoods, assumptions, etc.) of the final model structure will be provided in a later report once it is decided upon.

Stages and dynamics

The model tracks the latent (i.e., true but only ever partially or imperfectly observed) abundance states of several life-stages each year for each of the four populations and fits these states to observed data wherever possible. Reproduction in the model takes the form of a Beverton-Holt relationship that produces total summer parr from spawning salmon the year prior. These parr are then partitioned into two life-history groups: headwaters-rearing and valley-rearing (i.e., spring migrants vs. fall migrants). Life-history-specific density-dependent overwinter survival terms are applied to these parr to obtain the number of smolts that migrate to Lower Granite Dam. After surviving the transition from tributary habitat to the Snake River mainstem, the model moves smolts through the hydropower system which has additional survival terms that the model internally estimates to place them in the ocean, where they are assumed to suffer known and time-constant ocean mortality. The model estimates maturity schedules that control what fraction of the remaining ocean juveniles will return and make the spawning migration each year. There are currently no mechanisms built in for mortality moving upstream through the hydropower system as adults. The returning adults reach the spawning grounds and following pre-spawn mortality, they feed into the Beverton-Holt recruitment relationship to produce summer parr for the next brood year in the cycle.

Dynamics parameters

The model needs to estimate many parameters in carrying out these state transitions, most of which have hierarchical structure in two levels: there is an aggregate population mean and variance which controls the mean parameters for each population, then within each population there are year-specific random effects on most parameters. Spawner-parr productivity and capacity are time-invariant and so have only the first level of the hierarchy. Because of the state-space nature of the model, it estimates parr recruitment states as process errors around the expected Beverton-Holt curve. The model incorporates some population synchrony in the recruitment of parr: recruitment residuals (representing higher- or lower-than-expected survival from egg to parr) for each population have two components: one that is shared with other populations and one that is unique to each population. Additional parameters are (a) the fraction of each population's summer parr that become the fall migrant life-history strategy, (b) logistic-regression parameters governing life-history-specific density-dependent overwinter survival and the random year effects from the expected logistic curves, (c) survival from the initiation of outmigration to Lower Granite Dam (assumed equal between the life-histories, but unique to each population and year), (d) downstream hydropower survival (assumed equal between life-histories, but unique to each population and year), and (e) maturity schedules by population and year.

Observation model and data

The model needs to be fitted to observed data to enable estimation of these numerous parameters. These take the form of three main types and all are subject to (possibly substantial) observation errors: abundance, survival, and age composition (for adults). Abundance of adults (prior to pre-spawn mortality), fall trap juveniles, and spring trap juveniles are the only abundance states that are ever directly estimated by sampling programs and they serve to set the scale of the populations, as well as inform the interannual dynamics. Survival data all come from PIT-tag programs and track survival of fish tagged at different points to Lower Granite Dam. These tagging events include (but are not limited to) (a) fish in summer prior to separation into life-history types, (b) fish that pass the screw trap in the fall (prior to overwinter mortality), and (c) fish that pass the screw trap in the spring (following overwinter mortality). This program operates on all four populations in the basin, though sampling was initiated in different years for each population. The model is fitted to all three sources of survival estimates treating each piece as independent of all others and using some measure of observation uncertainty as a weighting mechanism (all of which are obtained externally to the model). Finally, because adult Chinook salmon can return at multiple ages, the model is fitted to age composition to correctly allocate the abundance of returning adults each year to the brood year in which they were spawned. Currently, the model only tracks returns of age 4 and 5 fish.

Habitat linkages

Currently, all notions of freshwater habitat or environmental conditions are captured in a quantity referred to as "pool equivalent units", which are intended to represent the amount of suitable habitat for rearing in each basin as an index to inform the strength of density dependence – more fish per effective pool is assumed to equate to lower survival after hatching and while overwintering. The quantity was obtained essentially by determining the relative abundance of summer parr in pool units versus other habitat unit types (via snorkel survey) and calculating a weighted sum of all habitat in each basin. This metric is used to predict spawner-to-parr capacity from an internally estimated regression relationship (intercept fixed at zero) and to scale parr abundance for density-dependent survival calculations. All aspects of future restoration scenarios and climate scenarios operating in freshwater are then translated into how the abundance of pool equivalent units is likely to change in each subbasin, which then affects these density-dependent components of the subbasin-specific population dynamics.

Planned Improvements in the NOAA-ODFW-CRITFC Model

In collaboration with NOAA and ODFW, we have several improvements planned for the current state-space model. We feel compelled to note that we are very impressed with the work that has been done thus far at bringing the seemingly disparate data sources together into a cohesive modeling framework. Thus, the discussion that follows should be seen less as criticisms of the current model, but rather refinements to an approach that we believe is already the most comprehensive life cycle modeling effort in the Grande Ronde basin to date. At this point, not all ideas for improvements are fully fleshed out, but have been discussed with all collaborators. Improvements are broken down into (a) explicit covariance of population dynamics, (b) additional age and sex structure, (c) incorporation of auxiliary hydropower survival information, (d) incorporation of pre-spawn mortality data, and (e) improved modeling of habitat and environmental conditions on population dynamics. We believe that if it is possible to incorporate these improvements, they will enhance our ability to capture more realism in the system, both to explain historical data and for populating the forward simulation components.

Population covariance

There is some evidence that the estimates of survival from various life stages to Lower Granite Dam are correlated among the populations (Figure 30). The current state-space modeling framework ignores these aspects of shared survival rates following recruitment to the parr stage. It is of course possible that there are no real correlations, and those apparent in Figure 30 are caused by some factor related to sampling or survival estimation that causes the survival rates among populations to be biased in a similar way each year (e.g., an unknown global detection probability effect). We deem this unlikely and are operating under the assumption that the correlations as detected are real in nature. We would like to improve the state-space model by building in

correlated process errors in at least some of the survival terms and maturation terms in the model (likely to be implemented via a multivariate logit-normal distribution). Further, we believe the recruitment dynamics component can be improved upon by using a multivariate log-normal distribution – this would accomplish essentially the same thing as the model currently does, but it is cleaner (no need to employ modeling tricks that force the shared time-series to be mean-zero) and derived estimates of the strength of the correlation would be available. Granted, the 4x4 covariance matrices for these components will be difficult to estimate, as will selecting the appropriate priors, but we believe it is worth implementing given there is evidence that these aspects are correlated. One potential advantage of doing so is the model can estimate the covariance in years where the data time series overlap between populations, which can then help inform the states in years where not all populations have data.

Additional compositional structure

The current state-space modeling framework tracks abundance of adults returning at age 4 and 5 and essentially states that returning at age 3 is not possible. From our understanding, this was due to all age 3 fish being males (i.e., jacks) and there was concern that high jack years would skew the metric of annual reproductive potential. However, because age 3 returns are a component of the life cycle, we believe they should be accounted for and the data exist to do so. The concern about skewed reproductive output could be remedied by adding sex composition of adults to the model, which we believe is also available.

Auxiliary hydropower survival information

The current state-space modeling framework estimates survival from Lower Granite Dam to the ocean, then assumes ocean survival is known, and estimates maturity schedules for surviving fish. We believe this could be improved upon by borrowing from the wealth of information on hydropower survival rates in the Columbia River basin, which assuming these data are relatively informative, would then allow estimation of the ocean survival terms. We believe that more is known about hydropower survival than ocean survival, so it makes sense to us that we should supply the model with the better information and allow it to estimate the source that is more uncertain. This would be implemented by the use of strong prior distributions on the hydropower survival terms, likely informed from the COMPASS model.

Incorporation of pre-spawn mortality data

The current state-space modeling framework assumes that pre-spawn mortality is known perfectly and is constant each year for each population. However, based on carcass counts of individuals that are still gravid, there are data to inform this aspect. We may even be able to link pre-spawn mortality rates to environmental conditions (e.g., August mean temperature) via an embedded logistic-regression type model (see White et al. 2018, Appendix A therein).

Improvement of habitat/environmental linkages

Although the pool equivalent units concept is straight-forward, we believe it can be improved upon. Essentially, it is difficult to translate habitat restoration actions or climate scenarios defensibly into changes in pool equivalent units. We believe it should be possible to develop more rigorous fish-habitat relationships that can be used to construct a single metric of freshwater rearing potential that incorporates aspects such as large wood, frequency of large pools, and stream temperature. This metric would replace pool equivalent units in scaling population capacity and density-dependent mortality and would provide more transparent "levers" for manipulating future conditions. Further, the model incorporates a large amount of annual variation in the various survival terms. Currently, these terms are treated as white noise random deviations around a constant mean. We believe it should be possible to embed logistic models that predict these annual fluctuations from the environmental conditions each year (namely stream flow and temperature, calculated at spatiotemporal scales germane to each survival component). We plan to perform fairly exhaustive exploratory data analyses before embedding any of these data in the model to investigate if any variables are useful in predicting the annual variation in the various survival terms. The finding that the survival estimates are correlated among populations (Figure 30) suggests that the annual variability is mediated by some largely shared environmental covariate(s).

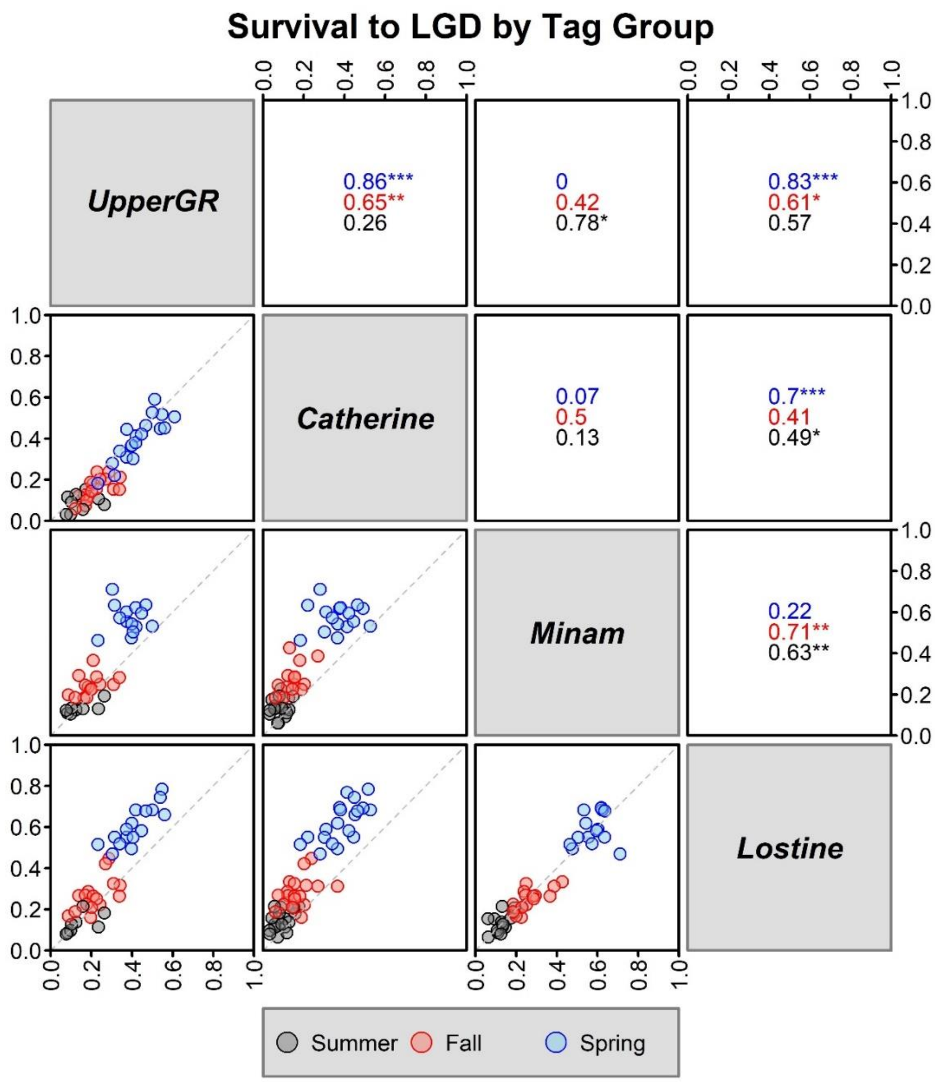

Figure 30. Scatterplot matrix showing correlations among population-specific estimates of survival from the basin to Lower Granite Dam derived from PIT-tag data. Summer (grey points) and fall (red points) tagging occur one year before migration to the ocean fish are spawned, and spring (blue points) tagging occurs the year after. The upper panels show the corresponding Pearson correlation statistics with p-values denoted (*** <0.001, ** < 0.01, * < 0.05); color codes match those of the points. Diagonal lines display the 1:1 equality line. Note that for many of the populations and for most of the survival rates, high and low survival years are shared. Data provided by M. Liermann (NOAA) who obtained them from ODFW for use in development of the Grande Ronde basin state-space life cycle model.

Work Plan

The development of the two models (one state-space for estimation, the other purely a forward simulation with no estimation) will occur to some extent in parallel, however the structure of the simulation will depend to a degree on the quantities that the state-space model can estimate. First

and foremost, we have compiled an updated data request and submitted it to ODFW. The data request asks for much of the same data as currently used by the model, but is intended to ensure the modelers are developing the models with the most complete, current, and consistent information. We have further requested data in a more consistent and reliable format, as many of the observations we have access to now have been compiled from various sources (personal communications, reports, etc.) and uncertainty estimates have previously been provided in inconsistent expressions (some confidence intervals, some standard errors, etc.). We can continue development of the model on the current data set while this request is completed and can even use simulated data if necessary. CRITFC and the other principle modelers will continue with development (adding additional age/sex structure, reassessing density-dependence assumptions, testing various environmental relationships on survival terms, investigating the influence of alternative priors, etc.) while others work to develop the revised composite habitat metric that serves as an index of capacity. We will eventually settle on one or several final model structures from which we can obtain the joint posterior(s) for (almost certainly using program JAGS, Plummer 2003) to be passed to the forward simulation component. We will then come up with a limited but informative range of plausible and defensible scenarios under which to simulate the populations – this will not be a simple task. Scenarios will likely involve various types and/or intensities of habitat restoration activities and time trending freshwater and marine conditions that affect survival. We will use a set of performance metrics (e.g., number of years populations fell below a critical threshold), which can then be summarized to evaluate how effective management actions may be in the long term.

We have plans to wrap these two primary aspects of the work into two corresponding journal articles: one will be completely state-space model-oriented and the other will entirely focus on policy choices, environmental uncertainty, and likely status outcomes. We anticipate making significant progress on at least the state-space model work and manuscript this year.

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4. Adaptive Management

__Note__: A draft of the manuscript discussed in this section is available in Appendix C – "Progress Towards a Comprehensive Approach for Habitat Restoration in the Columbia Basin: Case Study in the Grande Ronde River".

4.1 Progress on an Adaptive Management Framework

Summary

The Independent Science Review Panel (ISRP) previously recommended that our group engage with Grande Ronde Model Watershed (GRMW) in developing an adaptive management framework. In response to this recommendation, we worked with GRMW, Confederated Tribes of the Umatilla Indian Reservation (CTUIR), Oregon Department of Fish and Wildlife (ODFW), U.S. Forest Service (USFS) and several other partners on two related tasks: (a) a needs assessment workshop and manuscript documenting our progress and setbacks towards a comprehensive approach to habitat restoration in the Columbia River basin and (b) involvement in a multi-agency workgroup developing a 5- and 20-year adaptive management plan for the Grande Ronde basin.

Progress Towards a Comprehensive Approach for Habitat Restoration in the Columbia Basin: Case Study in the Grande Ronde River

Despite immense resources directed towards habitat restoration, recovering fish populations remains a daunting and perplexing issue. Advances in our understanding of technical aspects of restoration will continue to help, but slow progress can also be attributed to a deficiency of a comprehensive approach to restoration that integrates ecological and social sciences (Hand et al. 2018), as well as hesitance to adopting formal models of adaptive management (Conroy and Peterson 2013). In 2015, recommendations for a comprehensive approach to habitat restoration in the Columbia River basin were articulated (Rieman et al. 2015). The approach recommended using concepts of landscape ecology and resilience, gaining broad public support, implementing a governance strategy for collaboration and integration, and incorporating a framework for learning and adaptation. In spring and summer of 2019, stream restoration partners in the Grande Ronde basin (collectively known as "Grande Ronde Atlas") formed a workgroup to implement a formal adaptive management strategy. Using a case study from the Grande Ronde River in Northeast Oregon, we communicated our progress in collaboration with GRMW and other partners to achieve the recommendations of Rieman et al. (2015), highlighted areas for improvement, and outlined next steps.

Initial responses to the directives of Rieman et al. (2015) were developed in two, half-day workshops with Atlas partners and were refined while drafting a manuscript with several partners

as co-authors. We provided examples of how we are already answering these calls to action, where we are falling short, and how the framework could be improved to better address tributary habitat restoration (Table 11). We envision the lessons learned from this local case study will have broad applicability for practitioners and researchers of habitat restoration across the Columbia River basin. These responses and our assessment of progress towards the directives of Rieman et al. (2015) are documented in a manuscript currently in revision in *Fisheries* (see draft manuscript attached as Appendix C). We considered this response as a stepping-stone—not the final answer—towards realizing the directives from Rieman et al. (2015).

Development of an Adaptive Management Framework

Building on lessons learned from our collaborative review of the Grande Ronde basin habitat restoration program (Appendix C), we have begun the process of developing a formal adaptive management plan to guide future salmon habitat restoration actions. This process is being spearheaded by the Grande Ronde Model Watershed with active participation from numerous partners including CRITFC, CTUIR, ODFW, and USFS. The primary goal of this project is to develop a comprehensive framework by which the progress of restoration actions towards meeting our objectives can be measured and used to inform future management actions. The adaptive management plan will consist of six key components including assessment, vision, objectives, strategy, projects, and monitoring and evaluation (Figure 31). Monitoring, evaluation, and assessment form the backbone of learning and revising the vision, goals, objectives, strategies, and projects intended to improve tributary habitat conditions in support of salmon recovery and river ecosystem health. While this plan is early in the development phase, basin partners have recognized a few critical aspects of the plan that will be needed to ensure successful implementation. The first is that management objectives are quantified and not generalized (see "Objectives" in Figure 31 for examples). This is critical because it is the only way we will be able to measure progress and determine if we need to change course with our management actions. The second is that we need a consistent system for tracking restoration actions and reporting monitoring results across all organizations engaged in salmon restoration. It is not possible to track basin-wide progress towards salmon and ecosystem recovery if implementation and monitoring data are not reported in a consistent and tractable manner by all parties. Finally, a successful adaptive management plan will require steady financial and policy support for monitoring and research to ensure that sufficient quantitative data is available to evaluate progress and guide future management actions.

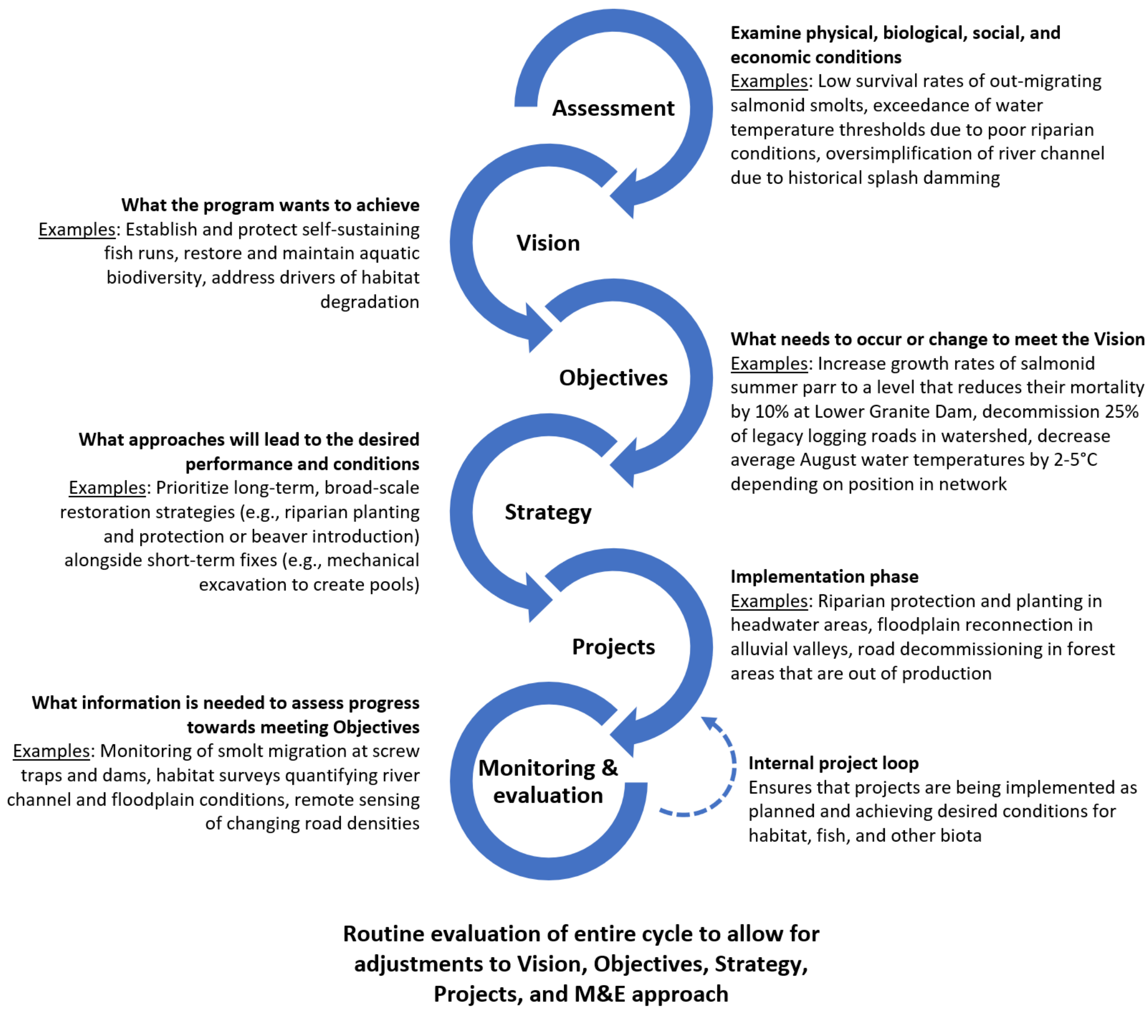

Figure 31. Adaptive management loop with examples from the Grande Ronde Basin. Monitoring, evaluation, and assessment form the backbone of learning and revising the vision, goals, objectives, strategies, and projects intended to improve tributary habitat conditions in support of salmon recovery and river ecosystem health.

Table 11. Recommended actions towards a comprehensive approach for habitat restoration in the Columbia Basin (from Rieman et al. 2015), with examples of progress in the upper Grande Ronde Basin.

Action	Directive	Examples of progress in the Grande Ronde basin
Rebalance the goals	Develop and communicate goals and measurable objectives for biological diversity that are held as equal priority to the goals and objectives for abundance	Atlas prioritizes restoration in areas with overlap in salmonid species use, life stages; Multiple life history strategies of salmonids are considered; tribal First Foods concept emphasizes ecological diversity and resilience
	Directly engage all stakeholders and the general public to broaden understanding of the critical value of biological diversity	Public outreach efforts emphasize the ecological value and ecosystem services provided by salmon life history diversity, freshwater mussels, beaver, Pacific lamprey, and Columbia spotted frogs
	Develop indicators for monitoring that measure and communicate progress on abundance and biological diversity at multiple scales across the basin	Abundance criteria and indicators for VSPs exist at the population scale; Life-stage specific indicators for salmonids are expressed at the reach scale; Indicators for biological and ecological abundance and diversity are proposed
	Consider the implications of hatchery production for carrying capacity and diversity of wild fish as a basis for integrating hatchery production with habitat restoration	HGMPs list performance standards for limiting impact on carrying capacity; Life cycle models incorporating the contribution of supplemented to natural populations are in development
Strengthen linkages between science and management	Use landscape sciences and technology in assessment and restoration planning and support and expand common application of relevant research, monitoring, modelling, and analytical tools	Remotely sensed information (LiDAR and FLIR) used to develop a water temperature model and potential vegetation map, used for prioritizing areas where riparian restoration could mitigate future climate change in conjunction with life cycle model; carcass additions as a management tool evaluated from field experiments

Action	Directive	Examples of progress in the Grande Ronde basin
	Create and support communities of practice and peer-learning networks that demonstrate science-management integration; highlight new tools and analyses that are innovative and promote those with real potential for success	GRMW provides interface between science and management and coordination of restoration; Development of Atlas involved intensive exchanges between researchers and managers including an annual “State of the Science” meeting
	Recommit to options for broadly based technical assistance to provide analytical support, constructive criticism, and feedback to proposed and ongoing projects	Projects are scrutinized internally by Atlas technical committee and reviewed by GRMW board of directors; Broadly based technical assistance from outside the subbasin’s expertise was identified as a need
Increase public engagement	Include education and outreach specialists as key players at the earliest stages of project development	Wallowa-Whitman NF uses public outreach specialist to communicate broad forest management plans; More resources are needed to support efforts at local scales
	Engage people and organizations early through forums that encourage dialogue between managers, researchers, and stakeholders associated with a range of resource values	Atlas has the explicit goal of bringing together managers, researchers, and stakeholders; More engagement with the public as stakeholders is needed, requiring policy and funding support
	Align ecological needs with social and economic incentives and consider benefits and costs to people and their communities	The NRCS and Freshwater Trust use incentives for landowners to engage in conservation measures; Restoration contractors purchase trees from local landowners
	Use a wide diversity of media and forums for public and community engagement	GRMW publishes *Ripples in the Grande Ronde* with broad distribution to the community; NOAA, GRMW, and CRITFC are producing a short public outreach film to gain broad support for salmon conservation efforts; Fig. 3 of Appendix C provides an example of printed outreach materials for landowner incentives
	Make public involvement and active learning through citizen science in monitoring and research a central element in project implementation	Opportunities to engage citizen science include K-12 classrooms monitoring nearby restoration projects;

Action	Directive	Examples of progress in the Grande Ronde basin
		Efforts to enlist citizen scientists are just now gaining momentum
	Recognize the social sciences as a critical element of scientific review and guidance and include social scientists as primary contributors to the advisory, review, and planning process	GRMW solicited guidance from a social scientist at EOU on community outreach efforts; Diverse boards of directors at GRMW and UCSWD provide social and economic review of restoration projects
Work across traditional ecological and social boundaries	Highlight and support experiments in governance for collaborations that bridge agency and intellectual groups, local and regional organizations, governments, landowners, and science-management disciplines	Atlas is founded on partnerships between managers and researchers from multiple local, state, federal, and tribal organizations; Union County's Place-based Water Planning program has strong interdisciplinary and multiagency participation
	Bring innovative and successful examples (including those from other resource and restoration disciplines) to others in the basin	Guidance for restoration prioritization draws from a wealth of literature from the PNW and from the Umatilla tribe's *River Vision*; landscape-scale watershed assessment approaches applied in the basin (e.g., River Styles and Water Framework Directive) were imported from Australia and Europe, respectively; Lessons can be learned about applying adaptive management from the upper Columbia River basin groups
Learn from experience	Identify clear, quantitative objectives, including diversity objectives that form the baseline for the adaptive management cycle	Quantitative objectives for fish abundance are more clearly defined (e.g., natural origin spawner abundance) but diversity objectives are gaining attention; Examples of quantitative objectives for the Sheep Creek project are provided
	Implement intentional, science-based management experiments that promote learning about landscapes, cost effective restoration actions, and understanding of their socio-ecological implications	Landscape scale water temperature model used to evaluate which restoration strategies would be most effective under future climate change scenarios; Regional AEM program will provide general guidance on project-scale restoration effectiveness; Experimental additions of fish carcasses conducted in upper Grande

Action	Directive	Examples of progress in the Grande Ronde basin
		Ronde River helped evaluate carcass additions as a management tool
	Incorporate options for citizen science in monitoring and experiential programs that help reduce monitoring costs and promote broader understanding of the results	New monitoring coordinator position at GRMW provides support for citizen science programs alongside USFS; Plans include amphibian egg mass, freshwater mussel, and aquatic invertebrate surveys using citizen scientists
	Use formal models to guide more structured decision making and to communicate a broader vision of the system and its critical uncertainties to all involved	Quantitative life-stage and life-cycle models have assisted in decision-making, but the overall adaptive management process could be improved by using formal models such as SDM. Atlas includes many—but not all—components of SDM. Continued funding and logistical support for monitoring programs will be required to meet this goal

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Dissemination of Project Findings in 2019

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Appendix A – Draft Tributary Habitat Assessment Protocol

Tributary Habitat Assessment Protocol

April 2020 Draft

Funded by:

Columbia Basin Fish Accords

BPA Project No. 2009-004-00

Prepared by: Casey Justice, Lauren Burns and Seth White

Columbia River Inter-Tribal Fish Commission

Portland, OR

Table of Contents

Acknowledgments

Many of the methods described here were based directly on or were modified from the Columbia Habitat Monitoring Program (CHaMP 2016) and the Oregon Department of Fish and Wildlife (ODFW) Aquatic Inventories Program (AIP; Moore et al. 2019) and we thank all contributors to these programs for their excellent efforts. This protocol has been developed and refined based on lessons learned from many years of field data collected by dedicated field technicians and crew leaders whose hard work made this possible. We also thank our funding source, Bonneville Power Administration (BPA) for supporting this program (BPA Project # 2009-004-00).

