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A Multivariate Water Quality Index for Use in Management of a Wildland Watershed

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IN MANAGEMENT OF A WILDLAND WATERSHED

by

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EXECUTIVE SUMMARY

Summary

Multivariate statistical techniques were used to define a method for establishing a water quality index (WQI) for use in protecting the stream environment in a high mountain watershed. The purpose of the WQI was to aggregate water quality parameters in such a way that the effects of low level increments in mining, grazing, logging and other activities could be related to a change in the value of a single entity, aquatic environmental quality, in a linear programming (LP) management model. Several data aggregation methods were explored, using water quality data collected over 5 years (1975-1979) by the USDA Forest Service in the upper Blackfoot River watershed in southeastern Idaho. The WQIs thus generated were compared with indices of benthic invertebrate community composition as determined from samples collected late in the summer of 1981. Community composition indices were based on emergent community properties (biomass and diversity) and on taxonomic composition as revealed by principal components analysis.

Significant results of the study include the following:

1. Existing deterministic general purpose WQIs (such as the National Sanitation Foundation Index) proved useless for guidance in protecting water quality in these high mountain watersheds, because stream water quality often remains excellent by drinking water standards, even though subtle changes in water quality parameters may significantly affect instream habitat.

2. An increasing scale, multivariate statistical WQI was created for the study area using 5-year May-October averages of ten water quality variables in eight streams. Removal of some streams from the data set, as well as aggregating or replacing some variables, did not significantly alter the rank order of the stream WQI values.

3. Changes in the calculation time step to 5-year bimonthly (May-June, July-August, September-October) or monthly averages, or to annual averages for four water years, provided little additional information, and resulted in decreasing sensitivity to changes in water quality variables because of larger standard deviations in the data sets.

4. The WQI was composed of four principal components that were easily interpretable as common factors (e.g., nutrient sources, suspended sediment sources, groundwater, and discharge) that affected groups of variables. These principal components,

or subindices, were positively correlated with the presence of certain benthic invertebrate taxa or groups of taxa.

5. Cluster analysis was useful in reducing the dimensionality of water quality data and in revealing relationships among invertebrate communities (Q-type analysis). However, R-type cluster analysis of the study streams showed no similar groups of streams based on water quality variables.

6. The WQI was highly negatively correlated (r^2=0.93) with benthic invertebrate standing stock biomass, a relationship described by a decreasing power function. There was no apparent relationship between benthic invertebrate diversity and the WQI values.

7. The WQI-biomass relationship may be useful in setting a constraint value on the WQI in an LP model. Additional data and information from more sites should be collected and analyzed, however, to strengthen the confidence in the correlation, and to establish causality between the variables contributing strongly to the WQI and community biomass.

8. The multivariate WQI was found to be heavily influenced by the relative standard deviations of the variables used to form the index. Inclusion of only similar (pristine) streams in a baseline data set will result in a lower standard deviation for each variable. The result is higher sensitivity to a given polluting factor than will be found in a mixed group of streams in which some are already impacted by anthropogenic activities.

9. High standard deviations for individual variables may mask relationships between environmentally significant parameters and biological communities.

10. Multivariate WQI indexing provides valuable insights into the relationship between water quality and biological community composition, even if application of the WQIs in predictive settings is premature or ultimately proves to be unacceptable.

Suggestions for Further Research

1. Collect additional invertebrate data at other seasons and on Upper Angus and Mabie Creeks in order to reinforce or refine the relationships reported here.

2. Collect more detailed habitat data in order to elucidate the relative importance of water quality and physical habitat in controlling benthic community composition. Artificial substrates may be useful in reducing physical habitat dissimilarity in order to focus on water quality effects.

3. Update the WQI using 1980-1982 data from the Forest Service and look for recent trends that would reinforce or alter the conclusions based on the older data.

4. Examine the use of standardized extreme values, rather than standardized means, to create a WQI.

5. Employ cannonical correlation as a means of further elucidating water quality-physical substrate-benthic community relationships.

6. Monitor changes in the WQI and benthic invertebrate community in one of the study streams in response to changing management practices (e.g., erosion control or additional phosphate mining).

7. Investigate the effects of a proposed change in management practice on a WQI using Monte-Carlo analysis to account for simultaneous changes in many variables.

8. Investigate the responses of the invertebrates in principal components 1 and 4 to nutrients and suspended sediments in controlled (artificial) ecosystems to test their suitability as water quality indicators in the study area.

CHAPTER 1

INTRODUCTION

Headwater streams in the Western states are important as drinking water supplies and as habitat for cold water trout fisheries that are an important source of recreation and tourism. These stream ecosystems have coexisted with environmentally sound mining, logging, and grazing activities in recent years, owing partly to the relatively low level and highly dispersed pattern of activity. However, as demands for minerals, timber, and livestock increase with a growing regional and national population, society may even prefer to barter some degradation in previously pristine streams in return for local jobs or decreased dependence on foreign goods. The budgetary pressures for a cost effective regulatory program and the increasing frequency of such trade offs require that managers be able to predict the level of degradation resulting from an incremental increase in an impacting use and to be able to transmit this information effectively to program administrators and ultimately the decision-making public.

This view is somewhat in contrast to the present policy of setting water quality standards that, if unviolated, are presumed to result in no environmental degradation. In fact, such standards are usually based on laboratory exposures of standard test organisms to single toxicants, and are virtually incapable of incorporating subtle, holistic effects on intact ecosystems. A safety factor is often employed to account for the uncertainties in extrapolating laboratory studies to field conditions. Water quality standards, in the above sense, allow any new use that degrades water quality up to some threshold level, with subthreshold effects assumed to be inconsequential.

Aside from any judgmental value as to the worth of natural ecosystems, those responsible for watershed management would be better informed by having and applying a mathematical tool that warns of the magnitude or probability of harm to natural ecosystems. Consequently, one of the more pressing research needs for protecting relatively unpolluted rivers and streams is a methodology for assessing marginal impacts resulting from low levels of resource development. As demands for these resources increase, setting water quality criteria so as to provide safety factors to compensate for the lack of knowledge on low level environmental effects will become harder to justify, and the public will demand to have input on trade-off decisions.

A frequently used method for conveying complex environmental information to the public is through "environmental indices." One such is the familiar PSI (Pollution Standards Index), reported on weather broadcasts in metropolitan areas to describe the ambient level of air pollution. Similar water quality indices have been developed for lakes, rivers, and streams. These environmental indices commonly assign a relative score (good vs. bad) to a series of pollutant concentrations and then aggregate the scored values to produce a single-valued index. Certain ranges of index scores may subsequently be assigned a qualitative descriptor such as good, fair, poor, hazardous, and so on (e.g., Inhaber 1976). Such environmental indices are invaluable in transmitting technical information to the public.

Environmental indices may also play an important technical role in manage-

CHAPTER 2

LITERATURE REVIEW

The history of water quality indexing has been reviewed by Landwehr (1974) and Ott (1978), and only a brief summary will be presented here. Ott (1978) categorized water quality indices into five basic types: 1) general purpose, 2) specific use, 3) statistical, 4) ecological, and 5) planning. The first three index types are generally applied to quality parameters (e.g., physical and chemical variables and pathogens) that affect water usability for humans, wildlife, or fish habitat. Ecological and planning indices, however, usually include or are composed entirely of parameters affected by water quality, e.g., benthic community composition or desirability of use by boaters or swimmers. Although the two categories of index types are not directly comparable, ecological indices may be helpful in corroborating water quality indices based on water chemistry. The following discussion briefly summarizes applications of the first four index types. Planning indices are often only subjectively quantifiable (Ott 1978, p. 247-254), and will not be considered here.

General Purpose Indices

The general purpose water quality indices (WQIs) are probably the most familiar and provide the clearest examples of the difficulties associated with environmental indexing. General purpose WQIs aggregate a variety of water quality attributes that describe characteristics such as potability, aesthetics, and fish habitat. They seem generally to have been applied to higher order rivers that receive major wastewater inputs. Although Horton (1965) was apparently the first to construct such an index, the National Sanitation Foundation Index (Brown et al. 1970) is probably the most widely used.

Ott (1978) divides the calculation of a deterministic environmental index into two phases: 1) calculation of a subindex for each pollutant variable and 2) aggregation of the subindices into an overall index. Subindices can take the form of an implicit or explicit linear function of the pollutant value, a segmented linear function, or a nonlinear function (Figure 2.1). Subindices (or their composite WQIs) are termed "increasing scale" if their values increase as conditions become less desirable, and "decreasing scale" if lower values represent less satisfactory water quality.

Although the shape of the subindex function may be derived empirically, it is more often arrived at through consensus by experts (often using some form of a Delphi technique). The most frequent criticism of subindexing techniques is the subjective nature of this expert opinion (e.g., Harkins 1974). An example of a less subjective empirical method for determining the values of a subindex function for corresponding values of a parameter of interest could be a fish bioassay for rating survivorship as a function of copper concentration. As additional bioassays are done, one would expect the expressed shape of the subindex function to become increasingly objective.

