Monitoring for Adaptive Management: Status and Trends of Aquatic and Riparian Habitats in the Lake Washington/Cedar/ Sammamish Watershed (WRIA 8)

April 2015

King County

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Prepared for:

Lake Washington/Cedar/Sammamish (WRIA 8) Salmon Recovery Council

Submitted by:

King County Water and Land Resources Division
Department of Natural Resources and Parks

Funded by:

U.S. Environmental Protection Agency under EPA grant number PO-00J09801
Lake Washington/Cedar/Sammamish (WRIA 8) Salmon Recovery Council
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Natural Resources and Parks
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Acknowledgements

A number of individuals contributed substantially to this report. Hans Berge was Project Manager during the field portion of the project. Curtis DeGasperi performed the majority of analyses and report writing, and compiled all the temperature and hydrologic metrics for analysis. He also was the main local resource for analytical tools in the R programming language. Scott Stolnack was Project Manager, writer and editor for the final report, and liaison between the project team and a large number of internal and external entities. Dan Lantz, Christopher Barnes, Doug Marconi, Eleanor Bosman-Clark and Jim Lissa led field crews during summer surveys. Roger Tabor (U.S. Fish and Wildlife Service) provided leadership and invaluable expertise for the fish survey portion of the project, and contributed the report found in Appendix B.

We wish to express our gratitude to the following individuals and agencies: King County Water and Land Resources (WLR) Division: Sevin Bilir, Dave Funke, Doug Henderson, Kate O'Laughlin, Ken Rauscher, Jim Simmonds, Dan Smith, Kerry Thrasher, Tom Ventur, Dong (Charlie) Zeng; WLR Environmental Lab: Christopher Barnes, Stephanie Hess, Jean Power, David Robinson, Susannah Rowles; Washington Department of Ecology: Bob Cusimano, Jack Janisch, Chad Larson, Jill Lemmon, Glenn Merritt, Christopher Moore; U.S. Fish and Wildlife Service: Rebecca Anderson, James Curtis, Audrey Djunaedi, Ashley Drossart, Michael Elam, Nathan Ereth, Howard Gearns, Tim Grun, Travis Hedrick, Ben Leonard, Mei Mei Li, Kira Mazzi, Zach Moore, Stephen Nelson, Jake Ponce, Keith Sweeney, Roger Tabor, Teal Waterstrat, Julie Weaver, Matt Wiley, Matt Wynn; U.S. Environmental Protection Agency (EPA): Lil Herger, Krista Mendelman; EPA National Health and Environmental Effects Research Laboratory, Western Ecology Division: Karen Blocksom, Tom Kincaid, and Tony Olsen.

We are grateful to the following reviewers for their significant contributions: Karen Blocksom, Lil Herger, Frank Leonetti (Snohomish County), Krista Mendelman, Glenn Merritt, Jason Mulvihill-Kuntz (King County), Kate O'Laughlin, Tony Olsen, Jim Simmonds, Rodger Tabor, Dave White (King County), and Jo Wilhelm (King County).

This project was performed under EPA grant number PO-00J09801, with additional support from the Lake Washington/Cedar/Sammamish (WRIA 8) Watershed Salmon Recovery Council, and King County.

Citation

King County. 2015. Monitoring for Adaptive Management: Status and Trends of Aquatic and Riparian Habitats in the Lake Washington/Cedar/Sammamish Watershed (WRIA 8). King County Water and Land Resources Division. Seattle, Washington.

Abstract

King County conducted physical and biological monitoring between 2010 and 2013 in the Lake Washington/Cedar/Sammamish (WRIA 8) watershed using common survey protocols and a probabilistic survey design. Hydrologic monitoring was also conducted at several locations to supplement physical and biological monitoring. The objectives of the project were to: (1) characterize conditions in small salmon streams using a spatially balanced, probabilistic sampling approach; (2) investigate relationships between landscape, hydrologic, biological and habitat metrics; (3) inform adaptive management actions recommended by the WRIA 8 Chinook Salmon Conservation Plan; and (4) communicate findings, methods and analytical approaches to local and regional forums. Data collected included habitat, fish composition, macroinvertebrate composition, hydrology, temperature, and land cover. Results included precision estimates (consistency of repeated measurements) of common habitat indicators, status and trend assessments, an analysis of land-cover/hydrology/habitat/biology relationships, and trend detection power analysis.

Findings:

- Stream biological conditions (as measured by the Benthic Index of Biotic Integrity or B-IBI) ranged from very poor in heavily urbanized areas to very good in rural, forested areas.
- Stream habitat conditions considered important for salmon (wood volume and water temperature) were found to be below standards considered supportive of salmon use even in rural areas. Wood volume was consistently below regional reference conditions and water temperatures frequently exceeded state standards.
- Specific metrics were identified that could be reliably measured over time and are recommended for use in a long term trend monitoring program. These metrics include important indicators of salmon habitat condition (wood volume, pool area, sediment composition, canopy cover, and B-IBI).
- For the most reliable metrics, it will take sampling annually for 10 to 20 years to reliably detect a 3 percent annual change in status or condition.
- Our study corroborated most other research on relationships between urbanization and benthic macroinvertebrate community condition as measured by B-IBI. Urban land cover and population density were the strongest predictors of declining B-IBI scores.
- Additional work is needed to establish properly functioning salmon habitat condition thresholds for relevant metrics that are specific to Puget Sound lowland streams.

Adaptive Management Recommendations:

Certain salmon recovery priority areas located inside Urban Growth Area boundaries, where development and infill are occurring and forest cover is diminishing, appear to be at the most risk of further degradation in the short term. We recommend that the WRIA 8

Technical Committee and Salmon Recovery Council consider the following actions:

- Update the watershed evaluation first performed for the (2005) WRIA 8 Chinook Salmon Conservation Plan, based on the new information in this report and other sources.
- Based on a new watershed evaluation, re-examine management recommendations for all tier areas.
- Request regional support to develop condition thresholds for biologically relevant metrics specific to Puget Sound lowland streams.
- Implement an integrated and scalable monitoring strategy for the future.

Conclusions

One of the key elements of a relevant status and trends monitoring program is that it is sustained over time. The information presented in this study provides a solid foundation for the development of a well-designed and sustainable long term WRIA 8 status and trends monitoring program. These tools would benefit not only local watershed management, but the region as well.

Future habitat status and trends monitoring that efficiently capitalizes on converging regional and local needs from multiple sectors (NPDES, salmon recovery, stormwater, etc.) would contribute substantially to a consistent and reliable long-term set of decision-making tools.

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EXECUTIVE SUMMARY

To inform salmon recovery efforts, King County conducted field surveys of wadeable salmon streams from 2010-2013 to assess habitat conditions in the Lake Washington/ Cedar/Sammamish Water Resource Inventory Area 8 (WRIA 8) watershed. The purposes of the project were to: (1) characterize conditions in small salmon streams using a spatially balanced, statistically rigorous sampling approach; (2) investigate relationships between landscape, hydrologic, biological and habitat metrics; (3) inform adaptive management actions recommended by the WRIA 8 Chinook Salmon Conservation Plan; and (4) communicate findings, methods, and analytical approaches to local and regional forums. This type of comprehensive multi-year effort at the watershed scale is seldom seen in the U.S. and has not yet been attempted elsewhere in the Puget Sound region.

Funding for the project was provided by the U.S. Environmental Protection Agency under grant number PO-00J09801, the WRIA 8 Salmon Recovery Council, and King County.

Watershed Context

The WRIA 8 watershed, encompassing Lake Washington and its tributaries in the central Puget Sound region, contains some of the most urbanized areas in Washington state. Despite this, salmon and trout are still found in urban streams, some of which are migratory routes for regionally important salmon runs. Conservation and recovery actions in the watershed are guided by the 2005 WRIA 8 Chinook Salmon Conservation Plan (hereafter the WRIA 8 Plan). Most Chinook salmon spawning and rearing occurs outside Urban Growth Area (UGA) boundaries where water quality is generally good and aquatic habitat conditions are considered excellent.

Findings

The data collected in this study provide important baseline information on the status and trends of wadeable salmon streams in the WRIA 8 watershed, as well as perspectives on the relationships between land cover, hydrology, habitat, and biological community response.

- Stream biological conditions (as measured by the Benthic Index of Biotic Integrity or B-IBI) ranged from very poor in heavily urbanized areas to very good in rural, forested areas.
- Stream habitat conditions considered important for salmon (wood volume and water temperature) were found to be predominantly not supportive for salmon use even in rural areas. Wood volume was consistently below levels needed to support properly functioning habitat conditions and water temperatures frequently exceeded state standards.
- Generally, four years is not a sufficient length of time to see trends in stream resources. However, we did see a statistically significant upward trend (improvement) in the Benthic Index of Biotic Integrity (B-IBI) in the watershed between 2010 and 2013. There was no corresponding improvement in habitat condition in those streams during those years. Comparison to a larger WRIA 8 and 9

dataset with many more years of data suggests that the increase in B-IBI scores, while real, is likely due to natural variability.

- The spatially-balanced data we collected are of sufficient precision to reliably test for trends in the sampled streams over time. We identified a short list of metrics representing important indicators of stream habitat conditions important to salmon (wood volume, pool area, sediment composition, canopy cover, and B-IBI) that are repeatable and precise.
- Our analyses indicated that for most of the metrics we measured, it will take an annual monitoring program 10 to 20 years to reliably detect a significant change (3 percent per year) in the status of the most relevant metrics. Currently no such program exists.
- Our study corroborated most other research on relationships between land cover stressors and benthic macroinvertebrate community response as measured by B-IBI. Urbanization and population density best explained the observed variance in B-IBI scores – low levels of urbanization and human population density coincide with highest B-IBI scores and high levels of urbanization and population density coincide with lowest B-IBI scores.
- Our study also provided the first test of the utility of a Fish Index of Biotic Integrity (F-IBI) developed especially for Puget Sound lowland streams. Our results indicate that the Puget Sound lowland F-IBI (although initially calibrated and validated with data collected primarily from King County streams) is confounded by contributing upstream basin area and/or stream size. Further research will be needed to identify a F-IBI that is comparable to the B-IBI, which is not confounded by natural landscape features.

Adaptive Management

As part of the 2005 Chinook recovery planning process, the watershed was organized into priority areas or "tiers" based primarily on Chinook use. Certain salmon recovery priority areas appear to be at risk of degradation in the short term. These areas include streams located inside the UGA boundaries where development and infill is occurring and forest cover is diminishing. Findings within the context of these recovery planning tiers follow:

- Tier 1 areas include primary spawning habitat as well as migratory and rearing corridors for Chinook salmon. Management strategies for Tier 1 areas involve the preservation of existing high quality habitat, and restoration where needed. Our surveys confirm that the majority of Tier 1 areas are of relatively higher quality than Tier 2 or Tier 3 sites. B-IBI and pool area were generally higher in Tier 1 areas. However, wood and temperature metrics were low in all tiers.
- Tier 2 areas contain streams with occasional Chinook use, and are important for preserving the overall spatial structure of Chinook in the watershed. Some Tier 2 areas include streams located completely inside the UGA boundaries. Tier 2 streams inside the UGA are at the most risk of degradation in the short term. It is likely that

the most high-functioning Tier 2 area within UGA boundaries (i.e., North Creek) will degrade further without focused efforts.

- Tier 3 areas are the most urbanized areas of the watershed, and have little or no use by Chinook salmon. These streams are generally in poor condition by most metrics. Strategies for Tier 3 areas focus on protecting or improving water quality or decreasing the effects of high flows from stormwater runoff. Current strategies are likely insufficient to support the long-term occurrence of coho salmon in these urban streams.

Adaptive Management Recommendations

- **Re-evaluate the tier strategy based on new information in this report and other sources.** Consider updating the watershed evaluation first performed for the (2005) WRIA 8 Chinook Salmon Conservation Plan. The information presented in this report and from other recent sources (e.g., land cover change and Chinook escapement reports) can be used to re-assess and update the classification framework.
- **Re-examine management strategies in light of the information on habitat quality in this report.** Strategies for Tier 1 and Tier 3 areas appear to appropriately match conditions in those areas. However, Tier 2 areas include some streams inside the UGA boundaries where development and infill is occurring, and forest cover is diminishing. Because Tier 2 areas inside the UGA appear to be at the most risk of degradation in the short term, additional management actions may be warranted.
- **Reclassify some areas based on information acquired since 2005.** The upper Cedar River and its tributaries above Landsburg Dam were classified as Tier 2 in the original WRIA 8 Plan because there was insufficient information on Chinook use above the dam. Data acquired since then confirms that this area has become a core area for Chinook and should be re-classified as Tier 1. Other areas, where watershed function and/or Chinook use has declined, may require reclassification to a lower level or increased efforts to support Chinook use.
- **Request regional support to develop condition thresholds for biologically relevant metrics that are specific to Puget Sound lowland streams.** Thresholds based on reference conditions are needed to classify or categorize metrics into poor, fair, or good condition; or supporting/non-supporting properly functioning habitat condition. In this study, we could only identify thresholds for B-IBI, F-IBI, wood volume and summer maximum stream temperatures. Additional work is needed by the region to establish condition thresholds for other biologically relevant metrics that are specific to Puget Sound lowland streams.
- **Implement a monitoring strategy for the future.** The information in this report provides baseline information collected in a spatially balanced and probabilistic sampling framework using appropriate methods with quantified precision. It provides estimates of precision that indicate it would take an annual monitoring effort about two decades to confidently detect a significant (3 percent) annual change.

Conclusions

One of the key elements of a relevant status and trends monitoring program is that it is sustained over a long period of time. It is hoped that the information presented in this study provides a solid foundation for the development of a well-designed and sustainable long term WRIA 8 status and trends monitoring program. A small number of habitat and biological community metrics with high precision and repeatability, sampled annually, using a proven framework, regional data repositories and established analytical tools, benefits not only the watershed but the region as well.

More broadly, future habitat status and trends monitoring that capitalizes on converging regional and local needs for multiple purposes (water quality permitting, salmon recovery, stormwater, etc.) could contribute substantially to a consistent and reliable long-term set of decision-making tools.

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1.0 INTRODUCTION

King County was awarded a grant by the U.S. Environmental Protection Agency (EPA) to monitor aquatic and riparian habitat of wadeable salmon streams in the Lake Washington/ Cedar/Sammamish watershed, also known as Water Resource Inventory Area 8 (WRIA 8). The purpose of the project was to characterize the conditions of small salmon streams in WRIA 8; to investigate relationships among land cover, hydrology, habitat, and biological systems across an urbanization gradient; and to provide information to support adaptive management of the WRIA 8 Chinook Salmon Conservation Plan (WRIA 8 SRC, 2005).

This report documents the purpose and objectives, management questions, methods, results, conclusions and recommendations of the WRIA 8 status and trends monitoring conducted from 2010 through 2013. The information will be used in the 2015 update of the WRIA 8 Chinook Salmon Conservation Plan (hereafter WRIA 8 Plan).

1.1 Background

Local governments throughout Puget Sound are in the process of implementing a number of watershed-scale management plans, including watershed-based salmon recovery plans and the Puget Sound Action Agenda,[1] but few local entities or watershed councils have the resources to adequately monitor the effects of those efforts. While some state and federal agencies conduct stream monitoring programs in the Puget Sound region, the geographic scope of those programs is too broad and the sampling intensity too limited for making decisions at the watershed scale.

Monitoring is a key component of watershed management in the Puget Sound region and is essential for adaptive management, which calls for making adjustments to management strategies as needed based on new information. Jurisdictions must monitor over time to track changing watershed conditions, and to determine whether habitat conservation and restoration policies are successful. Decision-makers need accurate information regarding the health of streams to determine if trends in habitat conditions are contributing to the recovery of Endangered Species Act (ESA)-listed Chinook salmon (*Oncorhynchus tshawytscha*) and other species. Stream "health" from the eyes of a salmon is a complex subject that includes the quantity and quality of streamside vegetation, insect communities, instream wood and sediment processes, hydrology, temperature, conventional water quality, and other factors. Most assessments of stream health are either focused on a single problem (e.g., water quality) or too local to adequately characterize the watershed as a whole with precision or confidence.

Objectives for habitat monitoring programs typically include estimating the current extent and status of a resource, estimating change in status between time periods, and estimating trends over time. To achieve these objectives, an appropriate, spatially balanced, and probabilistic sampling framework must be used. Monitoring protocols must be sufficient to

[1] Puget Sound Action Agenda Center: http://www.psp.wa.gov/action_agenda_center.php

evaluate the status of the resource at the appropriate scale and level of precision, yet be cost-effective. Metrics must be relevant to the monitoring question, and must be expected to respond in a measurable way to management actions. Measurements must be able to discriminate actual changes in the resource ("signal") from sampling errors or natural variation ("noise").

In addition to documenting the status of a resource over time, monitoring at the watershed scale can help clarify relationships between urbanization (e.g., extent of impervious surfaces, road density, forest cover and forest fragmentation), hydrology (e.g., processes affecting flow timing, frequency, magnitude and duration), stream habitat conditions (e.g., sediment character, wood volume, pool area, riparian cover) and biological resources (e.g. benthic macroinvertebrate and fish assemblages). Interpreting these relationships is made easier when sufficient data from each of these elements are collected together, using a common sampling framework.

This report describes the:

- Purpose and objectives of the project;
- Management questions, salmon recovery context, methods, data reduction approach and rationale for selection of metrics for more detailed analysis;
- Monitoring results (status and trends);
- Estimates of the extent of stream conditions in WRIA 8 for selected metrics;
- Precision, signal-to-noise and trend-detection power estimates for selected metrics;
- Assessment of relationships between land cover, hydrology, habitat and biological assemblages along an urbanization gradient; and
- Conclusions and recommendations for future monitoring and adaptive management.

1.2 Purpose and Objectives

The primary purpose of this project was to assess the condition of stream and riparian habitat along small (wadeable) salmon streams in the WRIA 8 watershed, in order to inform adaptive management of the WRIA 8 Chinook Salmon Conservation Plan. A secondary purpose was to investigate relationships between land cover, hydrology, habitat, and biological assemblages in the watershed along an urbanization gradient.

The project team conducted physical, biological, and hydrologic monitoring of 52 wadeable salmon stream reaches in WRIA 8 to accomplish the following objectives:

1. Characterize conditions in small salmon streams in WRIA 8;
2. Investigate relationships between development, land and water management, and biological and physical processes in streams, using modern protocols and spatially and temporally coherent datasets;
3. Inform adaptive management actions for salmon recovery in WRIA 8; and

4. Communicate findings, methods, and analytical approaches to other local and regional forums.

In order to help discern regional (e.g., climate) patterns from local patterns, the project also compared data collected at five EPA Sentinel stream sites located in the Puget Sound lowlands outside of WRIA 8.

1.3 Management Questions

The overall management questions we treat in this report are:

1. *Status:* What is the condition of small salmon streams in WRIA 8 based on common stream attributes (fish and macroinvertebrate community indices, stream substrate, wood, pools, streamside forest cover)?
2. *Trends:* Are stream conditions changing over time?
3. *Precision:* How precise and repeatable are the measurements?
4. *Trend detection power:* How often and at what level of effort would one need to monitor stream habitat in order to detect a change with reasonable confidence?
5. *Stressor-response relationships:* What is the relationship between land use/land cover and stream habitat/biological community conditions?

2.0 METHODS

The project used a probability-based survey design created by the Washington Department of Ecology (hereafter referred to as Ecology) to select sites on wadeable salmon streams throughout the WRIA 8 watershed (Ecology, 2008). Physical habitat, benthic macroinvertebrate assemblages, and fish species assemblages were surveyed over four years to characterize the status of the streams as well as begin to evaluate trends. Monitoring results are reported for 57 stream survey sites assessed between 2010 and 2013 (52 sites inside WRIA 8 and 5 EPA Sentinel sites).

In addition to habitat and biological data, land cover metrics were calculated for all sites and hydrologic data were compiled for a subset of sites. These data were collected for the purpose of investigating relationships between development, land and water management, and biological and physical processes in streams.

2.1 Study Area

The WRIA 8 watershed, located in the Puget Sound basin in western Washington, contains over 1.4 million inhabitants with a highly urbanized lowland, a less developed suburban fringe, and upland working forests and protected areas. Yet despite profound alterations to the watershed (including the lowering and "re-plumbing" of the second largest natural lake in the state),[2] several salmon stocks inhabit the watershed, including Chinook salmon (*Oncorhynchus tshawytscha*) and steelhead (*O. mykiss*) populations listed as threatened under the ESA. Most Chinook spawning and in-stream rearing occurs outside designated Urban Growth Area (UGA) boundaries and much of the upper watershed is in protected status or is the focus of restoration. Of the other salmonids found in the watershed, Puget Sound coho salmon (*O. kisutch*) are a federal Species of Concern, and sockeye salmon (*O. nerka*) are the focus of intense management (WDFW, 2012).

The WRIA 8 watershed comprises 692 mi^2 (1,792 km^2) and includes two major river systems (Cedar and Sammamish) and three large lakes (Washington, Sammamish and Union – Figure 1). It also includes the marine nearshore and numerous smaller basins that drain directly to Puget Sound, from West Point in the City of Seattle northward to Elliott Point in the City of Mukilteo. WRIA 8 is located predominantly in western King County, but about 15 percent of the watershed extends northward into Snohomish County. A portion of the upper (eastern) watershed is the municipal drinking water supply for the City of Seattle, and is managed under a Habitat Conservation Plan (City of Seattle, 2000).[3]

[2] Lake Washington was lowered by 2.4 m and flow into and out of the lake was redirected as a result of the completion in 1916 of a federal project to connect Lake Washington to Lake Union and Puget Sound. Details of these modifications can be found in Chrzastowski (1983).
[3] Cedar River Watershed Habitat Conservation Plan:
http://www.seattle.gov/util/environmentconservation/ourwatersheds/habitat_conservation_plan/

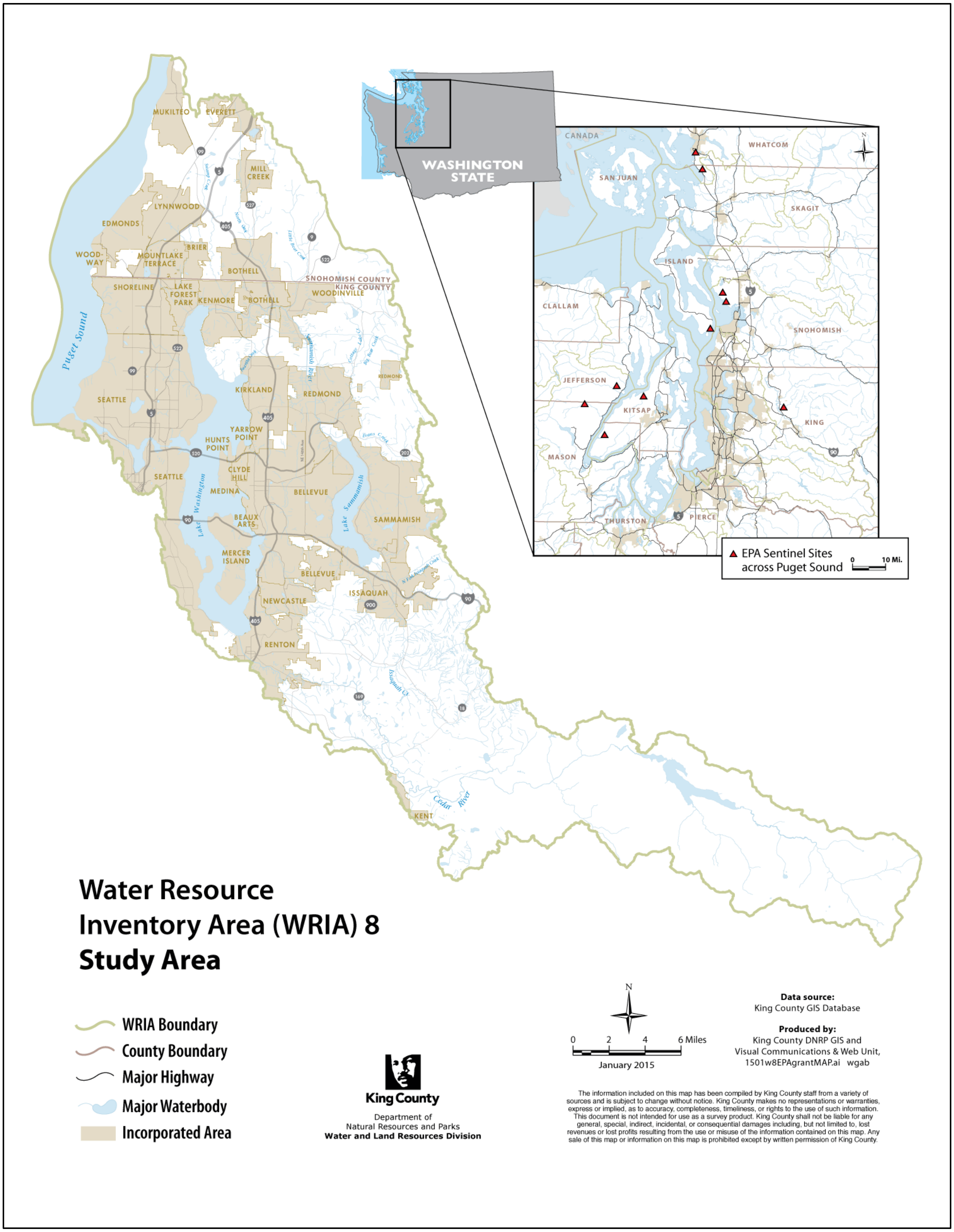

Figure 1. Map of WRIA 8 study area and EPA Sentinel sites.

The eastern portion of the WRIA 8 watershed lies in the Cascade Range and receives up to 102 inches of precipitation annually. The western portion occupies the Puget Lowland, and receives an average of 38 inches of rain per year. Only the upper Cedar River Basin, relatively high in the Cascades, develops an annual snowpack. The City of Seattle's water supply facility captures runoff from the upper portion of the basin; an instream flow plan mitigates the impacts of this diversion (City of Seattle, 2000). All other watershed streams rely primarily on groundwater to sustain summer and early fall baseflow.

Land cover varies considerably across the watershed: 18 percent is classified high/medium intensity development, 19 percent low density or developed open space, and 47 percent forested (2011 landcover data – NOAA Coastal Services Center, 2013). Most of the remaining easternmost land in the Cascades is designated for mixed use as state or federal parkland or private timber lands. Much of the lower/western portion of the watershed is heavily developed, and includes the cities surrounding Lakes Washington and Sammamish in King County as well as a portion of urbanized south Snohomish County.

Streams in the lower watershed are highly modified, and exhibit the effects of urbanization and development: altered hydrologic regimes, disconnected floodplains, degraded riparian conditions, and poor water quality (May et al., 1977; Booth et al., 2004; Alberti et al., 2007; Segura and Booth, 2010; Scholz et al., 2011). The shorelines of the three largest lakes in the watershed are heavily developed, with little natural shoreline remaining. Despite this, salmon and trout are still found in urban streams, some of which are migratory routes for regionally important salmon runs. Outside the UGA boundaries, water quality generally is good and aquatic habitat condition is considered excellent.

2.1.1 Salmon Recovery and Adaptive Management Context (Tiers)

For salmon recovery planning and implementation purposes, the WRIA 8 Chinook Salmon Conservation Plan (hereafter the WRIA 8 Plan) partitioned the watershed into three management "tiers" (Leonetti et al., 2005). This framework was based on a watershed evaluation using land cover and other spatial data (ca. 2001-2003), Benthic Index of Biotic Integrity (B-IBI) scores (1995-2003), and documented Chinook salmon use. These tiers serve as the basis for conservation strategies and adaptive management in the watershed.

Tier 1 areas (Figure 2 and Table 1) include primary spawning habitat as well as core migratory and rearing corridors. Management strategies for Tier 1 areas generally focus on preserving and improving existing high quality habitat. However, Tier 1 areas also include important migratory routes passing through urban or urbanizing zones where restoration or other actions are needed (i.e., Seattle, Renton, Issaquah, Redmond, Bothell, Lakes Washington and Sammamish, the Lake Washington Ship Canal and Chittenden Locks).

Tier 2 areas are either streams with high watershed function yet little Chinook use[4] <u>or</u> streams with lower watershed function, but with episodic Chinook use and potential to contribute to the overall spatial diversity of the salmon populations in the watershed (e.g., North and Kelsey Creeks). Management goals for Tier 2 areas are to improve their habitat quality and use by salmon where possible (i.e., improve their status from Tier 2 to Tier 1).

Tier 3 areas contain streams with lower watershed function and that are used by Chinook salmon infrequently or never, but are still important for water quality and flow management. Management goals for Tier 3 areas generally involve improving water quality and managing stormwater runoff. Most Tier 3 areas contain smaller streams in urbanized portions of the watershed with historically little use by Chinook salmon, though other salmonid species such as coho are (or have been) present.

Table 1. WRIA 8 Tier classification framework (modified from Leonetti et al., 2005).

Fish Use	Watershed Evaluation Rating		
	Higher Watershed Function	Moderate Watershed Function	Lower Watershed Function
High (Core/ Migratory)	**Tier 1.** Cedar River, Upper Bear Creek, Cottage Lake Creek, Issaquah Creek (Middle and Upper)	**Tier 1.** Urban reaches of Cedar River, Lower Bear Creek, Lower Issaquah Creek, Issaquah Creek (east and north forks), Sammamish River	**Tier 1.** Lake Washington, Lake Union/Ship Canal, Locks, Lake Sammamish
Moderate (Satellite)	**Tier 2.** Evans Creek, Taylor Creek, Upper Cedar Watershed[a]	**Tier 2.** Little Bear Creek, North Creek	**Tier 2/3.** Swamp Creek, Kelsey Creek[b]
Low (Episodic/ None)	**Tier 2.** Rock Creek, Peterson Creek, Walsh Creek	**Tier 3.** May Creek, Tibbetts Creek,	**Tier 3.** Marine Drainages, McAleer Creek, Juanita Creek, Thornton Creek, Coal Creek, Lyons Creek, Forbes Creek

[a] The upper Cedar River and its tributaries above Landsburg Dam were opened to Chinook salmon passage in 2003. That area was classified as Tier 2 on the basis of insufficient data on Chinook use at the time the framework was created.

[b] Kelsey Creek was designated Tier 2 due to larger than expected Chinook spawning in that creek reported during the 1990s and early 2000s.

[4] The upper Cedar River and its tributaries above Landsburg Dam were opened to Chinook salmon passage in 2003. Since the Technical Committee did not have sufficient information on Chinook use above the dam when they created their classification framework, that area was classified as Tier 2.

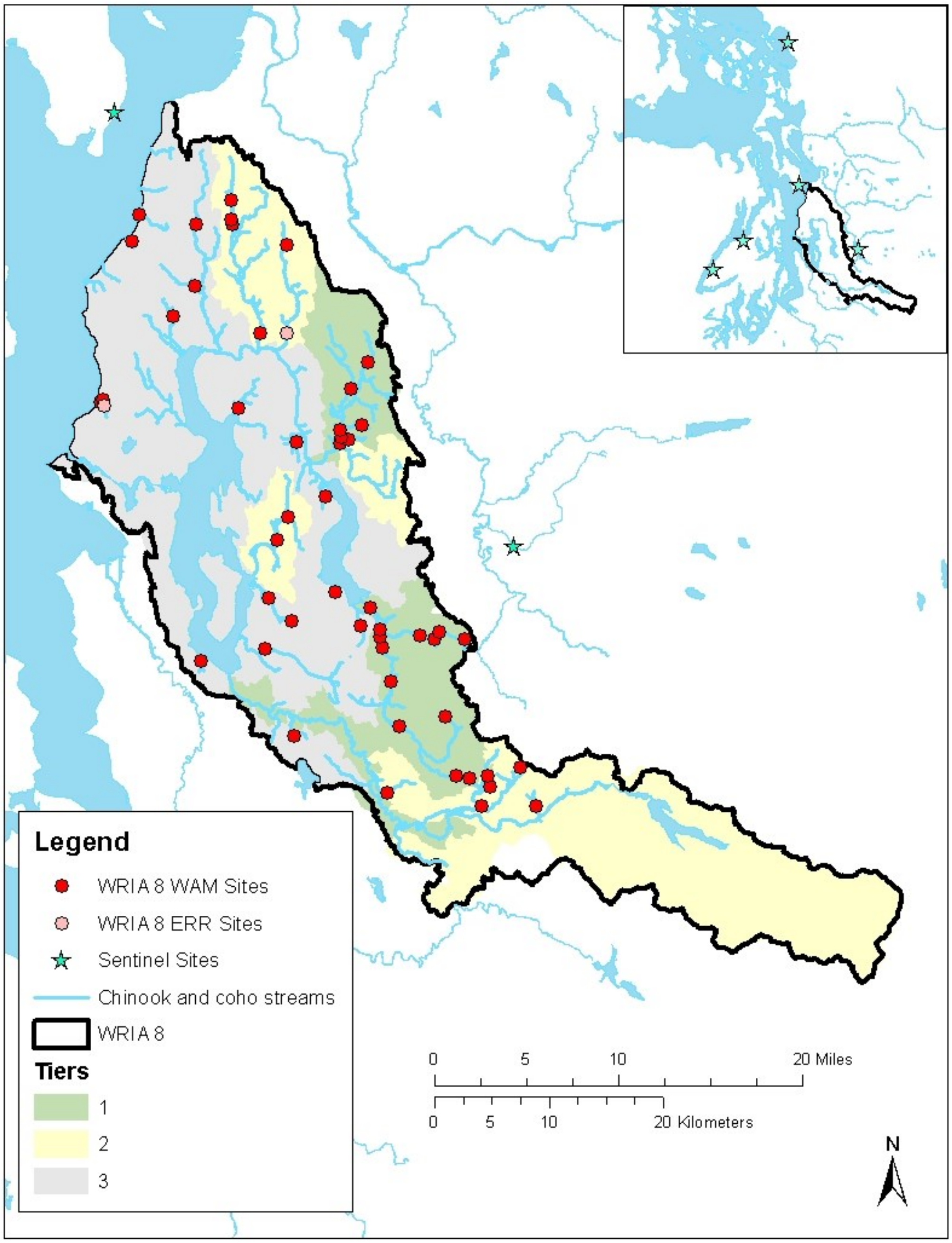

Figure 2. Map of WRIA 8 and EPA Sentinel sample locations and WRIA 8 salmon recovery area Tiers. (Tier 1 migratory areas not shown.)

Note: Tiers in WRIA 8 denote priority habitat areas for Chinook salmon. Tier 1 areas are highest priority and include primary spawning areas as well as migratory and rearing corridors. Tier 2 areas are second priority and include areas less frequently used by Chinook salmon for spawning. Tier 3 areas are infrequently used by Chinook salmon, but are still important areas for water quality and flow management. WRIA 8 WAM Sites refers to the 50 sites that met the probabilistic sampling criteria and are included in GRTS-based survey statistical analyses. WRIA 8 ERR Sites refers to two sites that did not meet the requirements of the probabilistic sampling design. These two sites are included with the WRIA 8 WAM sites in the other statistical analyses presented in this report.

2.2 Probability-Based Survey Design

To efficiently extrapolate from a relatively small number of stream sample sites to the entire population of stream sample sites (i.e., sample frame), a statistically-based study design approach is needed. One such study design is the Generalized Random Tessellation Stratified (GRTS) design, which can produce a spatially balanced probability-based survey design (Stevens and Olsen, 2004; Olsen et al., 2012). Because the WRIA 8 survey design is spatially balanced and probabilistic, it is possible to extrapolate the observed metric values from the relatively small number of sites sampled to the entire sample frame. Details of the development of the survey design are provided below.

Potential sampling sites were randomly selected using the state-wide Ecology Master Sample (Ecology, 2008) limited to sites within WRIA 8. The Master Sample was developed by Ecology as part of a comprehensive probability-based monitoring strategy designed to evaluate state-wide watershed health and salmon recovery efforts (Cusimano et al., 2006; Larsen et al., 2008; Roper et al., 2010). Ecology developed the Master Sample as an appropriate framework for their status and trends monitoring program and to facilitate stream sampling by a variety of agencies with the potential for integrating monitoring data across multiple scales (Larsen et al., 2008).

The Master Sample is based on a GRTS survey design for linear resources (Olsen et al., 2012). The Master Sample is a spatially balanced random set of sites that can be organized in a variety of ways that allow selection of sites over different geographic areas, stream types or sizes, or other features of interest. Each sample point represents approximately 1 km of stream length on a 1:24,000-scale stream network.

The WRIA 8 streams targeted for sampling were wadeable salmon bearing streams. Candidate sites had to meet the following criteria to be considered for sampling: (1) be wadeable, (2) have perennial flowing water, (3) be mapped as accessible to anadromous salmon on the King County GIS stream layer, and (4) include at least one riffle in the 150 m reach for benthic macroinvertebrate collection. An additional requirement for sampling was that sites on private property needed landowner permission for access.

In accordance with the probabilistic GRTS protocol, sites were assessed in sequence until a sufficient number of sites were identified for sampling. The first 868 sites were assessed using a combination of geographic information system (GIS) pre-screening and field visits to determine whether they met criteria for inclusion in the sample frame.

Analyses conducted to extrapolate the sample data to the wadeable salmon bearing streams in WRIA 8 required adjustment of the initial spatial weights (inclusion probabilities) because over sample sites were used.[5] Although the survey was not stratified

[5] Over sample sites were generated as part of the Ecology Master Sample GRTS design. These sites are used in the event that one or more sites selected in the initial sample cannot be used for some reason (e.g., owner access denial). This enables the replacement of sites that cannot be sampled with over sample sites that maintain the spatial balance of the original sample.

in the design stage, strata (Tiers 1, 2 and 3 described above) were defined in the analysis phase. Therefore, spatial weights were adjusted for each tier using the spsurvey analysis package in R[6] (Kincaid and Olsen, 2013). Details of the extrapolation methods are described in Section 3.1 below.

As noted above, our survey design was based on a random tessellation stratified sample, which spread our sampling sites randomly across the targeted streams in WRIA 8 and reduced the overall sample variance compared to simple random sampling (Urquhart, 2012). We also used what is described as an "always revisit" panel design plan. This plan consists of visiting the same fixed number of locations every year (2010-2013). There are many other possible designs or panels, but habitat monitoring research has shown that the "always revisit" design generally has relatively high statistical power to detect trends compared to other possible survey designs (Urquhart et al., 1998; Urquhart, 2012).

In addition to the sites selected with the GRTS design, five of ten EPA and state-designated Puget Sound Sentinel sites outside WRIA 8 were also surveyed annually, in partnership with the EPA and Ecology (Figure 2). Initial GIS and field surveys were conducted to select the Sentinel sites sampled in this study. The five sites were chosen because they were generally smaller wadeable streams that were most similar to the types of streams sampled in WRIA 8.

These Sentinel sites are intended to describe the status and trends of wadeable stream health in the relative absence of human disturbance (Herger et al., 2012); therefore, comparing their condition over time to the WRIA 8 sites should help discriminate regional trends, (e.g., climate change) from local ones. These sites are not included in the GRTS-based sample statistical analyses, though they are compared to WRIA 8 sites elsewhere in this report.

2.3 Aquatic and Riparian Habitat

Stream and riparian habitat data were collected during summer (July through August; 2010-2013) at the 57 sites identified in Figure 2. Habitat sampling followed the monitoring protocols currently in use by Ecology and local agencies (Merritt, 2009) and the methods outlined in the Quality Assurance Project Plan (QAPP) developed for this study (Berge, 2010).

The Ecology protocol requires sample reach lengths to be 20 times the average bankfull width, or no less than 150 m. Since the majority of our sites were less than 8 m bankfull width, we standardized our sample reach length for all sites to 150 m.

Data collected along each sample reach included important stream characteristics such as the number and depth of pools, channel width and depth, vegetative cover along the stream, and detailed channel profiles (e.g., cross-sections, thalweg profiles, sediment

[6] R Core Team. 2014. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna Austria, http://www.R-project.org.

composition). These characteristics describe stream attributes that are directly or indirectly related to limiting factors for salmon recovery (Ecology, 2006). Five randomly selected sample reaches were re-surveyed each year (2010-2013) by a separate crew to assess measurement precision (see Section 2.8.1).

Field data were loaded into Ecology's Status & Trends Riverine Ecology & Assessment Monitoring (STREAM) Environmental Information Management System (EIM), which generated a large number of metrics from the raw data (Janisch, 2013; Ecology, 2014b). The metrics fell into the following categories:

- Substrate (size characteristics, embeddedness)
- Wood (volume and number of pieces)
- Channel dimensions (width, depth)
- Pools (area, average depth)
- Bed stability
- Riparian canopy cover (extent and character)
- Human disturbance (characteristics and extent)

The large number of metrics generated in the EIM was reduced for the statistical analyses conducted as part of this study by excluding metrics with more than 50 percent of the values equal to zero. The list was also reduced by including only summary metrics for wood volume (LWDSiteVolume100m and LWDVolumeMSq) and the number of wood pieces (LWDPieces100m) and excluding the metrics for individual size classes. The 38 metrics selected for investigation are described in Table 2.

Table 2. List and description of habitat metrics assessed as part of this study.

PARAMETER	Category	Description (detailed definitions can be found in Janisch, 2013)
BFWidth_BFDepth	Channel dimensions	Bankfull width:depth ratio
D50	Substrate	Median particle diameter, from size class estimates
LRBS	Bed stability	Relative bed stability, Log10 transformed (Kaufmann et al., 2008)
LWDPieces100m	Wood	Number of LWD pieces standardized per 100 m of site reach
LWDSiteVolume100m	Wood	Volume of LWD standardized per 100m of site reach (m^3/100 m)
LWDVolumeMSq	Wood	Volume of LWD standardized per m^2
PCT Cobble	Substrate	Percentage of substrate classified as 'cobble' (>64-250 mm)
PCT Fines	Substrate	Percentage of substrate classified as 'fine' (silt, clay, non-gritty)
PCT GravelC	Substrate	Percentage of substrate classified as 'coarse gravel' (>16-64 mm)

PARAMETER	Category	Description (detailed definitions can be found in Janisch, 2013)
PCT GravelCx	Substrate	Percentage of substrate classified as 'coarse gravel and larger' (>16 mm)
PCT GravelF	Substrate	Percentage of substrate classified as 'fine gravel' (>2-16 mm)
PCT GravelFb	Substrate	Percentage of substrate classified as 'fine gravel and smaller' (<16 mm)
PCT Pool	Pools	Percentage of site classified as 'pool'
PCT PoolScour	Pools	Percentage of site classified as 'scour pool'
PCT Sand	Substrate	Percentage of substrate classified as 'sand' (0.06-2 mm)
PCT SandFines	Substrate	Percentage of substrate classified as 'sands and fine' (<2 mm)
PCT Wood	Wood	Percentage of substrate classified as 'wood'
PPN CanConif	Riparian canopy cover	Proportion of canopy classified as 'coniferous'
PPN CanDecid	Riparian canopy cover	Proportion of canopy classified as 'deciduous'
PPN CanMixed	Riparian canopy cover	Proportion of canopy classified as 'mixed'
PWP All	Human disturbance	Proximity weighted presence metric, all disturbance classes combined
PWP Path	Human disturbance	Proximity weighted presence metric, human foot path
RBS	Bed stability	Relative bed stability (Kaufmann et al., 2008)
ResPoolArea100	Pools	Vertical residual pool area, standardized m^2 per 100 m of site reach
SD BFDepth	Channel dimensions	Standard deviation, bankfull depth (cm)
SD BFWidth	Channel dimensions	Standard deviation, bankfull width (m)
SD Embed	Channel dimensions	Standard deviation, substrate embeddedness
SD EmbedCtr	Channel dimensions	Standard deviation, substrate embeddedness at channel center
SD PoolUnitDepth	Channel dimensions	Standard deviation, pool depth (cm)
SD TWDepth	Channel dimensions	Standard deviation, thalweg depth (cm)
X BFDepth	Channel dimensions	Reach average, bankfull depth (cm)
X BFWidth	Channel dimensions	Reach average, bankfull width (m)
X DensioBank	Riparian canopy cover	Reach average, densiometer readings at bank
X DensioCenter	Riparian canopy cover	Reach average, densiometer readings at channel center
X Embed	Substrate	Reach average, substrate embeddedness
X EmbedCtr	Substrate	Reach average, substrate embeddedness at channel center
X PoolUnitDepth	Pools	Reach average, pool depth (cm)
X TWDepth	Channel dimensions	Reach average, thalweg depth (cm)

2.4 Aquatic Community

Aquatic community data were also collected each year from the same 57 sites identified in Figure 2 using standardized monitoring protocols currently in use by Ecology, EPA, the U.S.

Fish and Wildlife Service (USFWS), King County, and other agencies, as described in the following sections.

2.4.1 Benthic Macroinvertebrates

A brief description of the benthic macroinvertebrate field sampling and laboratory methods follows. For more detail on the methods used in this study, the reader is referred to the QAPP (Berge, 2010).

Benthic macroinvertebrate sampling was conducted on the same dates as riparian and stream habitat sampling, prior to any other work that might disturb the stream bed. Benthic macroinvertebrates were collected using a Surber sampler with a 500 µm mesh net on a 1x1-ft^2 folding frame with a detachable cod end (the part of the net where the organisms are retained). Samples (1 ft^2 each) were collected from eight riffles or fast-moving, non-depositional areas and combined to create one composite (8 ft^2) sample for the site. Slackwater areas were not sampled for benthic macroinvertebrates. If less than eight riffles were present at a site, additional samples were allocated to existing riffles within or adjacent to the sampling reach. Once the sample was collected, the contents of the Surber net were transferred to a sample container and preserved in the field with 95 percent denatured ethanol. Each year, five randomly selected sites were re-sampled (2010-2013) for benthic macroinvertebrates to assess measurement precision (see Section 2.8.1).

Taxonomic analyses were performed by certified taxonomic laboratories according to standard laboratory protocols with a targeted minimum subsample of 600 organisms. Samples were typically analyzed to a "medium" level of standard taxonomic effort (STE).[7] However, in 2010 eighteen samples were analyzed at a "coarse" STE level; in addition, in 2011, the taxonomic laboratory identified taxa in the subclass Acari (mites) to genus level; in all other years mites were identified to subclass. All data were uploaded to the Puget Sound Stream Benthos (PSSB) data management system (http://www.pugetsoundstreambenthos.org), which enables downloads of B-IBI scores and metrics or raw taxonomic composition.

The benthic macroinvertebrate metric selected for use in this study was the Puget Lowland 0 to100 scale Benthic Index of Biotic Integrity (B-IBI) (King County, 2014a). Scoring of each sample was based on the associated sample metadata, which resulted in comparable B-IBI scores for samples regardless of the STE level. B-IBI is based on ten component metrics that can be scored from 0 to 10 resulting in a total B-IBI range from 0 to 100. The component metrics include four broad community characteristics that include taxa richness and composition (five metrics: total taxa richness, Ephemeroptera taxa richness, Plecoptera taxa richness, Trichoptera taxa richness, number of long-lived taxa), tolerant and intolerant taxa (two metrics: number of intolerant taxa, percent tolerant individuals), functional groups (two metrics: number of clinger taxa, percent predator individuals) and percent dominance of the three most abundant taxa (one metric).

[7] Puget Sound Stream Benthos: Standard Taxonomic Effort: http://pugetsoundstreambenthos.org/Standard-Taxonomic-Effort.aspx

The Puget Sound lowland B-IBI was selected for use in this study because it has been the primary assessment tool used to evaluate biological conditions in Puget Sound lowland streams since the 1990s (King County, 2014b). The Puget Sound lowland B-IBI has also recently been updated to reflect the most recent scientific information on taxa attributes and rescaled from a 10 to 50 to a 0 to 100 scale resulting in improved precision based on an analysis of signal to noise ratio (King County, 2014b). The Puget Sound lowland B-IBI has also been shown to be correlated with measures of land cover change and land cover fragmentation metrics (e.g., Booth et al., 2004; Alberti et al., 2007; Shandas and Alberti, 2009) and hydrologic metrics (Booth et al., 2004; DeGasperi et al., 2009).

2.4.2 Fish

A brief description of the fish sampling methods follows. For more detail on the methods used in this study, the reader is referred to the QAPP (Berge, 2010).

Fish sampling was conducted cooperatively with trained personnel from USFWS each summer when spawning salmonids were not present. Sampling was conducted by single-pass electrofishing (Tabor et al., 2007). Fish and other aquatic invertebrates (e.g., frogs and salamanders) were netted and identified in the field (species and life stage) and released. For species that can be difficult to identify (e.g., species of sculpin or dace) a few individuals were sacrificed to confirm field identification. No same-year re-sampling was conducted for fish surveys; therefore measurement precision could not be evaluated.

The fish metric selected for use in this study was the Fish Index of Biotic Integrity (F-IBI) based on the work of Matzen and Berge (2008). The F-IBI was selected for use in this study because it was developed specifically for the assessment of the effects of urbanization on fish assemblages in Puget Sound lowland streams (Matzen and Berge, 2008). Unlike B-IBI, however, the Puget Sound lowland F-IBI has not been evaluated in any other studies. Therefore, use of the F-IBI in our study provided an opportunity to demonstrate the utility of F-IBI as an indicator of fish community health in Puget Sound lowland streams.

F-IBI is based on six component metrics that can be scored 1 to 4 resulting in a total F-IBI range from 6 to 24. The component metrics include: percent invertivores, percent invertivores-piscivores, percent coho, percent cutthroat, percent sculpin (*Cottus* spp.), and percent individuals of the most abundant species (Matzen and Berge, 2008).

2.5 Land Cover

Land cover and other geospatial data were developed for the upstream contributing area delineated for the 57 stream survey sites identified in Figure 2. The term land cover is used rather loosely throughout this document to describe watershed physical characteristics (e.g., area, elevation, precipitation); road, population and stream density metrics; land use and land cover (e.g., agriculture, urban and forest); and land cover fragmentation metrics. These metrics were chosen to evaluate relationships with our biological response variables and natural basin features (i.e., watershed physical characteristics) and land cover metrics

associated with human disturbance (see Section 2.8.3). The 23 land cover metrics included in this study are listed and described in Table 3.

Details regarding the geospatial data sets and Geographic Information System (GIS) analyses conducted to derive these metrics are provided below. In addition to compiling data on watershed characteristics upstream of the stream habitat sampling sites, a similar data set was developed for the stream gauging sites selected for use in this study (see Section 2.6).

Contributing upstream basin area for each sampling site was calculated in GIS using 10-m, LIDAR-derived digital elevation models (DEMs). Average annual precipitation for each sub-watershed was modeled with the Zonal Statistics geoprocessing function in ArcGIS, using the parameter-elevation regressions on independent slopes model (PRISM) 30-year normal raster dataset (1981-2010; PRISM Climate Group, 2014). Stream density was calculated using the 1:24,000-scale National Hydrography Dataset (NHD) adapted by Ecology (Ecology, 2014a). Road density was calculated using roads data from the National Map transportation data layer (USGS, 2014). Population was derived from 2010 Census block data (Washington State Geospatial Data Archive, 2014). Population density was estimated using the percentage of each census block in the contributing basin area and multiplying the block population by that percentage.

Land cover data were downloaded from the NOAA Coastal Change Analysis Program (C-CAP) regional land cover dataset for 2011 (NOAA Coastal Services Center, 2013). The three C-CAP forest classes (deciduous, evergreen, and mixed) were combined into a single "forest" category. Likewise, the "urban" category is a combination of the four C-CAP "developed" classes (high, medium, low intensity urban and developed open space). Impervious land cover data were downloaded from the National Land Cover Database (NLCD) percent developed imperviousness layer for 2011 for the conterminous United States (Multi-Resolution Land Characteristics Consortium, 2013). Both C-CAP and NLCD datasets used in this project were developed from LandSat imagery at a scale and minimum mapping unit of 30 m.