Intents and motivations

This document describes field methods for collection of physical habitat data in wadeable tributaries during low-flow with the overall goal of assessing habitat conditions and viability of Endangered Species Act (ESA)-listed salmonid populations. Drone-based areal imagery is coupled with ground-based measurements to produce spatially referenced measurements of in-channel and floodplain-characteristics. These survey methods aim to strike a balance between intensive reach-scale (site length 0.1 – 0.5 km) monitoring programs such as CHaMP (CHaMP 2016) and PacFish InFish Biological Opinion (PIBO; Archer et al. 2016) and rapid-assessment watershed-scale (10 - 100 km) surveys such as the ODFW Aquatic Inventories Project (Moore et al. 2019). Taking stock of lessons learned from historic regional (ISEMP/CHaMP 2017; Roper et al. 2019;) and tribal monitoring programs (Jones et al. 2015; White et al. 2019), we focused on methods that are both quantitative and repeatable (e.g., aerial imagery, measurement of large wood and channel dimensions, pebble counts), while excluding those that are more subjective (e.g., visual estimation of riparian cover and substrate size, complex channel unit classification). This protocol offers improved efficiency and repeatability over previously developed habitat assessment protocols by reducing the number of ground-based measurements, utilizing more objective survey methods, and harnessing new and emerging remotely sensed technology and data products (e.g., LiDAR, drone, and satellite imagery).

Spatio-temporal scale and survey design

These methods are intended to describe fish habitat conditions in wadable streams during low-flow conditions. While some portions of this protocol could be applied to larger rivers or higher flow conditions (e.g., drone-based methods, year-round temperature monitoring), alternative protocols should be utilized if detailed habitat assessments for large river/high flow conditions are required.

The protocol allows assessment of fish habitat conditions across a range of spatial scales from geomorphic channel unit (i.e., pool, fast turbulent, fast non-turbulent; length 1 – 100 m), to reach, segment (0.5 – 1 km), or whole network/watershed scales. Ground-based data is collected at the channel unit scale (i.e., the finest grain of resolution), but can be aggregated to larger scales depending on the goals of the monitoring program. At a minimum, channel unit data will be summarized at the reach scale for calculation of common habitat metrics (e.g., pool frequency, large wood frequency, side channel area, etc.) and analysis of fish-habitat relationships. While the specific methods used to aggregate data to larger spatial scales are beyond the scope of this field protocol, we emphasize that aggregation methods should account for differences in natural channel morphology (i.e., slope, discharge, sediment supply, valley confinement; Montgomery and Buffington 1997; Beechie and Imaki 2014).

The location of data collection will depend on the desired scale of inference. For example, if the goal is to quantify habitat conditions within a single stream segment or small watershed (< 100 km total stream

length), then it is feasible to conduct a spatially continuous census of all available habitat during a single season. Organizations may also choose to collect census data covering different portions of a watershed over a number of consecutive years and then merge the data together. If the desired scale of inference is too extensive to census (i.e., large watershed > 100 km stream length, Major Population Group (MPG), or Evolutionarily Significant Unit (ESU)), then a randomized sampling design is recommended where a subsample of the total extent is surveyed to produce an estimate of average habitat conditions. A good choice for this approach is the Generalized Random Tessellation Stratified (GRTS) design (Stevens and Olsen 2004), which provides a spatially balanced sample across a stream network and has been widely used for aquatic habitat monitoring in the Pacific Northwest (CHaMP 2016; Moore et al. 2019). Ideally, GRTS sample locations would be drawn from the Columbia River basin-wide master sample to facilitate integration of survey data across multiple monitoring programs (Larsen et al. 2008).

The temporal frequency of data collection also depends on program goals and the habitat characteristics being measured. If a program aims to evaluate effectiveness of specific restoration actions at a relatively small number of sites and over a short time frame using a treatment versus control experimental design such as before-after-control-impact (BACI), it may make sense to collect data annually for multiple years both before and after treatment. However, if the goal is to evaluate status and trends in habitat conditions across a large spatial extent and over long time frames, then less frequent sampling (e.g., 5-10 years) is probably sufficient. Less frequent sampling is advisable for monitoring habitat characteristics that may take decades to change (e.g., riparian tree cover, natural large wood recruitment).

Stream segments

Stream segments set the spatial boundaries for measurements of fish habitat and biota and help to organize the survey workflow. Segments typically correspond to the National Hydrography Dataset High Resolution (NHDPlus HR, 1:24K scale) flowlines but will be merged in some cases to ensure a minimum segment length of 1 km. Topographic maps and GPS coordinates detailing segment boundaries will be provided to crews prior to each survey. While habitat surveys are organized by stream segment, metric calculations will not necessarily be confined to segment boundaries.

Survey workflow

This protocol consists of two main components including a ground-based habitat survey and an unmanned aerial vehicle (UAV; drone) survey which work together to provide a comprehensive assessment of in-channel and floodplain/riparian habitat characteristics. Ground-based measurements are intended to provide accurate yet efficient measurements of physical habitat features that can't be easily or reliably measured from UAV imagery or other remotely sensed data (e.g., LiDAR, satellite imagery) such as channel unit class, large wood counts, substrate size, water temperature, etc. UAV surveys provide precise and efficient measurements of stream surface area, riparian vegetation canopy cover and side channel habitats (i.e., length, area, node density) and will likely be used to produce numerous other relevant metrics as image processing tools are developed and refined. LiDAR and other remotely sensed data (e.g., NAIP, LANDFIRE Figure 1 provides a generalized workflow for the main components of the protocol—specific details about each component are provided in subsequent sections. A full list of habitat metrics generated from this protocol is provided in Appendix A.

The specific workflow of an organization or crew will depend upon the number of crew members, watershed size and complexity, and the availability of sampling equipment. Ground-based measurements require at least a two-person crew. One crew member will primarily be responsible for operating a high-accuracy GPS, while the second crew member collects habitat measurements. To prevent errors and improve data quality, it is essential that crew members keep a similar pace for ease of communication

and to aid with measurements when needed. Crew members should maintain their role for the entirety of a stream segment to facilitate consistency in measurements. The UAV survey can be conducted with a one person crew, but a second crew member is useful to help maintain line of site to the UAV during flight and assist with set up and ground control layout.

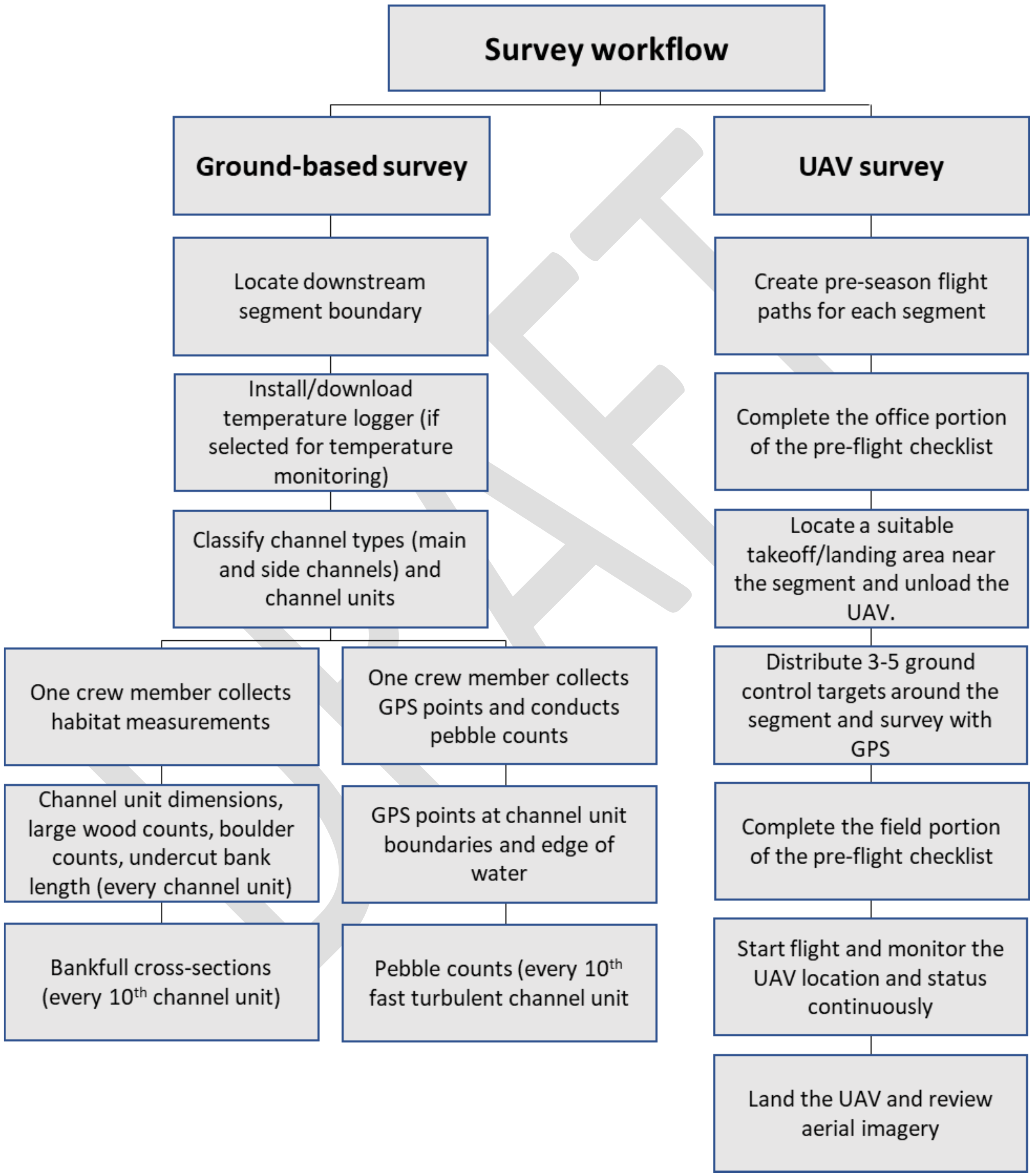

Figure 1. Generalized survey workflow.

1.0 Ground-based survey methods

1.1 Channel types

Channel types are used to differentiate the main channel from qualifying side channels. Unique channel type numbers within each segment are assigned to the main channel and all qualifying side channels in the sequential order in which they are encountered while working upstream (Figure 2).

The **main channel** is defined as the channel containing the largest amount of flow.

Qualifying side channels are defined as portions of the active channel (below bankfull elevation) that are separated from the main channel or other side channels by an island that has a surface elevation greater than or equal to the bankfull elevation for a length greater than or equal to the average bankfull width (see 1.7 Bankfull cross-sections for a description of bankfull elevation).

> Note: If a channel is separated from another channel by a sediment deposit that is shorter than the average bankfull width or not meeting the height criteria (i.e., a sediment bar), then the channel is considered part of the adjacent channel.

All qualifying side channels are further classified as large or small based on flow criteria. Qualifying side channels with ≥ 25 % of the total flow (main channel plus side channel flow) are designated as **large side channels** and channel units within the side channel are uniquely classified (see 1.2 Channel unit classification; Figure 3). Qualifying side channels with < 25 % of the total flow are designated as **small side channels** and the entire side channel area is classified as either **slow water dominated** ("Slow small side channel") or **fast water dominated** ("Fast small side channel") based on the dominant habitat type. For small side channels with discontinuous flow, estimate the percentage of the channel length that is wet.

Non-qualifying side channels are distinguished from qualifying side channels by possessing one or more of the following characteristics:

1) The elevation of the streambed is above bankfull at any point.
2) The channel lacks a continuously defined streambed or developed streambanks.
3) The channel contains abundant terrestrial vegetation (i.e., ≥ 25% of the streambed area is covered by terrestrial vegetation).

Non-qualifying side channels are not assigned channel numbers and channel units are not classified within them. However, if an off-channel unit occurs at the junction of a non-qualifying side channel and a larger channel, the off-channel unit is included in the survey and is considered part of the larger channel.

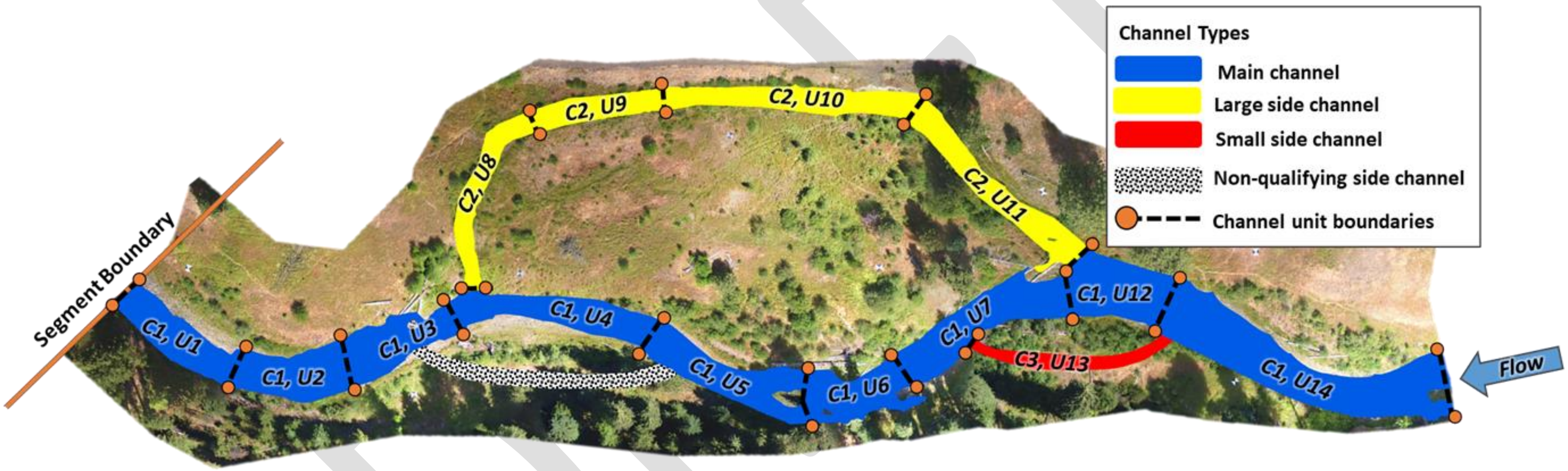

Figure 2. Example of a segment with correctly numbered channel types and units. Channel types have the prefix "C" followed by the sequential channel number (e.g., C1-C3) and channel units with the prefix "U" (e.g., U1-U21).

1.2 Channel unit classification

Channel geomorphic units are relatively homogeneous areas of the wetted channel with unique bedform shape, depth, velocity, and substrate characteristics from those of adjacent units. Measurements of habitat and biota such as large wood, substrate size and fish abundance are collected individually by channel unit, thus making it the most basic level of data collection for these metrics. Channel units within each survey segment are classified using a 2-tiered hierarchical classification system modified from Hawkins et al. (1993; Figure 3).

With a few exceptions, channel geomorphic features must have a maximum surface dimension (length or width) that is at least as large as the average wetted channel width in that location to qualify as distinct channel units. For example, a 3 m long by 2 m wide pool in a side channel where the wetted width is 2 m would qualify, but a pool of the same size in the main channel where the wetted width is 8 m would not qualify. Additionally, channel-spanning features that are relatively short (e.g., plunge pools or short fast turbulent units) qualify as distinct channel units because they are at least as wide as the average wetted width. Features that do not meet this minimum size criteria should be considered part of the adjoining channel unit.

Exceptions to this minimum size criterion include off-channel and special case units. Off-channel units must have a maximum length or width that is at least 50% of the average wetted width in the channel it is associated with to qualify. Dry channel units must be channel spanning (flow is completely subsurface) in at least one location to qualify. Other special case units do not have minimum size criteria.

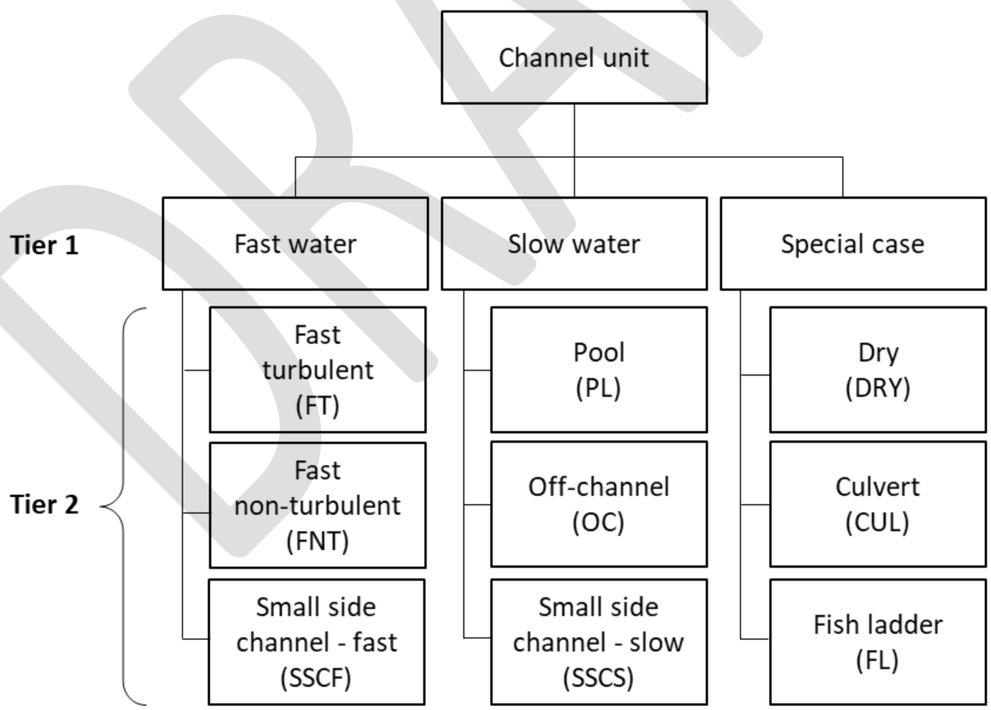

Figure 3. Hierarchical channel unit classification system

1.2.1 Fast water units

Fast turbulent (FT) channel units are high points in the streambed profile that feature moderate to steep gradients (> 1 %), coarse substrate (gravel to boulders) and supercritical flow (i.e., hydraulic jumps sufficient to entrain air bubbles and create localized patches of white water). The bedform of these units generally lacks lateral and longitudinal concavity. Fast turbulent units include several finer-scale channel unit types such as cascades, chutes, rapids, and riffles, but we do not distinguish among these to increase survey repeatability. Waterfalls, which typically have near-vertical gradients over very short distances, are classified as steps rather than fast turbulent units (see 1.2.4 Steps).

Fast non-turbulent (FNT) units, commonly called runs or glides, generally feature low gradients (< 1 %), a uniform or planar bed profile and relatively smooth, non-turbulent flow. Fast non-turbulent units are distinguished from pools by their general lack of lateral and longitudinal concavity and often higher water velocity. These units are generally deeper than fast turbulent units and often contain substrate ranging from sand to cobbles. Fast non-turbulent units also include "sheets", which are common in bedrock-dominated streams and occur where shallow water flows uniformly over smooth bedrock of variable gradient (often exceeding 1%).

Small side channels - fast (SSCF) are small side channels (< 25% of total flow) that are dominated by fast water habitat.

1.2.2 Slow water units

Pools (PL) are low points in the bed profile that feature very low gradients (< 1 %), smooth non-turbulent flow, and a bed shape that possesses both lateral and longitudinal concavity. Substrate size in pools is variable (ranging from fines to boulders) but is typically smaller than faster water units. Pools consist of various types including scour, dammed, trench and plunge pools, though these are not distinguished separately to improve survey repeatability.

Off-channel (OC) units consist of low gradient (often 0%) alcoves and backwaters along channel margins that are connected to the main channel or side channels but have little (< 1%) to no flow through them during low flow conditions. The bedform profile in off-channel units is generally similar to pools with substrate dominated by finer sediment (silt to gravel) and/or organic matter. Off-channel units are often formed during high flows by eddy scour around obstructions on the channel margins or flow through small side channels that are disconnected during low flow.

Small side channels - slow (SSCS) are small side channels (< 25% of the total flow) dominated by slow water habitat. Small side channels lacking continuous flow will typically fall into this category.

1.2.3 Special case units

Special case units account for situations where typical channel geomorphic units do not apply due to low streamflow or man-made structures such as culverts and fish ladders.

Dry (DRY) units are channel-spanning sections of the main channel or large side channels that are dry at the time of the survey. Typical examples are riffles with subsurface flow or portions of side channels surrounding isolated pools. If small puddles exist within a mostly dry channel but they are shorter or narrower than the active channel width in that segment, they should be considered part of the surrounding dry channel unit.

Culvert (CUL) units are sections of stream that pass-through culverts. This classification does not apply to open-bottom culverts which have a defined streambed and can generally be classified as another unit type.

Fish Ladders (FL) are man-made structures often consisting of a series of step pools designed to facilitate fish passage.

1.2.4 Steps

Steps are abrupt, vertical or near-vertical breaks in channel gradient formed by obstructions in the channel or drops over bedrock or other relatively immobile substrates. Steps usually occur over very short (almost negligible) distances, and therefore are not treated as separate channel units. However, the presence/absence of steps is documented due to their importance as potential fish migration barriers or in creating high quality fish habitat (e.g., beaver dams). Steps are classified according to the feature forming the step (i.e., dam, beaver dam, beaver dam analog, large wood, culvert, fish ladder, waterfall) and are assigned to the adjoining upstream channel unit.

Waterfalls sometimes consist of a series of vertical drops separated by lower-gradient channel unit types (usually fast-turbulent habitat). In these scenarios, vertical drops > 1.5 m are classified as steps while the lower-gradient portions are classified as either fast water or slow water channel units based on their physical characteristics as described above.

Short, channel-spanning sections of fast turbulent habitat commonly found separating pools in very low gradient (pool-riffle) and high gradient (step-pool) channel types are not included as steps because they are already classified as fast turbulent channel units.

1.3 Channel unit dimensions

1.3.1 Unit length, width and depth

Ground-based measurements of channel unit dimensions (length, width, and depth) provide the foundational information needed to quantify fish habitat and supplement drone-based measurements where high canopy cover may be prohibitive.

> Note: Future comparisons of ground- and drone-based measurements of surface area across a range of canopy densities will be used to determine a threshold below which ground-based measurements of channel unit dimensions will not be needed. In the meantime, channel unit dimensions will be measured on the ground at all channel units.

Channel units are visually divided into equally spaced transects located at approximately 25, 50, and 75 % of the unit length. At each transect, the wetted width is recorded using a measuring tape or laser rangefinder and three depth measurements are taken perpendicular to flow at 25, 50, and 75 % of the wetted width for a minimum of nine depth and three width measurements per channel unit (Figure 4). In slow water pool units, two additional depth measurements are collected at the pool tail crest and maximum depth (Figure 4; green squares in “*U3*”).

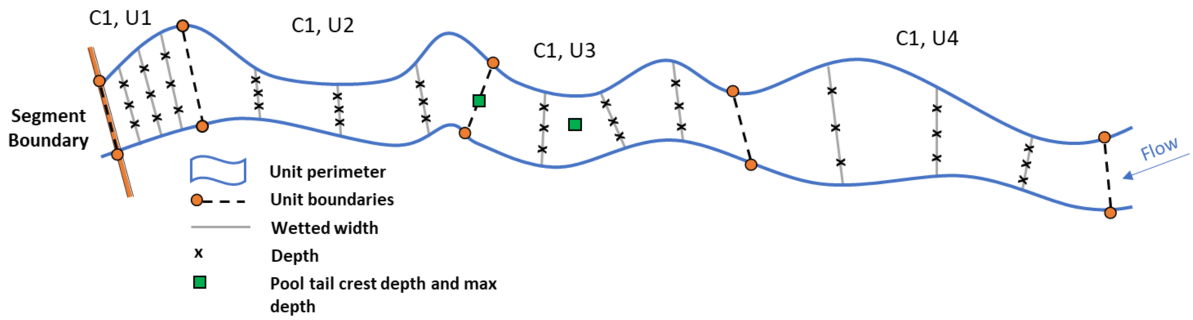

Figure 4. Aerial view of channel unit numbering and the location of wetted width and depth measurements taken within each unit.

<u>Field procedures:</u>

1) Starting from the downstream segment boundary and working upstream, assign channel numbers to the main channel and any qualifying side channels sequentially as they are encountered (*C1, C2, C3*, etc.; Figure 2). The main channel is always designated as channel 1 (*C1*).
2) Using the channel unit characteristics described above, classify and sequentially number each channel unit (*U1*, *U2*, *U3*, etc.) working upstream until the upstream boundary of the segment is reached. Reset the channel type and unit numbering sequences when starting a new stream segment.
   a) If a side channel is encountered, continue numbering channel units sequentially in the channel with the most flow until the upstream start/inflow of the side channel is located, then move to the downstream end of the side channel.
      i) For large side channels (≥ 25% of the total flow), proceed with numbering channel units in the side channel, assigning them to a new channel number (Figure 1).
      ii) For qualifying small side channels (< 25 % of the total flow), treat the side channel as a single channel unit and classify the dominant habitat type as fast or slow. If the small side channel has discontinuous flow, estimate the percentage of the small side channel length that is wet.
3) Record whether each channel unit is flow-connected. For a unit to be considered flow-connected, it must be connected by surface water (of any depth) to the downstream boundary of the stream segment.
4) If a stream segment has been selected for fish sampling, place flagging at channel unit boundaries labeled with the channel number, unit number, and unit type for fish survey crews to reference.
5) If a step is present at the downstream end of the channel unit, record the step type (dam, beaver dam, beaver dam analog, large wood, culvert, fish ladder, waterfall) and measure the step height from the water surface at the bottom of the step to the water surface at the top of the step.
   a) Step height for fish ladders should be measured at a single step within the ladder that is representative of the average step height. The step that is formed by the dam (or other obstruction) that the fish ladder is bypassing should be assigned to the channel unit upstream of the dam (usually a pool) and not to the fish ladder.
6) Measure the length of each channel unit along the unit's centerline to the nearest 0.1 m using a laser rangefinder or measuring tape. Capture channel curvature by taking multiple shorter measurements that follow the channel centerline and adding them together.

a) If a step is present at the downstream end of the channel unit, include the length of the step in the length measurement.

7) Measure the wetted width of each channel unit to the nearest 0.1 m at three equidistant transects located at approximately 25, 50, and 75 % of the unit length and perpendicular to the direction of streamflow (Figure 4).

8) At each width transect, measure depth with a depth rod to the nearest 0.01 m at 25, 50, and 75 % of the wetted width.

9) Measure maximum depth at all slow water channel units. Be sure to probe the streambed thoroughly to find the deepest point in the channel unit.

10) Measure the pool tail crest depth (Figure 5) at all pool units (not including off-channel and slow small side channels).

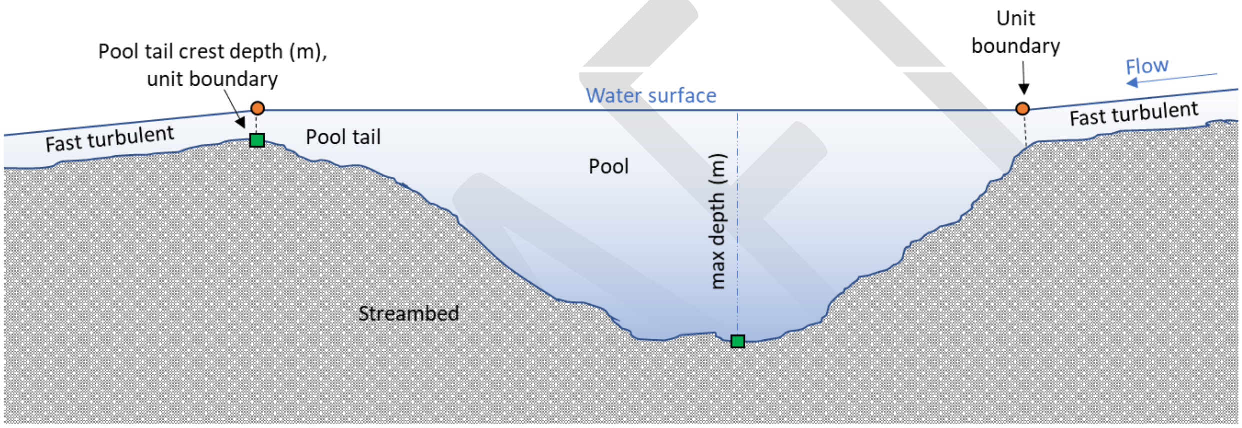

Figure 5. Cross-sectional view of the location of additional pool tail crest and maximum depth measurements taken within pool units.