Even empirically derived subindex values ignore the importance of ecological interactions, however. Krenkel (1979) notes several problems in interpreting bioassays, as well as confounding effects of temperature and dissolved oxygen concentrations on heavy

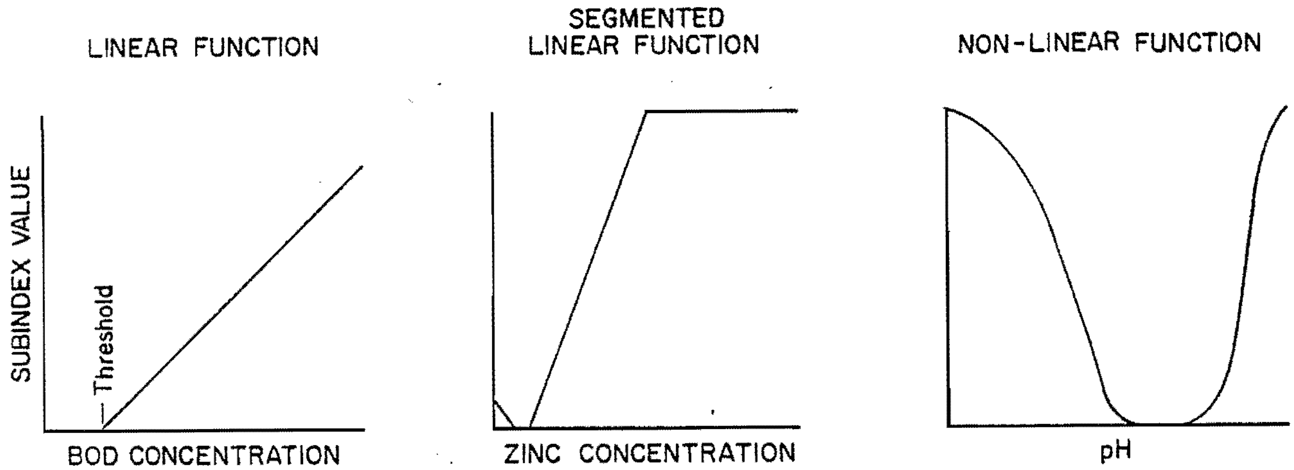

Figure 2.1. Some categorical examples of water quality subindex functions (all examples are for an increasing WQI).

metal toxicity. Enhancement or amelioration of metal toxicity to many forms of aquatic biota by hardness, organics, or by other metal ions also has been demonstrated (e.g., Giesy et al. 1977, Rai et al. 1981), and short term, acute bioassays usually do not reveal effects of chronic, low-level exposures (Klapow and Lewis 1979). Consequently, subindex functions are, in fact, multidimensional surfaces, rather than two-dimensional curves, which can only be derived by assuming some constant value for all the other parameters. This complexity confounds intuitive, subjective description by an "expert." Unfortunately, there are usually insufficient environmental and chemical data to enable multidimensional "fine-tuning" in deriving subindex functions or for applying them to specific streams.

Aggregation, the process whereby multidimensional subindex information is reduced to manageable levels, may take one of several additive forms, a multiplicative form, or the form of a maximum or minimum operator (Table 2.1). Aggregation techniques exhibit both substantive and structural shortcomings (Ott 1978). Linear sum aggregation (Table 2.1.a) can result in an unacceptable index because simple linear addition of acceptable subindex values exaggerates the severity of a pollution problem (termed "ambiguity"). The probability of such a problem occurring increases with the number of subindex terms and is eliminated by multiplying each subindex by weighting factors (Table 2.1.b) which sum to 1.0. However, while "ambiquity" is now impossible, "eclipsing" may occur. Eclipsing happens when the effect of a very high (perhaps catastrophic) subindex value is lost in the aggregated index because of a low weighting factor. Root-sum-power (Table 2.1.c) and root-mean-square (Table 2.1.d) aggregation functions greatly reduce ambiguity or eclipsing, respectively.

Ott (1978) points out the utility of the root-sum-power form of aggregation as the power approaches infinity, called the maximum operator:

$$\lim_{p\to\infty} \{[I_1^p + I_2^p + \ldots + I_n^p]^{1/p}\}$$

$$= \max \{I_1, I_2, \ldots, I_n\} \quad . \quad . \quad . \quad . \quad (2.1)$$

The maximum operator is virtually immune to ambiguity or eclipsing, although it does fail to distinguish between one and many critical or near-critical subindices. Multiplicative aggregation techniques (Table 2.1.e) or maximum or minimum operators can be used in decreasing scale WQIs. Landewehr (1979) has described some of the effects of particular aggregating functions on the ability to demonstrate a statistically significant response to some perturbation.

Specific Use Indices

A common problem encountered in general purpose indexing is establishing criteria levels that are mutually appropriate to two or more uses. For example, high phosphate levels may be beneficial in irrigation water but detrimental in a reservoir. Similarly, saturation with dissolved oxygen may be crucial to fish habitat but undesirable in boiler feed water. One approach by Dinius (1972) was to select different criteria values for different water uses in a general purpose WQI.

Deininger and Landwehr (1971) developed a public water supply (PWS) WQI for surface streams by coalescing

Table 2.1. Methods of aggregating subindices into a water quality index (based on Ott 1978).

a.	Linear sum	$WQI_a = \sum^n I_i$
b.	Weighted linear sum	$WQI_b = \sum^n w_i I_i \quad ; \quad \sum^n w_i = 1$
c.	Root-sum-power	$WQI_c = \left[\Sigma I_i^p\right]^{1/p}$
d.	Root-mean-power	$WQI_d = \left[\Sigma I_i{}^p/p\right]^{1/p}$
e.	Weighted product	$WQI_e = \prod^n I_i^{w_i} \quad ; \quad \sum^n w_i = 1$
f.	Maximum operator	$WQI_f = \max \{I_1, I_2, \ldots, I_n\}$
g.	Minimum operator	$WQI_g = \min \{I_i, I_2, \ldots I_3\}$

I_i = subindex value for i'th subindex

w_i = weighting factor for i'th subindex

p = some power

n = number of subindices

expert opinion through a Delphi technique. They produced an 11- and a 13-variable PWS WQI and used both summation and geometric mean aggregation techniques. They found good agreement between all of their indices and the NSF WQI (Brown et al. 1970), despite the fact that the PWS and NSF WQIs had only seven variables in common. They concluded that there is much redundancy in specific use indices, and that their construction is probably unjustified, although it may be argued that specific use indices can usually be expressed in terms of only a few key variables.

O'Conner (1972) developed two water quality indices (fish and wildlife (FAWL) and PWS) through expert opinion and extensive Delphi-style consensus building. A 9-variable FAWL index and 13-variable PWS index were constructed and compared on the same surface streams. The aggregation technique summed weighted subindex values, but the sum was multiplied by zero if a toxic substance exceeded recommended limits. Correlations between O'Conner's two indices were generally lower ($0.5<r^2<0.7$) than between either index and the NSF WQI ($0.7<r^2<0.9$). This result led O'Conner to conclude that the best approach to water quality indexing is to construct an index value for each major water, e.g., fish habitat, livestock water, reservoir inputs, and hydropower. If a general purpose WQI is desired, he recommended using a weighted sum of the individual indices. It appears likely that the difference in interpretation between O'Conner and the earlier study of Deininger and Landwehr (1971) is more one of degree than fundamental substance.

Walski and Parker (1974) produced a recreational water quality index combining four categories of subindices; those which effect aquatic life, health, taste and odor, and aesthetics. Explicit subindex functions were fitted to data from the literature and aggregated using a geometric mean.

Stoner (1978) outlined a concept for a specific WQI that could be adapted to any water use, although he considered only public water supply and irrigation. Subindices included toxic variables (Type I), which were treated as step functions at their recommended EPA (1976) limit, and aesthetic or "nontoxic" (Type II) variables, which were treated as explicit mathematical functions. The rationale for the step function approach for toxic constituents was the difficulty in assessing responses to very low, subcritical concentrations. Subindices were aggregated by adding the Type I subindices (values = -100 at the critical level) to the weighted sum of the Type II variables (ideal values = +100, criteria limit = 0). Thus the index value becomes negative if any Type I criterion is exceeded. Application to several streams yielded indices ranging from 87.5 for a spring-fed river in Florida to -8,560 for low-water discharge in Buffalo Bayou, Texas.

Nemerow and Sumitomo (1970) developed three WQIs, one each for human contact (e.g., swimming), indirect contact (e.g., fishing), and remote contact use (e.g., navigation, aesthetics). These indices are unique because of the aggregation function in which the maximum subindex value was combined with the weighted mean of all subindices in a root-mean-square manner:

$$I_j = \frac{(\max_i I_{ij})^2 + (\frac{1}{n}\ (\Sigma I_{ij}))^2}{2} \quad . \qquad (2.2)$$

thus providing information on extreme values as well as central tendency. An overall index was computed using a weighted sum of the three specific use indices.

Statistical Indices

One approach to increasing objectivity in structuring subindex functions has been to use the statistical properties of the data set itself to define the index functions. The essence of this approach is to compare deviations from the mean of some subindex or aggregation of subindices resulting from some perturbation with deviations representing some "normal," or baseline, value. Changes in mean values, or unusual deviations from the mean, might be expected to result in ecological stress on the biotic component and thus result in a deleterious change in community structure or function (e.g., Odum 1971, Ulanowicz 1978). The statistical treatments range from the simple ranking technique of Harkins (1974) to the multivariate models of Shoji et al. (1966) and Shannon and Brezonik (1972).

Harkins (1974) employed Kendall's nonparametric rank correlation procedure to produce a WQI that does not depend on subjective expert opinion. The data are transformed by subtracting the rank order of the "control" value from the rank order of each observation for a particular variable (ties receive the average value of their ranks), and dividing the subtrahend by the standard deviation of the ranks for that variable. The control value is usually chosen to be the water quality standard or criterion value for that parameter, which would appear to remove some of the objectivity claimed for the index. Aggregation is accomplished by summing the squares of the transforms, to produce an increasing scale index. Although this method for calculating a WQI does not require assumption of a normal statistical distribution, the value of the index changes if new observations are added to old data sets.