Forest fragmentation metrics were produced in ArcGIS from our forest category using Landscape Fragmentation Tool v2.0 (Parent and Hurd, 2008). The Landscape Fragmentation Tool maps four types of landscape patterns present for a specified land cover (e.g., forest). "Core" regions are solid forested areas, "edge" and "perforated" occur along the periphery of core areas, and "patch" regions make up small fragments that are completely isolated from core areas. Additionally, the core regions are split into three size classes: large (>500 ac), medium (250-500 ac), and small (<250 ac). Forest-cover patches were classified as perforated, edge, patch, or core based on a specified edge width of 100 m.

Table 3. List and description of watershed land cover and geospatial metrics used in this study.

Metric	Description (units)	Source
Watershed physical characteristics		
WA_ha	Watershed area (ha)	King County GIS
Elev_mean	Mean elevation (ft)	King County GIS
PCT_slope_mean	Mean percent watershed slope (%)	King County GIS
Precip_mean_mm	Mean precipitation (mm), 1981-2010	PRISM Climate Group
Road, population and stream density metrics		
Rd_xings_perkm	Number of road/stream crossings per kilometer of stream in the reporting unit (count)	USGS National Map
Rd_xings_total	Total number of road/stream crossings (count)	USGS National Map
Rd_dens_persqkm	Road density derived from USGS National Map transportation data layer (km/km^2)	USGS National Map
Stream_dens_persqkm	Stream density derived from 1:24,000-scale National Hydrography Dataset (km/km^2)	Ecology
Pop_dens_perskkm	Population density derived from 2010 census ($\#/km^2$)	2101 Census
Land use/Land cover metrics		
PCT_Agriculture	Percent agriculture - cultivated, and pasture/hay (%)	C-CAP (2011)
PCT_Barren	Percent barren - bare land (%)	C-CAP (2011)
PCT_Forest	Percent forest - deciduous, evergreen and mixed (%)	C-CAP (2011)
PCT_Grassland	Percent grasslands - grassland (%)	C-CAP (2011)
PCT_Shrub	Percent shrub - scrub/shrub (%)	C-CAP (2011)
PCT_Urban	Percent urban - high intensity, medium intensity, low intensity, and open space developed (%)	C-CAP (2011)
PCT_Wetland	Percent wetland - palustrine forested, scrub/shrub, emergent wetlands (%)	C-CAP (2011)
PCT_Imp	Percent developed impervious surface (%)	NLCD (2011)
Land cover fragmentation metrics [a]		
PCT_EDGE	Percent of land cover in watershed classified as forested 'edge' (100 m perimeter of core areas)	C-CAP (2011)
PCT_LG_CORE	Percent of land cover in watershed classified as forested 'large core' (100 m from the nearest non-forest pixel). Large core patches have an area greater	C-CAP (2011)

Metric	Description (units)	Source
	than 500 ac	
PCT_MED_CORE	Percent of land cover in watershed classified as forested 'medium core' (100m from the nearest non-forest pixel). Medium core patches have an area between 250-500 ac	C-CAP (2011)
PCT_PATCH	Percent of land cover in watershed classified as forested 'patch.' Patch pixels are small forested areas that do not contain any core pixels	C-CAP (2011)
PCT_PERF	Percent of land cover in watershed classified as forested 'perforated.' Perforated pixels are those pixels along the inside edges of small non-forested gaps	C-CAP (2011)
PCT_SM_CORE	Percent of land cover in watershed classified as forested 'small core' (100m from the nearest non-forest pixel). Small core patches have an area less than 250 ac	C-CAP (2011)

[a] Landscape Fragmentation Tool v2.0; King County GIS

2.6 Hydrology

This study relied primarily on data from existing stream discharge monitoring networks maintained by various agencies, including King County, U.S. Geological Survey (USGS), Seattle Public Utilities, Snohomish County, Kitsap County and the City of Bellingham. The locations of gauging stations maintained by these agencies were compiled and stations in proximity to study monitoring locations were identified for further analysis. As a supplement to ongoing gauging efforts, additional gauging stations were established as part of this study at previously occupied, but discontinued gauging locations located in relatively close proximity (within 6.5 km or less) to monitoring locations. Gauging methods followed the protocols established in the QAPP developed for this study (Berge, 2010).

A total of 9 gauging stations were established, but due to difficulties of maintaining continuous flow monitoring stations on small streams, reliable stage data and stage-discharge relationships could not be developed for two locations (Lunds Gulch Creek and Lewis Creek (see Table 4). Of the remaining seven gauges, two represented study locations that might also be represented by existing gauging stations (Lyon Creek [34b by 34a] and Carey Creek [25i by 12120600]). The gauging stations were established on these two creeks because the existing gauges were relatively distant from the study site locations. The remaining five gauges were established on Dewatto Creek (DW_KC), Coal Creek (06b), Tibbetts Creek (67a), Kelsey Creek (38C) and Peters Creek (51O).

Data from a total of 37 stream discharge monitoring stations potentially representing hydrologic conditions at 31 stream monitoring locations were assessed (Figure 3 and Table 4). The term “potential” is used to acknowledge that gaps in the continuous gauging records further reduced the number of useable pairs of stream gauging and study monitoring locations.

Daily average flow data were compiled for the stream gauge records and Matlab scripts were used to calculate 12 hydrologic metrics (Table 5). Eight of these metrics were selected based on a previous study that identified hydrologic metrics that showed a statistically significant relationship with watershed percent total impervious area, percent forest cover and B-IBI scores (DeGasperi et al., 2009). An additional 4 metrics were calculated based on the hypothesis that they may be correlated with measures of fish community structure.

Metrics were calculated for each year of available data. Depending on the metric, the calculation basis was Calendar Year (e.g., CY 2012 = Jan 1-Dec 31 2012), Water Year (e.g., WY 2012 = Oct 1-Sep 30 2012) or summer (e.g., summer 2012 = Jul 1-Oct 31 2012) (Table 5). In addition to metric calculations, the records were also analyzed for the number of missing days each year during each of the three time windows. The number of missing days in any particular time window was used to exclude data with many missing records from inclusion in statistical analyses. Ideally, only periods with no missing records would be used to ensure the reliability of the calculated metrics. However, such a strict criterion would result in a significant reduction in the number of useable hydrologic gauging stations.

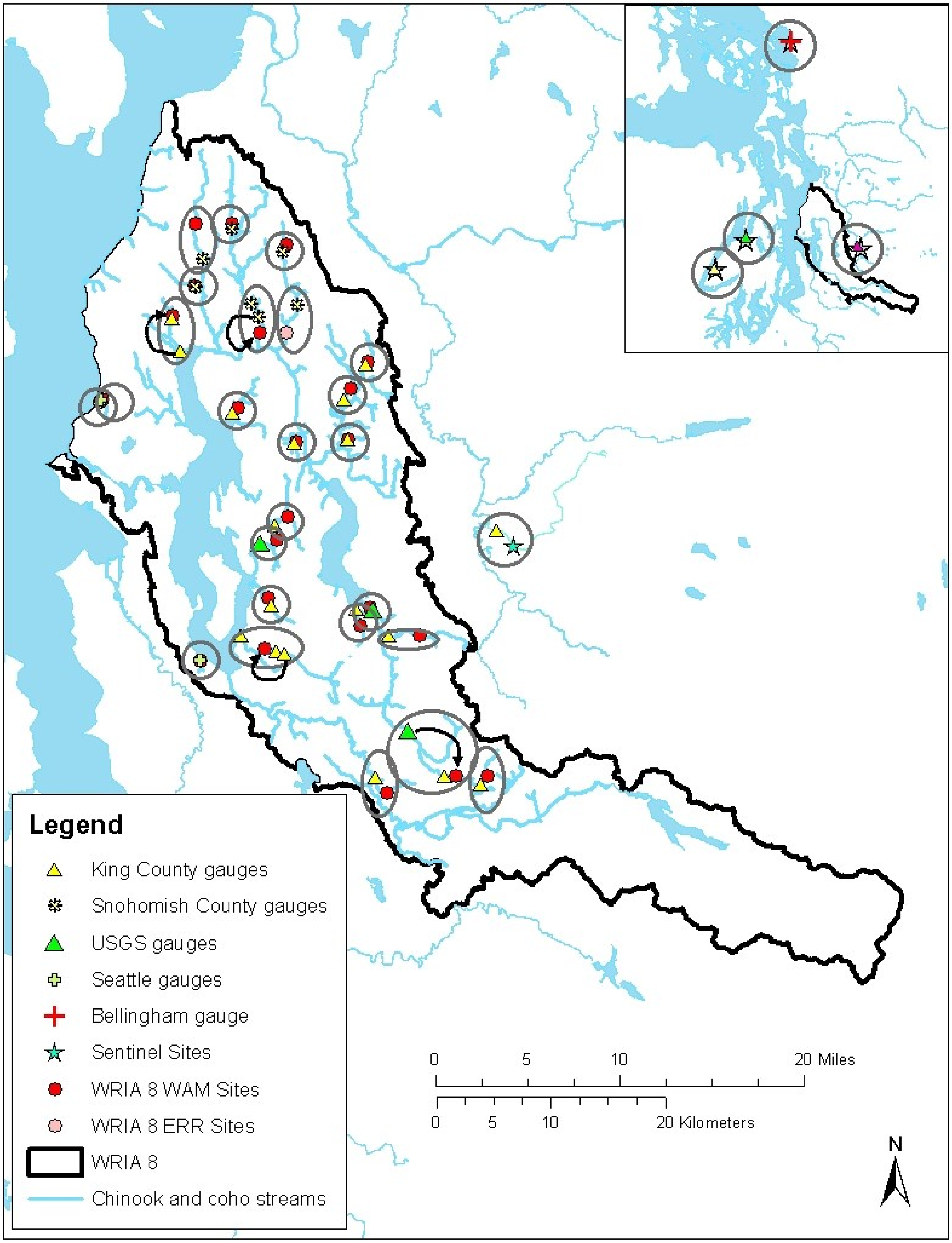

Figure 3. Map showing paired stream gauging and WRIA 8 and EPA Sentinel monitoring sites.

Note: Lines with arrows indicate which stream gauge was used when more than one gauge was located near a stream habitat monitoring site.

An analysis was conducted to evaluate the effect of varying the tolerance for missing data on the number of useable station years in the analysis. Based on that analysis, a threshold of no more than 5 missing days in any metric calculation period was chosen to maximize the number of useable station-year data, while minimizing the potential errors introduced by missing data.

Where more than one gauge was considered to potentially represent hydrologic conditions at a particular stream habitat monitoring location, the number of useable station-year data points was used to determine which gauge to use in the statistical analyses describe in Section 2.8.3. Ultimately, four EPA Sentinel sites and 24 WRIA 8 sites were paired with 28 stream gauging sites for statistical analysis (see Table 4 and Figure 3).

A comparison of selected land cover metrics between stream flow gauging and stream monitoring sites was conducted to evaluate how representative the stream gauging location was of conditions in the stream monitoring reach (see Appendix A). Selected hydrologic metrics calculated between nearly co-located stream gauging locations or stations located on the same stream network were also compared to evaluate the effect of gauging location on hydrologic metric variability. Based on these comparisons, we believe these paired gauge-study site locations were suitable for use in our exploration of potential flow-ecology relationships (see Section 2.8.3).

2.7 Stream Temperature

Continuous (15-minute) temperature data were collected at 48 of the 52 WRIA 8 and 4 of the 5 Sentinel sampling sites during July through August of 2012 and 2013 (Figure 4). This period was selected because it is during these two months that the highest stream temperatures typically occur in this region (Booth et al., 2014). This is also the period when state temperature standards for the protection of cold water fish such as salmon and trout are typically exceeded in King County streams (King County, 2014c).

Temperature measurements were made using a thermistor anchored on the stream bottom in the thalweg. All thermistors were checked in an ice bath for accuracy (i.e., within ±0.2 ^{o}C) prior to deployment. All data were downloaded and checked for anomalies. Obvious anomalies, typically due to air exposure as stream flow declined, were removed before loading the data into King County's Hydrologic Information Center.[8]

There were a few sites where thermistors were lost or no useable data were collected in one or both years. Sites where no data were collected included two in the Bear Creek basin (WAM06600-017111 and WAM06600-013031), one in the Issaquah Creek basin (WAM06600-100519) and one in the North Creek basin (WAM06600-126891). Glendale Creek was the only Sentinel site where no temperature data were collected in either 2012 or 2013.

[8] King County Hydrologic Information Center: http://green2.kingcounty.gov/hydrology/

Table 4. Summary list of potential stream flow gauging locations co-located with WRIA 8 and Sentinel monitoring sites.

Site ID	Stream Gauge ID	Creek name	Description	Operator	Habitat/Biota Sampling	Years of Useable Records (<6 missing days in year/season)		
						Water Year	Calendar Year	Summer (Jul-Oct)
Sentinel Sites								
WAM06600-001639[*]	*12069550*	*Big Beef Creek*	*Big Beef near Seabeck, WA*	*USGS*	*2010-2013*	*5*	*5*	*5*
EPA06600-DEWA01	*DW_KC*	*Dewatto River*	*Dewatto Creek near Dewatto, WA*	*King Co - this study*	*2010-2013*	*1*	*-*	*3*
EPA06600-CHUC01	*ARRO*	*Chuckanut Creek*	*Chuckanut Creek in Arroyo Park*	*Bellingham*	*2010-2013*	*2*	*2*	*3*
SEN06600-GRIF09	*21A*	*Griffin Creek*	*Griffin Creek*	*King Co*	*2010-2013*	*5*	*5*	*5*
WRIA 8								
Puget Sound								
WAM06600-063051	LGC	Lunds Gulch Creek	Lunds Gulch Creek	King Co - this study		-	-	-
WAM06600-057739	*STA505*	*Venema Creek*	*Venema Creek*	*Seattle*	*2010-2013*	*4*	*4*	*4*
WAM06600-063831	*STA508*	*Pipers Creek*	*Pipers Creek*	*Seattle*	*2010-2013*	*4*	*4*	*4*
Lake Washington								
WAM06600-038087	*38C*	*Kelsey Creek*	*Kelsey at NE 8th*	*King Co - this study*	*2009-2013*	*1*	*1*	*2*
WAM06600-080407	*12120000*	*Kelsey Creek*	*Mercer Creek near Bellevue, WA*	*King Co*	*2009-2013*	*5*	*5*	*5*
WAM06600-000391	06b	Coal Creek	Coal Creek blw Coal Creek Pkwy crossing	King Co - this study	2009-2013	-	-	1
WAM06600-035963	34B	Lyon Creek	Lyon Creek abv 244th	King Co - this study	2010-2013	1	-	2
WAM06600-035963	*34a*	*Lyon Creek*	*Lyon Creek near mouth in Lake Forest Park*	*King Co*	*2010-2013*	*4*	*4*	*4*
WAM06600-081267	37a	May Creek	May @ mouth	King Co	2010-2013	4	4	4
WAM06600-081267	*37H*	*May Creek at 143 Pl SE*	*May Creek at 143 Pl SE*	*King Co*	*2010-2013*	*4*	*4*	*4*
WAM06600-081267	37b	May Creek at Coal Creek PKWY	May Creek at Coal Creek PKWY	King Co	2010-2013	-	-	-
WAM06600-083959	*27a*	*Juanita Creek*	*Juanita Creek at mouth*	*King Co*	*2010-2013*	*4*	*4*	*4*
WAM06600-115443	*31h*	*Taylor Creek*	*Taylor Creek at mouth*	*King Co*	*2009-2013*	*5*	*5*	*5*
WAM06600-065043	*STA401*	*Taylor Creek*	*Taylor (Seattle)*	*Seattle*	*2010-2013*	*3*	*3*	*3*
Sammamish River								
WAM06600-083131	*Sc*	*Swamp Creek*	*Swamp Cr @ I-405*	*Snohomish Co*	*2010-2013*	*3*	*2*	*3*
WAM06600-015067	*So*	*Scriber Creek*	*Scriber Cr @ Oak Way*	*Snohomish Co*	*2010-2013*	*4*	*4*	*4*
WAM06600-049499	Nt	North Creek	North Cr @ 228th St	Snohomish Co	2009-2013	1	2	2
WAM06600-049499	*Nc*	*North Creek*	*North Cr @ County line*	*Snohomish Co*	*2009-2013*	*2*	*2*	*2*
WAM06600-067147	*No*	*North Creek*	*North Cr @ 164th St SE*	*Snohomish Co*	*2009-2013*	*4*	*3*	*4*
ERR06600-091291	*Bc*	*Little Bear Creek*	*Little Bear Cr @ 228th St SE*	*Snohomish Co*	*2010-2013*	*1*	*1*	*3*
WAM06600-023691	*Lb*	*Little Bear Creek*	*Little Bear Cr @ 51st St SE*	*Snohomish Co*	*2009-2013*	*2*	*3*	*3*
WAM06600-050295	*51O*	*Peters Creek*	*Peters Creek tributary to Sammamish River*	*King Co - this study*	*2010-2013*	*1*	*-*	*3*
WAM06600-036971	*02f/02f2*	*Big Bear Creek*	*Bear Creek at NE 162nd*	*King Co*	*2009-2013*	*5*	*5*	*5*
WAM06600-111639	*02N*	*Stensland Creek*	*Stensland Creek at NE 95th ST, Redmond WA*	*King Co*	*2009-2013*	*2*	*2*	*2*
WAM06600-076119	*02g*	*Cottage Lake Creek*	*Cottage Lake Creek at Avondale RD NE*	*King Co*	*2009-2013*	*5*	*5*	*5*
Lake Sammamish								
WAM06600-062567	*67a*	*Tibbetts Creek*	*Tibbetts Creek above Tributary 0170*	*Issaquah - this study*	*2010-2013*	*2*	*2*	*2*
WAM06600-020391	63a	Lewis Creek	Lewis Creek at West Lake Sammamish Parkway SE	King Co - this study		-	-	-
WAM06600-123207	*12121600*	*Issaquah Creek*	*Issaquah Creek near mouth*	*USGS*	*2009-2013*	*5*	*5*	*5*
WAM06600-039815	*14b*	*East Fork Issaquah Creek*	*East Fork Issaquah Creek @ NE Birch*	*King Co*	*2009-2013*	*5*	*5*	*5*
WAM06600-002259	*12120600*	*Issaquah Creek*	*Issaquah Creek near Hobart, WA*	*USGS*	*2009-2013*	*5*	*5*	*5*
WAM06600-002259	25i	Carey Creek	Carey Creek at 287th	King Co - this study	2009-2013	-	-	3
WAM06600-022259	*31q*	*Webster Creek*	*Webster Creek*	*King Co*	*2009-2013*	*4*	*4*	*5*

Note: The 28 paired locations used in statistical analyses (described in Section 2.8.3) are italicized and highlighted in gray above.

** There may be some confusion regarding this site ID. This site ID is used in our database developed for this study. Ecology's Environmental Information Management system uses EPA06600-BEEF01 as our site ID and the ID above is used for Ecology sampling events that have occurred at nearly the same location.*

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Table 5. List and description of the hydrologic metrics used in this study.

Flow component	Metric name	Description	Expected Response to Urbanization	units	basis	Reference
	High Flow Pulse					
Frequency	High Pulse Count	Number of times each water year that discrete high flow pulses occur.	Increase	Count	WY	Richter *et al.* (1996, 1997, 1998)
Duration	High Pulse Duration	Annual average duration of high flow pulses during a water year.	Decrease	Days	WY	Richter *et al.* (1996, 1997, 1998)
Duration	High Pulse Range	Range in days between the start of the first high flow pulse and the end of the last high flow pulse during a water year.	Increase	Days	WY	DeGasperi et al. (2009)
	Low Flow Pulse					
Frequency	Low Pulse Count	Number of times each calendar year that discrete low flow pulses occurred.	Decrease	Days	CY	Richter *et al.* (1996, 1997, 1998)
Duration	Low Pulse Duration	Annual average duration of low flow pulses during a calendar year.	Decrease	Days	CY	Richter *et al.* (1996, 1997, 1998)
	Various					
Frequency	Flow Reversals	The number of times that the flow rate changed from an increase to a decrease or vice versa during a water year. Flow changes of less than 2 percent are not considered.	Increase	Count	WY	Richter *et al.* (1998)
Flashiness	TQ_mean	The fraction of time during a water year that the daily average flow rate is greater than the annual average flow rate of that year.	Decrease	Unitless	WY	Konrad (2000), Konrad and Booth (2002)
Flashiness	R-B Index	Richards-Baker Flashiness Index – A dimensionless index of flow oscillations relative to total flow based on daily average discharge measured during a water year	Increase	Unitless	WY	Baker *et al.* (2004)
Additional metrics potentially related to fish community structure						
	Low flow					
Magnitude	7-day summer minimum flow	Centered 7-day moving average of summer (Jul-Oct) minimum flow.	Depends on water management activities	cfs	summer	
Timing	Julian date of summer minimum flow	Date of summer (Jul-Oct) minimum flow.	Depends on water management activities	Julian Date	summer	
Magnitude	30-day summer low flow	Centered 30-day moving average of the summer (Jul-Oct) minimum flow	Depends on water management activities	cfs	summer	
	High Flow					
Magnitude	Qmax:Qmean	Ratio of the annual water year maximum flow to the long term mean annual flow.	Increase	Unitless	WY	

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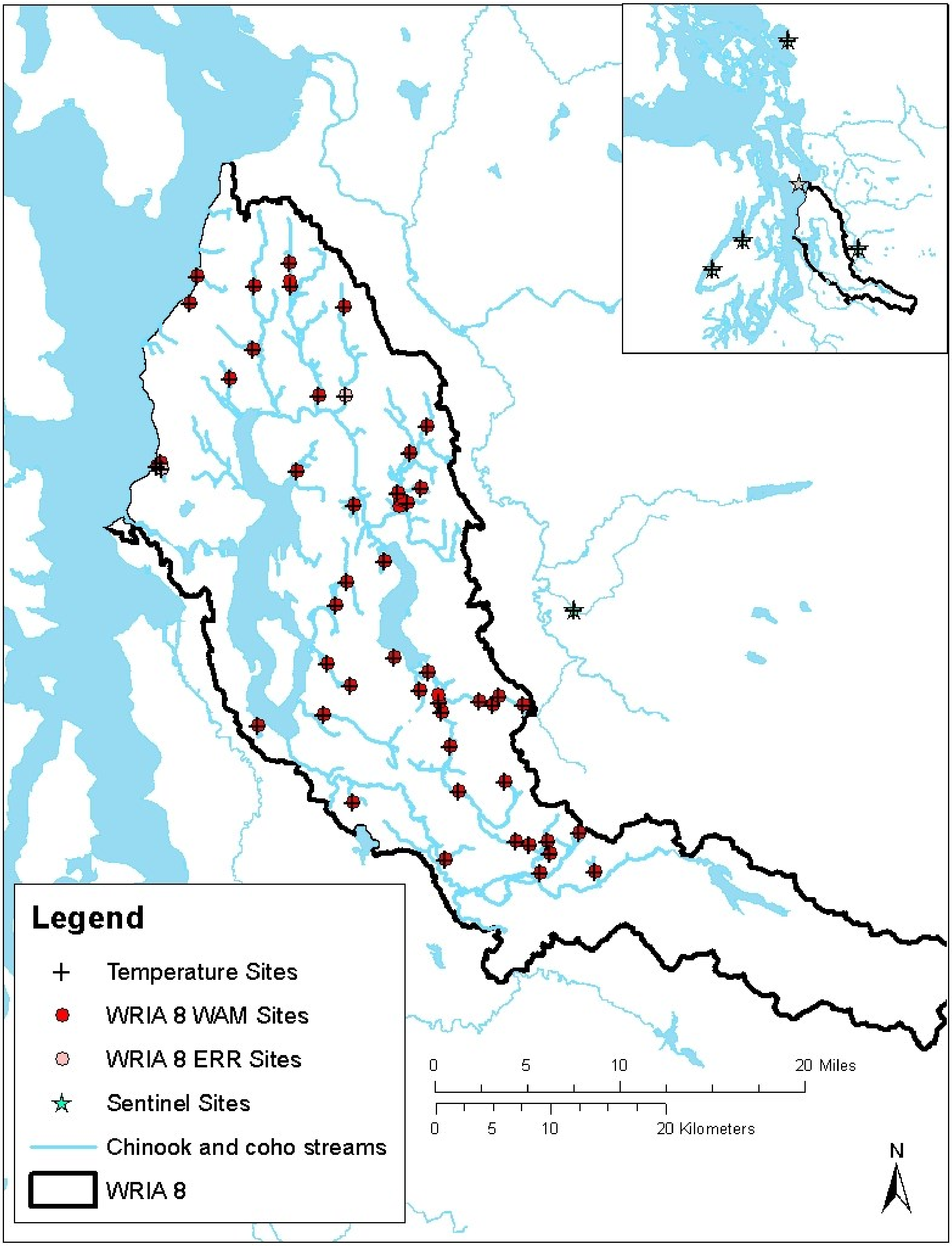

Figure 4. **Map showing continuous summer (July-August) temperature monitoring locations in 2012 and 2013.**

There were a few WRIA 8 sites where useable data were collected only in 2103. These sites included Perrinville Creek (WAM06600-083243), Lunds Gulch Creek (WAM06600-063051), Lewis Creek (WAM06600-020391), and Piper's Creek (ERR06600-035863). Only one year of useable data was collected at the Chuckanut Creek Sentinel site in 2012.

The July-August water temperature data were compiled and used to calculate eight temperature metrics (Table 6).

In addition to metric calculations, the data were also analyzed for the number of missing days each year during July and August where data were missing. The number of missing days was used to exclude data with many missing records from inclusion in statistical analyses. Ideally, only periods with no missing records would be used to ensure the reliability of the calculated metrics. There were five sites/years with incomplete data between July and August. The number of missing days of data ranged from 16 for Kelsey Creek (WAM06600-038087) in 2013 to 23 for Carey Creek (WAM06600-002259) in 2012. Years with any missing data were excluded from the statistical analyses described in Section 2.8.3.

Table 6. List and description of temperature metrics used in this study.

Metric	Description
7DMax	Maximum (July-August) 7-Day moving average of the daily maximum temperature
1DMax	Maximum (July-August) daily maximum temperature
DielRange	Average (July-August) 24-hr range in temperature
MeanT	Average (July-August) temperature
MinT	Minimum (July-August) daily minimum temperature
DaysGT16	Number of days (July-August) that temperature exceeds 16 ^{o}C **(a)**
DaysGT17p5	Number of days (July-August) that temperature exceeds 17.5 ^{o}C **(b)**
DaysGT23	Number of days (July-August) that temperature exceeds 23 ^{o}C **(c)**

a *Washington Administrative Code (WAC) 173-201A – Aquatic life temperature criterion for the protection of core summer salmonid habitat*
b *WAC 173-201A – Aquatic life temperature criterion for the protection of salmonid spawning, rearing, and migration*
c *WAC 173-201A – Criterion to prevent acute lethality and barriers to migration of moderately acclimated adult and juvenile salmonids*

2.8 Statistical Analyses

Statistical analyses conducted for this study had four objectives: (1) evaluate the precision of replicated habitat and biological community metrics (i.e., habitat and benthic macroinvertebrate metrics) through variance component analysis and calculation of precision in order to identify metrics with the highest power to detect trends, (2) describe the status and trends of the most precise metrics with quantified confidence bounds,

(3) explore relationships between metrics representing stressors (i.e., land cover, habitat, hydrology, and temperature) and responses (benthic macroinvertebrate and fish metrics) and (4) using the results of the variance components analysis, conduct a power analysis of the ability to reliably detect trends in selected metrics that included field replicated data (i.e., B-IBI and habitat metrics).

All of the data generated as part of this study are available through the project website[9] to allow other investigators to improve and build upon the analyses presented in this report. The following sections outline the methods used to conduct the four broad categories of statistical analyses identified above.

2.8.1 Precision Analysis

Precision as used in this report is defined generally as the ability to consistently reproduce a particular measurement. Ideally, field crews following the same protocols can revisit the same site on the same or nearly the same day and produce nearly the same value of a particular stream attribute (i.e., very similar results can be obtained). The degree to which these replicated results differ provides an estimate of precision, which is critical to the statistical design of any monitoring program. The methods used to estimate precision are described below.

Environmental status and trends programs need to evaluate whether the aquatic resource conditions are improving, declining, or maintaining current condition beyond the site scale (Larsen et al., 1995). Implicit in that need is the need for monitoring programs to consider the aquatic resource as a statistical population and focus on sampling approaches that allow for regional extrapolation from the sampled population and that quantify uncertainty.

A critical step in the development of a well-designed status and trends monitoring program is the evaluation of the components of variance of particular indicators. The relative magnitude of the components of variance for a particular indicator affects uncertainty and statistical power to evaluate status and trends and may identify potential approaches for minimizing a particular variance component (Larsen et al., 1995). The components of variance (σ^2) of a typical status and trends program can be described as follows:

$$\sigma^2_{Total} = \sigma^2_{Site} + \sigma^2_{Year} + \sigma^2_{Site:Year} + \sigma^2_{Residual}$$

Total variance	=	Population variance	+	Year variance	+	Interaction effects variance	+	Residual variance

Population variance describes the variance of a measurement made on a subsample of sites representing the population of interest during an index year. In the absence of other

[9] WRIA 8 Wadeable Streams Project website: http://www.kingcounty.gov/environment/wlr/sections-programs/science-section/doing-science/wadeable-streams.aspx

sources of variance, these measurements would provide an estimate of status and associated variance for that year.

Year variance measures how much all sites (collectively) are higher or lower each year than the long term mean, or in the presence of a trend, the variation from the trend line each year. Regional trend detection power is very sensitive to this component of variance. This component of variance can be thought of as a common regional pattern of variance caused by regional-scale factors such as regional climate conditions and is sometimes referred to as a year effect or temporal coherence (Larsen et al., 1995).

Site:Year interaction variance represents the year to year fluctuation among individual sampling sites. These fluctuations reflect responses to effects operating at the site level that is not already described by year effect described above. The Year and Site:Year variance can be separated by revisit samples collected at multiple sites each year over a number of years.

Residual variance is the variance estimated from repeat sampling at multiple sites within a year. If residual variance of a particular measurement is relatively high, it may not be a useful indicator of status or trend. However, based on the information generated as part of the estimation of measurement variance, it may be possible to reevaluate and improve measurement methods. For example, residual variance might be reduced through sampling technology improvements, improved survey team training, or refinement of sampling protocols (Larsen et al., 1995).

Note that Site:Year and Year variance are irreducible natural components of variance. If the variance of these components is relatively high, then a monitoring program may consider an increased number of sites sampled or increase the expectation of the number of years that would have to be monitored in order to detect policy relevant changes in status. Another possibility would be to identify covariates that could be used to reduce these components of variance (e.g., eliminate effect of climate variability using stream flow, air temperature or precipitation measurements).

Variance Components Analysis

Because the WRIA 8 Status and Trends monitoring replicate design was not balanced (all sites were not revisited each year and one site was not sampled in 2013 due to access limitations) we used a linear mixed-effects model to estimate the components of variance (Kincaid et al., 2004; Larsen et al., 2004). The model was of the form:

$$Y_{ijk} = \mu + S_i + T_j + ST_{ij} + I_{ijk}$$

where Y_{ijk} is the response for the kth visit to stream site *i* during year *j*, μ is the overall mean, S_i is the random effect due to stream site *i*, T_j is the random effect due to year *j*, ST_{ij} is the random effect due to the interaction of site *i* and year *j*, and I_{ijk} is the residual variation for the kth visit at site *i* during year *j*. Subscript *i* ranges from 1 to the number of stream sites in the survey, subscript *j* ranges from 1 to the number of years of data, and subscript *k*

ranges from 0 to the number of site revisits during year *j* at site *i*. The variance model assumes no linear trend is present.

The linear mixed effects model was fit using the lme4 R package (Bates et al., 2014) and took the form:

```
lmer(RESULT ~ 1 + (1|SITE_ID) + (1|YEAR) + (1|SITE_ID:YEAR))
```

Other measures of precision

Other useful indicators of a measurement's precision and utility for status and trend monitoring include signal to noise ratio (S:N = $\sigma^2_{site}/\sigma^2_{rep}$) , coefficient of variation (CV = 100 $\sigma_{rep}/\bar{Y}$), residual standard deviation (σ_{rep}) and the ratio of residual standard deviation to the maximum potential range (Rg_{pot}) of a measurement (σ_{rep}/Rg_{pot}) (Kaufmann et al., 1999; Kaufmann et al., 2014a).

The S:N compares the variance of the measurement across a regional sampling of streams (signal) with the variance estimated from repeat visit sampling (noise). The advantage of S:N is its relevance to many types of statistical analyses. Relatively low S:N (i.e., high noise relative to signal) reduces statistical power to detect differences among sites or groups of sites and limits the ability to detect trends. Noise also affects the amount of variance that can be explained by regression models. This also implies that noise compromises the ability to discern likely stressor-response relationships that could diagnose probable causes of impairment or potential management actions for recovery. Previous research indicates that S:N > 10 indicates negligible effects of noise, becoming minor through S:N of 6 and increasing to moderate as S:N reaches 2 (Kaufmann et al., 1999). As S:N approaches zero, noise becomes severely limiting and at 0, all variance is associated with noise. Measures of S:N within a survey are useful for identifying metrics with the greatest potential for discriminating among sites and detecting trends, but S:N may not be useful for comparison to surveys in other regions because the absolute range of a metric may not be the same among regions.

The CV is a typical measure of precision used by researchers; however, this measure may be of limited use when making comparisons to other regional status and trend monitoring efforts due to differences in grand measurement means ($\bar{Y}$) in each study area.

The square-root of the repeat visit variance (σ_{rep}) is an absolute measure of precision and is equivalent to the pooled standard deviation of repeat measurements made within a given year and averaged over all sites and years. This is a useful way to compare the precision of methods used to measure the same metric using different field methods or crews. However, the magnitude of σ_{rep} varies among metrics and for a particular metric can vary among survey regions.

To evaluate the utility of σ_{rep}/Rg_{pot} as a measure of metric precision, σ_{rep} was standardized by dividing σ_{rep} by the range of observations within our survey (Rg_{obs}, σ_{rep}/Rg_{obs}) rather than using Rg_{pot} as in Kaufmann et al. (2014a). We chose to use Rg_{obs} because many of our

metrics were not scaled from 0 to 1 and we were primarily interested in precision measures specific to our study. Since we report σ_{rep}, anyone interested in calculating σ_{rep}/Rg_{pot} can do so by assigning a value for of Rg_{pot} for any particular metric.

Kaufmann et al. (2014a) used an analysis of the minimum detectable difference (D_{min}) for a range of D_{min}/Rg_{pot} to characterize the relative precision of σ_{rep}/Rg_{pot}. Adapting the relative precision evaluation presented by Kaufmann et al. (2014a) to our study, metrics with $\sigma_{rep}/Rg_{obs} \leq 0.052$ would be considered to have relatively high precision, while metrics with $\sigma_{rep}/Rg_{obs} \geq 0.15$ would have relatively low precision. To put these thresholds in context, Table 2 found in Kaufmann et al. (2014a) is adapted to show the relationship between different increments of relative minimum detectable differences and increments of σ_{rep}/Rg_{obs} (Table 7).

Table 7. Calculated levels of relative precision required to detect ($p < 0.05$) specified minimum differences between mean metric values [adapted from Table 2 in Kaufmann et al. (2014a)].

D_{min}/Rg_{obs}	Relative Precision	Minimum Detectable Difference ($p \leq 0.05$)	σ_{rep}/Rg_{obs}
1/20 = 0.050	High	2 observations differing by 1/20 of Rg_{obs} are different	0.018
1/10 = 0.100	High	2 observations differing by 1/10 of Rg_{obs} are different	0.036
1/9 = 0.111	High	10 streams evenly spanning Rg_{obs} are all different	0.040
1/7 = 0.143	High	8 streams evenly spanning Rg_{obs} are all different	0.052
1/6 = 0.167	Moderate	2 streams different by 1/6 of Rg_{obs} are all different	0.060
1/5 = 0.200	Moderate	6 streams evenly spanning Rg_{obs} are all different	0.072
1/4 = 0.250	Moderate	5 streams evenly spanning Rg_{obs} are all different	0.090
1/3 = 0.330	Moderate	4 streams evenly spanning Rg_{obs} are all different	0.12
1/2.4 = 0.416	Low	3 streams evenly spanning Rg_{obs} are all different	0.15
1/2 = 0.500	Low	3 streams evenly spanning Rg_{obs} are all different	0.18
1/1 = 1.000	Low	2 streams at extremities of Rg_{obs} are barely discernible	0.36
>1.000	Low	2 streams at min. and max. of Rg_{obs} are not different	>0.36

Note: D_{min} = minimum detectable difference, Rg_{obs} = range of observation, σ_{rep} = repeat-visit or residual variance

2.8.2 Status and Trends Assessment

In addition to standard boxplots describing the median and interquartile range of selected metrics, we used cumulative distribution function analyses to extrapolate metric values over the target sample frame (Kincaid and Olsen, 2012). We focused these analyses on metrics with the highest precision. The methods used to assess status and trends are described in the following sections.

2.8.2.1 Status: Continuous and Categorical Analysis

Cumulative distribution function (CDF) plots were used to quantitatively describe particular metrics extrapolated over the target sample frame (for example see Figure 5). The CDF describes the percentage of the target population that is less than or equal to each possible value of a metric (Kincaid and Olsen, 2012). The cumulative distribution plots (i.e., the CDF plots) developed in this study (and other studies based on probabilistic sampling designs - e.g., Stoddard et al., 2005; Merritt and Hartman, 2012) are more complicated than a standard CDF plot of a data set because sample weights (see Section 2.2) must be included to account for unequal probability of sample site selection.

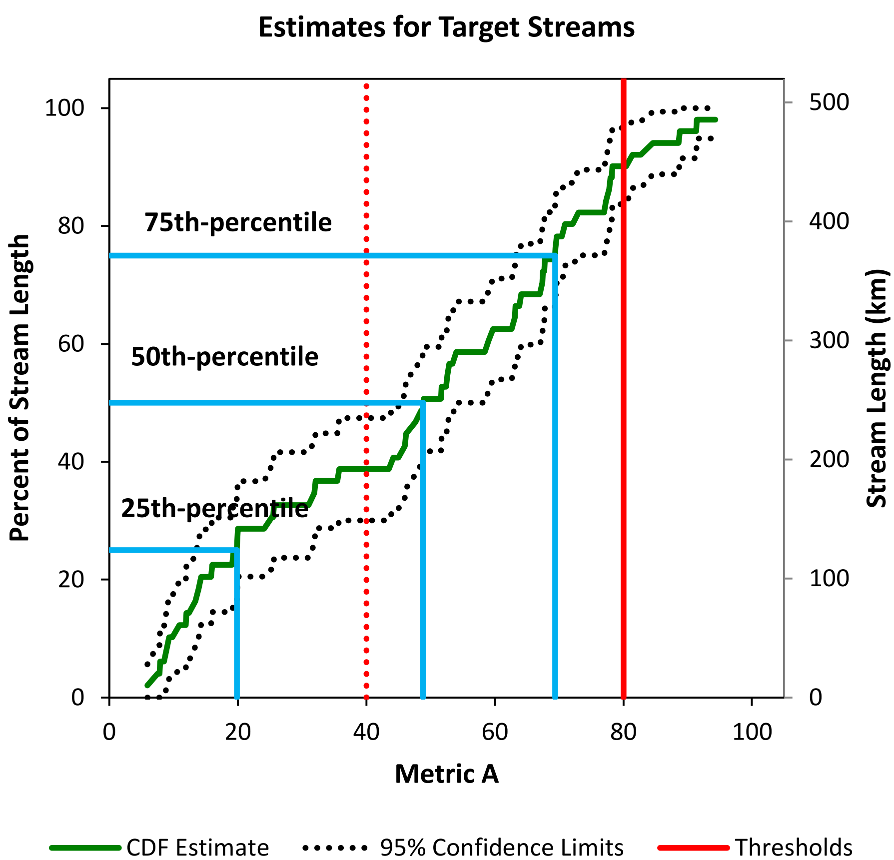

Figure 5. Cumulative distribution function (CDF) plot for a hypothetical metric, including 95% confidence limits of CDF.

A CDF plot for a particular target sample population sampled in a particular year establishes a baseline against which future surveys (using the same probabilistic design) can be compared. Change over time (or between subpopulations of the target sample frame) can be detected not only in some measure of central tendency such as the mean or median value of a particular metric, but in certain portions of the CDF via visual comparison of the two (or more) CDF plots. Depending on the expected response of a particular metric to environmental stressors or to restoration measures, the CDF will be

expected to shift to the left or right. Confidence intervals for each CDF provide a statistical basis for assessing change. The R package spsurvey (Kincaid and Olsen, 2013) was used to generate CDF plots for all metrics stratified by tier over the 2010-2013 sampling period. The Wald F test was used to identify statistically significant differences between CDFs (between years or between strata) based on the recommendation in Kincaid and Olsen (2012).

In addition to providing complete information about the distribution of a particular metric, CDF plots can be readily transformed into a categorical analysis using thresholds established by regulatory standards (e.g., stream temperature not to exceed 16 ^{o}C), a reference threshold (e.g., volume of wood per unit of stream length indicative of properly functioning condition), or by some other established thresholds (e.g., good, fair and poor B-IBI scores). The categorical analysis results in an estimate of the percentage (and in the case of this study, the corresponding stream length) of the target population that is above or below (or within in the case of multiple thresholds) a particular categorical. The R package spsurvey (Kincaid and Olsen, 2013) was used to perform categorical analyses of selected metrics stratified by tier over the 2010-2013 sampling period.

Because of the absence of categorical values for many of the metrics investigated in this project, only four categorical analyses were conducted as part of this study. Categorical analyses were conducted for the two biological metrics (B-IBI and F-IBI), one habitat metric (wood volume), and one temperature metric (7-day moving average of the daily maximum). The thresholds selected for use in each categorical analysis are provided in Table 8. Analyses were conducted to provide assessments of the relative proportion within each tier across multiple years (2010-2013), across tiers within each year (2010-2013) and across tiers for all years (2010-2013) combined.

In addition to the help documents available from the Comprehensive R Archive Network (http://cran.r-project.org/), Nahorniak (2012) provided useful guidance on the development of R scripts to generate CDF plots and perform categorical analyses.

Table 8. Thresholds and associated categories used in the categorical analyses of biological and habitat metrics conducted as part of this study.

Metric	Poor	Fair	Good	Reference
B-IBI	<40	>=40 and <60	>=60	1
F-IBI	<=10	>10 and <=15	>15	2
Wood Volume (m^3/100 m)	< 28	>=28 and <=99	>99	3
	Supporting	**Not-supporting**		
7-DMax Temperature	<=16 °C	>16 °C		4

1 Puget Sound Stream Benthos (http://pugetsoundstreambenthos.org/About-BIBI.aspx)
2 Matzen and Berge (2008)
3 Fox and Bolton (2007)
4 Water Quality Standards for Surface Waters of the State of Washington, Chapter 173-201A WAC (https://fortress.wa.gov/ecy/publications/SummaryPages/0610091.html)

2.8.2.2 Trends

Regional trends (i.e., mean trend across all WRIA 8 sites) were evaluated for each replicated metric (i.e., B-IBI and habitat metrics) by using a linear mixed effects model of the form:

$$Y_{ijk} = \mu + S_i + T_j + \beta_j + ST_{ij} + I_{ijk}$$

This model is similar to the model used to estimate the components of variance (see Section 2.8.1 above) with one additional parameter (β_j) that represents the average slope or trend over all sampling sites (Urquhart et al., 1998; Anlauf et al., 2011; Urquhart, 2012). The remaining parameters are as defined in Section 2.8.1 above.

The linear mixed effects model was fit using the lme4 R package (Bates et al., 2014) and took the form:

lmer(RESULT ~ 1 + YEAR + (1|SITE_ID) + (1|YEAR) + (1|SITE_ID:YEAR))

Following Anlauf et al. (2011), we used restricted maximum likelihood to estimate the variance components and based all hypothesis tests on the type III test of fixed effects with the Kenward-Roger method to estimate the degrees of freedom for the denominator using the lmerTest package in R (Kuznetsova et al., 2014). We report the mean trend (i.e., slope) for each metric (2010-2013) and the estimated statistical significance of the trend slope (i.e., p-value).

Because no replicated data were collected at the Sentinel sites, it is not possible to apply the model above to evaluate trends at Sentinel sites. In order to evaluate the mean trend at Sentinel sites for comparison to WRIA 8 trends, we modified the model to remove the Site:Year interaction term. Evaluation of trends at Sentinel sites was conducted only for those metrics that indicated statistically significant trends based on WRIA 8 sites.

2.8.3 Stressor-Response Relationships

Developing models that predict a biological response (e.g., B-IBI) to various biophysical stressors (e.g., land cover and habitat metrics) is a fundamental goal of ecology (Olden and Jackson, 2000; De'ath and Fabricius, 2000). There are at least two goals related to stressor-response modeling: (1) improvement in the understanding of the various processes in space and time (including human-caused changes) that affect the biological condition of streams, and (2) development of statistical and/or mechanistic models to make predictions of ecological status at other locations or forecast future status (Olden and Jackson, 2000; Waite et al., 2010). Both of these goals are important for natural resource management.

Improved understanding begins through construction of conceptual models, hypothesis testing, and model refinement (Austin, 2007). We adopted the conceptual model outlined by Waite et al. (2010) that is based on the hypothesis that landscape characteristics control stream hydrogeomorphology which in turn controls the baseline biological assemblages (Figure 6). This conceptual model assumes that abiotic factors (e.g., landscape character, watershed size, physical habitat) are the primary driver of stream biological condition and that biotic interactions (e.g., predation, competition for food resources), although present, are of secondary importance. Human-induced change in landscape characteristics (primarily clearing and grading for farming and development) and more intense land use are the primary drivers of stream biological alteration. These changes on the landscape often affect stream riparian zones that influence nutrient and organic matter inputs to streams and increase light input and heat loads. Landscape changes also result in alterations of sediment, nutrient and contaminant inputs to the stream and alter the magnitude and timing of stream flow. Other potential effects of increasing intensity of human-related activities in a watershed include complex changes in stream water quality due to increasing inputs of sediment, nutrients and contaminants. The resulting changes in the chemical and physical character of the stream result in alterations in stream biological communities that include loss of taxa intolerant to change and increases in the numbers of taxa tolerant to these changes.

Because we measured a wide range of metrics in each of several stressor categories (i.e., land cover, habitat, temperature, and hydrology), a modeling approach was needed to minimize effects of metric redundancy within categories and reduce the chance of finding spurious relationships with response variables that arise when one attempts to mine large data sets to identify statistical relationships between stressors and response metrics (Olden and Jackson, 2000; Van Sickle, 2003).

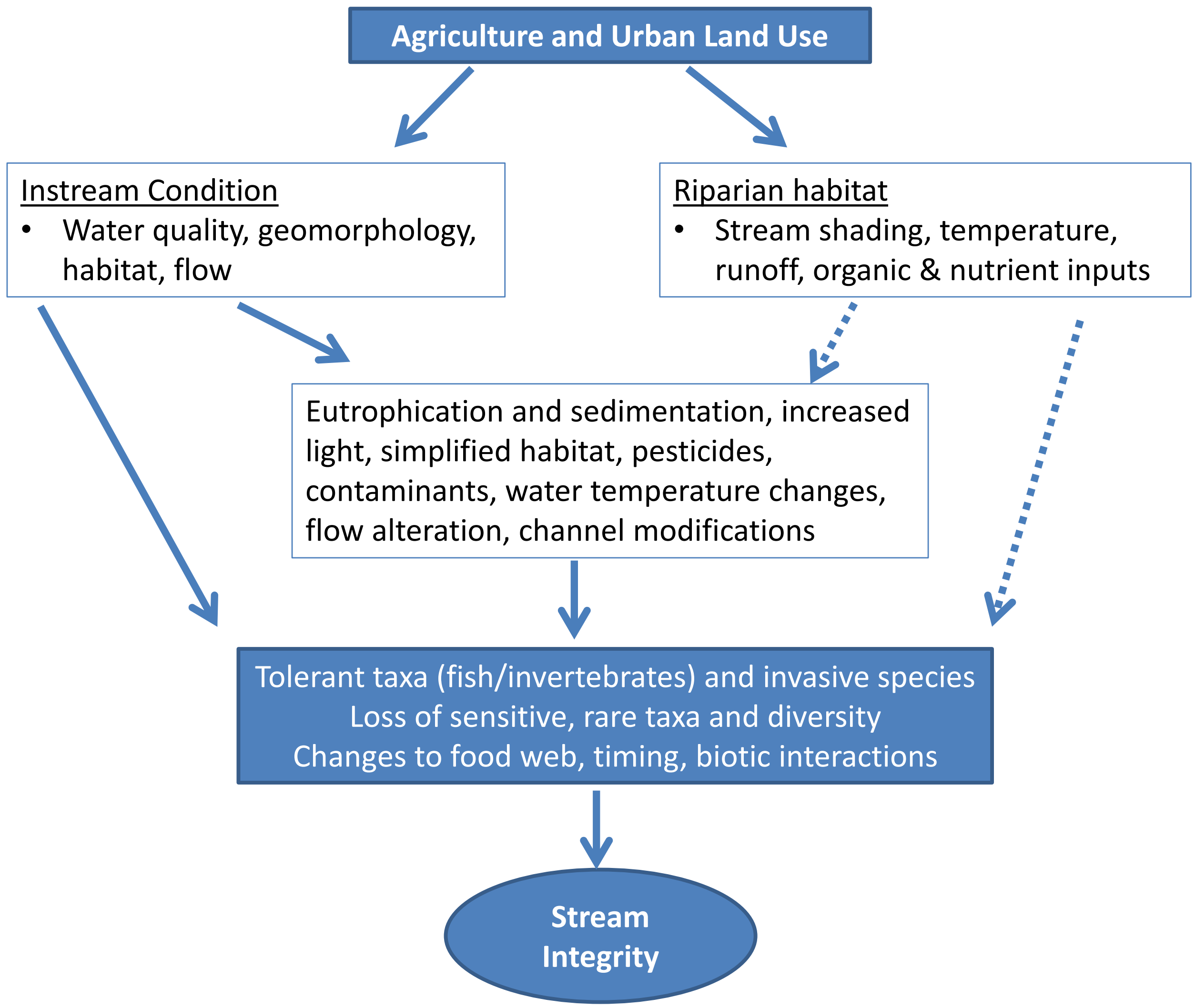

Figure 6. Conceptual model relating the influence of land use on factors that affect stream biological condition (from Waite et al., 2010)).

Note: Solid arrows indicate direct pathways and dashed lines indicate indirect pathways. Also, direction of response may be positive or negative even within on conceptual box.

Instead of attempting to reduce the number of metrics for more detailed analysis using parametric statistical techniques followed by the development of parametric multiple linear regression models (MLR) (e.g., Keenan et al., 2010; Waite et al., 2010), we chose to use a completely non-parametric approach. Non-parametric methods are generally better suited to problems where the number of predictor variables exceeds the number of samples, interactions exist among variables, non-linear relationships occur, data are missing and variables do not satisfy requirements of parametric statistical approaches (De'ath, 2007; Waite et al., 2012). This is often the case for ecological data (De'ath and Fabricius, 2000) and is the case with our dataset.

We considered and explored non-parametric modeling approaches such as classification regression trees (CART), random forests (RF) and boosted regression trees (BRT). Based

on our experience with these methods and the evaluation of these non-parametric modeling approaches and MLR conducted by Waite et al. (2012), we chose to develop BRT models. Waite et al. (2012) were able to develop MLR, CART, RF and BRT stressor-response models for two ecoregions in Oregon (including the Willamette Valley which is similar to the Puget Lowland ecoregion) and another in California. Although Waite et al. (2012) determined that the significant stressor-response relationships were generally linear (i.e., MLR performed well), BRT models showed significant improvement over MLR models for each region.