1.3.2 Unit boundaries and edge-of-water points

Boundaries of the wetted stream channel and geomorphic channel units are delineated using a high-accuracy (submeter) GPS receiver to provide spatial reference for ground-based measurements and aid in processing of drone-collected aerial imagery. Edge-of-water points represent the location where the water surface meets the stream bed or bank. The number and location of edge-of-water points collected is determined by the amount of channel overhanging canopy cover within each stream segment. At a minimum, every channel unit should have two edge-of-water points which mark the lower boundary of the channel unit (Figure 4). Additional edge-of-water points are collected at major inflection points in channel morphology (e.g., around meander bends) where dense overhanging vegetation obstructs the view of the channel from the sky.

<u>Field procedures:</u>

1) Delineate the downstream boundaries of each channel unit by collecting at least two boundary points (one on each bank) with a high-resolution (submeter) GPS.

    a) Unit boundary points should be collected at the edge-of-water and coded as "*U*" for unit combined with the sequential unit number (e.g., *U1, U2*, etc.; Figure 4).

b) If the unit geometry is complex, collect additional points within the wetted channel to accurately capture the perimeter of the unit. Unit boundary points collected within the wetted channel should be coded as "*UW*" for "unit wetted" combined with the sequential unit number (e.g., *UW1, UW2*, etc.).

2) If the adjoining upstream segment will not be surveyed during the same field season, collect a minimum of two additional boundary points at the upstream boundary of last channel unit in the segment.

3) Where dense riparian vegetation is present or as outlined on the provided stream segment maps, collect edge-of-water points while working upstream through the unit. Code edge-of-water points as "*LW*" for "left wetted" and "*RW*" for "right wetted" corresponding to each bank (left of right) looking downstream.

1.4 Large wood

All large wood that meets the minimum size criteria and is within, partially within, or suspended over the active channel is counted using methods adapted from the Oregon Department of Fish and Wildlife (ODFW) Aquatic Inventories Program (AIP; Moore et al. 2019). The minimum size requirement for wood to be counted is 15 cm diameter and 3 m in length. Diameter is measured at 2m from the base of the stem (i.e., where the root wad meets the stem) or, if no root wad exists, from the end of the stem with the largest diameter (Figure 6). Root wads < 3 m in length are an exception and are counted if the stem diameter is ≥ 15 cm. Large wood pieces must be dead or will be soon (i.e., newly fallen trees with detached roots) to be counted.

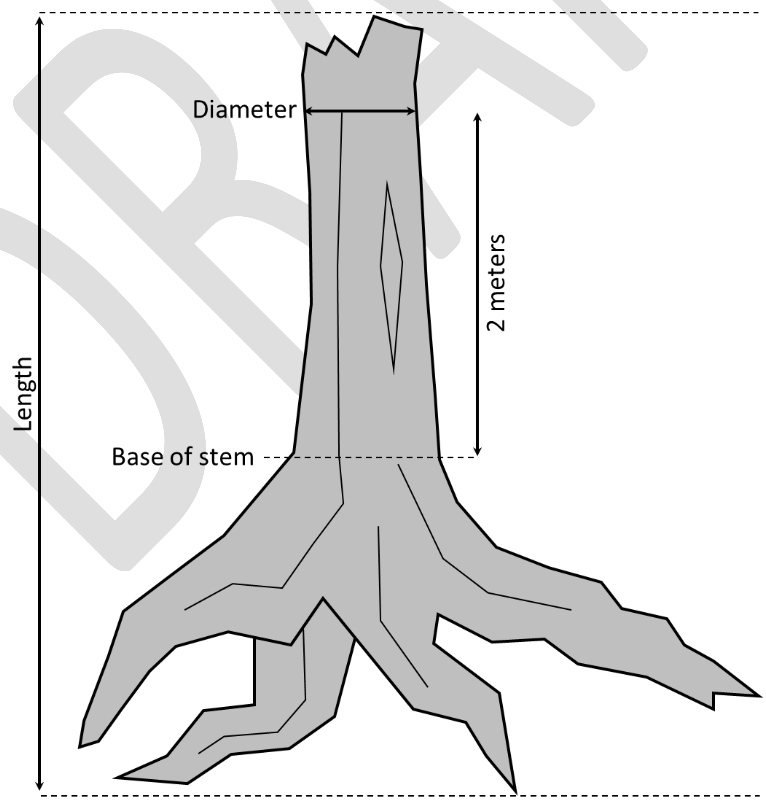

Figure 6. Measurement locations for large wood.

Field procedures:

1) Tally all large wood pieces within each channel unit that meet the minimum size criteria. The first 10 pieces within each segment should be measured with a depth rod to calibrate visual estimates to the minimum size criteria. Any pieces that are close to the minimum size criteria (i.e., within about 0.5 m length and 10 cm diameter) should be measured to ensure accuracy. All remaining large wood pieces within the segment can be tallied without measuring.
    a) If a piece of wood spans multiple channel units, assign that piece to the unit that contains the largest volume of the piece.
    b) If the piece is not within the wetted perimeter of a channel unit, assign it to the nearest channel unit.
2) Record whether each piece of large wood is wet or dry. For a piece to be considered wet, any portion of the wood must be in contact with water within the active channel.

1.5 Boulder counts

All exposed boulders larger than 0.5 m diameter within each channel unit are counted. For a boulder to qualify, it must be in contact with water in the active channel and some portion of it must be exposed above the water surface. Boulders in dry units are not counted.

Field procedures:

1) Count large boulders within each channel unit. Measure the first 10 qualifying boulders within each segment with a depth rod to calibrate visual estimates to the minimum size criteria. Each boulder is measured along its intermediate or b-axis as described in section 1.8 Substrate size.
    a) If a boulder spans multiple channel units, attribute it to the unit that contains the largest volume.

1.6 Undercut banks

Undercut banks are important stream features that provide cover for fish. Undercuts can be identified where dense mats of roots or streambank material overhang the wetted channel.

Field procedures:

1) Record the length and associated channel unit of all undercuts that are ≥ 1 m long and ≥ 20 cm wide.
    a) Undercut width is measured as the wetted horizontal distance from the outermost edge of the overhanging bank to the back “wall” of the undercut at its widest point (Figure 7).
    b) The undercut bank must be at least 20 cm wide at all points along its length.
2) If an undercut spans two channel units, split the length measurement at the channel unit boundary and record the length of undercut bank within each channel unit.

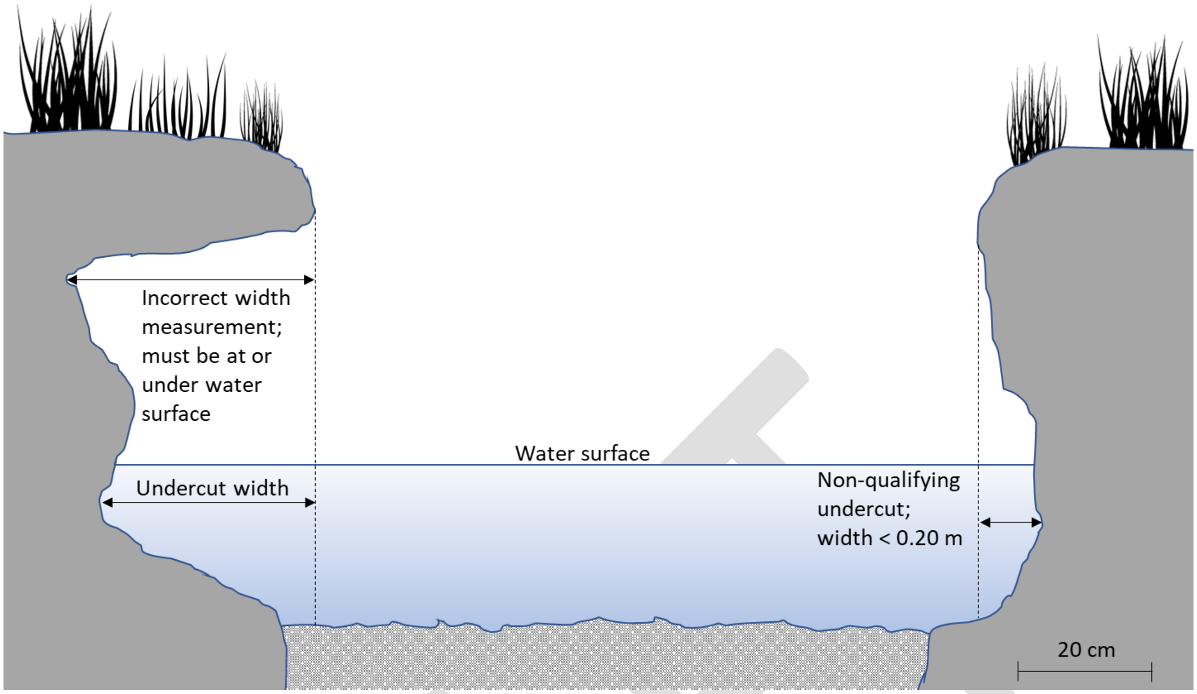

Figure 7. Channel cross-section showing where to measure undercut bank width.

1.7 Bankfull cross-sections

Bankfull elevation is the location along the stream banks where streamflow fills the channel to the top of the banks and water begins to overflow onto the floodplain (Leopold et al. 1964), an event that occurs approximately every 1.5 years. The portion of the stream channel that is at or below the bankfull elevation is termed the active channel. Numerous habitat metrics are generated from cross-sectional measurements of the active channel (e.g., bankfull width, bankfull depth, width-to-depth ratio) and depend on accurate identification of bankfull elevation.

Bankfull elevation is identified in the field using various physical indicators as defined by Harrelson et al. (1994; Table 1). Bankfull elevation is generally easier to distinguish in unconstrained channel types where streambanks are well defined and indicators such as abrupt changes in bank slope, tops of point bars, changes in substrate, and permanent vegetation are more prevalent. In deeply incised or constrained channels, especially those dominated by boulders and bedrock substrate, bankfull indicators may be more difficult to identify and the crew may have to depend on stain lines or move further up or downstream to find reliable indicators.

Regional hydraulic geometry curves (Castro and Jackson 2001, Bieger et al. 2015) provide modeled estimates of bankfull width and depth throughout a stream network as a function of watershed area and mean annual flow. These curves should be consulted prior to conducting field measurements to provide crews with an expected bankfull stage height and thereby help them to accurately identify bankfull elevation in the field.

Table 1. Indicators used to determine bankfull elevation (Harrelson et al. 1994).

Indicator	Description
Change in slope	The change from a vertical bank to a horizontal surface is the best identifier of bankfull, especially in low-gradient meandering streams. Many banks have multiple breaks, so examine banks at several sections of the site for comparison. Slope breaks also mark the extent of stream terraces which are old floodplains above the active bankfull elevation. Terraces will generally have soil structure and perennial vegetation. Avoid confusing the elevation of the lower terrace with that of bankfull; they may be close in elevation.
Top of point bars	Point bars consist of bed material deposited on the inside of meander bends. The top elevation of point bars usually indicates the lowest possible bankfull stage. Multiple point bar elevations may be left from flows both above and below the bankfull elevation.
Change in Vegetation	Look for the lower limit of perennial vegetation on the bank or a sharp break in the density or type of vegetation. Often willow and alders form root lines near the bankfull elevation. The lower limit of mosses or lichens on rocks or banks, or a break from mosses to other plants may also help identify the bankfull elevation.
Change in Bank Materials	Look for changes in bank particle size, usually from coarse particles to a finer particle matrix (which is often associated with a change in slope).
Undercuts Banks	Look for bank sections where the perennial vegetation forms a dense root mat. Feel up beneath this root mat and estimate the upper extent of the undercut. This is usually slightly below bankfull stage. Undercut banks are best used as indicators in steep channels lacking floodplains.
Stain Lines	Look for water lines on rocks that indicate where rocks are frequently inundated. Stain lines are often left by lower, more frequent flows, so stain lines should only be used to assist in identifying bankfull along with another indicator or when no other indicators exist at a site.

<u>Field procedures:</u>

1) Measure bankfull cross-sections within the first channel unit in each segment and every 10th unit thereafter. If the 10th channel unit is an off-channel or small side channel unit, skip to the next upstream unit. Try to avoid measuring cross sections with undercut banks, wood jams, or uneven water surfaces (i.e., pitched riffles).
    a) In slow-water channel units, the cross-section is located at the pool tail crest (Figure 5).
        i) The location of the cross section can be moved upstream or downstream of the pool tail crest a maximum distance of one half the average bankfull width to find suitable bankfull indicators or to avoid undesirable channel features (see above). If no suitable bankfull indicators exist within this area, skip to the next upstream channel unit.
    b) In fast water units, the cross section is located wherever the bankfull indicators are most clear.

2) Stretch a measuring tape across the active channel perpendicular to flow and level with the bankfull indicators on each bank.
    a) Ensure the tape is securely fastened on both banks, is taut, and level to reduce additional error.
    b) If bankfull indicators are only clear on one bank, stretch the tape so that it is approximately level with the one clear indicator. Use the bankfull height as measured from the water surface to the bankfull elevation at the bank with good bankfull indicators as a guide.
3) Measure bankfull width to the nearest 0.10 m while subtracting the width of any islands or bars that are above the bankfull elevation and intersect the transect.
    a) Side channels and any other features that are below the bankfull elevation are included in the measurement of bankfull width.
4) Divide the bankfull width by 10 to obtain spacing between depth measurements (Figure 8). This results in 9 in-channel measurements and two bank measurements (always 0 depth).
    a) Beginning on the left bank (facing downstream), measure bankfull depth (i.e., where the measuring tape intersects the depth rod) to the nearest 0.01 m at each location. Record the distance on the measuring tape where each depth measurement is collected.
    b) In multi-threaded channels, distribute depth measurements in proportion to the width of each channel by maintaining the established point spacing within the active channel (main channel and side channels) and bypassing areas that are above bankfull elevation.
    c) If the channel is so large that the measuring tape bows excessively or it’s difficult to determine if the measuring tape is level, use a hand level and stadia rod to measure bankfull depth at each point.
        i) One crew member (the rod man) holds the stadia rod level at the bankfull elevation on the left bank. The other crew member (the surveyor) stands in a fixed location, sites to the stadia rod ensuring that the device is level, and measures the height on the stadia rod. This is your starting height. Enter the starting height in the data collection app.
        ii) The rod man moves to each subsequent depth measurement point and the surveyor measures the height on the rod.
        iii) The starting height is subtracted from each depth measurement to get bankfull depth. This calculation is done automatically by the data collection app.
5) Record the channel unit(s) that the bankfull cross section was measured in.

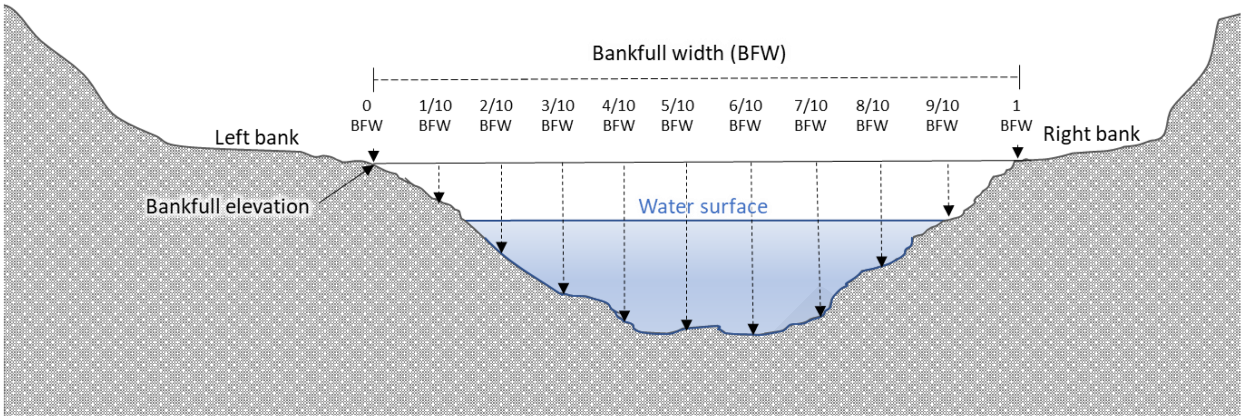

Figure 8. Diagram of a channel cross-section showing measurements locations.

1.8 Substrate size

Streambed particle size is measured using a Wolman pebble count procedure (Wolman 1954) at every 10th fast turbulent unit within each segment. Pebble counts are conducted along transects perpendicular to the stream channel and spanning the width of the bankfull channel (from toe of bank to toe of bank). The toe of bank refers to the line formed by the intersection of the general plane of the sloping side of the stream bank with the general plane of the channel bed. A minimum of 100 particles is measured within each stream segment a using a square-hole template (gravelometer) with size classes corresponding to the Wentworth scale (Table 2).

<u>Field procedures:</u>

1) Conduct a pebble count (100 particles) at the first fast turbulent unit in each segment and every 10th fast turbulent channel unit thereafter. Do not conduct pebble counts in small side channels (< 25 % of the total flow).
2) Starting at the downstream unit boundary at the toe of either bank, select a particle by looking away and extending a finger straight down to the tip of a boot and picking up the first contacted particle.
   a) Ensure that sampling occurs only within the active bankfull channel and do not measure stream bank particles.
3) Use a gravelometer to classify the intermediate axis (b-axis) of the particle (Figure 9). Record the size of the largest square hole that the particle does not fit through—this corresponds to the low end of the size category for that particle. For example, if a particle fits through the 180 mm square but does not fit through the 128 mm square, the size category is > 128 – 180.
4) After measuring the first particle, proceed to the next sample location by taking one pace.
   a) Avoid changing the pace or trajectory of sampling to avoid large boulders, deep water, or other obstacles. A consistent location on the boot should be used to minimize bias against smaller particles.
   b) Do not measure the same particle twice and take extra caution, by tossing measured particles behind or downstream to prevent double counting.

c) For particles larger than 180 mm or particles that cannot be removed from the streambed, use the gradations along the edge of the gravelometer or a depth rod to measure the b-axis of the exposed portion of the particle (Figure 9). The edge of the gravelometer, which is 2 mm thick, can be used to identify particles less than 2 mm.

d) If a layer of fine sediment completely covers larger rock beneath, measure the fine sediment. Conversely, if individual fine sediment particles are partially covering the larger rock below measure the underlying rock.

e) When bedrock is encountered at sample points, record the size as "bedrock" and measure additional particles as necessary to ensure a minimum of 100 particles (not including bedrock) are measured.

f) When the end of the first transect is reached, take a pace upstream using the same spacing to establish the next transect. Proceed with measuring particles along each transect in the same fashion described above until 100 particles have been measured.

5) If the upstream boundary of the unit is reached before completing the pebble count, continue to the next fast turbulent unit until 100 particles are measured. Record the channel unit number(s) that pebbles were measured in.

a) If the pebble count was extended into multiple channel units, conduct the next pebble count at the 10th fast turbulent unit after the last unit that was sampled.

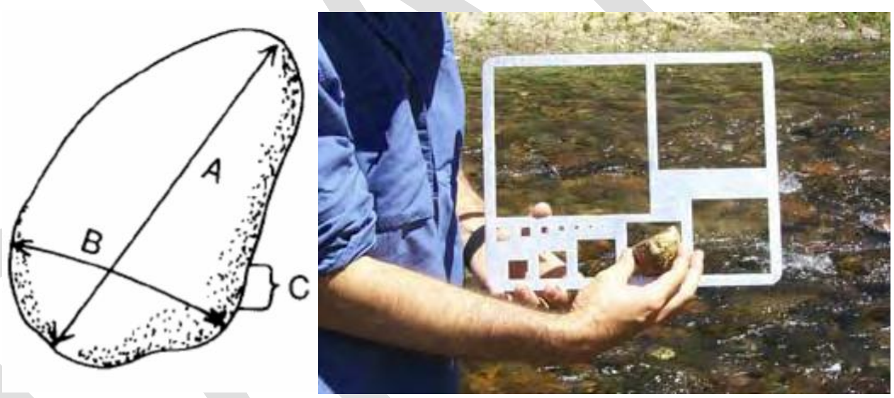

Figure 9. Left: particle axis from Harrelson et al. (1994). Right: Gravelometer used to measure the b-axis of each particle. Photo from CHaMP (2016).

Table 2. Size gradation for sediment in the range of fines (sand, silt, clay) to boulders (Wentworth scale).

Particle size description		Particle size (mm) Minimum	Maximum
Bedrock		NA	NA
Boulder	mega	> 4096	NA
	very large	> 2896	4096
		> 2048	2896
	large	> 1448	2048
		> 1024	1448
	medium	> 724	1024
		> 512	724
	small	> 362	512
		> 256	362
Cobble	large	> 181	256
		> 128	181
	small	> 90.5	128
		> 64	90.5
Gravel	very coarse	> 45.3	64
		> 32	45.3
	coarse	> 22.6	32
		> 16	22.6
	medium	> 11.3	16
		> 8	11.3
	fine	> 5.66	8
		> 4	5.66
	very fine	> 2.83	4
		> 2	2.83
Fines (Sand, Silt, Clay)		< 2	2

1.9 Water temperature

Year-round, hourly water temperature is measured using Onset HOBO temperature data loggers (± 0.2 °C accuracy) at pre-designated stream segments. Ideally, loggers should be installed no later than July 1 to ensure that peak summer temperatures are captured and downloaded again in the fall prior to high winter or spring flows.

Temperature monitoring locations will vary based on the monitoring program's resources and objectives. Generally, loggers should be placed in strategic locations to capture significant changes in water temperature such as near tributary junctions and across a range of stream sizes and elevations throughout the stream network of interest. Additionally, it is advisable to place loggers near the upstream and downstream extents of the study area (i.e., boundary conditions). Program leaders and/or crew supervisors will typically provide guidance to field technicians on the desired location of each logger.

There are two recommended options for logger installation: the epoxy method and the cable method. The epoxy method is the preferred option and should be used unless there is no suitable attachment surface for the epoxy method (see Epoxy method below). In both cases, the logger is placed in a PVC housing unit to protect it from direct solar radiation and damage during high flows. Housing units are drilled with multiple holes (1/4 – 1/2 in diameter) to ensure adequate exchange of flowing water.

Epoxy method: Refer to Isaak et al. (2013) for complete details. Search for a large rock or boulder that will be immobile during large floods and is easy to identify on subsequent site visits. Optimal placement locations for the epoxy method include: 1) large rocks, boulders, or structures that will not move during high flows, 2) boulders large enough that they protrude above the low flow water surface and wide enough that they can effectively shield the logger from moving rocks or debris during high flows, 3) areas downstream of large rocks in pockets of relatively calm water with smaller substrate sizes, 4) a relatively flat downstream attachment surface that is deep enough to remain submerged in flowing water for the entire year. If a suitable attachment surface is not available, use the cable method.

<u>Field procedures for epoxy method:</u>

1) Clean the attachment surface of the boulder with a wire brush prior to installation.
2) Use a 2-part underwater epoxy (FX-764 Hydro-Ester® Splash Zone Epoxy manufactured by Fox Industries, Baltimore, MD, http://www.foxind.com/) to glue the PVC logger housing to the boulder.
   a) Use approximately 1 golf ball sized portion of each part of the epoxy (white and grey) and mix together thoroughly with wet gloved hands for approximately 1 minute.
   b) Apply the epoxy to the bottom of the housing in a thick layer (approximately 0.5 – 1 inch thick) and press the housing against the rock surface.
   c) Gently smooth the epoxy with the gloved hand around the perimeter of the housing to maximize contact with the rock.
3) Brace the housing in place using a cobble and leave overnight to achieve a secure bond.

Cable method: Use the cable method if there is not a suitable boulder near the desired monitoring site for the epoxy method. Optimal placement locations for the cable method have the following attributes: 1) a secure anchor point such as the base of a living tree or root (> 20 cm diameter) near the stream bank, 2) sufficient water depth to ensure the logger remains submerged year round, but outside of strong currents, 3) non-depositional area where the logger is unlikely to get buried by sediment, 4) well-mixed streamflow, usually in fast-water channel units (i.e., avoid pools with stratified water temperatures), 5) not near groundwater seeps or other cold-water anomalies, 6) camouflaged or inconspicuous location when installed near high public use areas.

<u>Field procedures for cable method:</u>

1) Attach the logger housing to a tree or root using a stainless steel cable ≥ 1/16 in diameter and aluminum crimps. Note that galvanized cable will rust and break rapidly and is not recommended.
   a) If a suitable tree or root is not present at the site, attach the cable to a metal stake or rebar driven securely into the streambed (cement form stakes 2 – 2.5 ft long are recommended).
   b) Use a long enough length of cable that the logger housing can be lifted out of the water during low flows to download the data without having to cut the cable.
2) Attach a 1-2 oz weight to the cable to ensure the logger and housing unit remain submerged.

Office procedures before leaving for the field:

1) Check the accuracy of all temperature loggers using an "ice bucket" method prior to installing in the field (Dunham et al. 2005). If the logger measurements are outside of the range of ± 0.2 °C, the logger should not be used.
2) Ensure the laptop computer battery is fully charged and the date and time are correct.
3) Open the HOBOware software and check that it is set to standard international (SI) units (this ensures that temperature is recorded in degrees Celsius, not Fahrenheit).
4) Connect the HOBO shuttle to the laptop using a USB cable and check the battery level on the HOBO shuttle. Replace if necessary.
5) Sync the shuttle with the laptop. This ensures that any temperature loggers launched with the shuttle are programmed with the correct date and time. **Critical note: the shuttle must be re-synced with the laptop any time the shuttle batteries are replaced prior to launching or downloading any temperature loggers.**
6) If you're planning to install temperature loggers at new locations (i.e., locations where a logger doesn't already exist), it's recommended to pre-launch several loggers in the office prior to departing for the field.
   a) Attach the logger to the shuttle and squeeze the black plastic lever on the shuttle coupler to establish a connection with the logger. Once connected, launch the logger. Set the start date and time for 12:00 AM of the next day and set the logging interval to 1 hour. Setting the launch time for 12:00 AM ensures that air temperatures are not recorded prior to installation. Ensure that the launch was successful (see message at the bottom of the HOBOware screen), then disconnect the logger.
   b) Place pre-launched loggers in a labeled bag or otherwise mark them to ensure they are easily distinguished from unlaunched loggers.

Field procedures (installing new loggers):

1) Identify a suitable logger location and installation method using the guidance above.
2) Record the logger serial number.
3) If the logger was not pre-launched in the office, connect the shuttle to the laptop computer, attach the logger to the shuttle and squeeze the black plastic lever on the shuttle coupler to establish a connection with the logger. Once connected, launch the logger. Set the start date and time for the next hour (on the hour) of the current day and set the logging interval to 1 hour. Ensure that the launch was successful (see message at the bottom of the HOBOware screen), then disconnect the logger.
4) Attach the logger to the inside of a PVC housing unit using plastic zip ties and install the logger.
5) Record GPS coordinates at the logger location (Preferred format UTM, NAD83).
6) Record the stream bank (facing downstream) that the logger is nearest to and the distance from the stream bank. If cable is attached to a tree on the bank, record the distance from bank as 0.
7) Record the attachment method ("Cabled to tree/roots", "Cabled to stake", or "Epoxy").
8) Record the condition of the logger as "In flowing water".

9) Record the action taken with the logger as “Installed new logger” and the date/time the action was taken.

10) Write a detailed description of the logger location. The description should include distance from the nearest segment boundary, nearby tributary junctions, and any other pertinent information for relocating the logger. The more detail the better. For example: “Logger attached to grey, rectangular boulder 1 m in diameter near river left (~1.5 m from bank), 5 m upstream from the lower boundary of segment 1, in a fast non-turbulent unit”.

11) Attach flagging to a nearby tree or other object to mark the location of the logger and take a photo of the logger location. Include enough of the surrounding environment to relocate the logger.

<u>Field procedures (previously installed loggers):</u>

1) Use existing GPS coordinates, photographs, and site maps to locate the previously installed logger. If the logger location is found but the logger is missing, search downstream for the missing logger. If it cannot be found, install a new logger using the criteria outlined above.

2) Remove the logger from the housing unit and confirm that the correct logger serial number was recorded when originally installed. Avoid removing the logger from the water when it will be recording one of its hourly temperature measurements (on the hour). Rubber gloves, large pliers, or an oil filter wrench may be helpful for unscrewing housings that are difficult to open.