Schaeffer and Janardan (1978) modified Harkins' WQI by transforming it to a beta distribution, the Beta Function Index. The resulting index has two advantages: 1) it ranges from 0 to 1, and 2) because it is nonparametric, it can be used to compare groups of observations from different data sets. Although both forms of the Harkins' index are claimed to correlate well with expert opinion on water quality (Ott 1978), examination of a limited data base on Illinois streams by Schaeffer and Janardan (1978) suggests that their index overpredicts aquatic community "quality."

The advent of the high speed computer in the 1950s and 1960s provided the computational power needed to apply multivariate statistics to create water quality indices that would describe large data bases. Ordination could be employed to reduce the dimensionality of the variable data set in order to facilitate communication and comprehension. Although by no means the only ordination technique (e.g., Gauch 1982), principal components analysis (PCA) is certainly one of the most popular. In PCA, certain common factors (principal components) are sought which can explain a maximum amount of variation among variable values. These principal components are mathematically orthogonal and thus completely uncorrelated.

In order to illustrate application to a relatively simple case, assume that the water quality variables nitrogen, phosphorus, BOD, and temperature are measured on two sets of samples, one downstream from a sewage treatment plant (STP) and the other below the cooling water outlet from a nuclear power plant. PCA might give the following equations

$$PC_1 = 0.86\ N + 0.92\ P + 0.88\ BOD + 0.02\ T \quad . \quad . \quad . \quad (2.3)$$

$$PC_2 = 0.02\ N + 0.06\ P + 0.01\ BOD + 0.97\ T \quad . \quad . \quad . \quad (2.4)$$

Each coefficient in Equations 2.3 and 2.4 is the square root of the variance in the parameter accounted for by that factor. For example, the common factor PC_1 accounts for 74 percent (0.86^2)

of the variance in the nitrogen values, 85 percent in the phosphorus values, 77 percent in the BOD values, and <1 percent in the temperature. PC_1 accounts for

$$\frac{\Sigma_{j=1}^{n} a_{j1}^{2}}{n} \quad . \; . \; . \; . \; . \; . \; . \; . \; (2.5)$$

or 59 percent of the total variance in the four parameters. PC_2 is heavily associated with temperature and explains 24 percent of the total variance. The first factor is apparently associated with the STP, and the second with the cooling water outfall. Reducing the dimensionality of the data set from four variables to two (indices or PCs) retains 83 percent of the explanatory power of the original model (e.g., Kim 1975). Each PC can be thought of as a subindex, whose value can be calculated and aggregated to produce a final WQI, as explained in Chapter 3.

Shoji and Yamamoto (1962) and Shoji et al. (1966) were apparently the first investigators to apply multivariate statistical procedures to water quality data to develop a WQI. Principal component analysis was applied to 19 water quality parameters plus air temperature measured at 12 stations in the Yodo River, Japan, over a 2-year period. Data were normalized by subtracting each value from the mean and dividing by the standard deviation. The analysis revealed four eigenvalues whose factor loadings indicated that the components were associated with 1) dissolved pollutants (except nitrate), 2) high water and air temperature, 3) turbidity (= rainfall?), and 4) high pH and nitrate. A composite WQI was produced using the β weights from the first principal component only (excluding the temperature variables). The resulting WQI values ranged from −0.9 to +2.1 and accurately reflected increasing pollution downstream from Lake Biwa on the Yoda River. The β value for dissolved oxygen was positive (although small), which was intuitively unsatisfactory to the authors, who expected decreasing dissolved oxygen would accompany the remaining pollutant variables. The slight positive value may be indicative of the greater importance of algal nutrients than BOD, however. Such insights are a potentially valuable byproduct of indexing based on multivariate statistical approaches.

Shannon and Brezonik (1972) used multivariate statistical analysis to produce a trophic state index (TSI) for central Florida lakes. Trophic state was a difficult concept to quantify in the 1960s, inasmuch as its manifestations ranged across the entire gamut of biological and chemical parameters used to measure water quality, many of which were poorly understood. Shannon and Brezonik first used cluster analysis to reduce their multivariate data set to two sets of lakes (colored and clear). They then used principal components analysis to define a trophic state index (TSI) for each lake type. TSI's ranged from a high of 18.1 for a highly eutrophic lake to 0.8 for an ultraoligotrophic sandhill lake.

Snyder (1980) applied multivariate techniques to define a WQI for high mountain wilderness lakes in the Bridger-Teton National Forest. Clustering techniques indicated that sampling lake effluent streams was equivalent to open water sampling, which could save considerable effort in monitoring programs.

Ecological and Planning Indices

Ecological WQIs measure the integrated effects of water quality on the biological community, rather than the physico-chemical variables that cause those effects. Perhaps the most important value gained in basing a WQI on relatively immobile aquatic communities (e.g., periphyton or benthic invertebrates) is that their characteristics integrate the effects of their physico-chemical environment over time. That is, episodic inputs of pollution that may go unnoticed in physico-chemical sampling because sampling intervals are long relative to the episode length or because some toxicants are unmonitored, may cause the disappearance of one or more sensitive species. The result is ecosystem simplification, a decrease in species diversity (e.g., Odum 1971, pp. 140-154) measurable by a variety of techniques (Cairns 1979).

The earliest ecological WQI was apparently the Saprobiensystem of Kolkwitz and Marsson (1908). This system classified waters into a hierarchy of good (oligosaprobic) to bad (polysaprobic), based on the presence or absence of a wide variety of indicator species. Sladecek (1973) and Wuhrman (1974) have described the development of this system in Europe, where it is more popular than in the United States. The principal drawbacks of using indicator species are that their absence may be the result of absence of recruitment, unsuitable physical habitat not relating to a pollution source, niche competition, or failure of detection because of low population density (Cairns 1979). Another problem pointed out by Cairns is the absence of knowledge regarding the requirements for a wide variety of individual species. The approach for dealing with such an intractable (or incomplete) data base in ecology is to shift from internal to external analysis, i.e., from explaining how the system works to searching for emergent properties of a system that is essentially treated as a black box (e.g., Kerr 1976).

Such analyses generally focus on community structural attributes such as biomass, taxonomic diversity, or community metabolism. In general, organic pollutants or nutrients tend to produce communities with high biomass represented in the form of a reduced number of tolerant species (e.g., Hynes 1966). Toxic wastes may reduce biomass, as well as diversity, through ecological stress. Community metabolic measures would be expected to be higher in the first case, although some metabolic measures such as ATP concentrations may increase in response to some levels of stress. Examples of analyzing ecological communities to monitor pollution include periphytic diatoms (Williams and Soltero 1978, Rushforth et al. 1981), sessile protozoan communities (Henebry and Cairns 1980), benthic invertebrates (Seagle et al. 1980), and benthos and fish (Kaesler et al. 1978). Green (1979) provides a critical overview of biomonitoring methods.

Ideally, WQIs would be composed of subindices relating to biomass, diversity, and metabolic parameters. Difficulties arise, however, in differential responses of biomass and metabolism to different pollutants. Also, the measurement and comparison of diversity measures is fraught with both theoretical and practical difficulties (e.g., Hurlburt 1971, Kaesler et al. 1978, Mills and Wassel 1980, Alatalo 1981). Furthermore, the relative "goodness" of highly diverse and stable aquatic ecosystems with lower net productivity depends on the relative desirability of an oligotrophic lake for body-contact water sports versus a productive warm water fishery.

An alternative to using predefined indicator species assemblages or emergent community attributes is using multivariate statistical techniques to reduce the dimensionality of community taxonomic data. Classification (clustering) and ordination (e.g., principal components analysis) techniques have been used to combine assemblages of taxa that have ecological meaning. For example, Jeffers (1978, pp. 103-110) and Meeter and Livingston (1978) used principal components analysis on water quality (as well as on substrate variables) to describe the physico-chemical habitat of assemblages of estuarine organisms. Such analyses have not yet been widely applied to freshwater stream communities, but they were used in the work of Sheldon and Haick (1981) on the effect of flow and substrate composition on benthic fauna in a Montana stream. It should be noted that in order to use PCA to produce an ecological index value, it would be necessary to prespecify whether an increase in each species is "good" or "bad" from an environmental quality standpoint. Green (1979) and Gauch (1982) provide useful introductions to the possibilities and pitfalls of multivariate data reduction in environmental studies.

Planning indices are separated from other water quality indices by Ott (1978), principally on the basis that they contain variables not associated with water quality. These include subindices such as stream miles affected by pollution, gross national product, population in a drainage basin, and presence of ethnic groups, as well as subjective indices involving aesthetic appeal and other values dependent on user preference. Planning indices will not be considered further here, even though many of the variables in a planning index are frequently water quality subindices such as those described above. Planning indices, then, share the attribute of biological indices that effects (as well as causes) of the pollution variables are included directly in the index, rather than being used solely to scale subindex functions. While planning indices are not directly comparable to the first three groups, some of their subindices may be useful, as will be demonstrated below.

Summary of WQIs

Water quality indices may be classified into two groups. The rational, deterministic group compares subindex values with accepted norms for general or specific uses and aggregates the subindices into overall WQIs. The statistical group of indices reduces the dimensionality of a data set by searching for combinations of a small number of uncorrelated factors that account for the maximum amount of variance in a large number of correlated water quality variables. This approach essentially identifies univariate or multivariate outliers and assigns them a relatively bad (or good) index score. Biological indices integrate the effects of changes in physico-chemical variables over time and may be useful in setting constraints on the first two types of indices. The relative merits of these indices, together with their use by various water-user agencies, have been well summarized by Ott (1978), and their statistical properties have been described by Landwehr (1979).

