Development of a Stormwater Retrofit Plan for Water Resources Inventory Area (WRIA) 9 and Estimation of Costs for Retrofitting all Developed Lands of Puget Sound

DEVELOPMENT OF FLOW AND WATER QUALITY TARGETS

Status Report, January 5, 2012

By Richard Horner

INTRODUCTION

Project Fundamentals

A preceding technical memorandum titled Development of Flow and Water Quality Indicators and dated April 12, 2011 laid out a conceptual framework for the WRIA 9 stormwater retrofit planning project ("the project") linking watershed land use and land cover (LU/LC), aquatic ecosystem habitats, aquatic biota, stormwater management practices, and climate change. That memorandum further introduced and defined the term "**metrics**", that is quantities that can potentially be measured to quantify the many variables operating in these components and contribute to understanding relationships existing within the system. It reasoned that, faced with innumerable variables and the impossibility of measuring many of them, a manageable and valid course of action is to identify those variables that can best represent a component and its relationships to other components. The memorandum termed these key variables "**indicators**". The main test for acceptance as an indicator is a demonstrated ability to link events in one system component to responses in another. The specific indicators and the demonstration of their capabilities for this purpose came from research performed in the Puget Sound region documenting linkages between stream hydrology and water quality metrics and watershed conditions on the one hand and aquatic biological community integrity on the other. The research further provides the basis to set numerical "**targets**" for these habitat indicators to achieve specific biological goals, attained through appropriate stormwater management strategies. This technical memorandum covers that subject.

The earlier memorandum illustrated how the project will apply the indicators and targets to achieve its purposes, repeated here as Figure 1. Indicator values will be predicted by the System for Urban Stormwater Treatment and Analysis INtegration (SUSTAIN) model, after LU/LC, climate change, hydrologic, and tentative stormwater management best management practice (BMP) inputs. These values will be compared to the targets as determinants of the management scenario's ability to meet set aquatic ecosystem protection or restoration goals. Not meeting targets will trigger reiteration with altered management actions until a management plan does achieve the goals. Of course, the resulting plan may or may not be feasibly implementable in reality, which could condition goal revision and further assessment.

Tentatively Selected Indicators

Earlier work in the project, documented in the April memorandum, evaluated 20 candidate hydrologic indicators with respect to seven specific selection criteria, key ones being the strength of their linkages to LU/LC characteristics and aquatic biological integrity. Two candidates stood out over all others in meeting the overall criteria:

- *High pulse count* (HPC)—number of days in each water year that discrete high flow pulses occur, with twice the mean flow rate taken as the threshold to identify a high pulse; and

- *High pulse range* (HPR)—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.