3) Attach the logger to the shuttle and squeeze the black plastic lever on the shuttle coupler to download the data. If working properly, the indicator light on the shuttle will blink orange during data transfer, and then blink green when the transfer is complete. If the light blinks red (indicating an error), clean the optical sensor on the logger and the shuttle connection surface and try again. If the data transfer fails after multiple tries, replace the logger and notify a project leader.

4) Attach the shuttle to the laptop computer, download the data, and briefly review the temperature data from the previous season. Look for erroneous spikes in temperature (> 30 °C), lack of variability (i.e., flat line), errors with the date/time (e.g., dates that don’t vary or make sense), or other odd patterns in the data. Also check to ensure there is sufficient battery life in the logger. Replace the logger if the data looks erroneous or the battery is low.

5) After downloading the logger, note whether the red light on the logger is blinking (indicating that it is launched and operational). If there is no blinking light, attempt to relaunch the logger (Step 1c). If there is still no blinking light, replace the logger and notify a project leader.

6) Record the condition of the logger (i.e., “Buried”, “Out of water”, “In flowing water”, “In non-flowing water”, or “Missing”). Loggers that are partially out of water are designated as out of water.

7) Record the action taken with the logger (i.e., “Installed new logger”, “Left in place”, “Moved”, “Removed”, “Replaced”, or “Didn’t replace”) and the date/time the action was taken. Move the sensor if it is in non-flowing water, out of water, or buried in sediment. Replace missing loggers with a new one unless otherwise instructed by a project leader. If a logger is removed and replaced with a new logger, the logger that is removed is assigned the action “Removed”, and the replacement logger is assigned the action “Installed new logger”.

8) Verify and update the logger location information as needed such as stream bank, distance from bank, attachment method, location description, and GPS coordinates. Only record new GPS coordinates if the logger was moved or if the original coordinates were erroneous. Take a new photo of the sensor only if the previous photo is no longer representative of the logger location or the photo is not stored in the temperature data entry application.

2.0 UAV survey methods

This section outlines an idealized workflow for the drone-based portion of this protocol which can be broken down into three major steps: 1) Legislation and regulation; 2) Segment reconnaissance and pre-flight fieldwork; and 3) Flight mission. As with the ground-based portion, the specific workflow of an organization or crew may depend further upon the number of crew members, tributary size and complexity, and equipment. Our intent is not to provide specific guidance on the range of available unmanned aerial vehicles (UAVs or drones), sensors, flight planning and post-processing software, or any combination of the prior, but rather provide a high-level overview of standard considerations for integrating unmanned aerial vehicles into stream habitat surveys. A more detailed step-by-step checklist for pre-flight planning can be found in Appendix C along with an example flight log in Appendix D of this document.

2.1 Legislation and regulation

The Federal Aviation Administration (FAA) is the governmental entity in charge of regulating the use of unmanned aerial vehicles. Advancements in technology and availability of consumer grade UAVs have resulted in an increased need to more highly regulate the use of drones by the FAA. To account for the rapidly growing number of UAV pilots and platforms, regulations and legislation are frequently evolving, and the FAA has accounted for this by requiring recurring remote pilot certification testing (every two years) and UAV registration (every three years). Commercial operators are required to hold a valid Part 107 remote pilot license issued by FAA. The FAA requires all drones to be registered and proof of registration (FAA registration number) to be clearly visible on the hull of the UAV. The remote pilot must comply with all FAA regulations including proof of remote pilot certification and aircraft registration during all flight missions. It is the responsibility of each remote pilot to maintain their certification and UAV registration.

To ensure the safety and success of any flight mission, the pilot in command (PIC) and crew members should adhere to all outlined FAA flight rules. It is recommended that organizational standard operating procedures (SOPs) are generated, personal liability and aircraft insurance are obtained, and proper reporting and record keeping are maintained for each mission. At a minimum, the PIC should complete a pre-flight checklist (one such suggested in Appendices C of this document) and keep a flight log (Appendix D). It is important to note that the PIC takes full responsibility for all aspects of a given flight including ensuring the safety of equipment, personnel, and surrounding area (people and landscape) and therefore, the PIC must be sufficiently prepared for flight - these may include health, environmental pressures, and site related hazards. Proper flight planning is a multistep process that should be completed by the crew supervisor or PIC prior to flight.

2.2 Segment reconnaissance and pre-flight fieldwork

Pre-season planning is conducted by the crew supervisor and/or PIC. Similarly, to the ground-based portion of this protocol, flight missions will be created for each stream segment of interest. Depending on the flight planning software and additional resources available to each organization, a portion of the reconnaissance and mission planning can be completed before physically visiting the site; for example, some flight planning software allow for automatic adjustments to flying altitude based on terrain. However, additional reconnaissance should be conducted once at each segment to identify local unforeseen hazards, identify alternative takeoff and landing locations for use during potential emergency procedures, and to verify the minimum safe flying altitude.

Additionally, establishing ground control within each stream segment should be conducted during this phase of pre-flight fieldwork. High accuracy ground control points (GCPs) are key in obtaining precise data products from a flight mission and have been shown to be 5-10 times more accurate than the onboard GPS of UAVs (Turner et al. 2012). A minimum of three GCPs should be distributed throughout the survey area and be both visible in imagery from overhead and at locations that exemplify the topographic variability of the sampling area. GCPs should be surveyed in to obtain coordinates using a high-resolution GPS and targets should be placed over each point prior to flight. If no ideal locations exist within the segment to place ground control, permanent structures (e.g., houses, fence posts, etc.) or landforms (e.g., large boulders, rock outcroppings, etc) can alternatively be used.

2.3 Flight mission

Flight missions require a substantial amount of pre-planning and post-processing but are generally completed in a very short amount of time. Additional considerations should be taken into account for each stream segment where flight duration may be dependent on the area to be flown, the complexity and/or topography, and weather conditions. No flight should be conducted until the previous two steps (Legislation and regulation, Segment reconnaissance and pre-flight fieldwork) have been completed. The use of a pre-flight checklist and flight log are suggested to maintain physical records of each flight as added assurance for reporting purposes; examples of each can be found in Appendices C and D respectively.

Collecting high-resolution imagery, coupled with ground control, is paramount to obtaining precise data products. The accuracy and completeness of each product is dependent on the altitude of flying and paths created, number and orientation of images collected, and the density of riparian floodplain vegetation. To reduce the effect of any one of these it is suggested to collect imagery from multiple viewing angles (nadir and oblique), reduce the flying altitude if possible to decrease the ground sampling distance and increase imagery resolution and accuracy, and collect more imagery which can generally be achieved by increasing image overlap to at least 70% if not more for both sidelap and frontlap. Depending on the UAV platform, sensors or technology used, and metrics of interest, additional considerations such as stream orientation, time-of-day, or lighting and weather conditions may need to be taken into account. A list of potential metrics that can be derived from this protocol including those from imagery collected with a UAV are available in Appendix A.

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Appendix A: Metrics

Metric type	Sub-type	Metric	Description	Data source
Habitat quantity	River channel	Length of accessible Chinook habitat	Length (km) of accessible main channel habitat that is currently (or was historically) used by Chinook Salmon for spawning, rearing or migration	Modeled/Field
	River channel	Length of accessible steelhead habitat	Length (km) of accessible main channel habitat that is currently (or was historically) used by steelhead for spawning, rearing or migration	Modeled/Field
	River channel	Slow water area	Surface area (m^2) of slow water habitat (e.g., pools, off-channel units, slow small side channels) during summer low flow	Field/UAV
	River channel	Fast water area	Surface area (m^2) of fast water habitat (e.g., fast turbulent, fast non-turbulent, fast small side channels) during summer low flow	Field/UAV
	Floodplain/side channels	Connected floodplain area	Surface area (m^2) of connected floodplain habitat at 2 X bankfull depth (NetMap 2020, Benda et al. 2016)	LiDAR
	Floodplain/side channels	Connected off-channel habitat area	Surface area (m^2) of connected off-channel habitat at 0.75 X bankfull depth (NetMap 2020; Benda et al. 2016).	LiDAR
	Floodplain/side channels	Side channel length	Length (m) of side channels during low flow	Field/UAV
	Flow	Mean summer flow	Mean of all daily flow measurements ($m^3 \cdot s^{-1}$) during summer (Jun 1 - Sep 30; USFS 2015).	Field/ Modeled
	Flow	Mean annual flow	Mean of all daily flow measurements ($m^3 \cdot s^{-1}$) within a water year (Oct 1 - Sep 30; USFS 2015).	Field/ Modeled
	Flow	Center of flow mass	Flow-weighted mean day of the water year (i.e., center of flow timing; USFS 2015)	Field/Modeled
Habitat quality/ diversity	River channel (pools)	Slow water percent	Percentage of total surface area in slow water habitats	Field

Metric type	***Sub-type***	***Metric***	***Description***	***Data source***
	River channel (pools)	Large pool frequency	Number of large pools (> 20 m² area and > 0.80 m max depth) per kilometer of stream (McIntosh et al. 2000)	Field
	River channel (pools)	Residual pool depth	Mean residual pool depth (max depth - thalweg exit depth in meters; Mossop and Bradford 2006)	Field
	River channel (cover)	Boulder frequency	Number of partially exposed boulders within the wetted channel per 100 m stream length	Field/UAV
	River channel (cover)	Undercut bank frequency	Length of undercut banks within the wetted channel per 100 m stream length	Field
	River channel (cover)	Large wood frequency	Number of large wood pieces within the bankfull channel per 100 m stream length (Moore et al. 2017)	Field
	River channel (cover)	Large wood area	Surface area (m²) of large wood within the wetted channel during low flow	UAV
	River channel (substrate)	Median sediment particle size (D50)	Median sediment particle size on the streambed surface in riffles (Wolman 1954)	Field
	River channel (depth)	Bankfull width to depth ratio	Average bankfull width to depth ratio (Rosgen 1996)	Field/LiDAR
	Floodplain/side channels	River channel complexity index	RCI = S*(1+J) where S = stream sinuosity, J = # of side channel junctions (Brown 2002)	Field/UAV
	Floodplain/side channels	Side channel ratio	Length of side channels divided by length of main channel during low flow (Beechie et al. 2017)	Field/UAV
	Riparian condition	Overhanging vegetation	Percentage of stream surface area covered by vegetation during low flow	UAV
	Riparian condition	Riparian tree cover	Average percent tree canopy cover in the riparian zone (50 m stream buffer)	UAV/LiDAR/Satellite
	Riparian condition	Riparian tree height	Average tree height (m) in the riparian zone (50 m stream buffer)	UAV/LiDAR/Satellite
	Riparian condition	Riparian vegetation departure index (RVD)	Ratio of existing vegetation cover to pre-European settlement vegetation cover in the valley bottom (Macfarlane et al. 2017)	Satellite
	Water quality	Water temperature	Various measures of water temperature (°C) magnitude, variability, frequency, duration, and timing (Heck et al. 2018)	Field/Modeled

Metric type	Sub-type	Metric	Description	Data source
	Water quality	Coldwater refuges	Percentage of total stream area in coldwater refuges (Dugdale et al. 2015)	FLIR
	Biological	Chinook density	Number of juvenile Chinook Salmon per habitat area (fish/m²)	Field
	Biological	Steelhead density	Number of juvenile steelhead/rainbow trout per habitat area (fish/m²)	Field
	Biological	Observed/Expected (O/E) benthic macroinvertebrates	Ratio of observed to expected benthic macroinvertebrate taxa as predicted by the River Invertebrate Prediction and Classification System (RIVPACS; Hawkins et al. 2000)	Field

Appendix B: Equipment list

Equipment	Quantity	Check	Notes
HABITAT			
Protocol	2	❑	
iPads or tablest with loaded site data	2	❑	
Topo maps and segment metadata	1	❑	
Arrow 200 high-resolution GPS with spare battery	1	❑	
1.5m fixed-height survey rod (for GPS receiver)	1	❑	
Measuring tape (50 m)	1	❑	
Telescoping leveling rod (i.e., stadia rod; ≥ 3 m)	1	❑	
Gravelometer	1	❑	
Flagging (2 colors)	4	❑	
Permanent markers and pencils	4	❑	
Waterproof laser rangefinder	1	❑	
Compass	1	❑	
Write-in-rain field notebooks	3	❑	
Clipboard to store manuals and datasheets	2	❑	
Backpack	2	❑	
Candy cane stakes for bankfull cross-sections	4	❑	
Small spring clamps to hold measuring tape	4	❑	
DRONE			
Drone with spare batteries	1	❑	
Launch pad	1	❑	
iPad or tablet with flight planning software with sun shade / hood	1	❑	
Pre-flight checklist and log binder	1	❑	
Controller	2	❑	
Spare SD cards	3	❑	
Circular polarizing (CP) camera filter	1	❑	
"Drone pilot at work - Do not disturb" sign	1	❑	
High visibility safety vests	4	❑	
Safety cones	2	❑	
Hex key / Allen wrench set	1	❑	
Spare propellers	4	❑	
Two-way radios with spare batteries	4	❑	
TEMPERATURE			
HOBO Tidbit Temperature loggers	10	❑	
HOBO Onset Shuttle and USB cable	2	❑	
Photos and notes of previous locations	1	❑	

Computer	1	❑	
Flagging	2	❑	
Stainless steel wire (1/16” diameter)	40 ft	❑	
Cable crimps for 1/16” cable	25	❑	
Crimping tool	1	❑	
Heavy duty pliers with cable cutter	10	❑	
Thermometer	2	❑	
1.5" PVC male adapter	3	❑	
1.5" PVC female screw cap	3	❑	
Two part epoxy (Fox Industries FX-764 Hydro-Ester® Splash Zone Epoxy)	1	❑	
Wire brush	1	❑	
Nitrile gloves	10 pairs	❑	
Metal detector	1	❑	
Sledge hammer 2 lb	1	❑	
1/4" rebar or cement form stakes (2-2.5 ft length)	20	❑	
SAFETY			
GPS and spare batteries	2	❑	
Road maps	1	❑	
Topo maps	1	❑	
Satellite phone	1	❑	
First aid kit (2 regular, 1 WFA)	3	❑	
AED (Automated External Defibrillator)	1	❑	
Tool kit (wrench, pliers, screws drivers, etc.)	1	❑	
Road safety kit (includes jumper cables, air compressor, flares, flashlight, etc.)	1	❑	
Safety vests	4	❑	
Water container (5 gal)	1	❑	
Cooler	1	❑	
Ice packs	2	❑	
Large tarp	1	❑	
Rope (100 ft)	1	❑	
Travel vouchers and tax exemption forms	1	❑	
Scientific research permits	1	❑	
Fire extinguisher	1	❑	
Inverter	1	❑	
PERSONAL FIELD EQUIPMENT			
Wading boots	1	❑	
Wading socks	1	❑	
Waders	1	❑	
Rain gear	1	❑	

Hat	1	❑	
Sunscreen	1	❑	
Polarized sun glasses	1	❑	
Bug repellant	1	❑	
Pocket knife or multi-tool	1	❑	
Water bottle (1 qt)	2	❑	
Backpack	1	❑	
Cell phone	1	❑	
Cell phone charger	1	❑	
Toilet paper	2	❑	
Food for lunch, snacks, and lunch bag	1	❑	

Appendix C: Flight mission checklist

Legislation and regulation

- ❒ Print off VFR Sectional Chart of flight area
- ❒ Check for NOTAMs and TFRs
- ❒ Check weather for location and time of flight
- ❒ File NOTAM at www.1800wxbrief.com (if applicable) and complete flight log

Segment reconnaissance and pre-flight fieldwork

- ❒ Prepare pre-season flight paths for each stream segment
- ❒ Ensure maps and flight plans are saved and cached to the ipad(s)
- ❒ Identify additional unforeseen hazards (trees, cliffs, people, property, power lines) within each segment
- ❒ Establish 3-5 ground control points (GCPs) per 1 km
    - Using a high-accuracy GPS or other surveying equipment (total station or real time kinematic GNSS) establish randomly distributed GCPs throughout the segment flagging each with the corresponding number
- ❒ Adjust pre-established flight paths to account for hazards
- ❒ Stake out ground control targets
- ❒ Meet with the crew to layout flight plan, address additional concerns, and test radios

Flight mission

- ❒ Establish primary takeoff and landing zones
    - These areas should be flat and free of obstacles such as trees or shrubs within a 3 m radius. The use of a launch pads or an alternative surface (e.g., plywood) should be used to help tamp down tall grasses when necessary
- ❒ Stake out ground control targets
- ❒ If takeoff and landing locations are on or adjacent to a road, set out safety cones and signage to alert the public to an active work site
- ❒ Unload the UAV, ensure equipment is fully charged, and visually inspect the equipment
    - Inspect rotors and propellers, gimbal(s) and payload(s), and check for visible defects
    - Ensure sufficient storage is available on the SD card within the camera and clean the lens to remove any dust, debris, or water particles prior to takeoff
    - Install UAV batteries
- ❒ Prepare to launch the UAV
    - Turn on the UAV and remote controller(s) and check connectivity
    - Set camera parameters
    - Review flight path and mission details
    - Set the “home” location and verify emergency protocols
    - If present, check radio connection between PIC and visual observer(s).
    - Complete the pre-flight checklist and update the flight log
    - If not yet complete and necessary, contact air traffic control (ATC) or local dispatch to receive authorization to launch the UAV

    - After receiving authorization, emergency procedures have been reviewed, and potential hazards have been accounted for and identified proceed with launching the aircraft
- ❒ Continue to monitor the mission status and UAV
    - Maintain line-of-sight with the UAV and utilizes visual observers when necessary
    - Monitor the flight path, connection between the UAV and controller(s), and battery levels
    - Be prepared to take control in the event of a system malfunction
- ❒ Verify the landing area is clear and safe to land the UAV
- ❒ Land the aircraft and review imagery ensuring the desired extent was captured including all ground control targets and determine whether a secondary flight is needed to collect additional imagery
- ❒ Power down the UAV
- ❒ Complete the Flight Log for the mission

Appendix D: UAV Flight Log[1]

Pilot in Command (PIC):____

Organization: ______________________________ Proposed Flight Date: ______/______/______

Stream Segment ID: ____

Local Airport Code(s): _______ Proximity: __________(miles) Airspace Class: _____________

ATC/ Dispatch Contact Date: _____/______/______ Permission Granted: Y / N

ATC/ Dispatch Contact Info: ____

Airport Emergency Phone Number: _____________ ATC/CTAF Freq: ____________________________

DROTAM (NOTAM) Filed (1-877-487-6867) Date: _______/________/_______

Flight Coordinates: _________________________________ Radius: _________ ALT: _______________

Flight Date /Time: ____

DROTAM (NOTAM) Number: __________________________ Phone Operator Initials: _______________

METAR:____

____

❐ Minimum 3 SM visibility, ceiling 500 (ft) MSL above flight max ALT

Temporary Flight Restriction (TFR): Y / N ____

____

NOTAM Check: Y / N

- **I**LLNESS
- **M**EDICATION
- **S**TRESS
- **A**LCOHOL
- **F**ATIGUE
- **E**MOTION

- **P**ILOT
- **A**IRCRAFT
- EN**V**IRONMENT
- **E**XTERNAL PRESSURES (EGO, OUTSIDE STRESSES, ETC)

- PEOPLE
- PROPERTY NEARBY
- FORCED LANDING AREA
- PARTICIPANT WAIVER

Crew Brief (If present)

- EMERGENCY PROCEDURES
- MISSION BRIEF

Pre-flight Complete: ______/______/_______

Flight Notes (Include Date, Start/Stop Time, Visual Observers, Any Training, Maneuvers, etc):

____

____

____

____

____

____

____

____

[1] This form is a guide and should not be considered comprehensive. The PIC takes full responsibility for all actions or events that occur during a given flight. This form was modified from SFI 2017.

Appendix B – Draft manuscript on snorkel survey detection efficiency model

A hierarchical approach for joint estimation of fish abundance and snorkel survey detection efficiency

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Target Journal: *Methods in Ecology and Evolution*

Running Headline: Estimation of snorkel detection efficiency

Abstract

1. Snorkel surveys are used widely to assess abundance and distribution of fishes (particularly juvenile salmonids) in small streams. However, the method is imperfect in the sense that observers rarely count all fish present at a site. To correct for this imperfect detection, snorkel counts are generally calibrated to an independent measure of abundance (e.g., via mark-recapture) at a subset of locations, but the imprecision or inaccuracy of these independent measures is often ignored. This practice may cause biases or overstatements in the confidence of these data sets. Our objective was to develop, assess via simulation, and apply a hierarchical approach that accommodates uncertainty in both sources of information when estimating the detection efficiency of snorkel surveys.
2. The framework assumes that both mark-recapture and snorkel surveys sample the same local abundance with error, allowing the construction of a joint likelihood function for both data sets. The model estimates coefficients that link snorkel detection efficiency to local habitat covariates through a logit-linear model. To assess the validity of the method, we simulated data under a variety of scenarios including data quality and quantity, true habitat effects, and assumption violations. Additionally, we fitted the model to a real data set of over 100 paired snorkel and mark-recapture surveys conducted in the Grande Ronde Basin in northeastern Oregon.
3. Simulation analyses revealed that the hierarchical approach performs better than basic logistic regression and that it is reasonably robust to violated assumptions and poor data quality. For Grande Ronde empirical data, the selected covariates that best explained variability in snorkel detection efficiency included species, large wood density, visibility, channel unit type, and unit depth, though much variability was attributed to a site-level random effect. Estimated snorkel efficiency ranged from 0.02 to 0.79 between surveys and was higher for Chinook salmon (*Oncorhynchus tshawytscha*) juveniles (average 0.36) than for *O. mykiss* (average 0.21).

4. This model represents an improvement over previous snorkel calibration methods by applying a more rigorous statistical treatment of the sources of variability in the data while explicitly describing the mechanistic link between local stream conditions and efficiency of snorkel surveys.

1 Introduction

Snorkel surveys are a widely used method of assessing the abundance and distribution of fishes in small streams. They are frequently used for juvenile salmonids in the early freshwater component of their life cycle (Thompson and Lee 2000; Constable and Suring 2015; Som et al. 2018), but have been used for adult salmonids (e.g., Pinter et al. 2018; Korman et al. 2002; Thurow et al. 2006), other taxonomic groups of fishes, (Ulibarri et al. 2017; Weaver et al. 2014; Lawson et al. 2011), and characterizing fish assemblages (Plichard et al. 2017) as well. Counts obtained from these surveys index the density or presence of fish by species and/or size classes, which can then inform fine-scale patterns of fish-habitat associations unavailable from other basin-level monitoring methods alone (e.g., rotary screw traps in the case of anadromous salmonids). Further, because the observer never handles the fish, these surveys are more rapid and less intrusive than other survey methods (e.g., backpack electrofishing or piscicide applications) making them well-suited for monitoring the abundance and distribution of threatened and endangered species at large spatial scales.

However, given the difficult nature of counting many small and mobile organisms in flowing water, the counts are also subject to substantial observation errors. A wide variety of errors may be made when conducting snorkel surveys, for example, the observer may (*a*) fail to see some of the fish present at a site (i.e., partial detectability), (*b*) incorrectly assign a fish to species or size class (i.e., misclassification), or (*c*) incorrectly record the data from memory to a more permanent form (i.e., transcription). These sources insert inaccuracy and imprecision into the observed counts and the frequency and magnitude of the various errors govern the consistency of the data with the true abundance. In the absence of partial detection, we may be able to assume that misclassification and transcription errors insert only variability (i.e., noise) in the data, but that on average the counts are accurate representations of the true abundance. Further, these sources can be reduced to some extent with better training and more experience on the part of the observer. However, partial

detection introduces a directional bias in the counts that underestimate true abundance (Kellner and Swihart 2014), indicating it is the most important source of error to correct for. Additionally, the same factors that influence partial detectability may also affect fish distribution (e.g., large wood density), which could exacerbate biased perceptions of fish distribution and habitat associations if ignored or incorrectly accounted for.

Previous efforts directed at quantifying detection efficiency in snorkel surveys have relied on paired estimates of total fish abundance and snorkel counts to obtain estimates of the fraction of the population that may be counted while snorkeling (e.g., Thurow et al. 2006). Direct estimates of abundance (via mark-recapture estimators; Chapman 1951, or depletion estimators; Carle and Strub 1978; see Peterson and Cederholm 1984, for a comparison) over some spatial extent are paired with snorkel counts over the same extent during a short enough time frame to assume the population is closed. A statistical relationship is then obtained that attempts to explain the variability in abundance for a given snorkel count using covariates (i.e., habitat conditions that index the ease with which fish may be counted). The estimated relationship can then be used as a means to correct future snorkel counts to place them on the scale of population abundance.

The reliability of these kinds of corrective relationships is of great importance because they are used for out-of-sample predictive purposes that may be used to inform species status designations, guide restoration actions, and/or generate hypotheses about fish-habitat associations. As such, the best available statistical methods should be used in obtaining estimates of detection efficiency. Methods that ignore uncertainty in the independent estimate of abundance (e.g., as done by Thurow et al. 2006; Jonasson et al. 2016; Hillman et al. 1992; Hankin and Reeves 1988) are likely to overstate confidence in the detected relationships. Further, unaccounted variability in the independent abundance estimate may mask the effects of covariates on detection efficiency, thus hindering the ability of model selection procedures to identify the most important variables for prediction. Normal regression models have been applied to predict abundance from snorkel counts

directly (e.g., Jonasson et al. 2016), however, they do not acknowledge the uncertainty in abundance (constituting a violation in assumption) and they tend to make hidden assumptions about how snorkel detection efficiency varies with the count. Methods that model detection efficiency directly and acknowledge that abundance is not known perfectly are preferable and N-mixture models have been used for this purpose (Som et al. 2018). However, the N-mixture model approach may not be ideal for all use cases given the intensive nature of data collection (high replication within and among sites) and necessary strong assumptions (e.g., population closure between replicated counts). Thus, it would be desirable to have a method for quantifying snorkel survey detection efficiency that (*a*) is applicable to more commonly collected data sets (paired abundance estimates and snorkel counts), (*b*) accommodates uncertainty in the independent abundance estimates, (*c*) allows direct modeling of local covariates on detection efficiency, (*d*) is amenable to robust selection of which covariates are important for prediction, and (*e*) allows propagation of the uncertainty (within and between candidate models) in the estimated relationship to out-of-sample applications.

In this article, we present a widely applicable analytical method for quantifying snorkel survey detection efficiency intended to meet these criteria. Our method jointly estimates abundance and efficiency of snorkel surveys by treating the former as latent (i.e., true but only partially observed) states that are observed by two information sources: snorkel counts and mark-recapture experiments. Simultaneously, the model estimates the magnitude, direction, and importance of covariate effects on snorkel detection efficiency. After describing the statistical structure and assumptions underlying the modeling framework, we illustrate the application of the method using an example case with empirical data collected in the Grande Ronde Basin in northeastern Oregon and an extensive simulation study designed to test its validity in the face of various levels of data quality and violated assumptions. Although we illustrate the application of the approach with juvenile salmonids, it could be applied to a wide variety of species found in stream habitats for

which similar data have been collected.

2 Methods

2.1 Modeling framework

Our goal was to describe how snorkel detection efficiency (denoted by p_i) for each observation (i; a unique species $\times$ channel unit combination) varied as a function of covariates. we define detection efficiency (or equivalently, probability) as the proportion of the true population that is counted during the survey. Thus, given known abundance (N_i) and snorkel count (y_i), a basic estimator is:

$$\hat{p}_i = \frac{y_i}{N_i}, \tag{1}$$

which could be modeled as a function of covariates $x_{1,i}, \ldots, x_{n,i}$ via standard logistic regression methodology. However, N_i is rarely (if ever) a known quantity, preventing us from performing such a simplified analysis. Instead, we constructed a hierarchical model that enabled simultaneous estimation of N_i and the covariate effects influencing p_i. The approach proceeded by viewing N_i as a latent parameter, i.e., a true but only partially observed state. Two separate data sources existed that made observations of N_i: the mark-recapture data and the snorkel count data. The task was to construct an observation model that would better represent the process of jointly observing both data sources conditional on the latent abundance than one that assumed N_i was known without error. We chose to employ the Bayesian inferential framework because even in the absence of prior information it is useful for (*a*) hierarchical modeling, (*b*) propagating estimated uncertainty and parameter correlations to derived quantities, and (*c*) variable selection using direct and transparently interpretable probabilistic output.

