Development of a Stormwater Retrofit Plan for Water Resources Inventory Area 9: **Flow and Water Quality Indicators and Targets**

FINAL REPORT

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King County
Department of Natural Resources and Parks

Development of a Stormwater Retrofit Plan for Water Resources Inventory Area 9: Flow and Water Quality Indicators and Targets

Prepared for:
King County Water and Land Resources Division
King County Department of Natural Resources and Parks

Submitted by:
Richard R. Horner

Department of Natural Resources and Parks
Water and Land Resources Division
Science Section
King Street Center, KSC-NR-0600
201 South Jackson Street, Suite 600
Seattle, WA 98104
206-296-6519 TTY Relay: 711
dnr.metrokc.gov/wlr

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Chris Thorn	City of Auburn	Doug Navetski	King County
Ben Parrish	City of Covington	Curt Crawford	King County
Diane Gamlem	City of Covington	Giles Pettifor	King County
Don Robinett	City of SeaTac	Jeff Burkey	King County
Ed O'Brien	WDOE	Curtis DeGasperi	King County
Mindy Roberts	WDOE	Allison Vasallo	King County
Dino Marshalonis	U.S. EPA	Chris Knutson	King County
Michelle Wilcox	U.S. EPA	Elissa Ostergaard	King County
Krista Mendelman	U.S. EPA	Mark Wilgus	King County
Emily Santee	Floyd Snyder	Dave White	King County
Tamie Kellogg	Kellogg Consulting	Beth Ledoux	King County
Brendan Grant	King County	Erkan Istanboulouglu	Univ. of Wash.
Jim Simmonds	King County	Bob Edmonds	Univ. of Wash.
Dan Smith	King County	Olivia Mary Wright	Univ. of Wash.
David Batts	King County	Mary Roderick	Univ. of Wash.
Dave Funke	King County	Nate Sterr	Univ. of Wash.
Doug Osterman	King County	Tim Nyerges	Univ. of Wash.
Larry Jones	King County		

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EXECUTIVE SUMMARY

Context and Definitions

King County was awarded a grant by the U.S. Environmental Protection Agency to develop a stormwater retrofit plan for most of Water Resources Inventory Area (WRIA) 9. The project's scope is to: (1) identify the most cost-effective low impact development (LID) and other stormwater management techniques to meet in-stream flow and water quality goals in WRIA 9; (2) develop a prioritized retrofit plan for the study area; and (3) extrapolate the results to estimate planning-level costs to retrofit all developed lands in the Puget Sound region. Watershed modeling output from Hydrologic Simulation Program – FORTRAN (HSPF) is being used as input to the System for Urban Stormwater Treatment and Analysis INtegration (SUSTAIN) model to optimize the selection of management techniques to achieve the goals. This report covers the goal-setting phase, accomplished with selected flow and water quality metrics and numerical values assigned to these metrics determined to be necessary to meet the goals.

The project conceptualizes the WRIA 9 aquatic ecosystem in terms of a linked system of components. Watershed land use and land cover affect stream habitat conditions, upon which aquatic life forms depend. Humans manage land, with varying care and success, to allow their occupancy while sustaining other life. With stormwater runoff from the landscape having the greatest influence on this watershed's aquatic habitats, and hence its aquatic life, the project's main concern is to determine the most cost-effective combination of practices for managing its stormwater discharges. The project is emphasizing low impact development (LID) methods, backed up by conventional stormwater management practices as needed to produce the optimally cost-effective strategy. The scope recognizes that climate change likely will affect the system components, and the analyses will examine its possible effects on management strategies.

An early effort in the project was to select the appropriate flow and water quality metrics, termed "**indicators**". Indicators are variables that can <u>best</u> represent an ecosystem component and its linkages to other components. Key indicators fall in the groups hydrologic and water quality. Past research in the Puget Sound region provided a basis for evaluating candidate hydrologic indicators to identify those most assuredly linked with watershed land use and land cover, on the one hand, and the aquatic biological community on the other. The research data further permitted setting numerical "**targets**" for these indicators to achieve specific ecological "**goals**", framed as measures of benthic index of biotic integrity (B-IBI). SUSTAIN determines the optimum set of management practices to produce the hydrologic target values found to be necessary to maintain existing B-IBI or raise the score to some desired level.

The project's original scope set TSS as the primary water quality indicator. However, there is interest in estimating how other water quality variables, serving as a basis for WDOE regulatory water quality criteria, would react with the application of management practices to control hydrology and TSS. Available data permitted establishing statistical relationships between TSS and several of these variables, which are hence *de facto* indicators. The goals in this case are to meet these criteria in the water receiving stormwater discharges, and the targets are the criteria values.

Two principles guided target selection:

- A range of outcomes approach, whereby a spectrum of possible goals and associated targets can be investigated, instead of a few discrete, and perhaps somewhat arbitrarily set, goals and specific targets; and

- Framing all goal assessments in terms of a best estimate of the hydrologic and water quality targets needed to achieve the goal and the uncertainty associated with that estimate.

Hydrologic Indicators and Targets

Finding the best hydrologic indicators involved investigating a set of candidates with linkages, documented by the research, to both watershed conditions and aquatic biological community health. Following hydrologic indicator selection, the work then turned to setting numerical targets for the chosen indicators to achieve biological goals, represented by B-IBI, in a range from no further losses to various levels of improvement.

Hydrologic indicators were selected from a candidate list of 20 according to seven criteria. Those initially chosen were high pulse count (HPC), high pulse range (HPR), time above 2-year mean flow, and the 2-year frequency peak flow:mean winter base flow ratio (PEAK:BASE). Time above 2-year mean flow was subsequently dropped when additional analysis showed that the underlying data are unreliable. HPC is the number of stream flow increases above twice the water-year mean flow. HPR is the span in days between the first and last excursions above twice the mean flow in the water-year. While these two indicators tend to be highly correlated, and thus offer much the same information, the PEAK:BASE ratio is less closely associated with the others, and hence can help give a broader view of how stream flow management actions are likely to affect biology.

The HPC and HPR targets were developed statistically according to the range of outcomes approach from a King County data set assembled by DeGasperi et al. (2009). This process resulted in logarithmic-linear regression equations in the form ln(% of maximum B-IBI) = ax + b, with confidence limits on both the coefficient a and the constant b (ln is the natural logaritmn; x is either HPC or HPR).

The PEAK:BASE targets were developed similarly using a data set from University of Washington stream research (Cooper 1996). The best fits are logistic regression equations to predict if stormwater management practices are expected to control the indicator value sufficiently to place B-IBI within or outside a numerical group (e.g., > 56 percent of the maximum possible value).

Water Quality Indicators and Targets

To expand the project's water quality considerations beyond TSS, a large King County Green River watershed database was used to examine relationships between TSS and turbidity and total recoverable and dissolved copper and zinc. Finding relationships with predictive ability would permit assessing risks of failing to meet water quality criteria in pursuing alternative management strategies aimed directly at control of the hydrologic indicators and TSS.

For water quality the project's strategy is somewhat different than in the case of hydrology. There are no specific targets on TSS. An estimate of this measure is produced as SUSTAIN output and used with the relationships derived from the Green River watershed data base to evaluate if the management strategy devised through the model's optimization is likely to result in observance of water quality criteria in the receiving water.

The database yielded linear regression equations forecasting turbidity as a function TSS with relatively high ability to explain variance in the dependent variable associated with variance in the independent variable. The equations consequently give a means of predicting turbidity in a relatively small range of uncertainty.

The statistical relationships linking TSS and the metals are not as strong but still can give estimates of dissolved copper and zinc for comparison with the criteria in reasonable ranges of uncertainty. The stormwater management practices would also likely reduce the dissolved metals independently of TSS decrease. The project's methodology does not account for this possibility, and thus is conservative in estimating the likely benefits of management.

1.0 INTRODUCTION

1.1 Overall Project Context

King County was awarded a grant by the U.S. Environmental Protection Agency to develop a stormwater retrofit plan for most of Water Resources Inventory Area (WRIA) 9.[1] The project's scope is to: (1) identify the most cost-effective combination of low impact development (LID) and other stormwater management techniques to meet project-defined, catchment-specific in-stream flow and water quality goals in WRIA 9; (2) develop a prioritized retrofit plan for the study area; and (3) extrapolate the results to estimate planning-level costs to retrofit all developed lands in the Puget Sound region. Watershed modeling utilizing Hydrologic Simulation Program – FORTRAN (HSPF) is being performed based on a number of data sets, including stream flow and water quality measurements, existing land use/land cover, future land use/land cover based on population projections, surficial geology, historic climatic data, and future climate projections. The watershed modeling output is being used as input to the System for Urban Stormwater Treatment and Analysis INtegration (SUSTAIN) model to optimize the selection of management techniques to achieve the goals. This report covers the goal-setting phase, accomplished with selected flow and water quality metrics (indicators) and numerical values (targets) assigned to the indicators determined to be necessary to meet the goals.

1.2 Conceptual Framework

Figure 1 presents a basic concept of the major components of concern in WRIA 9 stormwater retrofit planning project and the relationships between them. Watershed land use/land cover (LU/LC) characteristics affect stream habitat conditions, upon which aquatic life forms depend.

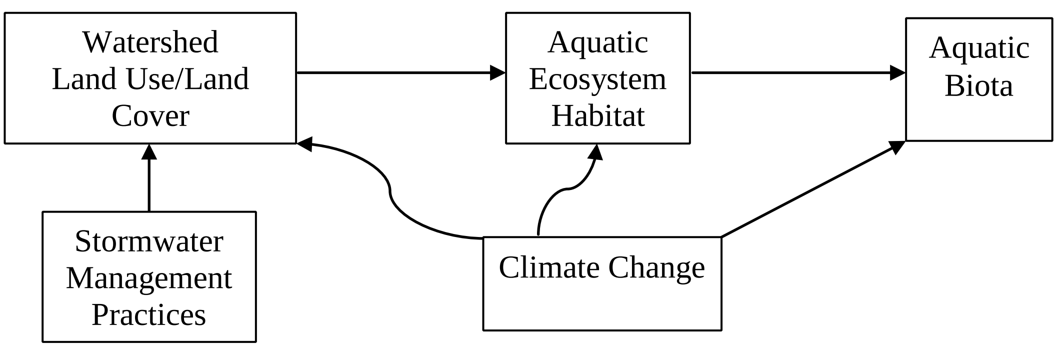

Figure 1. Components and Relationships of a Watershed Ecosystem

The term "land use" refers to functions served by terrain for human purposes, such as agriculture, residential, and commercial. "Land cover" means the surface description of a parcel; for example, forested, pasture grass, lawn, impervious material. "Habitat" represents numerous conditions, such as water flow and water quality, each measured in many different ways; soil and geological materials making up the bed and banks; and riparian vegetation. Among the aquatic biota are fish, invertebrate animals, attached and planktonic algae, and rooted plants.

[1] The Green-Duwamish watershed plus adjacent direct drainages to Puget Sound, excluding headwaters above Howard Hanson Dam, the main stem of the Green River and its lower reach (Duwamish River), and tributaries thereto within the City of Seattle

Aquatic organism physiology and behavior evolved in relation to the complex of habitat attributes existing over the thousands of years of their presence. A water body's habitats, in turn, developed as a direct result of its physiographic setting (latitude, elevation, topography, geology, etc.) and delivery of water and materials from the landscape making up the area contributing drainage to it (i.e., the watershed). Changes in land use, land cover, or both imposed by humans modify water and materials delivery, and possibly even physiographic elements; and, consequentially, alter habitats. These changes occur over very short time frames in relation to the original development period of habitats and evolution of aquatic biota, which are challenged to adjust abruptly. Often, they cannot adapt and decline in numbers or go locally or broadly extinct as a result of loss in efficiency of their life-supporting processes (e.g., growth, reproduction, mobility) or direct mortality.

Management practices are intended to allow humans to occupy a watershed and use its land for their purposes while sustaining other life. Stormwater runoff from the landscape is the largest and most pervasive influence on this watershed's aquatic habitats, and hence its aquatic life. Accordingly, the principal concern of this project is to determine the most cost-effective combination of practices for managing stormwater in the defined study area. The project will accomplish its purpose with the use of computerized, mathematical, predictive models representing the system components and calibrated with measured data taken on their key elements.