CHAPTER 3

SITE DESCRIPTION

Basin Geography

The upper Blackfoot River basin is located in the Wasatch Mountains in southeastern Idaho between latitudes 42°37' and 42°59'N and longitudes 111°09' and 111°27'W (Figure 3.1). The Blackfoot originates from first order streams draining elevations as high as 2736 m above MSL into a mountain valley between the Webster Range and Dry Ridge and leaves the valley through Blackfoot Narrows at an altitude of 1935 m. The mean elevation of the watershed is 2161 m above MSL. The river flows into the 292 km^3 Blackfoot Reservoir and ultimately joins the Snake River above American Falls Reservoir. The total area of the drainage basin above the Blackfoot Narrows is 258 km^2, approximately two thirds of which lies within Caribou National Forest.

Within the Blackfoot River drainage, the USDA Forest Service has water quality sampling stations on five streams, Diamond Creek, Stewart Creek, Mill Creek, Angus Creek, and Sheep Creek, as well as on Blackfoot River at the narrows (Figure 3.1). Some geographical data for these watersheds are presented in Table 3.1. Less extensive water quality data have been collected on Kendall Creek and Mabie Creek, the latter being outside of the delineated study area (Figure 3.1).

Climate and Hydrology

Southeastern Idaho is characterized by cold winters and warm summers. Mean annual temperatures at local meteorological stations range from 3-5°C, all of which at least 270 m below the average elevation in the study site, suggesting that average annual temperatures on site are 1-2°C colder. Most of the precipitation falls as snow during the winter, with higher elevations receiving considerably more precipitation than the surrounding valleys. The valleys receive approximately 35 cm of precipitation and experience about 50 cm of potential evapotranspiration in an average year. Summer thunderstorms occur at the higher elevations. Stream hydrographs are dominated by snowmelt, and many of the smaller tributaries run dry in the summer during below average water years.

Groundwater flow paths are extremely complicated in the study area due to the complex folding and faulting of sedimentary rock (Ralston and Williams 1979). Two limestone and siltstone aquifers of Triassic and Carboniferous age are separated by the Permian Phosphoria formation, which is commercially mined where it crops out in the area. The upper Rex Chert Unit of the Phosphoria formation may be permeable, where fractured, but the phosphate rich shale of the lower Meade Peak Unit acts as an effective aquiclude. During low flow periods, the streamflow is dominated by springs discharging from these aquifers. Consequently, the water tends to be harder and more alkaline than when flows are dominated by snowmelt in the late spring and early summer. Springflow originating from outside the topographic watershed boundaries also may affect water quality.

Land Use

Land use in the study area has been extensively documented by James et al. (1982). Cattle and sheep are grazed on both Forest Service leases and private

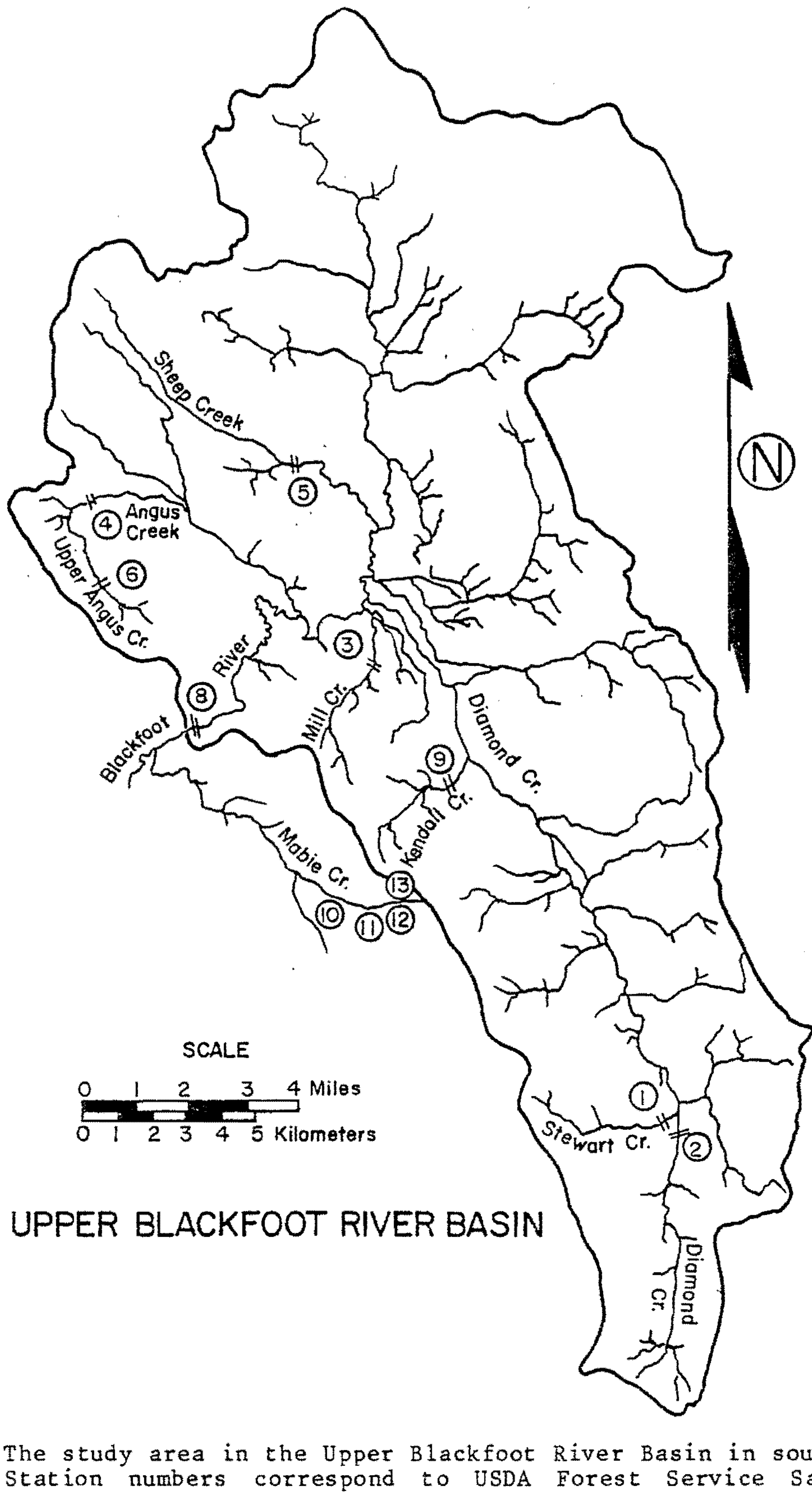

Figure 3.1. The study area in the Upper Blackfoot River Basin in southeast Idaho. Station numbers correspond to USDA Forest Service Sampling sites listed in Table 3.3.

land. Commercial (shelterwood) logging and firewood gathering occur in the Aspen/Douglas fir forests, and a moderate amount of loss to spruce budworm infestation has occurred in recent years. There are two active phosphate mines in the area (Angus Creek and Mabie Creek), and the spoil piles for the latter mine extend into the headwaters of Mill Creek. Hunting (deer, elk, gamebirds) and trout fishing are popular in the watershed, and a small campsite for ORVs is available. ORV trails are common throughout the area, and often cross streams at grade. Logging roads are better maintained. The few ranchers in the watershed do not generally overwinter, so the year round population is essentially zero. Land uses for the catchments tributary to each water quality gaging station are summarized in Table 3.2.

Methods

WQI construction

Water quality data for the study area were obtained from the United States Environmental Protection Agency

Table 3.1. Geographical attributes of watersheds.

Watershed	Maximum Elevation (m)	Minimum Elevation (m)	Mean Elevation (m)	Stream length (m)	Area (km^2)
Stewart Creek	2,740	2,130	2,390	2.45	7.0
Diamond Creek	2,680	2,100	2,350	7.53	27.7
Mill Creek	2,380	1,980	2,140	2.53	4.3
Lower Angus Creek	2,350	2,010	2,140	5.86	10.8
Sheep Creek	2,530	2,010	2,180	8.43	19.1
Blackfoot River	2,736	1,935	2,190		258

Table 3.2. Land uses in the Upper Blackfoot River study area watersheds.

Watershed	Land Use			
	Logging[1]	Grazing[2]	Mining[1]	Roads[1]
Stewart Creek	**	C, S		*
Diamond Creek	*	C, S		**
Mill Creek		S		*
Lower Angus Creek	*	C	*	*
Upper Angus Creek	**		**	**
Sheep Creek		S		
Kendall Creek	*	S	*	*
Mabie Creek		C	**	**
Blackfoot River	*	C, S	*	*

[1]** = heavy use, * = moderate use, and blank = little or no use

[2]C = cattle, S = sheep

(USEPA) STORET files. The data were collected for 12 stations, four of which were on Mabie Creek (Figure 3.1), which lies outside of the upper Blackfoot drainage. The station STORET identification numbers are shown in Table 3.3. The water quality variables monitored were 1) temperature, 2) flow, 3) turbidity, 4) conductivity, 5) pH, 6) alkalinity, 7) nitrite-nitrogen, 8) nitrate-nitrogen, 9) total Kjeldahl nitrogen, 10) total phosphorus, 11) dissolved ortho-phosphorus, 12) total hardness, 13) total dissolved solids, and 14) suspended solids (mg/l).

Samples are collected by Forest Service personnel at two week intervals in the summer and fall, but access is difficult during winter and spring, and

Table 3.3. STORET stations identification numbers for study streams.