2.1.1 *Likelihood components*

First, we constructed the likelihood function for the mark-recapture data. The sampling theory underlying the assumptions of two-sample mark-recapture estimators (described in Section 2.1.4) require that the number of recaptures (r_i) are generated by a hypergeometric random process (Chapman 1951), i.e., that:

$$r_i \sim \mathrm{H}(m_i, N_i - m_i, k_i), \tag{2}$$

where m_i is the number of fish marked in the first period, $N_i - m_i$ is the number of unmarked fish in the population, and k_i is the total number of fish captured in the second period (of which r_i are known recaptured fish based the presence of marks put in place in the first period). A random variable R following a hypergeometric process has a probability mass function equal to:

$$\Pr(R = r_i) = \Pr(r_i \mid m_i, k_i, N_i) = \frac{\binom{m_i}{r_i}\binom{N_i - m_i}{k_i - r_i}}{\binom{N_i}{k_i}}, \tag{3}$$

where $\binom{a}{b}$ is the binomial coefficient. We can use this probability mass function as a likelihood function for estimating N_i from mark-recapture observations r_i, m_i, and k_i, that is, we can calculate the probability of obtaining exactly r_i recaptures under the assumption that N_i takes on some value. However, Chapman (1951) illustrated that this estimator for N_i is biased for small sample sizes, and proposed a simple modification which can be expressed by assuming the following random process:

$$r_i + 1 \sim \mathrm{H}(m_i + 1, N_i - m_i, k_i + 1). \tag{4}$$

We used this formulation in likelihood calculations.

For snorkel surveys, We assumed the counting of fish was a binomial random process

at the channel unit level: each of the N_i fish present is either seen or not seen, and these outcomes have probabilities equal to p_i and $1 - p_i$, respectively. That is,

$$y_i \sim \mathrm{B}(p_i, N_i). \tag{5}$$

Expressing the process that generates the snorkel count (y_i) in this fashion makes a variety of assumptions that are discussed in Section 2.1.4. If these assumptions are reasonably met, then we can say a random variable Y takes on the value of y_i with probability mass function equal to:

$$\Pr(Y = y_i) = \Pr(y_i \mid p_i, N_i) = \binom{N_i}{y_i} p_i^{y_i} (1 - p_i)^{N_i - y_i}, \tag{6}$$

which we can use as a likelihood function to estimate p_i and N_i from y_i.

Note that the binomial likelihood function in equation 6 conditions the observation of y_i on two unknown quantities: p_i and N_i, rendering neither estimable from the snorkel data alone. For this reason, we constructed a joint likelihood that allowed N_i to be informed by both the mark-recapture and snorkel data, i.e., that:

$$\Pr(y_i, r_i \mid m_i, k_i, p_i, N_i) = \Pr(r_i \mid m_i, k_i, N_i) \cdot \Pr(y_i \mid p_i, N_i), \tag{7}$$

which makes a further assumption about the independence of sampling variability between snorkel and mark-recapture data collection. We can use this joint likelihood function to estimate the unknown parameters: latent states of N_i and any factors that influence p_i.

2.1.2 *Influence of covariates on detection efficiency*

Estimation of p_i for cases with paired snorkel and mark-recapture data was of little interest alone. Rather, we aimed to quantify the effect of covariates $x_{1,i}, \ldots, x_{n,i}$ on p_i, which would

allow prediction of p_i for units with snorkel and covariate data only (which constitute the majority of all snorkel data collection by monitoring programs). We used a logit-linear model to predict how the log odds of p_i varies with covariates. Assuming adequate replication, any number of random effects can be added to the model, for example, we use a random site effect (sites indexed by j) as a way to account for replication of counts at the site level and to accommodate any over-dispersion found in the snorkel count data. Thus, the model had the form:

$$\text{logit}(p_i) = \alpha + \beta_1 x_{1,i} +, \ldots, +\beta_n x_{n,i} + \varepsilon_{j(i)}, \tag{8}$$

where α is the intercept, $\beta_1, \ldots, \beta_n$ are coefficients quantifying the effect that each covariate has on the log odds of detection, and ε_j are site-specific effects which are mean zero normal random deviates with variance of σ^2.

2.1.3 *Variable selection and model-averaging*

A pervasive question is whether each covariate is important for explaining variability in p_i and useful for prediction, i.e., the concept of model uncertainty. We built in additional parameters into our model that allowed estimation of the probability that each covariate should be included in an optimal predictive model. These "indicator variables" (Hooten and Hobbs 2015), denoted by $\omega_1, \ldots, \omega_n$, were estimated as parameters and were Bernoulli random variables (0/1 outcomes). The ω parameters were multiplied by each of the β coefficients giving the expression for the logit-linear model:

$$\text{logit}(p_i) = \alpha + \omega_1 \beta_1 x_{1,i} +, \ldots, +\omega_n \beta_n x_{n,i} + \varepsilon_{j(i)}, \tag{9}$$

which had the purpose of toggling on ($\omega = 1$) or off ($\omega = 0$) the effect of each covariate, thus evaluating multiple models during the fitting process. This approach was first

proposed by Kuo and Mallick (1998), and has been used fairly widely for Bayesian multi-model inference in ecological studies (Hooten and Hobbs 2015; see example applications in Coggins et al. 2014; Dorazio et al. 2011; Gwinn et al. 2019). The posterior mean of each ω term represents the probability that the corresponding covariate x is a member of the optimal predictive model, with values greater than 0.5 generally seen as evidence that the covariate should be included (Barbieri and Berger 2004). The posterior of the coefficients are calculated from $\omega\beta$ rather than β, which provides model-averaged posteriors. The relative frequency with which the various ω terms are jointly equal to 1 or 0 provides posterior model probabilities.

2.1.4 Model assumptions

First and foremost, the model assumes that the population vulnerable to sampling by mark-recapture experiments is the same as that able to be seen and counted by observers (e.g., fish so small as to not be seen are not tagged or counted as captures) and vice versa – this vulnerable population size is what is represented by N_i. The key assumptions of the hypergeometric model as the recapture-generating process as in equation 4 are that (*a*) the population is closed to immigrants or emigrants and no deaths occur between the first and second visits, (*b*) all fish in the population (marked and unmarked) have equal and independent probabilities of capture, (*c*) fish do not lose marks, and (*d*) marked fish are not mistakenly identified as unmarked fish and vice versa. Use of the binomial model as the snorkel count-generating process as in equation 5 assumes that (*a*) all members of N_i have homogeneous probability (p_i) of being seen, (*b*) observations of individuals are independent (i.e., seeing one fish has no bearing on whether the next fish will or will not be seen), and (*c*) individual fish are counted only once and they are correctly identified to the species of interest. Finally, combining the two data sources in the joint likelihood of equation 7 assumes that sampling variability is independent between mark-recapture and snorkeling events, e.g., performing snorkel counts do not harass the fish to an extent that

would affect mark-recapture sampling.

2.1.5 Computation and diagnostics

The model was fitted using Bayesian integration implemented with Markov chain Monte Carlo (MCMC) methods using program JAGS (Plummer 2003) invoked through program R (R Core Team 2019) with the "jagsUI" package (Kellner 2018). MCMC sampling was conducted with 110,000 iterations per two chains, each with a burn-in period of 10,000 and thinned by 20 leaving a total of 10,000 retained samples for posterior inference. Convergence of MCMC algorithms was examined visually using trace plots and quantitatively using the $\hat{R}$ statistic proposed by Brooks and Gelman (1998). Adequate sampling behavior was further assessed using the estimated effective number of MCMC samples, which provides an indication of how many of the 10,000 retained samples were independent for each estimated parameter. Model fit to the data was assessed visually by comparing the observed data against the corresponding posterior predictive values to verify the data were generally within the range of variability expected by the model assumptions.

Prior distributions were selected to be as minimally informative as possible while simultaneously excluding implausible values from being considered by the sampling algorithm. Logit-scale parameters (α and $\beta_1, ..., \beta_n$) were assigned a t-distribution with standard deviation and degrees of freedom parameters of 1.566 and 7.763, respectively, as suggested by Dorazio et al. (2011) because it is quite uniform from 0 to 1 on the inverse logit-scale. Latent abundance states were required to be discrete-valued, however flat priors on discrete parameters (a categorical distribution with many groups, all with equal prior probability) exhibited exceedingly slow sampling. Thus, a continuous uniform distribution was used for abundance states and the outcome was rounded prior to usage in likelihood calculations. The prior for each N_i was bounded by $[\max(m_i + k_i - r_i, y_i), 1000]$: the minimum population size must be at least as large as the number of uniquely captured fish in the mark-recapture experiment but also at least as large as the snorkel count; we

deemed it unlikely that channel units in our samples had abundances greater than 1,000 individuals which was further confirmed by the absence of any posterior distributions forced against the upper bound of the prior. The standard deviation of site-level random effects (σ) was assigned a uniform prior bounded by [0,5]. Finally, the Bernoulli indicator variables ($\omega_1, \ldots, \omega_n$) were assigned prior probabilities of 0.5. The exception was for those corresponding to interaction terms, in which case the prior was $\omega_u \omega_v 0.5$ where u and v correspond to the main effects altered by the interaction term in question (i.e., the interaction would only be considered if both main effects were also considered).

All code and data to perform the analyses described in the sections below including simulation, JAGS model statements, model fitting, and output summarization is provided in Staton (2020).

2.2 Empirical use case

2.2.1 Study system

[INSERT SOME DETAILS ABOUT THE GRANDE RONDE BASIN]

- Tributaries in sample
- Include a map that shows the basin and the locations of the channel units sampled
- Some history of snorkel surveys being conducted there and how the data have been used
- Some history of population dynamics and status listing

2.2.2 Data collection

The study design and details of data collection are fully described in (Jonasson et al. 2016) and we therefore provide only a brief overview here. Channel units spanning a wide variety of habitat types in the upper Grande Ronde River and Catherine Creek were included in the study and sampling occurred in the summers of 2012 and 2015. Habitats were classified according to a hierarchical channel unit classification system using the Columbia Habitat Monitoring Program protocol (CHaMP 2016). These channel unit

delineations provided the spatial scale at which snorkel surveys were conducted using the protocol of White et al. (2012). Target species were Chinook salmon *Oncorhynchus tshawytscha* and steelhead/rainbow trout *O. mykiss*; all Chinook salmon were juveniles but it is possible that some of the *O. mykiss* were mature resident rainbow trout. Prior to conducting mark-recapture sampling, block nets were inserted on the upstream and downstream ends of the channel unit as a means of ensuring the population closure assumption was met. Fish were captured with backpack electrofishing in both events and marked using fin clips in the first event. Although approximately 150 channel unit visits were conducted, only 104 channel unit visits had valid data including non-zero marked and recaptured fish and paired snorkel and mark-recapture data that occurred within a two-day time frame. We further censored observations in which the Chapman (1951) estimate of abundance had a coefficient of variation (SE/estimate) greater than 30% (29 observations excluded for this reason) or a snorkel count that was greater than 1.5 times the Chapman (1951) estimate for that species (3 observations excluded for this reason), as both are indications of unreliable data. This left us with 105 total observations (unique species by unit visit combination) which included 82 unique channel units (34 and 48 in 2012 and 2015, respectively) across 40 unique sites; 29 of the retained observations were of Chinook salmon and 76 were of *O. mykiss*.

Associated with these count and abundance data were additional covariates intended to describe fish behavior and local habitat conditions that we hypothesized would have a meaningful and measurable effect on snorkel detection efficiency. These covariates included: unit type classification (pool versus non-pool), average unit depth (m), density of large wood (pieces $\cdot\, m^{-2}$), snorkeler-determined quality of visibility (poor, average, good), and species of observation (Chinook salmon versus *O. mykiss*).

2.2.3 Analysis

The model we applied to explain variability in snorkel survey detection efficiency for Grande Ronde empirical data had the form:

$$
\begin{aligned}
\text{logit}(p_i) = \alpha &+ \omega_1\beta_1\text{Chinook}_i + \omega_2\beta_2\text{Pool}_i \\
&+ \omega_3\beta_3\text{LWD2}_i + \omega_4\beta_4\text{LWD3}_i \\
&+ \omega_5\beta_5\text{VIS1} + \omega_6\beta_6\text{VIS3} \\
&+ \omega_7\beta_7\text{Depth}_i + \omega_8\beta_8\text{Depth}_i \times \text{Pool}_i + \varepsilon_{j(i)}.
\end{aligned} \tag{10}
$$

See Sections 2.1.2 and 2.1.3 and Table 1 for a description of the parameter and covariate meanings.

Subcategories of non-pool units (i.e., riffles versus runs) did not have sufficient replication to allow estimating effects for these units separately, which is why we binned pool units versus non-pool units. Furthermore, although large wood density was collected as a continuous variable, the contrast was limited such that many of the observations had no wood and non-zero wood observations were largely stacked near zero with a few observations with very high large wood density. We were concerned that large outliers would have undue influence on the fitted surface if left continuous and so chose to categorize them. The contrast in average depth was relatively good, and so we chose to retain its continuous nature but it was z-transformed prior to model fitting. Note that levels corresponding "average" visibility (VIS2) and no wood present (LWD1) have no associated β coefficients so they are quantified by the intercept term (α).

For inference, posterior model probabilities were obtained using the relative frequency that all sets of ω terms were jointly sampled as 1 or 0 (e.g., model 11111111 which includes effects of all assessed covariates versus model 11000000 which includes effects of species and unit type only). The marginal posterior probability that each coefficient should be included in a predictive model was calculated as the posterior mean of each ω term. Model-averaged coefficient estimates for covariate n were obtained as the posterior median of $\omega_n\beta_n$. Together, these summaries provide inferences about which covariates

have credibility for explaining variability in snorkel survey detection probability as well as the magnitude and direction of the effect each has. The full joint posterior was used to obtain predictive relationships that integrate across within- and between-model uncertainty while accounting for parameter correlations. These relationships are useful in visualizing the covariate effects and for predicting snorkel detection efficiency in future cases where only the covariates and snorkel counts are available.

2.3 Simulation study

Given the novelty of combining the hypergeometric and binomial probability mass functions into the joint likelihood in equation 7, we thought it important to examine the reliability of this approach. Because the true features of the system are known, stochastic simulation provides an opportunity to test the ability of the framework we developed to return robust estimates. Given that the behavior of mark-recapture estimation in the face of violated assumptions is well understood and because its assumptions are generally easier to meet, we were more interested in the reliability of the snorkel detection component of the model. We had several leading research questions:

(1) Can the hierarchical model return unbiased estimates of true values for both training data (covariates plus paired snorkel and mark-recapture data available) and prediction data (covariates and snorkel data alone)?

(2) Does the hierarchical approach perform better than an approach that does not account for uncertainty in mark-recapture sampling?

(3) Do the inferences in questions 1 and 2 depend on varying degrees of sample size, violated assumptions of the binomial count model, quality of mark-recapture data, and unmeasured covariate effects?

(4) Does the variable selection approach we used perform well relative to a hypothetical case in which the covariates of the true model are known?

To investigate these questions, we set up a series of models of which the parameters

could be altered to reflect scenarios intended to isolate their effect on the reliability of the estimation model. For each simulation scenario, 100 replicates of true states, data sets, and fitted estimates were obtained and the performance metrics were calculated. The sections that follow describe specific attributes of the various models used in this analysis and Table 2 summarizes the scenarios applied.

2.3.1 Operating model

We assumed fish were distributed randomly across channel units with mean and variance equal to the distribution of fish abundances in the Grande Ronde data. We simulated five channel units at a given site such that site-level random effects in detection could be introduced. Each channel unit had six associated habitat covariates: three continuous (all on the z-scale) and three categorical (all binary). These covariates were not correlated with each other nor were they correlated with abundance.

2.3.2 Data generating model

A portion of the simulated channel units were selected to be members of the training data set in which both mark-recapture and snorkel survey data would be collected and the remaining portion had only snorkel sampling conducted (prediction data set). 200 channel units were used in the prediction set and the size of the training set varied among 25, 50, and 100 observations. Habitat covariates were assumed to be measured without error at all channel units.

Mark-recapture data collection was simulated following the assumptions of the hypergeometric sampling process, except that having zero recaptured fish was not allowed. Sampling was driven by a capture probability (common to all individuals at a channel unit and equal between the first and second capture periods) that followed a beta distribution with parameters a and b. These parameters could be altered to vary the quality of mark-recapture information: lower capture probabilities (expected value is $a/(a+b)$) lead to

more variable data, less informative mark-recapture estimates, and can still result in biases of the the Chapman (1951) estimator. Between-unit variability in capture probability can be controlled by the scale of a and b - higher values result in less variability. For most scenarios, $a = 10$ and $b = 10$, which were obtained by simulating data while tuning a and b until the sampled capture efficiencies (r_i/k_i) followed a similar beta distribution as found for the Grande Ronde data set.

Snorkel data were generated using a mixture of beta and binomial random processes, thus the count generating process was more complex than assumed by the estimation models. Common to all scenarios was a true snorkel detection efficiency model similar in form to equation 8, which had non-zero effects for two continuous covariates, two categorical covariates, and one interaction – the remaining covariates had zero-valued effects (we were interested in whether the model could discern important from unimportant covariates). This model provided an expected overall detection efficiency at a given channel unit, around which three beta random variables were drawn to apply to individuals randomly assigned to one of three "groups" of fish within each unit. The groups were intended to represent clusters of fish, or fish occupying microhabitats within a unit that may have variability beyond that explained by the channel unit level covariates. By altering the scale of the beta distribution parameters, more within-unit heterogeneity in detection efficiency could be introduced which inserts over-dispersion in the counting process (simulation block C). In another block of scenarios (block D), binomial sampling was violated by allowing fish to be double counted: individuals in a channel unit had some non-zero probability of being double counted conditional on being counted once. An additional block of scenarios (block F) added unobserved random effects to the true detection efficiency in each channel unit to simulate the effect of unmonitored covariates.

2.3.3 *Estimation models*

Two estimation models were fitted for each simulated data set. One model exactly mimicked the hierarchical approach described in Section 2.1 and the other differed only by using the maximum likelihood estimate of abundance from mark-recapture data as known without error. The latter approach is referred to as the "external" abundance estimation approach and the former is referred to as the "hierarchical" approach. In one block of scenarios (block A), the estimation models were constrained to include only the truly non-zero effect covariates and in all other scenarios the variable selection and model-averaging framework described in Section 2.1.3 was used. This was done to benchmark the performance of the model selection routine against a hypothetical "best case scenario" of knowing which covariates are truly important.

2.3.4 *Performance metrics*

For each observation from each data set, we obtained the model fitted values (for training data) or predicted values (prediction data) for abundance ($\hat{N}_i$) and detection probability ($\hat{p}_i$) and calculated the error from the true quantity (estimate - true value). Posterior medians were used as the point estimates in these calculations. Errors were summarized within each simulated data set using the median proportional error (MPE; error/true value) as a measure of accuracy (MPE should be near zero if method is accurate) and the median absolute proportional error (MAPE; |error|/true value) as a measure of precision (smaller MAPE reflects greater precision). The resulting distribution of MPE and MAPE across replicated simulations were compared across scenarios for snorkel detection efficiency and abundance, grouped by whether the data were in the training or prediction set. The standard deviation of site-level random effects was compared to the true value to investigate which cases tended to estimate more or less variability unaccounted for by fixed effects. To summarize performance with respect to variable selection, we calculated how frequently the approach placed high weight (posterior probability of $\omega > 0.5$) on

covariates with truly non-zero effects and placed low weight (posterior probability of $\omega <$ 0.5) on covariates with truly zero effect. Finally, we calculated the fraction of true values that fell within the obtained credible intervals (prediction set only) at the 95% level as a measure of coverage – if model accounting for uncertainty is ideal, then true values should fall within the 95% credible intervals for 95% of the predictions within a data set.

3 Results

3.1 Grande Ronde analysis

3.1.1 Model fit/convergence

Fit of the hierarchical model to the data was good, especially for the snorkel count data (Fig. 1a). There were, however, some observations for which the number of recaptures was under-predicted (Fig. 1b). Still, the observed values fell within the 95% posterior predictive intervals in 95% of the data points for recapture data and in 97% of snorkel data points, indicating no major discrepancies in the ability of the model to explain patterns in the data. In general, hierarchically estimated latent abundance states were similar to abundance estimates obtained by applying an external Chapman (1951) estimator (Fig. 2) – discrepancies in these two estimates are due to the need of the hierarchical model to explain sampling variability in both the mark-recapture and snorkel data. Convergence of MCMC sampling was also quite good – all estimated parameters had $\hat{R}$ statistics less than 1.05 (except one abundance state with a value of 1.28) and the majority of parameters had effective sample sizes greater than 2,000 and all greater than 1,000.

3.1.2 Variable selection and coefficients

The hierarchical model strongly suggested that some of the covariates we incorporated were important for predicting snorkel survey detection efficiency in our sample. We found strong evidence that detection probability varied by unit type, and that the effect of depth

varied depending on whether a channel unit was a pool or non-pool type (depth and depth $\times$ pool interaction; Fig. 3). The species effect was strongly positive, which indicates that individual Chinook salmon juveniles were seen with greater probability than *O. mykiss* juveniles (Fig. 3). Coefficients associated with these covariates all had parameter inclusion probabilities of 1 (i.e., no uncertainty as to whether they should be included). Visibility was only important to account for if the observer determined it was "good" ("VIS3" effect in Fig. 3). "Poor" visibility ("VIS1") had a low probability of inclusion and small effect size, indicating units assigned to this category by the observer had similar detection efficiencies to those rated as "average". Similarly, units with non-zero but low large wood density ("LWD2" in Fig. 3) behaved similarly to units with no large wood at all, but the presence of high large wood density ("LWD3") had a pronounced negative effect on snorkel survey detection efficiency.

In terms of particular discrete model choices (i.e., in which unique sets parameters were jointly included or excluded), there was some uncertainty as to which exact model was the best (Table 3). The model with the highest posterior probability (0.441) included all covariates except those for low large wood density and poor visibility. The model with the next highest posterior probability (0.213) was identical except that it excluded high large wood density. The top model had approximately twice the probability of the second best model, and the second best model had approximately twice the probability of the third best model (Table 3). The model with an intercept term and site-level random effects alone (i.e., the null model) was never considered by the indicator variable selection routine and the full model had very low posterior probability (0.02).

3.1.3 Detection probability

The model-averaged detection probability response curves (Fig. 4) highlight the patterns suggested by the coefficient estimates. Clearly, most observations for both species occurred in channel units with no large wood present and with average visibility. Some large wood

by visibility combinations had few or no observations, which prevented the investigation of interactions between these variables, as well as species interactions with the other variables. However, there was relatively good contrast in the range of average depths available within each unit type, allowing the estimation of the interaction between these two covariates. As seen in Fig. 4, this interaction was estimated such that increasing depth had a positive effect on detection efficiency in non-pool units, but a negative effect in pool units. As suggested by the direction and magnitude of the effects in Fig. 3, the detection efficiency curves were higher for Chinook salmon than for *O. mykiss* and there was little difference between no wood and low wood and between poor visibility and average visibility. The scatter of the points around the fixed-effect curves in Fig. 4 is a result of the random site effects; the standard deviation of these effects was estimated to be quite large (1.23; 95% credible limits 0.9-1.65) considering they are on the logit-scale. Median detection probability for observed data ranged from 0.08 to 0.78 (average 0.36) for Chinook salmon and 0.02 to 0.73 (average 0.21) for *O. mykiss*.

3.2 Simulation study

3.2.1 Overall summary

In cases where model assumptions were met and reasonable data quality was available (blocks A, B, and F), both the hierarchical and external (mark-recapture-derived abundance assumed to be the true value known without error) approaches returned nearly unbiased fits to the data and predictions for out-of-sample data. Average MPE for abundance and detection efficiency across replications was generally less than 5% (positive or negative) for both modeling approaches. The hierarchical model tended to produce slight negative biases for detection probability and slight positive biases for abundance and the external abundance method exhibited the opposite pattern (e.g., Fig. 6a). Rarely did the MPE from any replication exceed 10% positive relative bias for either method. In terms of precision, the hierarchical model tended to produce fits and predictions closer to the true

values, as evidenced by smaller MAPE values (e.g., Fig. 6b). Performance of the variable selection approach was not perfect in all cases (i.e., truly non-zero effects were sometimes assigned low probability of inclusion and truly zero effects were sometimes assigned high probability of inclusion), but overall the hierarchical model performed at least as well as or better than the external method. In particular, the external method less frequently assigned low weight to unimportant covariates than the hierarchical model (e.g., Fig. 6c2). Credible interval coverage was generally better for detection efficiency than for abundance, and frequently the hierarchical model had better coverage than the external abundance approach (Fig. 6d). Finally, the external abundance approach resulted in large positive biases in the estimate of the standard deviation of site-level random effects – the hierarchical model did not suffer from this issue (e.g., Fig. 6e).

3.2.2 Block A: Effect of sample size without model uncertainty

When the models were forced to consider only covariates that truly had a non-zero effect on detection efficiency, the primary effect of increasing sample size from 25 channel units to 50 or 100 channel units was to improve the precision of predictions. This is seen by reduced ranges of MPE outcomes and lower overall values of the MPE values (Fig. 5a,b). Contrary to what might be expected, increasing sample sizes also had the effect of reducing credible interval coverage for the prediction set, primarily for abundance (Fig. 5d).

3.2.3 Block B: Effect of sample size with model uncertainty

Increasing sample size resulted in a larger improvement in model performance when the true model was unknown (block B) than when the true model was known (block A). In particular, the scale of the errors made when predicting abundance at sites without mark-recapture data was more responsive to increasing sample size in block B than in block A (compare Fig. 6b2 to Fig. 5b2). For both methods, the ability to assign high weight to covariates with truly non-zero effects was a function of the sample size (Fig. 6c1).

3.2.4 Block C: Effect of unaccounted over-dispersed binomial counts

Challenging the models with over-dispersed counts of varying degrees had little effect on the accuracy of either estimation method (Fig. 7a), but had a much more substantial effect on the precision (Fig. 7b). For example, the average MAPE of abundance predictions for scenario 9 (highly over-dispersed counts) was nearly double that of scenario 6 (equivalent in all ways to scenario 9 except that counts were not at all over-dispersed). The ability of the hierarchical model to correctly place low weight on unimportant covariates was sensitive to the amount of over-dispersion, however not as much so as the external abundance method (Fig. 7c2) – a similar result was found for credible interval coverage (Fig. 7d).

3.2.5 Block D: Effect of double-counted individuals

When the possibility of double-counting individuals in the snorkel survey was introduced, the primary effect was to result in positive biases in the estimated and predicted snorkel detection efficiencies (Fig. 8a3,a4). This makes intuitive sense: mark-recapture data remained the same, yet the observer reported counting more fish, leading the model to believe that a larger fraction of the population was counted than was truly counted. Estimation and prediction of abundance was also affected, but not nearly to the same extent as detection efficiency (Fig. 8a1,a2).

3.2.6 Block E: Effect of mark-recapture data quality

Low quality data were simulated by having a low probability of capture in the mark-recapture sampling (scenario 13; expected probability of capture of 0.2) which led to small sample sizes and substantial biases in abundance and detection for the external method (Fig. 9). However, the hierarchical method was largely unaffected by this case of low quality mark-recapture data. Very high mark-recapture data quality (scenario 15) resulted in nearly perfect estimates for both approaches.

3.2.7 Block F: Effect of unobserved covariate effects

Introducing additional effects that the models were completely ignorant of had very little effect on the performance of either estimation approach. The one effect was at very high degrees of unaccounted covariates (scenario 18), the precision was lower (higher MAPE; Fig. 10b).

4 Discussion

In this article, we have presented a hierarchical approach for combining multiple information sources that are commonly collected for correcting snorkel counts for the ever-present and dynamic issue of partial detectability. When applied to a real data set from the Grande Ronde basin, the model uncovered several useful and intuitive patterns in how local conditions affect the ability of observers to see individual fish when conducting snorkel surveys. Through simulation trials, we showed that the method can return reasonably accurate and precise predictions in out-of-sample circumstances and that it generally performs better than a more simplistic logistic regression approach that does not acknowledge variability in the mark-recapture sampling process.

We believe the method we have developed and presented here is general enough as to be applied to a wide variety of systems in which similar data (paired snorkel counts, mark-recapture data, and explanatory covariates) have been collected. However, we feel it important to mention that the method itself is general, not the particular inferences we made by applying the model on Grande Ronde data. That is, we advise that future practitioners use the hierarchical approach we presented to fit a new model to data for their particular use case and to not rely on the coefficient estimates we present (all model code and data are contained in Staton 2020). These estimates are based on data from a limited time frame and may be specific to the particular habitats and crew(s) that performed the sampling in those years.

The magnitude and direction of the estimated coefficients for the Grande Ronde data set were highly intuitive. For example, it makes sense that high densities of large wood in the stream should negatively affect the observers' ability to see and count fish but that low amounts of wood have a negligible effect relative to units with no wood present. Further, experienced snorkelers have indicated that the behavior of *O. mykiss* (less prone to schooling and more evasive) make them more difficult to see than Chinook salmon. We were interested in the finding that units assigned as "good" visibility by the snorkeler had higher efficiency than "average" visibility, but that "poor" visibility was not important. We hypothesize that perhaps the distinction between poor and average is not as clear as that between good and average. This finding has led us to believe that we should collect a more quantitative measure of visibility prior to conducting snorkel surveys. Overall, our findings were largely consistent with consistent with another study focused on quantifying the effects of local conditions on snorkel detection efficiency. Thurow et al. (2006) used beta-binomial regression (to accommodate over-dispersion, though their analysis did not acknowledge uncertainty in abundance) to investigate the effects of a wide variety of habitat covariates and found important effects of wood density, species, and visibility. Further, the scale of detection efficiencies we found were similar to Thurow et al. (2006): their mean detection efficiency for *O. mykiss* ranged between approximately 0.15 and 0.2 (depending on size class), with individual observations ranging from 0 to approximately 0.6 – our study estimated an average of 0.21 and a range of 0.02 to 0.74.