The project's scope recognizes that climate change likely will affect the three fundamental system components, over and above human-induced LU/LC alterations, through the approximately 30-year time interval over which it will perform analyses. Accordingly, the analyses will incorporate plausible climate-change scenarios to examine their possible effects on conclusions regarding strategies. Work by the Climate Impacts Group (2009) at the University of Washington is available to support this assessment.

1.3 Definitions and Summary of Methods

Watersheds and aquatic ecosystems embrace immense numbers of variables, all of which have some role in their definition and operation. Hydrologic cycle inputs (precipitation, surface runoff and groundwater discharges) and outputs (evapotranspiration, groundwater recharge) govern fluvial processes such as stream flow hydrography (flow rate over time). Thousands of materials, in the categories of sediments, nutrients, metals, organic chemicals, and microorganisms, entering with the hydrologic inputs, constitute the physical and chemical quality of water and underlying sediments. As already pointed out, many characteristics, and associated variables, go into making up a habitat. Each aquatic life form consists of distinct species populations, each of which represents an individual biological variable; and combinations of species assemblages comprise community variables. All of these variables represent "**metrics**", that is quantities that can potentially be measured and contribute to understanding relationships existing within the system.

Obviously, no study can measure all, or even a substantial fraction, of these variables. An assessment of this sort relying on data supporting computer models is likewise limited in the number of variables it can consider. Even those variables that can be measured generally differ in their contributions to understanding. The solution is to identify those variables that can <u>best</u> represent a component and its linkages to other components. In this project such variables are termed "**indicators**." Designation as an indicator signifies a metric with demonstrated ability to link events in one system component to responses in another. Indicators apply to the watershed, habitat, and biotic components of the system as portrayed in Figure 1. Once indicators were selected, the project's next task was to assign numerical values (called "**targets**" in this project) to the habitat indicators necessary to achieve specific ecological outcomes, which are designated by the term "**goals**" in this project. Goals would be attained through appropriate management strategies to control the quantity and quality of stormwater discharges to a receiving water from a watershed of given land use and land cover.

This project's goals embrace both the biological and water quality components of WRIA 9's aquatic ecosystem. Biological goals are framed in terms of the benthic index of biotic integrity (B-IBI), a measure of the composition of the bottom-dwelling macroinvertebrate stream community (Karr, Fore, and Wisseman 1996). These goals are linked to hydrologic targets derived from research that quantitatively defined the LU/LC-hydrology-biology linkages depicted in Figure 1 (see summary in section 2.0). Water quality goals represent meeting criteria for certain water quality components in receiving waters set by Washington Department of Ecology (WDOE) based on decades of research on the effects of these components on aquatic test organisms. Goals will aim, in general, at protection to sustain no further losses of biological integrity or water quality in the watershed's streams and at selected enhancements to restore some lost resources. This report covers the selection of indicators and assignment of targets to achieve a range of goals.

Figure 2 illustrates how the project functions. The project team is using LU/LC data already assembled for near-present-day and future (based on population forecasts) conditions as starting-point scenarios. With the addition of climate-change projections, these scenarios provide input data sets for running the calibrated HSPF model. Its time-series flow predictions, in turn, serve as input to the SUSTAIN model. SUSTAIN allows convenient testing of extensive stormwater best management practice (BMP) scenarios for their predicted ability to regulate discharges to meet targets set for the selected hydrologic and water quality indicators and achieve protection or restoration goals. These goals are being set and the modeling is being performed for multiple, key locations in the watershed stream network.

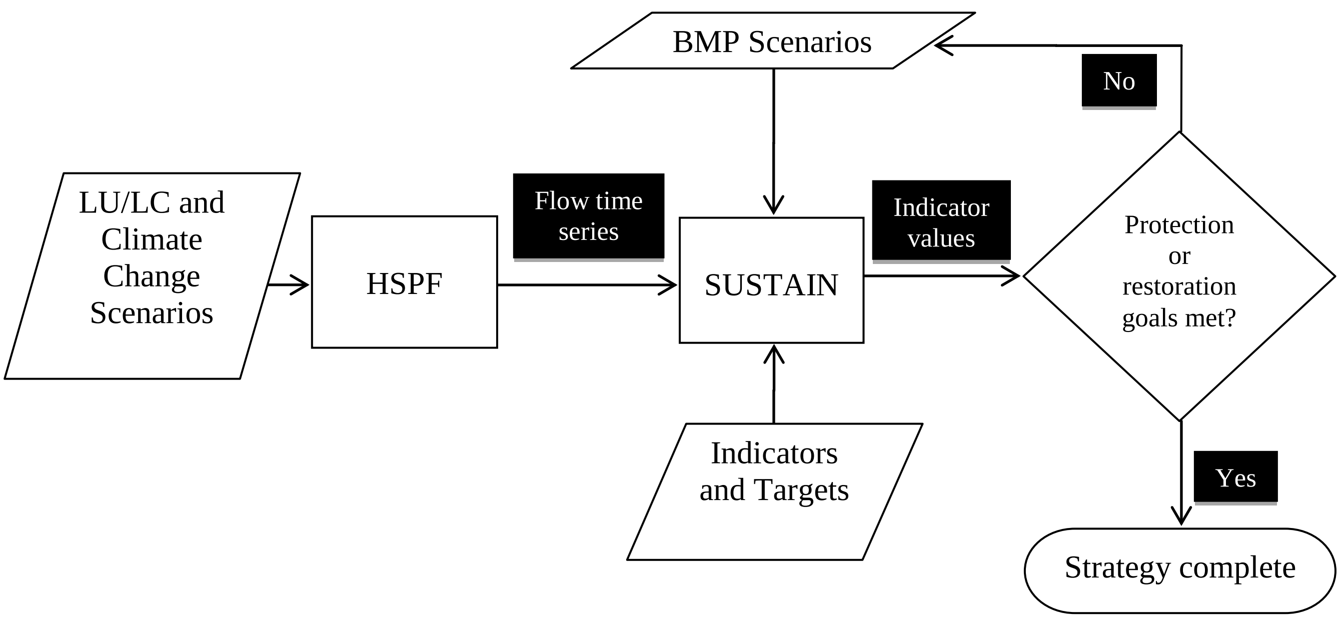

Figure 2. Project Modeling Framework

Project scenarios cover three stages of watershed land use change: (1) new developments on "greenfields", (2) redevelopment of already developed property, and (3) retrofitting static existing development. Most management heretofore has concentrated on the first of those stages. However, redevelopment presents significant opportunities for bringing in protective measures where none previously existed. All urban areas are redeveloped at some rate, generally slowly (e.g., roughly one or at most a few percent *per annum*) but still providing an opportunity to ameliorate aquatic resource problems over time. Extending stormwater requirements to redeveloping property also gradually "levels the playing field" with new developments subject to the requirements. It is important to mention that not only residential and commercial properties redevelop, but also streets and highways are periodically rebuilt.

Opportunities to apply stormwater management practices are obviously greatest at the new development stage, somewhat less but still present in redevelopment, but most limited when land use is not changing. Still, it is extremely important to utilize all readily available opportunities and develop others in static urban areas, because compromised aquatic ecosystem health is a function of the development in place, not what has yet to occur. To meet the project study area's goals, the expectation is that it often will be necessary to retrofit a substantial amount of the existing development with stormwater management measures. A major question for this project is, To what extent can goals be met through management of new development and redevelopment, and how much retrofitting will be necessary to achieve them?
Stormwater management approaches being applied in the project emphasize natural drainage system designs, frequently termed "low impact development" (LID), but also include longer-used conventional practices. LID aims at reducing the quantity of surface runoff produced, above that generated by a natural landscape, and improving the quality of any remnant by exploiting vegetation and soils to infiltrate and evapotranspire water. Soils can be amended, generally with organic compost, to increase water storage and advance these processes. Additional, and equally important, LID strategies are preventing pollutant contact with rainfall or runoff (source controls) and harvesting rainwater for some use, such as gray and irrigation water supply.

Conventional stormwater practices include detention devices, which reduce runoff peak flows but often not total volumes and durations of elevated flows, and treatment facilities, whose main purpose is to capture pollutants and lower their concentrations in the effluent discharged. They differ from LID practices in not emphasizing runoff reduction, taking incidental advantage of whatever water loss occurs, but not explicitly designing to boost water extraction through infiltration, evapotranspiration, and harvesting. Some such practices, for example media filters constructed in a concrete chamber, capture pollutants but do not reduce runoff quantity. Compared to conventional methods, the LID-based practices have been found to be clearly superior in runoff quantity control and cumulative pollutant mass loading reduction and usually better in decreasing the concentrations[1] of pollutants in the remnant effluent (Horner 2010).

[1] Pollutant concentration is the mass per unit volume of a water sample. Loading is the mass delivered per unit time and equals the multiplication product of concentration times flow volume over time.

2.0 SYNOPSIS OF THE SCIENCE

2.1 Aquatic Biological Patterns in Relation to Land Use/Land Cover

Research was initiated at the University of Washington in 1994 to test the broad hypothesis that watershed and riparian characteristics determine habitat conditions, which, in relation to evolved organism preferences and tolerances, set the composition of the biological communities (i.e., the premise represented by Figure 1 above). This hypothesis was tested across a gradient of urbanization, as represented by the total impervious area (TIA) as a proportion of the entire watershed area draining to a stream sampling point. Biological health was assessed according to: (1) the benthic index of biotic integrity (B-IBI); and (2) the ratio of young-of-the-year coho salmon (*Oncorhynchus kisutch*, a relatively stress-intolerant fish) to cutthroat trout (*Oncorhynchus clarkii*, a more stress-tolerant species). B-IBI is a benthic (streambed-dwelling) macroinvertebrate community measure composed of multiple variables expressing the presence of certain species or organism types (Fore, Karr, and Wisseman 1996).

Both biological measures declined with TIA increase without exhibiting a threshold of effect; i.e., declines accompanied even small levels of urbanization (May 1996, Horner et al. 1997, May et al. 1997). However, stream reaches flanked by relatively intact, wide riparian zones in wetland or forest cover exhibited higher B-IBI values than reaches equivalent in TIA but with less riparian buffering. TIA increase also appeared to have less of a negative effect on the biota with a relatively greater degree of upland forest retention. Accompanying LU/LC alteration was a loss of habitat features, like large woody debris and pool cover, and deposition of fine sediments that reduce dissolved oxygen in the bed substrata where salmonid fish deposit their eggs.

With these results in hand, the research turned to investigating in more detail how watershed and riparian zone land cover affects stream biology and devising formal mathematical constructs to increase the utility of the biological and watershed indices as assessment and management tools (Horner, May, and Livingston 2003). Geographic information system (GIS) analysis delineated watershed pervious and impervious cover. GIS data were used to develop a multi-variable Watershed Condition Index (WCI). Variables composing the WCI are either relatively highly correlated to biological indices or were identified in preliminary stepwise multiple and logistic regression exercises as instrumental in linking watershed and aquatic biological states. The WCI is composed of three variables applied in one or more zones (all as percentages of the total area represented by each zone):

VARIABLE / ZONE	TIA	FOREST COVER[a]	PAVED + URBAN GRASS-SHRUB COVER
Overall watershed	X	X	
300-meter wide band on both sides of stream	X	X	X
50-meter wide band on both sides of stream	X	X	

[a] ≥ 86% of pixels in forest cover

Achieving B-IBI ≥ 85 percent of maximum integrity only occurred when WCI was at least 75 percent of the best value, with most of the highest B-IBI scores lying above a WCI of 90. While these watershed conditions are generally necessary for good biological health, they are not sufficient alone, as demonstrated by the numerous points representing lower biological integrity at relatively high WCI values. B-IBI was inevitably below 50 percent of the best if WCI fell beneath 35 percent, and always dropped again to under 30 percent with WCI less than 20 percent.

Booth et al. (2001) added to the Puget Sound database in research also employing the B-IBI and land cover measures. The work demonstrated that urban land cover correlated approximately equally well with B-IBI at each of three spatial scales (Booth et al. 2001, Morley and Karr 2002): (1) subbasin (i.e., the entire watershed area contributing to the sample point), (2) riparian (a 200-meter-wide buffer on each side of the stream extending the full length of the upstream drainage network), and (3) local (a 200-meter-wide buffer on each side of the stream extending 1 km upstream). Even with the general equivalence of correlations, though, seven of the ten variables that comprise B-IBI were better predicted by subbasin rather than local land cover.