STORET Station Number	Study Station Number	Station Location
050201600151	1	Stewart Creek above confluence with Diamond Creek
050201600251	2	Diamond Creek above confluence with Stewart Creek
050201600351	3	Mill Creek 91 m (100 yds) above National Forest boundary
050201600451	4	Angus Creek 805 m (one-half mile) above National Forest boundary
050201600551	5	Sheep Creek at foot bridge 2.4 km (1.5 mile) above National Forest boundary
050201600651	6	Angus Creek near the headwaters
050201600751	7	Mabie Creek at National Forest boundary
050201600851	8	Blackfoot River below National Forest boundary
050201600951	9	Kendall Creek at National Forest boundary
050201601051	10	Mabie Creek 402 m (one-fourth mile) above National Forest boundary
050201601151	11	Mabie Creek 91 m (100 yds) above National Forest boundary
050201601251	12	Mabie Creek 220 m (250 yds) below National Forest boundary

sampling during these seasons was more irregular and less frequent. Temperature was measured in the field, flow was determined using calibrated staff gages, and pH was determined upon return to the Forest Service station. The remaining samples were preserved and sent to a commercial laboratory for analysis following standard methods (EPA 1981, APHA 1981).

In analyzing the data, redundant water quality variables were eliminated by examining the cross correlations of the complete variable set (R-type analysis, Sneath and Sokal 1973), using the statistical package CLUSTAR (Marshall and Romesburg 1978). The reduced set of water quality variables for all streams then was used to produce a series of seven resemblance matrices based on different resemblance coefficients. The coefficient with the highest cophenetic correlation (Farris 1969, Williams and Clifford (1971) was chosen for future calculations. The streams then were clustered, using the selected resemblance coefficient, to form logical groupings based on physico-chemical properties.

Groupings were investigated using the 5-year averages of all historical water quality data available for each stream. The cluster analysis was subsequently repeated for 5-year May through October averages (to eliminate the data base difference in the historical records) and bimonthly and monthly averages (to investigate the temporal water quality changes). Additional cluster analyses were run using annual (rather than 5-year) May-October averages, and with various sets of object streams. Such object (stream) rather than attribute (chemistry) clustering is known as Q-type analysis (Sneath and Sokal 1973).

In addition to cluster analysis correlation matrices based on the physico-chemical data also were calculated for 5-year May through October averages, bimonthly averages, monthly averages, and for annual May-October averages, and the principal components for each of the correlation matrices were obtained using the FACTOR routine of SPSS (Kim 1975). Only principal components which were associated with eigenvalues > 1.0 were retained for analysis. Principal components rotations were performed to maximize loadings of meaningful variables on each component. Two types of orthogonal rotations, Varimax and Equimax, were attempted by using SPSS (Kim 1975, Haan 1977). The principal components analysis was repeated with flow expressed per unit area of watershed for each stream. The resulting principal components served as the basis for the water quality index. Further information on the theory behind clustering and principal components analysis can be found in Sneath and Sokal (1973), Kendall (1975), and Everitt (1980).

The principal components extracted from the water quality data are linear functions of the standardized water quality variables as follows:

$$z_j = \sum_{i=1}^{10} a_{ij} \left(\frac{x_i - \bar{x}_i}{\sigma_i}\right), \quad j=1, 2, \ldots, n \qquad \text{. . . . . (3.1)}$$

where

z_j = the jth principal component,

a_{ij} = coefficients of the ith variable in the jth principal component,

x_i = ith variable,

$\bar{x}_i$ = the mean of the ith x's,

σ_i = standard deviation of the ith variable, and

n = number of principal components, where $n \leq P$

P = number of variables used in the index

The significant principal components can be combined to produce a water quality index, but the axes of each component must first be shifted to avoid negative values. The amount of shift is:

$$c_j = \sum_{i=1}^{m} a_{ij} \left(\frac{\bar{x}_i}{\sigma_i}\right) \quad , \quad \text{for } a_{ij} > 0,$$

$$\text{and } i = 1, \ldots, n \quad . \quad . \quad . \quad (3.2)$$

where

c_j = shift of axis for ith principal component,

m = number of variables with $a_{ij} > 0$, $m \leq P$, and

n = number of significant components.

Each component after the shift will be called a subindex as follows:

$$SBI_j = z_j + c_j \quad . \quad . \quad . \quad . \quad . \quad (3.3)$$

where

SBI_j = subindex j,

z_j = principal component j, and

c_j = axis shift.

Using the orthogonality property of these subindices, they can be summed as vectors, and their resultants determine the water quality index (WQI) as follows:

$$WQI = \left(\sum_{i=1}^{n} SBI_j^2\right)^{\frac{1}{2}} \quad . \quad . \quad . \quad . \quad . \quad (3.4)$$

where

WQI = water quality index

SBI_j = jth subindex, and

n = the resultants of the number of subindices, $n \leq P$.

Note that the shift of the axis may bias the resultant, due to a larger shift of a particular subindex (Equation 3.3), because the resultant always shifts closer to the larger vector. Therefore, all the subindices were shifted by the same amount, so that the difference among the different subindices in Equation 3.3 is due only to z_i's. The shift is:

$$c = \text{MAX}\ (c_1, \ldots, c_n) \quad . \quad . \quad (3.5)$$

where

c = the shift of axes for all subindices.

Benthic invertebrates

In order to develop the benthic invertebrate WQI, invertebrates were sampled at stations 1, 2, 3, 4, 5, 7, and 8 on September 18, 1981. Sampling locations were chosen in riffles within 50 m of the water quality station. Triplicate samples were taken in each riffle in upstream order as randomly as possible using a Hess invertebrate sampler. This allowed a bottom area of 0.10 m^2 to a depth of about 10 cm to be scraped clean and the invertebrates to be collected in a #60 mesh net. Some of the streams sampled were only slightly wider than the Hess samples.

The collection of sand and small gravel containing the invertebrates was then placed in a wide-mouth plastic jar and preserved in 70 percent ethanol. The jars were transported back to the lab, where salt flotation was used to separate the organisms from the sand and gravel. The organisms were then separated from organic detritus and placed in 70 percent ethanol for later identification. Following identification, major taxa were composited and dried to constant weight in a 105°C oven, and subsequently ashed for 2 hr at 550°C to determine ash free dry weight.

CHAPTER 4

DEVELOPING A WQI FOR A HIGH MOUNTAIN WATERSHED: RESULTS AND DISCUSSION

Problems with Deterministic and Specific Use WQIs

As pointed out in the introduction, initial attempts to create a deterministic WQI, or to impliment a pre-existing WQI, were unsuccessful due to two factors. First, the water quality was quite good, relative to river reaches heavily impacted by organics, nutrients, or toxic chemicals. Indeed, only the turbidity standard of 1.0 NTU for class IA Idaho streams was ever exceeded in any of the streams in the study watersheds. However, it is unlikely that any stream in the area ever meets the 1.0 NTU standard during spring runoff, and the standard is undoubtedly meant to avoid excessive siltation during low flow periods. The second factor relates to the fact that water quality or quantity required for most offsite uses of the discharge from the watershed can effectively be summarized with one water quality parameter or subindex, thus rendering a WQI superfluous.

As an heuristic excercise, chemical data from the study watersheds (Table 4.1) were used to estimate the NSF WQI (Brown et al. 1970) and compare index values. Although certain subindices could not be included due to lack of data (e.g., fecal coliforms, BOD_5), it is unlikely that the pollutant sources encountered in the study area cause pollution of these types in amounts likely to contribute significantly to the aggregated value. The results (Table 4.2) indicate that the stream with the lowest index value (Upper Angus Creek) has a WQI only 3 percent below that of the stream with the highest water quality (Mill Creek). It is also interesting that, even though Upper Angus and Mabie Creeks drain phosphate mines and show unusually high phosphorus concentrations for mountain streams, the phosphorus subindex is insufficiently sensitive to register any difference among the creeks, and suspended sediment differences account for the variation in index values. It is possible that deterministic indices would be more useful if expressed as some function of worst case, rather than average conditions (e.g., average highest quartile of WQI values).

Phosphorus concentrations illustrate another problem with developing specific use WQIs. Blackfoot Reservoir, which receives the flow from the Blackfoot River, is eutrophic, although it maintains a healthy cutthroat trout fishery (Perry 1977). Application of the Vollenweider (1976) trophic state model to the reservoir, based on limited data, suggests that the phytoplankton community is nitrogen limited, and that internal loading from the lake sediment supplies the majority of the water column phosphorus supply (Messer, unpublished manuscript). Consequently, a safe criterion value for phosphorus in the Blackfoot River or its tributaries would be 0.0 mg/l. This value would increase slowly as internal sedimentary supplies of phosphorus to the reservoir were depleted. Therefore a specific use WQI for downstream recreational use that incorporated the threshold (criterion) value for a phosphorus subindex would allow no new phosphate mining (or any other use) in the Upper Blackfoot River drainage, even though cessation of present mining activity may not affect the trophic state of Blackfoot Reservoir

Table 4.1. Annual 5-year May through October averages for water quality variables in the Upper Blackfoot River Basin.