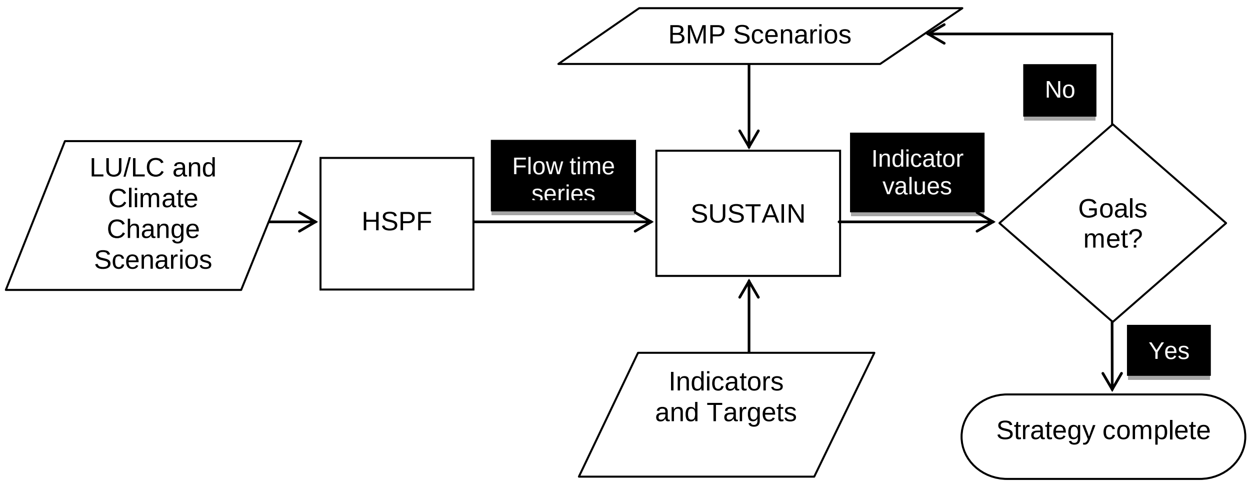

Figure 1. Project Modeling Framework

Available data showed these indicators to be highly correlated with both total impervious area (TIA), an important expression of LU/LC, and benthic index of biotic integrity (B-IBI), the most commonly used aquatic biological metric in the region. They also can be established reliably by stream gauge data and calculated by the HSPF model in relatively good agreement with gauge data and are relatively independent of potentially confounding variables (basin area, channel slope, soil type, elevation, precipitation).

Two additional hydrologic indicators demonstrated compliance with the selection criteria, with the exception of not having a demonstrated close correspondence in computation results from both gauged and modeled data. However, they were judged to offer the potential to add information not afforded by high pulse count and range. These indicators are:

- *Time above 2-year mean flow* ($T_{Q > 2\text{-y } Qmean}$)—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; and

- *2-year peak:mean winter base flow ratio* (PEAK:BASE)—ratio of peak flow rate with a 2-year return frequency to the mean base flow rate during the period October 1-April 30.

The original project scope designated total suspended solids (TSS) as the principal water quality indicator. However, TSS is not the subject of Washington Department of Ecology (WDOE) water quality criteria. Also, the association between TSS and biological integrity has not been established. 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. Water quality criteria are predicated on another sediment measure, turbidity, as well as dissolved metals, for all of which a substantial WRIA 9 data set exists. Those data required analysis before final selection of water quality indicators over and above TSS, a task that was performed during the latest phase of work and is reported upon in this memorandum.

As recounted in the April memorandum, the analysis involved, first, examining if a statistically justified relationship between TSS and turbidity allows setting turbidity targets on the basis of water quality criteria; if so, translating the targets to TSS terms based on the relationship; and using those terms to gauge the effectiveness of stormwater management scenarios. Second, the analysis assessed if sufficiently strong relationships link TSS, total recoverable metals, and dissolved metals, to support quantitative, or at least qualitative, judgments regarding the probability of meeting metals water quality criteria as a function of success in controlling TSS.

APPLICATION OF TARGETS FOR GOAL ASSESSMENT

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 will be 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 of this memorandum 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.

The Nature of Goals

The goals to be investigated in this project will be fundamentally rooted in biological outcomes. Substantial past research, summarized in the April memorandum, quantitatively linked the tentatively selected hydrologic indicators with biological metrics, principally B-IBI. Goals will be expressed as B-IBI targets, and the quantitative relationships will 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, will be the basis for water quality targets. Essentially, the goals will be meeting those criteria for the selected indicators according to all WDOE stipulations, including anti-degradation requirements.

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 will be 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.

HYDROLOGIC TARGETS

Results of Literature and Data Review

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.

The indicator *time above 2-year mean flow* had to be eliminated because of unreliability discovered in the available data. This problem subverted the objective of supplementing HPC and HPR 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.

High Pulse Count and High Pulse Range Targets

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.

Basic Analyses

Figures 2 and 3 depict B-IBI in relation to HPC and 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 in the April memorandum, in which specific environmental conditions were found to be <u>necessary</u> but <u>not sufficient</u> 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 <u>guarantee</u> inevitably low biological integrity.