We had some concern regarding the use of BRT with the relatively small number of sites we sampled (n=52). [10] May et al. (2015) indicated that regions with less than 75 sites would be less than ideal for BRT modeling, although they included regions with as few as 53 sites in their study. By including regions with smaller numbers of sites, they explicitly chose not to develop validated predictive models, which would require splitting the data into model development and validation data sets. The number of sites used to develop MLR, CART, RF and BRT models in the study by Waite et al. (2012) ranged from 55 to 148. They also did not split their data set and at least with respect to their MLR models (Waite et al., 2010) indicated that with further development they could be used to better understand causal linkages or predict biological conditions at unsampled sites.

BRT and RF models are part of a group of statistical techniques built on the single CART models that average the results from multiple tree models. Unlike RF models where many different CART models are generated through random selection of subsets of the input data, BRT models are based on fitting the response to reweighted versions of the input data based on the fit to previous trees, resulting in performance improvements over RF models (De'ath, 2007). BRT and RF models also provide an ordered list of the importance of input variables and assessment of variable interactions. Plotting tools are also provided to visualize the effect of a specific explanatory variable on the response variable after accounting for the average effects of all other input variables. These partial dependence plots are especially useful for visualizing the non-linear interactions between any stressor and response metric.

BRT models were developed using the dismo (Hijmans et al., 2014) and gbm (Ridgeway, 2013) packages in R following guidance provided by Elith et al. (2008) and Elith and Leathwick (2014). Models were developed using a bag fraction of 0.75, a learning rate of 0.001 and a tree complexity of 5. A tree complexity of 5 allows the assessment of up to 5-way interactions among input variables. A bag fraction of 0.75 means that a random selection of 75 percent of the data is used each time a tree is developed. The learning rate affects the total number of trees needed to fit the model. Models were not pruned to find the most parsimonious set of predictor variables as in Waite et al. (2010; 2014) or May et al. (2015). This was due primarily to the added difficulty of evaluating model goodness of fit against model complexity in terms of the numbers of variables used (e.g., May et al., 2015). Furthermore, Elith and Leathwick (2014) described a method to reduce model

[10] Analysis of stressor-response relationships used data from the probabilistic survey design (N=50) plus the two ERR sites. Refer to Section 0

complexity, but indicated that their view was that a small data set (in their case n=1,000 with 11 predictor variables) wouldn't benefit from further simplification.

The output from the BRT models is somewhat different than that of parametric linear regression models. Model results reported include the cross-validation coefficient of determination (CV R^2), which gives an indication of the amount of variance in the response variable explained by the model. Cross-validation refers to the technique used to test the predictive capability of the model, which entails randomly partitioning the data into training (model fitting) and validation (testing) data sets. Variable relative importance (VRI) values and partial dependence plots can also be reported. VRI values are the proportion of explained variance that can be attributed to each independent variable. Partial dependence plots display the effect of a single predictor variable on the dependent variable after accounting for the average effects of all other variables. We reported VRI values and provided partial dependence plots of the six most import variables in each model as well as a scatter plot matrix of the same six variables including the response variable. The top six variables in any model always included variables that had a VRI value of 10 percent or more.

A further complication of the BRT models that included hydrologic metrics was that the model specified above would not run successfully with the smaller set of sample sites. In these cases, Sentinel sites were included and the bag fraction was increased to 0.9, which allowed the models to run to completion. These modifications undoubtedly compromised the reliability of the CV R^2 and comparability of the model results including hydrologic metrics to the other models and for generalizations to WRIA 8.

In order to have a single set of consistent stressor and response inputs to BRT models, average values of metrics measured between 2010-2013 in all WRIA 8 study streams were used along with the single values of the land cover metrics. Sentinel sites were excluded from these analyses so that the results would be unequivocally relevant to WRIA 8, with the exception of models that included hydrologic metrics as mentioned above.

The stressor-response analysis focused first on relating metrics in each stressor category to a response variable (here B-IBI or F-IBI) so as to identify metrics with the greatest potential relevance within a particular category. More complicated models were then developed by combining stressor categories.

Note that in BRT models that considered land cover metrics, we included physical variables that are not stressors, but rather natural features of the watersheds (e.g., watershed area, elevation, slope). We included these metrics because it is important to understand if, and to what degree, natural landscape features influence B-IBI and F-IBI. Biological response metrics that are not sensitive to natural physical variables will be more precise measures of human disturbance. Biological metrics that are sensitive to natural physical variables might require some modification to minimize significant natural influences.

2.8.4 Trend Detection Power

Here we will address the trend model introduced in Section 2.8.2.2 that can be used to evaluate regional or average trend over all sampling sites.

Surveys such as the one documented in this report provide essential information needed to design effective and efficient monitoring programs. A major component of salmon recovery programs is investment in efforts designed to improve overall habitat conditions[11] that sustain not only salmon, but also native aquatic and riparian biota. Two factors control the ability to detect consistent improvements in habitat conditions of biotic responses that result from these investments: (1) the magnitude of spatial and temporal variation of measured habitat metrics and (2) the design of the monitoring network (Larsen et al., 2004). The first factor will be addressed through the analyses previously described in Section 2.8.1. The methods used to address the second factor are described here.

Avoiding statistical error is critical to trend detection analyses. Of particular concern in any statistical analysis is the avoidance of Type I and Type II errors. These errors are illustrated in Table 9. Trend analysis Type I error is when the test falsely rejects the null hypothesis and one concludes that trend is present when none really exists. Type I errors can be controlled by the selection of the statistical significance level (p). In general, the lower the value of p used to determine statistical significance, the less likely Type I errors will occur. Typically, a significance level of <0.05 is selected to identify "statistically significant" trends.

Table 9. Description of statistical trend testing errors.

		Does a trend exist?	
		Yes (H_0 false)	No (H_0 true)
Has a trend been detected?	Yes (Reject H_0)	Power = 1-β	**Type I Error (α):** False trend detected when none exists.
	No (Fail to reject H_0)	**Type II Error (β):** Failure to detect an existing trend due to weakness of the trend, weakness of the methodology, or the short length of the record.	Probability = 1-α

α = Probability (reject $H_0|H_0$ true) and $1 - \beta$ = Probability (reject $H_0|H_0$ false)

[11] In this context, habitat conditions refer not only to conditions represented by the habitat metrics described above, but also other stream habitat attributes such as temperature and hydrology.

It is more difficult to avoid Type II errors. Trend test Type II errors occur when the statistical trend test does not suggest a trend, but a trend really exists. Type II errors (β) are related to the power ($1-\beta$) to reliably detect trends when they are present. Although there are no formal standards for power, generally a value of 0.8 ($1-\beta$; $\beta=0.2$) is a standard analogous to the use of a probability of avoiding a Type I error of 0.95 ($1-\alpha$; $\alpha=0.05$).

As noted above, our survey design was based on an “always revisit” panel plan that consists of visiting the same fixed number of locations every year. The estimated variance components from Section 2.8.1 above were used to calculate trend detection power over a 20-year monitoring period for hypothetical trends of 1, 2, and 3 percent per year for an “always revisit” panel plan for B-IBI and habitat metrics selected primarily based on the relatively most important habitat variables identified in the stressor response models. The calculations were performed based on the approach described by Urquhart (2012) using functions written in R provided by Tom Kincaid (personal communication, EPA Corvallis, 8 January 2015).

3.0 RESULTS

This section describes results of the four broad categories of statistical analyses identified above, i.e., (1) evaluation of the precision of replicated metrics (habitat and benthic macroinvertebrate metrics), (2) description of the status and trends of important habitat and biological community metrics, (3) exploration of relationships among metrics (e.g., land cover and benthic invertebrates, hydrology and fish, etc.), and (4) power analysis of the ability to reliably detect trends in selected metrics that included field replicated data.

The statistical analysis of the survey design and the details of the sampling work conducted between 2010 and 2013 are documented in the first section below.[12]

3.1 Survey Design Implementation

Target streams for this project were: (1) wadeable, (2) perennial, (3) accessible to anadromous salmon, and (4) included at least one riffle for benthic macroinvertebrate collection. Of the 868 sites assessed through GIS analysis and field visits, 105 (12.1 percent of sites) were identified as target sites, and 763 (87.9 percent of sites) were classified as non-target (Table 10). Over half the points assessed as target sites (55/105) were not sampled for various reasons: 41 denied access by landowner (38.9 percent of sites), 4 physically inaccessible (3.8 percent of sites), and 10 not sampled for other reasons (9.6 percent of sites), including 2 sites that were located on the wrong tributary (see Section 4.1.2 for a more complete explanation of this error).[13] Of the 105 target sites assessed, 37 (35.2 percent of sites) were classified as Tier 1, 35 (33.3 percent of sites) were Tier 2, and 33 (31.4 percent) were Tier 3 reaches.

The majority of the sites assessed were classified as non-target (763/868 or 88 percent). Of the non-target reaches, 514 (59 percent) were inaccessible to anadromous salmon. The majority of inaccessible streams in WRIA 8 occurred above natural barriers in the Upper Cedar River watershed.[14] Other reasons for sites being classified as non-target were that the GIS points did not fall on a stream, the stream was non-wadeable or other reasons (Table 10).

The total extent of mapped streams in WRIA 8 was 2,668 km (Table 11). Based on our GIS and field evaluation of 868 sites, the presumed amount of anadromous, wadeable stream length in Tiers 1, 2 and 3 was estimated at 111.78, 106.78, and 104.78 km for a total in WRIA 8 of 323.3 ± 0.3 km. This estimate includes sampled target stream sites and stream sites presumed to be targets that could not be verified primarily because of landowner

[12] Note that a discussion of the results is presented in the subsequent Section 4.0.
[13] Data from these two locations were excluded from the calculations of survey weights and associated continuous and categorical analyses, but the data from these sites were included in all other analyses.
[14] The Landsburg diversion dam at mile 21 on the Cedar River, operated by Seattle Public Utilities to supply drinking water to the city of Seattle, has been passable to Chinook, coho and steelhead since 2003. This reestablished access to approximately 17 miles of mainstem and tributary stream habitat; the only barriers to Chinook, coho and steelhead in the upper watershed are natural ones.

Table 10. Stream sampling target assessment summary.

Category	N	Estimated Percent	Std Error Percent	95% Confidence Interval	Population Estimate (km)	Population Std Error (km)	95% Confidence Interval (km)
Target Sampled	50	5.8	0.7	4.5-7.1	154.1	17.4	119.9-188.2
Target Presumed	55	6.4	0.7	5.0-7.7	169.3	17.7	134.5-204.0
Non Target	763	87.9	0.8	86.2-89.5	2,344.7	22.3	2,300.1-2,388.4
Total	868	100	0	100	2668	0.83	2,666.4-2,669.6

Category: TARGET	N	Estimated Percent	Std Error Percent	95% Confidence Interval	Population Estimate (km)	Population Std Error (km)	95% Confidence Interval (km)
Target Sampled	50	47.7	4.2	39.5-55.8	154.1	13.4	127.7-180.4
Inaccessible	4	3.8	1.5	0.8-6.8	12.3	4.9	2.7-21.9
Denied Access	41	38.9	3.8	31.5-46.4	125.6	12.3	101.8-149.9
Unknown	8	7.7	2.0	3.9-11.5	24.9	6.3	12.5-37.3
Wrong Tributary	2	1.9	1.2	0.0-4.2	6.2	3.8	0.0-13.7
Total	105	100	0	100	323.3	0.33	322.7-324.0

Category: NON TARGET	N	Estimated Percent	Std Error Percent	95% Confidence Interval	Population Estimate (km)	Population Std Error (km)	95% Confidence Interval (km)
No Watercourse	134	17.7	1.1	15.5-19.8	413.9	25.5	363.9-464.0
Not Salmon Stream	514	67.4	1.2	65.2-69.7	1,580.9	27.1	1,527.8-1,634.0
Non Wadeable	91	11.8	0.8	10.3-13.2	275.9	17.5	241.6-310.2
Wetland	12	1.6	0.4	0.9-2.3	36.6	8.5	20.0-53.2
Ambiguous Location	2	0.3	0.2	0.0-0.6	6.1	3.8	0.0-13.5
Ditch_StandingWater	2	0.3	0.2	0.0-0.6	6.1	3.6	0.0-13.1
No Riffles	2	0.3	0.2	0.0-0.6	6.4	3.9	0.0-14.0
Culvert	4	0.5	0.2	0.1-1.0	12.5	5.3	2.2-22.9
Dry	2	0.3	0.2	0.0-0.6	6.2	3.8	0.0-13.6
Total	763	100	0	100	2,344.7	0.82	2,343.1-2,346.3

access denial. Because of the potential bias introduced primarily by the relatively high proportion of landowner access denials, our frame of inference is limited to the sampled stream reaches. One would have to assume that the stream sites where landowners would deny access are no different than streams where landowners would grant access in order to believe that inferences can be made for the entire target population estimate. Therefore, the sampled stream extent is a little less than half the assumed target stream extent (see Figure 7). The sampled amount of anadromous, wadeable stream length in Tiers 1, 2 and 3

was estimated at 60.4, 39.7, and 54.0 km for a total in WRIA 8 of 154.1 ± 17.4 km. Spatial weights for estimating the extent of sampled streams were calculated by tier and included adjustment for the over sample (Table 11).[15] In summary, 50 sampling sites are assumed to represent 154.1 km of wadeable anadromous salmon bearing streams in WRIA 8.

Table 11. Summary of the size of the WRIA 8 stream network, presumed target frame, sample frame and estimated sample weights (km/site) by tier.

Tier	Mapped Streams (km)	Target Streams (km)	Sampled Streams (km)	Sample Sites	Weight (km/site)
1	719	111.8	60.4	20	3.02
2	1,260	106.8	39.7	13	3.05
3	689	104.8	54.0	17	3.18
Total	2,668	323.3	154.1	50	3.08

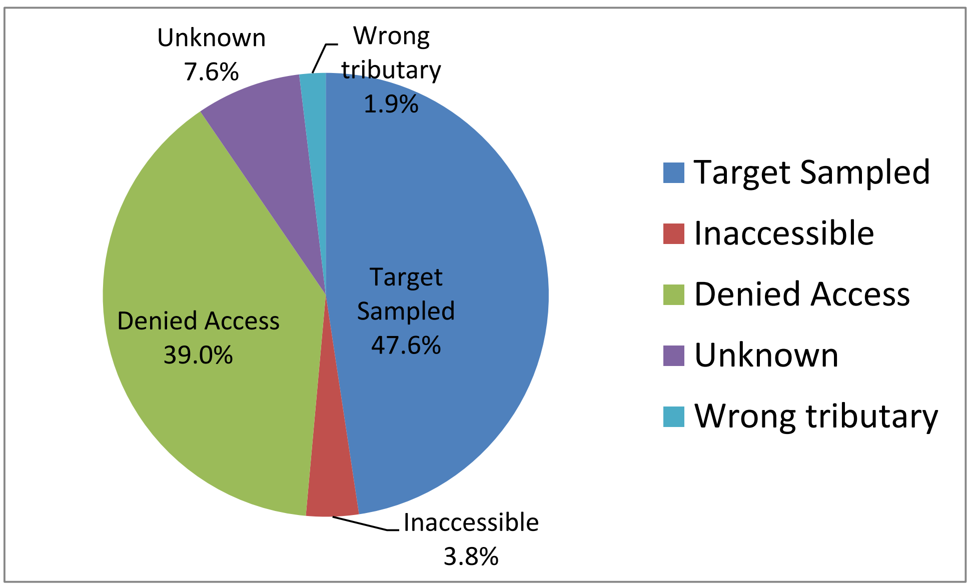

Figure 7. Pie chart showing the assessment of presumed target and sampled target sites in the WRIA 8 status and trends study.

[15] Over sample sites are included in this GRTS design to account for frame errors, landowner denials, and physically inaccessible stream sites.

3.1.1 Sampling Summary

In 2010-2012, a total of 52 WRIA 8 sites were sampled for habitat, benthic invertebrates, and fish. In 2013, one site on Issaquah Creek (WAM06600-051507) could not be sampled because of active construction in the reach, so 51 sites were sampled (Table 12). The availability of flow and temperature data for each WRIA 8 site from 2010 to 2013 is also documented in Table 12.

It was discovered that two of the WRIA 8 stream sampling sites were not located on the targeted stream reach as determined by the Washington Master Sample, but were erroneously located on an adjacent tributary. These sites were renamed from the originally targeted Washington Master Sample ID by changing the original sample ID prefix "WAM" to "ERR." The revised site IDs became ERR06600-035863 for Piper's Creek and ERR06600-091291 for Little Bear Creek (Table 12). Data from these two locations were excluded from the calculations of survey weights and associated continuous and categorical analyses, but the data from these sites were included in all other analyses.

King County conducted sampling at all five Sentinel sites from 2011 through 2013, including the collection of habitat, benthic macroinvertebrate, and fish data. In 2010, sampling was divided between King County and EPA as follows: Sampling at the Sentinel sites for habitat and stream benthic invertebrates was conducted by King County, with the exception of the Chuckanut Creek site which was sampled by EPA. In 2010, fish data were collected at Big Beef Creek by King County/USFWS and by EPA at the other four Sentinel sites (Table 12). The Glendale Creek site was the only Sentinel location where no flow or temperature data were collected during the study. The availability of flow and temperature data for the other Sentinel sites is documented in Table 12.

Table 12. Sampling data summary, 2010-2013.

Note: An "x" denotes reaches sampled by King County for habitat, benthic macroinvertebrates and fish, except where noted. EPA indicates the site that was sampled by EPA in 2010 for habitat, benthic macroinvertebrates and fish. An "r" indicates that replicate habitat and benthic invertebrate sampling was conducted. Two sites (Site IDs with ERR06600-) were not part of the GRTS frame.*

Creek Name	Site ID	2010	2011	2012	2013
	Tier 1				
Bear	WAM06600-013031	x	x	x	r
Bear	WAM06600-017111	x	x	x	x
Bear	WAM06600-036971	r [a,b]	x [a,b]	x [a,b,c]	x [a,b,c]
Bear	WAM06600-057527	X	x	x [a]	x [c]
Bear (trib)	WAM06600-111639	x [a,b]	x	x [a]	x [c]
Carey	WAM06600-002259	x [a,b]	r [a,b]	x [a,b,c]	x [a,b,c]
Carey	WAM06600-006355	x	x	x [a]	x [c]
Cottage	WAM06600-076119	x [a,b]	x [a,b]	x [a,b,c]	x [a,b,c]
EF Issaquah	WAM06600-039815	x [a,b]	x [a,b]	x [a,b,c]	x [a,b,c]
EF Issaquah	WAM06600-041095	r	x	x [c]	x [c]
EF Issaquah	WAM06600-082291	x	x	x [c]	x [c]
EF Issaquah	WAM06600-108711	x	x	x [c]	x [c]
Holder	WAM06600-098963	x	x	x [c]	x [c]
Issaquah	WAM06600-035623	x	x	r [c]	r [c]
Issaquah	WAM06600-047779	r	r	x [c]	x [c]
Issaquah	WAM06600-051507	x	x	x [c]	[d]
Issaquah	WAM06600-100519	x	x	r	X
Issaquah	WAM06600-110035	x	x	x [c]	x [c]
Issaquah	WAM06600-123207	x [a,b]	x [a,b]	x [a,b,c]	x [a,b,c]
Mackay	WAM06600-122423	x	x	x [c]	x [c]
Total		20	20	20	19
	Tier 2				
Coal	WAM06600-000391	x	x	x [b,c]	x [c]
EF Rock	WAM06600-086867	x	x	x [c]	x [c]
Hotel	WAM06600-083667	x	x	x [c]	x [c]
Kelsey	WAM06600-038087	x	x	x [b,c]	x [a,b,c]
Kelsey	WAM06600-080407	x [a,b]	x [a,b]	x [a,b,c]	x [a,b,c]
Little Bear	ERR06600-091291	x [b]	x [a,b]	x [b,c]	x [c]
Little Bear	WAM06600-023691	x [a,b]	x	x [c]	x [b,c]
North	WAM06600-049499	x [a,b]	x	x [c]	x [c]
North	WAM06600-067147	x [a,b]	r [a,b]	x [a,b,c]	x [c]
North	WAM06600-126891	r	x	r	x
Rock	WAM06600-027251	x	x	x [c]	x [c]
Sitka	WAM06600-053755	x	x	x [c]	x [c]

Creek Name	Site ID	2010	2011	2012	2013
Taylor	WAM06600-115443	x [a,b]	x [a,b]	x [a,b,c]	r [a,b,c]
Webster	WAM06600-022259	x [a,b]	x [a,b]	x [a,b,c]	x [a,b,c]
Williams	WAM06600-015443	x	x	x [c]	x [c]
Total		15	15	15	15
	Tier 3				
Coal	WAM06600-073831	x	x	x [c]	r [c]
Idlywood	WAM06600-097975	x	x	r [c]	x [c]
Juanita	WAM06600-083959	x [a,b]	x [a,b]	x [a,b,c]	x [a,b,c]
Lewis	WAM06600-020391	x	r	x	x [c]
Lunds Gulch	WAM06600-063051	r	x	x	x [c]
Lyon	WAM06600-035963	x [a,b]	x [a,b]	x [a,b,c]	x [a,b,c]
Madsen	WAM06600-092899	x	x	x [c]	x [c]
May	WAM06600-081267	x [b]	x [a,b]	x [a,b,c]	r [a,b,c]
Perrinville	WAM06600-083243	x	x	x	x [c]
Peter’s	WAM06600-050295	x	x [f]	x [b,c]	x [a,b,c]
Piper's	ERR06600-035863	x	x	x	x [c]
Piper's	WAM06600-063831	x [a,b]	r [a,b]	x [a,b,c]	x [a,b,c]
Scriber	WAM06600-015067	x [a,b]	x [a,b]	x [a,b,c]	x [a,b,c]
Swamp	WAM06600-083131	x [a,b]	x [a,b]	x [a,b,c]	x [c]
Taylor (Seattle)	WAM06600-065043	x [a,b]	x [a,b]	x [a,b,c]	x [c]
Tibbetts	WAM06600-062567	x	x	x [a,b,c]	x [a,b,c]
Venema	WAM06600-057739	x [a,b]	x [a,b]	x [a,b,c]	x [a,b,c]
Total		17	17	17	17
	Sentinel Sites				
Big Beef *	WAM06600-001639	x [a,b]	x [a,b]	x [a,b,c]	x [a,b,c]
Chuckanut	EPA06600-CHUC01	EPA [e]	x [a,b]	x [a,b,c]	x [b]
Dewatto	EPA06600-DEWA01	x [e]	x [b]	x [b,c]	x [a,b,c]
Glendale *	WAM06600-299887	x [e]	x	x	x
Griffin	SEN06600-GRIF09	x [a,b,e]	x [a,b]	x [a,b,c]	x [a,b,c]
Total		5	5	5	5
Grand Total		57	57	57	56

[a] Useable continuous flow data for flashiness metrics.
[b] Useable continuous flow data for summer low flow metrics.
[c] Continuous temperature site.
[d] This location on Issaquah Creek was not sampled in 2013 due to construction activity at this site.
[e] EPA conducted fish sampling at this site in 2010.

** There may be some confusion regarding these site IDs. These site IDs are used in our database developed for this study. Ecology’s Environmental Information Management system uses EPA06600-BEEF01 and EPA06600-GLEN01 as our site IDs and the IDs above are used for Ecology sampling events that have occurred at nearly the same locations.*

3.2 Precision Analysis

3.2.1 Habitat Metrics

The relative contribution of the four components of variance for each habitat metric is summarized in Figure 8. The dominant source of variation in many of the habitat metrics was associated with variation across sites, which is to be expected given that the streams sampled included relatively undeveloped rural stream reaches to stream reaches in highly urbanized settings. Generally, habitat metrics with relatively higher contributions of site variance had relatively low residual variance (and vice versa), resulting in metrics with the highest S:N also having the highest contribution from site variance (Figure 8).

The precision analysis identified 24 of the initial list of 38 metrics (see Table 2) with a S:N greater than 2.0 (Table 13 and Figure 8). Nine metrics had S:N greater than 10. These metrics represented measures of canopy character and density (PPN CanConif, X DensioCenter, X DensioBank), substrate composition (PCT SandFines) and channel characteristics (ResPoolArea100, X TWDepth, SD TWDepth, X BFWidth and X BFDepth). Fourteen metrics had very low S:N (i.e., <2.0). These metrics included substrate metrics (PCT GravelC, PCT GravelF, X Embed, SD Embed), relative bed stability (RBS, LRBS), channel metrics (PCT Pool, PCT PoolScour, SD PoolUnitDepth) and a wood metric (PCT Wood).

A figure showing the same relative variance component contributions for the habitat metrics, but sorted by σ_{rep}/Rg_{obs} presents a different picture of the relative precision of the habitat metrics (Figure 9). In this figure, high precision is generally associated with relatively low σ_{rep} and relatively high Rg_{obs} that results from the wide range of habitat disturbance sampled across WRIA 8. Based on the criteria in Kaufmann et al. (2014a), 10 of the 38 metrics would be considered to have relatively high precision (i.e., $\sigma_{rep}/Rg_{obs} \leq 0.052$; Table 13 and Figure 9). These metrics represent channel characteristics (X TWDepth, SD TWDepth, X BFWidth, ResPoolArea100, X BFDepth), wood volume (LWDVolume100m, LWDPieces100m, LWDVolumeMSq) and canopy character and density (PPN CanConif, X DensioBank). All but three of the remaining metrics would be considered to have moderate precision (i.e., $0.052 > \sigma_{rep}/Rg_{obs} < 0.15$). The three metrics that would be considered to have poor precision ($\sigma_{rep}/Rg_{obs} \geq 0.15$) were PCT GravelF, PCT Pool and PCT PoolScour.

Contrary to the findings of Kaufmann et al. (2014a), there was a relatively high correlation between natural log transformed S:N and σ_{rep}/Rg_{obs} (Pearson r = -0.74, p<0.001). However, our data set did not have nearly the same geographic scope (contiguous U.S.). Consistent with Kaufmann et al. (2014a), low σ_{rep}/Rg_{obs} did not guarantee high S:N, although all metrics classified as having high precision based on σ_{rep}/Rg_{obs} had S:N greater than 2.0. S:N greater than 10 did not consistently correspond to metrics with high precision based on σ_{rep}/Rg_{obs}. There were however a number of metrics with S:N greater than 10, that were classified as having moderate precision based on σ_{rep}/Rg_{obs}, including X DensioCenter and PCT SandFines.

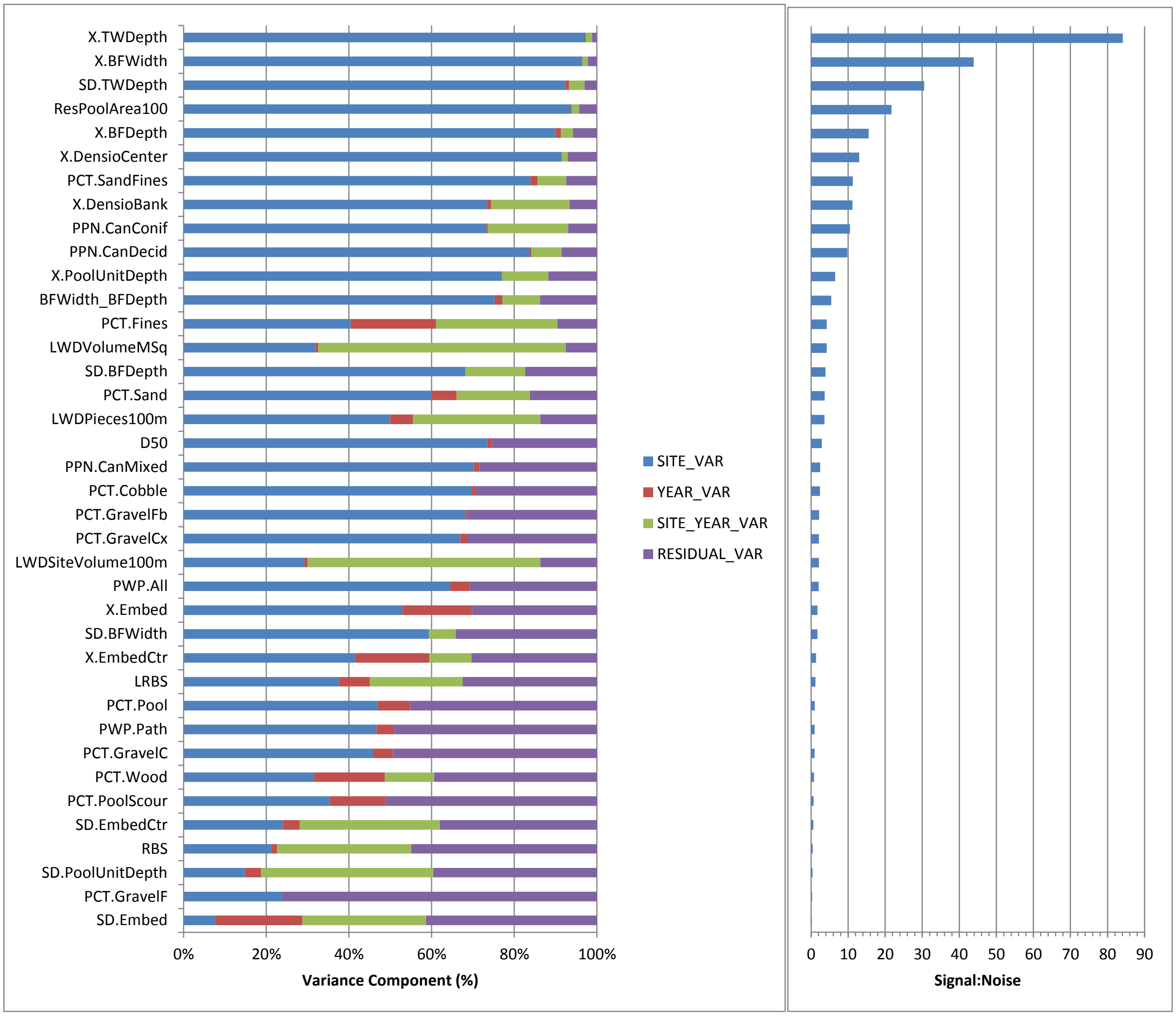

Figure 8. Relative magnitude of the four components of habitat metric variance (left) based on data collected from 50 randomly chosen stream sites in WRIA 8 (2010-2013), including replicate samples collected at 5 randomly chosen locations each year. Signal-to-Noise (S:N) for each metric also shown (right).

Note: Metrics sorted by increasing S:N. See Table 2 for metric descriptions.

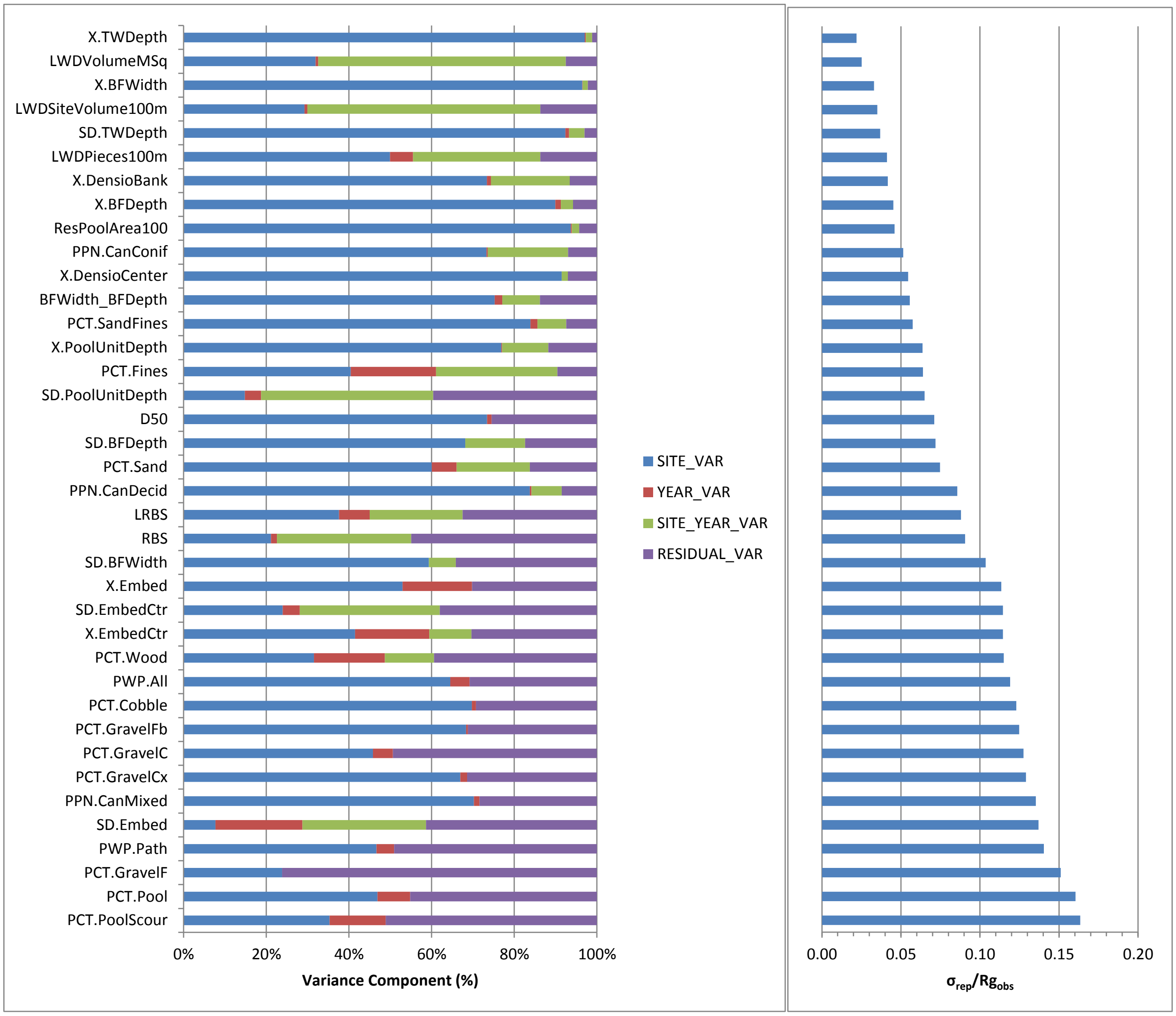

Figure 9. **Relative magnitude of the four components of habitat metric variance (left) based on data collected from 50 randomly chosen stream sites in WRIA 8 (2010-2013), including replicate samples collected at 5 randomly chosen locations each year. σ_{rep}/Rg_{obs} for each metric also shown (right).**

Note: Metrics sorted by decreasing σ_{rep}/Rg_{pot}. See Table 2 for metric descriptions.

Table 13. Summary of habitat metric precision analysis.

Metric	MEAN	CV	σ_{rep}	Rg_{obs}	$\sigma_{rep}:Rg_{obs}$	S:N
BFWidth_BFDepth	11.5	0.10	1.13	20.4	0.056	5.5
D50	11.8	0.49	5.78	81.4	0.071	2.9
LRBS	-2.11	-0.11	0.24	2.68	0.088	1.2
LWDPieces100m	**26.9**	**0.36**	**9.80**	**238.0**	**0.041**	**3.6**
LWDSiteVolume100m	**33.5**	**0.60**	**20.20**	**576.2**	**0.035**	**2.1**
LWDVolumeMSq	**0.067**	**0.47**	**0.03**	**1.3**	**0.025**	**4.2**
PCT Cobble	11.7	0.48	5.59	45.5	0.123	2.4
PCT Fines	6.63	0.46	3.04	47.6	0.064	4.2
PCT GravelC	26.6	0.32	8.44	66.23	0.127	0.93
PCT GravelCx	42.3	0.25	10.67	82.7	0.129	2.1
PCT GravelF	23.9	0.42	9.94	65.80	0.151	0.31
PCT GravelFb	54.1	0.20	10.65	85.3	0.125	2.2
PCT Pool	23.6	0.48	11.23	70.00	0.160	1.04
PCT PoolScour	19.2	0.59	11.28	69.00	0.163	0.69
PCT Sand	23.5	0.22	5.22	69.9	0.075	3.7
PCT SandFines	*30.2*	*0.14*	*4.22*	*73.6*	*0.057*	*11*
PCT Wood	2.60	0.54	1.39	12.12	0.115	0.80
PPN CanConif	***0.060***	***0.58***	***0.04***	***0.7***	***0.051***	***11***
PPN CanDecid	0.579	0.15	0.09	1.0	0.086	9.8
PPN CanMixed	0.271	0.48	0.13	1.0	0.135	2.5
PWP All	0.835	0.57	0.48	4.0	0.119	2.1
PWP Path	0.153	1.00	0.15	1.09	0.140	0.95
RBS	0.0112	0.61	0.01	0.08	0.091	0.47
ResPoolArea100	***11.2***	***0.18***	***2.07***	***45.0***	***0.046***	***22***
SD BFDepth	14.0	0.25	3.51	48.8	0.072	3.9
SD BFWidth	1.33	0.26	0.35	3.40	0.104	1.7
SD Embed	33.4	0.11	3.64	26.60	0.137	0.19
SD EmbedCtr	27.5	0.17	4.55	39.70	0.115	0.63
SD PoolUnitDepth	14.6	0.44	6.41	98.63	0.065	0.37
SD TWDepth	***13.4***	***0.10***	***1.37***	***37.1***	***0.037***	***31***
X BFDepth	***52.2***	***0.10***	***5.23***	***115.8***	***0.045***	***16***
X BFWidth	***5.98***	***0.07***	***0.44***	***13.3***	***0.033***	***44***
X DensioBank	***94.5***	***0.02***	***2.05***	***49.2***	***0.042***	***11***
X DensioCenter	*81.8*	*0.06*	*4.50*	*82.5*	*0.055*	*13*
X Embed	56.7	0.15	8.34	73.50	0.113	1.8
X EmbedCtr	43.7	0.22	9.49	82.80	0.115	1.4
X PoolUnitDepth	44.0	0.19	8.28	130.0	0.064	6.5
X TWDepth	***27.9***	***0.07***	***1.96***	***89.7***	***0.022***	***84***

Note: Metrics classified as having high precision based on σ_{rep}/Rg_{obs} ≤0.052 are in bold. Those classified as having high precision based on S:N>10 are italicized. See Table 2 for metric descriptions.

3.2.2 B-IBI

The relative contribution of the four components of variance to B-IBI is summarized in Figure 10. Consistent with the habitat metrics, the dominant source of variation was associated with variation across sites due to the gradient of development and habitat condition across the study area. The proportion of variance due to year-to-year variability across all sites was lowest. Residual and Site:Year interaction variance (σ_{rep}) were also relatively low compared to variance across sites. B-IBI had S:N of 16.1 indicating relatively high precision and σ_{rep}/Rg_{obs} of 0.067 that would classify B-IBI as having moderate precision (Table 14 and Figure 10).

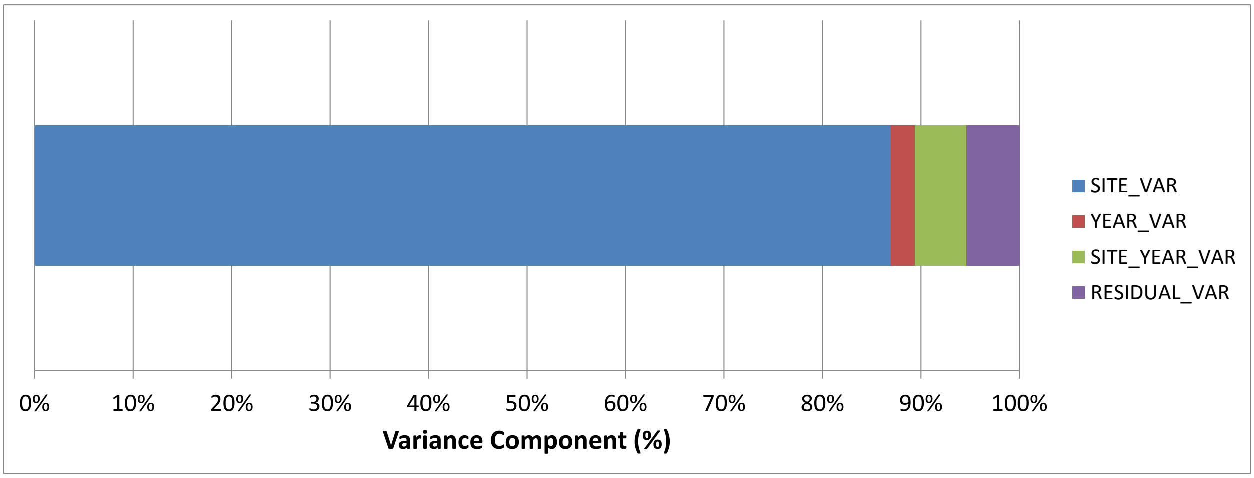

Figure 10. Relative magnitude of the four components of B-IBI variance based on data collected from 50 randomly chosen stream sites in WRIA 8 (2010-2013), including replicate samples collected at 5 randomly chosen locations each year.

Table 14. Summary of benthic macroinvertebrate precision analysis.

Metric	MEAN	CV	σ_{rep}	Rg_{obs}	σ_{rep}:Rg_{obs}	S:N
B-IBI	51.8	0.127	6.60	98	0.067	16.1

3.3 Status and Trends

3.3.1 Status

The ecological status (and condition for those metrics for which we have developed categorical thresholds) of WRIA 8 streams is summarized below by tier (Tiers 1, 2 and 3) for B-IBI, F-IBI, and habitat metrics representing instream wood (LWDSiteVolume100m), riparian canopy cover (PPN CanConif and X DensioBank), fine sediment (PCT SandFines), pools (ResPoolArea100) and water temperature (7DMax). The habitat categories of wood, canopy cover, fine sediment, and pools are targeted here because these are commonly considered to be important for salmon and other aquatic species, are often targeted in restoration activities, and are expected to respond to improved management practices (Larsen et al., 2004).

3.3.1.1 B-IBI

B-IBI scores in WRIA 8 streams ranged from 10.2 to 99.6 between 2010 and 2013. There was a fairly distinct pattern in the distribution of B-IBI across Tiers 1 through 3, with B-IBI in Tier 1 being generally the highest and Tier 3 scores lowest, with Tier 2 scores covering the range in Tier 1 and 3 scores (Figure 11). The range in B-IBI scores at the five Sentinel sites was variable among years, but generally higher than B-IBI observed in WRIA 8 Tier 3 streams (Figure 11).

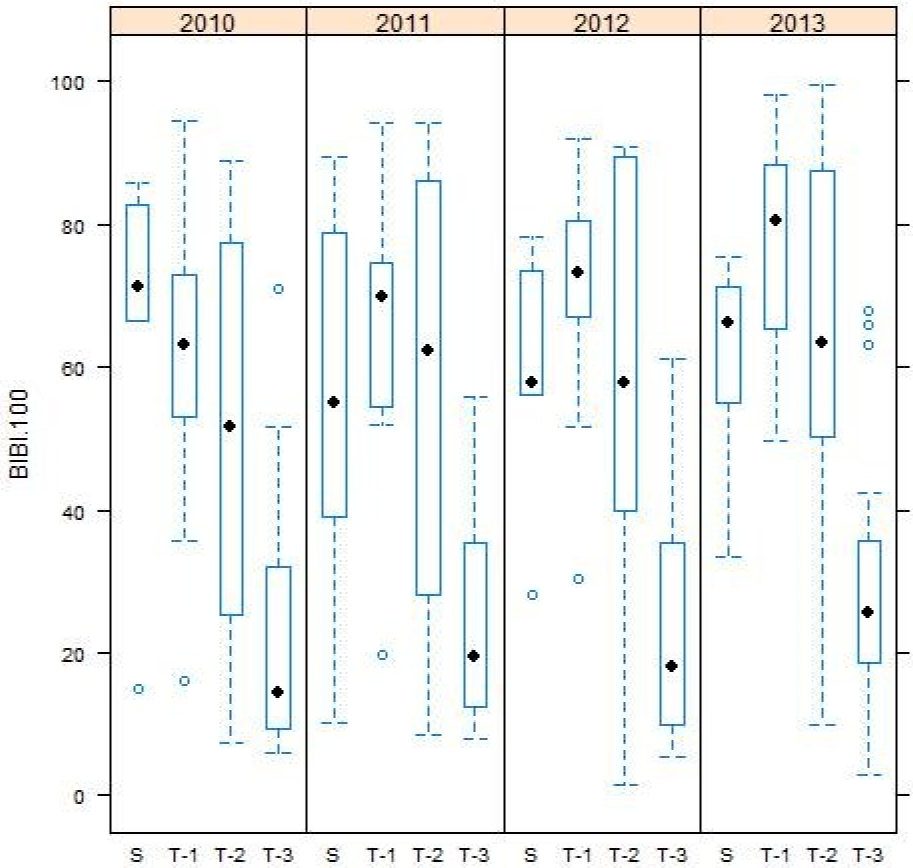

Figure 11. Box plots showing range of B-IBI scores in WRIA 8 Tier 1, 2 and 3 (T-1, T-2, T-3) and Sentinel (S) streams, 2010-2013.

Comparisons of CDFs of B-IBI for 2010 to 2013 in Tier 1, 2 and 3 streams, reveals a similar pattern to that noted above with higher scores in Tier 1, lower scores in Tier 3 and the full range of scores in Tier 2 (Figure 12). Although the 95 percent confidence intervals generally overlap, there also appears to be a trend toward higher B-IBI scores, with qualitatively more apparent increases in B-IBI scores observed in 2013 in Tier 1 streams. Wald F paired comparison tests seem to bear this out, at least for trends in Tier 1 streams, with statistically significant ($p<0.05$) differences identified in all comparisons with the exception of differences between 2010 and 2011 and between 2012 and 2013 (Table 15).

Except for a statistically significant difference in Tier 3 sites between 2010 and 2013, no statistically significant differences were noted for any other comparisons within Tiers 2 or 3 (Table 15).

Table 15. Results of multiple comparison tests of B-IBI scores for Tiers 1 through 3, 2010-2013.

Tier	Comparison	Wald F	p-value
Tier 1	2010 to 2011	1.68	0.20
Tier 1	2010 to 2012	4.81	**0.014**
Tier 1	2010 to 2013	4.29	**0.022**
Tier 1	2011 to 2012	7.65	**0.0018**
Tier 1	2011 to 2013	10.47	**0.0003**
Tier 1	2012 to 2013	2.62	0.087
Tier 2	2010 to 2011	0.93	0.41
Tier 2	2010 to 2012	3.17	0.061
Tier 2	2010 to 2013	3.02	0.068
Tier 2	2011 to 2012	1.39	0.27
Tier 2	2011 to 2013	0.44	0.65
Tier 2	2012 to 2013	0.95	0.40
Tier 3	2010 to 2011	2.76	0.079
Tier 3	2010 to 2012	0.44	0.65
Tier 3	2010 to 2013	6.12	**0.0058**
Tier 3	2011 to 2012	0.80	0.46
Tier 3	2011 to 2013	0.65	0.53
Tier 3	2012 to 2013	2.62	0.089

Note: Statistically significant tests ($p<0.05$) shown in bold. Paired comparison test p-values were not adjusted for multiple comparisons.

Based on the thresholds in Table 8 (i.e., poor<40, fair >=40 and <60,good>=60), the B-IBI condition in WRIA 8 Tier 1, 2 and 3 streams varied somewhat from year to year and followed the pattern described above – a small portion of Tier 1 streams and a large portion of Tier 3 streams were in poor condition (Figure 12). An intermediate amount of Tier 2 streams were in poor condition. Conversely, a small proportion of Tier 3 streams and a major portion of Tier 1 streams were in good condition. An intermediate proportion of Tier 2 streams were in good condition (Figure 12).

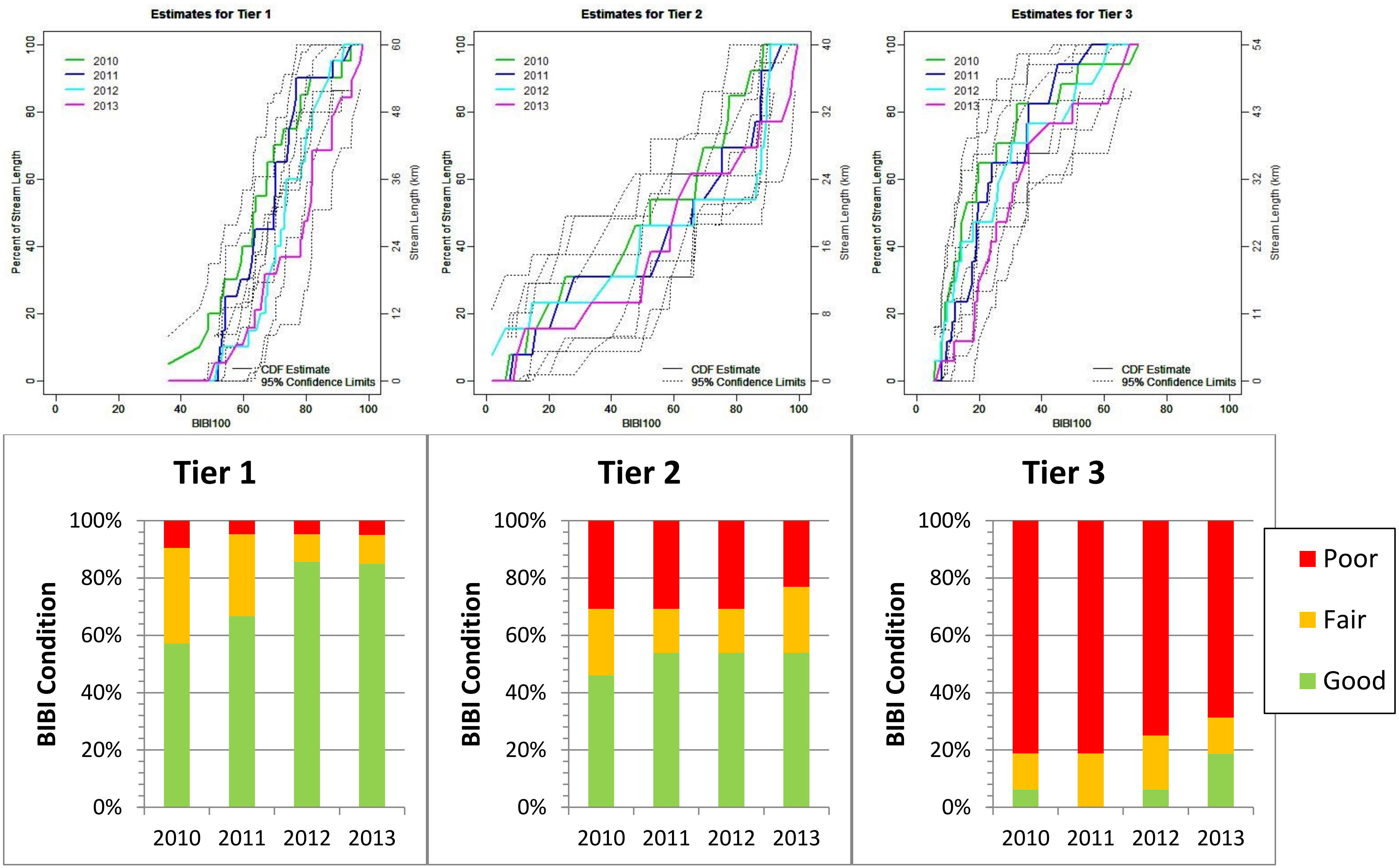

Figure 12. Cumulative distribution function (CDF) plots (top) and categorical analysis bar plots for B-IBI, 2010-2013 for Tier 1, Tier 2 and Tier 3.