Observations on two streams with multiple sampling locations were revealing in regard to the smaller scales. All Swamp Creek sites had watershed urban land cover of about 60-65 percent, local-scale urban land cover generally around 50 percent, and B-IBI scores in the range 22-32. Little Bear Creek was overall less urbanized, at approximately 50 percent for the watershed; but urban land cover varied from 32 to 71 percent at the local scale. In that stream B-IBI ranged with the local urban land cover from 40 to 16, demonstrating the strong effect of nearby urbanization (Booth et al. 2001). These results and those of Horner, May, and Livingston (2003), through somewhat different analyses, thus consistently demonstrated the principal role of watershed-scale land use and cover and the secondary, but still important, function of cover near streams, in general, and in the riparian corridor in particular.

McBride and Booth (2005) examined physical habitat conditions at 70 sites on three urban streams and a non-urban reference stream. They found that the independent variables “intense and grassy urban land” in the watershed overall and in a zone within 500 meters of the site, as well as “proximity of a road crossing” best explained variance in habitat in the three urban streams. Analyses of longitudinal trends within the three urban watersheds showed that conditions improved when a stream flowed through an intact riparian buffer with forest or wetland vegetation and without road crossings.

McBride and Booth (2005) concluded that a strategy that imposes only a watershed-wide limit on development to protect streams is inadequate. Local land cover is also important to physical stream conditions, and therefore this zone of the watershed should have high priority in planning and regulations. If urban development can proceed while maintaining intact, undeveloped riparian buffers, the impact of urbanization should be less than from traditional development patterns. The results also suggest restoration potential for degraded urban streams. If riparian buffers can be reforested and road crossings eliminated or avoided in certain reaches of streams in watersheds with moderate urbanization, partial recovery of a stream’s physical and biological integrity is possible.

2.2 Hydrology Linkages with Land Use/Land Cover and Aquatic Biology

The regional research described above also examined the occurrence and consequences of what is often termed hydrologic “flashiness;” i.e., the frequency and rapidity of short-term changes in stream flow, especially during runoff events (Baker et al. 2004). Flashiness can be expressed in a number of ways. One productive measure was the ratio of the 2-year frequency peak flow rate to the winter (October 1-April 30) base flow rate characteristic of each stream, obtained generally through modeling verified with stream flow records when available (Cooper 1996, Horner et al. 1997, May et al. 1997). The highest biological integrity (> 90 percent of maximum possible B-IBI) was possible only if the ratio remained below 10, as it did only with TIA < 5 percent. Ratios above 30, always the case with TIA > 45 percent, were associated with invertebrate communities exhibiting indices half or less of the maximum B-IBI. These results demonstrate the use of an **indicator** (2-year peak:mean winter base flow ratio), conclusively linked to both watershed conditions and aquatic biological health, and identification of **targets** (e.g., indicator value < 10) necessary to meet a protection **goal** (e.g., B-IBI > 90 percent of maximum).

Booth et al. (2001) and Konrad and Booth (2002) gave substantial attention to the contrast of storm and base flow patterns (i.e., hydrologic flashiness) that are likely to have a persistent influence on the biological conditions of streams. They defined three hydrologic statistics and related them to B-IBI. The two with the most strengths and least limitations are: (1) T_{Qmean}—fraction of a year that mean daily discharge rate exceeds annual mean discharge for a forested condition; and (2) $T_{0.5y}$—cumulative duration that stream flow exceeds the discharge of a flood occurring, on average, twice a year. TQmean is a reliable meaasure of hydrologic change over time in a stream basin, but it varies with drainage area and other physiographic conditions. T0.5 yr shows little sensitivity to drainage area but must be estimated using discharge data of high temporal resolution (e.g., 15-minute or hourly) from a period of multiple years. The highest levels of biological integrity (B-IBI > 80 percent of the maximum) occurred only with TQmean > 0.35 and T0.5yr > 0.03. These statistics, along with the the 2-year peak:mean winter base flow ratio described earlier, are candidate hydrologic indicators for assessing watershed-hydrology-aquatic biology linkages.

Researchers elsewhere have also taken an interest in possible indicators linked to watershed conditions and aquatic biology (e.g., Richter et al., 1996, 1997, 1998; Clausen and Biggs 2000; Baker et al. 2004). Altogether, the various workers have introduced more than 50 hydrologic metrics. King County investigated the utility of many of them as a first step in developing a valid and defensible set of hydrologic and biological indicators as a basis for flow assessment and formulating flow management actions (Cassin et al. 2005). DeGasperi et al. (2009) performed additional evaluation of a subset of 15 metrics for the strength of their associations with urbanization and biological response and relative insensitivity to potentially confounding variables. Indicator selection for this project made heavy use of this work.

2.3 Water and Sediment Quality Linkages with Land Use/Land Cover and Aquatic Biology

Setting water quality criteria, generally in terms of concentrations in receiving waters, is well institutionalized in Washington and other states. Ironically, though, water quality variables have not been directly examined in the same detail as hydrologic metrics in relation to watershed conditions and actual aquatic biological responses. Perhaps the relative dearth of equivalent research stems from the large number of pollutants with numerical criteria and the even much larger number of water contaminants emanating from point and dispersed sources of pollution. Also, the strong role of hydrology in determining the health of the Pacific Northwest's salmonid spawning and rearing streams has been recognized for at least 30 years (e.g., Pederson 1981, Richey et al. 1981, Perkin, 1982, Richey 1982, Scott et al. 1986).

The research beginning in 1994 at the University of Washington described above did give substantial attention to the subject (Bryant 1995, May et al. 1997, Horner et al. 1997). Water quality was examined in wet and dry season base flow and during runoff from a range of storm sizes. Storm event mean concentrations of several water quality variables were found to be related to both storm size and TIA. B-IBI was significantly, negatively correlated with total suspended solids (TSS) and total zinc. However, zinc concentrations were well below regulatory water quality criteria with TIA < 40 percent, beyond which those concentrations approached and in some cases exceeded the criteria.

Sediment metals concentrations were also measured and compared to effect thresholds set by Washington Department of Ecology (1991). Lead and zinc concentrations were significantly correlated with TIA (positively) and B-IBI (negatively). However, sediment metals concentrations never approached the thresholds and did not exhibit a consistent increase until TIA was above 40 percent (Bryant 1995, May et al. 1997, Horner et al. 1997). It thus did not appear that water column or sediment contamination could explain the biotic decline seen at relatively low and moderate levels of urbanization, which appeared to be associated more strongly with hydrologic alteration. However, reduced water quality would be an additional burden to aquatic life, along with hydrologic stress, at greater levels of urbanization.

3.0 INDICATOR SELECTION

3.1 Procedure

As addressed above, the central focus of this project is to identify the most cost-effective combination of stormwater management practices to meet stream habitat targets necessary to achieve defined goals offering protection or enhancement of aquatic biological integrity for most of WRIA 9. The intention is to set numeric stream habitat targets on the basis of a small set of hydrologic and water quality indicators with documented linkages to watershed conditions on the one hand and aquatic biological community integrity on the other. An initial task, therefore, was selecting effective indicators, to be followed by establishing the targets. The search was broadest for hydrologic indicators, because the project scope *a priori* had been delineated to concentrate on TSS as the water quality indicator (Simmonds et al. 2010). However, relationships were also explored between TSS and other water quality variables having known aquatic biological effects, often the subject of water quality criteria, and supported by data collected mainly within WRIA 9.

As the first step, all potential hydrologic indicators were gathered. This collection went beyond the measures of "flashiness" discussed earlier to include the full range of hydrologic metrics introduced in the literature. The full compilation was pared to some degree based on the King County work described earlier to produce a candidate list. It should be noted that the hydrologic metrics considered are those most related to the patterns represented by stormwater discharges. Washington has issued flow guidelines pertaining only to low flows, mainly applying to water withdrawals from relatively large rivers. The elevated flows associated with stormwater discharges are of considerable interest not only in those cases but also in relatively small streams (i.e, third order and smaller) hosting salmonid spawning and rearing.

Next, selection criteria were drafted, reviewed by the full project team, and refined. Candidates were evaluated relative to criteria based on objective evidence (e.g., documented statistically significant correlation between candidate indicator and criterion variable). The evaluations were then tallied for each candidate and each criterion and compiled for all criteria to reach final selections.

3.2 Candidate Hydrologic Indicators and Evaluation Criteria

Appendix A lists and defines all candidate hydrologic indicators. The assessment considered 20 candidates classified in five groups based on similarity in the hydrologic phenomena represented.

The criteria for final selection among candidates were:

1. Extent and quality (relative certainty) of the research database linking the metric to watershed land use/land cover, and demonstrated ability to track trends in these system components and support adaptive management;

2. Extent and quality (relative certainty) of the research database linking the metric to aquatic biological integrity, and demonstrated ability to track trends in these measures;

3. Demonstrated ability of the metric to be established reliably by the available stream gauge data and calculated by HSPF in relatively good agreement with gauge data;

4. Relatively independence from potentially confounding variables (basin area, channel slope, soil type, elevation, precipitation);

5. Ability to add information independent of other metrics;

6. Strength of the basis for setting numerical targets for the metric; and

7. Ability to obtain SUSTAIN model output for the metric.

The principal reference for applying criteria 1 and 2 was the work by DeGasperi et al. (2009), which investigated correlations between hydrologic metrics and measures of urbanization and biological integrity on 16 streams with continuous flow gauge records. The results were generally consistent with those of Cassin et al. (2005), which used gauged and HSPF-generated flow data on a somewhat larger number of sites but drawn from fewer different watersheds. Also, that work covered some metrics of potential interest not assessed by DeGasperi et al. (2009), notably time above 2-year mean flow and onset of fall flows. The latter metric is problematic in that the 7-day minimum flow often does not actually occur in the fall season. Subsequent work under this project constraining the period to September 1-November 30 found a lack of significant correlation between the metric and TIA and B-IBI, and it was dropped from further consideration. The King County work did not consider the 2-year peak:mean winter base flow ratio candidate indicator, and the data of Cooper (1996) were used to evaluate it.

The analysis of Cassin et al. (2005) of the significance of correlations between metric values computed from gauged and modeled data was the primary basis for judging candidate adherence to criterion 3. Cooper (1996) did not independently calculate values of 2-year peak:mean winter base flow ratio with both data types, and thus a correlation analysis could not be done in this case.

DeGasperi et al. (2009) was the main source for assessing criteria 4 and 5. Cooper's (1996) data were employed under this project to do an equivalent analysis of potentially confounding variables for the 2-year peak:mean winter base flow ratio candidate. Judgments by Cassin et al. (2005) and participants in this project added to evaluating candidates for ability to add independent information.

Criterion 6 was ultimately judged to be equivalent to criterion 2, because the ability to set a target for an indicator is directly related to the extent and quality of the database linking it to biological integrity. Criterion 7 did not come into the selection, because the hydrologic output available from SUSTAIN applies no better to calculating one metric than another.

3.3 Application of Criteria to Select Hydrologic Indicators

Table 1 ranks the candidates according to criteria 1 and 2 based on the correlation coefficients in cases where there is a significant correlation ($p < 0.01$) between the candidate indicator and TIA or B-IBI, respectively. The table designates those metrics that meet criterion 3 by having a significant correlation between values computed from gauged and HSPF data. As attested by table notes, there is little distinction among the candidates for criteria 4 and 5, because most are independent of potentially confounding variables; and only two have a clear ability to add information independent of others, at least those ranking highly in terms of the first three criteria.