	Water Quality Variable									
Station Number[1]	Temperature (°F)	Flow (cfs)	Turbidity (NTU)	Conductivity (μmhos)	pH	Alkalinity (mg/l $CaCO_3$)	Total Nitrogen (mg/l N)	Total Phosphorus (mg/l P)	Dissolved Phosphorus (mg/l PO_4-P)	Suspended Solids (mg/l)
1	43 (76)[2]	4.9 (73)	4.9 (75)	313 (75)	7.7 (29)	163 (75)	1.04 (72)	.096 (69)	.074 (11)	41 (75)
2	45 (64)	17.5 (57)	6.1 (64)	294 (64)	7.6 (19)	144 (64)	1.49 (64)	.140 (61)	.113 (11)	47 (64)
3	46 (86)	2.7 (81)	1.5 (87)	318 (87)	7.4 (23)	172 (87)	.97 (87)	.112 (85)	.124 (14)	11 (87)
4	49 (81)	3.0 (69)	6.7 (81)	310 (81)	7.4 (17)	158 (81)	1.08 (81)	.126 (79)	.076 (10)	15 (81)
5	47 (84)	10.8 (88)	4.5 (84)	317 (84)	7.6 (20)	170 (84)	1.00 (84)	.102 (79)	.085 (12)	22 (84)
6	52 (79)	1.3 (55)	6.1 (82)	321 (82)	7.2 (21)	146 (82)	1.30 (82)	.168 (80)	.195 (14)	17 (82)
8	51 (88)	294.0 (92)	3.6 (88)	312 (88)	7.5 (22)	168 (88)	.98 (88)	.088 (82)	.118 (15)	18 (88)
10	44 (80)	2.8 (76)	6.5 (81)	352 (81)	7.5 (17)	189 (81)	1.26 (81)	.125 (74)	.090 (15)	32 (81)
X[3]	47	42.1	5.0	320	7.5	164	1.14	.120	.109	25
s[4]	3	101.9	1.8	17	.2	13	0.19	0.026	.040	13

[1] For Stations Identifications see Table 3.3

[2] The number between parentheses is the number of observations from which the averages were obtained

[3] Mean

[4] Standard deviation

Table 4.2. National Sanitation Foundation (NSF) index values for study streams.

Stream	Weighted NSF Subindices						NSF Index
	pH Subindex	Nitrogen Subindex	Phosphorus Subindex	Temp. Subindex	Turbidity Subindex	Total Solids Subindex	
Stewart Creek	16.10	15.00	15.00	13.95	11.25	2.00	73.30
Diamond Creek	16.10	15.00	15.00	13.95	10.88	3.40	74.33
Mill Creek	16.45	15.00	15.00	13.95	12.13	3.40	75.93
Angus Creek	16.45	15.00	15.00	13.95	10.63	3.50	74.52
Sheep Creek	16.10	15.00	15.00	13.95	11.38	2.00	73.43
Upper Angus Creek	16.10	15.00	15.00	13.95	10.88	2.00	72.93
Blackfoot River	16.45	15.00	15.00	13.95	11.50	3.40	75.30
Mabie Creek	16.45	15.00	15.00	13.95	10.75	2.00	73.15

over any reasonable planning horizon. However, downstream reservoirs may not be nitrogen limited, and minimizing phosphorus concentrations in Blackfoot River flows may be worthwhile for these latter reservoirs alone.

It may be argued that a special use index for downstream reservoirs should be based on nitrogen in the case of the upper Blackfoot watershed. However, an attempt to control eutrophication through nitrogen depletion may result in more frequent blue-green algal nuisances due to their ability to fix atmospheric nitrogen. One is thus not even sure which direction of change in a subindex value means added algal problems. A similar case could be made for a specific use index relating to instream productivity within the watershed itself. Finally, if sediment concentration is the only important variable, inasmuch as it relates to the useful life of a reservoir or to siltation of fish habitat, then an index is unnecessary. Sediment concentration is its own index. These arguments do not prove that available deterministic WQIs are useless in wildland watersheds, but together with the difficulties in achieving objective subindex aggregation they pose some very difficult questions.

Ultimately, we turn to the evaluation of water quality as it relates to instream uses, i.e., by fish and their supportive trophic networks. As stated previously, routinely measured water quality parameters were within a range that were not likely to produce deleterious acute effects on fish or invertebrates, nor would they pose problems for potable or irrigation use of the water. Although there has been some concern expressed over high heavy metal concentrations in the Phosphoria Formation (USDI 1981), random sampling of metal concentrations in both water and fish tissue during 1970-1976 failed to reveal alarming values (Platts and Martin 1978). An analysis of copper concentration in conjunction with stream hardness and pH based on the model of

Howarth and Sprague (1978) indicated that even the highest concentrations reported (~16 μg/l) would not be toxic to adult trout (B. Doebley, UWRL, unpublished data), although effects on eggs and larvae are unknown. Consequently, for purposes of generating a single valued WQI for use in the watershed LP model it was decided to turn from a deterministic or empirically determined WQI to a multivariate statistical WQI in order to seek out water quality patterns that would allow a quantitative estimate to be made of the level of stress exerted on aquatic communities by unusual variations in physico-chemical water quality parameters.

Development of a Multivariate Statistical WQI

Elimination of redundant water quality variables

Preceding classification of the streams according to water quality by cluster analysis, the water quality variables were examined for redundancy by computing a cross-correlation matrix in order to exclude highly correlated variables (Kendall 1975). The cross-correlation matrix is a symmetrical matrix having values of unity along the diagonal and with the other elements giving correlation coefficients (r) between all the possible pairs of variables. The resulting matrix (Table 4.3) shows that 1) conductivity was highly correlated with total dissolved solids ($r = 0.976$), and 2) that alkalinity was highly correlated with hardness ($r = 0.957$). Other high correlations ($r > 0.9$) were 3) alkalinity and hardness with total dissolved solids, 4) turbidity with suspended solids, and 5) total Kjeldahl nitrogen with suspended solids.

The first correlation simply provides a check on the chemical analyses. The second and third correlations indicate that alkaline earth bicarbonates (calcite, magnesian calcite, and dolomite) dominate the dissolved solids in the watershed. This is to be expected because of the groundwater flow network through the limestone that feeds the springs that supply low flows (Ralston and Williams 1979). The final correlation suggests that the suspended solid load in these streams is either composed of or transported with nitrogen rich material. Such material could be dominated by leaf litter, sediments, or fecal material from wildlife or livestock.

The correlation matrix was used as the resemblance matrix between the physico-chemical variables to form the dendrogram shown in Figure 4.1. A single linkage clustering method was used to define the distance between objects or clusters of objects instead of average linkage clustering (Sneath and Sokal 1973). In the latter method the correlation between the midpoint of a cluster and the next closest object is calculated, rather than the distance between the next closest object and its nearest neighbor in the cluster. This would be conceptually wrong because the resulting correlation coefficients would not be additive. The same types of observations can be drawn from the dendogram as from the cross correlation matrix.

Based on the cross-correlation matrix results, conductivity and alkalinity were arbitrarily included, and the redundant total dissolved solids and total hardness values discarded. Kendall (1975) suggested that two variables, with their correlation coefficient equal or above certain somewhat arbitrary value, could be considered similar; hence only one of these variables need be used. Implicit in this criterion, however, is the assumption that the high correlation between two variables results from direct cause and effect and not from some third factor which affects them both. This seems to be the case with the parameters relating to limestone geochemistry, but it may not be true

Table 4.3. Correlation matrix for annual averages of water quality variables.

	Temperature (^oF)	Flow (cfs)	Turbidity (NTU)	Conductivity (mmhos)	pH	Alkalinity (mg/l $CaCO_3$)	NO_2-N (mg/l)	NO_3-N (mg/l)	TKN (mg/l)	Total Phosphorus (mg/l P)	Dissolved Phosphorus (mg/l PDD-P)	Total Hardness	Total Dissolved Solids	Suspended Solids
Temperature	1.000													
Flow	0.415	1.000												
Turbidity	-0.358	0.244	1.000											
Conductivity	-0.176	0.232	0.610	1.000										
pH	-0.306	-0.051	-0.137	0.120	1.000									
Alkalinity	-0.337	0.174	0.362	0.865	0.458	1.000								
NO_2-N	-0.353	-0.270	0.772	0.268	-0.420	-0.048	1.000							
NO_3-N	-0.395	-0.512	0.703	0.324	-0.607	0.014	0.867	1.000						
TKN	-0.735	-0.197	0.795	0.462	-0.130	0.298	0.744	0.781	1.000					
Total P	-0.375	-0.441	0.174	0.157	-0.526	-0.018	0.422	0.582	0.555	1.000				
Dissolved P	-0.302	-0.022	0.706	0.384	-0.629	0.060	0.818	0.867	0.782	0.722	1.000			
T.H.	-0.325	-0.121	0.363	0.895	0.258	0.947	0.026	0.182	0.354	0.110	0.167	1.000		
TDS	-0.302	-0.200	0.596	0.976	0.292	0.903	0.244	0.252	0.502	0.100	0.304	0.905	1.000	
SS	-0.597	-0.142	0.916	0.549	-0.123	0.368	0.810	0.762	0.916	0.405	0.813	0.367	0.555	1.000