3.3.1.2 F-IBI

F-IBI scores in WRIA 8 streams ranged from 6 to 23 between 2010 and 2013. The pattern for F-IBI scores across Tiers 1 through 3, was similar to that observed for B-IBI. Tier 1 generally had the highest scores and Tier 3 had the lowest scores, with Tier 2 scores covering the range in Tier 1 and 3 scores (Figure 13). The range in F-IBI scores at the five Sentinel sites was variable among years, but generally higher scores than WRIA 8 Tier 2 and 3 streams (Figure 13).

However, based on the stressor-response analysis for F-IBI (see Section 3.4.2 below), we do not believe this multi-metric fish index, although developed and tested specifically for Puget Sound lowland streams, is a useful indicator for assessment of fish community health at this time. This is due to a previously unidentified confounding relationship between contributing basin area (or stream size) and F-IBI (see the discussion in Section 4.4.2 for more details on this issue). In general, F-IBI scores are more likely to be higher in larger streams with greater upstream contributing basin area. Tier 1 stream sites have less upstream development, but many of them tend to also be larger streams with larger upstream contributing watershed area, which result in a spurious pattern in F-IBI across tiers (i.e., a pattern more related to contributing basin area than the percent of upstream urbanization).

Tier 1 streams are not only less developed; they also tend to include the mouths of some of the larger tributary basins (e.g., Issaquah and Bear-Evans creeks) suitable for Chinook spawning and rearing. The distribution of contributing basin area for each sampling site by tier is shown in Figure 14, which illustrates that the range in basin area is greatest for Tier 1 streams with small basins representing lower order stream sites near basin headwaters and higher order stream sites near the basin mouths. Bankfull width, a measure of stream size closely related to watershed area (e.g., Faustini et al., 2009) reveals a pattern that is very similar to basin area, with Tier 1 streams having a larger range in bank full width (X BFWidth) (Figure 15).

Further F-IBI status assessment results are presented for completeness below, but should viewed with the large caveat outlined above in mind. We note that previous studies and analyses conducted as part of this study (see Section 3.4.1**Error! Reference source not ound.**) have verified that B-IBI is not confounded by basin area (or stream size) within the range of wadeable streams sampled in our study.

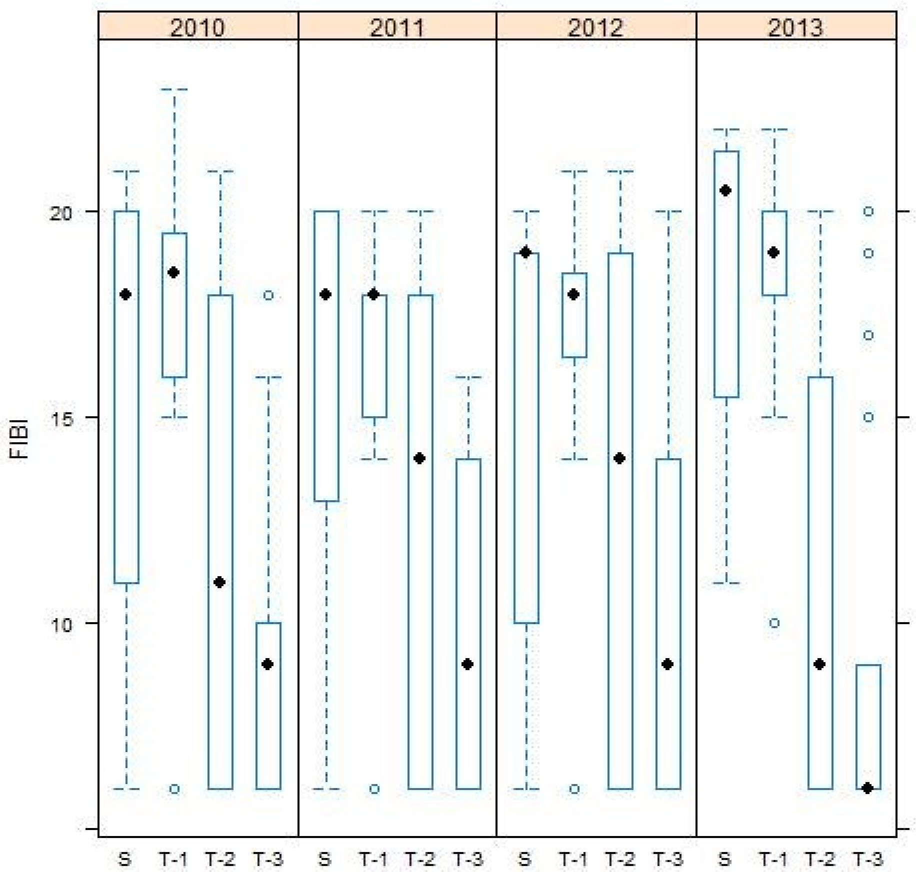

Figure 13. Box plots showing range of F-IBI scores in WRIA 8 Tier 1, 2 and 3 (T-1, T-2, T-3) and Sentinel (S) streams, 2010-2013.

Note: Refer to Section 4.4.2 for a discussion of the confounding effect of basin area and/or stream size on F-IBI scores.

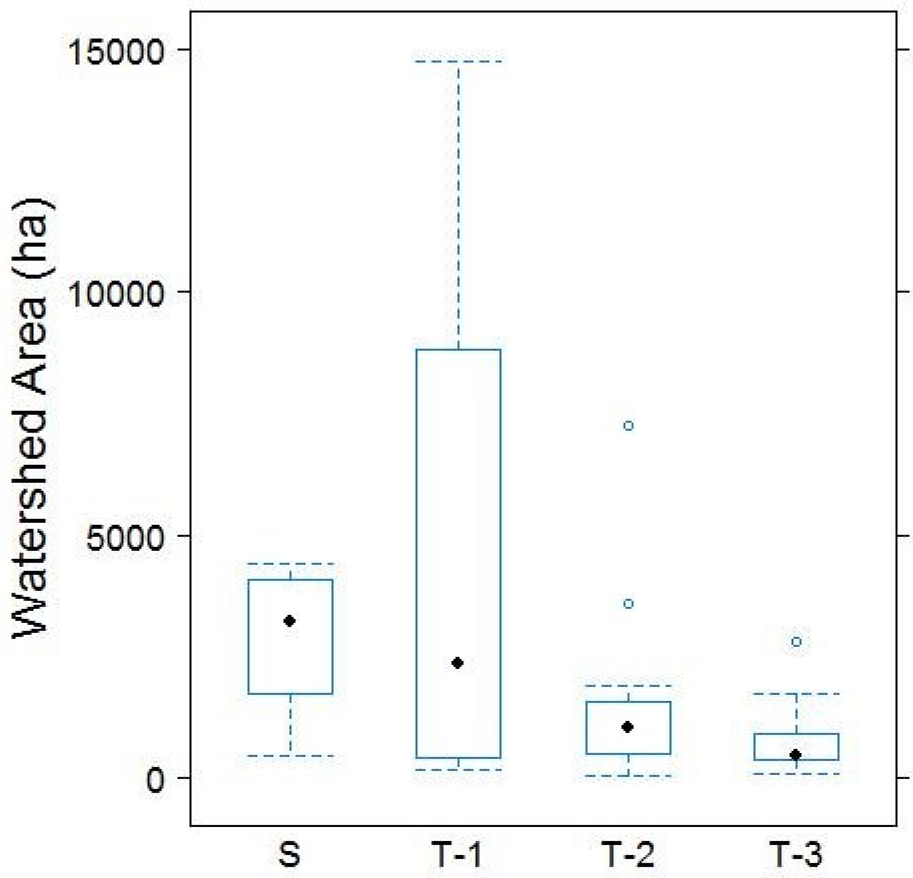

Figure 14. Box plot showing sampling site contributing watershed area (in hectares) in WRIA 8 Tier 1, 2 and 3 (T-1, T-2, T-3) and Sentinel (S) streams.

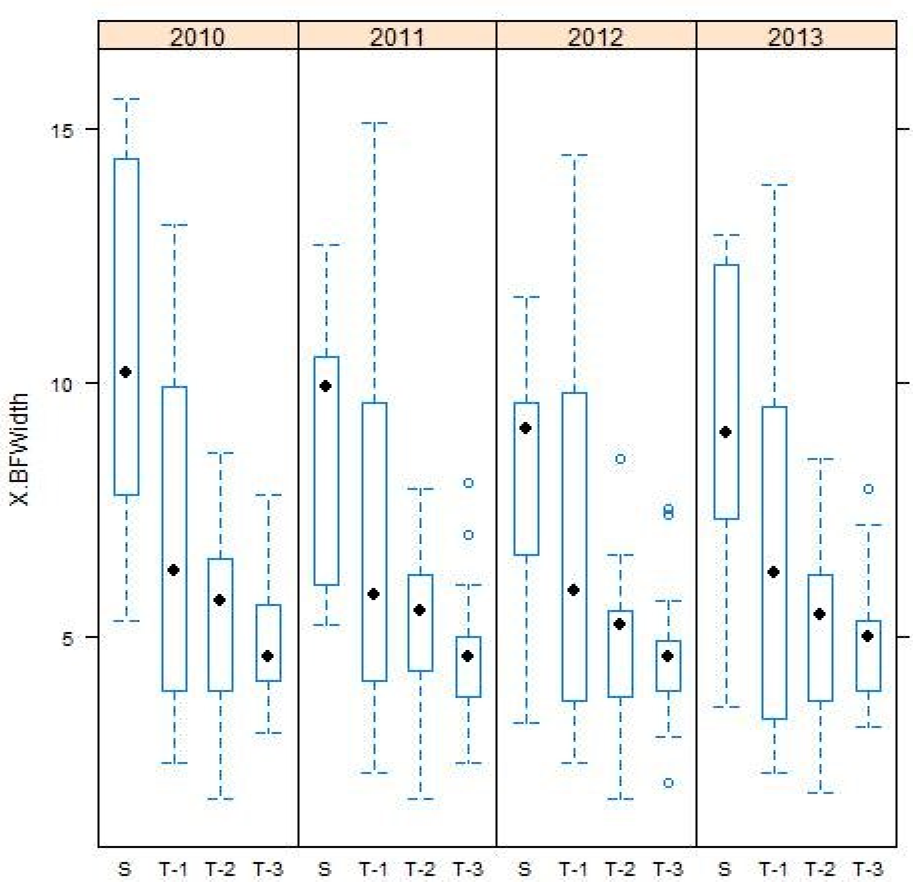

Figure 15. Box plots showing range of bankfull width (X BFWidth, m) in WRIA 8 Tier 1, 2 and 3 (T-1, T-2, T-3) and Sentinel (S) streams, 2010-2013.

Comparisons of CDFs of F-IBI for 2010 to 2013 in Tier 1, 2 and 3 streams, reveals a similar pattern, with higher scores in Tier 1, lower scores in Tier 3 and nearly the full range of scores in Tier 2 (Figure 16). There did not appear to be a trend in F-IBI scores based on visual inspection of the F-IBI CDFs, although two paired comparison tests did indicate some statistically significant (p<0.05) differences in Tier 1 between years (i.e., 2010 to 2011 and 2010 to 2012) (Table 16). No statistically significant differences were noted for any other comparisons within Tiers 2 or 3 (Table 16).

Table 16. Results of multiple comparison tests of F-IBI scores for Tiers 1 through 3, 2010-2013.

Tier	Comparison	Wald F	p-value
Tier 1	2010 to 2011	4.34	**0.021**
Tier 1	2010 to 2012	3.39	**0.045**
Tier 1	2010 to 2013	1.95	0.158
Tier 1	2011 to 2012	0.10	0.902
Tier 1	2011 to 2013	2.37	0.109
Tier 1	2012 to 2013	2.51	0.096
Tier 2	2010 to 2011	0.140	0.870
Tier 2	2010 to 2012	0.000	1.00
Tier 2	2010 to 2013	0.140	0.870
Tier 2	2011 to 2012	0.143	0.868
Tier 2	2011 to 2013	0.145	0.866
Tier 2	2012 to 2013	0.124	0.884
Tier 3	2010 to 2011	0.844	0.440
Tier 3	2010 to 2012	1.47	0.246
Tier 3	2010 to 2013	0.383	0.6852
Tier 3	2011 to 2012	1.33	0.278
Tier 3	2011 to 2013	0.424	0.658
Tier 3	2012 to 2013	0.350	0.708

Note: Statistically significant tests ($p<0.05$) shown in bold. Paired comparison test p-values were not adjusted for multiple comparisons. .

Based on the thresholds in Table 8 (i.e., poor<=10, fair >10 and <=15, good>15), the F-IBI condition in WRIA 8 Tier 1, 2 and 3 streams varied somewhat from year to year and followed the pattern described above – a small portion of Tier 1 streams and a large portion of Tier 3 streams were in poor condition (Figure 16). An intermediate amount of Tier 2 streams were in poor condition, but generally, Tier 2 stream condition was more similar to Tier 3 than Tier 1. Conversely, only a small portion of the Tier 3 stream length was in good condition, while the majority of Tier 1 streams were. An intermediate length of Tier 2 streams were in good condition (Figure 16).

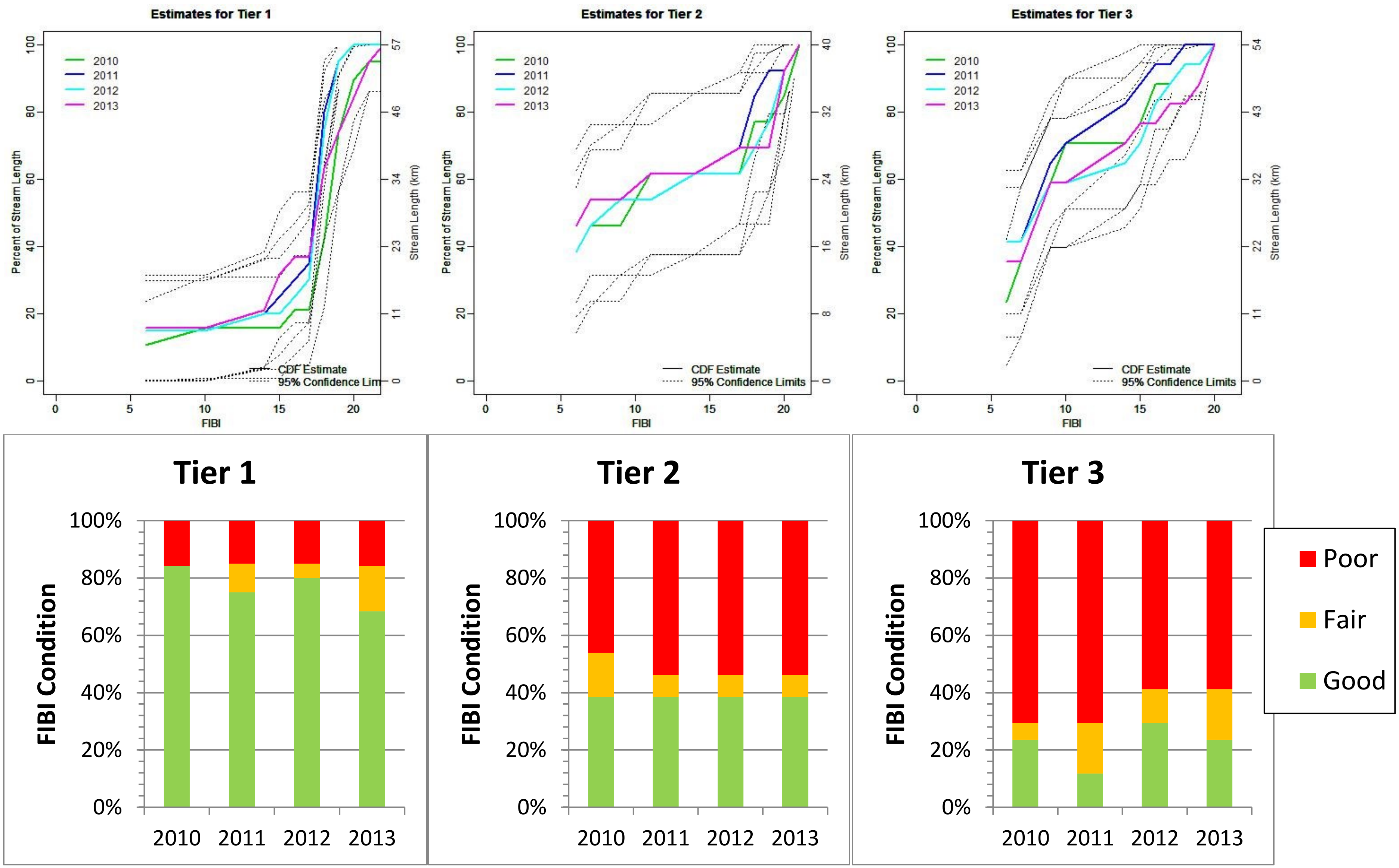

Figure 16. Cumulative distribution function (CDF) plots (top) and categorical analysis bar plots for F-IBI, 2010-2013 for Tier 1, Tier 2 and Tier 3.

Note: Refer to Section 4.4.2 for a discussion of the confounding effect of basin area and/or stream size on F-IBI scores.

3.3.1.3 Wood Volume

Wood volume (LWDSiteVolume100m) in WRIA 8 streams ranged from 0 to 576 m^3/100 m between 2010 and 2013. Wood volume was generally low (< 100 m^3/100 m) and similar across tiers, although much higher volumes were observed at single sites in some years (Figure 17). The range in wood volume at the five Sentinel sites was more variable among years, but generally similar to that observed in WRIA 8 streams (Figure 17).

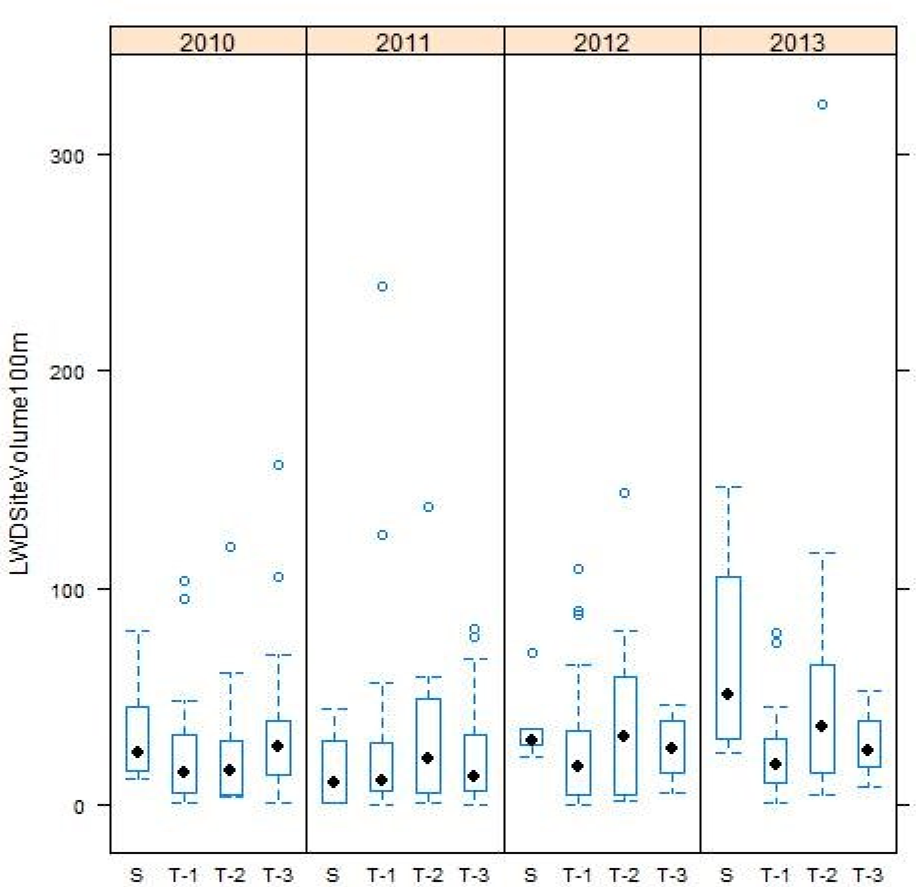

Figure 17. Box plots showing range of LWDSiteVolume100m (m^3 per 100 m) in WRIA 8 Tier 1, 2 and 3 (T-1, T-2, T-3) and Sentinel (S) streams, 2010-2013.

Note: Value of 576 m^3 per 100 m measured in Tier 3 in 2010 not shown.

Comparisons of CDFs of wood volume for 2010 to 2013 in Tier 1, 2 and 3 streams, reveals a similar pattern, with relatively low values in all tiers with higher values observed in some years (Figure 18). There did not appear to be a trend in wood volume based on visual inspection of the CDFs, although a few paired comparison tests did indicate some

significant differences in tiers 2 and 3 between some years (i.e., 2011 to 2013 in Tier 2 and 2010 to 2011 and 2011 to 2013 in Tier 3) (Table 17).

Table 17. Results of multiple comparison tests of wood volume (m^3/100 m) for Tiers 1 through 3, 2010-2013.

Tier	Comparison	Wald F	p-value
Tier 1	2010 to 2011	0.38	0.69
Tier 1	2010 to 2012	0.39	0.68
Tier 1	2010 to 2013	0.24	0.79
Tier 1	2011 to 2012	0.40	0.67
Tier 1	2011 to 2013	1.21	0.31
Tier 1	2012 to 2013	1.01	0.38
Tier 2	2010 to 2011	0.96	0.40
Tier 2	2010 to 2012	1.54	0.24
Tier 2	2010 to 2013	2.43	0.11
Tier 2	2011 to 2012	3.04	0.068
Tier 2	2011 to 2013	4.66	**0.020**
Tier 2	2012 to 2013	0.76	0.48
Tier 3	2010 to 2011	4.31	**0.022**
Tier 3	2010 to 2012	1.21	0.31
Tier 3	2010 to 2013	0.09	0.92
Tier 3	2011 to 2012	1.87	0.17
Tier 3	2011 to 2013	4.20	**0.024**
Tier 3	2012 to 2013	1.68	0.20

Note: Statistically significant tests ($p<0.05$) shown in bold. Paired comparison test p-values were not adjusted for multiple comparisons.

Over half of the WRIA 8 stream lengths in each of the three tiers was consistently in poor condition with respect to wood volume (poor <28, fair >=28 and <=99, good >99 m^3 per 100 m), with the exception of Tier 2 streams sampled in 2013 (Figure 18). Conversely, very little of the stream length in Tier 1, 2 or 3 streams was in good condition (Figure 18). In fact, none of the stream length in Tier 3 streams sampled in 2012 or 2013 were classified as in good condition.

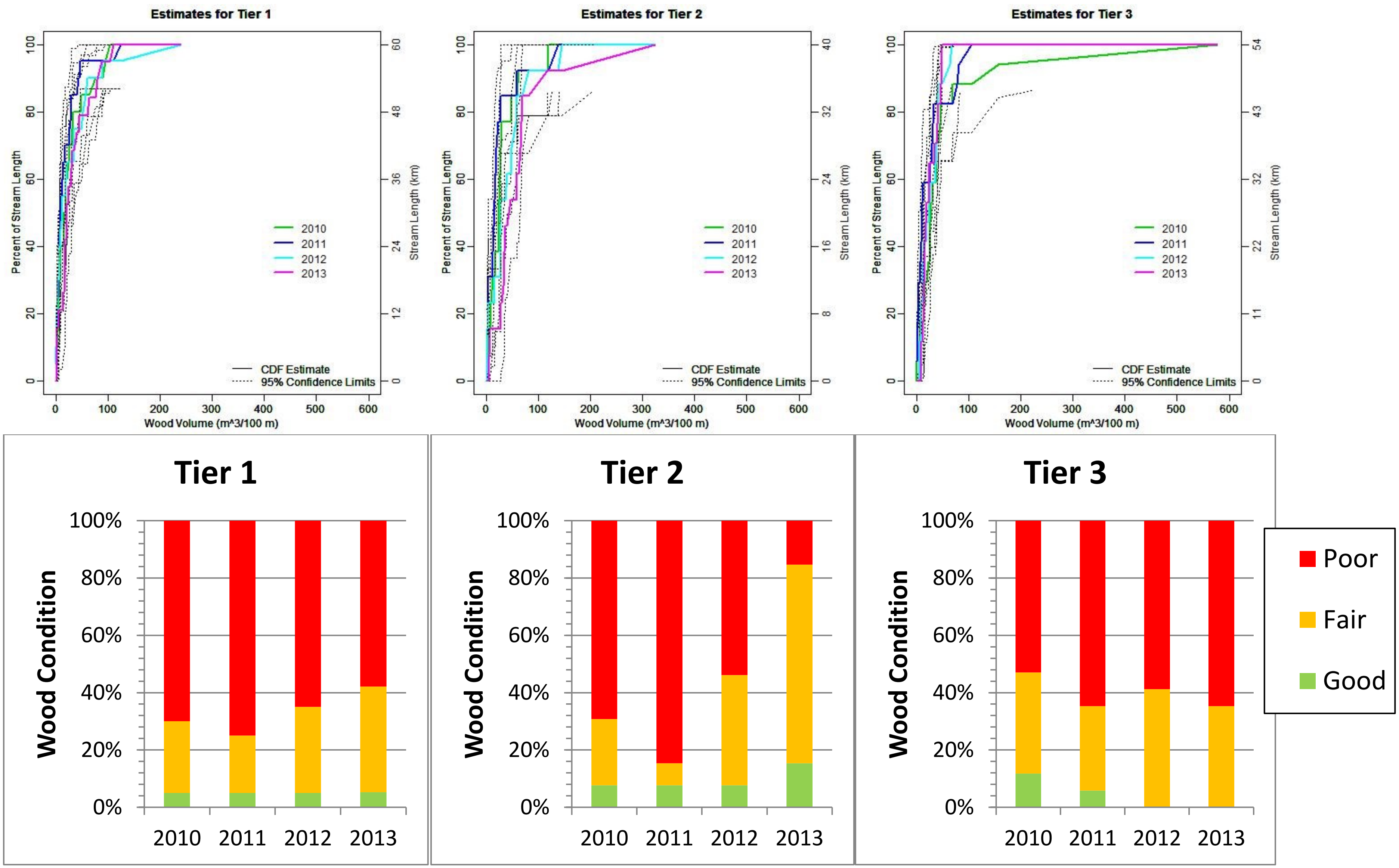

Figure 18. Cumulative distribution function (CDF) plots (top) and categorical analysis bar plots for wood volume, 2010-2013 for Tier 1, Tier 2 and Tier 3.

3.3.1.4 Riparian Canopy Cover

The proportion of riparian coniferous canopy (PPN CanConif) in WRIA 8 streams ranged from 0 to 0.682 between 2010 and 2013. PPN CanConif was generally highest in Tier 2 streams, somewhat lower in Tier 1 streams and lowest in Tier 3 and Sentinel streams (Figure 19).

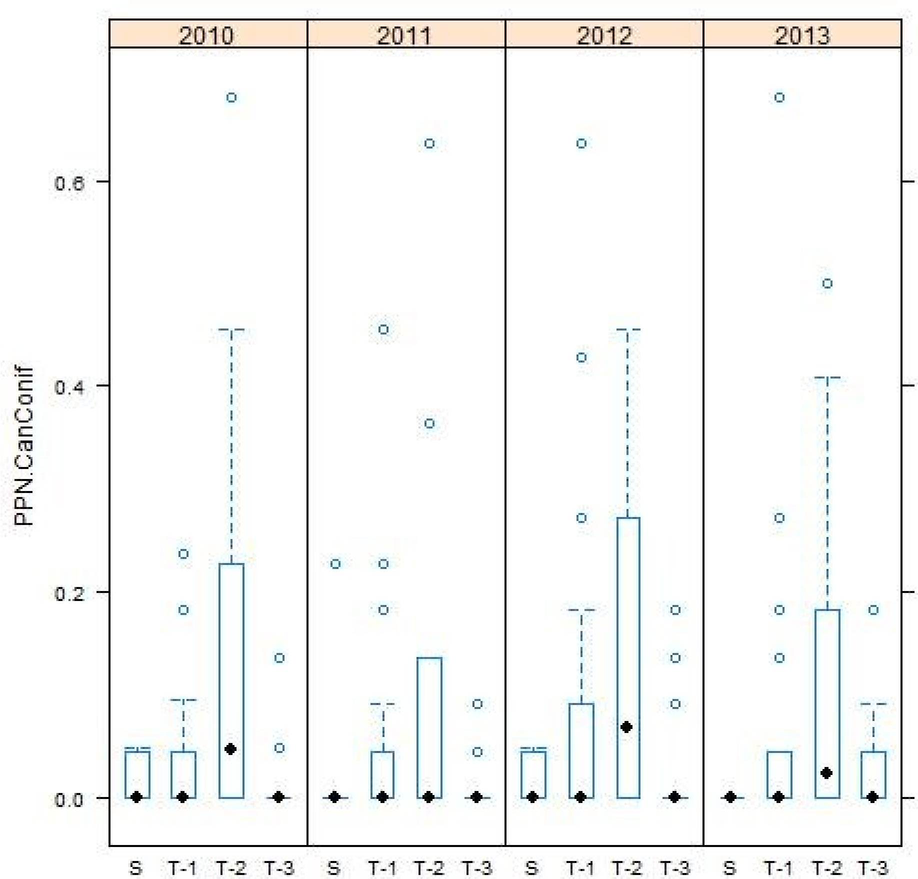

Figure 19. Box plots showing range of PPN CanConif (fraction) in WRIA 8 Tier 1, 2 and 3 (T-1, T-2, T-3) and Sentinel (S) streams, 2010-2013.

Comparisons of CDFs of PPN CanConif for 2010 to 2013 in Tier 1, 2 and 3 streams, revealed a similar pattern, with lowest range of values in Tier 3 with higher values observed in Tiers 1 and 2 (Figure 20). There did not appear to be a trend in PPN CanConif based on visual inspection of the CDFs and no paired comparison tests indicated any significant differences between years for any tiers.

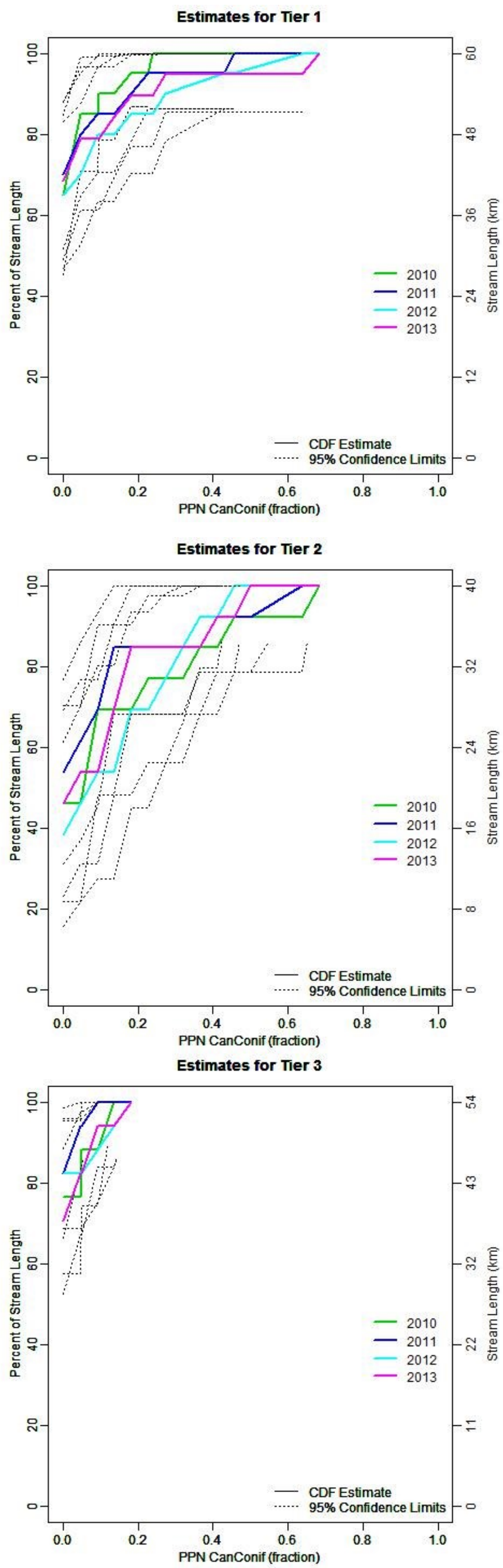

Figure 20. Cumulative distribution function (CDF) plots for PPN CanConif (fraction), 2010-2013 for Tier 1, Tier 2 and Tier 3.

The average riparian canopy density along the sampling site banks (X DensioBank) in WRIA 8 streams ranged from 50.8 to 100 percent between 2010 and 2013. X DensioBank was generally highest in Tier 3 streams and somewhat lower in Tier 1 and 2 streams (Figure 21). X DensioBank in Sentinel streams was also generally lower than in Tier 3 streams and similar to X DensioBank in Tier 1 streams (Figure 21).

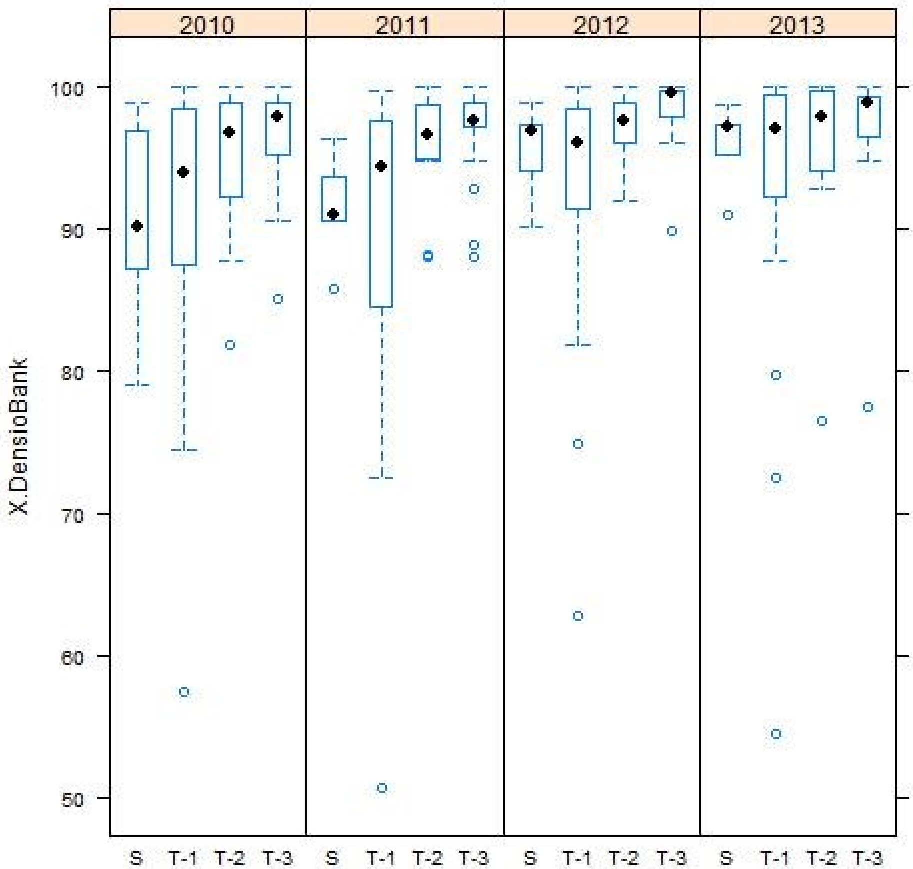

Figure 21. Box plots showing range of X DensioBank (percent) in WRIA 8 Tier 1, 2 and 3 (T-1, T-2, T-3) and Sentinel (S) streams, 2010-2013.

Comparisons of CDFs of X DensioBank for 2010 to 2013 in Tier 1, 2 and 3 streams, revealed a similar pattern, with lower values typical in Tier 1 with higher values observed in Tiers 2 and 3 (Figure 22). There did not appear to be a trend in X DensioBank based on visual inspection of the CDFs and no paired comparison tests indicated any significant differences between years for any tiers.

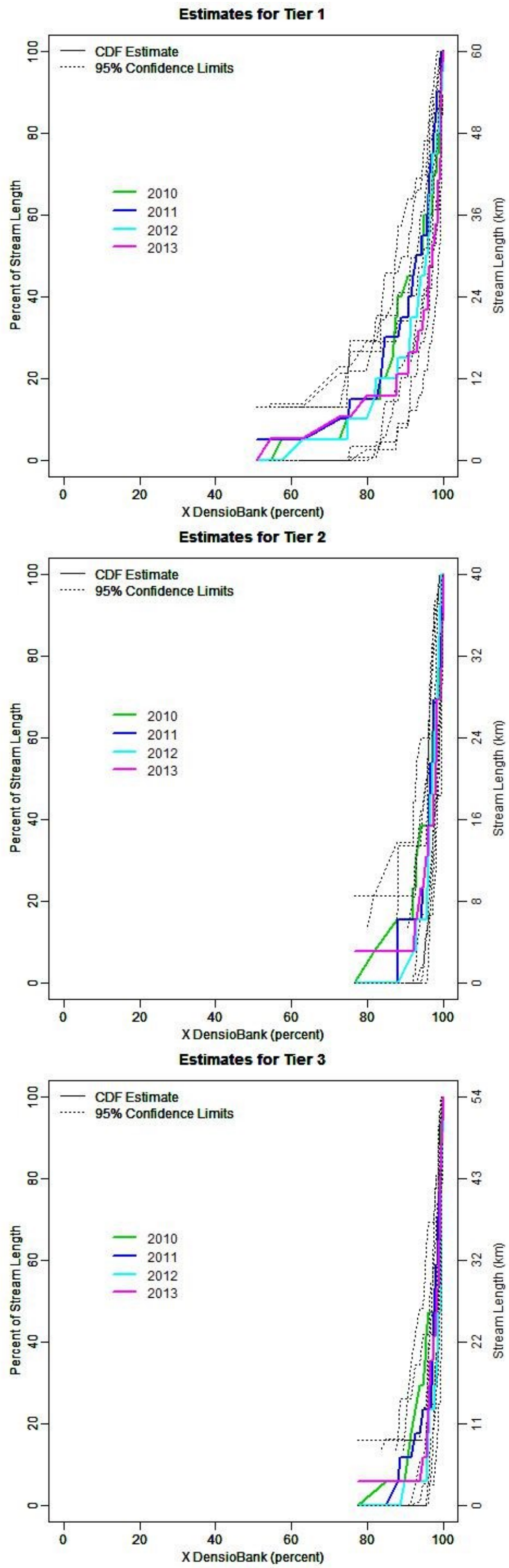

Figure 22. Cumulative distribution function (CDF) plots for X DensioBank, 2010-2013 for Tier 1, Tier 2 and Tier 3.

It is perhaps somewhat surprising that the lowest X DensioBank values were observed in Tier 1 streams. As noted above, some of the widest streams occurred in Tier 1, but X DensioBank should not be significantly affected by stream width. Nonetheless, there does seem to be some tendency for the wider Tier 1 streams to have lower values of X DensioBank (Figure 23). However, the widest Tier 1 stream sampling sites also tended to be near the mouths of larger streams, which also tended to be located in or near cities. For example, the lowest mean value of X DensioBank (56.4 percent) was found at the most downstream site on Issaquah Creek within the city limits of Issaquah.

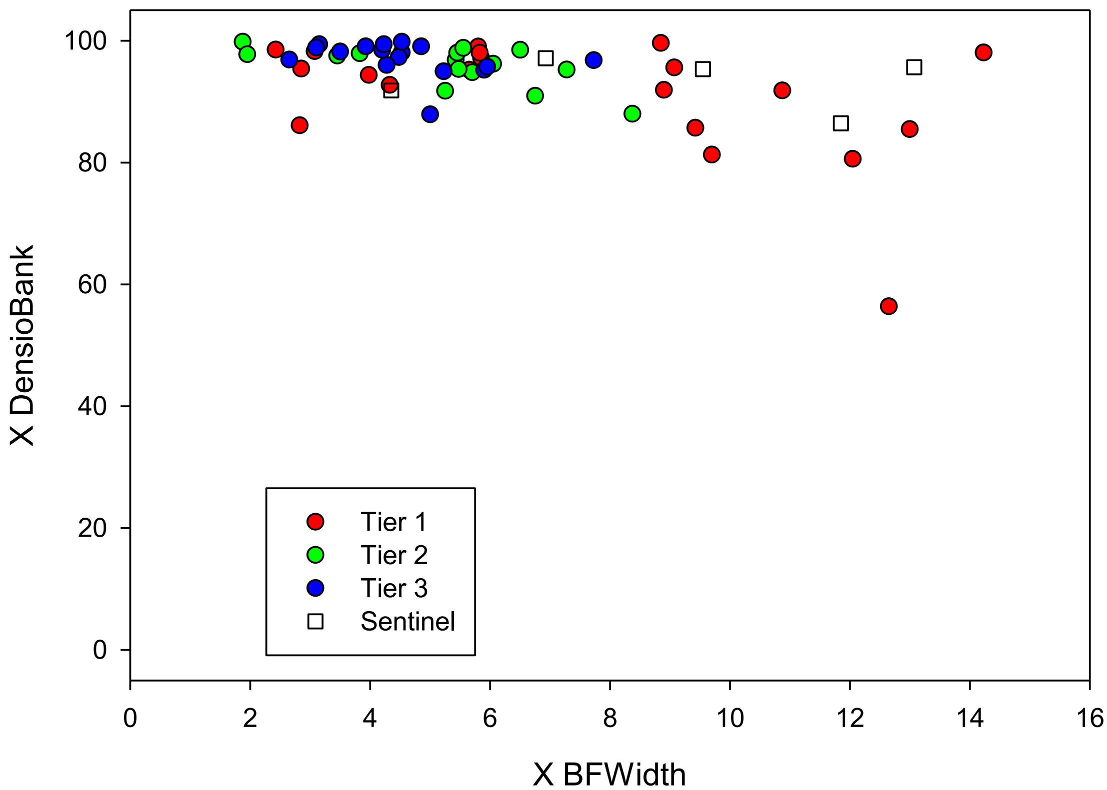

Figure 23. Scatter plot showing average (2010-2013) X BFWidth versus X DensioBank in WRIA 8 Tier 1, 2 and 3 (T-1, T-2, T-3) and Sentinel (S) streams.

3.3.1.5 Fine Sediment

The percent of fine stream sediment (represented by PCT SandFines) in WRIA 8 streams ranged from 2.2 to 75.8 percent between 2010 and 2013. The range of PCT SandFines was generally similar in Tier 1, 2 and 3 streams (Figure 24). PCT SandFines in Sentinel streams was typically lower than in Tier 1, 2 or 3 WRIA 8 streams (Figure 24).

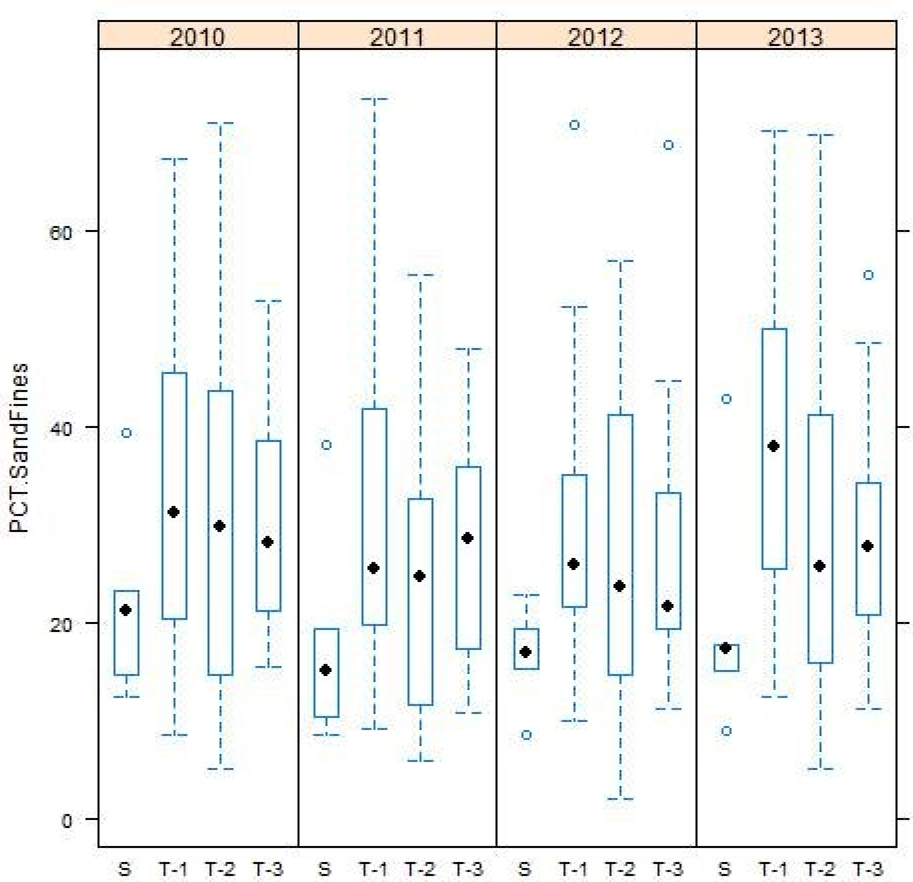

Figure 24. Box plots showing range of PCT SandFines (percent) in WRIA 8 Tier 1, 2 and 3 (T-1, T-2, T-3) and Sentinel (S) streams, 2010-2013.

Comparisons of CDFs of PCT SandFines for 2010 to 2013 in Tier 1, 2 and 3 streams, revealed a similar pattern, with a similar distribution of values in Tier 1, 2 and 3 streams (Figure 25). There did not appear to be a trend in PCT SandFines based on visual inspection of the CDFs and no paired comparison tests indicated any significant differences between years for any tiers.

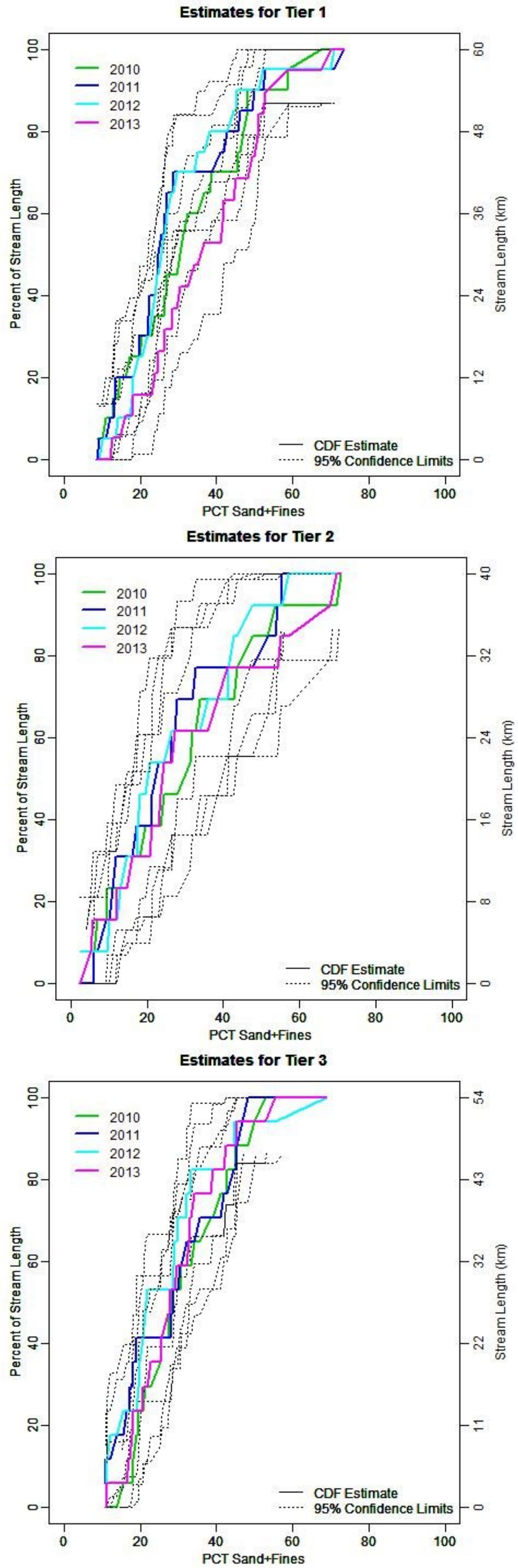

Figure 25. Cumulative distribution function (CDF) plots for PCT SandFines, 2010-2013 for Tier 1, Tier 2 and Tier 3.

3.3.1.6 Pools

The residual pool area (ResPoolArea100) in WRIA 8 streams ranged from 0.3 to 45.3 m^2 per 100 m between 2010 and 2013. The distribution of ResPoolArea100 across tiers generally indicated a gradient of higher ResPoolArea100 in Tier 1, somewhat lower in Tier 2 and lowest in Tier 3 (Figure 26). ResPoolArea100 in Sentinel streams was generally similar to Tier 1 and 2 streams (Figure 26).

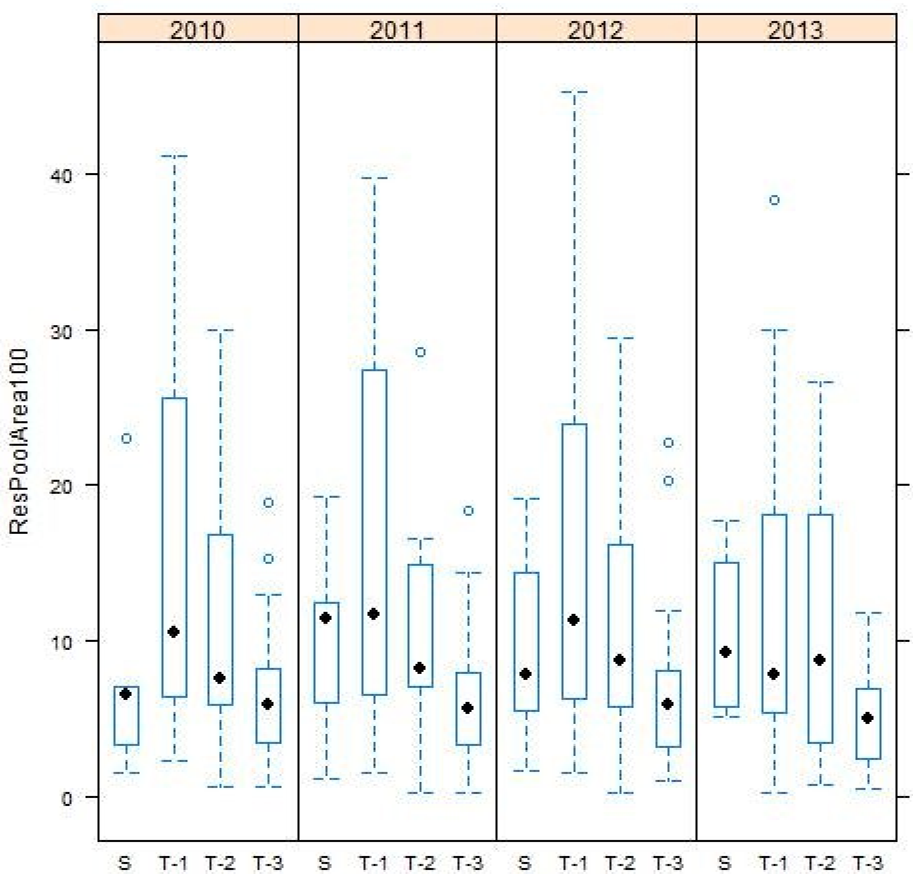

Figure 26. Box plots showing range of ResPoolArea100 (m^2 per 100 m) in WRIA 8 Tier 1, 2 and 3 (T-1, T-2, T-3) and Sentinel (S) streams, 2010-2013.