Table 1. Ranking of Candidate Indicators for Criteria 1-3

CANDIDATE INDICATOR	CRITERION 1	CRITERION 2	CRITERION 3	NOTES
Low Pulse Count	ns[a]	7	sig[a]	
High Pulse Count	4	2	sig	Strong match with criteria 1-3
Low Pulse Duration	8	4	ns	
High Pulse Duration[b]	7	3	ns	
Low Pulse Range	ns	ns	ns	
High Pulse Range	2	1	sig	Very strong match with criteria 1-3
7-day Annual Minimum Flow	ns	ns	ns	
Date of the 1-day Minimum Flow	ns	ns	ns	
Onset of fall Flows[c]	ns	ns	sig	
Fall count	ns	ns	ns	
Rise Count	ns	ns	ns	
Fall Rate	ns	ns	sig	
Rise Rate	ns	ns	ns	
Flow Reversals[b]	5	8	ns	
T_{Qmean}[b]	ns	6	sig	
R-B Index[b]	3	5	ns	
Time above 2-Year Mean Flow[c]	1	10	ns	Strong match with criteria 1-2; potential ability to provide independent information
2-Year Peak:Mean Winter Base Flow Ratio[c]	6	9	na[a]	Strong match with criteria 1-2; potential ability to provide independent information
Normalized Effective Stream Power	ns	ns	ns	
$Q_{2\ current}$:$Q_{10\ forested}$	ns	ns	ns	

[a] ns—not statistically significant correlation between candidate indicator and TIA (criterion 1) or B-IBI (criterion 2); sig—significant correlation at $p < 0.01$; na—not available
[b] Significantly correlated with a potentially confounding variable and thus does not meet criterion 4
[c] Not highly correlated with other candidates and therefore can provide independent information according to criterion 5

The exercise revealed two clear choices for indicators, high pulse count and high pulse range. Most other candidates significantly correlated to both TIA and B-IBI are subject to potentially confounding variables. Time above 2-year mean flow is not subject to this drawback, and 2-year peak:mean winter base flow ratio is considered by the project team to be in the same category. Both can add information independent of the two pulse indicators. Although neither have demonstrated close correspondence in computation results from both gauged and modeled data, their close associations with LU/LC and biological measures and ability to add information were taken as overriding considerations. Accordingly, they were also tentatively selected as indicators.

Subsequent investigation discovered unreliability in the available data for the indicator time above 2-year mean flow, and it had to be eliminated from further consideration. This problem subverted the objective of supplementing high pulse count and high pulse range with additional indicators expected to supply different information. While the 2-year peak flow:mean winter base flow indicator still remained for that purpose, a search ensued for a replacement for the lost indicator.

Disturbance frequency of spawning gravels, i.e. frequency of flows capable of mobilizing spawning gravel as an average number of events per year, was identified as a possible replacement, with a target of < 3/year based on limited data (Doyle et al. 2000, Hartley personal communication). However, applying the indicator is complicated by the existence of several important variables, in addition to hydrologic measures, affecting its value (e.g., substrata composition, large woody debris). Its use is further complicated by obtaining suitable model output for quantification. It appears that using the indicator would require extensive assumptions and post-processing after SUSTAIN runs. This indicator will be held in reserve with a decision on its use delayed until results with the three remaining indicators are available and the ability of the project to support the greater post-processing burden can be evaluated.

In addition to ranking highly in extent of correlation with TIA, the two pulse indicators are highly correlated with two other LU/LC measures. DeGasperi et al. (2009) found high pulse range to rank first and high pulse count second in correlation with percent urban land cover and percent forest cover.

Along with being significantly correlated with B-IBI, the selected indicators all have relatively strong associations with other biological system components as well. As shown by Cassin et al. (2005), high pulse count is significantly correlated with two B-IBI components, clinger invertebrates and total number of taxa that have one or fewer generations per year (univoltine plus semivoltine taxa). Time above 2-year mean flow is significantly correlated with those two variables plus Baetids, a mayfly family. High pulse count has a significant correlation with univoltine plus semivoltine taxa. Work under this project with Cooper's (1996) data showed that the 2-year peak:mean winter base flow ratio is significantly correlated with the ratio of young-of-the-year coho salmon to cutthroat trout at $p < 0.05$ (but not $p < 0.01$).

3.4 Further Discussion of Selected Hydrologic Indicators

Figures 3 to 6 graphically portray the four chosen hydrologic indicators. Figures 3 and 4 compare high-flow pulses with urban development versus pre-developed LU/LC. A greater high pulse count and range tend to accompany development. Figure 3 shows a high pulse range from a date in November to late June, while pre-development the range extended from December to April. A protection goal in this case would be to apply stormwater management to hold the high pulse count and range within the current parameters, while a partial restoration goal could be controlling runoff discharges to reduce the count and range toward the former state.

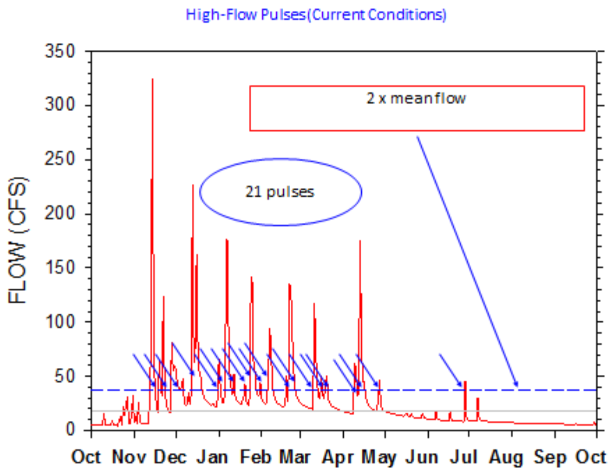

Figure 3. Hydrograph Displaying High-Flow Pulses with Developed Use/Land Cover

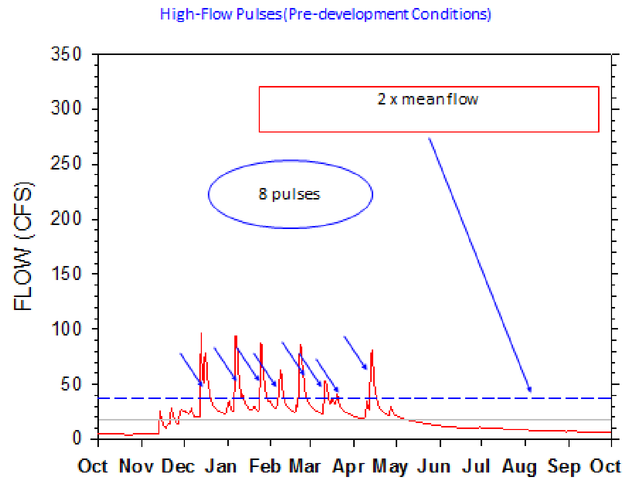

Figure 4. Hydrograph Displaying High-Flow Pulses Land Pulses with Pre-development Land Use/Land Cover

Figure 5 depicts the third selected hydrologic indicator. The 2-year peak:mean winter base flow ratio is computed by dividing the flow rate exceeded with a 2-year frequency by the average base flow in the months October through April. Values of the indicator tend to increase with landscape conversion from natural to developed LU/LC.

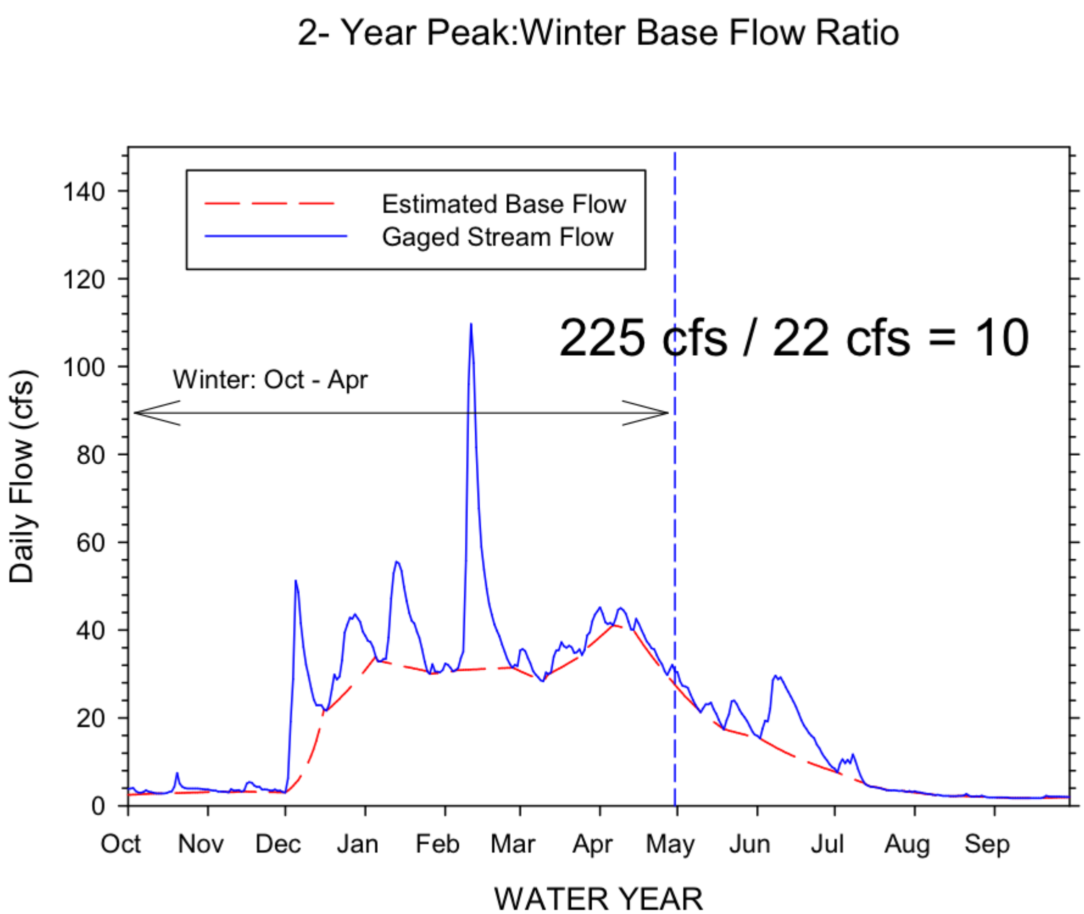

Figure 5. Hydrograph Illustrating Determination of 2-Year Peak:Mean Winter Base Flow Ratio (note: 2-year frequency peak flow rate did not occur in the year portrayed)

3.5 Water Quality Indicators

As pointed out above, the project scope designated TSS as the principal water quality indicator. The primacy of sediments is appropriate, in that they are an instrumental feature of water quality because of their numerous ecological consequences, including:

- Covering and seeping into coarse bed materials where fish spawn and eggs develop; in filling the pore spaces, sediments restrict the flow of water carrying dissolved oxygen, resulting in asphyxiation of the young;
- Covering the surfaces serving as habitat for fish food sources (e.g., insects, algae);
- Filling deeper areas, tending to produce a more homogeneous bed and less habitat diversity and specifically reducing pools where fish rest and seek refuge from predators;
- Reducing visibility, making it harder for fish to find food and avoid predators;
- Reducing light penetration to underwater plants and algae;
- Abrading the soft tissues of fish, especially gills; and
- Transporting other pollutants present in the soil or picked up in transport.

Regarding the latter impact, sediments are a transport medium for many contaminants in other categories of water pollutants: metals, organic chemicals, nutrients, and pathogens.

Despite this high level of importance, the association between TSS, or any other measure of sediments, and biological integrity has not been established or even much investigated for regional streams. Unlike with the selected hydrologic indicators, therefore, a basis does not exist to set TSS targets to meet specific goals for the protection or restoration of aquatic life.

Furthermore, water quality criteria are not formulated in terms of TSS. Turbidity, a measure of the light scattering ability of particles suspended in a water sample, is a basis for existing criteria. However, SUSTAIN provides only TSS as sediment output and not turbidity. Other criteria are stated as concentrations of specific metals (as dissolved quantities), organic chemicals, and pathogen indicator organisms. SUSTAIN does model metals discharge. There is a strong interest in this project in evaluating in some way the ability of stormwater management strategies to aid in meeting at least some of these water quality criteria and advancing protection and restoration goals.

Fortunately, a previous King County project in the Green River watershed produced a large database containing TSS, turbidity, three metals (copper, lead and zinc, all in both total recoverable and dissolved forms), and phosphorus (total and orthophosphate), as well as flow rate. The database has over 1000 measurements for TSS and turbidity and almost 900 for the other contaminants. These large numbers offered the potential ability to develop statistical relationships between TSS and other measures with strong confidence levels. These data were analyzed as described in section 6.0 to determine their capacity to support target selection and, therefore, the ability of the metrics to serve as indicators for this project.

4.0 APPLICATION OF TARGETS FOR GOAL ASSESSMENT

4.1 The "Range-of-Outcomes" Approach

The target-setting phase of work was initiated with a general consideration of how targets can best be applied in the project's framework, as illustrated in Figure 1, to yield the broadest range of information with the greatest convenience. It was decided to frame the exercise in a "range-of-outcomes" mode; i.e., instead of settling on a few specific targets, mechanisms would be developed to investigate a spectrum of possibilities. This decision took inspiration from Reeves and Duncan (2009), who recognized the dynamic, non-equilibrium nature of aquatic ecosystems and the historical variation of watershed conditions over time. They argued against using averages or any other single values as the basis for management actions in the face of variation in habitat conditions over time and the time dimension of succession to some ultimate state, itself subject to further change. They expressed the belief that, in the often highly modified state of aquatic ecosystems, static reproductions of past conditions are impossible on any broad scale.