The estimated standard deviation of site-level random effects for the Grande Ronde data set was quite large. This indicates that either some covariate(s) not included in the analysis is needed to explain this variability or the counting process is not truly binomial. Our simulation analyses illustrated that both of these cases can cause positive biases in the estimated standard deviation of site-level random effects. However, the reliability of the model to produce (largely) unbiased estimates of abundance in the presence of these unaccounted factors was nearly identical as in their absence. Coupled with the reasonably

good fit to the empirical data, this finding leads us to be mostly unconcerned by the large site effects from an estimation standpoint alone. However, it does have ramifications for when estimates from this model are applied for predictive purposes: the random effects were needed to accommodate the variability in the data, but they are not useful for out-of-sample predictions.

There are a wide variety of adaptations that could be made to the model for application to new use cases. First, as the snorkel component of the model is essentially a logistic regression model, its complexity is arbitrary and dependent on the types of data that have been collected. That is, if suitable replication is conducted then random effects for year or observer could be included as could higher order (e.g., quadratic) terms as well as more interaction terms. The data set we used did not have adequate replication for investigation of this additional model complexity. The indicator variable selection approach we embedded within the model to accommodate model uncertainty is general and can be expanded to perform the multi-model inference in these more complex cases. Second, if the independent abundance data take some form other than mark-recapture (e.g., depletion studies), we believe the model could be adapted to use the appropriate likelihood for informing abundance directly (e.g., for a multinomial rather than hypergeometric sampling process). Third, the model could plausibly estimate covariate effects on how abundance is distributed among channel units in a similar fashion as to the N-mixture model approach (Som et al. 2018). We did not embed these covariate effects on abundance because we were primarily interested in the covariate effects on snorkel detection efficiency such that a predictive model could be obtained for application to a much larger set of snorkel data on which we will conduct these fish-habitat association analyses. The joint posterior distribution obtained from the hierarchical model provides an intuitive way to carry the uncertainty from estimation forward to prediction. Finally, because snorkel counts often assign individuals to size classes as well as species (and if fish size is measured during mark-recapture), it is plausible that the model could be extended to accommodate

size class-specific detection probabilities. These avenues provide exciting possibilities for future research, and may help guide planning efforts for when designing studies targeted at further quantifying the effects of covariates on snorkel survey detection efficiency.

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TABLE 1. Summary of the notation used in presenting the hierarchical snorkel detection efficiency model described in the text.

Symbol	Description
Indices	
i	Unique channel unit × species observation
j	Site index
Unknown Parameters	
N_i	True abundance at for observation i
p_i	Snorkel detection probability for observation i
α	Intercept of logit-linear snorkel detection probability model
$\beta_1, \ldots, \beta_n$	Coefficients of logit-linear snorkel detection probability model
$\omega_1, \ldots, \omega_n$	Binary indicator variables for each β_n coefficient, used in variable selection and model averaging
ε_j	Site random effect in logit-linear snorkel detection probability model
σ^2	Variance of ε_j
Observable Fish Data	
y_i	Number of fish counted via snorkel survey in observation i
m_i	Number of fish marked in the first visit of the mark-recapture experiment for observation i
r_i	Number of fish captured in the second visit of the mark-recapture experiment also captured in the first visit for observation i
k_i	Number of total fish captured in the second visit of the mark-recapture experiment for observation i
Covariates for Snorkel Detection Probability	
$x_{n,i}$	Value in observation i for hypothetical covariate n
Chinook_i	Binary; 1 if observation i was of Chinook salmon, 0 if for *O. mykiss*
Pool_i	Binary; 1 if observation i was a pool unit, 0 otherwise
LWD1_i	Binary; 1 if no large wetted wood present for observation i, 0 otherwise
LWD2_i	Binary; 1 if large wetted wood present in observation i but less than the median wood density for non-zero observations, 0 otherwise
LWD3_i	Binary; 1 if large wetted wood present in observation i and greater than the median wood density for non-zero observations, 0 otherwise
VIS1_i	Binary; 1 if snorkeler determined visibility was "poor" for observation i, 0 otherwise
VIS2_i	Binary; 1 if snorkeler determined visibility was "moderate" for observation i, 0 otherwise
VIS3_i	Binary; 1 if snorkeler determined visibility was "good" for observation i, 0 otherwise
Depth_i	Continuous; average depth of the channel unit of observation i; z-transformed prior to model fitting

TABLE 2. Breakdown of the scenarios and blocks of scenarios conducted for the simulation study.

Block	Description	Scenario	Training Samples	ω Known	Overdispersed Counts	Double Count Prob.	Mark-Recap Cap. Prob.	Unobserved Covariates
A	Model assumptions met, true model known, vary training sample size	1	25	Yes	None	0.00	beta$(10, 10)$	None
		2	50	Yes	None	0.00	beta$(10, 10)$	None
		3	100	Yes	None	0.00	beta$(10, 10)$	None
B	Model assumptions met, true model unknown, vary training sample size	4	25	No	None	0.00	beta$(10, 10)$	None
		5	50	No	None	0.00	beta$(10, 10)$	None
		6	100	No	None	0.00	beta$(10, 10)$	None
C	Homogenous p_i assumption violated, vary the amount of over-dispersion	7	100	No	Little	0.00	beta$(10, 10)$	None
		8	100	No	Some	0.00	beta$(10, 10)$	None
		9	100	No	Lots	0.00	beta$(10, 10)$	None
D	Single count only assumption violated, vary the probability a fish is counted twice	10	100	No	None	0.05	beta$(10, 10)$	None
		11	100	No	None	0.10	beta$(10, 10)$	None
		12	100	No	None	0.20	beta$(10, 10)$	None
E	Model assumptions met, vary the quality of mark-recapture data	13	100	No	None	0.00	beta$(20, 80)$	None
		14	100	No	None	0.00	beta$(50, 50)$	None
		15	100	No	None	0.00	beta$(80, 20)$	None
F	Model assumptions met, vary the contribution of unobserved covariates	16	100	No	None	0.00	beta$(10, 10)$	Little
		17	100	No	None	0.00	beta$(10, 10)$	Some
		18	100	No	None	0.00	beta$(10, 10)$	Lots

TABLE 3. Posterior model probabilities obtained from different combinations of ω_n terms. Models are shown as rows and those that include a particular covariate are denoted by ■. Only models with posterior probabilities greater than 0.01 are shown.

Covariate								
Chinook	**Pool**	**LWD2**	**LWD3**	**VIS1**	**VIS3**	**Depth**	**Depth $\times$ Pool**	**Pr(Model)**
■	■		■		■	■	■	0.441
■	■				■	■	■	0.213
■	■		■	■	■	■	■	0.104
■	■	■	■		■	■	■	0.077
■	■	■			■	■	■	0.054
■	■			■	■	■	■	0.052
■	■	■	■	■	■	■	■	0.020
■	■	■		■	■	■	■	0.015

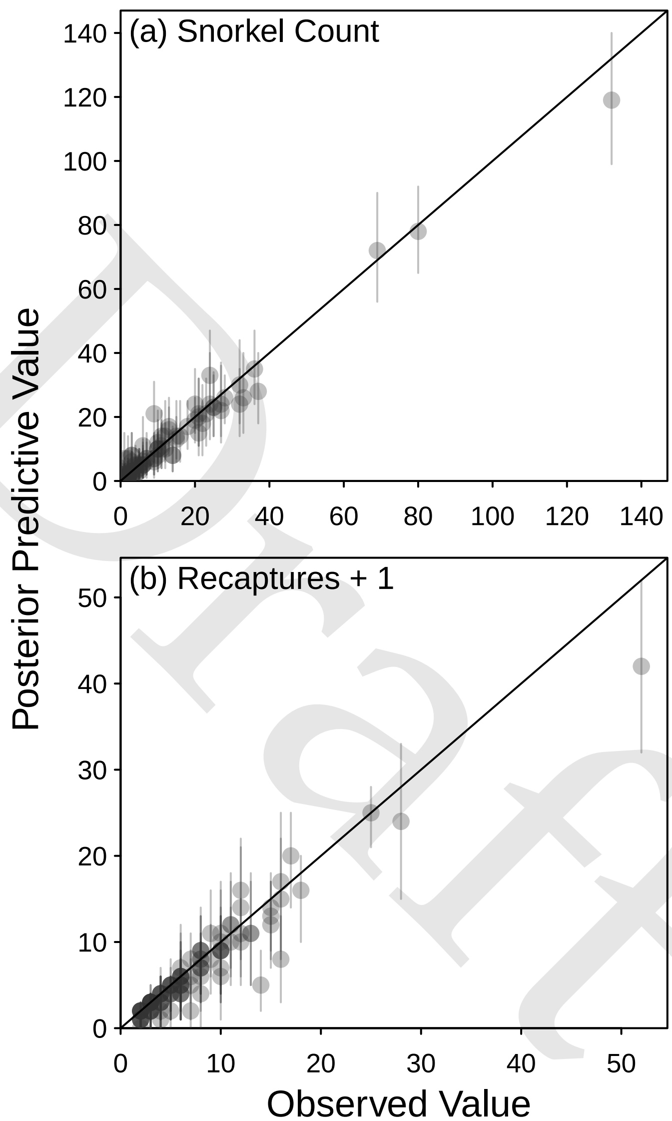


FIGURE 1. Posterior median predictive values versus observed values in each observation for (a) the snorkel count data and (b) the number of recaptures plus 1. The y-axis is similar to a fitted value, but includes all sources of uncertainty in the model; error bars represent 95% equal-tailed credible intervals.

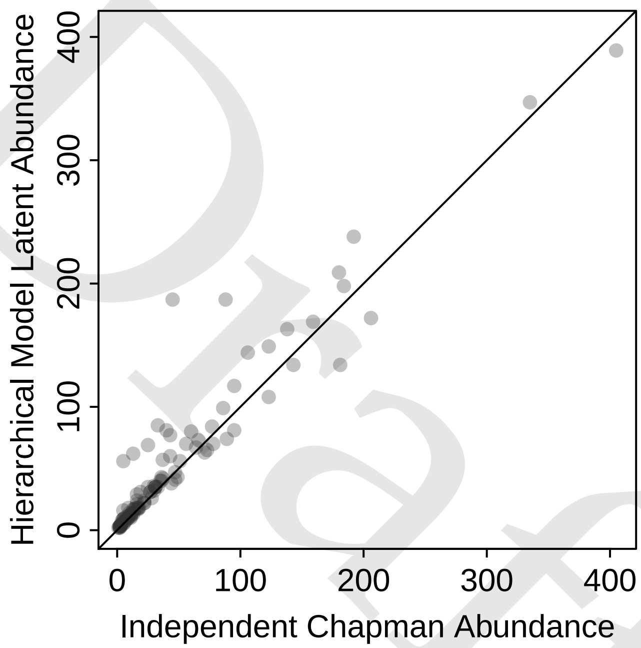


FIGURE 2. Comparison of posterior median abundance estimates from the hierarchical snorkel detection efficiency model (y-axis) and the Chapman (1951) estimator (x-axis) fitted to empirical data from the Grande Ronde basin.

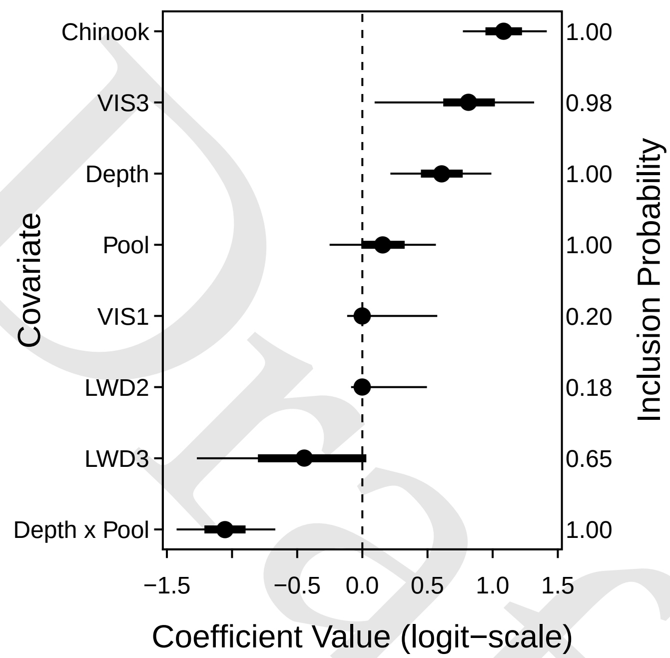


FIGURE 3. Model-averaged coefficient estimates ($\omega\beta$) from the Grande Ronde application of the hierarchical model. Positive coefficient values indicate that covariate increases snorkel detection efficiency; points represent posterior medians, thick bars represent the central 50% credible limits and the thin bars represent 95% credible limits. Also shown along the right axis are the posterior probabilities that each covariate should be included in an optimal predictive model (posterior mean of each ω term).

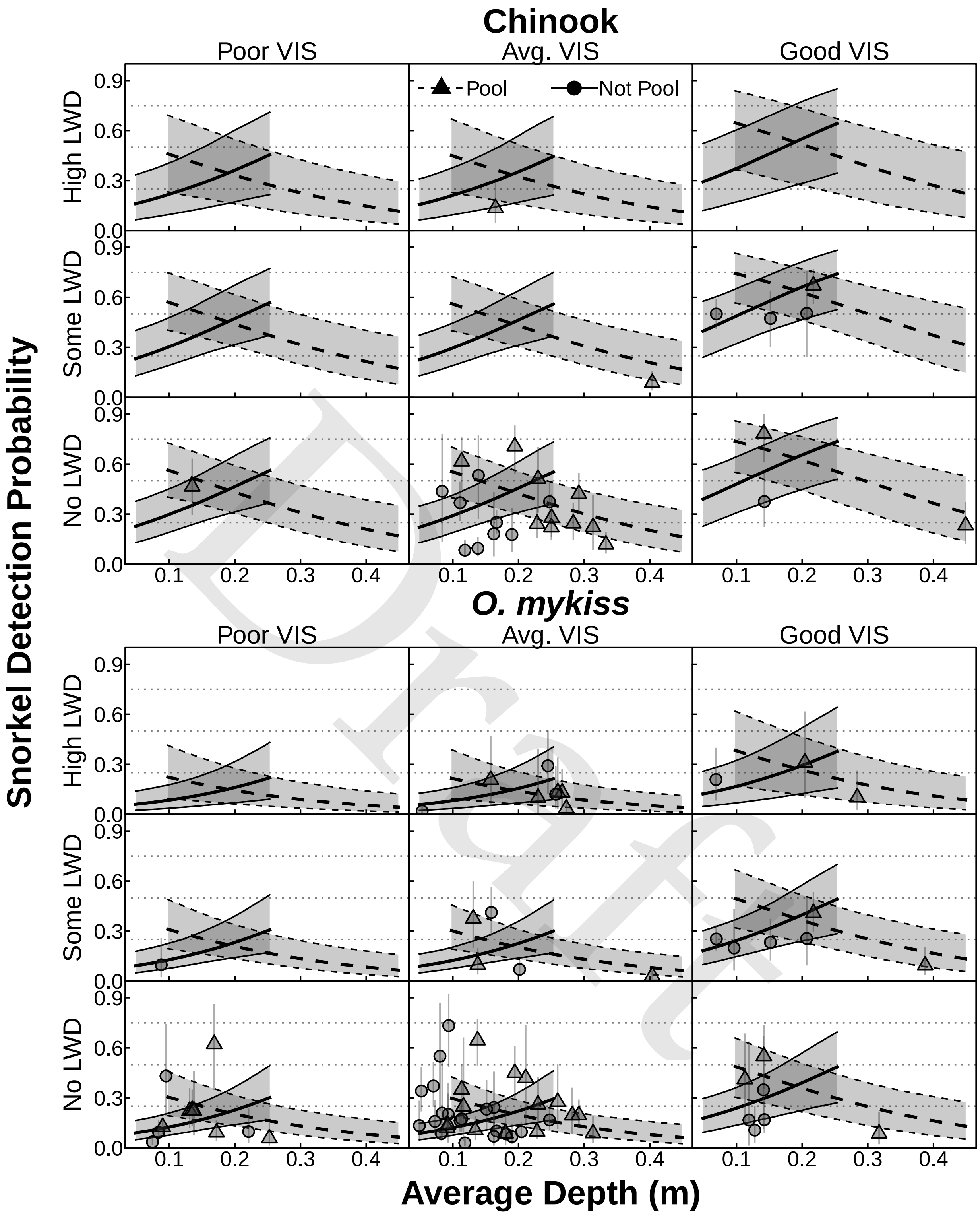


FIGURE 4. Response of snorkel survey detection probability to various covariates for two salmonid species in the Grande Ronde Basin in northeastern Oregon. Each panel shows a unique combination of large wood density (LWD; rows) and snorkeler-determined visibility (VIS; columns) grouped by species (axes extent equal for all panels). Curves and points display the model-averaged posterior median fixed-effect relationship and observation-specific detection probability, respectively, for non-pool and pool units. Grey bands and error bars denote 95% equal-tailed credible intervals.

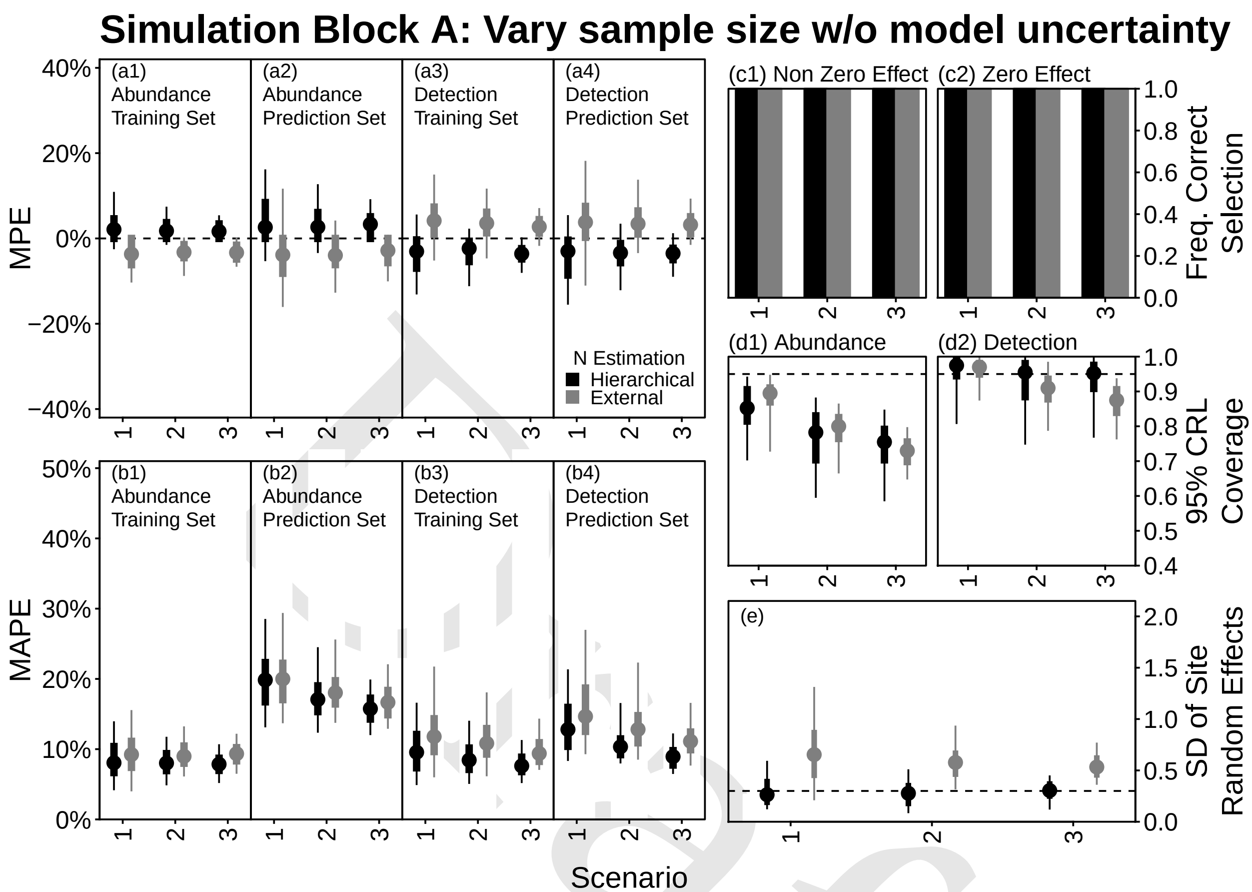


FIGURE 5. Summary of output from block A of the simulation trials. Points represent medians across 100 replicate data sets, thick error bars represent the central 50% of outcomes, thin error bars represent the central 95% of outcomes. (a) Distribution of median percent errors (MPE) across replicate data sets for abundance (a1 and a2) and detection probability (a3 and a4) – dashed line at 0 shows no error. (b) Same layout as (a), except for median absolute percent errors (MAPE). (c1) Proportion of the simulations in which truly non-zero effects were assigned probability of inclusion greater than 0.5. (c2) Proportion of the simulations in which truly zero-valued effects were assigned probability of inclusion less than 0.5. (d) Distribution of coverage statistics for abundance (d1) and detection (d2) – i.e., the fraction of 95% credible intervals that contained the true value (reference dashed line at 0.95 shows optimal coverage). (e) Distribution of estimated standard deviation of site-level random effects – dashed line shows the true value used to simulate the data. [*THIS FIGURE WILL BE SHOWN IN THE MANUSCRIPT ONLINE SUPPLEMENT ONLY*]

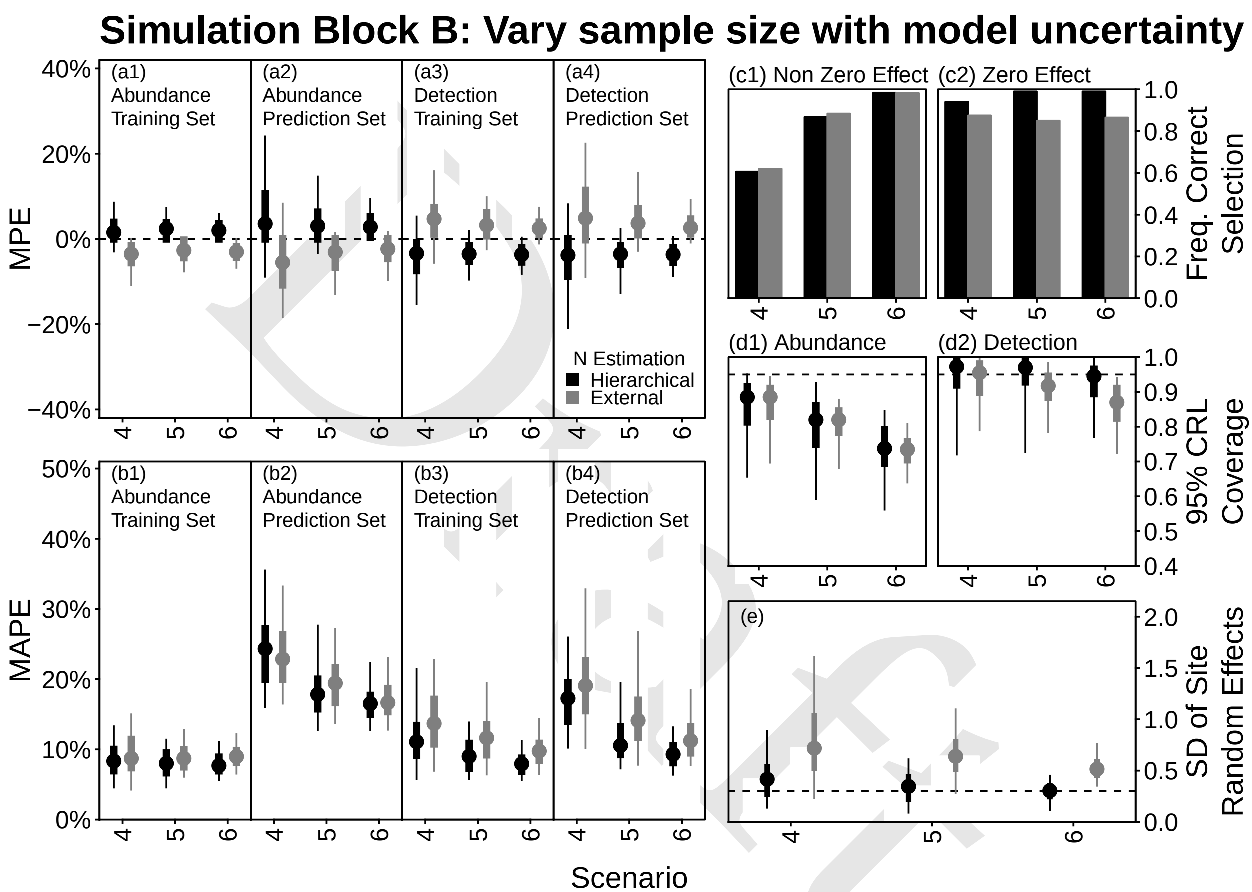


FIGURE 6. Summary of output from block B of the simulation trials. Layout of this figure is identical to Figure 5, consult that figure caption for a description. [*THIS FIGURE WILL BE SHOWN IN THE MANUSCRIPT MAIN TEXT AND ONLINE SUPPLEMENT*]

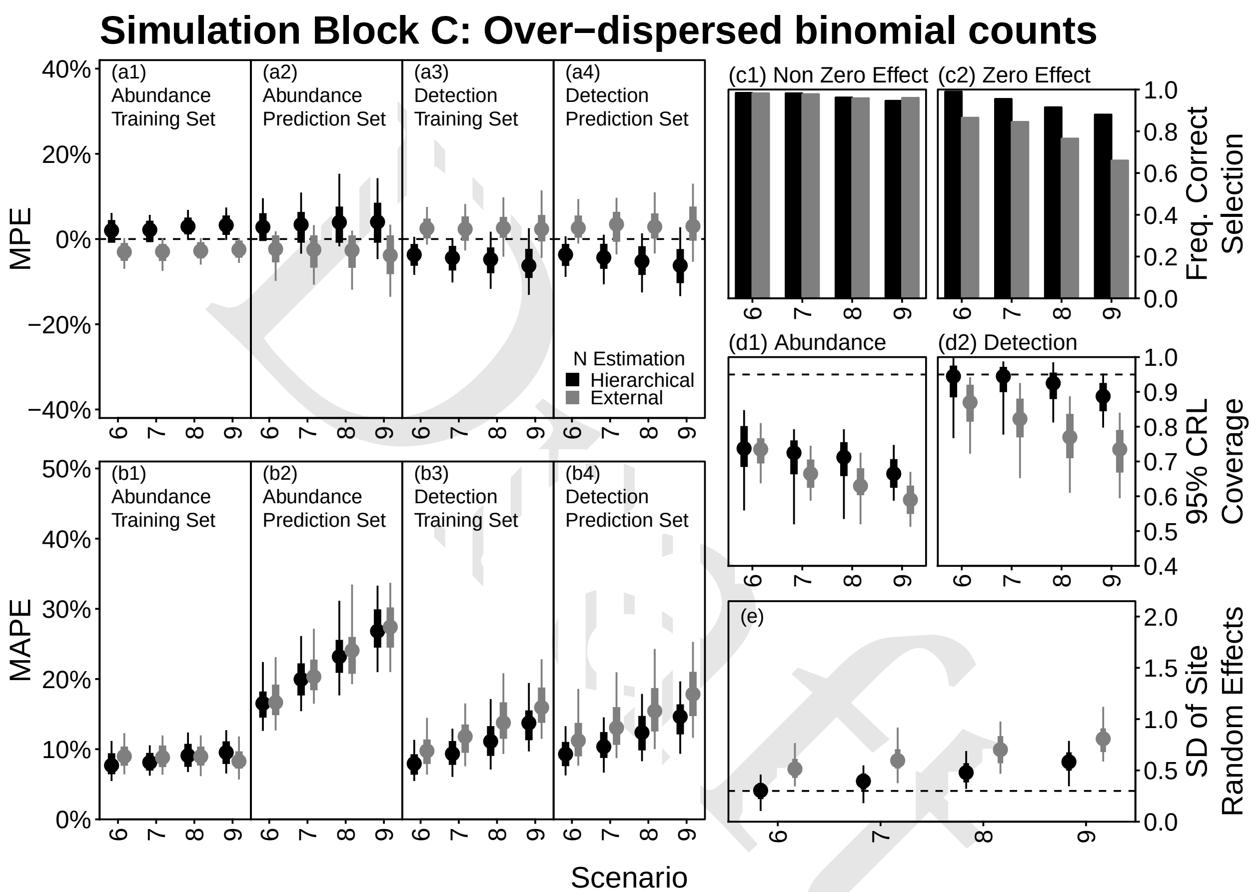


FIGURE 7. Summary of output from block C of the simulation trials. Layout of this figure is identical to Figure 5, consult that figure caption for a description. [*THIS FIGURE WILL BE SHOWN IN THE MANUSCRIPT ONLINE SUPPLEMENT ONLY*]