Comparisons of CDFs of ResPoolArea100 for 2010 to 2013 in Tier 1, 2 and 3 streams, revealed a similar pattern, with a gradient in the distribution of ResPoolArea100 from Tier 1 to Tier 3, with a tendency to higher residual pool area in Tier 1 and lower in Tier 3 (Figure 27). There did not appear to be a trend in ResPoolArea100 based on visual inspection of the CDFs and no paired comparison tests indicated any significant differences between years for any tiers.

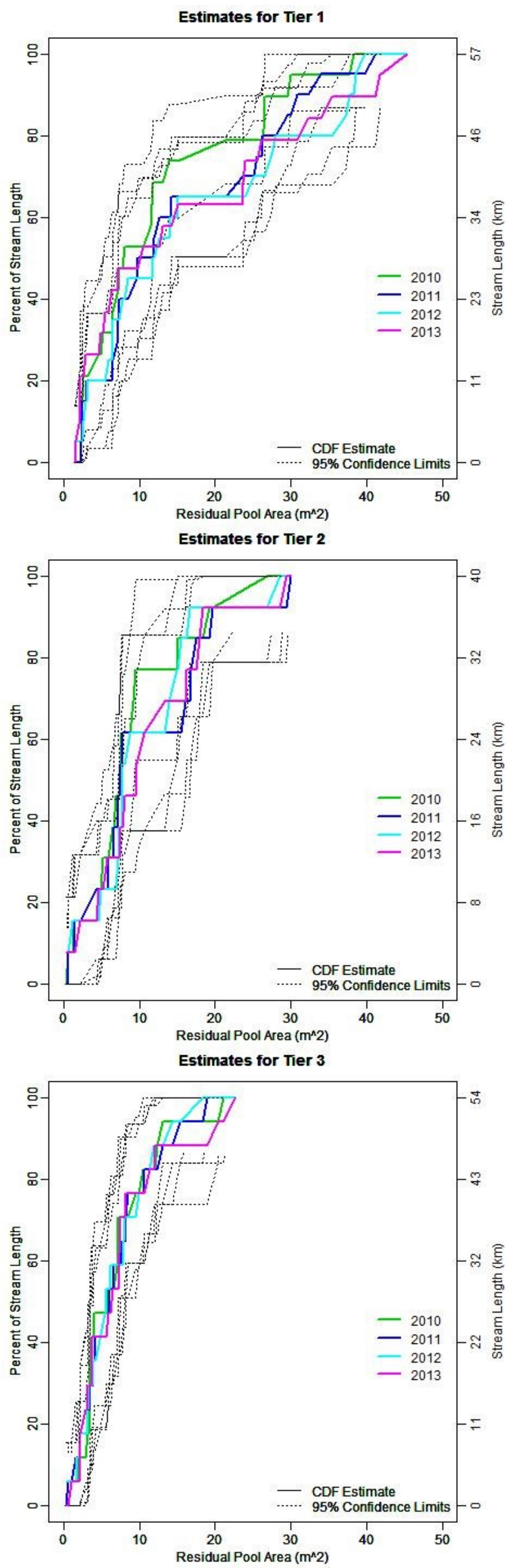

Figure 27. Cumulative distribution function (CDF) plots for ResPoolArea100, 2010-2013 for Tier 1, Tier 2 and Tier 3.

3.3.1.7 Temperature (7DMax)

7DMax in WRIA 8 streams ranged from 13.7 to 23 °C between 2012 and 2013. The range in 7DMax was similar across Tiers 1, 2 and 3 and 7DMax at the Sentinel sites was generally lower (Figure 28).

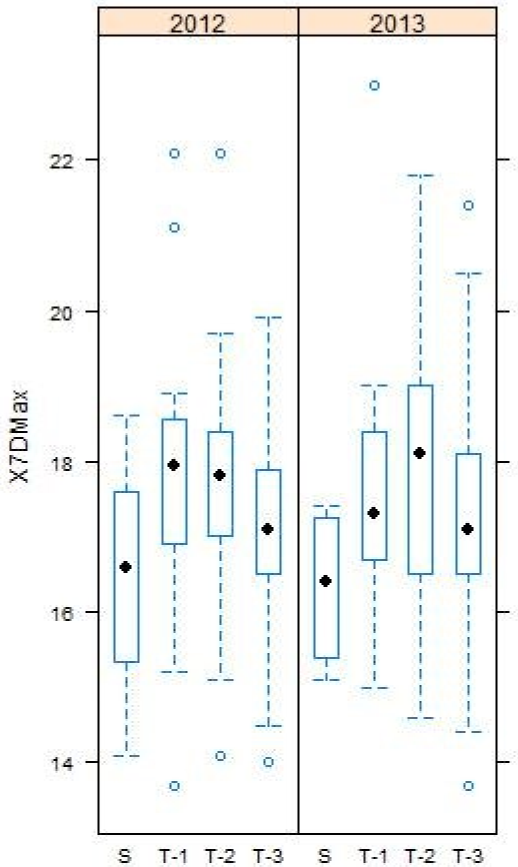

Figure 28. Box plots showing range of 7DMax (°C) in WRIA 8 Tier 1, 2 and 3 (T-1, T-2, T-3) and Sentinel (S) streams, 2010-2013.

Comparisons of CDFs of 7DMax for 2012 and 2013 in Tier 1, 2 and 3 streams, reveals a similar pattern, with a relatively similar range of values in all tiers (Figure 29). No statistically significant differences were detected between years in any tier (Table 18).

Table 18. Results of multiple comparison tests of 7DMax (°C) for Tiers 1 through 3, 2010-2013.

Tier	Comparison	Wald F	p-value
Tier 1	2012 to 2013	0.26	0.775
Tier 2	2012 to 2013	0.80	0.46
Tier 3	2012 to 2013	2.97	0.067

Note: Paired comparison test p-values were not adjusted for multiple comparisons.

Over 80 percent of the Tier 1 stream length and more than 60 percent of the streams in Tiers 2 and 3 were classified as not-supporting cold water salmonid habitat based on the threshold in Table 8 (i.e., 7DMax was greater than 16 ^{o}C) (Figure 29).

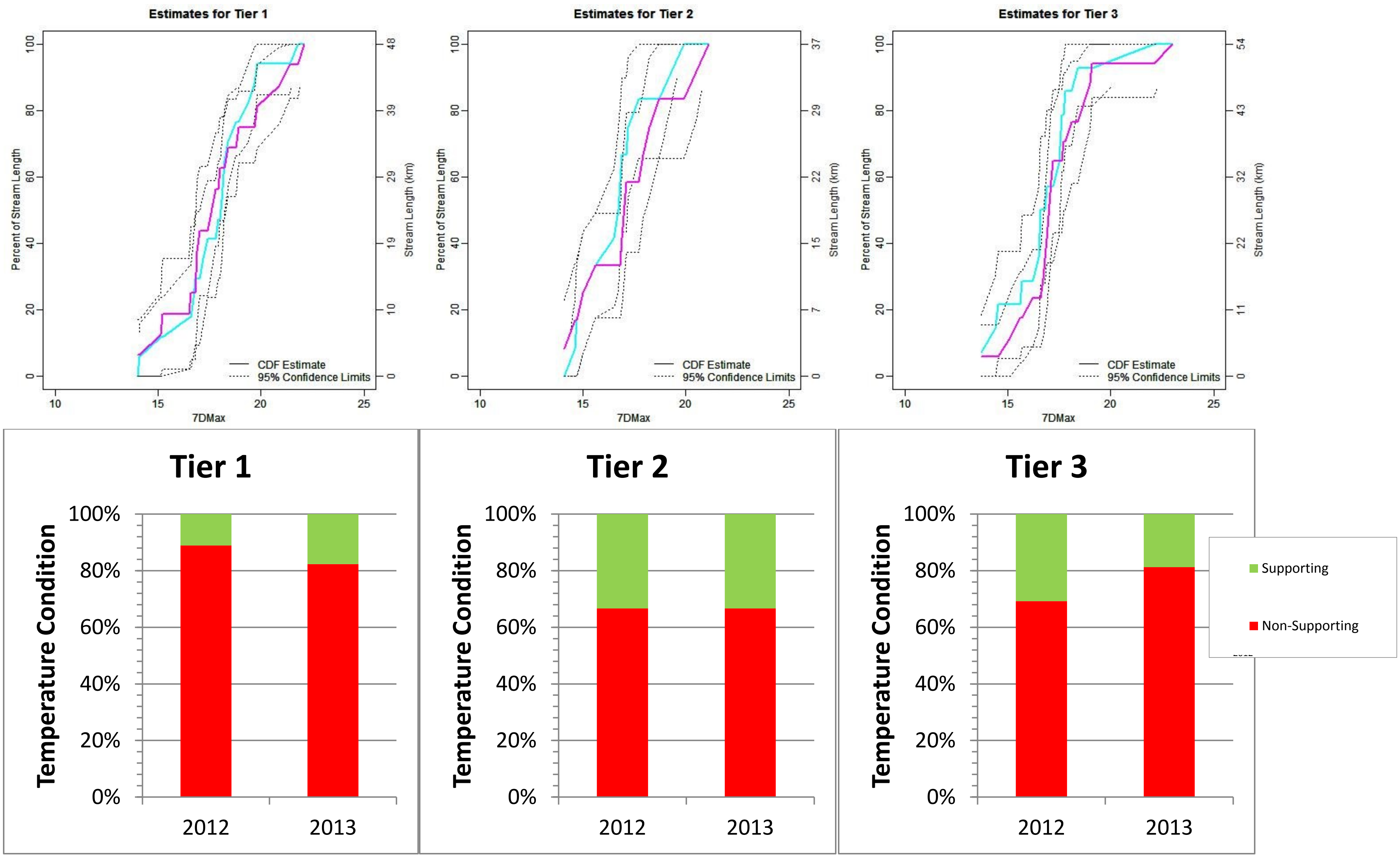

Figure 29. Cumulative distribution function (CDF) plots (top) and categorical analysis bar plots for 7DMax, 2010-2013 for Tier 1, Tier 2 and Tier 3.

3.3.2 Trends

Trends (2010-2013) in ecological status as measured by B-IBI and habitat metrics are summarized here.

3.3.2.1 B-IBI

The regional (WRIA 8) trend in B-IBI was statistically significant (*p* = 0.02) (Table 19). The trend was positive with a rate of change of 3.6 B-IBI points per year over the 2010-2013 monitoring period (Table 19). Application of the trend model to the ten component metric scores indicated that the trend in B-IBI was due primarily to upward trends in richness scores; specifically Plecoptera, Tricoptera, long-lived taxa and overall taxa richness scores (Table 19).. The overall mean trend at the five Sentinel sites was not statistically significant (trend = -0.78; *p* = 0.79).

Table 19. Summary of linear mixed effects model trend test results for B-IBI measured at WRIA 8 sites (2010-2013).

Metric	Trend	p-value
B-IBI	**3.6**	**0.02**
Component metrics		
Total Taxa Richness	**0.45**	**0.04**
Ephemeroptera Taxa Richness	0.01	0.97
Plecoptera Taxa Richness	**0.43**	**0.04**
Trichoptera Taxa Richness	**0.43**	**0.04**
Intolerant Taxa Richness	0.17	0.13
Clinger Taxa Richness and Percent	0.39	0.07
Long-lived Taxa Richness	**0.53**	**0.04**
Percent Tolerant	0.08	0.75
Percent Predator	0.51	0.21
Percent Dominance	0.55	0.06

Note: Statistically significant trends (p<0.05) shown in bold.

3.3.2.2 Aquatic and Riparian Habitat

There was only one statistically significant regional trend in the stream habitat metrics – PCT PoolScour (*p* = 0.04) (Table 20). The trend was positive with a rate of change of 4.5 percentage points per year over the 2010-2013 monitoring period (Table 20). The overall mean trend at the five Sentinel sites was not statistically significant (trend = -0.34; *p* = 0.86).

Table 20. Summary of linear mixed effects model trend test results for stream habitat metrics measured at WRIA 8 sites (2010-2013).

Metric	Trend	p-value
D50	0.1	0.95
LRBS	0.1	0.38
LWDPieces100m	-3.4	0.35
LWDSiteVolume100m	0.2	0.96
LWDVolumeMSq	0.0	0.73
PCT Cobble	-0.8	0.18
PCT Fines	-1.7	0.50
PCT GravelC	1.7	0.25
PCT GravelCx	0.9	0.59
PCT GravelF	-0.5	0.46
PCT GravelFb	-0.2	0.86
PCT Pool	3.5	0.08
PCT PoolScour	***4.5***	***0.04***
PCT Sand	2.1	0.18
PCT SandFines	0.3	0.80
PCT Wood	-0.6	0.19
PPN CanConif	0.01	0.39
PPN CanDecid	0.003	0.87
PPN CanMixed	-0.003	0.89
PWP All	-0.1	0.21
PWP Path	-0.04	0.06
RBS	0.001	0.20
ResPoolArea100	0.4	0.14
SD BFDepth	-0.3	0.41
SD BFWidth	-0.01	0.63
SD Embed	-0.2	0.90
SD EmbedCtr	-0.4	0.71
SD PoolUnitDepth	1.5	0.28
SD TWDepth	0.6	0.10
X BFDepth	-1.7	0.17
X BFWidth	-0.01	0.88
BFWidth_BFDepth	0.3	0.12
X DensioBank	0.7	0.12
X DensioCenter	0.5	0.25
X Embed	-0.5	0.91
X EmbedCtr	-0.4	0.94
X PoolUnitDepth	2.0	0.14
X TWDepth	0.2	0.71

Note: Statistically significant tests ($p<0.05$) shown in bold.

3.4 Stressor-Response Relationships

3.4.1 B-IBI

3.4.1.1 B-IBI vs Land Cover

The BRT model explained about 94 percent of the variance in B-IBI (Table 21). The six most important variables in the model in order of importance were PCT Urban, POP Dens, RD Dens, Elev mean, PCT Imp, and PCT Forest (Table 21, see Table 3 for land cover metric descriptions). PCT Urban was by far the most important variable (48 percent) compared to POP Dens, the second most important variable (18 percent) (Table 21). Approximately linear relationships between B-IBI and the six relatively most important BRT variables are evident in the matrix scatterplot as is the highly interrelated nature of the land cover metrics (Figure 30).

The partial dependence plots for the same six metrics illustrate the non-linear response of B-IBI to these stressor metrics – in particular to the relatively most important variables PCT Urban and POP Dens (Figure 31). The negative response of B-IBI to PCT Urban in the model is stepped, with small changes in B-IBI occurring as PCT Urban reaches about 30 percent with a large decrease in B-IBI associated with the change in PCT Urban from 30 to 40 percent. A second stepped response occurred near a PCT Urban value of 70 percent. The non-linear response in POP Dens was an initially steep negative response as POP Dens increased from the lowest value to a density of about 600 people per km^2 followed by no further reduction in B-IBI beyond that level of population density. Non-linear responses were also present in the less important of the six variables, including a negative non-linear response to RD dens, a positive non-linear response to Elev mean and smaller negative non-linear response to PCT Imp (Figure 31).

Table 21. Summary of boosted regression tree (BRT) results for B-IBI versus stressor categories and groups of stressor categories.

Model (n = number of sites included in model) / six most important model variables (variable relative importance in percent)	Cross Validation R^2
B-IBI ~ Land Cover (n=52)	
PCT Urban (48), POP Dens (18), RD Dens (11), Elev mean (6), PCT Imp (6), PCT Forest (3)	0.94
B-IBI ~ Habitat (n=52)	
PWP All (22), D50 (14), X DensioCenter (13), X BFWidth (8), X Embed (5), PCTFines (4)	0.24
B-IBI ~ Temperature (n=48)	
MinT (65), DielRange (9), X7DMax (9), MeanT (6), X1DMax (5), DaysGT17p5 (4)	0.64
B-IBI ~ Hydrology (n=28)	
High Pulse Duration (58), High Pulse Count (25), R-B Index (12), Flow Reversals (2), High Pulse Range (2), TQ Mean (1)	***0.51***
B-IBI ~ Land Cover + Habitat (n=52)	
PCT Urban (47), POP Dens (21), RD Dens (12), Elev mean (7), PCT Imp (5), PWP All (4)	0.88
B-IBI ~ Land Cover + Habitat + Temperature (n=48)	
PCT Urban (46), POP Dens (24), RD Dens (12), Elev mean (5), PWP All (4), PCT Imp (3)	0.91
B-IBI ~ Land Cover + Habitat + Temperature + Hydrology (n=28)	
PCT Urban (51), POP Dens (22), PWP All (11), High Pulse Duration (4), PCT Imp (4), RD Dens (4)	***0.88***
B-IBI ~ Habitat + Temperature + Hydrology (n=28)	
High Pulse Duration (55), PWP All (19), High Pulse Count (19), R-B Index (4), X BFWidth (2), MinT (0.1)	***0.93***

Note: The Cross Validation (CV) coefficient of determination (R^2) or CV R^2 results in red italics are intended to highlight that these models include hydrologic metrics, which require the inclusion of Sentinel Sites and an increase in the BRT model bag fraction from 0.75 to 0.9.

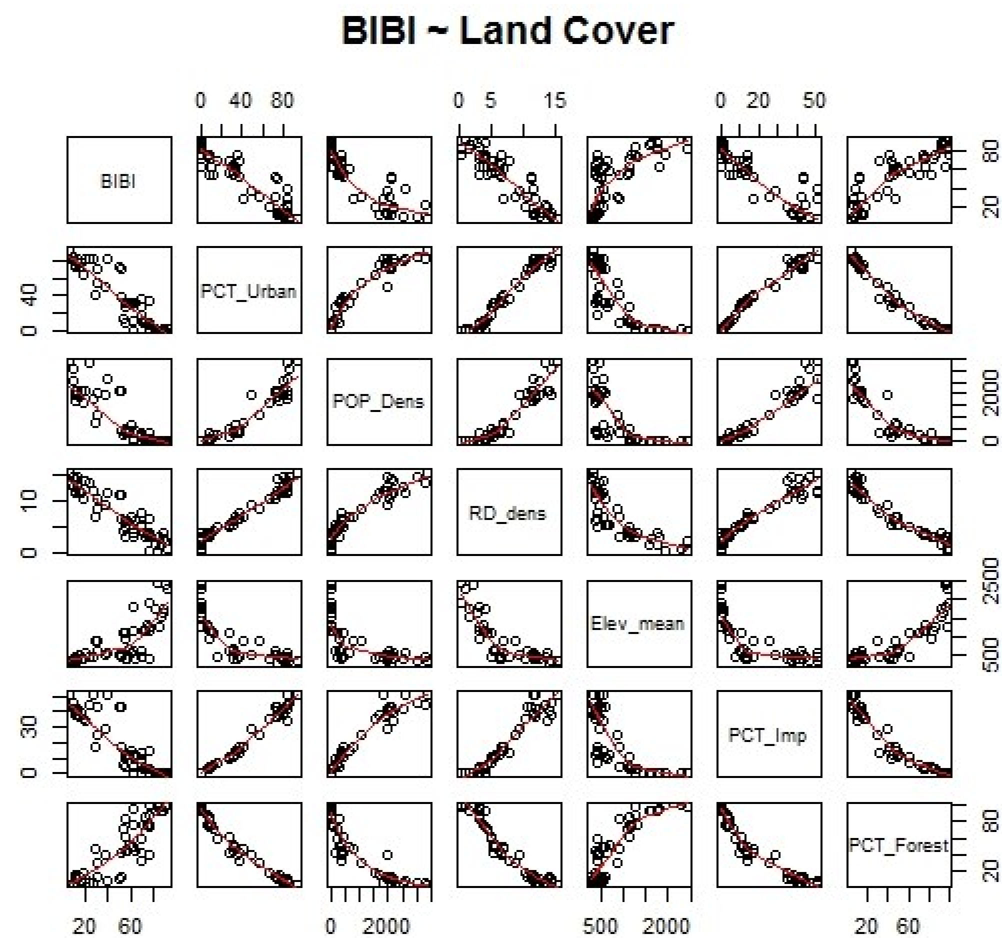

Figure 30. Scatterplot matrix of B-IBI versus six most important land cover metrics identified in the boosted regression tree (BRT) model.

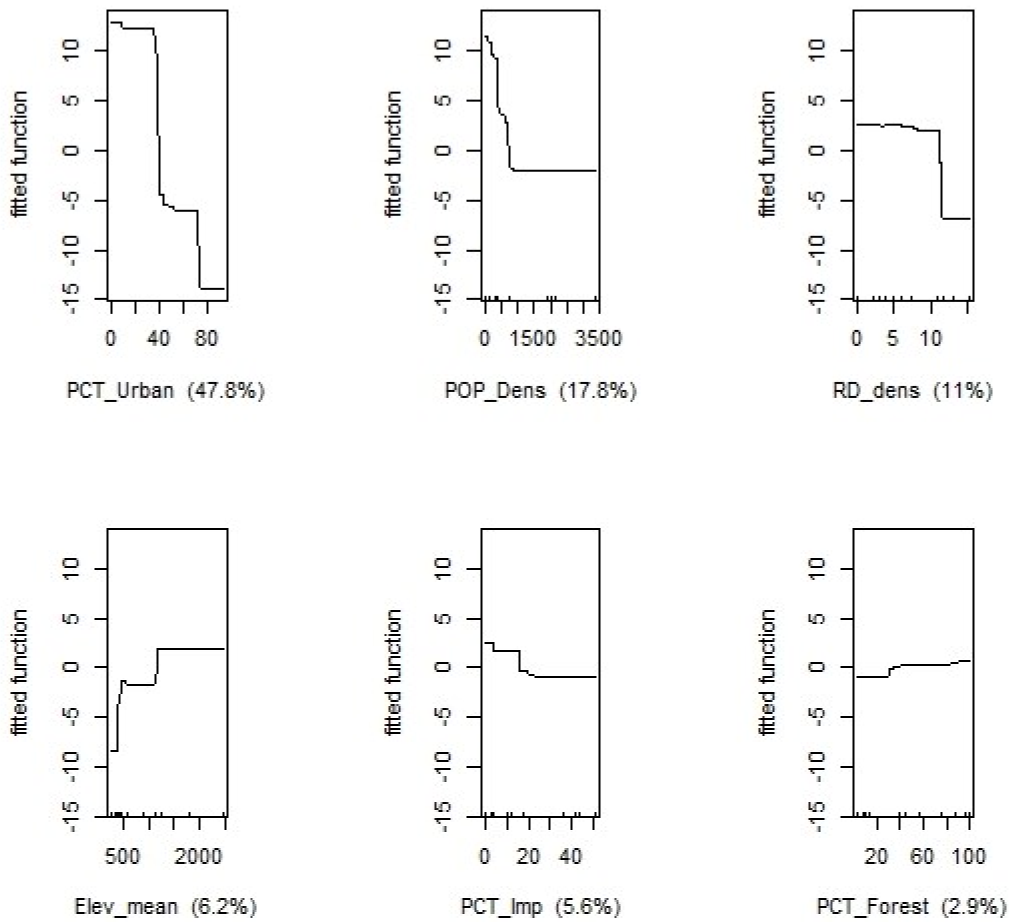

Figure 31. Partial dependence plots of the six most relatively important land cover metrics in the boosted regression tree (BRT) model of B-IBI (y-axis=fitted function of B-IBI) based on the effect of individual metrics with the response of all other metrics removed.

Note: Variables shown in order of importance from left to right beginning with PCT Urban. The proportion of variance explained by each variable is given by the percentage value below each plot. The fitted line within each plot shows the influence of the variable upon the dependent variable with all other variables held constant. The x-axes show the range of the predictor variable across all sites. The 'fitted-function' on the y-axis is the centered response metric value centered on zero.

3.4.1.2 B-IBI vs Habitat

The BRT model explained about 24 percent of the variance in B-IBI (Table 21). The six most important variables in the model in order of importance were PWP All, D50, X DensioCenter, X BFWidth, X Embed, and PCT Fines (Table 21, see Table 2 for habitat metric descriptions). The lack of clear linear relationships between B-IBI and these variables is evident in the scatterplot matrix (Figure 32).

The partial dependence plots for the same six metrics further illustrate the non-linear response of B-IBI to these stressor metrics – in particular to the relatively most important variables PWP All and D50 (Figure 33). The negative response of B-IBI to PWP ALL in the model is stepped, with a small decline as PWP All increases to about 1.0 followed by a rapid decline between 1.0 and about 1.5 and then leveling off thereafter. Non-linear responses were also evident in the less important of the six variables, particularly D50, X DensioCenter, X BFWidth and X Embed (Figure 33).

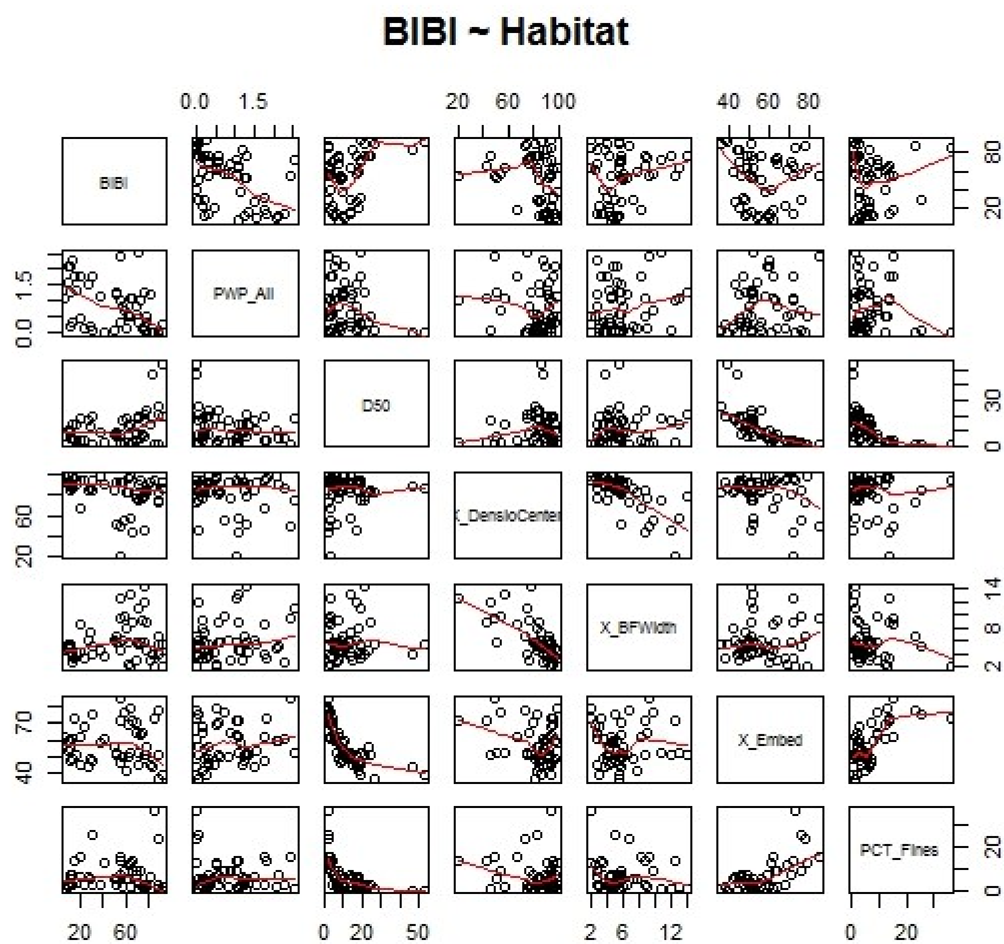

Figure 32. Scatterplot matrix of B-IBI versus six most important habitat metrics identified in the boosted regression tree (BRT) model.

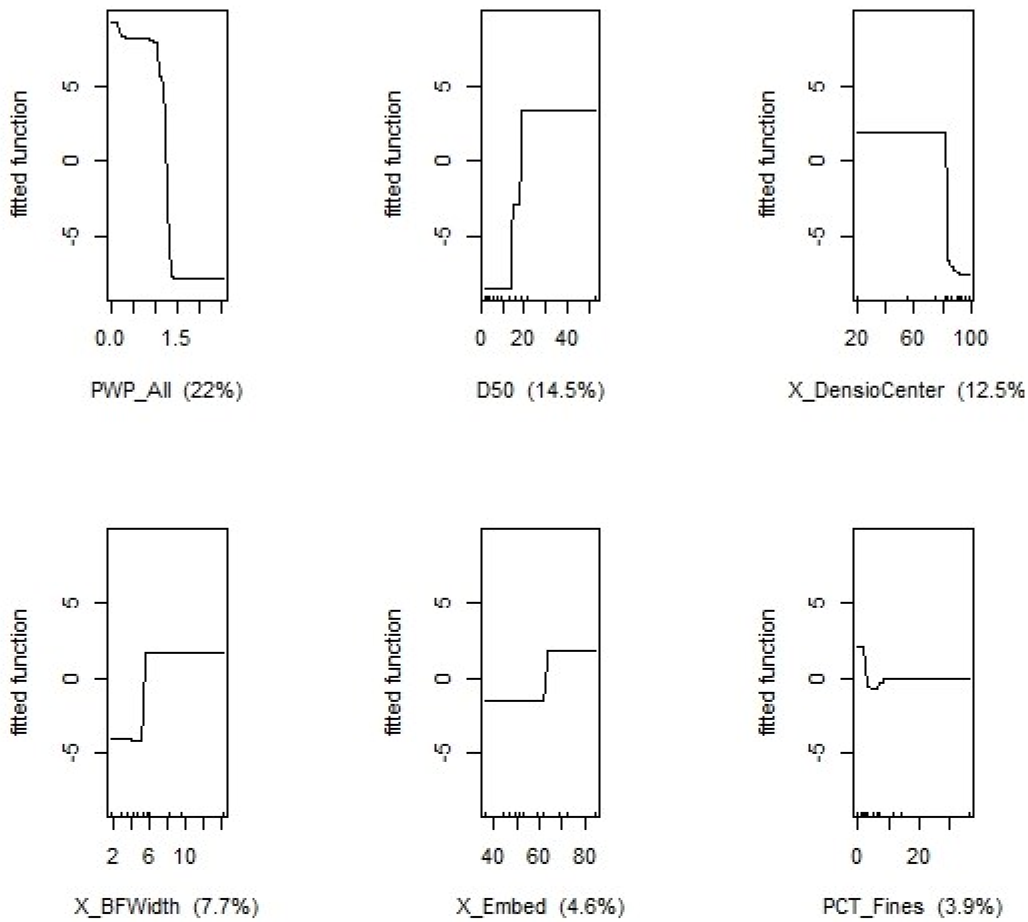

Figure 33. Partial dependence plots of the six most relatively important habitat metrics in the boosted regression tree (BRT) model of B-IBI (y-axis=fitted function of B-IBI) based on the effect of individual metrics with the response of all other metrics removed.

Note: Variables shown in order of importance from left to right beginning with PWP All. The proportion of variance explained by each variable is given by the percentage value below each plot. The fitted line within each plot shows the influence of the variable upon the dependent variable with all other variables held constant. The x-axes show the range of the predictor variable across all sites. The 'fitted-function' on the y-axis is the centered response metric value centered on zero.

3.4.1.3 B-IBI vs Temperature

The BRT model explained about 64 percent of the variance in B-IBI (Table 21). The six most important variables in the model in order of importance were MinT, DielRange, X7DMax, MeanT, X1DMax and DaysGT17p5 (Table 21, see Table 6 for a description of temperature metrics). MinT was by far the relatively most important variable (65 percent) compared to DielRange, the second most important variable (9 percent) (Table 21). The lack of clear linear relationships between B-IBI and these variables, with the possible exception of MinT, is evident in the matrix scatterplot (Figure 34). The scatterplot also illustrates the high degree of correlation among these temperature metrics, particularly among MeanT, X1DMax and X7DMax (Figure 34). The partial dependence plot for the same six metrics illustrates the particularly non-linear response of B-IBI to MinT (Figure 35). The negative response of B-IBI to MinT in the model is stepped, with no decline in B-IBI until MinT reaches 11 °C followed by a steep decline from 11 to a little over 12 °C and then leveling out thereafter.

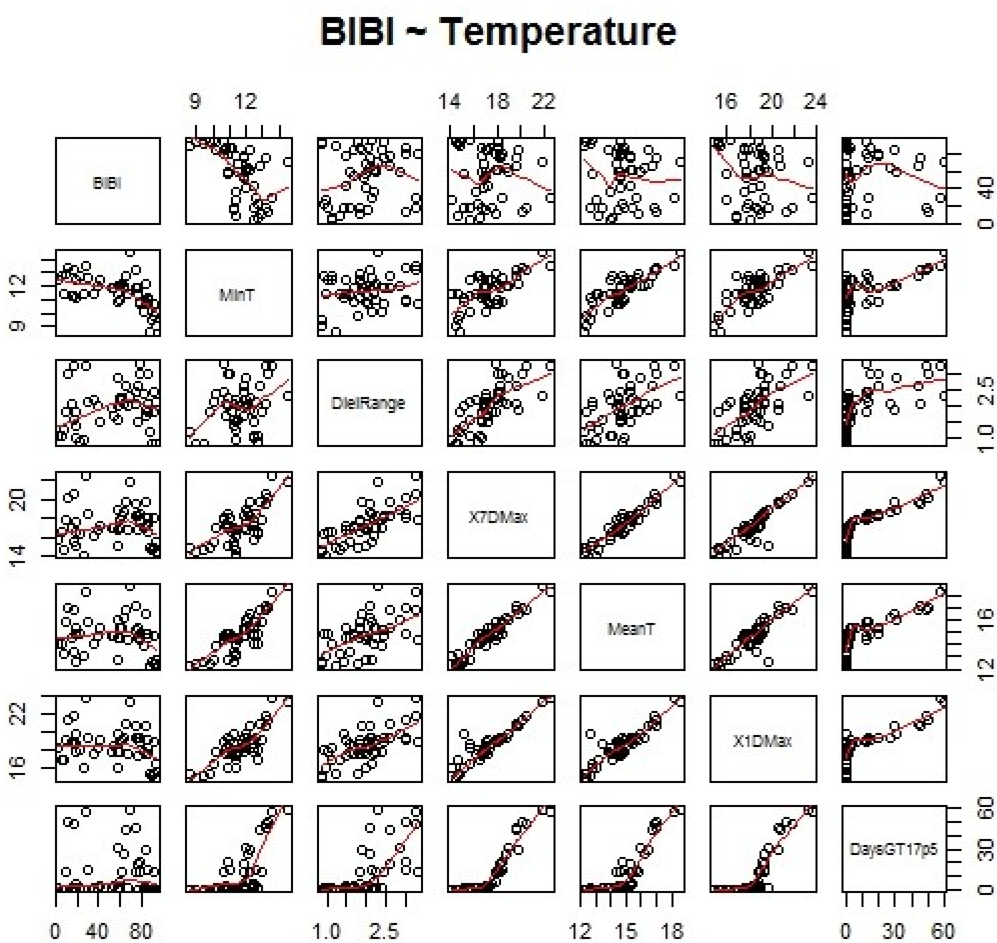

Figure 34. Scatterplot matrix of B-IBI versus six most important temperature metrics identified in the boosted regression tree (BRT) model.

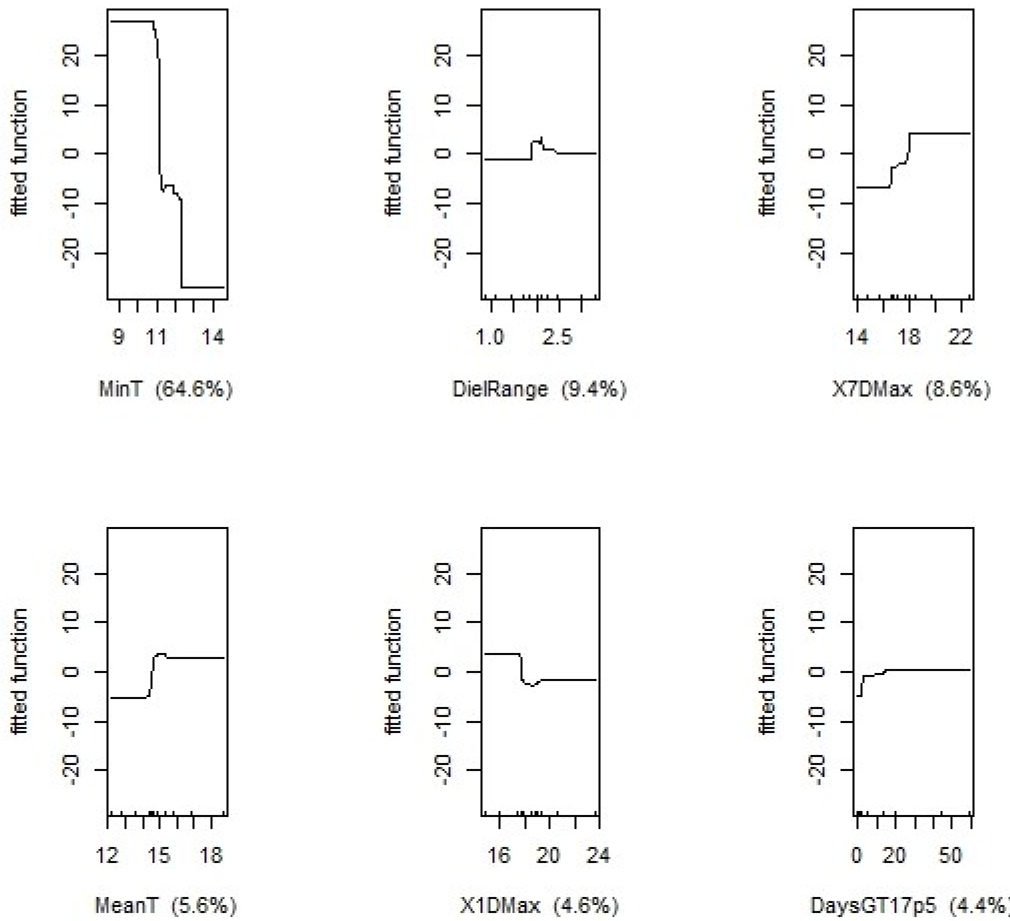

Figure 35. Partial dependence plots of the six most relatively important temperature metrics in the boosted regression tree (BRT) model of B-IBI (y-axis=fitted function of B-IBI) based on the effect of individual metrics with the response of all other metrics removed.

Note: Variables shown in order of importance from left to right beginning with MinT. The proportion of variance explained by each variable is given by the percentage value below each plot. The fitted line within each plot shows the influence of the variable upon the dependent variable with all other variables held constant. The x-axes show the range of the predictor variable across all sites. The 'fitted-function' on the y-axis is the centered response metric value centered on zero.

3.4.1.4 B-IBI vs Hydrology

The BRT model explained about 51 percent of the variance in B-IBI (Table 21). The six most important variables in the model in order of importance were High Pulse Duration, High Pulse Count, R-B Index, Flow Reversals, High Pulse Range and TQ mean (Table 21, see Table 5 for a description of the hydrologic metrics). High Pulse Duration was by far the relatively most important variable (58 percent) compared to High Pulse Count, the second most important variable (25 percent) (Table 21). The relatively non-linear relationships between B-IBI and these variables are evident in the matrix scatterplot (Figure 34). The scatterplot also illustrates the high degree of correlation among these hydrologic metrics, particularly between High Pulse Count and R-B Index (Figure 34). The partial dependence plot for the same six metrics illustrates the particularly non-linear response of B-IBI to High Pulse Duration, High Pulse Count and R-B Index (Figure 37). The positive response of B-IBI to High Pulse Duration in the model is stepped, with no decline in B-IBI until High Pulse Duration reaches 3 days followed by a steep increase from 3 to a little over 13 days and then leveling out thereafter (Figure 37). Stepped negative responses were found for High Pulse Count and High Pulse Duration (Figure 37). For High Pulse Count there is little response in B-IBI until near 13 followed by a steep decline from a High Pulse Count of 13 to about 15 and then leveling off thereafter (Figure 37).

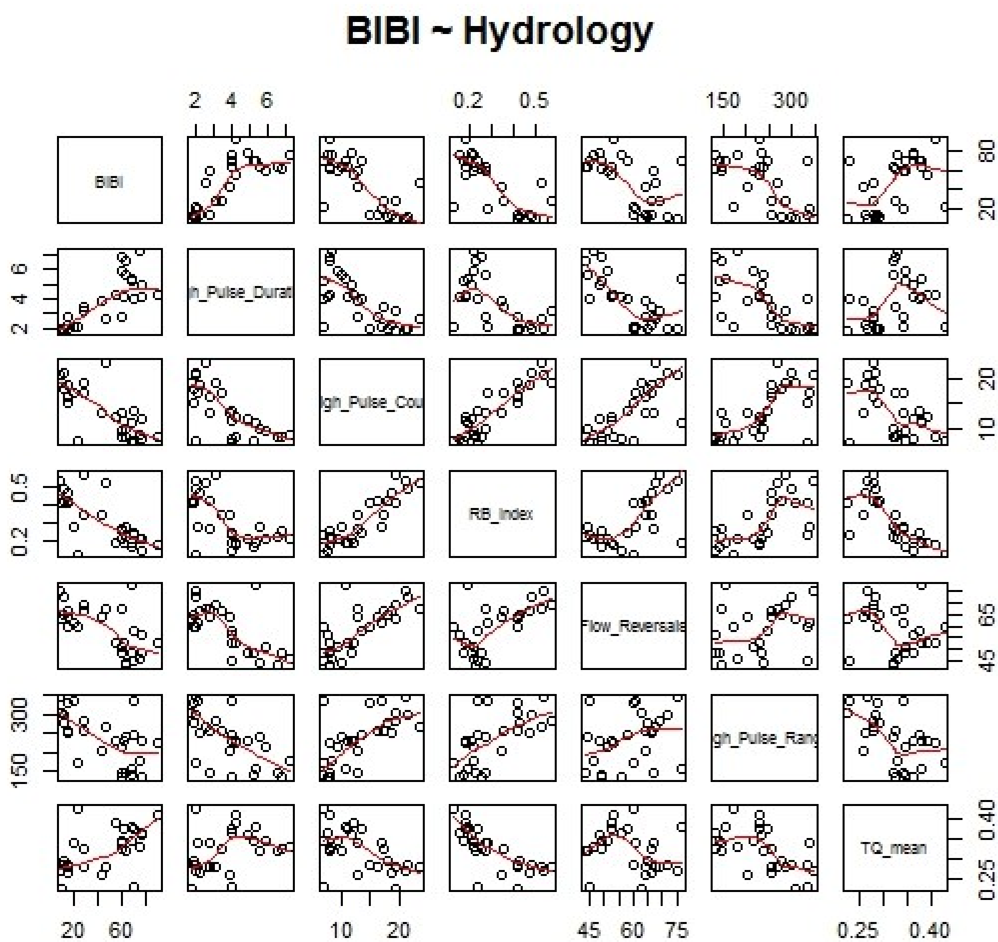

Figure 36. Scatterplot matrix of B-IBI versus six most important hydrologic metrics identified in the boosted regression tree (BRT) model.

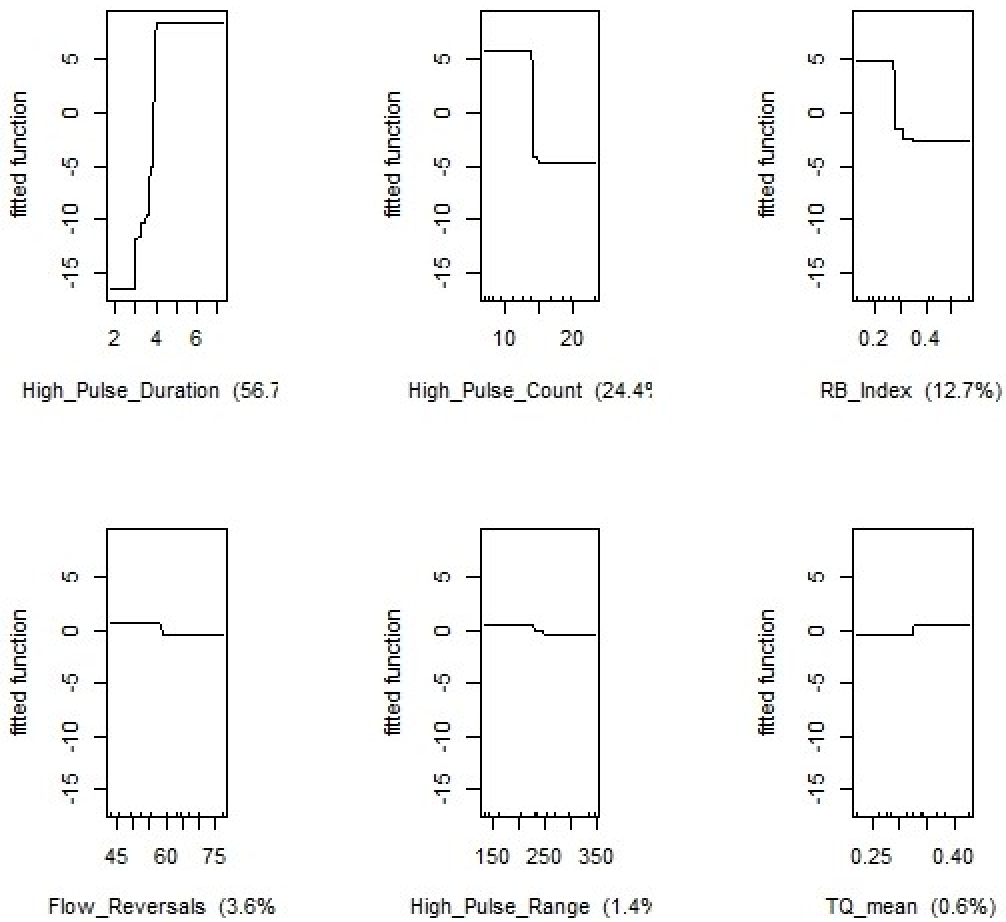

Figure 37. Partial dependence plots of the six most relatively important hydrologic metrics in the boosted regression tree (BRT) model of B-IBI (y-axis=fitted function of B-IBI) based on the effect of individual metrics with the response of all other metrics removed.

Note: Variables shown in order of importance from left to right beginning with High Pulse Duration. The proportion of variance explained by each variable is given by the percentage value below each plot. The fitted line within each plot shows the influence of the variable upon the dependent variable with all other variables held constant. The x-axes show the range of the predictor variable across all sites. The 'fitted-function' on the y-axis is the centered response metric value centered on zero.

3.4.1.5 Multiple Stressor Category B-IBI Models

Land cover and Habitat: The BRT model with just these two categories of variables explained about 88 percent of the variance in B-IBI (Table 21). The six most important variables in the model in order of importance were PCT Urban, POP Dens, RD Dens, Elev mean, PCT Imp and PWP All (Table 21). PCT Urban was by far the relatively most important variable (47 percent) compared to POP Dens, the second most important variable (21 percent) (Table 21). The only habitat variable to appear in the top six had the lowest relative importance (4 percent).

Land cover, Habitat and Temperature: The BRT model explained about 91 percent of the variance in B-IBI (Table 21). The six most important variables in the model in order of importance were PCT Urban, POP Dens, RD Dens, Elev mean, PWP All and PCT Imp (Table 21). PCT Urban was by far the relatively most important variable (46 percent) compared to POP Dens, the second most important variable (24 percent) (Table 21). The only habitat variable to appear in the top six had the next to lowest relative importance (4 percent). No temperature metrics appeared in the list of the six most important variables; DielRange was the 7^{th} most important variable (1 percent).

Land cover, Habitat, Temperature and Hydrology: The BRT model explained about 91 percent of the variance in B-IBI (Table 21). The six most important variables in the model in order of importance were PCT Urban, POP Dens, PWP All, High Pulse Duration, PCT Imp and RD Dens (Table 21). PCT Urban was by far the relatively most important variable (51 percent) compared to POP Dens, the second most important variable (22 percent) (Table 21). The list of six most important variables included one habitat metric (PWP All) and one hydrologic metric (High Pulse Duration) in addition to the four land cover metrics. No temperature metrics appeared in the list of the six most important variables; MinT was the 10^{th} most important variable (<1 percent).

Habitat, Temperature and Hydrology: The BRT model explained about 93 percent of the variance in B-IBI (Table 21). The six most important variables in the model in order of importance were High Pulse Duration, PWP All, High Pulse Count, R-B Index, X BFWidth and MinT (Table 21). High Pulse Duration was by far the relatively most important variable (55 percent) compared to PWP All, the second most important variable (19 percent) (Table 21).

3.4.2 F-IBI

3.4.2.1 F-IBI vs Land Cover

The BRT model explained about 84 percent of the variance in F-IBI (Table 22). The six most important variables in the model in order of importance were WA ha, PCT Shrub, PCT PATCH, Rd xings dens, PCT Urban, and POP Dens (Table 22, see Table 3 for a description of land cover metrics). WA ha was by far the relatively most important variable (62 percent) compared to PCT Shrub, the second most important variable (14 percent) (Table 22). Relatively non-linear relationships between F-IBI and the six relatively most important

BRT variables are evident in the matrix scatterplot (Figure 38). The partial dependence plot for the same six metrics illustrates the non-linear response of F-IBI to these stressor metrics – in particular to the relatively most important variables WA ha and PCT Shrub (Figure 39). The positive response of F-IBI to WA ha in the model indicates a steep increase in F-IBI as watershed size increases to about 1,000 ha and then levels off. The positive non-linear response of F-IBI to PCT Shrub was stepped with the increase from low to high F-IBI scores occurring over a range of PCT Shrub of 2 to 4 percent. Non-linear responses were also present in the less important of the six variables, including a positive non-linear response to PCT PATCH (Figure 39).

Table 22. Summary of boosted regression tree (BRT) results for F-IBI versus stressor categories and groups of stressor categories.

Model (n = number of sites included in model) / six most important model variables (variable relative importance in percent)	Cross Validation R^2
F-IBI ~ Land Cover (n=52)	
WA ha (62), PCT Shrub (14), PCT PATCH (10), Rd xings dens (2), PCT Urban (2), POP Dens (2)	0.84
F-IBI ~ Habitat (n=52)	
X BFWidth (42), X TWDepth (7), X PoolUnitDepth (7), ResPoolArea100 (5), X DensioCenter (5), PWP All (4)	0.77
F-IBI ~ Temperature (n=48)	
MeanT (34), DielRange (27), X7DMax (13), DaysGT16 (10), MinT (9), DaysGT17p5 (5)	0.50
F-IBI ~ Hydrology (n=28)	
Low Pulse Duration (32), X30dLow (32), High Pulse Duration (19), Flow Reversals (11), X7dLow (6), High Pulse Range (0.4)	***0.57***
F-IBI ~ Land Cover + Habitat (n=52)	
WA ha (36), X BFWidth (28), PCT Shrub (13), X PoolUnitDepth (11), PCT PATCH (8), X TWDepth (5)	0.79
F-IBI ~ Land Cover + Habitat + Temperature (n=48)	
WA ha (31), X BFWidth (26), PCT Shrub (14), X PoolUnitDepth (9), PCT PATCH (6), MeanT (4)	0.78
F-IBI ~ Land Cover + Habitat + Temperature + Hydrology (n=28)	
X BFWidth (56), X7DMax (12), High Pulse Duration (5), X30dLow (5), PCT_Shrub (5), DielRange (4)	***0.66***
F-IBI ~ Habitat + Temperature + Hydrology (n=28)	
X BFWidth (64), X7DMax (13), High Pulse Duration (7), X30dLow (5), DielRange (4), Low Pulse Duration (3)	***0.94***

Note: The Cross Validation (CV) coefficient of determination (R^2) or CV R^2 results in red italics are intended to highlight that these models include hydrologic metrics, which require the inclusion of Sentinel Sites and an increase in the BRT model bag fraction from 0.75 to 0.9.