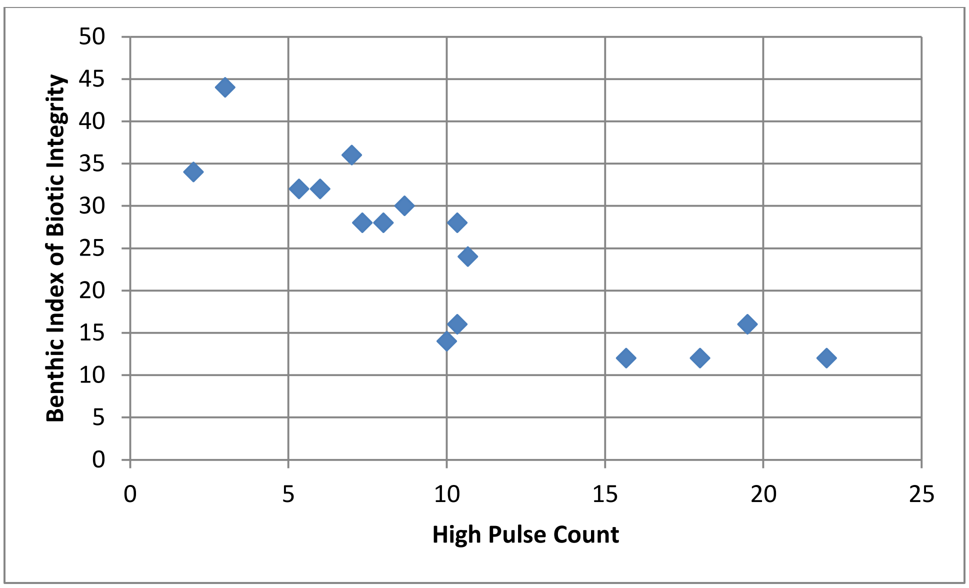

Figure 2. Benthic Index of Biotic Integrity in Relation to High Pulse Count

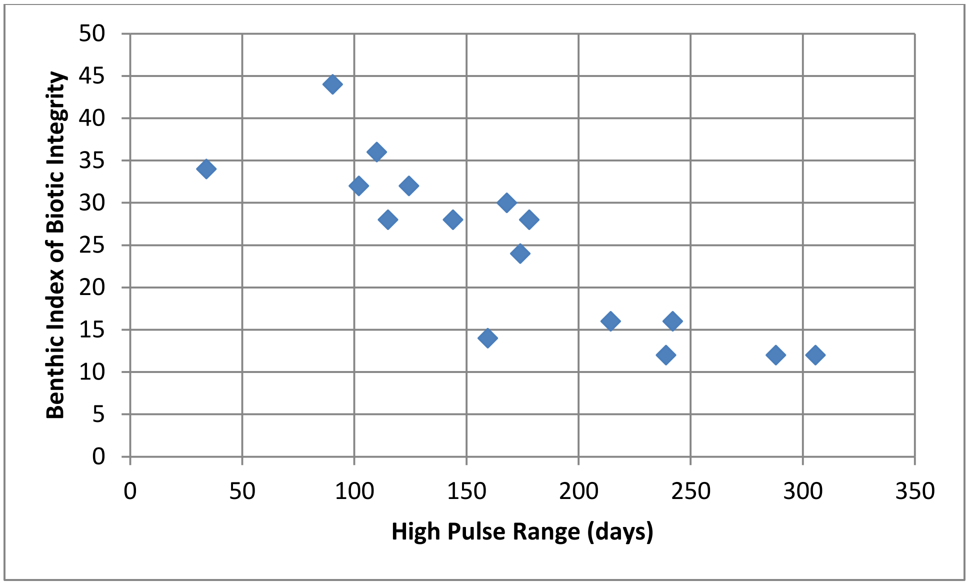

Figure 3. Benthic Index of Biotic Integrity in Relation to High Pulse Range

Taking this analysis farther, Table 1 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 1. 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.