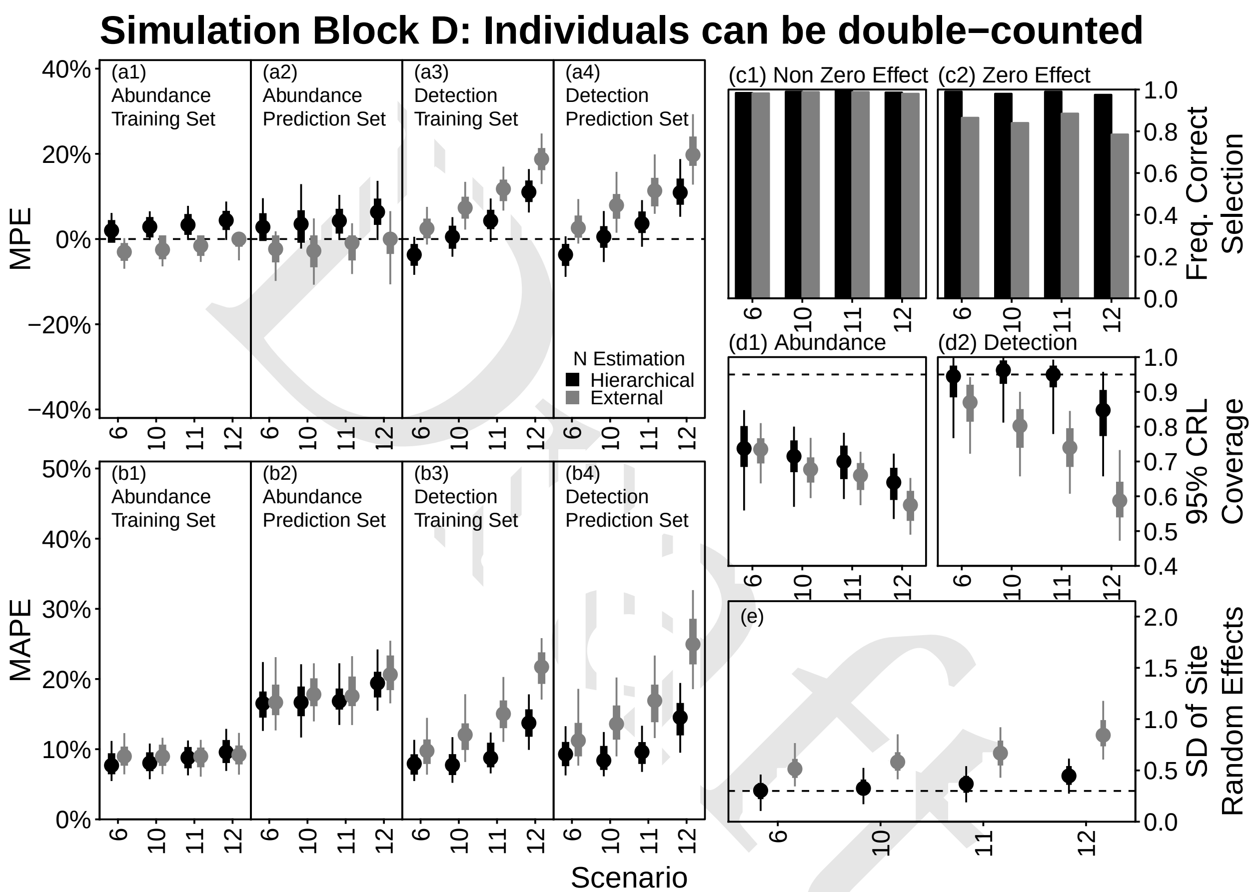


FIGURE 8. Summary of output from block D of the simulation trials. Layout of this figure is identical to Figure 5, consult that figure caption for a description. [*THIS FIGURE WILL BE SHOWN IN THE MANUSCRIPT MAIN TEXT AND ONLINE SUPPLEMENT*]

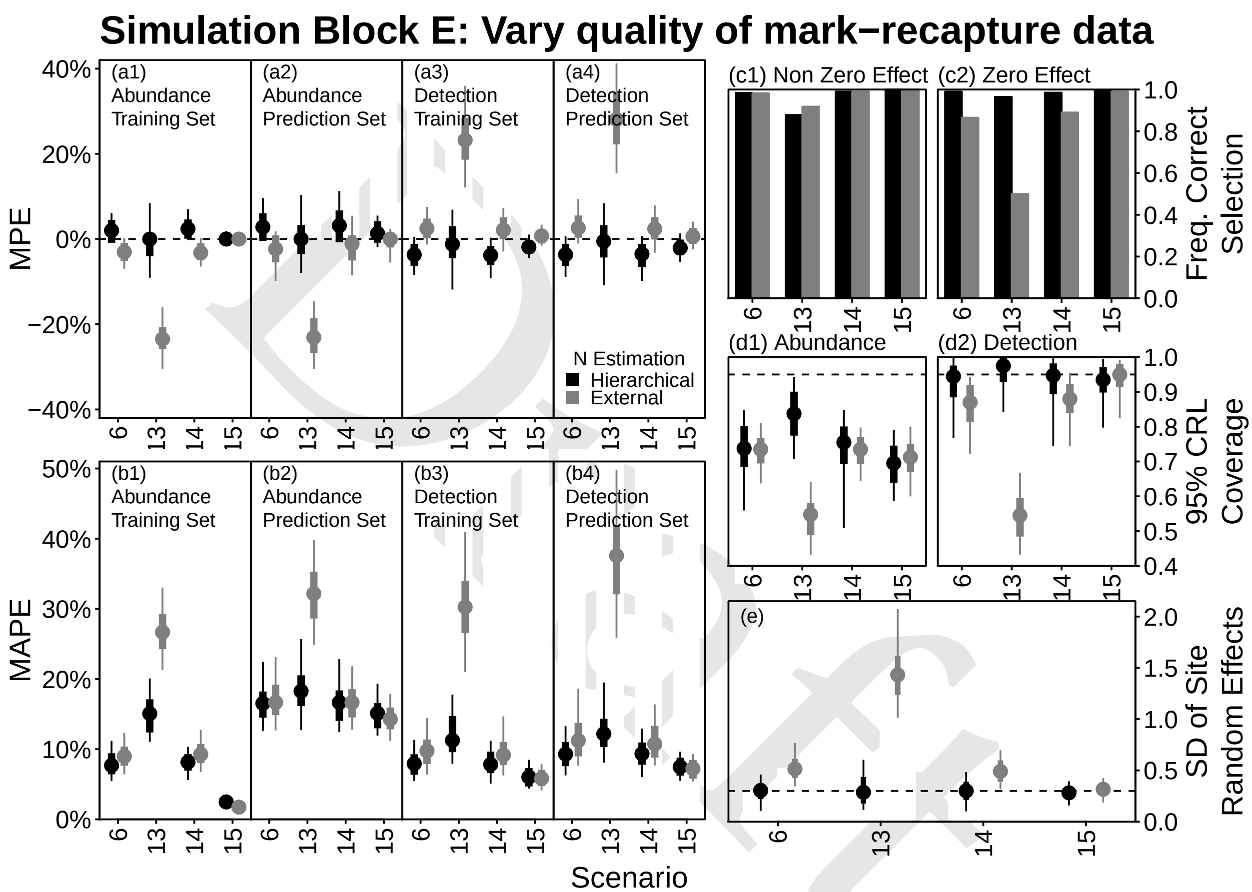


FIGURE 9. Summary of output from block E of the simulation trials. Layout of this figure is identical to Figure 5, consult that figure caption for a description. [*THIS FIGURE WILL BE SHOWN IN THE MANUSCRIPT ONLINE SUPPLEMENT ONLY*]

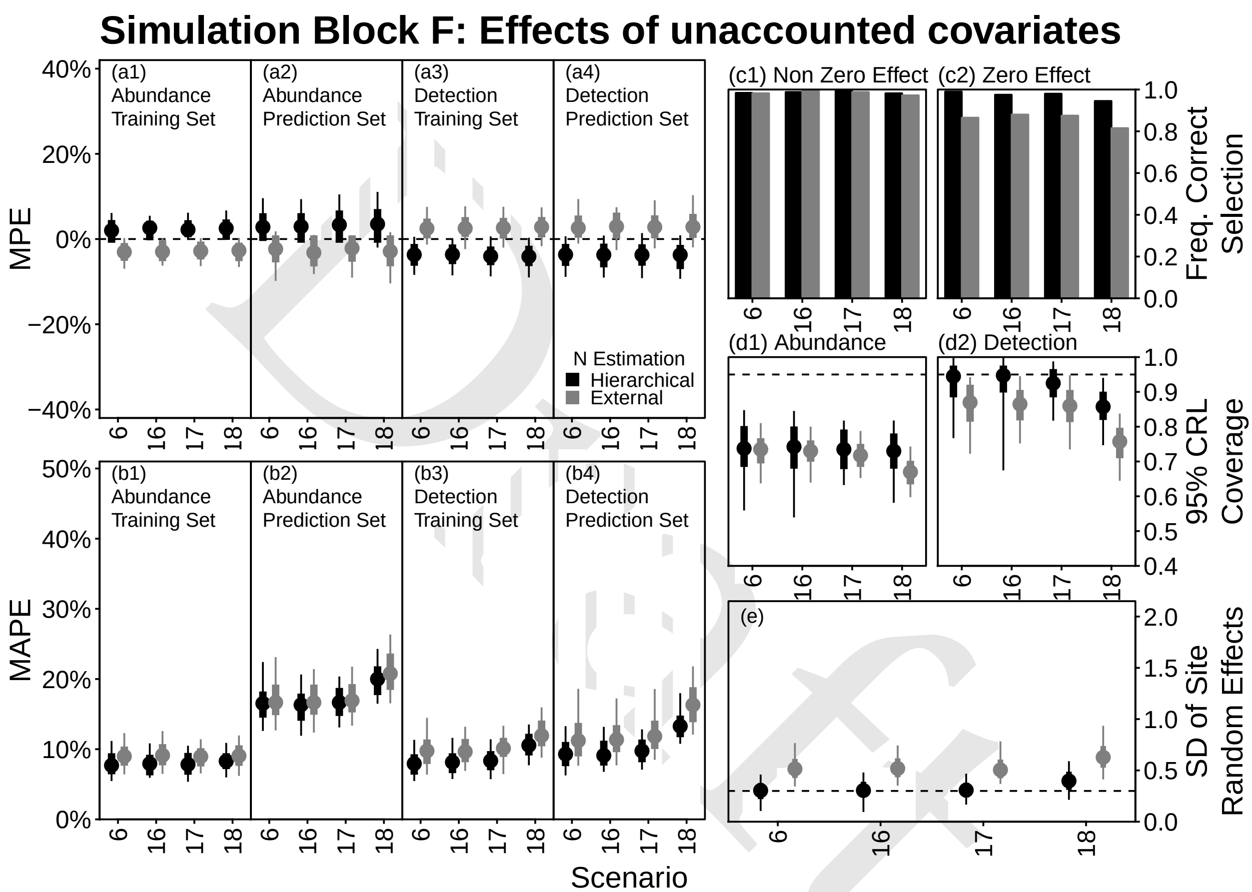
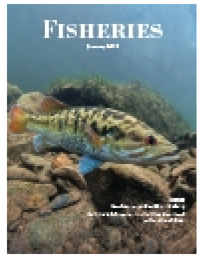


FIGURE 10. Summary of output from block F of the simulation trials. Layout of this figure is identical to Figure 5, consult that figure caption for a description. [*THIS FIGURE WILL BE SHOWN IN THE MANUSCRIPT ONLINE SUPPLEMENT ONLY*]

Appendix C – Draft *Fisheries* paper on the Grande Ronde basin as a case study for adaptive management



Progress Towards a Comprehensive Approach for Habitat Restoration in the Columbia Basin: Case Study in the Grande Ronde River

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Progress Towards a Comprehensive Approach for Habitat Restoration in the Columbia Basin: Case Study in the Grande Ronde River

Submission to *Fisheries*

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Abstract

Despite immense resources directed towards habitat restoration, recovering fish populations remains a perplexing issue. In 2015, recommendations for a comprehensive approach to habitat restoration in the Columbia River basin were published in *Fisheries* using elements of landscape ecology and resilience, broad public support, governance for collaboration and integration, and capacity for learning and adaptation. Using the Grande Ronde River basin as a case study, we concluded that collaborations in governance have been formed and research using a landscape perspective has been integrated into decision-making, but efforts would benefit from gaining broader public support and formalizing an adaptive management strategy. After the creation of a multi-agency restoration prioritization framework ("Atlas"), restoration focused on key limiting factors of high priority habitats. Continued progress will require consistent policy and funding support from the broader region. We envision this self-assessment at the five-year milestone would be helpful to other groups facing similar challenges.

Introduction

Historically, a diverse assemblage of fishes thrived in the Columbia River basin owing to the region's dynamic landscapes (McPhail & Lindsey 1986). Anadromous salmonids were particularly abundant, with pre-development run sizes estimated from 10 to 16 million on average (NPCC 1986) as compared to a recent minimum estimate of 2.6 million (ODFW & WDFW, n.d.). Although these declines are attributed to factors including ocean harvest, predation, and mortality from hydroelectric dams, degradation of tributary habitat conditions has also been implicated (McIntosh et al. 2000; NPCC 2004). Despite immense resources directed towards habitat restoration, recovering fish populations remains a daunting and perplexing issue. Advances in our understanding of technical aspects of restoration will continue to help, but slow progress can also be attributed to a deficiency of a comprehensive approach to restoration that integrates ecological and social sciences (Hand et al. 2018), as well as hesitance to adopting formal models of adaptive management (Conroy and Peterson 2013).

In 2015, recommendations for a comprehensive approach to habitat restoration in the Columbia River basin were articulated (Rieman et al. 2015). The approach recommended using concepts of landscape ecology and resilience, gaining broad public support, implementing a governance strategy for collaboration and integration, and incorporating a framework for learning and adaptation. In spring and summer of 2019, Grande Ronde Atlas (henceforth referred to as "Atlas") partners formed a workgroup to implement a formal adaptive management strategy. The present article communicates progress to achieve the recommendations of Rieman et al. (2015), highlights areas for improvement, and outlines next steps using a case study from the Grande Ronde River in Northeast Oregon.

The Grande Ronde River as a case study

The Grande Ronde River is a large tributary of the Snake River, originating in the Blue Mountains of Northeast Oregon and flowing approximately 340 km to its mouth in Southeast Washington. The

upper Grande River and its tributary Catherine Creek include the watershed upstream of the confluence of the Wallowa River (Fig. 1). Aquatic habitats been degraded since the mid-1800s by land use activities including beaver trapping, logging, grazing, mining, water withdrawals, road construction, and urban development (Ebersole et al. 2003; White et al. 2017; Favrot et al. 2018). Human-caused CO_2 emissions have contributed to a summer warming trend of Pacific Northwest streams of approximately 0.14 – 0.27 °C per decade between 1976 and 2015 (Isaak et al. 2018), and this trend is projected to continue (IPCC 2018). Habitat alterations along with other factors contributed to the decline and subsequent listing of local Chinook Salmon (*Oncorhynchus tshawytscha*), steelhead (*O. mykiss*), and Bull Trout (*Salvelinus confluentus*) populations under the Endangered Species Act (ESA) (NOAA 2008a).

There is a long history of watershed restoration in the Grande Ronde River basin (Beschta et al. 1991; Benge 2016), especially since the mid-1980s when the first Bonneville Power Association (BPA)-funded restoration project was implemented by the Oregon Department of Fish and Wildlife (ODFW). With the formation of the Grande Ronde Model Watershed (GRMW) Program in 1992, restoration expanded to include additional partners, initiating projects over subsequent decades. Early restoration efforts focused on small-scale passage and fish screening, streambank stabilization, road improvements, and riparian conditions (Sedell 2018). Initially there were concerns that restoration efforts may not be able to overcome the rate of habitat degradation in the watershed (Duncan 1998). The 2008 Federal Columbia River Power System (FCRPS) Biological Opinion (NOAA 2008b) delivered mandates for BPA, the U.S. Bureau of Reclamation, and U.S. Army Corps of Engineers to address habitat factors limiting salmon and steelhead populations in the upper Grande Ronde River and Catherine Creek, thus increasing funding for restoration.

Starting in 2014, prioritizing stream reaches and restoration actions addressing critical limiting factors by life stage for ESA-listed populations became a central focus. This led to a collaborative effort to develop the Atlas, a dynamic tool that utilizes existing scientific data, current research evidence, and

expert knowledge to prioritize restoration actions in biologically significant reaches (BSRs). Once identified, restoration opportunities are scored and ranked using biological and other criteria (see Atlas partners, 2015, for a detailed description).

Progress on Recommended Actions

Initial responses to the directives of Rieman et al. (2015) were developed in two, half-day workshops with Atlas partners and refined while drafting this article. We provide examples of how we are already answering these calls to action, where we are falling short, and how the framework could improve to better address tributary habitat restoration (Table 1). We envision these lessons, learned locally, have broad applicability for practitioners and researchers of habitat restoration across the Columbia River basin.

Develop and communicate goals and measurable objectives for biological diversity that are held as equal priority to the goals and objectives for abundance.

Regional goals such as those stated in the ESA Recovery Plan (NOAA 2017) remain weighted towards abundance and in-river productivity thresholds for salmonids, although the plan includes provisions for diversity in population spatial structure, genetics, and life history strategies. These goals represent minimum values intended to maintain populations above quasi-extinction thresholds (CBPTF 2019), yet several other plans in the region target higher abundances amenable to restoring ecosystem processes (e.g., NPT 2013). River restoration in the Grande Ronde basin historically focused on a narrow range of ecosystem components (e.g., instream habitat complexity and bank stability) over small spatial scales (hundreds of meters). Current restoration actions emphasize ecological or functional diversity (ISAB 2012) by initiating larger projects (kilometers of river) and restoring natural fluvial processes and channel complexity by improving floodplain connectivity and off-channel habitats, increasing hyporheic

exchange, and revegetating riparian zones. Atlas prioritizes restoration actions in locations with overlap among multiple salmonid species, life stages, and life history strategies. Incorporation of "First Foods" concepts from Columbia basin tribes into management practices embodies a shift towards managing rivers for ecological diversity and resilience (Quaempts et al. 2018). Although restoration and management decisions have increasingly emphasized ecological diversity, a more formalized effort is needed to develop and communicate quantifiable objectives for biological and functional diversity.

Directly engage all stakeholders and the general public to broaden understanding of the critical value of biological diversity.

The well-documented plight of salmonids has dominated headlines, meeting agendas, and outreach efforts for decades. Meanwhile, other species such as Columbia spotted frog (*Rana luteiventris;* Fig. 2), western pearlshell freshwater mussels (*Margaritifera falcata*), and beaver (*Castor canadensis*) have largely been overlooked, although this is changing. Pacific Lamprey (*Entosphenus tridentatus*) are regarded as having high cultural and ecological importance yet are at high risk of extirpation in many rivers of the American West (Wang and Schaller, 2015); stakeholder education is seen as a critical step towards their recovery (Clemens et al. 2017). Additional efforts to communicate biodiversity values to the general public in the Grande Ronde basin include a recent newsletter documenting the importance of freshwater mussels (Glidewell 2018).

Develop indicators for monitoring that measure and communicate progress on abundance and biological diversity at multiple scales across the basin.

Indicators related to salmon and steelhead abundance and productivity are well developed and data are robust owing to long-term collection of adult spawner and smolt data by ODFW and the Confederate Tribes of the Umatilla Indian Reservation (CTUIR). Although progress has been made in

collecting the requisite data to track diversity indicators, limited funding and uncertainty in measuring diversity has hindered progress. At the reach scale, life-stage specific indicators (e.g., juvenile salmon abundance, migration survival rates, pre-spawn mortality) are used to identify priority areas for restoration or adjust management actions (Sedell et al. 2018; White et al. 2018). Recent research in the Grande Ronde basin places a greater emphasis on biological diversity by evaluating stream metabolism (Kaylor et al. 2019a), fish growth rates, biological integrity via benthic macroinvertebrates (Hawkins et al. 2000), and salmonid food availability indices (Sullivan & White 2017). In addition, some useful physical habitat indicators related to functional and ecosystem diversity have been developed, including surface area of side channels (Bond et al. 2019), a river channel complexity index (Brown et al. 2002), thalweg depth variance (Kaufmann and Faustini 2012), and a riparian vegetation condition index (Macfarlane et al. 2017). A focused, collaborative effort among basin partners and funding agencies will be needed to reach consensus on high priority indicators; however, we began this task by proposing indicators that are relatively straightforward to calculate and can be collected in a robust, repeatable fashion (Table 2; Supplemental Table A).

Consider the implications of hatchery production for carrying capacity and diversity of wild fish as a basis for integrating hatchery production with habitat restoration.

Hatcheries in the Grande Ronde River basin are meant to serve two purposes: (1) conservation and recovery, and (2) harvest augmentation. All hatchery programs have a hatchery genetic management plan (HGMP) detailing production goals for supplemented stocks (see CTUIR 2011; ODFW 2011). These HGMPs have performance standards for spawning, rearing, migration, and estuarine habitat capacities. Monitoring of supplemented stocks includes measures of life-stage abundance and survival, distribution, and genetic composition. Contributions of hatchery fish to natural production are measured as relative reproductive success (RRS; Berntson et al. 2011). These metrics provide the

information needed to evaluate impact of the hatchery programs on the natural population. Life cycle models in development have an option to “turn off” hatchery supplementation, allowing managers to gauge hatchery impacts along with carrying capacity, habitat restoration, and climate change (Weber et al. 2018).

Use landscape sciences and technology in assessment and restoration planning and support and expand common application of relevant research, monitoring, modelling, and analytical tools.

Landscape sciences and population-scale analytical tools represent a critical component of the restoration planning process in the upper Grande Ronde basin. For example, remotely sensed thermal imagery and LiDAR data were coupled with ground-based habitat data to develop a water temperature model to assess restoration and climate change impacts on salmon populations (Justice et al. 2017). Additionally, basin-wide bathymetric, thermal profile, and hydrologic data were combined with remotely sensed data to assess limiting habitat factors and prioritize restoration actions (BOR 2012, 2014). Recent research evaluated stream metabolism and juvenile salmon abundance at the river network scale (Kaylor et al. 2019a) and a follow-up study of fish response to carcass additions (Kaylor et al. 2019b) have highlighted mechanisms driving spatial patterns in ecosystem processes. Life cycle models integrate population-scale biological and physical habitat data and assess long-term salmon population response to various restoration scenarios (Weber et al. 2018). Results from these studies have been used in the Atlas process to prioritize restoration actions. However, the link between these analytical tools and management could be strengthened.

Create and support communities of practice and peer learning networks that demonstrate science-management integration; highlight new tools and analyses that are innovative and promote those with real potential for success.

Integration of science and management requires a coordinating entity and ongoing commitment to invest in peer-learning opportunities. GRMW fills this niche by providing an interface between science and management and coordinating restoration on public and private land. Atlas participants rely on ongoing monitoring efforts (e.g., screw traps, adult weirs, and radio tracking data) and research findings (e.g., maps of modeled water temperature and baseline habitat conditions) to prioritize restoration. As new information comes in from research or management, Atlas updates priorities for restoration. These updates occur monthly at meetings attended by researchers, funders, regulatory partners, and restoration implementers. In addition, and annual State of the Science meeting hosted by GRMW provides an opportunity for scientists to showcase new research and monitoring techniques, as well as a forum for managers to communicate on-the-ground needs. Scoring of priority reaches for restoration is intended to be updated on a five-year basis.

Recommit to options for broadly based technical assistance to provide analytical support, constructive criticism, and feedback to proposed and ongoing projects.

Internally, Atlas has pathways for technical review during monthly implementation meetings, the annual State of the Science meeting, and GRMW's board of directors' semiannual review of proposed projects. GRMW is in the process of adding another level of technical review from the NOAA science center, Columbia River Inter-Tribal Fish Commission, and others. This additional review would take place early in project development phase and identify quantitative objectives and associated monitoring approaches. For a broader review from experts outside the basin, experts from throughout the Pacific Northwest and elsewhere could offer valuable input on lessons learned, novel techniques,

and the initiation of monitoring and interpretation of its results, among other topics. One option for facilitating this input is to invite restoration practitioners from outside the Grande Ronde basin to the annual State of the Science meetings to present findings from successful restoration strategies.

Include education and outreach specialists as key players at the earliest stages of project development.

Education and outreach are critical for articulating the work conducted in the basin; however, funding staff for these tasks is challenging. Partners rely on existing staff to work outside their job duties, or upon volunteers to fill the role of outreach specialists. The local Wallowa-Whitman National Forest employs public outreach specialists, but their focus has historically been on national forestland projects and recreation and safety updates—however this is changing to include press releases covering all forest activities including aquatic restoration. Outreach and education often follow project implementation, yet these efforts would benefit from engaging key players much earlier as recommended by Rieman et al. (2015).

Engage people and organizations early through forums that encourage dialogue between managers, researchers, and stakeholders associated with a range of resource values.

Atlas has the explicit goal of bringing together managers, researchers, and stakeholders to allocate limited resources. The initial prioritization framework involved meetings between program managers, project sponsors, researchers, restoration implementers, and other experts from multiple local, state, regional, and national organizations as members of a science technical advisory committee (Tetra Tech 2017). Although these meetings facilitated productive dialogue between managers and researchers, we acknowledge that the public has been largely excluded. Whereas others (e.g., Booth et al. 2016) have defined a more limited definition of stakeholders as tribal, federal, state, county, and nonprofit organizations, an inclusive definition should include the general public (Rieman et al. 2015).

Align ecological needs with social and economic incentives and consider benefits and costs to people and their communities.

Economic stimulation from restoration efforts has helped slow economic decline in rural economies (Hibbard and Karle 2002) and has spurred new approaches to rural development (e.g., Hibbard et al. 2015). Restoration contractors purchase numerous local goods and services such as trees from private forestlands for stream restoration projects, providing benefits to the local economy while promoting healthy forest stands. Restoration practitioners in the Grande Ronde basin use social and economic incentives for agricultural, ranching, and forestry operations. The Natural Resource Conservation Service (NRCS) has several incentive programs in exchange for implementation of conservation measures such as irrigation efficiency upgrades, riparian fencing, upland water source development, grazing management plans, forest thinning, and conservation easements. The Freshwater Trust also provides incentives for water quantity and quality conservation such as lining or piping ditches to prevent water loss and leasing or purchasing water rights. It should be noted that different groups will assign dissimilar weights to ecological, social, and economic values, making the process of “aligning” these needs complex. Columbia basin treaty tribes prioritize the ecological, subsistence, and cultural needs of fisheries resources above and beyond immediate economic incentives, with the expectation that the treaties would protect salmon so that tribes could always earn a moderate living through fishing (CRITFC 2014).

Use a wide diversity of media and forums for public and community engagement.

Community engagement is a key component of successful stream restoration (Hand et al. 2018), especially in rural communities where residents can be skeptical of restoration. Project information and accomplishments are often shared through individual agency websites and social media pages, local newspapers, professionally produced videos, and brochures (e.g., Fig. 3). The GRMW produces *Ripples in*

the Grande Ronde (https://grmw.org/#rippleBox), an online and print newsletter distributed along with local newspapers and other venues, with an average circulation of 10,000 print copies. NOAA Fisheries, GRMW, and CRITFC are currently collaborating on a short outreach film about river restoration in the Grande Ronde basin (www.grmw.org/ourwatershed). Strategic choice of photos and video play a critical role in creating public awareness of freshwater biodiversity values (Monroe et al. 2009).

Make public involvement and active learning through citizen science in monitoring and research a central element in project implementation.

Citizen science is a growing field that provides opportunities for the public to contribute to socio-ecological objectives of restoration while increasing awareness and promoting stewardship (Edwards et al. 2018; Church et al. 2019). Grande Ronde basin partners are actively seeking ways to increase public involvement in projects through citizen science and volunteer programs, including a proposal recently funded through a USFS Youth and Community Engagement program. The forthcoming work focuses on monitoring several large restoration projects and will provide learning opportunities for high school classrooms and the general public. However, funding for staff to continually recruit and train citizen scientists and volunteers will be necessary to maintain this momentum.