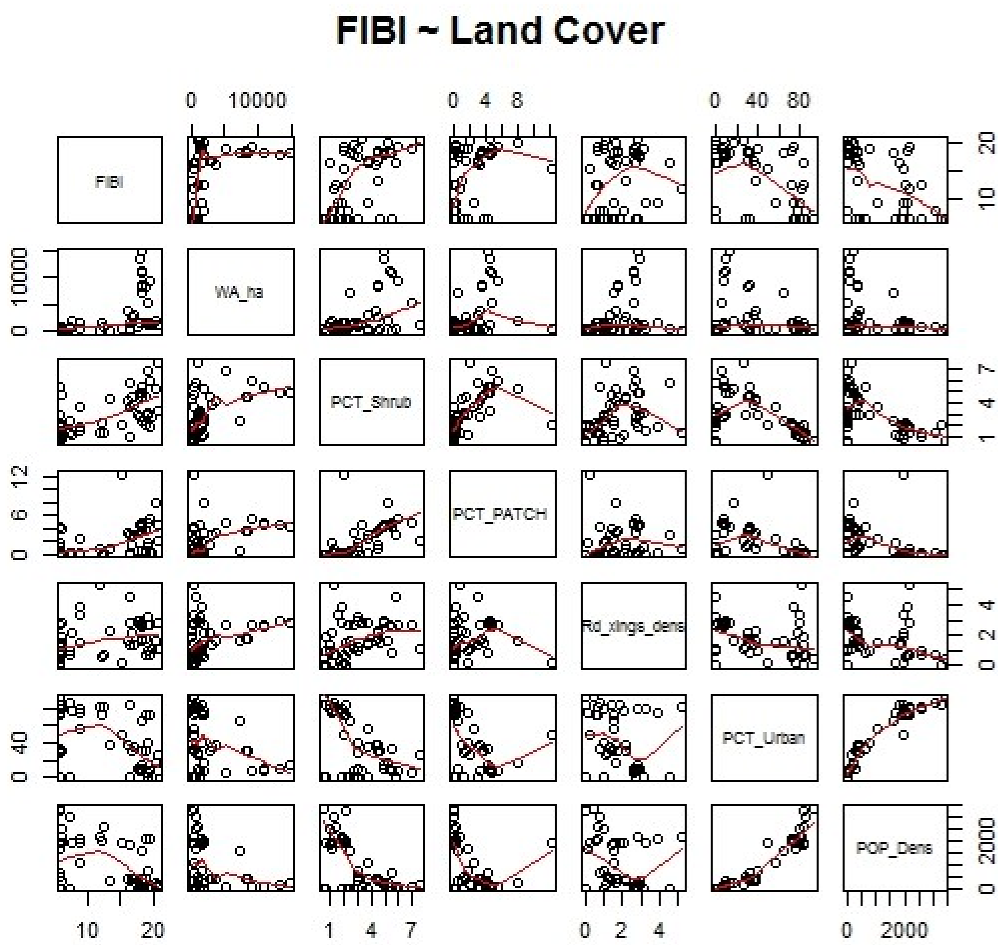

Figure 38. Scatterplot matrix of F-IBI versus six most important land cover metrics identified in the boosted regression tree (BRT) model.

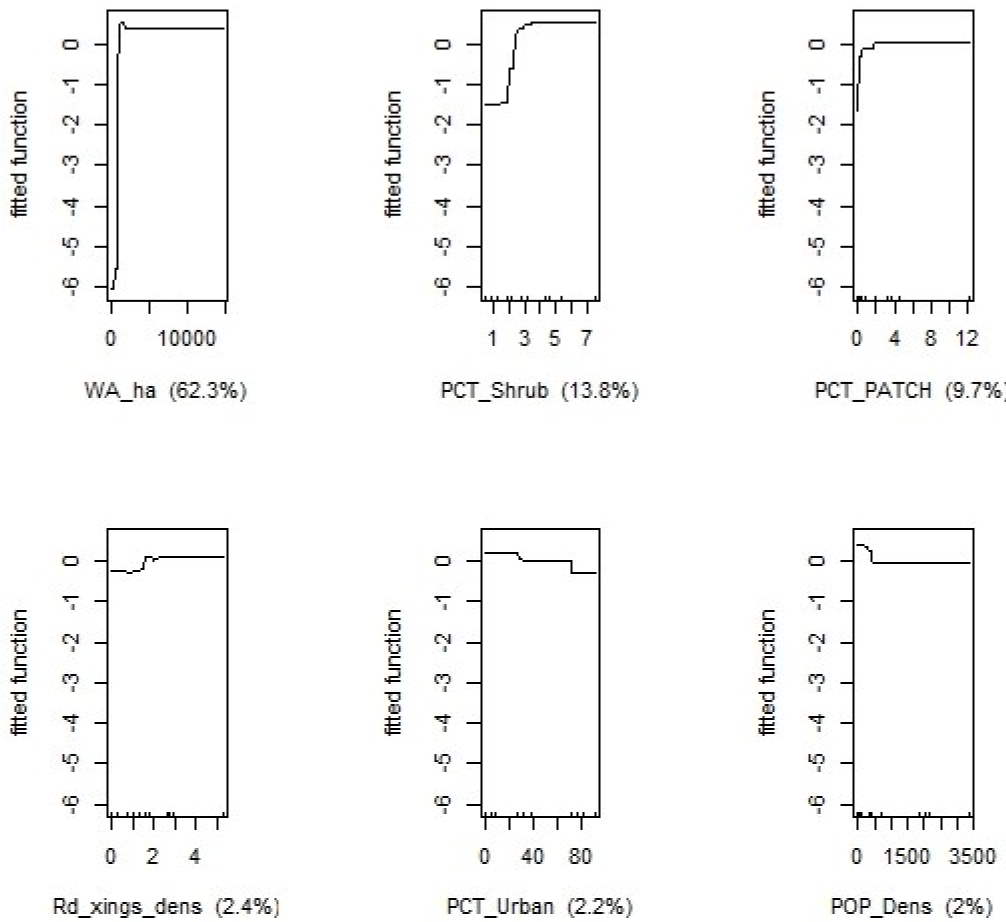

Figure 39. Partial dependence plots of the six most relatively important land cover metrics in the boosted regression tree (BRT) model of F-IBI (y-axis=fitted function of F-IBI) based on the effect of individual metrics with the response of all other metrics removed.

Note: Variables shown in order of importance from left to right beginning with WA ha. The proportion of variance explained by each variable is given by the percentage value below each plot. The fitted line within each plot shows the influence of the variable upon the dependent variable with all other variables held constant. The x-axes show the range of the predictor variable across all sites. The 'fitted-function' on the y-axis is the centered response metric value centered on zero.

3.4.2.2 F-IBI vs Habitat

The BRT model explained about 77 percent of the variance in F-IBI (Table 22). The six most important variables in the model in order of importance were X BFWidth, X TWDepth, X PoolUnitDepth, ResPoolArea100, X DensioCenter, and PWP All (Table 22, see Table 2 for a description of habitat metrics). X BFWidth was by far the relatively most important variable (42 percent) compared to X TWDepth, the second most important variable (7 percent) (Table 22). The lack of clear linear relationships between F-IBI and these variables is evident in the matrix scatterplot (Figure 40). The partial dependence plot for the same six metrics illustrates the non-linear response of F-IBI to these stressor metrics – in particular to the relatively most important variable X BFWidth (Figure 41). The positive response of F-IBI to X BFWidth in the model is stepped, with the step change from low to high F-IBI occurring between X BFWidth values of 5 and 6 m (Figure 41).

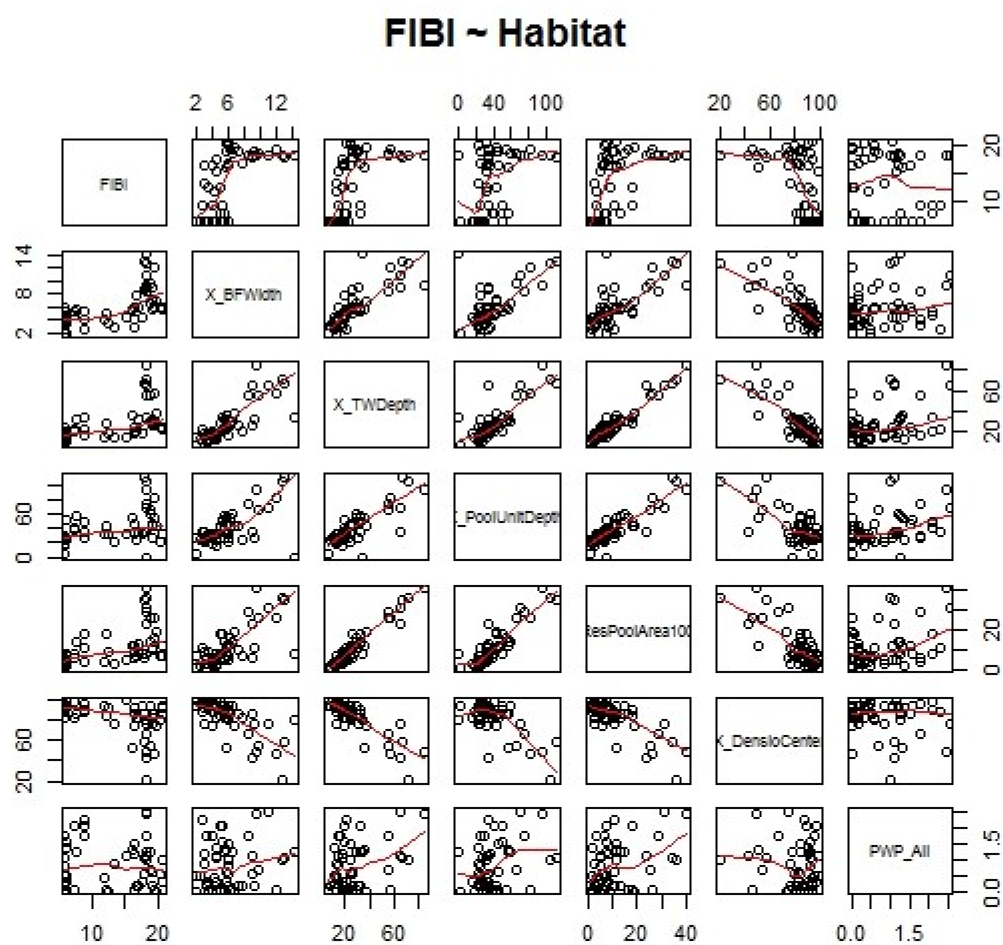

Figure 40. Scatterplot matrix of F-IBI versus six most important habitat metrics identified in the boosted regression tree (BRT) model.

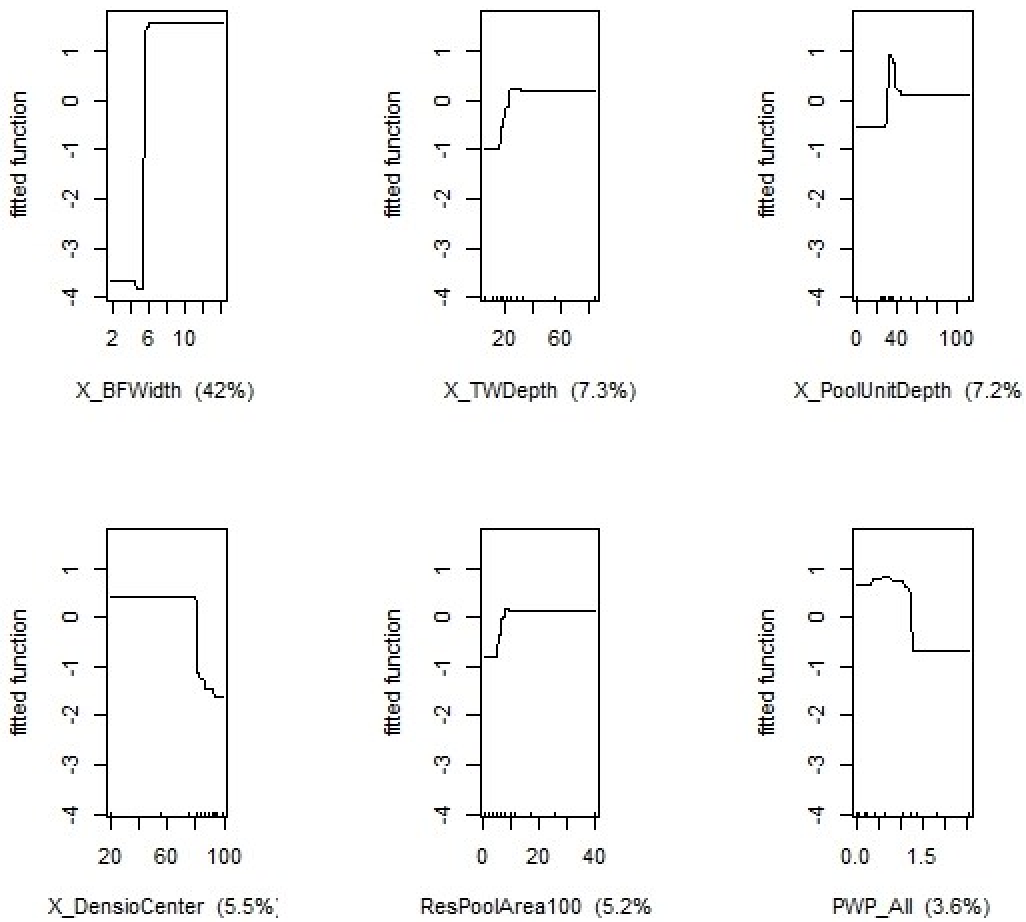

Figure 41. Partial dependence plots of the six most relatively important habitat metrics in the boosted regression tree (BRT) model of F-IBI (y-axis=fitted function of F-IBI) based on the effect of individual metrics with the response of all other metrics removed.

Note: Variables shown in order of importance from left to right beginning with X BFWidth. The proportion of variance explained by each variable is given by the percentage value below each plot. The fitted line within each plot shows the influence of the variable upon the dependent variable with all other variables held constant. The x-axes show the range of the predictor variable across all sites. The 'fitted-function' on the y-axis is the centered response metric value centered on zero.

3.4.2.3 F-IBI vs Temperature

The BRT model explained about 50 percent of the variance in F-IBI (Table 22). The six most important variables in the model in order of importance were MeanT, DielRange, X7DMax, DaysGT16, MinT and DaysGT17p5 (Table 22, see Table 6 for a description of temperature metrics). The lack of clear linear relationships between F-IBI and these variables is evident in the matrix scatterplot (Figure 42). The scatterplots also illustrate again the high degree of correlation among these temperature metrics, particularly between MeanT and X7DMax (Figure 42). The partial dependence plot for the same six metrics illustrates the particularly non-linear response of F-IBI to these temperature metrics (Figure 43). As an example, the positive response of F-IBI to MeanT in the model is stepped, with a sharp increase in F-IBI between 14 and 15 °C (Figure 43).

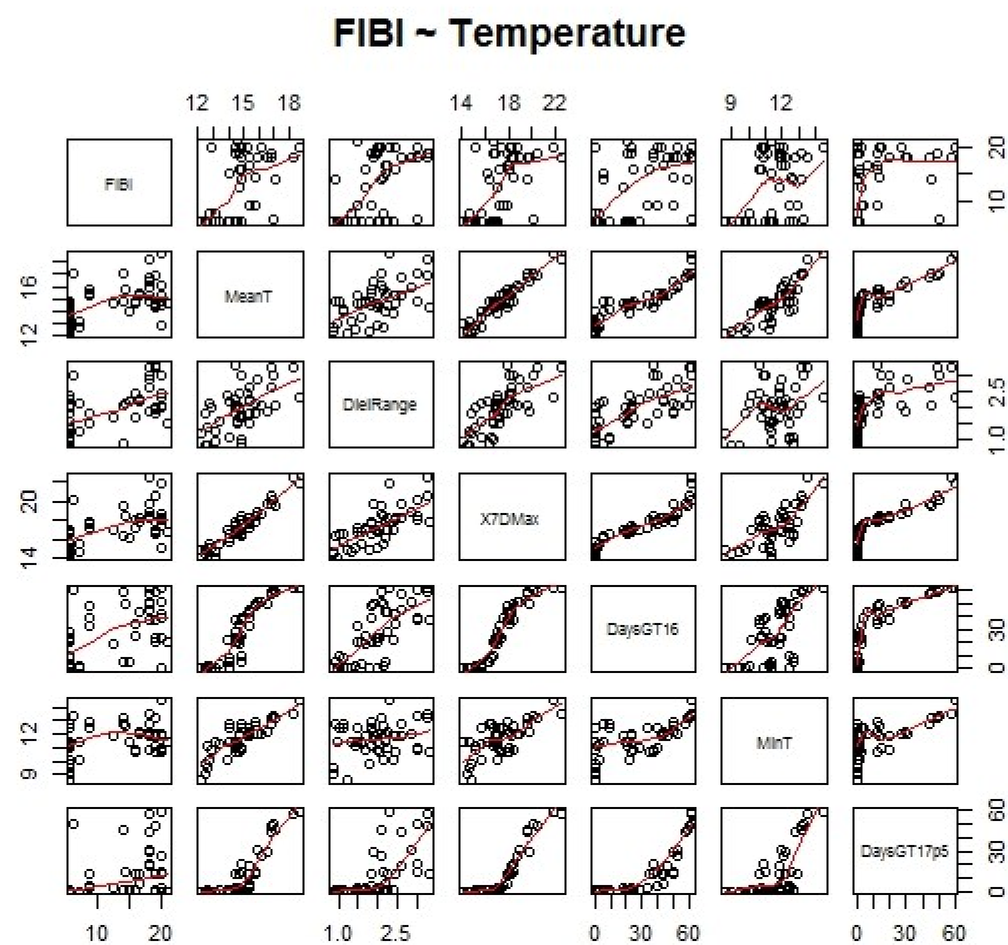

Figure 42. Scatterplot matrix of F-IBI versus six most important temperature metrics identified in the boosted regression tree (BRT) model.

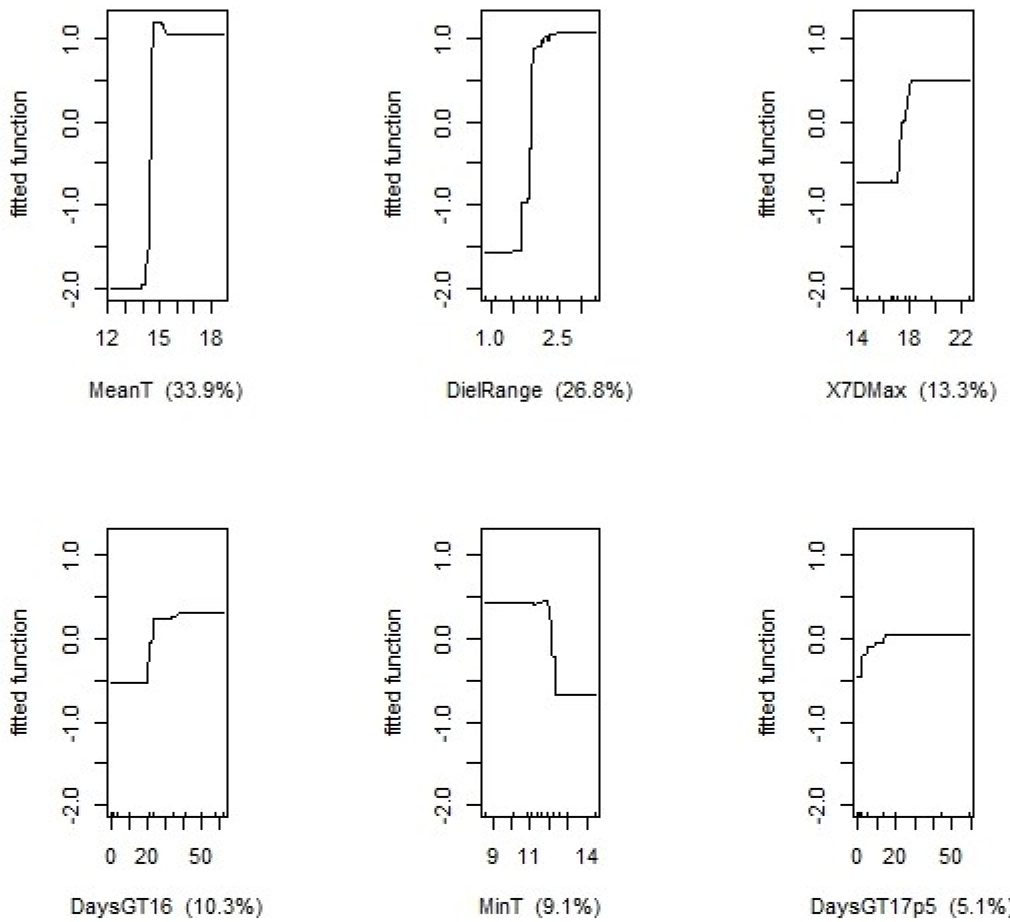

Figure 43. Partial dependence plots of the six most relatively important temperature metrics in the boosted regression tree (BRT) model of F-IBI (y-axis=fitted function of F-IBI) based on the effect of individual metrics with the response of all other metrics removed.

Note: Variables shown in order of importance from left to right beginning with MeanT. The proportion of variance explained by each variable is given by the percentage value below each plot. The fitted line within each plot shows the influence of the variable upon the dependent variable with all other variables held constant. The x-axes show the range of the predictor variable across all sites. The 'fitted-function' on the y-axis is the centered response metric value centered on zero.

3.4.2.4 F-IBI vs Hydrology

The BRT model explained about 57 percent of the variance in F-IBI (Table 22). The six most important variables in the model in order of importance were Low Pulse Duration, X30dLow, High Pulse Duration, Flow Reversals, X7dLow and High Pulse Range (Table 22, see Table 5 for a description of the hydrologic metrics). Low Pulse Duration and X30dLow were ranked equally important (32 percent) and relatively more important than the next highest ranked variable – High Pulse Duration (19 percent) (Table 22). The relatively non-linear relationships between F-IBI and these variables are evident in the matrix scatterplot (Figure 44). The scatterplot also illustrates the high degree of correlation among these hydrologic metrics, particularly between X7dLow and X30dLow (Figure 44). The partial dependence plot for the same six metrics illustrates the particularly non-linear response of F-IBI to these metrics (Figure 45). The positive response of F-IBI to Low Pulse Duration in the model is stepped, with no decline in F-IBI until Low Pulse Duration reaches about 15 days followed by a steep increase from 15 to 20 days and then leveling out thereafter (Figure 45). Stepped positive responses were found for X30dLow and High Pulse Duration and negative stepped response was found for Flow Reversals (Figure 45).

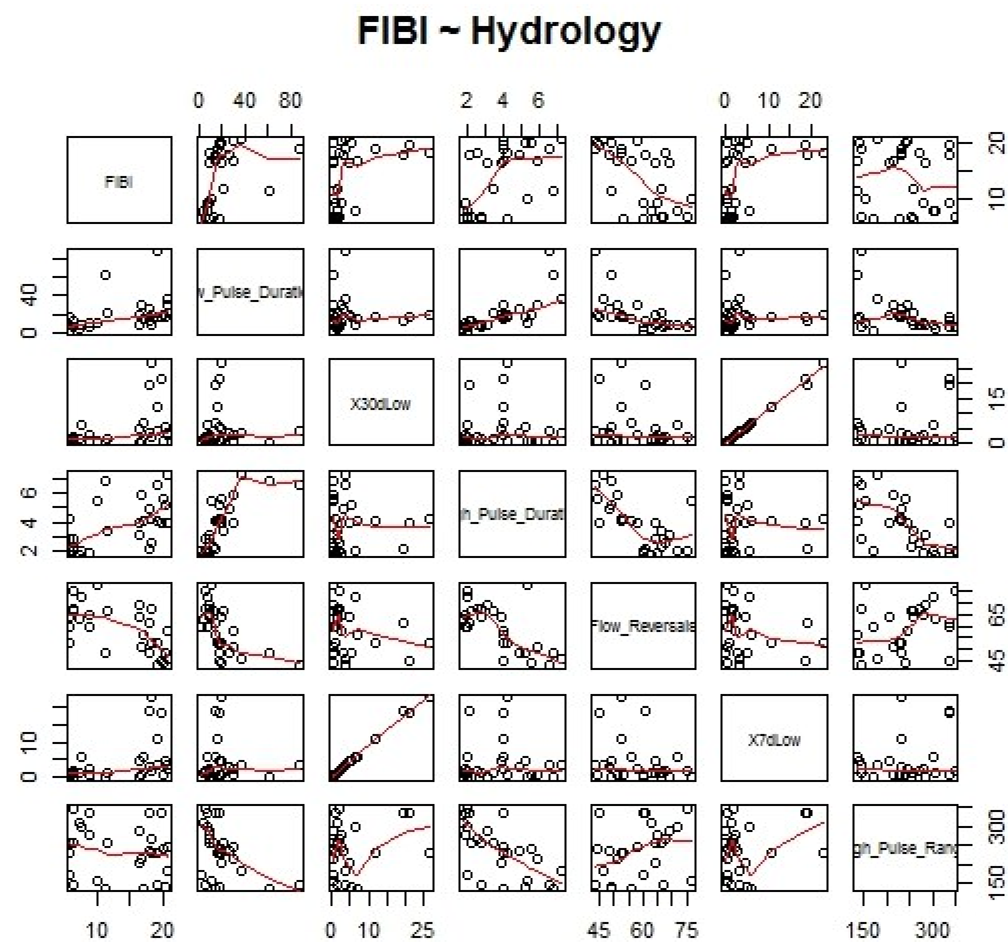

Figure 44. Scatterplot matrix of F-IBI versus six most important hydrologic metrics identified in the boosted regression tree (BRT) model.

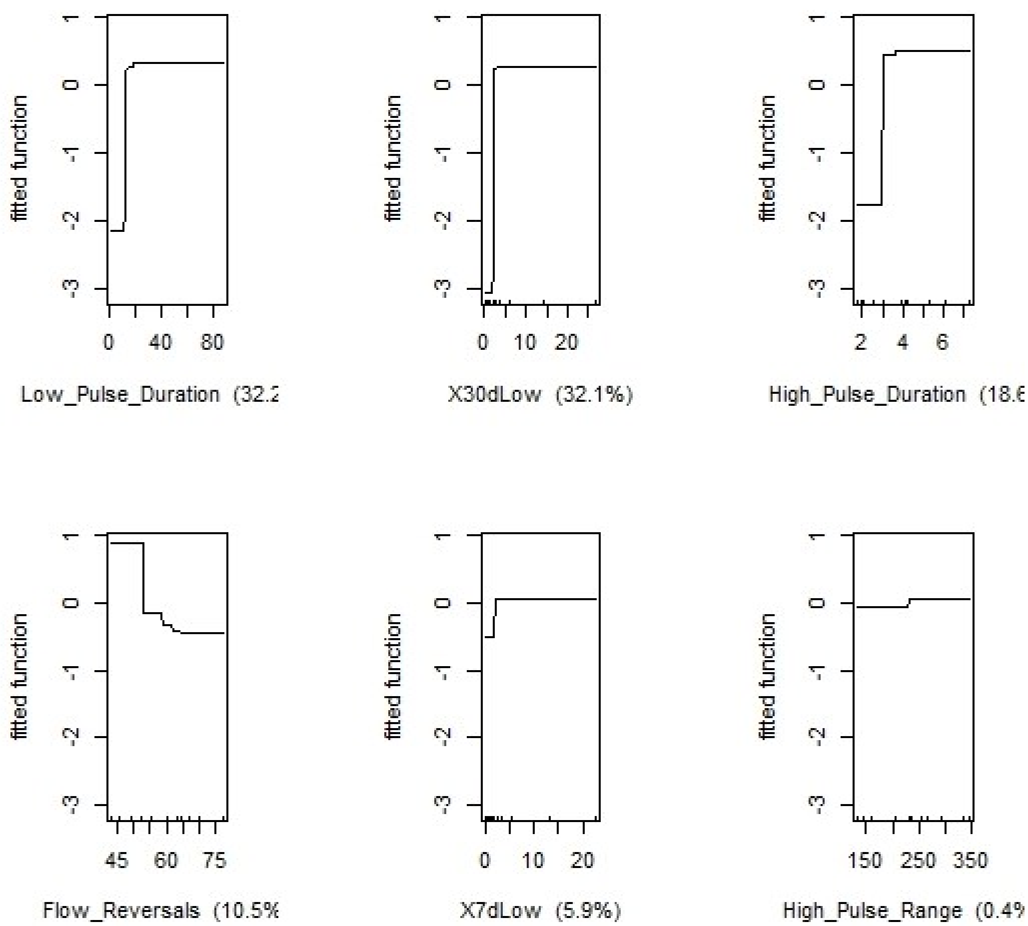

Figure 45. Partial dependence plots of the six most relatively important hydrologic metrics in the boosted regression tree (BRT) model of F-IBI (y-axis=fitted function of F-IBI) based on the effect of individual metrics with the response of all other metrics removed.

Note: Variables shown in order of importance from left to right beginning with Low Pulse Duration. The proportion of variance explained by each variable is given by the percentage value below each plot. The fitted line within each plot shows the influence of the variable upon the dependent variable with all other variables held constant. The x-axes show the range of the predictor variable across all sites. The 'fitted-function' on the y-axis is the centered response metric value centered on zero.

3.4.2.5 Multiple Stressor Category F-IBI Models

Land cover and Habitat: The BRT model with just these two categories of variables explained about 79 percent of the variance in F-IBI (Table 22). The six most important variables in the model in order of importance were WA ha, X BFWidth, PCT Shrub, X PoolUnitDepth, PCT PATCH and X TWDepth (Table 22). WA ha and X BFWidth were nearly equally as important (36 vs 28 percent) followed by PCT Shrub at 13 percent (Table 22). The only land cover variable to appear in the top six most important variables had the highest relative importance.

Land cover, Habitat and Temperature: The BRT model explained about 78 percent of the variance in F-IBI (Table 22). The six most important variables in the model in order of importance were WA ha, X BFWidth, PCT Shrub, X PoolUnitDepth, PCT PATCH and MeanT (Table 22). WA ha and X BFWidth were again nearly equally as important (31 vs 26 percent) followed by PCT Shrub at 14 percent (Table 22).

Land cover, Habitat, Temperature and Hydrology: The BRT model explained about 66 percent of the variance in F-IBI (Table 22). The six most important variables in the model in order of importance were X BFWidth, X7DMax, High Pulse Duration, X30dLow, PCT Shrub and DielRange (Table 22).). X BFWidth was by far the relatively most important variable (56 percent) compared to X7DMax, the second most important variable (12 percent) (Table 22). WA ha did not appear in the list off the top six relatively most important variables; WA ha was the 7^{th} most important variable (3 percent).

Habitat, Temperature and Hydrology: The BRT model explained about 94 percent of the variance in F-IBI (Table 22). The six most important variables in the model in order of importance were X BFWidth, X7DMax, High Pulse Duration, X30dLow, DielRange and Low Pulse Duration (Table 22). X BFWidth was by far the relatively most important variable (64 percent) compared to X7DMax, the second most important variable (13 percent) (Table 22).

3.5 Trend Detection Power

Based on the status and trends and stressor response results presented above, we selected several metrics for trend detection power analysis. These metrics were chosen because they included replicate field samples and were used in the status evaluation above (B-IBI, LWDSiteVolume100m, PCT SandFines, ResPoolArea100) or were identified as relatively important variables that explained the variance in B-IBI scores in WRIA 8 (PWP All, D50 and X DensioCenter).

Based on the estimated component variances for B-IBI and this study's repeat visit design for 50 sample sites, the power to detect a 1, 2 or 3 percent change in the overall mean B-IBI score of 52 is presented in Figure 46. For the smallest incremental change in B-IBI scores (1 percent per year) a power of 0.8 is not reached until near the end of a 20-year sampling period. Trend detection power increases substantially over time for the other two hypothesized rates of change, reaching 0.8 in about 12 to 13 years for a rate of change of 2 percent and in about 9 to 10 years for a 3 percent rate of change. Although it is not addressed explicitly here, it should be noted that these power curves have a certain degree of uncertainty as the variance estimates are just that – estimates (Skalski, 2012) and we are assuming no serial or spatial correlation across time or sites.

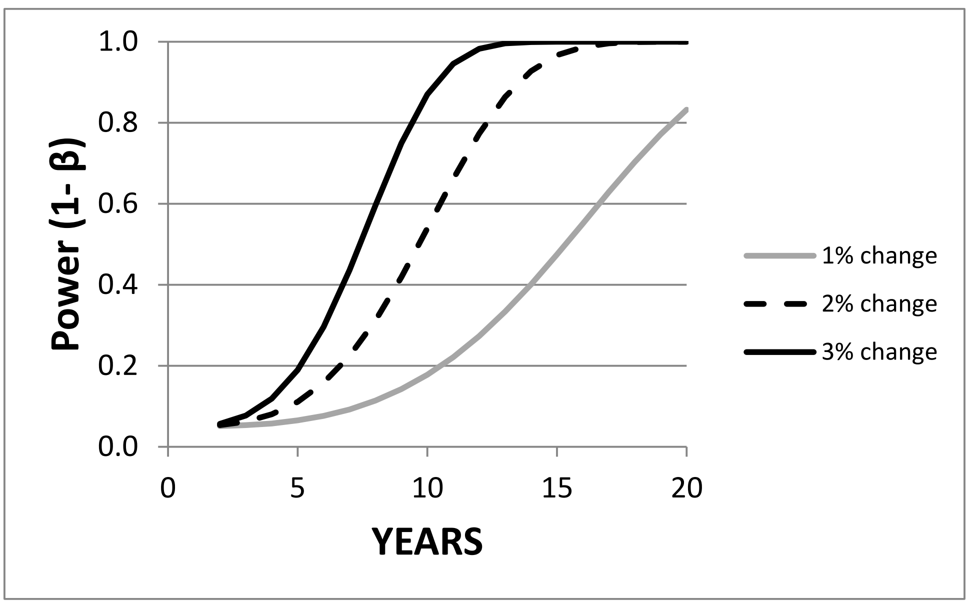

Figure 46. Plot illustrating the power to detect a 1, 2 or 3 percent change (average trend) in B-IBI scores over a 20-yr period based on a repeat visit sampling design of 50 random tessellation stratified sites across WRIA 8.

Based on the estimated components of variance for LWDSiteVolume100m, the power to detect a 1, 2 or 3 percent change in the overall mean of LWDSiteVolume100m of 33.5 $m^3/100$ m is presented in Figure 47. For the smaller incremental changes in LWDSiteVolume100m (1 and 2 percent per year), a power of 0.8 is not reached by the end of a 20-yr sampling period. Trend detection power increases substantially over time for the rate of change of 3 percent reaching 0.8 in about 17 to 18 years.

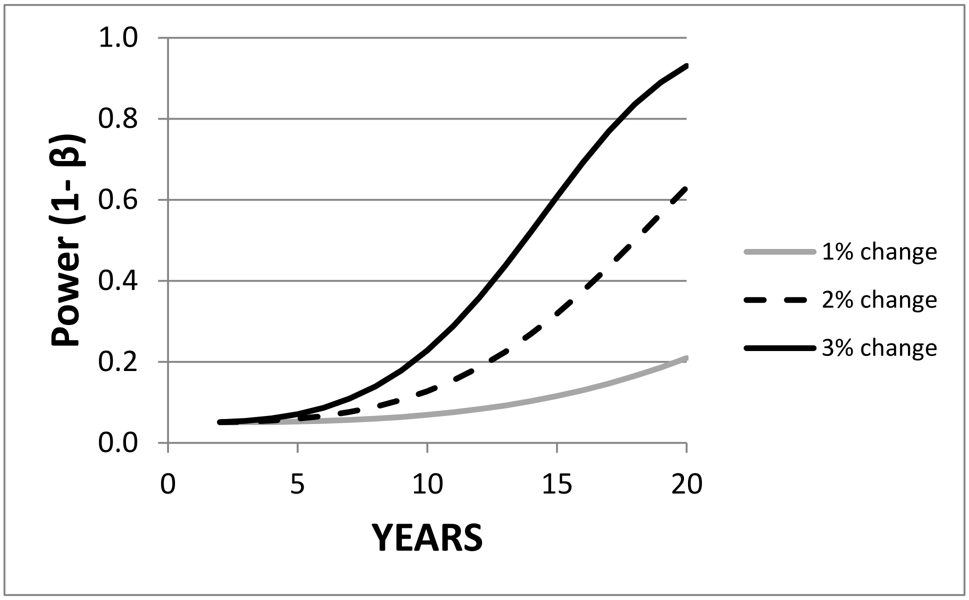

Figure 47. Plot illustrating the power to detect a 1, 2 or 3 percent change (average trend) in LWDSiteVolume100m over a 20-yr period based on a repeat visit sampling design of 50 random tessellation stratified sites across WRIA 8.

Based on the estimated components of variance for PCT SandFines, the power to detect a 1, 2 or 3 percent change in the overall mean of PCT SandFines of 30.2 percent is presented in Figure 48. For a 1 percent change in PCT SandFines, a power of 0.8 is not reached until year 16 or 17. Trend detection power increases substantially over time for the rate of change of 2 and 3 percent reaching 0.8 in about 11 and 8 years, respectively.

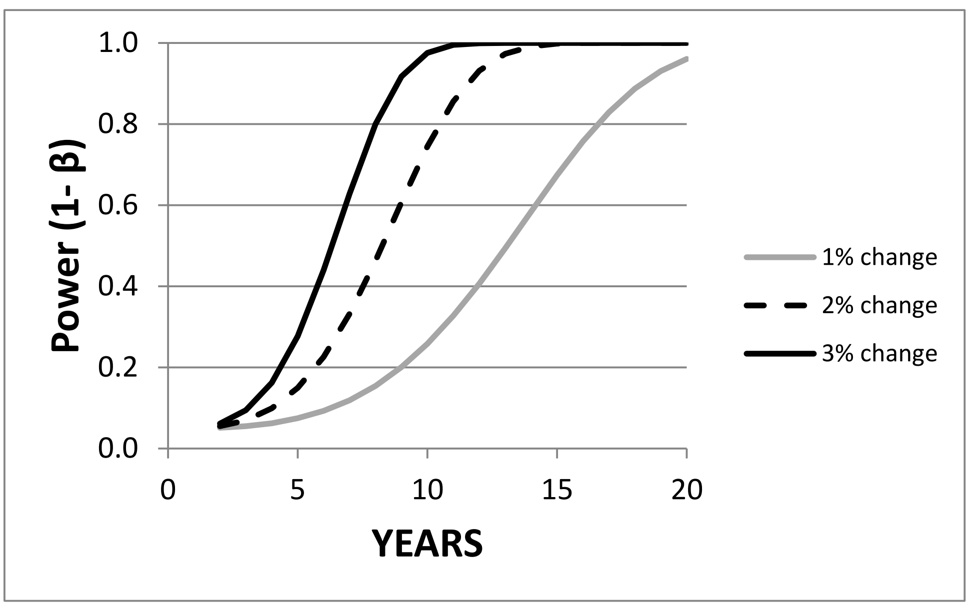

Figure 48. Plot illustrating the power to detect a 1, 2 or 3 percent change (average trend) in PCT SandFines over a 20-yr period based on a repeat visit sampling design of 50 random tessellation stratified sites across WRIA 8.

The power curves for ResPoolArea100 were very similar to those for PCT SandFines. Based on the components of variance for PCT SandFines, the power to detect a 1, 2 or 3 percent change in the overall mean of 11.2 m^2 is presented in Figure 49. For a hypothetical rate of change of 1 percent per year, a power of 0.8 is not reached until year 14. Trend detection power for a 2 percent change reaches a power of 0.8 in about 8 to 9 years. For a 3 percent change, a power of 0.8 is reached in 7 years.

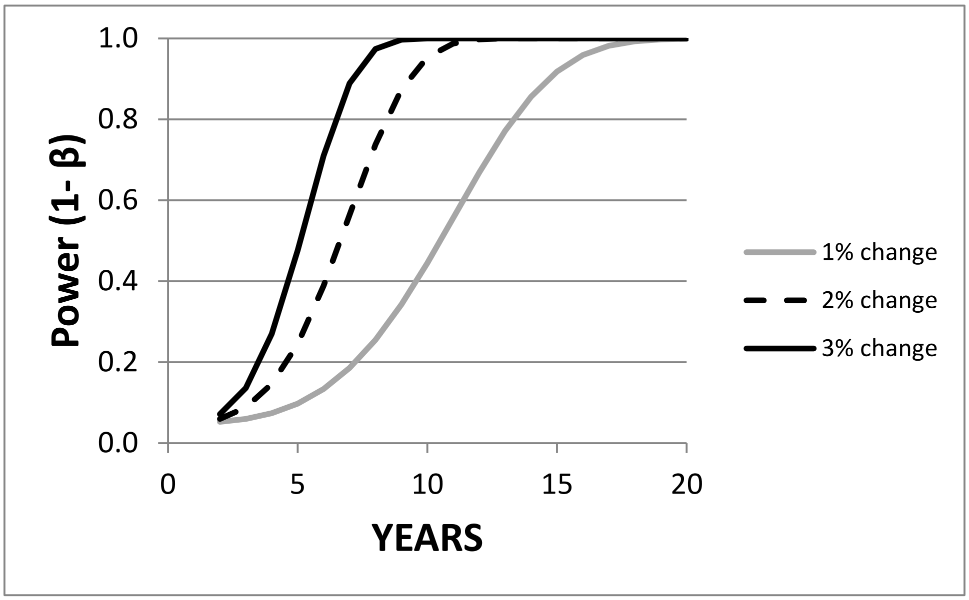

Figure 49. Plot illustrating the power to detect a 1, 2 or 3 percent change (average trend) in ResPoolArea100 over a 20-yr period based on a repeat visit sampling design of 50 random tessellation stratified sites across WRIA 8.

The power curves for PWP All were very similar to those for LWDSiteVolume100m. Based on the components of variance for PWP All, the power to detect a 1, 2 or 3 percent change in the overall mean of 0.84 is presented in Figure 50. For hypothetical rates of change of 1 and 2 percent per year, a power of 0.8 is not reached by the end of the 20-yr sampling period. Trend detection power for a 3 percent change does reach a power of 0.8 in about 17 to 18 years.

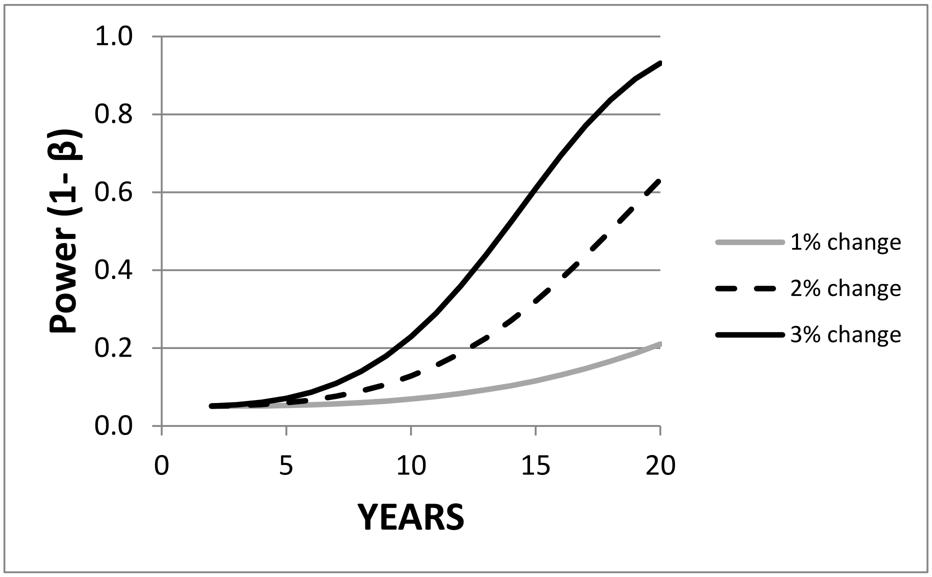

Figure 50. Plot illustrating the power to detect a 1, 2 or 3 percent change (average trend) in PWP All over a 20-yr period based on a repeat visit sampling design of 50 random tessellation stratified sites across WRIA 8.

The power curves for D50 were similar to those for B-IBI. Based on the estimate components of variance for D50, the power to detect a 1, 2 or 3 percent change in the overall mean of 11.8 is presented in Figure 51. For the smallest incremental change in D50 (1 percent per year), a power of 0.8 is not reached by the end of a 20-yr sampling period. Trend detection power increases substantially over time for the other two hypothesized rates of change reaching 0.8 in about 15 years for a rate of change of 2 percent and in about 11 to 12 years for a 3 percent rate of change.

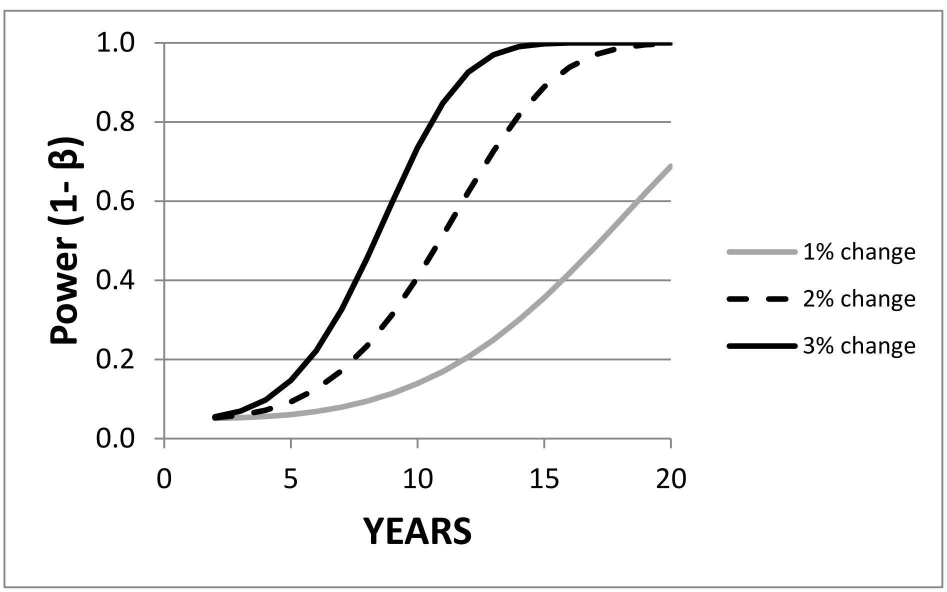

Figure 51. Plot illustrating the power to detect a 1, 2 or 3 percent change (average trend) in D50 over a 20-yr period based on a repeat visit sampling design of 50 random tessellation stratified sites across WRIA 8.

Based on the estimated components of variance for X DensioCenter, the power to detect a 1, 2 or 3 percent change in the overall mean of 81.8 percent is presented in Figure 52. Note that for all three incremental rates of change in X DensioCenter, a power of 0.8 is reached in two to three years.

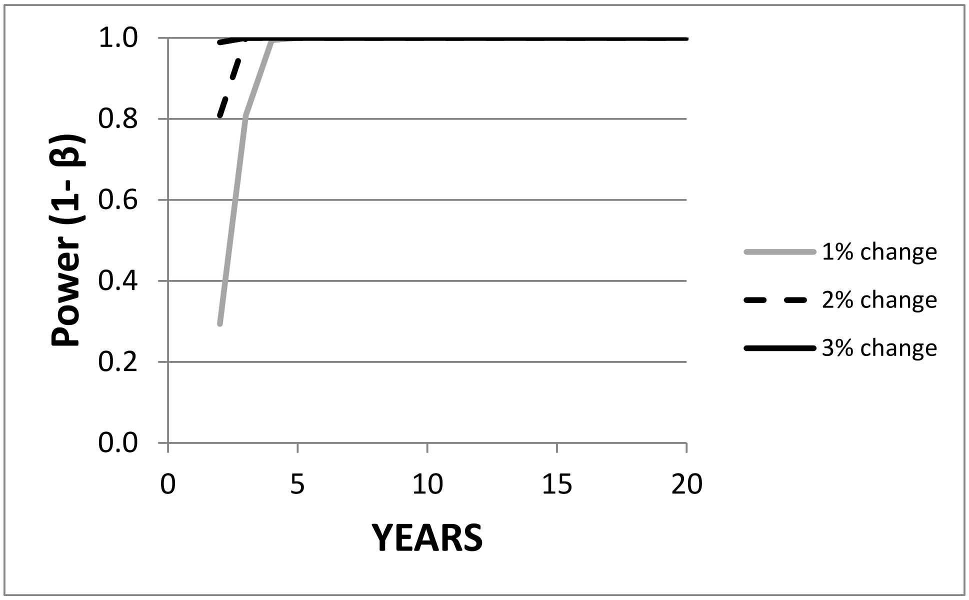

Figure 52. Plot illustrating the power to detect a 1, 2 or 3 percent change (average trend) in X DensioCenter over a 20-yr period based on a repeat visit sampling design of 50 random tessellation stratified sites across WRIA 8.

4.0 DISCUSSION

This section of the report discusses the results in the context of the project purposes and management questions described in Section 1. The primary purpose of this project was to assess the condition of stream and riparian habitat along wadeable salmon streams in the WRIA 8 watershed, in order to inform adaptive management as part of the WRIA 8 Chinook Salmon Conservation Plan. A secondary purpose was to investigate relationships between land cover, hydrology, habitat, and biological assemblages in the watershed along an urbanization gradient.

4.1 Survey Design Implementation

We used an "always revisit" sampling approach, visiting the same locations every year for four years (see Section 2.8.4). Because the survey design was spatially-balanced and probabilistic, it is possible to extrapolate the results to the sampled target stream population. This type of survey design has been used successfully in the state of Washington (Merritt and Hartman, 2012) and nationally (Kaufmann et al., 2014b). The approach chosen was known to be relatively powerful statistically, minimized the chance of bias, and allowed for extrapolation. However, at least two possible sources of bias (target population bias and selection bias) were present in our implementation of the survey design.

4.1.1 Target Population Bias

Ideally, the sampled population fully represents the population of interest. However, if some planned locations are not sampled, bias may be introduced. In our study, nearly 39 percent of the sites we initially identified as target reaches were not sampled due to lack of landowner permission. Landowner access is sometimes problematic along small streams, especially in heavily populated areas in WRIA 8, because small streams are often on private property. It may require the permission of many separate landowners to survey a single contiguous 150-meter reach. This inability to sample on private property may introduce bias toward sampling reaches in public ownership, where permission is generally given – and where habitat conditions might be different than in reaches running through private property. Of the 50 reaches sampled in WRIA 8, 32 (62 percent) were in public ownership. We cannot rule out the possibility of bias in our sample. Therefore, in our extrapolations we limited our frame of inference to the sampled stream extent rather than the assumed target stream extent.

4.1.2 Selection Bias

In two cases, ambiguous placement of the sample points on the map (equidistant between two tributaries) resulted in the survey team sampling the wrong reach. One case was in a Tier 2 area (tributary to Little Bear Creek) and one in a Tier 3 area (tributary to Piper's Creek). These errors were random and represented only a small proportion of the sites sampled. We chose to include the survey results from those tributaries in examinations of

stressor-response relationships, though we excluded them from the calculations of survey weights and associated continuous and categorical analyses.

4.2 Precision Analysis

The precision analysis confirmed that B-IBI developed on the 0-100 scale (King County, 2014a) has relatively high precision with a S:N of 16.1 and a σ_{rep}/Rg_{obs} of 0.067. Based on data collected at over 700 replicated sites throughout the Puget Sound lowlands, King County (2014b) estimated a B-IBI S:N of about 10.8. Compared to the other metrics with replicated measurements, only a few physical channel habitat features that could be consistently measured (e.g., X TWDepth, X BFWidth, ResPoolArea100m) had substantially higher S:N or lower σ_{rep}/Rg_{obs}.