In the context of this project, the range-of-outcomes philosophy is being applied by selecting quantitative protection or restoration goals for which to evaluate BMP strategies with SUSTAIN. With modeling, the goals to be investigated are limited only by the demands of time to input data and the required run time. Hence, the range of outcomes to be investigated could extend all the way from maintaining an existing state, to some fractional improvement (e.g., a 10 or a 50 percent increase in an ecological metric), to returning the metric to equivalence with a pre-European-settlement, fully forested condition. The main subject covered below is a report on the work performed to develop relationships linking prospective goals with hydrologic and water quality targets that must be met to achieve those goals. For any goal of interest, then, SUSTAIN, with post-processing of its output in some cases, will tell if the targets essential to achieving goals can be met and the costs of doing so. With this information, further refinement will then whittle goals to those most expeditious and feasible for the WRIA 9 retrofit plan.

4.2 The Nature of Goals

The goals being investigated in this project are fundamentally rooted in biological outcomes. Substantial past research, summarized earlier, quantitatively linked the tentatively selected hydrologic indicators with biological metrics, principally B-IBI. Goals are being expressed as B-IBI targets, and the quantitative relationships then translate these numbers to targets set for the selected hydrologic indicators, to be subjected to analysis by SUSTAIN and, as necessary, post-processing data work.

WDOE water quality criteria (173-201A WAC), also grounded in the requirements and tolerance limits of aquatic biota, are the basis for water quality targets. Essentially, the goals comprise meeting those criteria for the selected indicators according to all WDOE stipulations, including anti-degradation requirements.

4.3 Treatment of Uncertainty

Uncertainty is a constant fact of life in environmental explorations and should, in any case possible, be expressed as part of forecasts. Fortunately, sufficient data are available in both the hydrologic and water quality realms to perform the statistical analyses necessary to quantify uncertainty for this project. Therefore, all goal assessments are being framed in terms of the best estimate of the hydrologic or water quality target needed to achieve the goal and the probability or confidence interval associated with that estimate.

5.0 HYDROLOGIC TARGETS

5.1 General Procedure

The first task in hydrologic target setting involved reviewing the available literature and data relating the selected hydrologic indicators with biological indicators. Second was an evaluation of the adequacy of already completed statistical analyses to establish hydrologic targets for a range of biological outcomes (mainly working with B-IBI) with known levels of certainty. Where these results were not fully adequate and additional data existed to improve target setting, the work turned to further statistical analyses.

5.2 High Pulse Count and High Pulse Range Targets

5.2.1 *Data Available for Target Setting*

Two data sets are available for potential use in target setting. One set compiled by DeGasperi et al. (2009) has data from 16 stream stations with at least one full water year (October-September) and calendar year of continuously recorded flow data coincident with the year in which benthic organisms were sampled and B-IBI determined. The second data set is considerably larger, with 46 stations. However, the timing of flow gauging and benthic sampling varied substantially among these sites; and they were more heterogeneous in characteristics like watershed size, channel slope, geology, and soils. The resulting data exhibited much more variability than the data of DeGasperi et al. (2009), and statistical analyses produced less satisfactory relationships for target-setting purposes than those derived from the more homogeneous locations. Accordingly, the second data set was discarded and the exercise proceeded with the first one.

5.2.2 *Basic Analyses*

Figures 6 and 7 depict B-IBI in relation to high pulse count (HPC) and high pulse range (HPR), respectively, from the DeGasperi et al. (2009) data. There is a clear trend toward biological decline with increase of both hydrologic indicators. However, there is a dearth of relatively high B-IBI values, and a lack of any values between 16 and 24, deficiencies in the data set that impede target setting. It could be said that the highest B-IBI can only be achieved with HPC < 5 and HPR < 100, but that judgment is based on only one data point. Also, those hydrologic conditions clearly do not guarantee such a favorable biological outcome, since one point with low HPC and HPR falls much lower in B-IBI. This pattern mirrors that seen in data from earlier research, summarized above, in which specific environmental conditions were found to be necessary but not sufficient to produce a particular relatively high level of biological integrity. On the other hand, it can be seen in the graphs that B-IBI never rose above 16 if HPC exceeded 15 and HPR was above 200. This pattern was also evident in the earlier data, where it was found that certain specific environmental conditions appear to guarantee inevitably low biological integrity.

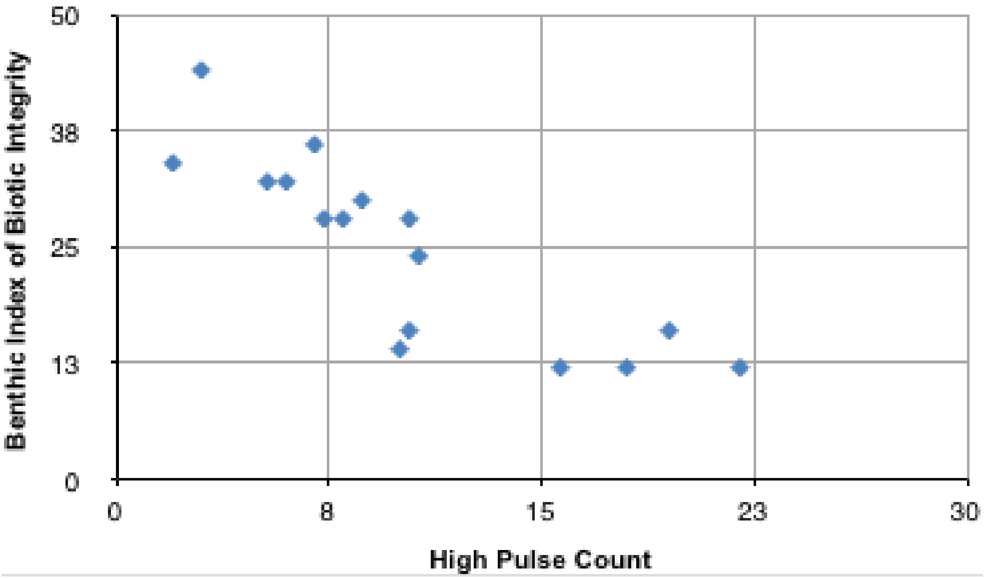

Figure 6. Benthic Index of Biotic Integrity in Relation to High Pulse Count

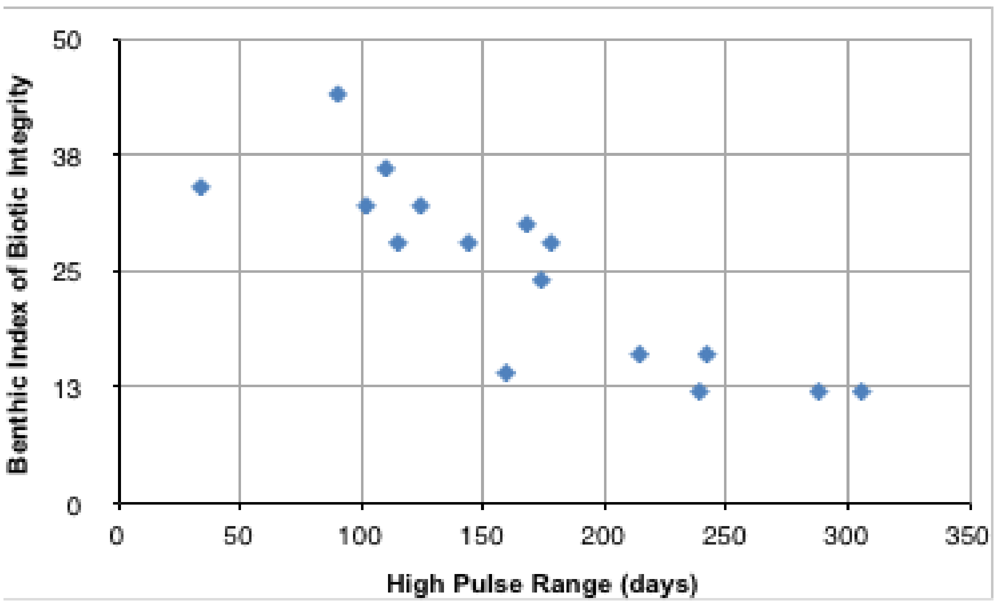

Figure 7. Benthic Index of Biotic Integrity in Relation to High Pulse Range

Taking this analysis farther, Table 2 gives the necessary conditions for several B-IBI levels, along with means and ranges of the hydrologic indicators associated with those levels. These numbers give direction for target setting but are still not sufficient to guarantee higher B-IBI levels (≥ 24). The table shows that mean HPC and HPR values are very close for the first two B-IBI categories and the ranges largely overlap. Overlap is less but continues through the next two categories. This lack of separation in the data complicates target setting and requires formal consideration of the relative certainty of any outcome, the purpose of statistical analyses reported below. One point that can be made with substantial confidence is that a goal of raising B-IBI out of the lowest tier (to > 16) cannot be achieved if HPC remains above 15 and HPR over 200.

Table 2. Limiting Values and Means and Ranges of High Pulse Count and High Pulse Range (Days) Associated with Certain Ranges of Benthic Index of Biotic Integrity

B-IBI	LIMITING VALUE		MEAN[a]		RANGE		NUMBER OF DATA POINTS
	HPC	HPR	HPC	HPR	HPC	HPR	
>35	≤7	≤110	5.0	100	3.0-7.0	90-110	2
30-35	≤9	≤168	5.5	107	2.0-8.7	34-168	4
24-29	≤11	≤178	9.1	153	7.3-10.7	115-178	4
≤16	>15	>200	15.9	241	10.0-22.0	160-306	6

[a] Medians are very similar to means.

5.2.3 *Statistical Analyses*

The data of DeGasperi et al. (2009) plotted in Figures 7 and 8, even with the gaps noted above, yielded relatively strong statistical relationships that can be used to aid in setting HPC and HPR targets based on selected B-IBI objectives. Importantly also, the statistical analyses allow expressing uncertainty and the confidence that can be attached to target assignments. Table 3 presents the regression equations best explaining variance in the dependent variable, which are logarithmic, and confidence limits for the model parameters. The percent of maximum B-IBI score was used in deriving the equations to allow comparison of results obtained using these two indicators with those from the 2-year peak:mean winter base flow ratio indicator. The data set for the latter indicator is based on an earlier B-IBI formulation with a maximum score of 45, whereas 50 is the maximum in the HPC and HPR database.

Table 3. Regression Equations and Associated Statistics Relating High Pulse Count and High Pulse Range with Benthic Index of Biotic Integrity Based on Data Compiled by DeGasperi et al. (2009)

STATISTIC			HIGH PULSE COUNT (HPC)	HIGH PULSE RANGE (HPR)
Equation			Ln (% Max. B-IBI Score) = - 0.066*HPC + 4.50[a] (Equation 1)	Ln (% Max. B-IBI Score) = - 0.005*HPR + 4.69[a] (Equation 2)
R^{2*}			0.745	0.755
Confidence limits (lower, upper)	90%	Coefficient	(-)0.084, (-)0.048	(-)0.007, (-)0.004
		Constant	4.29, 4.71	4.44, 4.95
	80%	Coefficient	(-)0.080, (-)0.052	(-)0.006, (-)0.004
		Constant	4.34, 4.66	4.50, 4.89
	60%	Coefficient	(-)0.075, (-)0.057	(-)0.006, (-)0.004
		Constant	4.39, 4.60	4.57, 4.82

[a] Ln signifies the natural logarithm.

[*] R^2 represents the fraction of variability in a data set explained by the statistical model. Both regressions are significant at $P < 0.001$.

5.2.4 *Examples*

Table 4 gives best estimates of B-IBI values resulting over ranges of HPC and HPR, as computed from the regression equations. The table also presents the lowest B-IBI expected at three confidence levels for each estimate. Color fonts indicate values discussed in the illustration.

For illustration, the best estimates for HPC and HPR targets to increase B-IBI from a lower level to **approximately 50 percent of the maximum value (25) are HPC < 5-10 and HPR < 150**. However, if one took a somewhat cautious stance and demanded **80 percent confidence of meeting the goal with the least optimistic forecast (low B-IBI estimate), HPC and HPR would have to be held to no more than 5 and 100, respectively**. As another illustration, suppose that the goal is to **keep B-IBI above the lowest tier in Table 1 (i.e., > 16, equivalent to > 32 percent of the maximum)**. The best estimates of hydrologic targets to reach that goal are **HPC = 15 and HPR = 200** or slightly less, similar to the conclusion from the less formal analysis presented above. However, those targets would not give strong confidence of meeting the goal, and values **around 10 and somewhat under 200, respectively, would be needed even for 60 percent confidence** of fairly certain achievement.