Statistical Analyses

The data of DeGasperi et al. (2009) plotted in Figures 2 and 3, 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 2 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 2. 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]	Ln (% Max. B-IBI Score) = - 0.005*HPR + 4.69[a]
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 $P < 0.001$.

Examples

Table 3 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 3. 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**
	200	40.0		**29.1**
	250	31.2		21.5
	300	24.3		16.0

2-Year Peak:Mean Winter Base Flow Ratio Targets

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 predating 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.

Basic Analyses—Benthic Data

Figure 4 plots B-IBI in relation to PEAK:BASE from the Cooper (1996) data. As in Figures 2 and 3, 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.

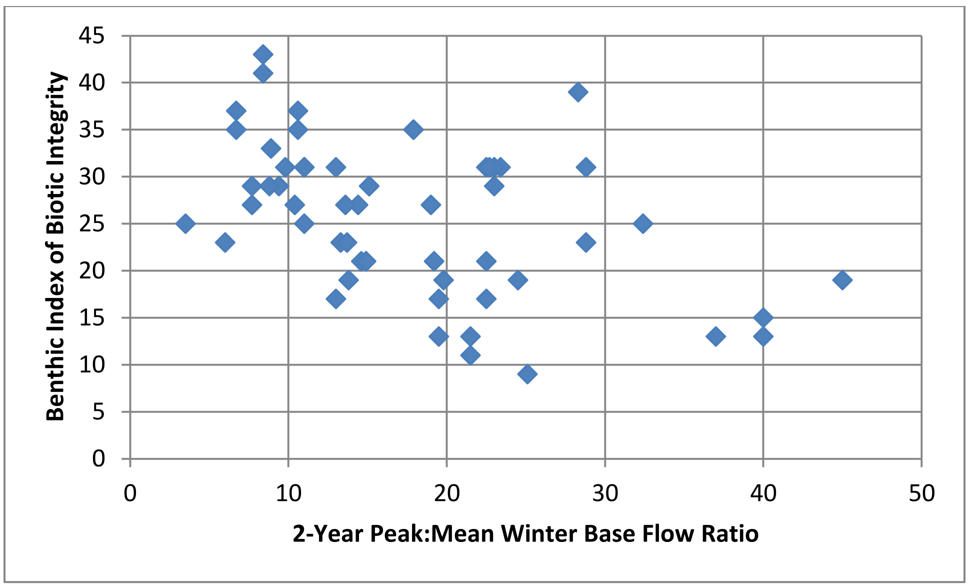

Figure 4. Benthic Index of Biotic Integrity in Relation to 2-Year Peak:Mean Winter Base Flow Ratio

Taking this analysis farther, Table 4 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.

Table 4. 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.

Statistical Analyses—Benthic Data

Mirroring the scatter evident in Figure 4, 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:

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

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:

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

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.

Examples

Table 5 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. Again, color fonts point out numbers discussed in the illustration below.

Table 5. 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 that level of confidence in reaching 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**.

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 5, 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.