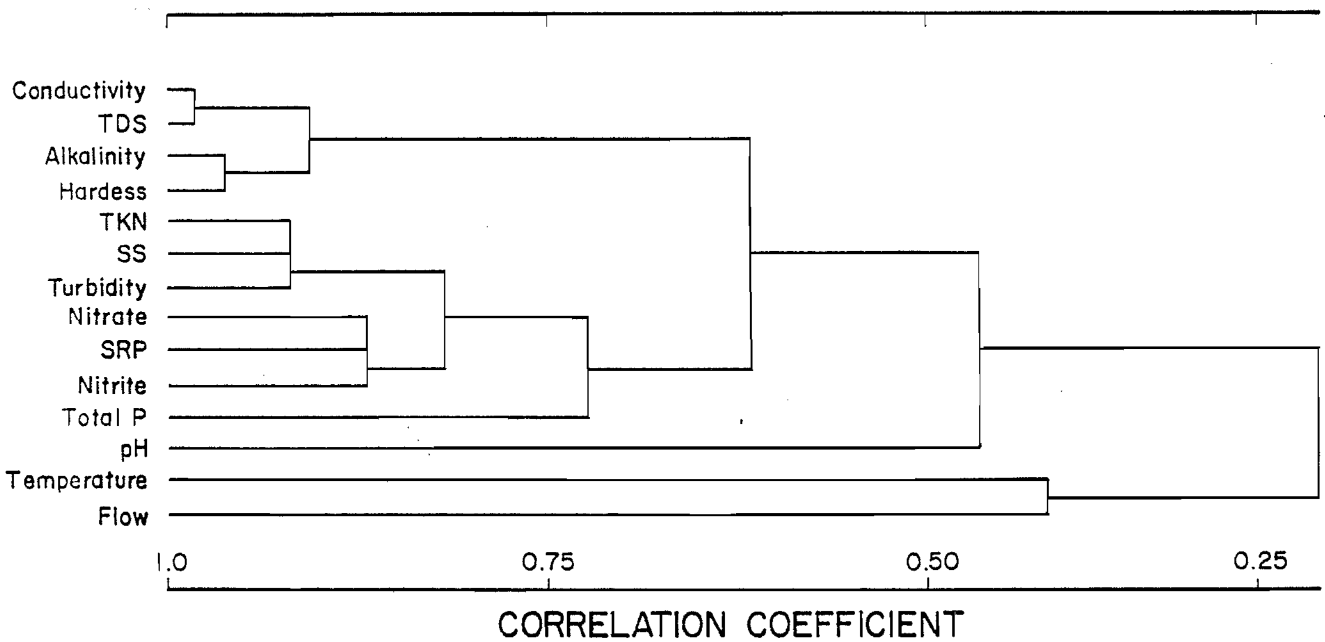

Figure 4.1. Water quality variable correlation dendrogram based on data collected at all Forest Service sampling stations.

for the TKN-suspended solids relationship, consequently both TKN and suspended solids were retained. TKN, nitrate, and nitrite concentrations were summed to form a new parameter, total nitrogen (TN). This appears justified based on their relatively high correlations (Table 4.3) and it simplified the statistical analyses.

Selection of resemblance coefficient

Using the reduced set of water quality variables as attributes, the stations were clustered using seven different resemblance coefficients: 1) correlation coefficient, 2) average euclidean distance, 3) cosine of an angle, 4) shape of difference, 5) Clifford-Stephenson, 6) Canberra metric, and (7) Bray-Curtis. The cophenetic correlation coefficient (the compatibility between the resemblance matrix from which the dendrogram was determined and the resemblance matrix generated from the dendrogram) were calculated for each of the resemblance coefficients. These cophenetic coefficients (Table 4.4) ranged from 0.95 (average euclidean distance) to 0.25 (Canberra metric coefficient). Average euclidean distance was thus associated with the highest cophenetic correlation coefficient and hence used for subsequent calculations. This similarity measure was also the one recommended for continuous variables by Clifford and Stephenson (1975).

Classification of streams

Cluster analysis was used for stream classification, with the average euclidean distance as a resemblance measure and the overall average of all the historical water quality data (Table 4.1) as input. All of the variables were standardized to a zero mean and a unit standard deviation, to compensate for scale differences among the variables. The resemblance matrix was then

Table 4.4. Cophenetic correlation coefficients for different resemblance coefficients applied to stream clusters on the basis of the reduced water quality variable set.

Resemblance Coefficient	Cophenetic Correlation
Correlation	0.91
Average Euclidean Distance	0.95
Cosine of an Angle	0.80
Shape of Difference	0.92
Clifford-Stephenson	0.89
Canberra Metric	0.25
Bray-Curtis	0.89

calculated for all the possible pairs of streams. The standardized variables and the resemblance matrix have been presented by Mahmood (1980). The dendrogram then was generated from the resemblance matrix using the average linkage clustering method.

The dendrogram (Figure 4.2) shows two broad groups; one group with three stations, all of them located in Mabie Creek, and another group composed of the rest of the stations. The former group has significantly higher suspended solids concentrations than the latter one (Table 4.1). No subgroups were obvious within the second group.

Unfortunately, the data base for the Mabie Creek group consisted of only a single year of data. Therefore the uniqueness of the group could have resulted simply from selecting a year in which suspended sediment loads were above average due to the amount or pattern of runoff. All subsequent analyses were restricted to May-October averages, which provided a consistent, five-year data base for all streams except Kendall Creek (7) and three stations on Mabie Creek (9, 11, and 12).

The remaining eight stations were clustered, using the new 5-year May through October averages. The resulting dendrogram (Figure 4.3) shows chaining but no distinctive grouping among the streams. It is apparent that Upper Angus Creek (6), and Diamond Creek (2) were the least similar to the other streams. The data (Table 4.1) indicate high total phosphorus at Station 6 which is located directly below a sedimentation pond in an operating phosphate mine, and high suspended solids and total nitrogen in Station 2. The dendrogram can be thought of as ranking the streams from most to least similar to average conditions on the basis of their standardized physico-chemical variables. In other words, Upper Angus Creek and Diamond Creek are characterized by wide departures from the population mean, measured as a multiple of the population variance, for one or more variables. Ordination by principal components analysis can be used to determine what variables or sets of variables are responsible for the dissimilarities in the streams.

Ordination of physico-chemical variables

Principal components analysis was used in order to reduce the dimensionality of the physico-chemical variables, and to render them uncorrelated (orthogonal). Four signifi-

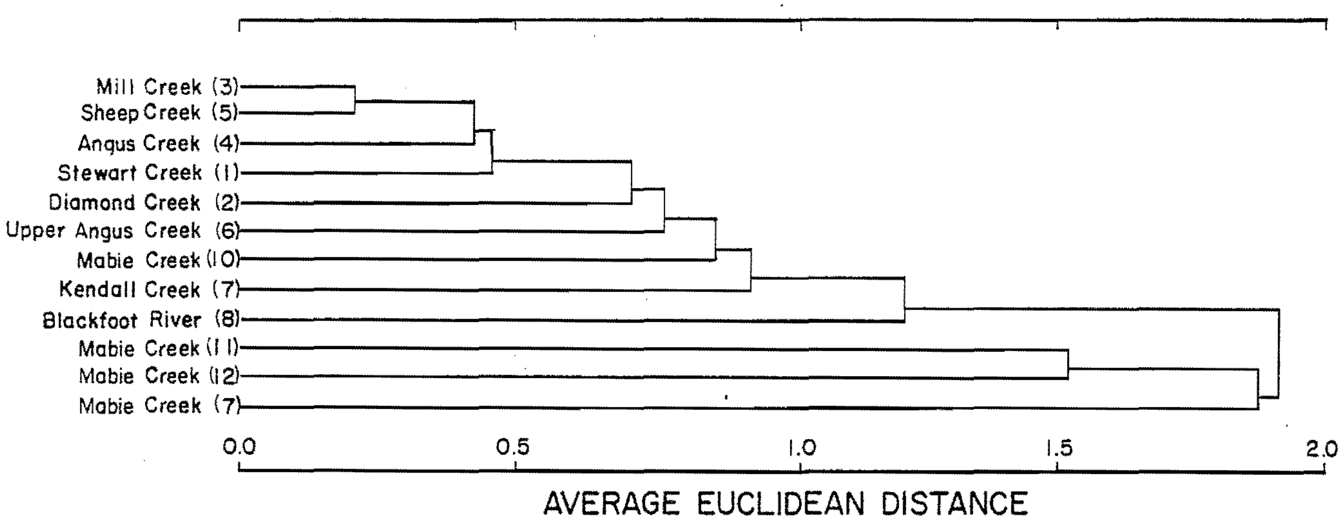

Figure 4.2. Dendrogram for all sampling sites using water quality data collected for water years 1975-1979.

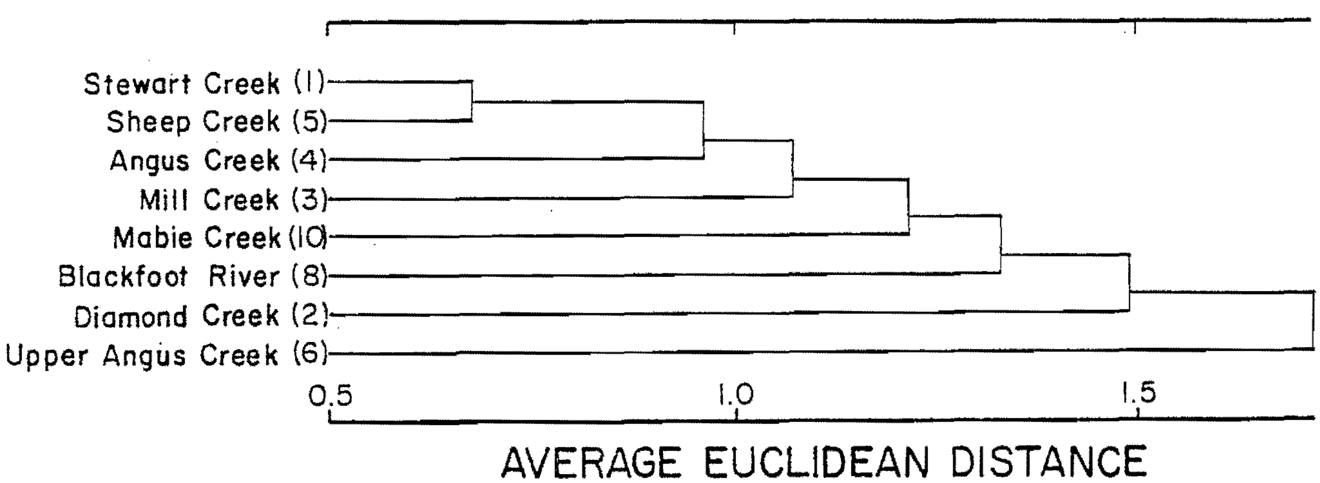

Figure 4.3. Cluster analysis based on May-October averages of physico-chemical variables.

cant principal components (eigenvalue > 1.0) were obtained from the annual correlation matrix, and together these account for 91.8 percent of total variability in the data set. The coefficients for the standardized data (Table 4.5) are shown in Table 4.6. The first component, which accounts for 37.1 percent of the total variability, can be considered as a nutrient factor, because it has the coefficients associated with total phosphorus, dissolved phosphorus, and total nitrogen. The second factor, which explains 30.6 percent of the total variability, can be considered as a suspended solids factor, although the coefficients for total nitrogen are almost the same in the first and second components. The third factor, which explains 13.8 percent of the total variability, can be considered as a conductivity (total dissolved solids) factor. Finally, the fourth factor, which explains 10.3 percent of the total variability, can be considered as a flow factor. The analysis thus reduces the dimensionality of the ten-variable data set to four variables, all of which have ecological meaning with respect to water quality.