It is evident in the table that meeting the highest biological goals (e.g., B-IBI > 75 percent of maximum) can be anticipated only with the very lowest levels of HPC and HPR. Even then, there would not even be 60 percent confidence that these goals would actually be achieved in the least optimistic prediction.

Ultimate goal and target setting hence must contend with the uncertainty inherent in the underlying data and the expressions derived from them. The range of possible outcomes can be assessed by applying the regression equations for best estimates and worst-case assumptions, and also with different confidence levels, to make the most judicious choices. Then, modeling can determine the stormwater management strategies needed to achieve potential goals and their associated targets. This is the recommended strategy for this project.

Table 4. B-IBI Best Estimates and Lower Confidence Bounds Determined from Regression Equations for Ranges of High Pulse Count and High Pulse Range

INDICATOR	TARGET	B-IBI BEST ESTIMATE (% OF MAX.)	CONFIDENCE LEVEL (%)	LOW B-IBI ESTIMATE (% OF MAX.)
HPC	2	78.9	90	61.7
	5	**64.7**		47.9
	10	**46.5**		31.5
	15	**33.4**		20.7
	20	24.0		13.6
	2	78.9	**80**	65.4
	5	64.7		**51.4**
	10	46.5		34.5
	15	33.4		23.1
	20	24.0		15.5
	2	78.9	**60**	69.4
	5	64.7		55.4
	10	46.5		**38.1**
	15	33.4		26.2
	20	24.0		18.0
HPR	50	84.8	90	59.7
	100	66.0		42.1
	150	**51.4**		29.7
	200	40.0		20.9
	250	31.2		14.7
	300	24.3		10.4
	50	84.8	**80**	66.7
	100	66.0		**49.4**
	150	51.4		36.6
	200	**40.0**		27.1
	250	31.2		20.1
	300	24.3		14.9
	50	84.8	**60**	71.5
	100	66.0		53.0
	150	51.4		**39.3**

Table 4 continued

	200	40.0		**29.1**
	250	31.2		21.5
	300	24.3		16.0

5.3 2-Year Peak:Mean Winter Base Flow Ratio Targets

5.3.1 *Data Available for Target Setting*

Cooper (1996) produced a data set incorporating B-IBI and the 2-year peak:mean winter base flow ratio (PEAK:BASE) indicator at 56 stations on 20 Puget Sound lowland streams. The data set also includes determinations of young-of-the-year coho salmon:cutthroat trout ratios at 11 stations. The anadromous coho are more sensitive to urban stream stresses and tend to be more prevalent than the resident cutthroat only at low levels of those stresses. The hydrologic variables were computed from model outputs, primarily derived from the King County Runoff Time Series (KCRTS) model. The Hydrologic Simulation Program – FORTRAN model was employed on four streams and, on four others, a stepwise multiple linear regression equation (after Cummans, Collings, and Nassar 1975) giving flow rate as a function of basin area and percent glacial till soil. B-IBI data were from Kleindl (1995), computed on a 45 point scale pre-dating the 50 base used in later years. The fish data were from a variety of previous studies compiled by May (1996).

PEAK:BASE values were computed for the stream stations in the DeGasperi et al. (2009) data set, with the thought that it would be ideal to use the same data for all hydrologic target setting, as well as keep B-IBI on the same 50 scale for all determinations. However, those data exhibited more scatter than the larger Cooper database. Data from the two sources could not be combined because of the differing B-IBI bases. Accordingly, the exercise proceeded with the Cooper data.

5.3.2 *Basic Analyses—Benthic Data*

Figure 8 plots B-IBI in relation to PEAK:BASE from the Cooper (1996) data. As in Figures 6 and 7, there is a clear trend toward biological decline with increase of the hydrologic indicator. While this larger data set has a more continuous distribution of B-IBI values than the data used for HPC and HPR target setting and extends to closer to the maximum score, it also exhibits more scatter. It can readily be seen that the highest B-IBIs can only be achieved with PEAK:BASE < 10, but that condition again far from guarantees such a favorable biological outcome. It is thus another necessary but not sufficient requirement. On the other hand, it can be seen in the graph that B-IBI never rose above 19 if PEAK:BASE exceeded about 35, a point that appears to guarantee inevitably low biological integrity.

Taking this analysis farther, Table 5 gives the necessary conditions for several B-IBI levels, along with means and ranges of the hydrologic indicator associated with those levels. Like in Table 1, PEAK:BASE range overlap is prevalent and the mean values are very close for the second and third B-IBI categories, and are in fact reversed in order from the expected. Once again, these circumstances in the data complicate target setting and require statistical analyses, reported below. One point that can be made with substantial confidence is that a goal of raising B-IBI out of the lowest tier (to > 19) cannot be achieved if PEAK:BASE remains above 35.

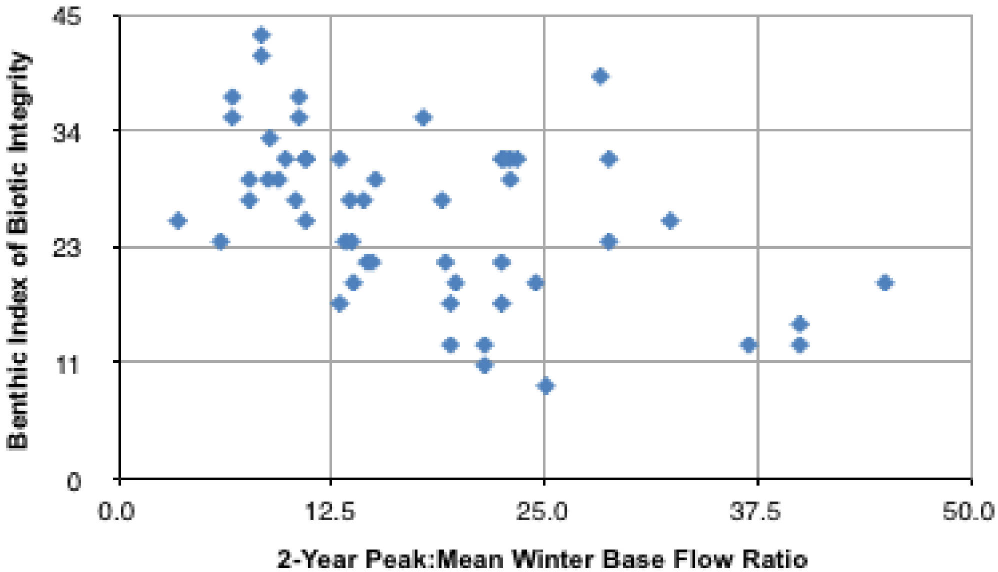

Figure 8. Benthic Index of Biotic Integrity in Relation to 2-Year Peak:Mean Winter Base Flow Ratio

Table 5. Limiting Values and Means and Ranges of 2-Year Peak:Mean Winter Base Flow Ratio Associated with Certain Ranges of Benthic Index of Biotic Integrity

GROUP	B-IBI		2-YEAR PEAK:MEAN WINTER BASE FLOW RATIO			NUMBER OF DATA POINTS
	SCORE	% OF MAX.	LIMITING VALUE	MEAN[b]	RANGE	
1	>35	>78	≤11[a]	12.5	6.7-28.3	5
2	26-35	57-78	≤30	14.9	6.7-28.8	25
3	19-25	42-56	≤33[a]	18.6	3.5-45.0	16
4	<19	<42	>35[a]	26.0	13.0-40.0	10

[a] One outlying data point was omitted in assigning this value.
[b] Median is approximately 4.0 less, except for Group 2 in which the median is 1.3 less.

5.3.3 *Statistical Analyses—Benthic Data*

Mirroring the scatter evident in Figure 9, regressing B-IBI and the PEAK:BASE indicator did not yield a strong relationship (best $R^2 = 0.23$ for a power function). Consequently, this indicator and its targets are considered to be secondary to HPC and HPR but still potentially useful as an independent confirmation of conclusions reached on the basis of the primary indicators.

To improve target setting ability for PEAK:BASE, the data were examined using logistic regression analysis, which predicts the probability of the dependent variable's falling in a given range with different values of the independent variable. The analysis was performed with SPSS Statistics 19 for MS Windows.

Logistic regression analysis develops an equation for the logit function, L, in the form $L = b_o + b_1x$, where in this case x = PEAK:BASE or log-transformed PEAK:BASE. L is the natural logarithm of the odds of a result being within or outside of a group. In the present context, the group is a B-IBI above a certain score versus below that value. The probability, P, of being in the group is $P = e^L/(1 + e^L)$, where e is the base of the natural logarithm system (≈ 2.718). To introduce uncertainty to the analysis, confidence limits on b_1 can be determined from the standard error (SE) of the estimate of b_1; e.g., 95 percent upper and lower confidence limits = $b_1 \pm 1.96*SE$ (Everitt and Dunn 2001, Sorensen 2006).

The quality of the outcome of logistic regression analysis can be assessed in a number of ways, all of which were applied in this project. They include (Kinnear and Gray 2000): (1) ability to predict group membership versus exclusion from membership, (2) Cox and Snell R^2, (3) Nagelkerke R^2, (4) Hosmer and Lemeshow significance test, and (5) Wald significance test.

Logistic regression models were generated for the following B-IBI groups (defined in Table 4): (1) Group 4 versus Groups 1-3, (2) Groups 3-4 versus Groups 1-2, (3) Groups 2-4 versus Group 1, (4) Group 4 versus Group 3, (5) Group 3 versus Group 2, and (6) Group 2 versus Group 1. Each analysis was performed with PEAK:BASE log-transformed and untransformed, for a total of 12 analyses.

Only two of these analyses yielded models capable of predicting both group membership and non-membership correctly more than half of the time. One of these models rated relatively poorly with respect to the other judgment criteria though. The remaining model was 73 percent correct in predicting membership in Groups 1 or 2 (B-IBI > 56 percent of the maximum) and 62 percent accurate in forecasting non-membership (i.e., falling in Groups 3 or 4). This model is:

$$L = 1.87 - 0.098*(PEAK:BASE) \qquad \text{(Equation 3)}$$

A third model was very effective (98 percent) at forecasting membership in Groups 1-3 (B-IBI ≥ 42 percent of maximum). Although less able to predict non-membership (30 percent), the model ranked the highest or among the highest in all other respects. This model is:

$$L = 9.40 - 6.17*\text{Log}(PEAK:BASE) \qquad \text{(Equation 4)}$$

Based on all of the quality criteria, these two models clearly rated above the rest and were adopted for use in project target setting. The most poorly performing models from the standpoints of predictive ability and statistical criteria were those delineating B-IBI in adjacent groups (e.g., Group 2 versus 1 or 4 versus 3). The available data are too dispersed for that level of differentiation.

5.3.4 Examples

Table 6 shows the probabilities estimated from the logistic regression models of achieving two levels of B-IBI increase for a range of PEAK:BASE ratio, along with the lowest expected probabilities at several confidence levels. Equation 3 was used for forecasts of raising B-IBI from Group 3 or 4 to Groups 1 or 2, while Equation 4 was the basis for predictions of B-IBI increase from Group 4 to Groups 1.3. Again, color fonts point out numbers discussed in the illustration below.

Table 6. Best and Lowest Probability Estimates for Achieving Two Levels of B-IBI Increase with a Range of 2-Year Peak:Mean Winter Base Flow Target Values Based on Logistic Regression Analysis

2-YEAR PEAK:MEAN WINTER BASE FLOW TARGET	B-IBI INCREASE	ESTIMATED PROBABILITY OF B-IBI INCREASE	LOWEST PROBABILITY ESTIMATE OF B-IBI INCREASE			
			95[a]	90[a]	80[a]	60[a]
5	From Group 4 to Groups 1-3	0.99	0.88	0.92	0.95	0.98
10		0.96	0.23	0.38	0.58	**0.79**
20		**0.80**	0.01	0.03	0.08	0.25
30		**0.57**	0.00	0.01	0.02	0.07
40		0.38	0.00	0.00	0.01	0.03
45		0.31	0.00	0.00	0.00	0.02
5	From Groups 3-4 to Groups 1-2	0.80	0.73	0.74	0.76	0.77
10		**0.71**	**0.54**	**0.56**	**0.60**	**0.64**
20		0.48	0.17	0.21	0.26	0.32
30		0.25	0.04	0.05	0.07	0.12
40		0.11	0.01	0.01	0.02	0.03
45		0.07	0.00	0.00	0.01	0.02

[a] Percent confidence. Logistic regression probabilities are normally based on 95 percent confidence, but results for other levels are given for illustration.