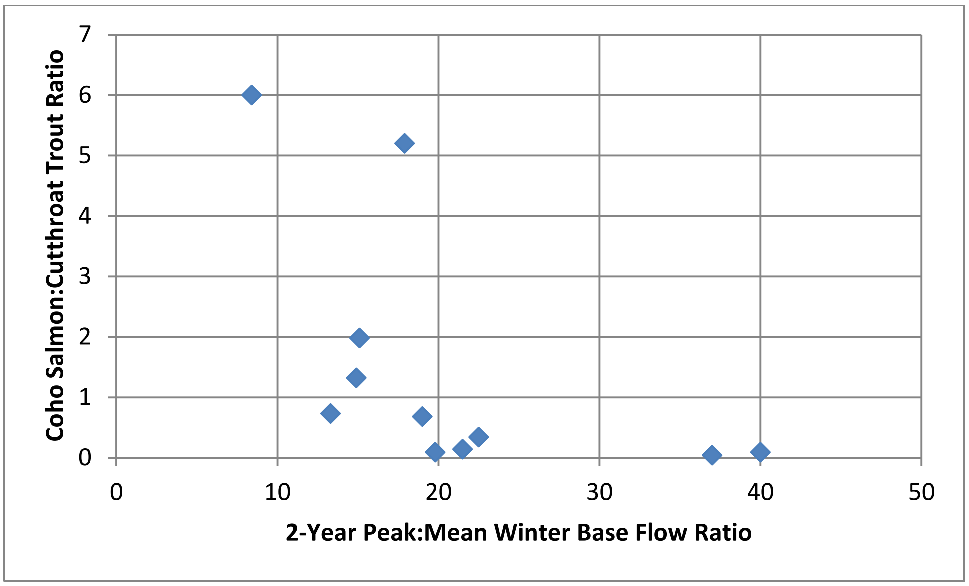

Figure 5. Young-of-the-Year Coho Salmon:Cutthroat Trout Ratio in Relation to 2-Year Peak:Mean Winter Base Flow Ratio

<u>Using Hydrologic Indicators and Targets in Concert</u>

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.

WATER QUALITY TARGETS

<u>Investigating Targets</u>

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.

For Solids

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

- If so, 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.

- If not, 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.

For 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).

- If so, 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.

- If not, 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.

Solids Targets

Strong linear relationship between TSS and turbidity were found in the Green River watershed data set. Table 6 presents the regression equations derived from all available data and from storm flow measurements, in both cases working with detectable values. Only 3.1 and 3.5 percent of TSS and turbidity 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 6. Regression Equations and Associated Statistics Relating TSS with Turbidity Based on All Data and Storm Flow Data in King County's Green River Watershed Data Set

Statistic		All Data	Storm Flow Data
Equation		TSS = 1.90*Turbidity – 4.20	TSS = 1.94*Turbidity – 5.07
R^{2*}		0.877	0.883
95% confidence limits (lower, upper)	Coefficient	1.85, 1.94	1.88, 1.99
	Constant	(-)5.23, (-)3.17	(-)6.71, (-)3.44

* 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, TSS was computed for turbidity varying from 1 to 350 NTU. The difference is < 10 percent with turbidity > 5 NTU, < 5 percent with turbidity > 8 NTU, and ≤ 2 percent with turbidity > 12 NTU. Thus, either equation can be used unless assessing relatively low solids transport.

TSS targets will be computed from 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. From the regression equation based on all data, the first criterion is equivalent to TSS increase above background of ≤ 5.3 mg/L,[1] with the 95 percent confidence interval = 4.0-6.5 mg/L.[2]

<u>Metals Targets</u>

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 7 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 (i.e., storm assessment or general overview).

[1] TSS = 1.90*5 – 4.20 = 5.3
[2] TSS_{min} = 1.85*5 – 5.23 = 4.0; TSS_{max} = 1.94*5 – 3.17 = 6.5

Table 7. 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 (µg/L) = 0.050*TSS (mg/L) + 2.70	TCu (µg/L) = 0.048*TSS (mg/L) + 3.15	DCu (µg/L) = 0.36*TCu (µg/L) + 0.93	DCu (µg/L) = 0.31*TCu (µg/L) + 1.21
R^{2*}		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

* 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 the equation based on all data:

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

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

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

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 8 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.

Table 8. 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 (µg/L) = 0.43*TSS (mg/L) + 8.76	TZn (µg/L) = 0.18*TSS (mg/L) + 12.3	DZn (µg/L) = 0.71*TZn (µg/L) – 2.56	DZn (µg/L) = 0.72*TZn (µg/L) – 3.20
R^{2*}		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

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

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 (i.e., storm assessment or general overview) and that uncertainty in the estimates always be determined.

Table 9 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 9. 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.

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, SUSTAIN implicitly assumes a reduction of those other quantities only in direct relation to TSS decrease. In reality, reductions of dissolved metals, for example, would most likely occur over and above decreases in those metals related to TSS decline. 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.

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