Recognize the social sciences as a critical element of scientific review and guidance and include social scientists as primary contributors to the advisory, review, and planning process.

The Grande Ronde basin is a rural community with limited access to social scientists and therefore it is challenging to find an expert willing and able to review restoration strategies on a regular basis. GRMW staff have sought guidance on effective community outreach about restoration opportunities from a social scientist from Eastern Oregon University (EOU). Among other suggestions, achieving long-term community involvement and support requires staff or volunteers dedicated to social

sciences and outreach (B. Grigsby, EOU, pers. comm.). However, GRMW and the Union Soil and Water Conservation District have diverse boards of directors that provide social and economic review of proposed projects, including representatives from agriculture, local governments, tribes, the conservation community, public and private land interests, educators, economic sector, and the general public.

Highlight and support experiments in governance for collaborations that bridge agency and intellectual groups, local and regional organizations, governments, landowners, and science management disciplines.

GRMW and its board, along with other cooperating agencies, have established partnerships and gained acceptance of restoration within the basin. Improved collaboration with fisheries scientists as a result of Atlas has been critical to refining restoration strategies and adaptive management. Another example includes Union County's Place-based Water Planning (http://union-county.org/planning/place-based-integrated-water-resources-planning/), and effort that has brought together landowners, natural resource agencies, state, federal, local government, tribes, and others to tackle issues such summer water deficit, declining aquifers, and flooding. The key to continued success of Atlas is the existence of a local coordinating entity and partner participation.

Bring innovative and successful examples (including those from other resource and restoration disciplines) to others in the basin.

The development of Atlas began by synthesizing previous, local planning efforts at the sub-basin (NPCC 2004), reach (USBR 2012; USBR 2014), and regional scales (NMFS 2013; USFWS 2014). The Independent Scientific Review Panel (ISRP 2018) has recommended drawing lessons from other similar frameworks in the Columbia River basin (e.g., UCRTT 2014; UCSRB 2014; Hillman et al. 2016). Broad-

level guidance on setting restoration priorities and using process-based restoration came from a wealth of regional literature (e.g., Roni et al. 2002; Beechie et al. 2008; Beechie et al. 2010). The CTUIR's *River Vision* incorporates innovative concepts of ecosystem resilience for river and floodplain management (Quaempts et al. 2018) as well as uplands (Endress et al. 2019). From outside the region (Australia), a modified version of the River Styles Framework (Brierly and Fryirs 2005) was used to map potential for geomorphic change, and subsequently informed analyses of historic river conditions and climate impacts (White et al. 2017; Justice et al. 2017). Other relevant examples that could be explored include findings from the European Union's Water Framework Directive (e.g., Hering et al. 2015; Hughes et al. 2016).

Identify clear, quantitative objectives, including diversity objectives that form the baseline for the adaptive management cycle.

Quantitative objectives and associated metrics employed in the upper Grande Ronde basin include those for abundance and diversity of species, biological assemblages, life history strategies, genetics, habitat function, and ecosystem processes. Objectives for fish abundance are admittedly more clearly defined, mainly due to unambiguous policy mandates (e.g., natural spawner abundance thresholds under ESA recovery plans). Diversity objectives have been more difficult to define but are gaining attention. However, for assessments of how individual or cumulative restoration projects affect either abundance or diversity, the key problem articulated by Rieman et al. (2015) remains, with many restoration efforts lacking measurable objectives, robust experimental designs, or a conceptual model for revising management plans using updated information. This problem is reiterated in a recent ISRP review of a synthesis of restoration effectiveness in the basin (ISRP 2018), and one which Atlas partners are actively seeking to address (Table 2; Supplementary Table A). Fig. 4 outlines quantitative objectives for habitat function of the Sheep Creek restoration project as an example.

Implement intentional, science-based management experiments that promote learning about landscapes, cost effective restoration actions, and understanding of their social–ecological implications.

To date, most restoration efforts in the upper Grande Ronde basin are evaluated on an individual project basis rather than the overall strategy and cumulative effects. One exception includes a watershed-scale assessment of riparian restoration required to cool water temperatures for salmonids facing climate change (Justice et al. 2017). The Columbia River basin-wide Action Effectiveness Monitoring (AEM) Program (Roni and O'Neal 2017) uses multiple before-after control-impact (MBACI) and post-treatment evaluations to assess effectiveness of various types of restoration, but findings are too coarse in scale to draw specific insights about local watersheds. In contrast, local researchers adopted the Columbia Habitat Monitoring Program (CHaMP 2016), with 471 visits to 162 sites within the sub-basin from 2011-2017 to assess status and trends in fish habitat conditions. Another effort involves compiling information on the type and intensity of over 700 restoration efforts conducted since the mid-1980s to evaluate the long-term, cumulative impacts of restoration (Benge 2016). A recent example of a science-based management experiment includes evaluating carcass additions as a management strategy (Kaylor et al. 2019b). These recent efforts have been promising but may benefit from using formal models such as structural decision making (Conroy and Peterson 2013).

Incorporate options for citizen science in monitoring and experiential programs that help reduce monitoring costs and promote broader understanding of the results.

A growing body of literature exemplifies the merits of using citizen science and volunteers in monitoring and research to increase capacity and broaden understanding of ecological objectives and responses in communities (Haywood et al. 2016; Miller-Rushing et al. 2019). This mounting evidence helped motivate the development of citizen science and experiential programs in the Grande Ronde basin. In 2018, a new monitoring network coordinator position at GRMW was created to increase public

outreach and involvement. In coordination with USFS staff, plans include training volunteers to conduct Columbia spotted frog surveys, monitor freshwater mussels in response to river restoration, and conduct aquatic macroinvertebrate surveys to assess river health.

Use formal models to guide more structured decision making (SDM) and to communicate a broader vision of the system and its critical uncertainties to all involved.

Quantitative models are used in the Grande Ronde basin to support decision making, including assessing limiting factors for salmon (Burke et al. 2010, Blair et al. 2009, NOAA 2017), estimating salmon population response to tributary habitat actions (USACE 2007) and climate change (Justice et al. 2017, Weber et al. 2018), and prioritizing restoration actions (Atlas partners 2015, Justice et al. 2017). But admittedly, these efforts have not been formally integrated into SDM as recommended by Rieman et al. (2015) and others (Hilborn 1992, Runge 2011, ISAB 2013). Prioritization of restoration is currently guided by Atlas, which does include some elements of SDM. These include reviewing existing information to identify habitat impairments and limiting factors, identifying and coordinating with stakeholders, defining objectives, developing alternative restoration actions, estimating consequences of alternatives using a quantitative ranking system, and strategically selecting projects to maximize biological benefit. This process could be improved by including more specific, quantitative objectives, developing a broader set of management alternatives, and establishing a clear feedback loop to inform future decision making (Fig. 5).

Conclusions

Our multi-agency workgroup came to several conclusions about the progress and setbacks towards a comprehensive approach to habitat restoration (Table 1). We concluded that clearly articulated goals and metrics for salmonid abundance exist, but we need more emphasis on biological

diversity. Research partners have developed robust landscape-scale analyses and models, but those models could be more effectively applied to decisions about restoration implementation. Public engagement, citizen science, and interaction with social scientists are wanting, but there are both strong interest and promising early developments. Atlas has created a unique and effective community of practice between research and management, however more effort could be spent engaging the public using a more formalized process. The latter would include a clearly articulated method for integrating results of monitoring and evaluation back to goal development, project planning, and project implementation (Fig. 5). To make significant progress towards these goals, consistent policy and funding is needed. These findings are consistent with the conclusions of Hand et al. (2018), who describe salmon conservation in the Columbia basin as embedded in a complex management landscape where ecological as well as socioeconomic and political factors need consideration.

We consider this response as a stepping-stone—not the final answer—towards realizing the directives from Rieman et al. (2015). Next steps include reaching out and learning from others who have successfully adopted similar approaches. Current efforts of Atlas partners involve developing a five-year adaptive management plan coupled with a 20-year vision, recognizing that work is needed at multiple time scales for a long-term view of restoration. Finally, we encourage other groups to engage in a similar process of self-assessment and to share findings with the broader restoration community. These self-assessments should communicate not only the strengths of their programs, but also barriers to achieving goals and opportunities for improvement towards developing a comprehensive approach to habitat restoration in the Columbia basin.

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Tables

Table 1. Recommended actions towards a comprehensive approach for habitat restoration in the Columbia Basin (from Rieman et al. 2015), with examples of progress in the upper Grande Ronde Basin. Citations and acronym definitions are in the corresponding sections of the text.

Action	Directive	Examples of progress in the Grande Ronde basin
Rebalance the goals	Develop and communicate goals and measurable objectives for biological diversity that are held as equal priority to the goals and objectives for abundance	Atlas prioritizes restoration in areas with overlap in salmonid species use, life stages (Fig. 1); Multiple life history strategies of salmonids are considered; tribal First Foods concept emphasizes ecological diversity and resilience
	Directly engage all stakeholders and the general public to broaden understanding of the critical value of biological diversity	Public outreach efforts emphasize the ecological value and ecosystem services provided by freshwater mussels, beaver, Pacific lamprey, and Columbia spotted frogs (Fig. 2)

Action	Directive	Examples of progress in the Grande Ronde basin
	Develop indicators for monitoring that measure and communicate progress on abundance and biological diversity at multiple scales across the basin	Abundance criteria and indicators for VSPs exist at the population scale; Life-stage specific indicators for salmonids are expressed at the reach scale; Indicators for biological and ecological abundance and diversity are proposed in Table 2 and Supplemental Table A.
	Consider the implications of hatchery production for carrying capacity and diversity of wild fish as a basis for integrating hatchery production with habitat restoration	HGMPs list performance standards for limiting impact on carrying capacity; Life cycle models incorporating the contribution of supplemented to natural populations are in development

Action	Directive	Examples of progress in the Grande Ronde basin
Strengthen linkages between science and management	Use landscape sciences and technology in assessment and restoration planning and support and expand common application of relevant research, monitoring, modelling, and analytical tools	Remotely sensed information (LiDAR and FLIR) used to develop a water temperature model and potential vegetation map, used for prioritizing areas where riparian restoration could mitigate future climate change in conjunction with life cycle model; carcass additions as a management tool evaluated from field experiments
	Create and support communities of practice and peer-learning networks that demonstrate science-management integration; highlight new tools and analyses that are innovative and promote those with real potential for success	GRMW provides interface between science and management and coordination of restoration; Development of Atlas involved intensive exchanges between researchers and managers including annual "State of the Science" meeting

Action	Directive	Examples of progress in the Grande Ronde basin
	Recommit to options for broadly based technical assistance to provide analytical support, constructive criticism, and feedback to proposed and ongoing projects	Projects are scrutinized internally by Atlas technical committee and reviewed by GRMW board of directors; Broadly based technical assistance from outside the sub-basin's expertise was identified as a need
Increase public engagement	Include education and outreach specialists as key players at the earliest stages of project development	Wallowa-Whitman NF uses public outreach specialist to communicate broad forest management plans; More resources are needed to support efforts at local scales
	Engage people and organizations early through forums that encourage dialogue between managers, researchers, and stakeholders associated with a range of resource values	Atlas has the explicit goal of bringing together managers, researchers, and stakeholders; More engagement with the public as stakeholders is needed, requiring policy and funding support

Action	Directive	Examples of progress in the Grande Ronde basin
	Align ecological needs with social and economic incentives and consider benefits and costs to people and their communities	The NRCS and Freshwater Trust use incentives for landowners to engage in conservation measures; Restoration contractors purchase trees from local landowners
	Use a wide diversity of media and forums for public and community engagement	GRMW publishes *Ripples in the Grande Ronde* with broad distribution to the community; NOAA, GRMW, and CRITFC are producing a short public outreach film to gain broad support for salmon conservation efforts; Fig. 3 provides an example of printed outreach materials for landowner incentives
	Make public involvement and active learning through citizen science in monitoring and research a central element in project implementation	Opportunities to engage citizen science include K-12 classrooms monitoring nearby restoration projects (e.g., Sheep Creek, see

Action	Directive	Examples of progress in the Grande Ronde basin
		Fig. 4); Efforts to enlist citizen scientists are just now gaining momentum
	Recognize the social sciences as a critical element of scientific review and guidance and include social scientists as primary contributors to the advisory, review, and planning process	GRMW solicited guidance from a social scientist at EOU on community outreach efforts; Diverse boards of directors at GRMW and UCSWD provide social and economic review of restoration projects
Work across traditional ecological and social boundaries	Highlight and support experiments in governance for collaborations that bridge agency and intellectual groups, local and regional organizations, governments, landowners, and science-management disciplines	Atlas is founded on partnerships between managers and researchers from multiple local, state, federal, and tribal organizations; Union County's Place-based Water Planning program has strong interdisciplinary and multiagency participation

Action	Directive	Examples of progress in the Grande Ronde basin
	Bring innovative and successful examples (including those from other resource and restoration disciplines) to others in the basin	Guidance for restoration prioritization draws from a wealth of literature from the PNW and from the Umatilla tribe's *River Vision*; landscape-scale watershed assessment approaches applied in the basin (e.g., River Styles and Water Framework Directive) were imported from Australia and Europe, respectively; Lessons can be learned about applying adaptive management from the upper Columbia River basin groups
Learn from experience	Identify clear, quantitative objectives, including diversity objectives that form the baseline for the adaptive management cycle	Quantitative objectives for fish abundance are more clearly defined (e.g., natural origin spawner abundance) but diversity objectives are gaining attention; Examples of

Action	Directive	Examples of progress in the Grande Ronde basin
		quantitative objectives for the Sheep project are provided in Fig. 4
	Implement intentional, science-based management experiments that promote learning about landscapes, cost effective restoration actions, and understanding of their socio-ecological implications	Landscape scale water temperature model used to evaluate which restoration strategies would be most effective under future climate change scenarios; Regional AEM program will provide general guidance on project-scale restoration effectiveness; Experimental additions of fish carcasses conducted in upper Grande Ronde River helped evaluate carcass additions as a management tool
	Incorporate options for citizen science in monitoring and experiential programs that help reduce monitoring costs and promote broader understanding of the results	New monitoring coordinator position at GRMW provides support for citizen science programs alongside USFS; Plans include amphibian egg mass, freshwater mussel, and

Action	Directive	Examples of progress in the Grande Ronde basin
		aquatic invertebrate surveys using citizen scientists
	Use formal models to guide more structured decision making and to communicate a broader vision of the system and its critical uncertainties to all involved	Quantitative life-stage and life-cycle models have assisted in decision-making, but the overall adaptive management process could be improved by using formal models such as SDM. Atlas includes many—but not all—components of SDM. Continued funding and logistical support for monitoring programs will be required to meet this goal

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Table 2. Examples of proposed indicators for biological and ecological abundance and diversity. The complete table of indicators and corresponding data collection methods, and spatial and temporal scale of status assessments, and references can be found in Supplemental Table A.

Indicator type	Sub-type	Indicator	Definition
Salmon/steelhead abundance	Adult abundance	Abundance of natural origin spawners	Number of natural origin adults (age 3+) on the spawning grounds
	Juvenile abundance	Abundance of natural origin smolts	Number of natural origin smolts surviving to Lower Granite Dam
Salmon/steelhead productivity	Adult productivity	Total productivity of natural origin spawners (adults per spawner)	The number of surviving natural origin adult offspring (age 3+) per parent
	Juvenile productivity	Freshwater productivity of natural origin spawners (smolts per spawner)	The number of natural origin smolt offspring surviving to Lower Granite Dam per parent
	Juvenile to adult productivity	Smolt-to-adult return rate (SAR)	Survival of natural origin smolts from Lower Granite Dam to returning adults at Lower Granite Dam
Salmon/steelhead diversity	Spawner distribution	Spatial extent or range of population	Proportion of historical range occupied and presence/absence of spawners in MaSAs

Indicator type	Sub-type	Indicator	Definition
	Phenotypic and genotypic variation	Major life history strategies	Distribution of major life history expression within a population
	Gene flow	Spawner composition	Proportion of hatchery origin natural spawners derived from a local (within population) brood stock program using best practices
	Occupancy of diverse habitats	Distribution of population across habitat types	Change in occupancy across ecoregion types
	Integrity of natural systems	Selective change in natural processes or impacts	Ongoing anthropogenic activities inducing selective mortality or habitat change within or out of population boundary
Habitat quantity	Accessible fish habitat	Quantity of accessible fish habitat	River kilometers of main channel habitat accessible to migrating fish
	River channel	Meso-habitat area	Surface area (m^2) of meso-habitats (e.g., pools, riffles, runs, small side channels, off-channel units

Indicator type	Sub-type	Indicator	Definition
	Floodplain/side channels	Side channel length	Length (m) of side channels
	Flow	Mean summer flow	Mean of all daily flow measurements (m^3/s) during summer (Jun 1 - Sep 30).
Habitat quality/diversity	River channel (pools)	Large pool frequency	Number of large pools (≥ 20 m^2 area and ≥ 0.80 m max depth) per kilometer of stream
	River channel (wood)	Large woody debris frequency	Number of large woody debris pieces within the bankfull channel per 100 m of stream length
	River channel (substrate)	Median sediment particle size (D50)	Median sediment particle size on the streambed surface in riffles
	Floodplain/side channels	Side channel ratio	Length of side channels divided by length of main channel
	Riparian condition	Riparian vegetation departure index (RVD)	Ratio of existing vegetation cover to pre-European settlement vegetation cover in the valley bottom
	Water quality	Water temperature	Various measures of water temperature (°C) magnitude, variability, frequency, duration, and timing

Indicator type	Sub-type	Indicator	Definition
	Biological integrity	Observed/Expected (O/E) benthic macroinvertebrates	Ratio of observed to expected benthic macroinvertebrate taxa as predicted by the River Invertebrate Prediction and Classification System (RIVPACS)

Figure Captions

Figure 1. The upper Grande Ronde River and Catherine Creek watersheds in northeast Oregon. Tier I-III restoration priority areas from Atlas are shown along with restoration projects initiated or planned since 2017, when Atlas projects were first realized on the ground. Some restoration projects in Tier III (low priority) areas (i.e., projects 2-4) are passage improvements allowing fish to migrate into their historical range.

Figure 2. A Columbia spotted frog overlooking a restored section of the upper Grande Ronde River. Other examples of biological biodiversity beyond salmon and steelhead include freshwater mussels, beaver, aquatic and terrestrial invertebrates, and Pacific lamprey. (Image courtesy of David Herasimtschuk, Freshwaters Illustrated.)

Figure 3. Example of public outreach materials that communicate alignment between ecological, social, and economic incentives in the Grande Ronde Basin. (Flyer courtesy of Grande Ronde Model Watershed.)

Figure 4. The Sheep Creek restoration project, a Tier I (high priority) project initiated in 2019 in the upper Grande Ronde River as an example of quantitative objectives and corresponding monitoring methods.

Figure 5. Adaptive management loop with examples from the Grande Ronde Basin. Monitoring, evaluation, and assessment form the backbone of learning and revising the vision, goals, objectives, strategies, and projects intended to improve tributary habitat conditions in support of salmon recovery and river ecosystem health. (Adapted from ISAB 2018.)

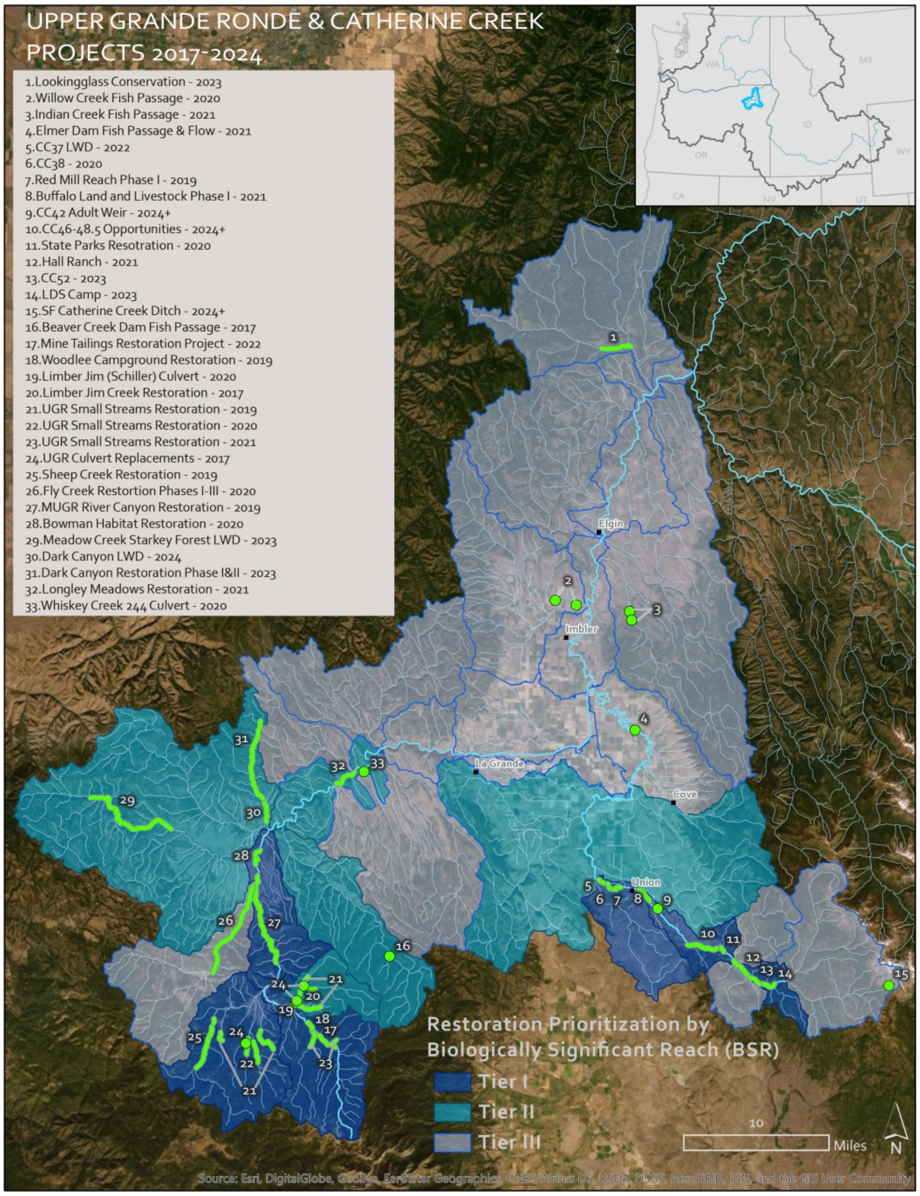

Figure 1. The upper Grande Ronde River and Catherine Creek watersheds in northeast Oregon. Tier I-III restoration priority areas from Atlas are shown along with restoration projects initiated or planned since 2017, when Atlas projects were first realized on the ground. Some restoration projects in Tier III (low priority) areas (i.e., projects 2-4) are passage improvements allowing fish to migrate into their historical range.

Figure 2. A Columbia spotted frog overlooking a restored section of the upper Grande Ronde River. Other examples of biological biodiversity beyond salmon and steelhead include freshwater mussels, beaver, aquatic and terrestrial invertebrates, and Pacific lamprey. (Image courtesy of David Herasimtschuk, Freshwaters Illustrated.)

705x470mm (72 x 72 DPI)

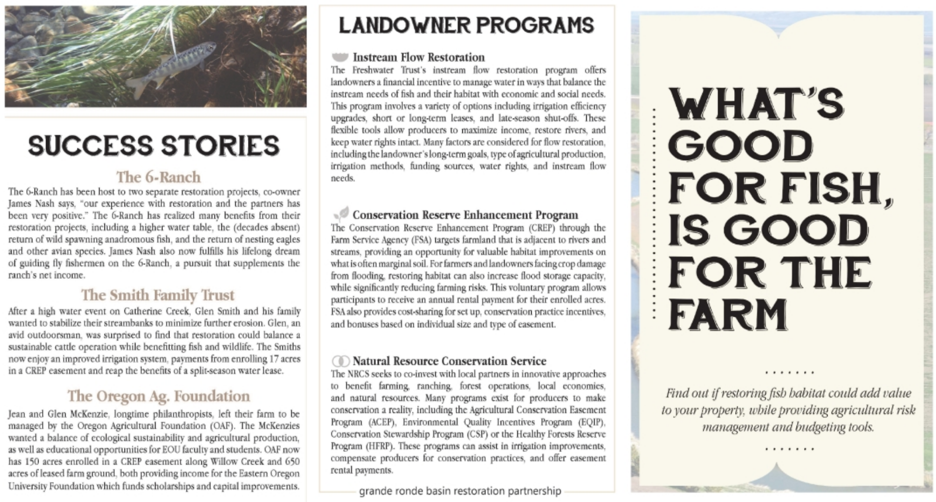

Figure 3. Example of public outreach materials that communicate alignment between ecological, social, and economic incentives in the Grande Ronde Basin. (Flyer courtesy of Grande Ronde Model Watershed.)

480x291mm (168 x 168 DPI)

QUANTITATIVE OBJECTIVES OF SHEEP CREEK RESTORATION

The Sheep Creek Restoration Project encompasses 4.5 miles of the upper Grande Ronde River. Sheep Creek and its meadow habitats were not in proper functioning ecological condition (hydrologic, geomorphic, vegetative composition) due to historical practices such as beaver trapping, overgrazing, logging, road building, and an altered fire regime. The Sheep Creek Restoration project was implemented in 2019 by Trout Unlimited and the U.S. Forest Service.

Quantitative objectives for habitat function included:

- Exclude cattle grazing from 145 acres of riparian habitat with 5.25 miles of fence to promote native riparian community
- Increase late-summer floodplain area by 30% after 2 years post-restoration
- Buffer seasonal high and low stream temperatures via increased groundwater inputs after 5 years of improved floodplain connection
- Add 1,500 pieces of large wood to the stream and floodplain
    - 72 channel spanning wood structures to backwater pools and activate side channels
    - 90 wood structures to provide velocity refuge and cover

Quantitative objectives are monitored via:

- Riparian transects to track vegetation species composition and density
- Aerial photography and GIS analysis to monitor floodplain inundation at high and low streamflows
- Stream temperature data loggers to evaluate changes in temporal thermal regime
- Habitat surveys to evaluate retention of large wood and subsequent adjustments to cover and stream channel morphology

Figure 4. The Sheep Creek restoration project, a Tier I (high priority) project initiated in 2019 in the upper Grande Ronde River as an example of quantitative objectives and corresponding monitoring methods.

338x451mm (96 x 96 DPI)

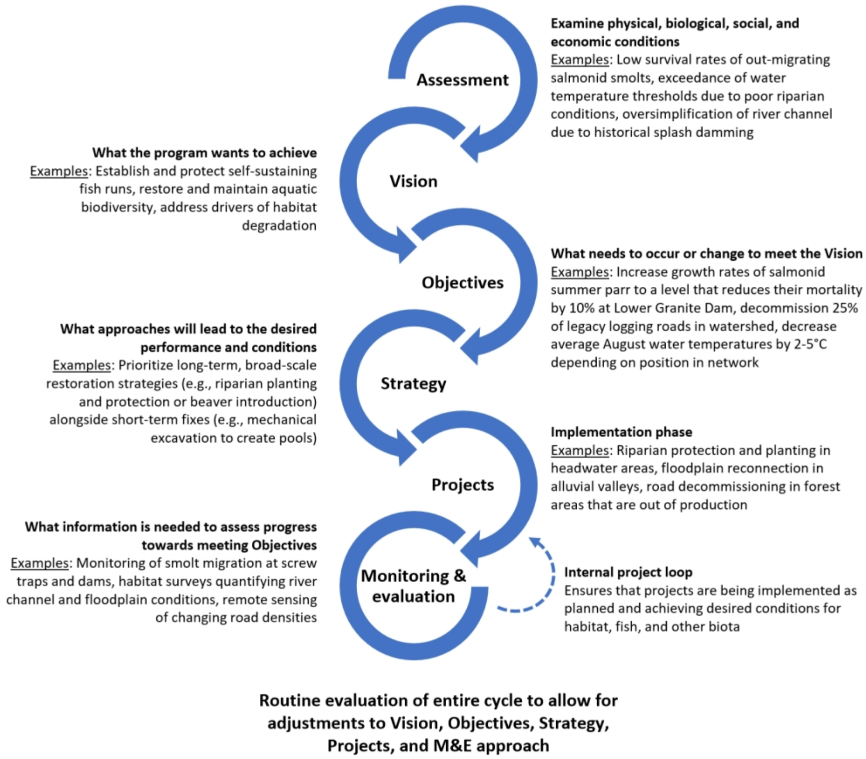

Figure 5. Adaptive management loop with examples from the Grande Ronde Basin. Monitoring, evaluation, and assessment form the backbone of learning and revising the vision, goals, objectives, strategies, and projects intended to improve tributary habitat conditions in support of salmon recovery and river ecosystem health. (Adapted from ISAB 2018.)