As an illustration, the best estimate of a PEAK:BASE target to reach **0.80 probability of increasing B-IBI from Group 4 to Groups 1-3 is PEAK:BASE = 20**. However, the probability could be as low as 0.25 even with 60 percent confidence and would require **a target of PEAK:BASE = 10 to have 60 percent confidence in reaching a probability of about 0.80**. This is a very low ratio only observed in the least urban cases. However, there is expected to be a **better than even chance (0.57 probability) of achieving the goal with PEAK:BASE = 30**. Raising B-IBI further, to **Groups 1 or 2, is more challenging yet, being at least somewhat likely (>0.50 probability) only if PEAK:BASE is around 10 or lower**.

5.3.5 *Fish Data Analyses*

Similar linear and logistic regression analyses were performed for the ratio of young-of-the-year coho salmon to cutthroat trout biological indicator. While significant relationships with relatively good statistics resulted, confidence bands were very wide, a consequence of the small data set for this indicator, as well as the data's variability. For example, while the best estimate of the probability to reach the highest values for the indicator is 66 percent with PEAK:BASE ≤ 10, even the 60 percent confidence band extends from 0 to 99 percent. Therefore, these analyses are not capable of adding reliable information to that gained from analyses of B-IBI and the three hydrologic indicators. Still, as portrayed in Figure 9, PEAK:BASE < 18 is necessary but not sufficient for coho numbers to exceed cutthroat, and increase above that level appears to drive the community to strong cutthroat dominance.

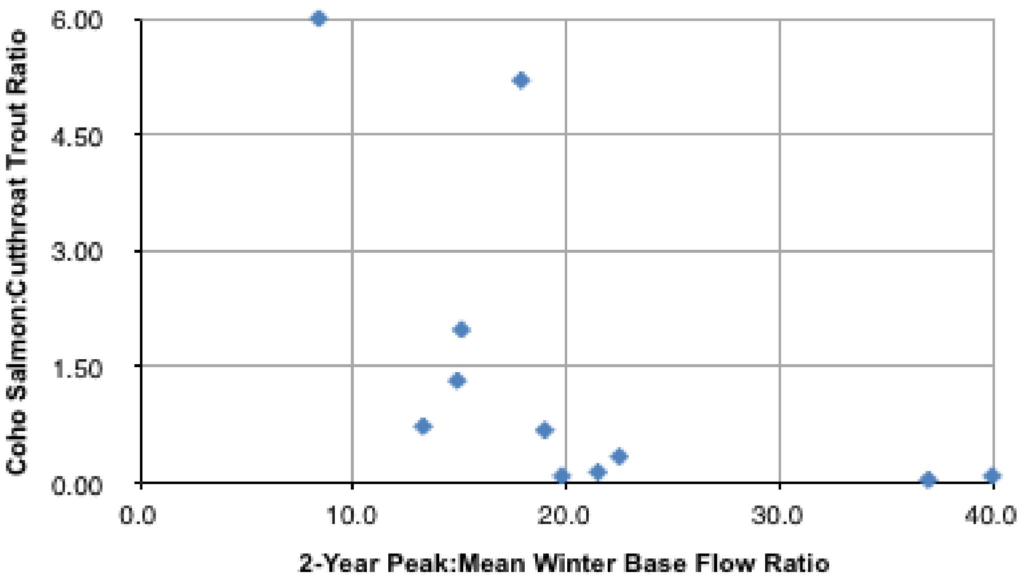

Figure 9. Young-of-the-Year Coho Salmon:Cutthroat Trout Ratio in Relation to 2-Year Peak:Mean Winter Base Flow Ratio

5.4 Using Hydrologic Indicators and Targets in Concert

In its present state of development SUSTAIN directly calculates HPC for the watershed LU/LC and optimally selected stormwater management practices. The two remaining indicators can be quantified with post-processing calculations.

The target-setting examples presented for the three selected hydrologic indicators show that the project must operate in an environment in which achieving any particular biological goal will have a fairly high degree of uncertainty. It is unlikely that application of the three indicators will yield a similar outcome with approximately equivalent confidence. However, the availability of multiple bases for judgment somewhat mitigates that disadvantage. While HPC and HPR are closely correlated, PEAK:BASE does offer a somewhat less closely associated indication. Ultimate strategies will have to be decided upon in relation to the weight of the evidence offered by the three best estimates of outcome and the associated uncertainty.

6.0 WATER QUALITY TARGETS

6.1 Investigating Targets

A previous King County project in the Green River watershed produced a large database containing TSS, turbidity, three metals (copper, lead and zinc, all in both total recoverable and dissolved forms), and phosphorus (total and orthophosphate), as well as flow rate. The database has over 1000 measurements for TSS and turbidity and almost 900 for the other contaminants. These large numbers offered potential ability to develop statistical relationships between TSS and other measures with strong confidence levels. The work proceeded, according to the following outline, to investigate relationships between TSS and each of the other water quality variables and between dissolved metals and both total recoverable metals and flow rate.

6.1.1 *Solids*

Determine if a statistically justified relationship (or a set of relationships for different portions of the watershed) exists to relate TSS and turbidity.

- <u>If so</u>, set turbidity targets on the basis of WDOE water quality criteria, translate to TSS based on the relationship(s), and use with SUSTAIN to gauge the effectiveness of stormwater management scenarios.

- <u>If not</u>, set TSS targets at values ranging from not surpassing a high concentration associated with a developed condition to selected reduction levels down to as low as the concentration associated with forested land cover. While these selections would not have an immediate tie to biological outcomes, they could be related to the results of applying hydrologic controls. If management were pointed first at controlling hydrology, the SUSTAIN TSS output for that strategy could be compared to TSS targets to see if, indeed, a protection goal of no further water quality degradation would be met or, alternatively, how much TSS reduction would occur toward meeting a restoration goal.

6.1.2 *Metals*

Determine if a statistically justified relationship (or a set of relationships for different portions of the watershed or different metals) exists to relate dissolved metals to other variables (e.g., total recoverable metals, TSS and/or flow rate).

- <u>If so</u>, set dissolved metals targets on the basis of WDOE water quality criteria, translate to other variables based on the relationship(s), and use with SUSTAIN to gauge the effectiveness of stormwater management scenarios.

- <u>If not</u>, but if reasonably strong relationship(s) are found, use them along with SUSTAIN output to make judgments about the probability of meeting metals water quality criteria as a function of success in controlling TSS.

6.2 Solids Targets

Strong linear relationship between turbidity and TSS were found in the Green River watershed data set. Table 7 presents the regression equations derived from all available data and from storm flow measurements, in both cases working with detectable values. Only 3.5 and 3.1 percent of turbidity and TSS measurements, respectively, were below detection levels. While non-detectable data could be incorporated by assigning values at half the detection limit or using a statistical technique, adding these fractional quantities to the data set of more than 1000 points would make little difference in the outcome of the analyses.

Table 7. Regression Equations and Associated Statistics Relating Turbidity with TSS Based on All Data and Storm Flow Data in King County's Green River Watershed Data Set

STATISTIC		ALL DATA[a]	STORM FLOW DATA[a]
Equation		Turbidity=0.46*TSS+3.26 (Equation 5)	Turbidity=0.46*TSS+4.02 (Equation 6)
R^2 [b]		0.877	0.883
95% confidence limits (lower, upper)	Coefficient	0.44, 0.47	0.44, 0.47
	Constant	2.77, 3.74	3.27, 4.78

[a] Units: turbidity—nephalometric turbidity units (NTU); TSS—mg/L
[b] R^2 represents the fraction of variability in a data set explained by the statistical model. Both regressions are significant at $P < 0.001$.

To investigate the difference in estimates with the two equations, turbidity was computed for TSS varying from 1 to 350 mg/L. The difference is 10-17 percent for TSS = 1-7 mg/L, < 10 percent with TSS > 7 mg/L, < 5 percent with TSS > 24 mg/L, and ≤ 2 percent with TSS > 75 mg/L. Thus, either equation can be used unless assessing relatively low solids transport, when the equation should be chosen according to the objectives of the analysis (i.e., storm assessment or general overview).

The equations are set up to estimate the turbidity associated with TSS concentrations forecast by SUSTAIN for comparison with the WDOE turbidity criteria: ≤ 5 NTU increase over background when the background is ≤ 50 NTU or ≤ 10 percent increase over background when the background is > 50 NTU. As an example, assume upstream (background) turbidity = 8 NTU and downstream of an urban stormwater discharge stream TSS = 12 mg/L. According to Equation 5, the best estimate of the downstream turbidity is 8.8 NTU.[1] The 95 percent confidence interval = 8.1-9.4 mg/L.[2] Therefore, turbidity is expected to increase by a maximum of 1.4 NTU over the background, which would meet the water quality criterion.

[1] Turbidity = 0.46*12 + 3.26 = 8.8 NTU
[2] $Turbidity_{min} = 0.44*12 + 2.77 = 8.1$ NTU; $Turbidity_{max} = 0.47*12 + 3.74 = 9.4$ NTU

6.3 Metals Targets

6.3.1 *Copper Targets*

Analysis of the Green River watershed data set found somewhat tenuous relationships between copper (Cu) and TSS. Regressing dissolved Cu (DCu) and both TSS and flow gave very poor fits. However, regressing total Cu (TCu) and TSS and TCu and DCu using all available data yielded equations with R^2 = 0.46-0.48. While by this measure alone the equations are not as satisfactory as the TSS-turbidity regressions, the very large underlying data set results in quite narrow confidence bands on estimates computed using them. Therefore, using the two equations in concert was judged to be a good basis for estimating the chances of meeting the WDOE DCu criterion. Table 8 presents the regression equations and statistics derived from all available data and from storm flow measurements, again working with detectable values. Only 0.3 and 1.0 percent of TCu and DCu measurements, respectively, were below detection levels; and their inclusion would make very little difference in results.

To investigate the difference in estimates with the equations based on all data and storm data only, TCu was computed for TSS varying from 1 to 350 mg/L. The maximum deviation is 16 percent; and the difference is < 10 percent with TSS > 25 mg/L, < 5 percent with TSS > 70 mg/L, < 2 percent with TSS > 133 mg/L and ≤ 1.2 percent with TSS > 158 mg/L. DCu was computed over the same range of values using the two equations. It deviated at most by 15 percent; and the difference is < 10 percent with TSS > 19 mg/L, < 5 percent with TSS in the range 48-169 mg/L, < 2 percent with TSS = 72-116 mg/L and < 1 percent TSS = 81-103 mg/L. Because the greatest interest is likely to be in distinctions at relatively low Cu concentrations, it would be best to select the equation complying with the objectives of the analysis.

Table 8. Regression Equations and Associated Statistics Relating Total Copper with TSS and Dissolved Copper with Total Copper Based on All Data and Storm Flow Data in King County's Green River Watershed Data Set

STATISTIC		TOTAL COPPER (TCU)		DISSOLVED COPPER (DCU)	
		ALL DATA	STORM DATA	ALL DATA	STORM DATA
Equation		TCu=0.050*TSS+2.70 (Equation 7)	TCu=0.048*TSS+3.15 (Equation 8)	DCu=0.36*TCu+0.93 (Equation 9)	DCu=0.31*TCu+1.21 (Equation 10)
$R^{2\ b}$		0.461	0.478	0.480	0.393
95% confidence limits (lower, upper)	Coefficient	0.047, 0.054	0.044, 0.052	0.33, 0.38	0.28, 0.35
	Constant	2.51, 2.89	2.92, 3.37	0.80, 1.07	1.04, 1.39

[a] Units: TSS—mg/L; TCu, DCu—µg/L
[b] R^2 represents the fraction of variability in a data set explained by the statistical model. All regressions are significant at P < 0.001.

As an example using the upper 95 percent confidence limits, TSS = 30 mg/L, and Equations 7 and 9:

$$TCu\ (\mu g/L) = 0.054*TSS\ (mg/L) + 2.89 = 4.5\ \mu g/L;$$

$$DCu\ (\mu g/L) = 0.38*TCu + 1.07 = 2.8\ \mu g/L.$$

This concentration would meet the WDOE criterion at a typical Puget Sound area stream water hardness.