The precision analysis confirms findings of other studies of habitat metric precision. For example, Scholz and Booth (2001) concluded that measures of riparian canopy, bank erosion and hardening and in-stream large woody debris would provide meaningful habitat measures. They considered that well trained field staff could also provide useful measurements of channel gradient, substrate composition and pools. We did not measure bank erosion/hardening and did not include channel gradient in our study (although it was measured in the field). However, we did find that canopy measurement (X DensioBank and X DensioCenter), substrate (PCT SandFines), pools (ResPoolArea100) and wood (LWDPieces100m, LWDSiteVolume100m, LWDVolumeMSq) had relatively high precision based on either S:N or σ_{rep}/Rg_{obs}.

Also of potential interest is how our survey precision compares to other surveys (e.g. Whitacre et al., 2007; Roper et al., 2010); in particular to the Puget Sound Status and Trends survey (Merritt and Hartman, 2012) in which our study was nested and with which we shared protocols. A complete comparison was not possible, because only ten habitat metrics had reported S:N and σ_{rep} results from both studies (Table 23). However, the precision values reported by Merritt and Hartman (2012) were generally for the metrics with the greatest precision and included many metrics already highlighted in this report as having relatively high precision and biological relevance. Although the absolute values of S:N were different, both studies were consistent in identifying X TWDepth, X BFWidth, and SD TWDepth as having high precision (S:N >10). This was also true for precision as measured by $\sigma_{rep}:Rg_{obs}$ (<0.052) using the maximum Rg_{obs} between the two studies (Table 23). Three other metrics had consistently lower precision (S:N <5) (LWDPieces100m, X Embed and PCT Pool), although LWDPieces100m was somewhat equivocal based on $\sigma_{rep}:Rg_{obs}$ (0.041 in our study). The remaining four metrics (PCT SandFines, X DensioBank, X PoolUnitDepth, PCT Fines) were not consistently classified as having high precision based on S:N with S:N values greater than 10 depending on the study. X PoolUnitDepth and PCT Fines were consistently classified as having high precision based on $\sigma_{rep}:Rg_{obs}$, while PCT SandFines and X DensioBank were not (Table 23).

Table 23. Comparison of survey precision for selected habitat metrics between this study and the initial 2009 Puget Sound Status and Trends survey (Merritt and Hartman, 2012).

	King Co	Ecology	King Co	Ecology	King Co	Ecology	King Co	Ecology
Metric	**S:N**		**σ_{rep}**		**Rg_{obs}**		**σ_{rep}:max(Rg_{obs})**	
X TWDepth (cm)	84	159	2.0	1.7	89.7	254	0.008	0.007
X BFWidth (m)	44	1,629	0.44	0.76	13.3	145.9	0.003	0.005
SD TWDepth (cm)	31	158	1.4	1.0	37.1	84.8	0.016	0.012
PCT SandFines (%) [a]	11	9.0	4.2	7.1	73.6	89.8	0.047	0.079
X DensioBank (%) [a]	11	2.1	2.0	7.0	49.2	64.7	0.032	0.108
X PoolUnitDepth (cm)	6.5	40	8.3	9.4	130	323	0.026	0.029
PCT Fines (%) [a]	4.2	44	3.0	1.7	47.62	84.5	0.036	0.020
LWDPieces100m (#/100 m)	3.6	3.8	9.8	14.2	238	92.7	0.041	0.060
X Embed (%) [a]	1.8	3.7	8.3	11.3	73.5	84.3	0.099	0.134
PCT Pool (%)	1.0	3.5	11.2	14.4	70.0	100	0.112	0.144

[a] Merritt and Hartman (2012) indicate that these metrics were arcsine square-root transformed before S:N was estimated. However, their reported residual error values do not appear to be based on transformed data.

Other metrics in our study (i.e., F-IBI, temperature and hydrology) were not replicated so we were not able to directly estimate their residual variance. In lieu of replicated data, it may be possible to derive estimates from other studies that might aid in the identification of metrics with high precision that would best discriminate differences among sites (status) and to focus long-term monitoring (trend) efforts.

Future efforts, particularly ones that include the potential for scaling up watershed scale studies such as ours to regional or state levels, should also direct resources to increasing the consistency and compatibility of measured stream metrics with other similar study efforts. For example, watershed-scale status and trends studies based on the Ecology Master Sample have the potential to be combined with Ecology's regional and state-wide status and trends monitoring effort (Cusimano et al., 2006; Larsen et al., 2008; Roper et al., 2010). Such a scaling-up of monitoring data has the potential to maximize the benefits of limited monitoring dollars by increasing the statistical power and scale of assessments (Larsen et al., 2007; Roper et al., 2010). In our study, our field crews were trained annually prior to the field season by Ecology, together with Ecology crews. At a minimum, measures to increase consistency and compatibility of monitoring data will require efforts to compare results from field teams within any particular monitoring agency and between agency teams that aim to share data (Roper et al., 2010).

4.3 Status and Trends

4.3.1 Status

Our spatially balanced probabilistic sampling design allowed us to quantify the status (condition) of Tier 1, 2 and 3 salmon streams in WRIA 8 for a number of metrics. These metrics provided an assessment of overall biological condition of these streams (based on B-IBI) and an assessment of habitat conditions considered important to ecosystem health. As a whole, the data collected have established a baseline to which future measurements can be compared.

Generally, B-IBI condition was good in Tier 1 streams. The relative proportion of stream kilometers in good condition decreased from Tier 1 to Tier 3 streams with Tier 3 streams predominantly in poor condition. This is consistent with what would be expected given the level of development in these watersheds: Tier 1 streams are generally found in rural areas, while Tier 2 streams are both inside and outside the UGA, and Tier 3 streams are predominantly found in the most urbanized areas.

The two habitat condition metrics with regionally recognized thresholds that we assessed, large wood volume (LWDSiteVolume100m) and maximum July-August 7-day moving average of the daily maximum temperature (7DMax), were predominantly poor across all tiers compared to regional standards. The poor condition of stream wood volume across all tiers – even in subbasins with no urbanization – was somewhat surprising. A similar habitat monitoring effort in Snohomish County also observed that wadeable stream wood volume was consistently below "properly functioning condition" thresholds (Leonetti et al., 2008). The widespread lack of wood may be the result of the legacy of riparian forest clearing and active removal of wood from streams (Booth et al., 1997; Collins et al., 2002; Booth and Fox, 2004). Recovery from such a legacy without widespread restoration is likely to take decades.

That urbanization is not a significant driver of summer maximum stream temperatures is consistent with the work of Booth et al. (2014), who found that local-scale and watershed-scale factors were at least as important as riparian shade in determining summer stream temperatures in Puget Lowland streams.

The lack of a consistent pattern between the habitat metrics we assessed and B-IBI is somewhat surprising. The relatively much weaker relationship between habitat metrics and biological response (as measured by B-IBI) compared to the relationship between watershed scale urbanization and biological response was confirmed in the stressor-response analysis. However, at least one metric (PWP All), did contribute to explaining the variance in WRIA 8 B-IBI scores. PWP All is the proximity-weighted presence of a combination of human influences (e.g., buildings, roads, foot paths, revetments) in the riparian corridor. Therefore, PWP All might also be considered a local measure of urbanization, or at least a measure of site-scale human riparian disturbance rather than a traditional measure of stream habitat.

In the tier framework created for Chinook salmon recovery planning, Tier 2 streams are either streams with high watershed function but little Chinook use or streams with lower watershed function, but with episodic Chinook use. Our stream surveys indicate that in many of the metrics we measured, on average, Tier 2 areas were intermediate in quality between the relatively "better" habitat conditions of Tier 1 areas and "poorer" habitat conditions of Tier 3 areas. Yet a closer examination of Tier 2 survey data indicates a wide disparity in conditions inside vs. outside UGA boundaries.

Tier 2 areas located outside the UGA boundaries had B-IBI scores higher than Tier 1 streams on average, while those inside the UGA more closely matched (were slightly higher than) Tier 3 streams (Figure 53). This result is explained by the fact that of the seven Tier 2 sites outside the UGA, five were located in the Cedar River Municipal Watershed. This 90,000 acre forested area is managed as the city-owned drinking water supply to the greater Seattle municipal area, and is protected under a 50-year Habitat Conservation Plan. In contrast, Tier 2 sites inside the UGA are located in the cities of Everett, Mill Creek, Bothell, Woodinville, and Bellevue.

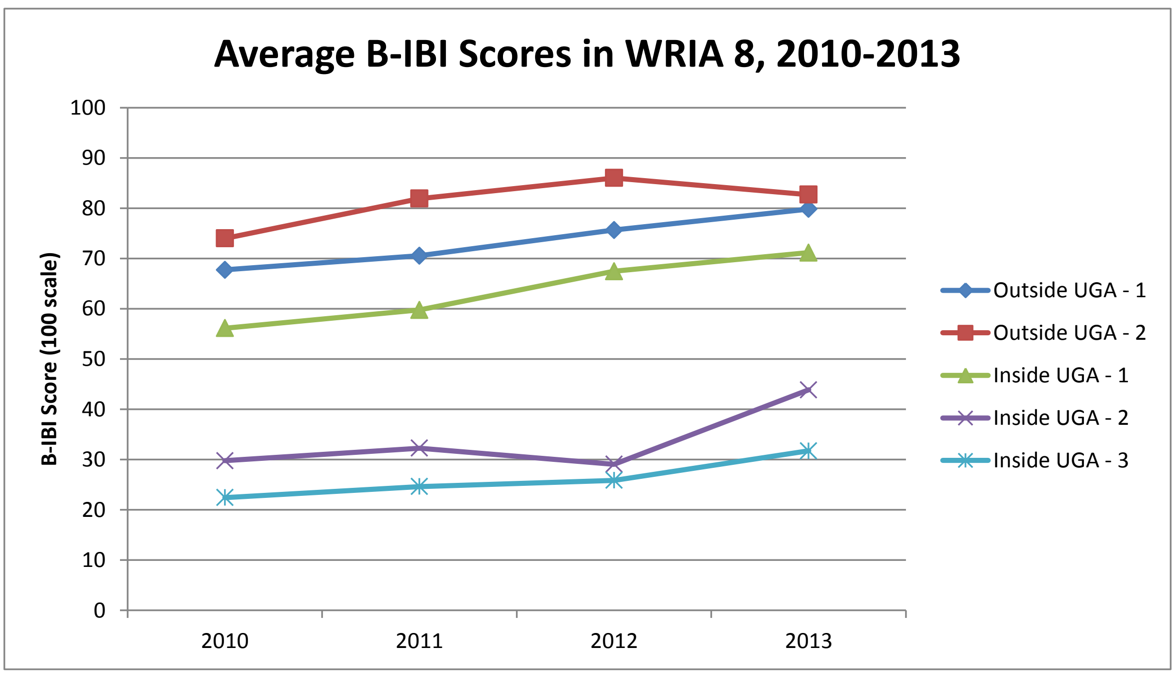

Figure 53. Average B-IBI scores inside and outside the Urban Growth Area boundaries (Tier 1, 2, 3) in WRIA 8, 2010-2013.

Recent work describing forest cover change in WRIA 8 indicates that Tier 2 areas inside the UGA boundaries are losing forest cover along streamside buffers (Vanderhoof et al., 2011; Jensen, 2012). This information on forest cover change and the habitat data from our study can assist WRIA 8 as they assess progress toward their salmon habitat conservation and restoration goals and consider adaptive management (see Section 4.6 below).

The pattern in F-IBI with respect to the three tiers was generally similar to that of B-IBI. However, it appears that the F-IBI pattern relative to tiers was primarily a consequence of a confounding relationship between F-IBI and contributing basin area (WA_ha); highest F-IBI scores were more likely to occur at locations with larger contributing watershed area. Tier 1 stream sites often happen to be larger streams with a larger contributing basin area. That Tier 1 stream basins are larger, is partly a consequence of the tier classification system based on Chinook salmon use – Chinook salmon generally use larger streams, which is a defining characteristic of Tier 1 sites.

4.3.2 Trends

The statistical evidence from the watershed-wide trend analysis suggests that the overall upward trend in B-IBI over the four year period (2010-2013) is real, and not reflected in an accompanying trend at the Sentinel sites. This short-term trend is corroborated in other B-IBI data collected annually in a spatially randomized manner in King County (WRIA 8 and WRIA 9) during 2010-2013 (Figure 54). While on the surface this may seem to be cause for optimism, examination of a longer period in the King County data (2002-2014) indicates a great deal of variability over the period of record (Figure 54). This reinforces that caution should be exercised in interpreting short term trends, even if statistically significant. Mazor et al. (2009) noted short term fluctuations in benthic invertebrate metrics recorded over a 20-yr period at four northern California sites with no obvious disturbances or changes in management. They cautioned that short term assessesments could lead to erroneous conclusions about trends in stream health and their causes. One of the key elements of a relevant status and trends monitoring program is that it is sustained over a long period (Urquhart et al., 1998; Larsen et al., 2004; Lovett et al., 2007; Lindenmayer and Likens, 2009). It is hoped that the results presented in this study provide a solid foundation and lead to the development of a well-designed and sustainable long term WRIA 8 Status and Trends monitoring program.

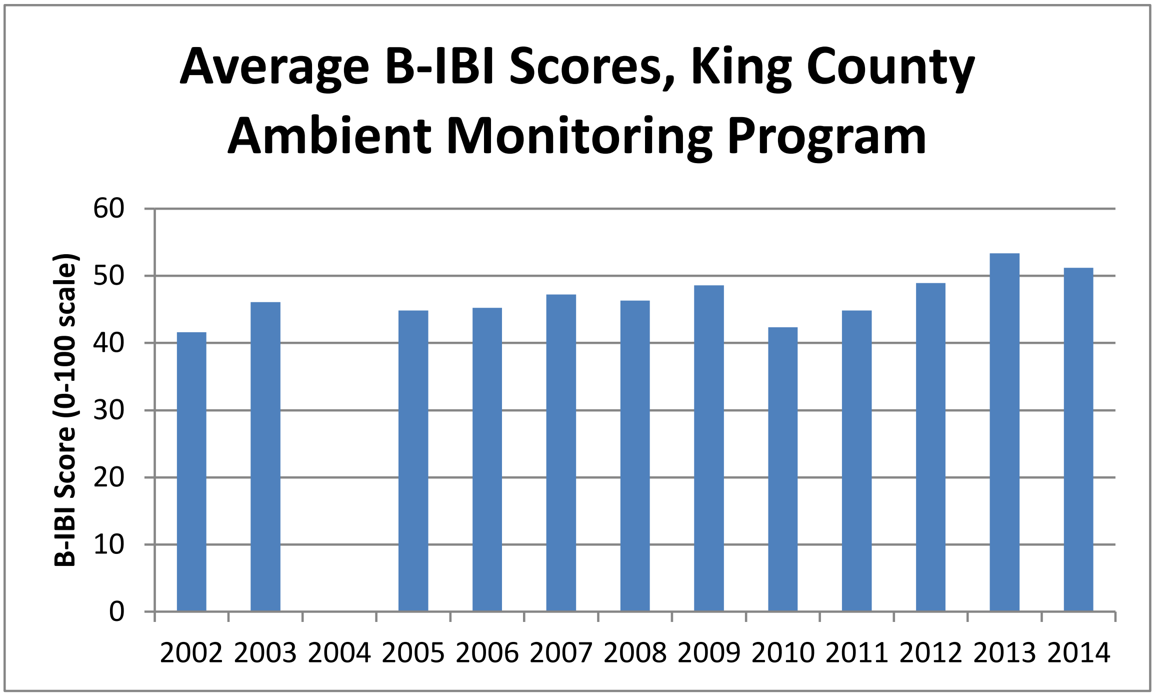

Figure 54. Average B-IBI scores King County,2002-2014 (Ambient Monitoring Program).

Note Data were filtered to return only those sites (75) with scores reported for all years except 2004. The program did not collect data in 2004. (Data source: www.Pugetsoundstreambenthos.org)

4.4 Stressor-Response Relationships

Developing an understanding of multi-scale stressors (in time and space) that cause various biological responses is extremely challenging (e.g., Van Sickle and Johnson, 2008; Cuffney et al., 2010; Waite et al., 2014). Beyond the development of statistical models is the establishment of causation rather than just correlation (Norris et al., 2012). The stressor-response models developed as part of this study should be considered a first step in developing a more in-depth understanding of stressor-response relationships and possible causes of biological impairment in WRIA 8 Chinook streams.

4.4.1 B-IBI

That urbanization (as represented by PCT Urban) is a primary driver of declining B-IBI scores as confirmed in this study has been documented in streams across the world (e.g., Walsh et al., 2005a) and specifically in Puget Sound lowland streams (e.g., Booth et al., 2004; Alberti et al., 2007). Most recently, an analysis of data collected at over 700 sites within the Puget Sound basin found that watershed percent urban land cover explained the majority of variance (49 percent) in B-IBI scores (King County, 2014d). The King County (2014d) analysis focused only on additional variables representing sampling error and natural site features (they did not have habitat data for their sites) which only explained an additional 7 percent of the variance in B-IBI scores.

In addition to PCT Urban, two other urbanization-related land cover metrics appeared to be relatively important explanatory variables in these models – POP Dens and RD Dens (population and road density). An initial investigation of the interaction between PCT Urban and POP Dens (which consistently entered in as the second highest relatively important variable in models that include land cover metrics) indicates that the addition of POP Dens improves model explanatory power by capturing the intensity of urban land use with the combination of higher PCT Urban and POP Dens translating into lower B-IBI scores. That urban development intensity, rather than simple measures of urban land cover, might provide a better land cover stressor metric related to changes in benthic macroinvertebrate communities has been noted in at least one other study covering nine metropolitan regions across the U.S. (Cuffney et al., 2010). Their urban intensity index was based on a combination of percent developed land cover, housing density and road density.

Stressor metrics other than land cover urbanization metrics also appeared to contribute to the explanation of variance in B-IBI scores in some cases. Additional metrics with relative importance greater than 10 percent in any model included stream habitat variables (PWP All, D50, X DensioCenter), a temperature metric (MinT), and hydrologic metrics (High Pulse Duration, High Pulse Count, R-B Index). This finding seems to corroborate the results of many other similar studies that have shown that land cover change as the result of land clearing and development affects stream ecosystems via multiple pathways, such as flow, habitat, sediment, and water quality impacts (e.g., Maloney and Weller, 2011).

Because of the analytical limitations resulting from having far fewer paired flow-habitat monitoring sites, quantitative comparisons of the explanatory power of all of the stressor-response models as a whole cannot be made.[16] However, for the models that utilized all or almost all of the WRIA 8 study sites (land cover, habitat, and temperature) the model based on just land cover data explained the most variance in B-IBI (94 percent). The model that used all three stressor categories also explained a significant amount of variance in B-IBI (91 percent), but primarily included land cover variables as the relatively most important variables, although PWP All was in the top six variables with a relative importance of four percent. As noted in Section 4.3.1 above, PWP All (proximity-weighted presence of a combination of human influences such as buildings, roads, foot paths, revetments in the riparian corridor) is more a measure of local riparian human disturbance likely related to urbanization than a traditional habitat metric. No temperature metrics appeared to be substantially important in explaining the variance of B-IBI scores in WRIA 8.

The stressor-response model that included all stressor categories, including hydrologic metrics, also identified watershed scale metrics as having the greatest relative importance - PCT Urban (51 percent) and POP Dens (22 percent). The third most relatively important explanatory metric was PWP All (11 percent). One hydrologic metric (High Pulse Duration) had a variable relative importance of only four percent. The relatively low importance of hydrologic metrics, specifically flashiness metrics like High Pulse Duration, in explaining

[16] Recall that this resulted in the need to use Sentinel sites in models with hydrologic metrics and increasing the bag fraction from 0.75 to 0.9 in the BRT models affecting the reliability of the cross-validation (CV) R^2 (Section 2.8.3).

B-IBI is somewhat surprising given the high degree of explanatory power of flashiness metrics (including High Pulse Duration) for the variance in B-IBI in an earlier study of 16 paired flow-B-IBI stream sites in King County (DeGasperi et al., 2009).

The stressor-response model using just habitat, temperature and hydrologic metrics (i.e., no land cover metrics), explained even more variance in B-IBI scores than the model using all four stressor category metrics (93 vs 88 percent). This may lend some credence to the hypothesis tested by Walsh (2004) and Walsh et al. (2005b) that the connectedness of the stream to watershed impervious surfaces may be more important than the overall level of catchment development. A similar concept was suggested by DeGasperi et al. (2009): that hydrologic flashiness metrics may be a more direct measure of the ecological effects of urbanization as these metrics might better capture the effects of effective (i.e., quick runoff generating) or connected impervious surfaces in the watershed.

Recent research on the importance of hydrological regimes in structuring benthic macroinvertebrate communities suggests that the influence of hydrology may be more nuanced than suggested by previous studies (Booker et al, 2015; Burns et al., 2015). Booker et al. (2015) found that hydrologic metrics contributed to the explanation of variation in benthic macroinvertebrate community metrics, but this contribution is overestimated if other explanatory factors aren't considered. Burns et al. (2015) found that the best statistical models using hydrologic indicators to predict benthic macroinvertebrate index scores were much less plausible than a model which used a metric representing attenuated imperviousness (AI), a landscape measure of connected imperviousness that inversely weights impervious area by its distance from the nearest stormwater drain or stream. Burns et al. (2015) suggested that AI is a better predictor of stream benthic community response because it integrates hydrologic and other stormwater driven stressors such as changes to stream habitat and water quality.

The difficulty of establishing continuous flow gauges at a large number of ecological monitoring sites is a well-known problem in flow ecology research (McMahon et al., 2003). Difficulties include the relatively high costs of maintaining a stage monitoring site that requires field work of sufficient frequency and duration needed to develop reliable stage-discharge relationships. Two approaches have been used to adapt to or overcome these limitations. McMahon et al. (2003) maintained flow stage recorders at all of their ecological monitoring sites and developed hydrologic metrics, including metrics representing flashiness and duration, from the stage data. Flashiness metrics developed from stage data were found to correlate strongly with urban intensity and benthic invertebrate richness metrics in many metropolitan regions of the U.S. in the study by Cuffney et al. (2010).

The second approach used to overcome the difficulty of establishing continuous flow gauges at ecological monitoring sites relies on the development of statistical or mechanistic models that can provide predictions of hydrologic metrics at ungauged sites. Kennen et al. (2008) used a process-based watershed hydrologic model for New Jersey to generate synthetic flow data for benthic invertebrate monitoring locations and then related hydrologic metrics to benthic macroinvertebrate community structure. Although other environmental variables were found to be important in explaining benthic

macroinvertebrate community structure, including land cover and habitat variables, several hydrologic metrics were also found to be important (Kennen et al., 2008). Significant hydrologic metrics included metrics representing stream flashiness.

Future monitoring efforts should explore the potential utility of measuring stage at a large number of biological and habitat monitoring sites. The flow data used here is based on stage data, so it may be possible to explore correlations between stage-based hydrologic metrics and B-IBI. Because King County has already developed watershed hydrologic models for much of King County, investigation of the use of synthetic flow data from these models might also begin to establish their utility for generating flow metrics at ungauged locations. Note that watershed hydrologic model output was used in King County's initial exploration of relationships between hydrologic metrics and benthic invertebrate community data, including B-IBI scores (Cassin et al., 2005).

4.4.2 F-IBI

Watershed area was found to be the primarily explanatory variable for F-IBI scores. This was unanticipated, given the calibration and validation work conducted specifically as part of the development of this fish index for Puget Sound lowland streams (Matzen and Berge, 2008). However, the difficulty of developing an index of biotic integrity based on fish assemblage data in coldwater streams (and rivers) is widely recognized due to the generally low species richness in these streams, which typically increases with increasing anthropogenic disturbance (Hughes et al., 2004).

In addition, a number of streams had small barriers that influenced the movement of sculpin that may have influenced the F-IBI scores (see report in Appendix B). Generally, fish assemblage metrics that capture the effects of migration barriers are not common (Roset et al., 2007). In a study of upstream passage of two migratory sculpin species in Puget Sound lowland streams unrelated to our study, it was found that structures built to benefit upstream migration of salmon and trout still inhibited the movement of sculpin (LeMoine and Bodensteiner, 2014). LeMoine and Bodensteiner (2014) also concluded that water quality, physical habitat and the presence of other fishes were not related to the presence or absence of sculpin species.

A limited review of available literature on the development of fish assemblage indicators suggests that longitudinal gradients, often represented by upstream basin area, often have a substantial influence on fish assemblages (Vannote et al., 1980; Hughes et al., 2004; Roset et al., 2007). For example, in their development of a fish index for coldwater streams of western Oregon and Washington, Hughes et al. (2004) adjusted their metrics where necessary to account for the effect of catchment area. Matzen and Berge (2008) did not evaluate the potential effect of watershed area (or stream size) on their F-IBI. Further work may be needed to determine which component metrics are strongly related to watershed area to develop a revised F-IBI indicator that is uncorrelated with watershed area or to determine if there is an upper limit on watershed size above which F-IBI is no longer determined primarily by urbanization and associated habitat changes.

Although watershed area appeared to be the dominant explanatory variable, models that did not include watershed scale land cover metrics indicated that habitat variables (in the general sense) could also explain a substantial amount of variation in F-IBI, although at least two of these variables were undoubtedly confounded by watershed size – bankfull width (X BFWidth) and thalweg depth (X TWDepth). The remaining variables that had a relative importance of more than 10 percent in any one model included stream habitat (PCT Shrub, X PoolUnitDepth), temperature (MeanT, DielRange, X7DMax, DaysGT16) and hydrologic (Low Pulse Duration, X30DLow, High Pulse Duration, Flow Reversals) metrics. The importance of stream temperature and flow to stream fish community structure is to be expected. Presumably, further refinement of F-IBI or the exploration of other useful fish community metrics will allow for a more definitive exploration of these relationships.

Note that we did not see a similar relationship between B-IBI and watershed area. No relationship was expected as previous evaluations of the Puget Sound lowland B-IBI have found no statistically significant relationship between B-IBI and basin area (e.g., Morley, 2000; King County, 2014d).

4.5 Trend Detection Power

The power analysis of the regional trend model applied in this study confirmed the results of similar studies of the power of trend detection monitoring programs (e.g., Larsen et al., 2004). That is, for replicated metrics with medium to high precision, reasonably high power to detect moderate levels of change (i.e., from 1 to 3 percent per year) is generally not achieved until a program has been in operation for over 10 years. It is surprising then that a statistically significant trend in B-IBI was detected over the relatively short four year duration of this study. This is due in large part to the large estimated rate of change – approximately seven percent per year. However, as indicated above, short term fluctuations in benthic invertebrate metrics, unconnected to obvious disturbance events or land management, are possible (Mazor et al., 2009).

Note that the results of the power analysis are based on revisiting the same sites every year. Substantial power is lost as sampling frequency decreases. A revisit design that samples the same sites less frequently (say every other year or every five years) will take longer to achieve the same statistical power. For example, sampling every other year would take twice as many years to achieve the same power for a particular metric.

There are also study designs other than the one used in this study that can enhance the reliability of assessments of status without significantly compromising trend detection power; for example rotating panel designs (Urquhart et al., 1998; Anlauf et al., 2011; Urquhart, 2012). The statistical tools applied to evaluation of our study design can also be used to explore other designs or potential improvements in power as a result of improvements in the precision of particular metrics.

4.6 Adaptive Management

Generally, four years is an insufficient period to detect meaningful change in watershed conditions with any degree of certainty. Our findings do not indicate that habitat conditions of small salmon streams in the watershed have changed over the four-year period of our project, and our findings confirm the more general assessments of watershed condition presented in the 2005 Chinook Salmon Conservation Plan. Based on B-IBI scores, Tier 1 areas generally remain in overall good condition, Tier 2 areas contain a range of conditions, and Tier 3 areas are generally in poor condition (e.g., see the categorical analysis bar plots in Figure 12). However, in most streams surveyed, regardless of tier, wood volume condition was generally below thresholds for properly functioning salmon habitat, and summer maximum stream temperatures exceeded state standards established to protect salmonid habitat.

In this section we consider possible adaptive management responses to these monitoring results in light of salmon conservation actions in WRIA 8. We also discuss longer term needs if adaptive management is to be successfully applied in this context.

4.6.1 Tiered Approach to Salmon Recovery

The WRIA 8 Plan partitioned the watershed into three management tiers (Leonetti et al., 2005). This framework was based on a watershed evaluation using land cover and other spatial data, B-IBI scores, and documented Chinook salmon use. The information presented in this report and in other current sources (e.g., land cover analyses and Chinook escapement reports) can be used to re-assess and update the classification framework. The WRIA 8 Technical Committee and Salmon Recovery Council now have the opportunity to use these newer data to verify and test the assumptions contained in the 2005 work. This could be combined with recent monitoring and adaptive management efforts by the watershed to align with regional reporting needs (e.g., WRIA 8 Technical Committee, 2014).

In addition, it may be appropriate to re-examine or fine-tune management strategies based upon the tier framework. In the WRIA 8 framework, Tier 2 areas were either streams with high watershed function but little Chinook use or streams with lower or moderate watershed function, but with documented (perhaps episodic) Chinook use. These two types of streams may require vastly different conservation approaches. Sorting the Tier 2 streams according to UGA status reveals a very large divergence between areas: Tier 2 sites located outside the UGA boundaries (e.g., five of the seven streams are in the upper Cedar River watershed, and managed for conservation) had average B-IBI scores *higher than* their Tier 1 counterparts; conversely, those inside the UGA scored on average only slightly above their Tier 3 counterparts (Figure 53).

Tier 2 streams (notably North Creek and Little Bear Creek) were called out in the conservation framework as exhibiting moderate watershed function and still supporting episodic use by Chinook salmon. Our B-IBI and other data suggest that Tier 2 areas inside the UGA score on average slightly higher than Tier 3 areas (though still classified as “poor”

condition). The WRIA 8 Plan indicated that it was a goal to turn Tier 2 areas into Tier 1. In our opinion it is more likely that Tier 2 areas inside the UGA will become Tier 3 without specific actions to prevent this. Given its location wholly inside the UGA boundary, North Creek appears to be at the most risk of degradation in the short term, probably due to continuing riparian forest cover loss (Vanderhoof et al., 2011; Jensen, 2012).

Tier 3 areas are the most urbanized areas of the watershed, and are generally in poor condition by most measures of habitat quality. Since these streams are not directly used by Chinook salmon, recommendations in the WRIA 8 Plan focusing on water quality and stormwater control appear appropriate and consistent with Chinook salmon conservation objectives. However, if land managers in Tier 3 areas intend to support or sustain coho salmon or other sensitive organisms inhabiting these small urban streams, then further actions are likely appropriate. Temperature data combined with biological and habitat measurements, as well as other research on urban stream syndrome and salmon pre-spawn mortality (e.g., Booth et al., 2004; Alberti et al., 2007; and Scholtz et al., 2011) suggest that current habitat conditions are likely insufficient to support the survival of coho salmon or other sensitive fish species long-term in these urban streams.

4.6.2 Condition Thresholds for Relevant Metrics

Although we identified quantitative expectations (thresholds) for habitat condition in Puget Lowland streams with respect to salmon for wood volume (LWDSiteVolume100m) and stream temperature (7DMax), we were unable to ascertain quantitative Puget Lowland condition thresholds, using the metrics as they are calculated by the Ecology EIM, for other important salmon habitat characteristics (e.g., riparian condition, pools, bottom substrate). While some standards might be adapted from guidance created for other purposes or for wider regions (e.g., NOAA Matrix of Pathways and Indicators, Washington State Forest Practices Board), additional work is needed to establish quantitative condition thresholds that are specific to Puget Sound lowland streams. Such an effort would benefit regional salmon recovery efforts and will likely require a larger Puget Sound-wide effort.

In the absence of such thresholds, cumulative distribution plots can still help us monitor for changes over time: a shift of the plot to the left or right outside the documented confidence bounds indicates changing conditions. Though no long-term monitoring program exists at this time, our project has demonstrated how continued monitoring and analyses can be used to assess such progress at the watershed scale.

4.6.3 Future Monitoring Needs

It is widely recognized that consistent, long-term environmental monitoring data are essential for effective watershed management and decision-making (e.g., Lovett et al., 2007; Lindenmayer and Likens, 2009; Burt et al., 2014). The WRIA 8 Plan stresses the need for habitat status and trends monitoring, tightly linked to decision-making, as an essential element for the success of the plan. Regionally, the lack of status and trends monitoring of salmon habitat at the watershed scale is a documented deficiency (e.g., NOAA, 2006; PSEMP, 2013).

The WRIA 8 status and trends monitoring project demonstrated the utility of a spatially balanced and probabilistic sampling framework using regional protocols at a watershed scale. Habitat and macroinvertebrate data are available on our project website as well as housed in regional databases.[17] The data from this project can be incorporated into other studies using the same regional framework and protocols.

A small number of habitat and biological community metrics with high precision and repeatability, sampled annually, using a proven framework, regional data repositories and established analytical tools, would benefit not only the watershed but help meet regional needs as well. Such a watershed-scale program could be supported by regional guidance on quantitative condition thresholds. Converging needs at the local and regional level for ambient monitoring for habitat, water quality, and stormwater could be combined to provide economies of scale that result in significant efficiencies and cost savings, both regionally and locally (Larsen et al., 2007; Stein and Berstein, 2008).

[17] WRIA 8 Habitat Status and Trends (http://www.kingcounty.gov/environment/wlr/sections-programs/science-section/doing-science/wadeable-streams.aspx), Ecology (http://www.ecy.wa.gov/PROGRAMS/eap/stsmf/index.html) and Puget Sound Stream Benthos (http://www.pugetsoundstreambenthos.org/).

5.0 CONCLUSIONS AND RECOMMENDATIONS

The data collected in this study provide important baseline information on the status and trends of wadeable salmon streams in WRIA 8, and relationships between land cover, hydrology, habitat, and biological community response. These data can be compared to future surveys of stream habitat conditions in WRIA 8. We offer the following concluding findings and recommendations.

5.1 Findings

- Stream biological conditions (as measured by the Benthic Index of Biotic Integrity or B-IBI) ranged from very poor in heavily urbanized areas to very good in rural, forested areas.
- Stream habitat conditions considered important for salmon (wood volume and water temperature) were found to be predominantly poor even in rural areas. Wood volume was consistently rated poor and water temperatures frequently exceeded state standards for core summer salmonid habitat.
- Generally, four years is not a sufficient length of time to see trends in stream resources. However, we did see a statistically significant upward trend (improvement) in the Benthic Index of Biotic Integrity (B-IBI) in the watershed between 2010 and 2013. This trend was in contrast to the lack of trends in habitat condition in those streams. Comparison to a larger WRIA 8 and 9 dataset with many more years of data suggests that the increase in B-IBI scores is likely due to natural variability in a highly variable resource.
- The spatially-balanced data we collected are of sufficient precision to reliably test for trends in the sampled streams over time. We identified a short list of metrics representing indicators of stream habitat conditions important to salmon (wood volume, pool area, sediment composition, canopy cover, and B-IBI) that are repeatable and precise.
- Our analyses indicate that for most of the metrics we measured, it will take an annual monitoring program 10 to 20 years to reliably detect a 3 percent annual change in the status of the most relevant metrics. Currently no such program exists.
- Our study corroborated most other research on relationships between land cover stressors and benthic macroinvertebrate community response as measured by B-IBI. Urbanization and population density best explained the observed variance in B-IBI scores – low levels of urbanization and human population density coincide with highest B-IBI scores and high levels of urbanization and population density coincide with lowest B-IBI scores.
- Our study also provided the first test of the utility of a Fish Index of Biotic Integrity (F-IBI) developed especially for Puget Sound lowland streams. Our results indicate that the Puget Sound lowland F-IBI (although initially calibrated and validated with

data collected primarily from King County streams) is confounded by contributing upstream basin area and/or stream size. Further research will be needed to identify a F-IBI that is comparable to the B-IBI, which is not confounded by natural landscape features.

For Chinook recovery planning purposes, the watershed was previously organized into three tiered priority areas based primarily on Chinook use. Findings within the context of these recovery planning tiers follow:

- Tier 1 areas include primary spawning habitat as well as migratory and rearing corridors for Chinook salmon. Management strategies for Tier 1 areas have generally involved the preservation of existing high quality habitat, and restoration where needed. Our surveys confirm that the majority of Tier 1 areas are of relatively higher quality than Tier 2 or Tier 3 sites. B-IBI, F-IBI and pool area were generally higher in Tier 1 areas. However, wood and temperature metrics were low in all tiers.
- Some Tier 2 areas include streams located completely inside the Urban Growth Area boundaries, where development and infill is occurring. Tier 2 streams inside the UGA are at the most risk of degradation in the short term. It is likely that the most high-functioning Tier 2 areas within the UGA boundaries (i.e., North Creek) will degrade further without focused efforts.
- Tier 3 areas are the most urbanized areas of the watershed, and are generally in poor condition by most metrics. From a Chinook salmon conservation perspective only, recommendations in the WRIA 8 Plan might be considered sufficient, notwithstanding the lack of evidence that such actions are resulting in improvements. However, current strategies are likely insufficient to support the long-term occurrence of coho salmon in these urban streams.

5.2 Recommendations

We recommend that the WRIA 8 Technical Committee and Salmon Recovery Council consider the following actions:

- **Re-evaluate the tier strategy based on new information in this report and other sources.** The WRIA 8 Plan partitioned the watershed into three management "tiers" (Leonetti et al., 2005). This framework was based on a watershed evaluation using land cover and other spatial data (ca. 2001-2003), Benthic Index of Biotic Integrity (B-IBI) scores (1995-2003), and documented Chinook salmon use. The information presented in this report and from other recent sources (e.g., land cover change and Chinook escapement reports) can be used by the WRIA 8 Technical Committee to re-assess and update the classification framework.
- **Re-examine management strategies in light of the information on habitat quality in this report.** Strategies for Tier 1 and Tier 3 areas appear to appropriately match conditions in those areas. However, Tier 2 areas inside the UGA boundary are intermediate in quality between Tier 1 and Tier 3 areas. Tier 2 areas include some streams inside the Urban Growth Area boundaries where development and infill is

occurring, and forest cover is diminishing. Tier 2 areas inside the UGA appear to be at the most risk of degradation in the short term. Decision-makers should determine whether these areas can (and should) be protected and improved enough to continue contributing to Chinook recovery in WRIA 8, and if so, develop and implement appropriate strategies.

- **Reclassify some areas based on information acquired since 2005.** The upper Cedar River and its tributaries above Landsburg Dam were classified as Tier 2 in the original framework because the Technical Committee did not have sufficient information on Chinook use above the dam. Data acquired since then confirms that this area has become a core area for Chinook and should be re-classified as Tier 1. Other areas, where watershed function and/or Chinook use has declined, may require reclassification to a lower level or increased efforts to support Chinook use.
- **Request regional support to develop condition thresholds for biologically relevant metrics that are specific to Puget Sound lowland streams.** Thresholds based on reference conditions are needed to classify or categorize measured metrics into poor, fair, good condition or supporting/non-supporting properly functioning habitat condition. In this study, we could only identify thresholds for B-IBI, F-IBI, wood volume and summer maximum stream temperatures. Additional work is needed to establish condition thresholds for other biologically relevant metrics that are specific to Puget Sound lowland streams.
- **Implement a monitoring strategy for the future.** The information in this report provides baseline information collected in a spatially balanced and probabilistic sampling framework using appropriate methods with quantified precision. It provides estimates of precision that indicate it would take an annual monitoring effort about two decades to confidently detect a 3 percent annual change. A small number of habitat and biological community metrics with high precision and repeatability, sampled annually, using a proven framework, regional data repositories and established analytical tools, benefits not only the watershed but the region as well.

5.3 Conclusions

One of the key elements of a relevant status and trends monitoring program is that it is sustained over a long period of time. It is hoped that the information presented in this study provide a solid foundation for the development of a well-designed and sustainable long term WRIA 8 status and trends monitoring program. A small number of habitat and biological community metrics with high precision and repeatability, sampled annually, using a proven framework, regional data repositories and established analytical tools, benefits not only the watershed but the region as well.

Furthermore, future habitat status and trends monitoring that capitalizes on converging regional and local needs from multiple sectors (NPDES, salmon recovery, stormwater, etc.) could contribute substantially to a consistent and reliable long-term set of decision-making tools. These tools would benefit not only local land management agencies, but the region as well.

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Appendix A: Comparison of Land Cover Between Paired Stream Habitat and Gauging Stations

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COMPARISON OF LAND COVER BETWEEN PAIRED STREAM HABITAT AND GAUGING STATIONS

Based on the results of the B-IBI stressor-response modeling (see Section 3.4.1), comparisons of upstream watershed land cover data between the paired stream habitat monitoring sites and stream gauge locations identified in Table 4 in Section 2.6 of the main report above are presented for watershed area (WA_ha), percent urban land cover (PCT Urban), population density (POP_Dens) and road density (RD_Dens) in Table A-1 below. It was expected that relative percent differences (RPDs) in upstream watershed area between some paired locations would be large due to the relatively large distances (up to 6.5 km for the Carey Creek site in the Issaquah Creek basin – see Figure **3** in Section 2.6). The RPD in watershed area between these two sites was 288 percent.[1] Although there were other paired habitat-gauge sites with large RPDs in watershed area, many of the other differences were relatively small so that the median RPD was 3.0 percent (Table A-1). A similar pattern was noted for PCT Urban, with the maximum RPD of almost 15,000 percent for the same pair of sites chosen to represent Carey Creek in the Issaquah basin. However, this RPD was somewhat anomalous and the relative amount of PCT Urban for both of the paired sites was generally low (0.04 and 5.9 percent). Again, the median RPD for all site pairs was relatively low - -0.1 percent (Table A-1). Also, the RPD in population density was extremely large for the Carey Creek site pairs (~2,000 percent), but the population density was relatively low at both sites (2 and 51 inhabitants per km^2). The median RPD was very small – 0.1 percent (Table A-1). The RPDs in road density were generally smaller with the greatest RPD of 34 percent for the paired sites on upper Little Bear Creek (WAM06600-023691 and Lb). Again, the median RPD was very small – 0.05 percent.

When more than one gauge was considered a potential candidate to pair with a habitat monitoring site, the decision to use one gauge over another was driven primarily by the relative amount of useable data at the candidate gauges. This resulted in the selection of some gauges that were relatively distant from the habitat site they were intended to represent. The decision of what constituted a representative stream gauge was rather subjective, but was based on the hypothesis that hydrologic metrics from two locations along a sub-basin stream network would have relatively similar hydrologic responses as long as the land cover characteristics that drive those responses were similar and the metrics under consideration were not significantly affected by watershed scale. DeGasperi et al. (2009) found that the flashiness metrics used in this study were highly correlated with percent urban land cover, so flow gauging locations along the same stream with similar proportions of urban land cover would be expected to have similar flashiness metric values. DeGasperi et al. (2009) also found that with the possible exception of R-B Index, TQ mean and Flow Reversals, these metrics were not significantly correlated with basin area. Therefore, differences in High Pulse Count, Duration and Range or Low Pulse Count and Duration would not be expected based on differences in basin area between gauges with similar proportions of urban area.

To test the hypothesis that hydrologic metrics along a stream network would be comparable (or would scale in a linear fashion) we identified one stream reach on May Creek, a tributary to Lake Washington, that could be used to conduct an initial test of this hypothesis. These gauges are identified in Table 4 in Section 2.6 of the main report and include 37a near the mouth of May Creek, 37b located closest to the habitat monitoring site and 37H upstream of 37b and the habitat monitoring location. 37H was chosen to represent the habitat monitoring site because no useable data were collected at 37b during our study as this site was discontinued and the gauge at 37H was established. Station 37a had useable data, but was located near the mouth of the creek and was likely relatively more urban, as much of the development in this basin is found in the lower watershed. Again based on the results of the B-IBI stressor-response modeling (see Section 3.4.1), comparisons were made for High Pulse Duration, R-B Index and High Pulse Count for 37a vs 37b (useable data for 1992-2009) and 37a vs 37H (useable data for 2010-2013).

Comparisons for High Pulse Duration indicate that although there is a fair amount of scatter in this metric when comparing results for 37a to 37b, the relationship is relatively linear (Figure A-1). The range in High

[1] Note that differences were calculated as the relative percent difference (RPD) between stream gauge and habitat sites [RPD = {(Gauge – Habitat)/Habitat}*100] so positive differences indicate that the value for the gauging site is greater and negative values indicate the value for the gauging site is lower.

Pulse Duration between 2010 and 2013 for both 37a and 37H was much smaller and the relationship between the most upstream and most downstream site was very close to a 1:1 relationship. The scatter in the long-term comparison of sites 37a and 37b was much less for R-B Index and High Pulse Count and the comparisons of 37a to 37H also indicate a close 1:1 relationship in these metrics (see Figures A-2 and A-3).

Table A-1 Comparison of watershed land cover upstream of paired stream habitat and stream gauge sites.

		Watershed Area (WA_ha) (ha)			Percent Urban (PCT_Urban) (percent)			Population density (POP_Dens) (people per km^2)			Road Density (RD_Dens) (roads per km2)		
Site ID	**Gauge ID**	Habitat	Gauge	RPD (%)[1]	Habitat	Gauge	RPD (%)[1]	Habitat	Gauge	RPD (%)[1]	Habitat	Gauge	RPD (%)[1]
EPA06600-CHUC01	ARRO	1,749	1,749	0.0	5.2	5.2	0.0	25	23	-4.7	2.9	2.9	-0.2
EPA06600-DEWA01	DW_KC	4,400	4,400	0.0	0.6	0.6	-0.4	4	5	4.6	1.5	1.5	0.1
ERR06600-091291	Bc	3,605	2,860	-20.7	37.9	34.8	-8.3	424	427	0.7	6.4	6.1	-4.2
SEN06600-GRIF09	21A	4,098	4,216	2.9	0.2	0.2	-2.0	1	3	89.4	3.5	3.5	1.6
WAM06600-001639	12069550	3,231	3,231	0.0	5.5	5.5	0.0	102	102	-0.1	2.6	2.5	-0.2
WAM06600-002259	12120600	1,309	5,076	287.8	0.04	5.9	14,605	2	51	2,049.8	3.1	3.6	14.9
WAM06600-015067	So	1,585	1,585	0.0	83.8	83.8	0.0	1807	1811	0.2	11.7	11.7	0.0
WAM06600-022259	31q	365	384	5.1	0.0	0.0	0.0	0	0	0	2.2	2.1	-3.9
WAM06600-023691	Lb	273	898	228.9	31.4	44.6	41.9	308	743	141.1	5.2	7.0	33.8
WAM06600-035963	34a	451	1,046	131.7	73.2	68.1	-7.0	1912	1762	-7.9	11.8	12.2	2.9
WAM06600-036971	02f2	1,761	1,868	6.0	16.9	17.4	2.9	239	249	4.2	4.8	5.0	2.3
WAM06600-038087	38c	789	1,797	127.9	80.1	77.7	-2.9	2543	2020	-20.6	12.5	12.2	-2.8
WAM06600-039815	14b	1,734	2,148	23.9	6.9	8.9	30.5	30	75	154.5	3.0	3.4	15.0
WAM06600-049499	Nc	7,263	7,001	-3.6	65.3	65.4	0.1	1584	1608	1.5	10.3	10.3	-0.4
WAM06600-050295	51o	365	359	-1.7	79.0	78.7	-0.4	1945	1959	0.7	14.3	14.4	0.4
WAM06600-057739	STA505	72	73	0.4	83.5	83.2	-0.4	3291	3296	0.1	13.3	13.2	-0.6
WAM06600-062567	67a	924	902	-2.4	9.0	8.3	-7.7	308	287	-6.7	3.1	2.9	-6.5
WAM06600-063831	STA508	665	659	-0.8	85.9	86.5	0.7	3021	3045	0.8	14.4	14.5	0.6
WAM06600-065043	STA401	319	319	0.0	79.7	79.7	0.0	2148	2147	0.0	11.5	11.5	0.0
WAM06600-067147	No	1,602	1,652	3.1	72.1	71.8	-0.4	2109	2074	-1.7	11.0	11.0	-0.2
WAM06600-076119	02g	2,979	3,129	5.1	35.0	34.8	-0.6	383	379	-1.0	6.3	6.4	0.5
WAM06600-080407	12120000	1,899	3,749	97.4	77.1	71.8	-6.8	1948	1475	-24.3	11.8	11.1	-5.3
WAM06600-081267	37H	1,033	1,420	37.5	27.0	28.1	4.0	142	137	-3.8	5.2	5.3	1.3
WAM06600-083131	Sc	1,738	2,514	44.7	72.5	70.5	-2.8	2053	1788	-12.9	10.4	11.0	5.3
WAM06600-083959	27a	1,690	1,744	3.2	73.8	73.4	-0.4	2112	2123	0.5	14.0	14.0	-0.2
WAM06600-111639	02N	179	179	0.0	36.9	36.9	0.0	368	351	-4.7	7.7	7.7	0.1
WAM06600-115443	31H	1,033	1,420	37.5	27.0	28.1	4.0	142	137	-3.8	5.2	5.3	1.3
WAM06600-123207	12121600	14,751	14,737	-0.1	13.2	13.2	-0.2	232	233	0.3	4.3	4.3	-0.1
Minimum		72	73	-20.7	0.0	0.0	-8.3	0	0	-24.3	1.5	1.5	-6.5
Maximum		14,751	14,737	288	86	87	14,605	3,291	3,296	2,050	14.4	14.5	33.8
Mean		2,209	2,540	36.2	42.1	42.2	523	1,042	1,011	84	7.6	7.7	2.0
Median		1,594	1,746	3.0	36	36	-0.1	376	403	0.1	6.4	6.7	0.05

*Note: RPD = [(Gauge – Habitat)/Habitat]*100. Some small inconsistencies are due to rounding of the calculated RPDs*

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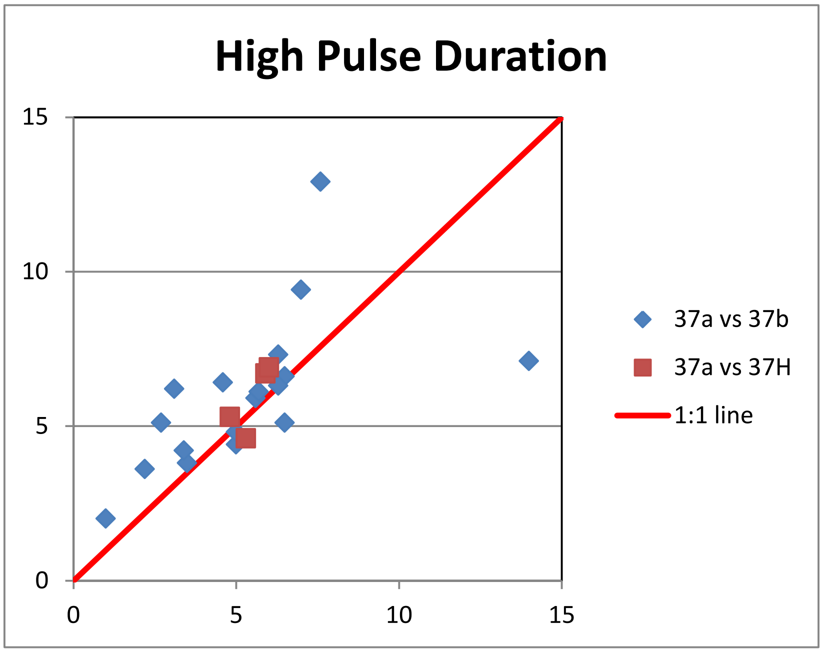

Figure A-1 **Comparison of High Pulse Duration for May Creek gauging stations 37a vs 37b (1992-2009) and 37a vs 37H (2010-2013).**

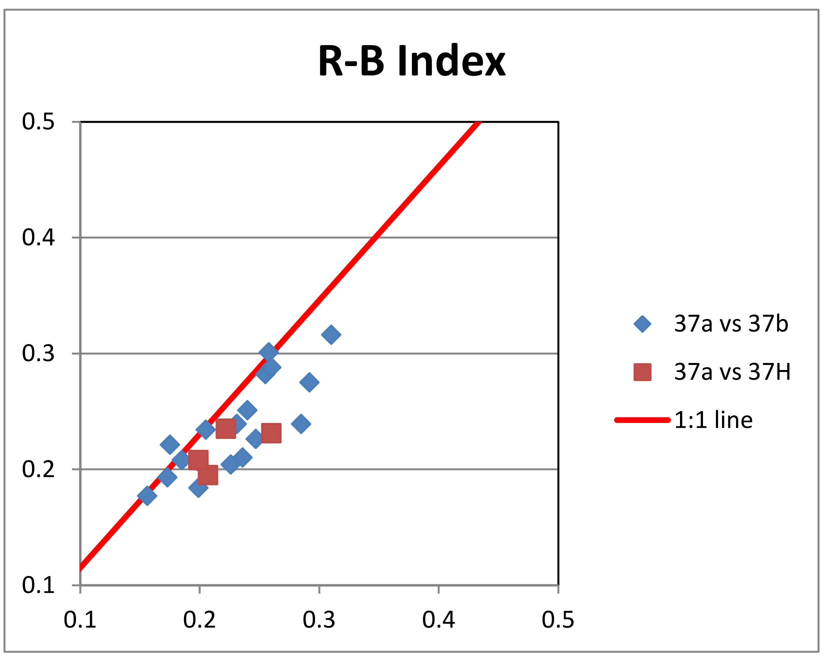

Figure A-2 **Comparison of R-B Index for May Creek gauging stations 37a vs 37b (1992-2009) and 37a vs 37H (2010-2013).**

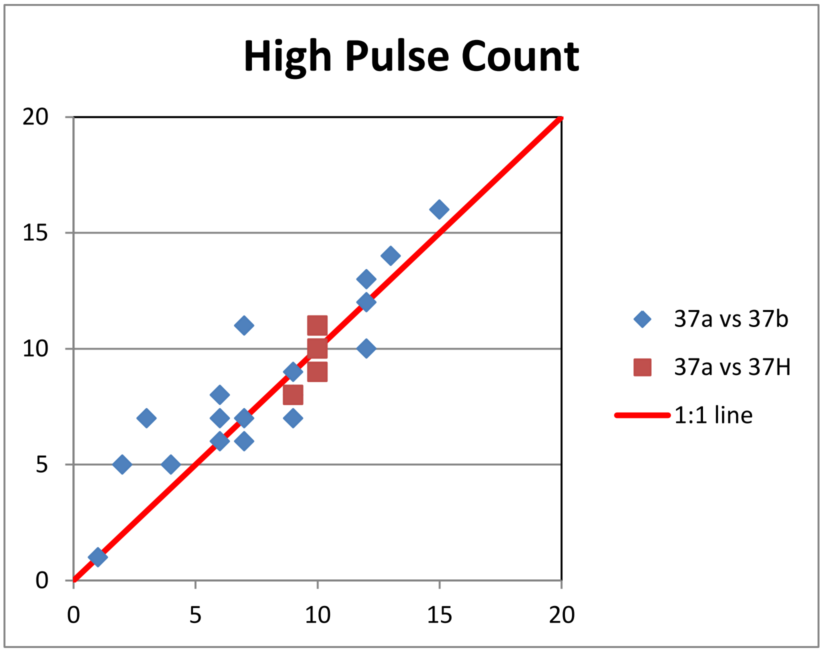

Figure A-3 Comparison of High Pulse Count for May Creek gauging stations 37a vs 37b (1992-2009) and 37a vs 37H (2010-2013).