6.3.2 *Zinc Targets*

The zinc situation is, in part, similar to copper. The DZn-TSS relationship is poor, but the DZn-TZn regression has a high R^2. Although the TZn-TSS relationship is not nearly as strong as TCu-TSS, the regression is significant and yields relatively narrow confidence intervals. Using the pair of equations was hence again judged to offer some utility, if used cautiously, in estimating the risk of surpassing the Zn water quality criterion with given control on TSS. Table 9 provides the equations and regression statistics derived from all available data and from storm flow measurements, again working with detectable values. Only 0.9 and 4.0 percent of TZn and DZn measurements, respectively, were below detection levels; and their inclusion would make very little difference in results.

To investigate the difference in estimates with the equations based on all data and storm data only, TZn was computed for TSS varying from 1 to 350 mg/L. Unlike with the TSS-turbidity and TSS-TCu-DCu relationships, the results deviate substantially over the entire TSS range, by as much as 53 percent. Although the DZn-TZn regressions are far superior to the TZn-TSS equations, the high variability of the TZn calculations also induces the same amount of disparity in the DZn computations. Therefore, it is essential that these equations be applied in strict compliance with the objectives of the analysis and that uncertainty in the estimates always be determined.

Table 9. Regression Equations and Associated Statistics Relating Total Zinc with TSS and Dissolved Zinc with Total Zinc Based on King County's Green River Watershed Data Set

STATISTIC		TOTAL ZINC (TZN)		DISSOLVED ZINC (DZN)	
		ALL DATA	STORM DATA	ALL DATA	STORM DATA
Equation		TZn=0.43*TSS+8.76 (Equation 11)	TZn=0.18*TSS+12.3 (Equation 12)	DZn=0.71*TZn–2.56 (Equation 13)	DZn=0.72*TZn–3.20 (Equation 14)
$R^{2\,b}$		0.124	0.090	0.815	0.816
95% confidence limits (lower, upper)	Coefficient	0.35, 0.51	0.14, 0.23	0.68, 0.73	0.69, 0.74
	Constant	6.61, 10.9	9.74, 14.9	(-)3.23, (-)1.81	(-)4.16, (-)2.24

[a] Units: TSS—mg/L; TZn, DZn—µg/L
[b] R^2 represents the fraction of variability in a data set explained by the statistical model. All regressions are significant at $P < 0.001$.

Table 10 presents results of example calculations of TZn and DZn at two TSS concentrations using the equations from both data subsets. Note that the ranges of estimates overlap at the lower TSS but not at the higher concentration. This observation accentuates the recommendation to take particular care in using the Zn regressions. Used in this way they can still be useful to make judgments on whether or not the estimated DZn concentration would meet the WDOE criterion at the prevailing water hardness. Since the equations from the two data subsets deviate less at relatively low than high TSS, this judgment would be less certain with higher sediment transport. It would also have to be rendered more carefully with relatively low water hardness than with the opposite condition, because the criterion is more likely to fall in the uncertain range in softer water.

Table 10. Best estimates and 95 Percent Confidence Limits for TZn and DZn at Two TSS Concentrations Based on Equations Derived from All Data and Storm Flow Alone

TSS (MG/L)		TZN (µG/L)		DZN (µG/L)	
		ALL DATA	**STORM FLOW DATA**	**ALL DATA**	**STORM FLOW DATA**
30	Best Estimate	21.7	17.7	12.8	9.5
	95% Confidence Limits	17.1-26.2	13.9-21.8	8.4-17.3[a]	5.5-13.9[a]
200	Best Estimate	94.8	48.3	64.7	31.6
	95% Confidence Limits	76.6-113	37.7-60.9	48.9-80.6[a]	21.9-42.8[a]

[a] DZn upper and lower confidence limits were computed using the lower and upper TZn confidence limits and the lower and upper limits for the DZn regression equations in Table 8.

6.4 An Explanation Regarding Applying Targets to BMP Assessments

The Green River watershed database used to develop water quality targets represents a situation with some but not heavy coverage with BMPs. Implementation of a retrofit program would increase that coverage substantially. BMPs would change the relationship between TSS and the other quantities (turbidity and metals), thus creating a distinction with the underlying database and the equations derived from it. However, the procedure outlined here implicitly assumes a reduction of those other quantities only in direct relation to solids settling and filtration. In reality, reductions of dissolved metals, for example, would most likely occur over and above decreases in those metals related to TSS decline, through other processes like ion exchange and adsorption. Ignoring those additional reductions would be conservative in terms of judging achievement of goals aimed at adherence to water quality criteria; i.e., there would be little risk of overestimating the benefit of BMPs. This is the framework under which the targets will be applied in investigating BMP strategies to meet goals.

7.0 SUMMARY AND CONCLUSIONS

7.1 Hydrology and Benthic Index of Biotic Integrity

High pulse count (HPC) and high pulse range (HPR) best met the criteria set to select the indicators most representative of linkages between stream hydrology and watershed land use/land cover (LU/LC), on the one hand, and aquatic biological integrity on the other. These indicators are highly correlated, but a third one, 2-year peak:mean winter base flow ratio (PEAK:BASE), offers additional insight on the linkages. The SUSTAIN model directly calculates HPC resulting from a drainage catchment's LU/LC and the set of stormwater management practices determined by the models optimization routine. Values of the other indicators can be determined in post-processing computations.

The most likely benthic index of biotic integrity (B-IBI) achievable in a WRIA 9 stream can be forecast in relation to HPC and HPR using logarithmic-linear regression equations derived from available Puget Sound region data:

$$\text{Ln}(\%\ \text{Max. B-IBI Score}) = -0.066 \cdot \text{HPC} + 4.50 \qquad \text{Ln}(\%\ \text{Max. B-IBI Score}) = -0.005 \cdot \text{HPR} + 4.69$$

The maximum B-IBI in the database underlying these equations is 50. They have $R^2 = 0.745$ and 0.755, respectively, indicating they can explain about 75 percent of the variance in B-IBI as a function of variance in HPC or HPR. Confidence limits at various levels were computed for both the coefficients and constants in each equation, allowing estimation of the minimum and maximum expected B-IBI, in addition to the most likely value, at the selected confidence level.

The most likely probability of B-IBI falling in a certain numerical group can be predicted using the PEAK:BASE indicator. That probability, P, is $P = e^L/(1 + e^L)$, where L derives from a logistic regression analysis of another Puget Sound region database. Two expressions for L are:

$$L = 1.87 - 0.098 \cdot (\text{PEAK:BASE}) \qquad L = 9.40 - 6.17 \cdot \text{Log}(\text{PEAK:BASE})$$

The first equation is most effective in predicting if B-IBI will be greater than or less than 56 percent of the maximum (45 in the underlying database). The second is best at forecasting if B-IBI will be above 42 percent of maximum. An uncertainty analysis with the data allows estimation of the lowest and highest probabilities of reaching the B-IBI level, in addition to the most likely.

7.2 Water Quality and Risk of Not Meeting Stream Criteria

The original scope set total suspended solids (TSS) as the principal water quality indicator to be employed in the project. However, there are no water quality criteria established for TSS, and there is interest in assessing if WRIA 9's streams will meet key existing criteria with the stormwater discharges likely to result from imposition of the stormwater practices. A large set of water quality data collected in the WRIA 9 watershed itself served as a basis for deriving linear regression equations relating TSS to turbidity, copper, and zinc, for which criteria have been established. The derivations included both the full data set and data points during storm flows only. Results do not differ much for turbidity and copper but deviate more for zinc. This summary presents the equations developed using all data.

The turbidity-TSS equation, with a relatively high R^2 at 0.877, is:

$$\text{Turbidity} = 0.46*\text{TSS} + 3.26$$

The most likely turbidity is estimated from SUSTAIN TSS output with this equation. Uncertainty analyses of the data established 95 percent confidence limits on both the coefficient and the constant in the equation. Thus, the highest (and lowest) turbidity likely to be achieved with 95 percent confidence can be estimated to broaden the assessment of risk of not meeting the turbidity criterion.

Water quality criteria for copper (Cu) and zinc (Zn) are in terms of the dissolved quantities (DCu and DZn). The best regression equations in each case first predict the total recoverable metal (TCu and TZn) from SUSTAIN TSS output, and then the dissolved from the total recoverable, instead of dissolved directly from TSS. The equations, with their R^2 values, are:

$\text{TCu} = 0.048*\text{TSS} + 3.15$, $R^2 = 0.461$ $\text{DCu}=0.36*\text{TCu}+0.9$, $R^2 = 0.480$

$\text{TZn} = 0.43*\text{TSS} + 8.76$, $R^2 = 0.124$ $\text{DZn} = 0.71*\text{TZn} – 2.56$, $R^2 = 0.815$

These equations are applied in the same fashion as the turbidity equation. The lower R^2 values indicate that these expressions must be used with greater caution than that equation, especially in the case of zinc. The large quantity of data underlying them, though, still makes the 95 percent confidence bands fairly narrow.

This procedure assumes that turbidity and metals would fluctuate only as a function of TSS; e.g., applying stormwater management practices is implicitly presumed to lower dissolved metals only in direct relation to TSS decrease through sedimentation and filtration processes. In reality dissolved metals would probably also decline through other processes. The analysis proposed for this project would not account for any such mechanisms, and hence will be conservative in forecasting risk of not achieving water quality criteria.

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Appendix A

APPENDIX A-1: CANDIDATE HYDROLOGIC INDICATORS AND THEIR DEFINITIONS

GROUP 1: PULSE METRICS

Note: A low-flow pulse is defined as the occurrence of daily average flows that are equal to or less than a low-flow threshold set at half (50 percent) of the long-term mean daily flow rate. A high-flow pulse is defined as the occurrence of daily average flows that are equal to or greater than a high-flow threshold set at twice (two times) the long-term mean daily flow rate.

Low Pulse Count— Number of days each calendar year that discrete low flow pulses occur

High Pulse Count— Number of days each water year that discrete high flow pulses occur

Low Pulse Duration—Mean number of days per occurrence that the daily time-step hydrograph is below the low-flow threshold for each calendar year

High Pulse Duration—Mean number of days per occurrence that the daily time-step hydrograph is above the high-flow threshold for each water year

Low Pulse Range— Range in days between the start of the first low-flow pulse and the end of the last high flow pulse during a water year

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

GROUP 2: MINIMUM FLOW METRICS

7-Day Annual Minimum Flow—Minimum mean flow rate over a 7-day period for each calendar year

Date of the 1-Day Minimum Flow—Julian date of each annual daily minimum flow

Onset of Fall Flows—Julian date of the day after the annual 7-day minimum flow period for the dry season

GROUP 3: HYDROGRAPH PATTERN METRICS

Fall Count—Number of days for each water year in which the change in daily flow from the previous day is more than 10 percent of the current day's flow rate and declining

Rise count—Number of days for each water year in which the change in daily flow from the previous day is more than 10 percent of the current day's flow rate and rising

Fall Rate—Mean rate of fall for all falling portions of the daily time-step hydrograph for each calendar year

Rise Rate—Mean rate of rise for all rising portions of the daily time-step hydrograph for each calendar year

Flow Reversals—Number of times per water year that a trend change occurred in the daily time-step hydrograph (rising to falling limb or falling to rising limb, except for minor variations [< 2 percent])

GROUP 4: FLASHINESS METRICS

T_{Qmean}—Fraction of the time in each water year that the daily time-step hydrograph exceeds annual mean discharge for a forested condition

Richards-Baker (R-B) Index—Mean daily rate of change (absolute value) of daily time-step hydrograph for each water year

Time above 2-Year Mean flow—Fraction of the time in each water year that the daily time-step hydrograph exceeds the 2-year mean flow rate for a forested condition

GROUP 5: RELATIVE STREAM POWER METRICS

2-Year Peak:Mean Winter Base Flow Ratio—Ratio of peak flow rate with a 2-year return frequency to the mean base flow rate during the period October 1-April 30

Normalized effective Stream Power—Percentage increase in stream power (rate of energy dissipation against the bed and banks of a stream) between forested condition and point in time of analysis

$Q_{2\ current}$:$Q_{10\ forested}$—Ratio of hourly flow rate with a 2-year return frequency at point in time of analysis to the hourly flow rate with a 10-year return frequency in a forested condition