Appendix B: Effect of Small Barriers on Populations of Sculpin in Puget Sound Lowland Streams

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Appendix B: Effect of Small Barriers on Populations of Sculpin in Puget Sound Lowland Streams

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Abstract

We examined the effect that small barriers had on populations of lowland sculpin (coastrange sculpin [*C. aleuticus*] and prickly sculpin [*C. asper*]). Because these species have pelagic larvae that drift downstream to quiet waters and juveniles and adults migrate upstream, barriers can affect their distribution. We compared sculpin populations immediately upstream and downstream of small barriers in 18 Puget Sound lowland streams. All streams had populations of coastrange sculpin and/or prickly sculpin in stream reaches downstream of the barrier. In 7 of the 18 streams studied, upland sculpin species (riffle sculpin [*C. gulosus*], torrent sculpin [*C. rhotheus*], and/or shorthead sculpin [*C. confusus*]) were also present. These species can complete their life cycle in a relatively small area and barriers are less likely to affect their distribution. In all streams examined, the abundance of lowland sculpin immediately upstream of the barrier was lower than immediately downstream of the barrier. In 11 of the 18 streams, lowland sculpin were not present immediately upstream of the barrier. The few lowland sculpin collected upstream of the barrier were considerably larger than those collected downstream of the barrier. In most streams with upland sculpin populations, upland sculpin were rare downstream of the barrier and abundant upstream of the barrier. Overall, barriers appear to have a strong effect on the distribution of lowland sculpin and need to be taken into account when assessing stream fish communities.

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Introduction

The distribution of fishes is often influenced by manmade and natural barriers. The importance of barriers to anadromous salmonids has been studied extensively; however, the effects of barriers on small, nongame species have received relatively little attention (LeMoine and Bodensteiner 2014). Barriers may alter fish abundance and species composition, which may indirectly affect other components of the aquatic community. Restoration activities in streams will often include low-head dams designed to increase the percentage of pool habitat. These dams are not barriers to anadromous fish movement; however, there is the potential for these barriers to affect the movement of sculpin and other small native fishes which can be highly influential to ecosystem health. Because small, nongame species may not be strong swimmers, their movements may be influenced by relatively small barriers. For example, LeMoine and Bodensteiner (2014) found barriers with a perch height of 0.15 m could block upstream movement of sculpin (*Cottus* spp.).

Freshwater sculpin are often an important component of lotic and lentic environments in cool- and coldwater ecosystems of North America and can be the most abundant fish present. Sculpin can have important effects on aquatic ecosystems through competition and predation (Rosenfeld 1999). Some species spawn in lower stream reaches and juvenile and adults migrate to upstream habitats. Because they are not strong swimmers, small barriers can limit upstream movement of these species (Shapovalov and Taft 1954; Mason and Machodori 1976).

The sculpins found within the streams of the Puget Sound region can be divided into two main types: lowland and upland species. Although there is often a large degree of overlap, these groups generally occupy different areas of a basin. Lowland freshwater species are widespread in lowland lakes and usually found in the lower reaches of streams and rivers including estuaries. Upland freshwater species are found in the middle and upper reaches of streams and rivers and upland lakes. Lowland freshwater sculpin consist of coastrange sculpin (*C. aleuticus*) and prickly sculpin (*C. asper*). Both species have pelagic larvae, relatively small eggs, and have higher fecundity rates than other freshwater sculpin in the Puget Sound region (Wydoski and Whitney 2003). They usually reproduce in lakes or lower reaches of rivers and larvae drift downstream to lakes, large rivers, or estuarine environments where food availability is high but risk of predation is also high (Goto et al. 2014). After larvae grow for a few weeks, they assume a benthic existence. Many juveniles and adults will then slowly move upstream to inhabit lower reaches of rivers.

Upland freshwater sculpins in the Puget Sound region consist of riffle sculpin (*C. gulosus*), shorthead sculpin (*C. confusus*), and torrent sculpin (*C. rhotheus*) (Tabor et al. 2007). These species have larger eggs and lower fecundity than the lowland species (Wydoski and Whitney 2003). They are generally thought to assume a benthic existence immediately after hatching, which is believed to be an adaptation for middle and upper reaches of rivers where food availability is low but predation risk is low (Goto et al. 2014). The entire life cycle of these species can be completed in a relatively small area; whereas lowland sculpin species generally complete their life cycle over a large area.

In streams without barriers, the distribution and relative abundance of lowland and upland sculpin species shows a gradual change as you move upstream (Tabor et al. 2007). Lowland sculpin typically are the dominant sculpin in lower reaches while upland sculpin are the dominant sculpin in upper reaches. The extent that lowland sculpin can move upstream is related to gradient and distance from quiet waters where the larval fish originated (Mason and Machodori 1976). In the Cedar River, coastrange sculpin extend upstream to river kilometer 22.4. The limit of their range is likely related to the distance to Lake Washington and an increase in stream gradient at river kilometer 22.4.

The overall objective of this study was to determine what effect small barriers have on lowland sculpin species and how they may indirectly affect other fish populations. We compared fish populations immediately upstream and downstream of small barriers in 18 Puget Sound lowland streams. All streams had populations of coastrange sculpin and/or prickly sculpin in stream reaches downstream of the barrier. In 7 of the 18 streams studied, upland sculpin species were also present.

Methods

Site selection.-- To locate barriers that may limit upstream migration of lowland sculpin, we walked the lower reaches to look for the first barrier that met the sculpin barrier criteria of LeMoine and Bodensteiner (2014). Potential barriers further upstream were not examined; these secondary barriers may limit the upstream movement of upland sculpin species but these species can complete their entire life cycle both downstream and upstream of the barrier and determining their ability to move upstream of the secondary barrier would require other methods than the species distribution survey that we conducted. A total of 18 streams were selected for this study (Table 1; Figure 1). With the exception of Issaquah Creek, Perrinville Creek, and Oyster Creek, barriers were small barriers that should have minimal effect on upstream movement of adult salmonids. The barrier at Issaquah Creek was a weir system to guide anadromous salmonids into the adjacent hatchery. The barrier at Perrinville Creek is a 0.73 m perched culvert and the barrier at Oyster Creek is a 1.1 m natural waterfall. At these sites, differences in fish abundance downstream and upstream of the barrier could also be related to differences in anadromous salmonid abundance.

Streams were sampled during the summer low-flow period in either 2013 or 2014. We also included data from two streams in the City of Seattle that were surveyed in 2005 or 2006 as part of a fish distribution study (Tabor et al. 2010).

Fish sampling.-- At each identified barrier, we attempted to sample at least three riffles and three pools immediately downstream and upstream of the barrier. Downstream of the Kelsey Creek barrier is Mercer Slough and we just sampled a small area immediately downstream of the barrier. Fish were collected through a one-pass backpack electrofishing technique (Tabor et al. 2007). For pools, personnel slowly moved upstream and collected stunned fish with dip nets. For riffles, we used frame nets that have a rigid metal frame with a 2-m wooden handle so that they can easily be held in place in swift water. The nets were 74-cm wide and 31.5-cm high with a 4-mm stretch mesh. One or two frame nets were

placed in the water. We then shocked an area approximately 3-m upstream from the nets by the width of the frame nets. Stunned fish floated downstream into the frame nets. With frame nets, all size classes of sculpin were captured; however, when stunned fish are visually netted in pools, small sculpin < 50 mm total length (TL) may be underrepresented because they are difficult to observe and net. All fish were identified and then measured for length (nearest mm); total length (TL) for sculpin and lamprey and fork length for other fish species. Due to some uncertainty in classification and distribution of riffle and reticulate sculpin (*C. perplexus*), we combined all sculpin with these characteristics into one category labeled riffle sculpin for our study (Tabor et al. 2007).

Habitat measurements.-- After fish were collected and processed, each habitat unit was surveyed for length, width, maximum and outlet pool depth, and substrate composition (visual estimate of percent sand, gravel, cobble, and boulder).

Table 1. -- Sample month, physical characteristics, and presence of upland sculpin species for 18 streams in Puget Sound lowland streams. Both lowland sculpin species (coastrange sculpin and prickly sculpin) were present at each site except East Fork Issaquah Creek, Issaquah Creek, Lund's Gulch Creek, and North Fork Issaquah Creek where only coastrange sculpin were present.

Stream type Area Stream name	Date month-year	River km	Elevation (m)	Mean wetted width (m)	Maximum depth (m)	Barrier type (number)	Upland species present
Without upland species							
Lake Washington Basin							
Idylwoood Creek	June-13	0.2	14	2.05	0.45	Concrete weirs (7)	
Kelsey Creek	August-13	0.0	6	5.92	0.95	Metal weirs (5)	
Lyon Creek	August-13	0.3	9	2.40	0.68	Metal weir (1)	
Taylor Creek	April-06	0.1	6	2.11	0.58	Waterfall (1)	
Thornton Creek	August-05	0.2	11	4.58	0.68	Concrete weirs (4)	
Other Puget Sound streams							
Chuckanut Creek	September-13	0.5	15	3.06	0.46	Metal weirs (3)	
Glendale Creek	September-13	0.1	7	1.41	0.39	Log weirs (3)	
Lund's Gulch Creek	August-13	0.2	7	2.43	0.36	Log weirs (5)	
Oyster Creek	September-13	0.3	8	1.90	0.52	Waterfall (1)	
Perrinville Creek	August-13	0.1	12	2.09	0.90	Perched culvert (1)	
Piper's Creek	July-13	0.1	5	3.32	0.55	Log weirs (9)	
With upland species							
Lake Washington Basin							
Coal Creek	June-13	1.3	13	4.56	0.78	log (5) and metal (4) weirs	torrent
East Fork Issaquah Creek	June-13	6.1	49	5.63	0.95	Log weirs (8)	riffle, shorthead
Issaquah Creek	August-13	5.6	26	8.56	1.55	Concrete weir (1)	riffle, shorthead
Little Bear Creek	July-13	0.2	10	4.90	0.78	Weir (3)	shorthead
North Fork Issaquah Creek	September-14	4.6	28	2.57	0.60	Boulder weir (1)	riffle, shorthead
Swamp Creek	August-14	3.1	17	7.03	1.20	Boulder weir (1)	shorthead
Other Puget Sound streams							
Goldsborough Creek	October-14	3.9	19	9.60	1.10	Concrete weirs (36)	riffle, shorthead

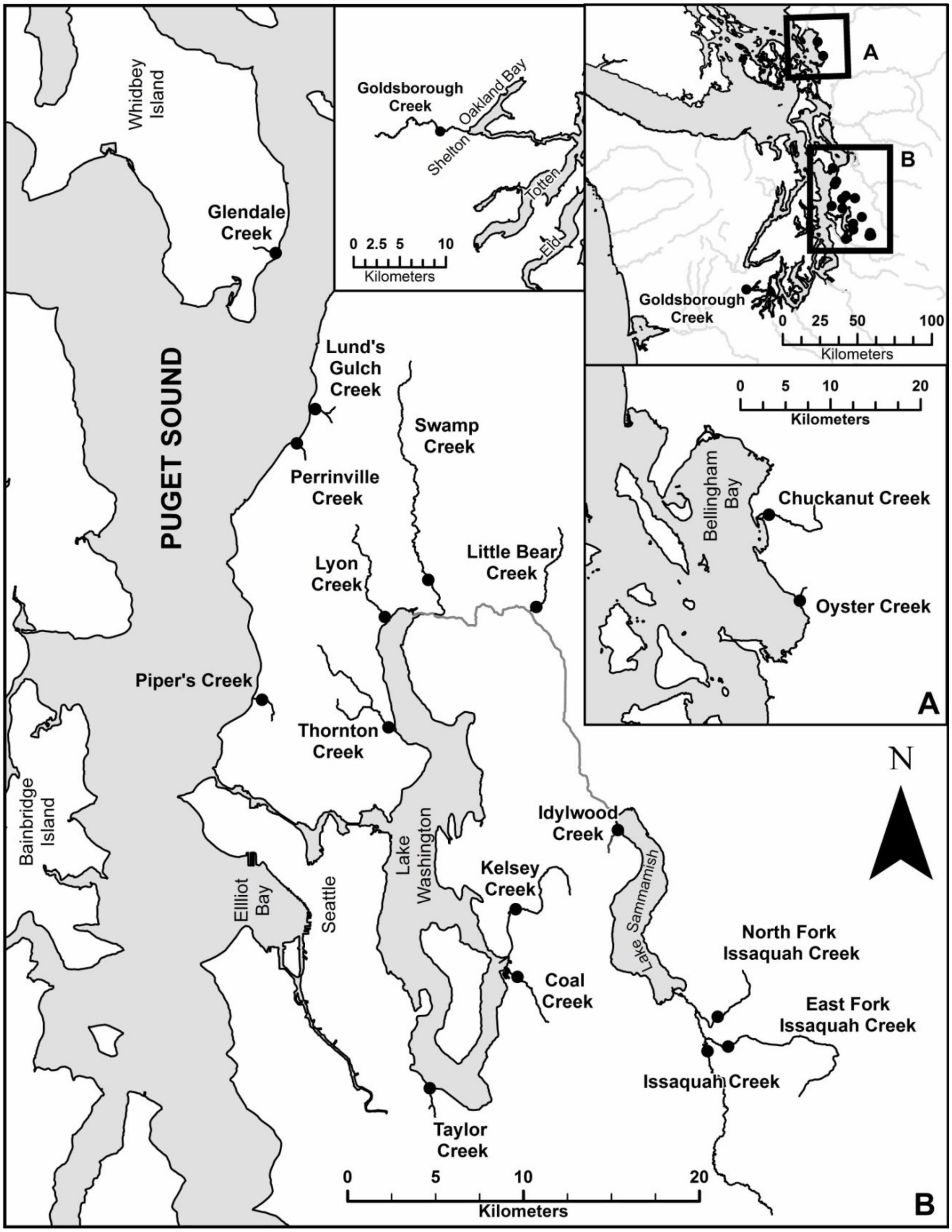

Figure 1.-- Map of Puget Sound, Washington showing the location of 18 lowland streams used to assess the effect of small barriers on populations of sculpin. Solid dots represent the location of each barrier assessed in this study.

Results

<u>Streams without upland sculpin species</u>

Relative abundance.— In streams without upland sculpin, lowland sculpin were found upstream of the barrier in only 3 of 11 streams (Figure 2) and in these three streams, the abundance of lowland sculpin was substantially higher immediately downstream of the barrier than upstream of the barrier.

Species composition.— In 10 of 11 streams, coastrange sculpin was the most abundant sculpin species collected (Figure 3). The only exception was Kelsey Creek which did not have any riffle habitat downstream of the barrier. For all streams and both habitat types combined, coastrange sculpin made up 77% of the sculpin collected. Coastrange sculpin made up 91.7% of the sculpin collected in riffles but only 65.0% in pools.

Size frequency.— The few sculpin collected upstream of barriers were considerably larger than those collected downstream of barriers (Figure 4). For all streams combined, the mean size of sculpin downstream of the barriers was 63.5 mm TL while it was 96.6 mm TL upstream of the barrier. Maximum sculpin size collected was 120 mm TL for coastrange sculpin and 159 mm TL for prickly sculpin.

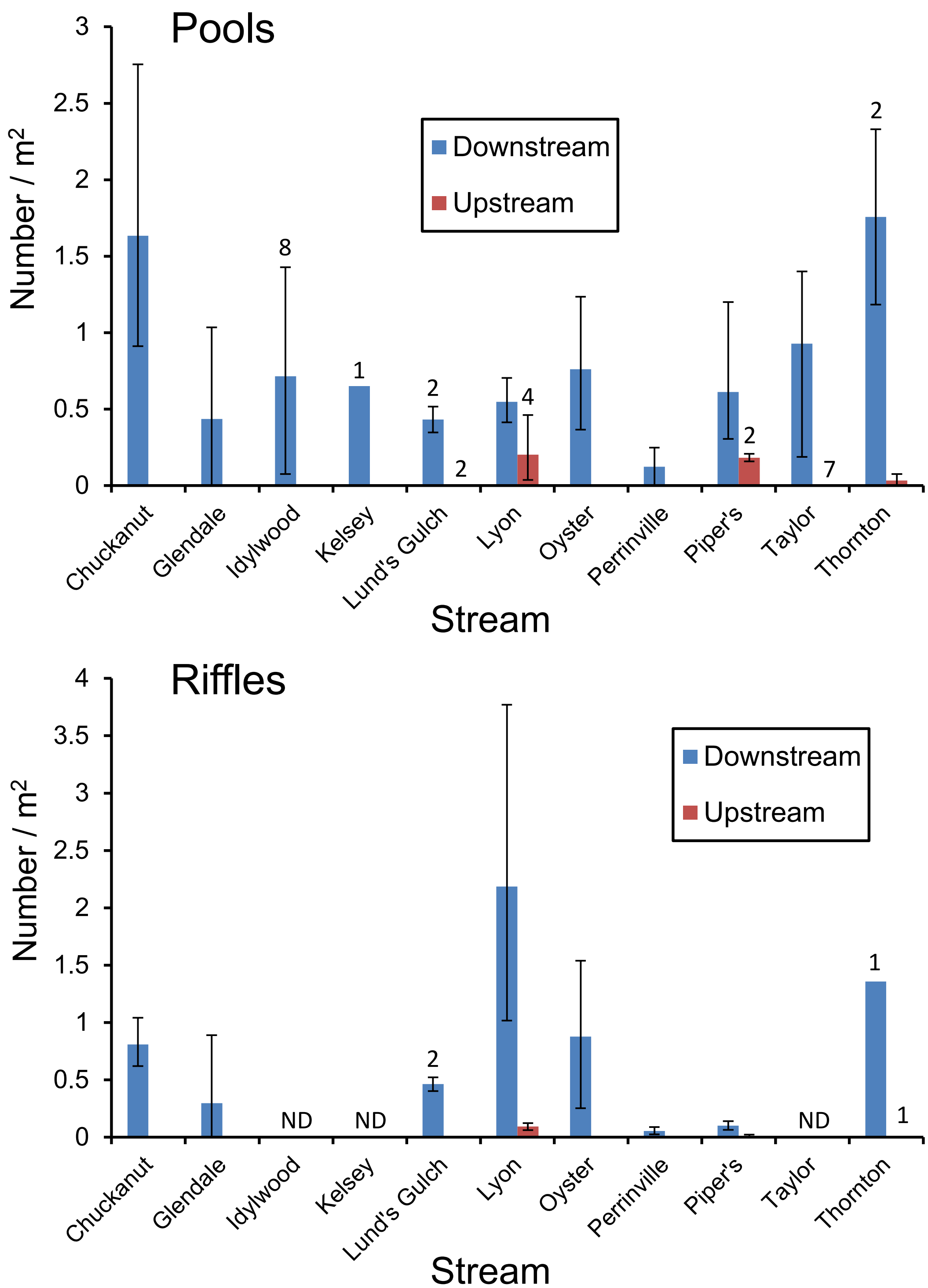

Figure 2.— Comparison of the relative abundance (mean number/m^2 ± range) of lowland sculpin species (coastrange sculpin and prickly sculpin combined) between habitat units immediately downstream and upstream of small barriers in 11 Puget Sound streams. Data are from one-pass electrofishing surveys. ND = no data. Numbers above bars are instances when the number of habitat units sampled was not equal to three.

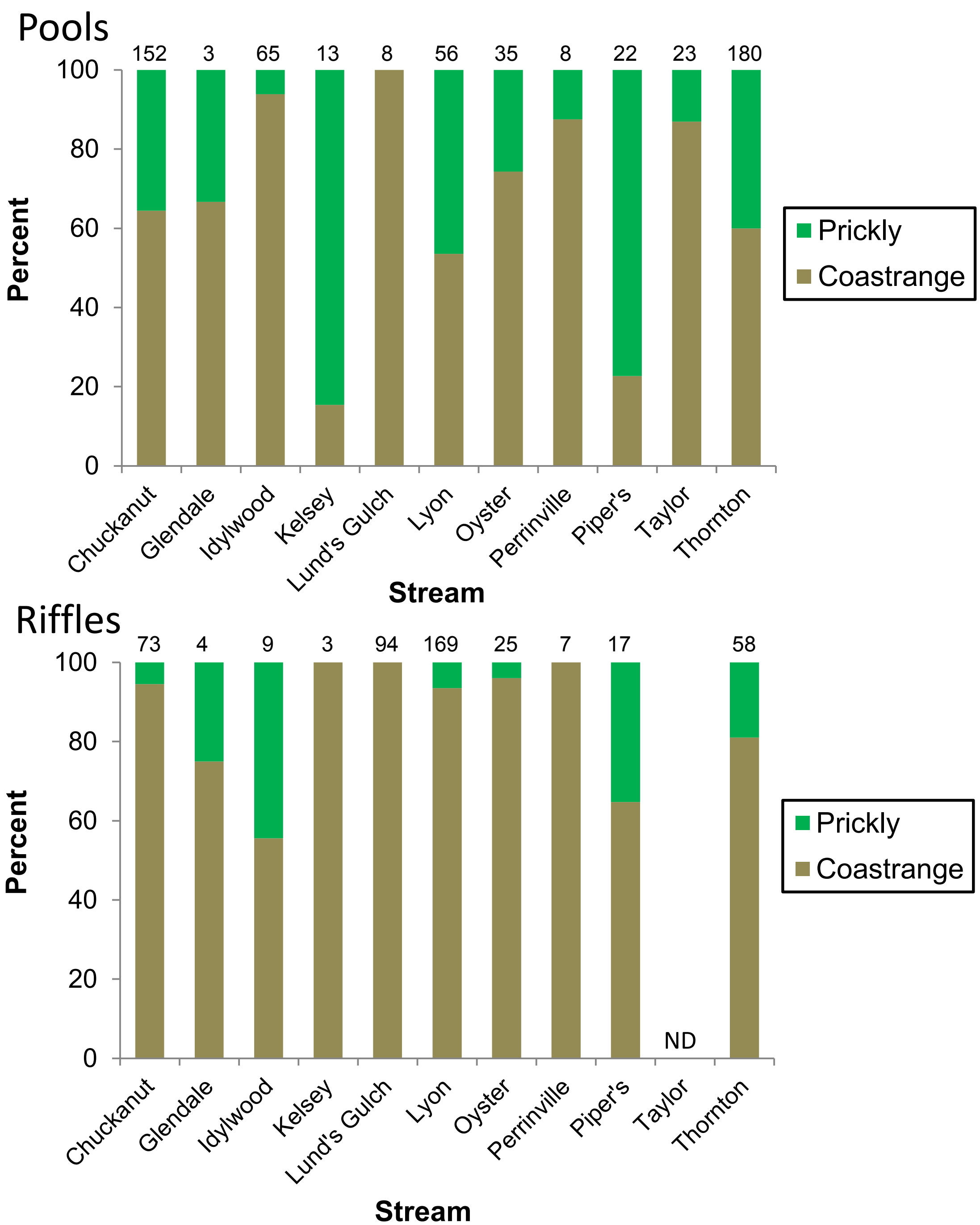

Figure 3.— Species composition (percent) of two lowland sculpin species in two habitat types of 11 Puget Sound streams. The number above each bar is the total number of sculpin collected. ND = no data.

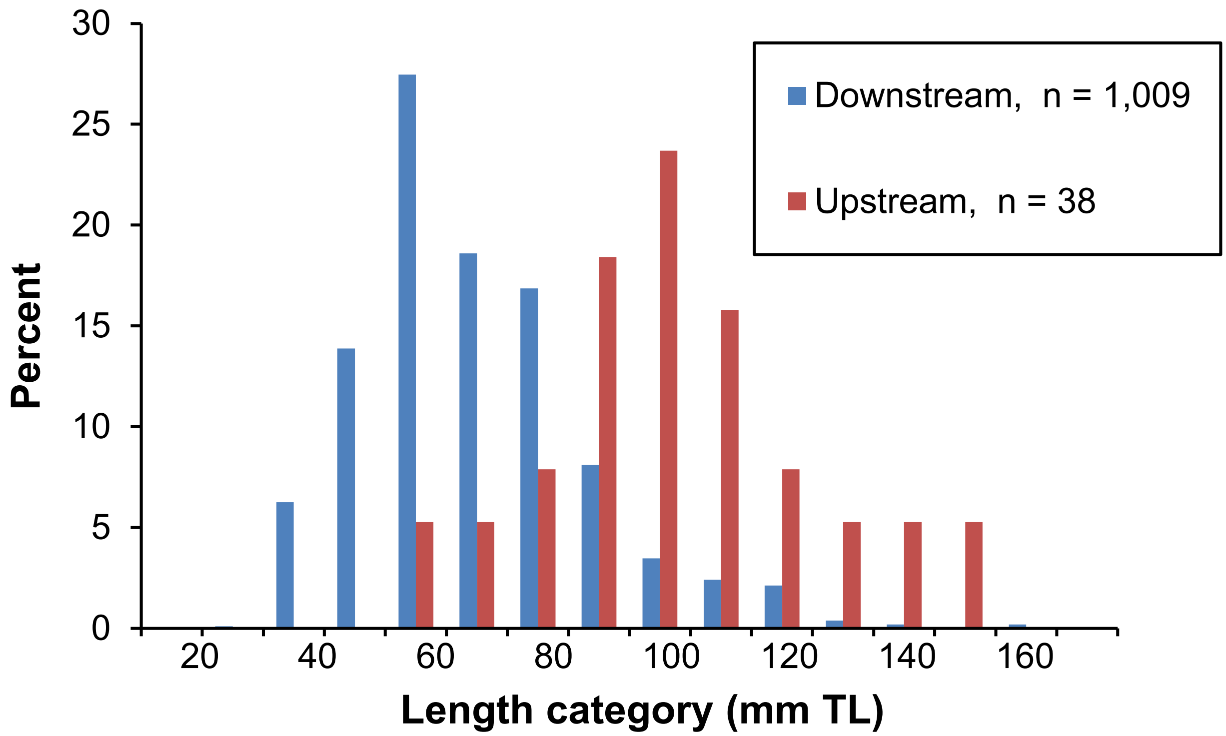

Figure 4.— Combined length frequency (10-mm TL increments) of lowland sculpin (coastrange sculpin and prickly sculpin combined) collected immediately downstream and upstream of small barriers in 11 Puget Sound streams. No other sculpin species were present in these streams. The total number of sculpin is also indicated.

Streams with lowland and upland sculpin species

Relative abundance.— In four streams (Coal, East Fork Issaquah, Issaquah, and Little Bear creeks) lowland sculpin (especially coastrange sculpin) were abundant downstream of the barrier and were either absent or rare upstream of the barrier (Figure 5). In contrast, upland sculpin were rare downstream of the barrier and abundant upstream of the barrier in these four streams. In Goldsborough Creek, lowland sculpin were only present downstream of the barrier; however, their abundance in this reach was substantially lower than upland sculpin. In the other six streams, the percentage of lowland sculpin downstream of the barrier ranged from 41.3 to 99.5%; however, in Goldsborough Creek they made up only 9.7% of the sculpin. The barriers in North Fork Issaquah Creek and Swamp Creek were small boulder weirs which did not appear to be major barriers to lowland sculpin. However, the overall abundance of lowland sculpin was higher downstream of the barrier than upstream for pools and riffles in both streams (Figure 5). The abundance of upland sculpin was not dramatically different between downstream and upstream of the barrier.

Species composition.— Except for Goldsborough and Swamp creeks, coastrange sculpin was the dominant sculpin species downstream of the barrier in both pools and riffles (Figure 6). Prickly sculpin only made up a major portion of the sculpin in Little Bear and Swamp creeks and were found primarily in pools. Torrent sculpin were only present in Coal Creek and were the only upland species present in that system. Riffle sculpin and shorthead sculpin were sympatric in East Fork Issaquah, Goldsborough, and Issaquah creeks with riffle sculpin found primarily in pools and shorthead sculpin found primarily in riffles. Both species were present in North Fork Issaquah Creek; however, shorthead sculpin were rare. Shorthead sculpin were allopatric upstream of the barrier in East Fork Issaquah Creek and occupied all pools and riffles.

Size frequency.—Lowland sculpin collected upstream of the barriers were considerably larger than those collected downstream of the barriers (Figure 7). For all streams combined, the mean size of lowland sculpin downstream of the barrier was 54.6 mm TL while it was 80.0 mm TL upstream of the barrier. Maximum lowland sculpin size collected was 131 mm TL for coastrange sculpin and 179 mm TL for prickly sculpin. In Coal Creek (only stream with torrent sculpin), most torrent sculpin downstream of the barrier were either 40 to 60 mm TL or were > 120 mm TL (Figure 8). Upstream of the barrier, most fish were 40 to 80 mm TL and few fish were > 100 mm TL. In Goldsborough Creek, where large numbers of upland sculpin were present downstream and upstream of the barrier, both riffle sculpin and shorthead sculpin were slightly smaller upstream of the barrier than downstream. For the other streams combined, there was little difference in upland sculpin size between those downstream and upstream of the barrier. Maximum size was 107 mm TL for riffle sculpin, 102 mm TL for shorthead sculpin, and 135 mm TL for torrent sculpin.

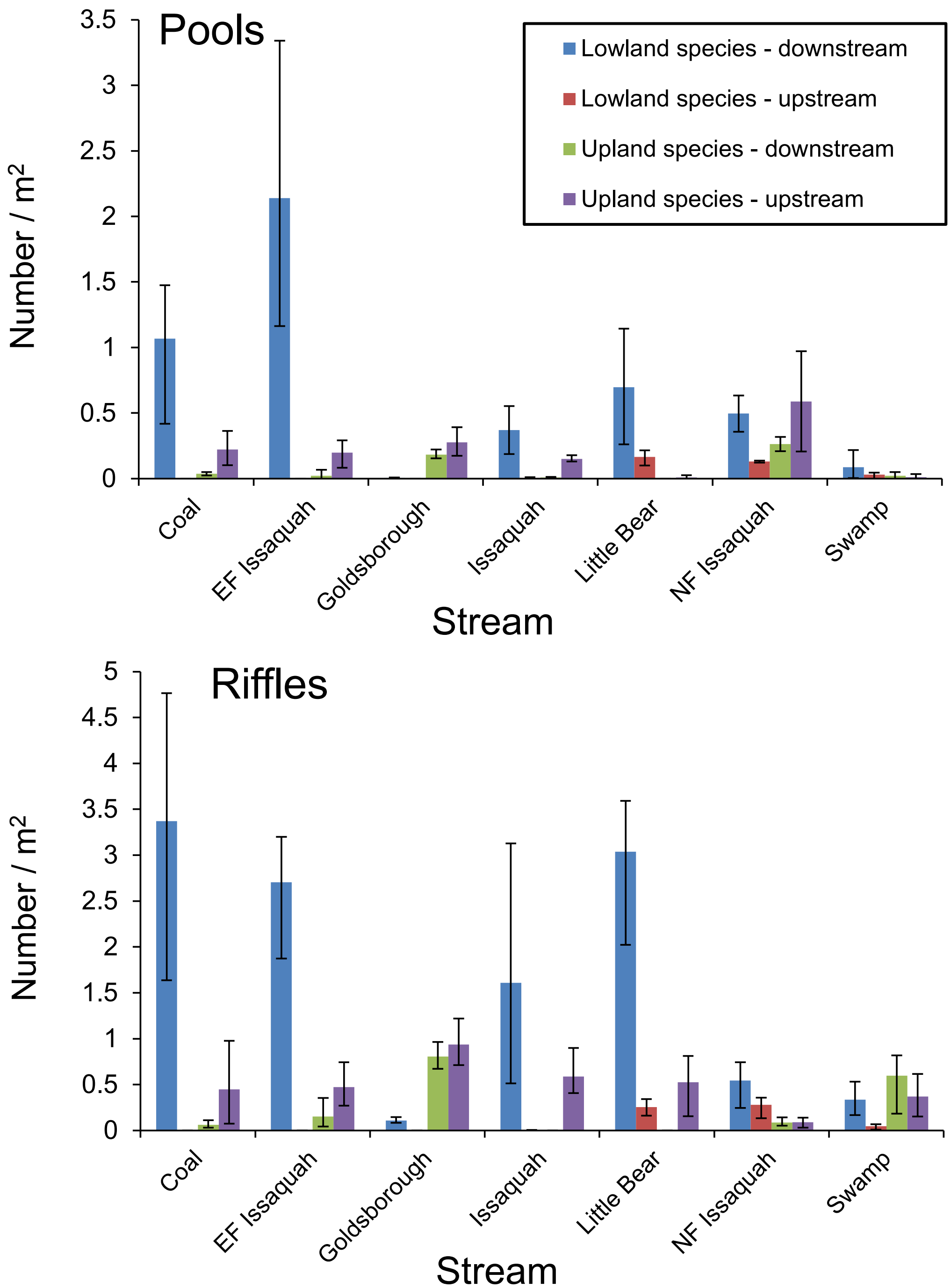

Figure 5.— Comparison of the relative abundance (mean number/m^2 ± range) of sculpin species between habitat units immediately downstream and upstream of small barriers in seven Puget Sound streams. Data are from one-pass electrofishing surveys. Lowland species consist of coastrange sculpin and prickly sculpin. Upland species consist of riffle sculpin, shorthead sculpin, and torrent sculpin. Three habitat units were sampled for each habitat type and location except only two pools were surveyed at each location in North Fork Issaquah Creek and the sample of habitat units sampled downstream of the barrier in Issaquah Creek was two pools and four riffles.

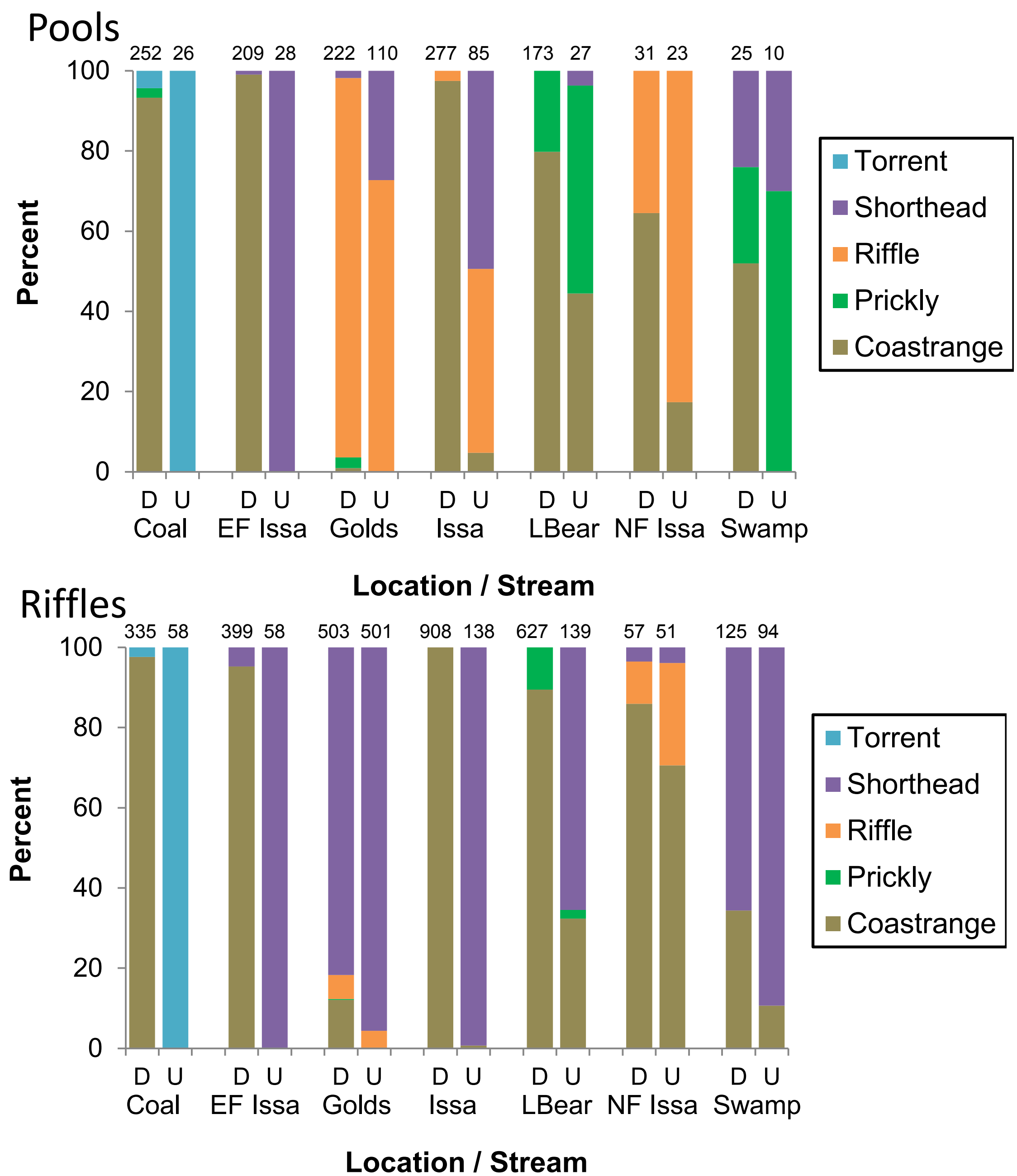

Figure 6.— Species composition (percent) of five sculpin species immediately downstream (D) and upstream (U) of small barriers in two habitat types of seven Puget Sound streams. The number above each bar is the total number of sculpin collected. EF Issa = East Fork Issaquah Creek, Golds = Goldsborough Creek, Issa – Issaquah Creek, LBear = Little Bear Creek. NF Issa = North Fork Issaquah Creek.

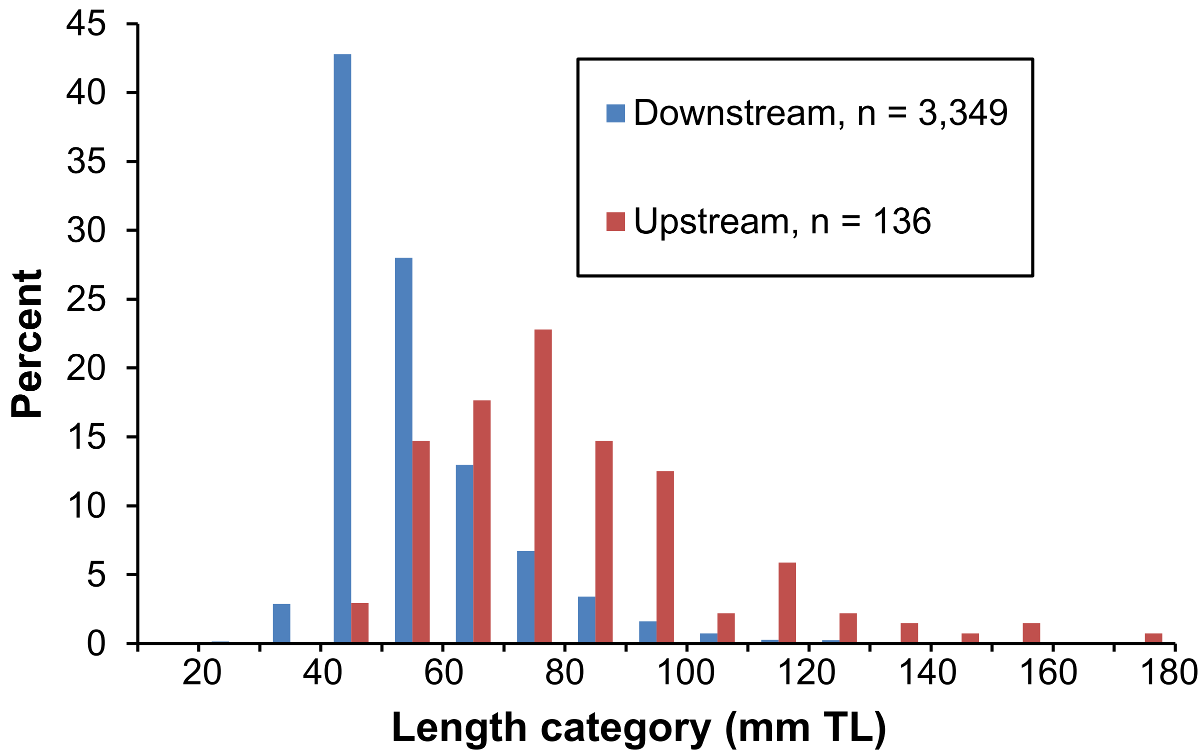

Figure 7.— Combined length frequency (10-mm TL increments) of lowland sculpin (coastrange sculpin and prickly sculpin combined) collected immediately downstream and upstream of small barriers in seven Puget Sound streams. Upland sculpin species were also present in these streams. The total number of sculpin is also indicated.

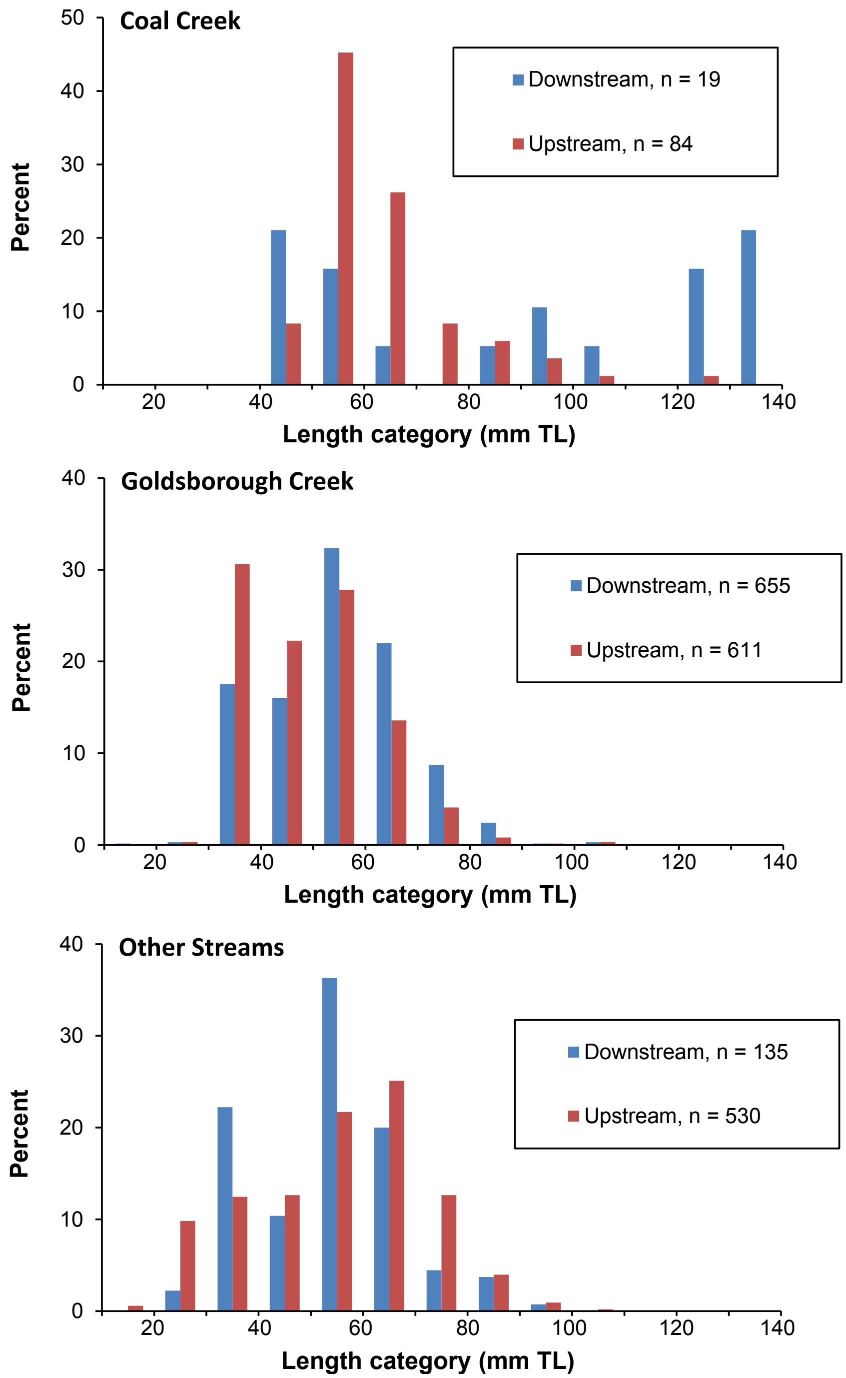

Figure 8.— Length frequency (10-mm TL increments) of upland sculpin (riffle sculpin, shorthead sculpin, and torrent sculpin) collected immediately downstream and upstream of small barriers in seven Puget Sound streams. The Other Streams panel includes the combined results for East Fork Issaquah, Issaquah, Little Bear, North Fork Issaquah, and Swamp creeks. Torrent sculpin were only collected in Coal Creek and were the only upland sculpin in this stream. Lowland sculpin species were also present in all streams. The total number of sculpin is also indicated.

Discussion

Previous studies have found that sympatric freshwater sculpin are often spatially segregated (Mason and Machodori 1976; Finger 1982; Tabor et al. 2007). Our results also appear to support these findings. Prickly sculpin and riffle sculpin generally inhabited quiet waters with prickly sculpin inhabiting reaches downstream of the barrier and riffle sculpin inhabiting reaches upstream of the barrier. Coastrange sculpin and shorthead sculpin were common in riffles with coastrange sculpin inhabiting reaches downstream of the barrier and shorthead sculpin inhabiting reaches upstream of the barrier. In streams without major barriers such as the Cedar River (Tabor et al. 2007), the relative abundance of lowland and upland sculpin gradually switches in upstream reaches but barriers provide a sharp delineation between the two groups. Lowland sculpin species appear to be dominant over upland sculpin species and upland sculpin are only abundant when lowland species are rare or absent.

Goldsborough Creek was unique in that coastrange sculpin and prickly sculpin were not the dominant sculpin species below the barrier or close to the stream mouth. Both shorthead sculpin and riffle sculpin were more abundant than coastrange sculpin and prickly sculpin immediately below the barrier and close to the stream mouth. Other studies of Puget Sound and Olympic Peninsula streams have not documented lower stream reaches where shorthead sculpin and riffle sculpin are more dominant than lowland sculpin species (Mongillo and Hallock 1997; Tabor et al. 2007). For example, Mongillo and Hallock (1997) found the minimum elevation of shorthead sculpin in eight major drainages on the Olympic Peninsula was 171 m. The shoreline area near the Goldsborough Creek estuary in highly developed which includes a large lumber mill. Habitat degradation in the estuary could reduce recruitment of coastrange sculpin and prickly sculpin; whereas riffle sculpin and shorthead sculpin can complete their life cycle in a small stream area and may be favored over species that are associated with the estuary.

Indicators of stream health have often included sculpin in the analysis. The F-IBI (fish index of biotic integrity) developed for Puget Sound lowland streams incorporates a sculpin abundance (percent of total fish collected) metric which is one of six metrics used in the index (Matzen and Berge 2008). Other metrics are also based on the percent of total fish collected and sculpin abundance can directly affect the scores of these other metrics. Therefore, small sculpin barriers may artificially reduce F-IBI scores and underestimate stream health. Because sculpin are often abundant and can affect macroinvertebrates populations, they could even affect B-IBI scores (benthic invertebrate index of biotic integrity).

In conclusion, our results clearly showed that small barriers can have a major effect on the distribution and abundance of sculpin. This was particularly evident in small streams where lowland sculpin are the only sculpin species present. Many barriers were close to the stream mouth and thus a large amount of potential sculpin habitat is unavailable. Fish passage requirements are usually based on passage of salmonids and movements of sculpin and other small, native fishes are not considered. Some of the barriers we examined, such as log weirs, were installed to help restore stream habitat. While they improve stream

habitat conditions (e.g. pool depth and frequency), they may have the unintended consequence of reducing sculpin populations, which in turn may impact the overall health of the ecosystem and the ultimate effectiveness of the restoration activity.

Acknowledgements

We would like to thank U.S. Fish and Wildlife Service (USFWS) employees Travis Headrick, Rebecca Anderson, Julie Weaver, Kaylee Moser, Michelle Pena-Ortiz, Tim Grun, Rachel Brooks, Alex Bell, Zach Moore, Michael Elam, Tracy Leavy, and Scott Sanders for their assistance with the field data collections. Suggestions by Denise Hawkins (USFWS) greatly improved an earlier version of the report. The findings and conclusions in this report are those of the authors and do not necessarily represent the views of the USFWS.

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