Often, principal components can be orthogonally rotated to increase the loadings (coefficients) of some variables on certain components (Gauch 1982). Because the variability explained by a given component (and the components as a whole) does not change with rotation (Haan 1977), rotation results in a decreased absolute loading of the remaining variables on the component. Consequently, the criterion for a successful orthogonal rotation is that the rotated component loadings are more easily (conveniently) interpreted from an ecological standpoint than those of the unrotated components.

The principal components were rotated using both the Varimax and Equimax routines of SPSS (Kim 1975). The resulting factor loadings for the Varimax rotations are shown in parentheses in Table 4.5. On the first component, rotation had the result of increasing the loading of temperature and dissolved phosphorus at the expense of total P and total N. Total N and P subsequently weighted more heavily on the second principal component, with turbidity replacing suspended solids. The remaining components remained qualitatively unchanged. Equimax rotation produced essentially the same result (Mahmood 1981). The overall result of the rotation was to convert a nutrient and a suspended solids component into a warm-orthophosphate and turbid-total nutrient component respectively. Deeper understanding of the stream ecosystem is required to know whether this represents an improvement over the unrotated factors.

<u>The water quality index</u>

Water quality indices were obtained for each station using the coefficient values in Table 4.6 and Equations 3.1 through 3.5. pH is substituted into all the indices as the absolute value of the deviation from 7, to change the scale of pH into a symmetric scale around 7, i.e., a pH of 8 has the same effect as a pH of 6 on the water quality index. This procedure has been followed by many investigators (Brown et al. 1970, Prati et al. 1971). The annual subindices and overall WQIs for all sampling stations are shown in Table 4.7.

The WQIs indicate that the "worst" stations (based on the highest positive deviations of the standardized variables) are Diamond Creek (2), Upper Angus Creek (6), and Mabie Creek (10). However, the highest index (Diamond Creek) was only 14 percent higher than the lowest (Mill Creek). The subindices, however, demonstrate more variability, and indicate that whereas Diamond Creek suffers abnormally high sediment loads, Upper Angus Creek is dominated by nutrients and Mabie Creek by dissolved solids (conductivity). These WQIs and subindices were calculated based on the unrotated principal components only. It was subsequently

Table 4.5. Standardized variables for 5-year May-October averages.[1]

Station Number	Temperature (^oF)	Flow (cfs)	Turbidity (NTU)	Conductivity (μmhos)	pH	Alkalinity (mg/l $CaCO_3$)	Total Nitrogen (mg/l N)	Total Phosphorus (mg/l P)	Dissolved Phosphorus (mg/l PO_4-P)	Suspended Solids (mg/l)
	Water Quality Variables									
1	-1.261	-0.365	-0.049	-0.391	1.369	-0.060	-0.543	-0.907	-0.894	1.191
2	-0.650	-0.242	0.627	-1.514	0.725	-1.176	1.853	0.782	0.092	1.648
3	-0.344	-0.387	-1.966	-0.096	-0.564	0.658	-0.900	-0.293	0.370	-1.095
4	0.573	-0.384	0.965	-0.569	-0.564	-0.458	-0.326	0.245	-0.843	-0.791
5	-0.038	-0.307	-0.275	-0.155	0.725	0.498	-0.740	-0.677	-0.616	-0.257
6	1.491	-0.401	0.627	0.081	-1.852	-1.415	0.828	1.857	2.163	-0.638
8	1.185	2.471	-0.782	0.731	0.081	0.339	-0.830	-1.214	0.218	-0.562
10	-0.956	-0.386	0.853	1.913	0.081	1.614	0.658	0.206	-0.490	0.505

[1]Standardized to a unit variance and zero mean.

Table 4.6. Principal components with eigenvalues > 1 based on standardized 5-year May-October averages.

Physico-chemical Variables	Variability Explained[1]			
	37.1% Factor 1	30.6% Factor 2	13.8% Factor 3	10.3% Factor 4
Temperature	0.572 (0.836)[2]	-0.701 (-0.086)	-0.188 (-0.120)	0.261 (0.448)
Flow	-0.237 (0.065)	-0.535 (-0.206)	-0.277 (0.115)	0.749 (0.959)
Turbidity	0.443 (0.003)	0.557 (0.847)	0.350 (0.022)	0.314 (-0.097)
Conductivity	-0.260 (0.140)	-0.429 (0.009)	0.810 (0.967)	0.267 (0.154)
pH	-0.753 (-0.976)	0.570 (-0.039)	-0.244 (-0.087)	0.177 (0.144)
Alkalinity	-0.766 (-0.371)	-0.229 (-0.362)	0.574 (0.838)	-0.056 (-0.045)
Total Nitrogen	0.626 (0.074)	0.635 (0.914)	0.197 (-0.209)	0.266 (-0.142)
Total Phosphorus	0.934 (0.614)	0.214 (0.647)	0.250 (-0.203)	-0.126 (-0.399)
Dissolved Phosphorus	0.789 (0.839)	-0.385 (0.191)	-0.011 -0.170)	0.056 (0.072)
Suspended Solids	-0.137 (-0.708)	0.903 (0.625)	-0.045 (-0.216)	0.321 (0.001)

[1]Percent of total variability explained by four factors = 91.8.
[2] Based on Varimax rotation of components.

learned that orthophosphate analyses were not performed in a timely fashion (within 24 hr), and it was felt that the reliability of the measured data could not support a heavily loaded orthophosphate component.

Utilizing May-October averages results in the loss of some information if the timing of poor water quality is important in assessing environmental impact on streams. That is, certain instars (life stages) of key species may be more sensitive to changes in water quality than others. Also, the higher temperatures during late summer may make stream communities more sensitive to a given chemical perturbation than they are during snowmelt periods. Consequently, the process outlined for development of the annual WQI was repeated using bimonthly and monthly

Table 4.7. Annual 5-year May-October water quality indices and subindices for all streams.

Station Name	Station #	Subindex				WQI
		1 Nutrients	2 S. Solids	3 Conductivity	4 Flow	
Stewart Creek	1	22.50	28.50	25.11	25.57	51.02
Diamond Creek	2	28.38	30.73	24.65	26.33	55.23
Mill Creek	3	24.37	23.03	25.46	24.13	48.52
Angus Creek	4	26.98	25.66	25.54	25.33	51.77
Sheep Creek	5	23.49	25.49	25.49	25.27	49.90
Upper Angus Creek	6	33.20	24.28	26.09	25.81	55.12
Blackfoot River	8	23.71	21.48	24.92	27.66	49.08
Mabie Creek	10	24.19	27.09	28.94	26.23	53.33

averages for each stream. This resulted in three times as many mean values for each variable in the case of bimonthly data, and six times as many for monthly data. The analysis suffers, however, because the large differences between water chemistry during snowmelt and late summer baseflow increase the standard deviation of each variable. This reduces differences between standardized variates to the point that for the monthly averages based on two biweekly samples for each stream the indices were largely meaningless (Mahmood 1980).

The effect of snowmelt is clearly indicated in the dendrogram of the bimonthly averages (Figure 4.4). The May-June averages for all streams (except Stewart Creek) cluster together, while the remaining averages apparently depend more on spatial than temporal variability. Water quality in the Blackfoot River, which integrates the water chemistry of all the tributary streams, remains that of the snowmelt period into July and August.

Three bimonthly principal components were obtained with eigenvalues > 1.0 (Table 4.8). The model explained 72.3 percent of the total variability with the first component accounting for 43.7 percent of the total. Turbidity, conductivity, low pH and alkalinity, total nitrogen, total phosphorus, and suspended solids were weighted higher in the first component; flow in the second, and dissolved phosphorus in the third. The rotated components loaded total phosphorus more highly in the second component, and there was almost no change for suspended solids. The remaining variable weights increased on the same components, thus the rotated components were used in order to separate the nitrogen and phosphorus subindices. It is arguable, however, that most of the variability in the system explained by the model could be contained within the first subindex, that would, if unrotated, represent turbid, nutrient rich water.

The bimonthly water quality index and its subindices (Table 4.8) are shown in Table 4.9. In all cases, the WQI decreases (improves) between spring and fall, primarily because of the first (turbidity-total N) subindex. The Total

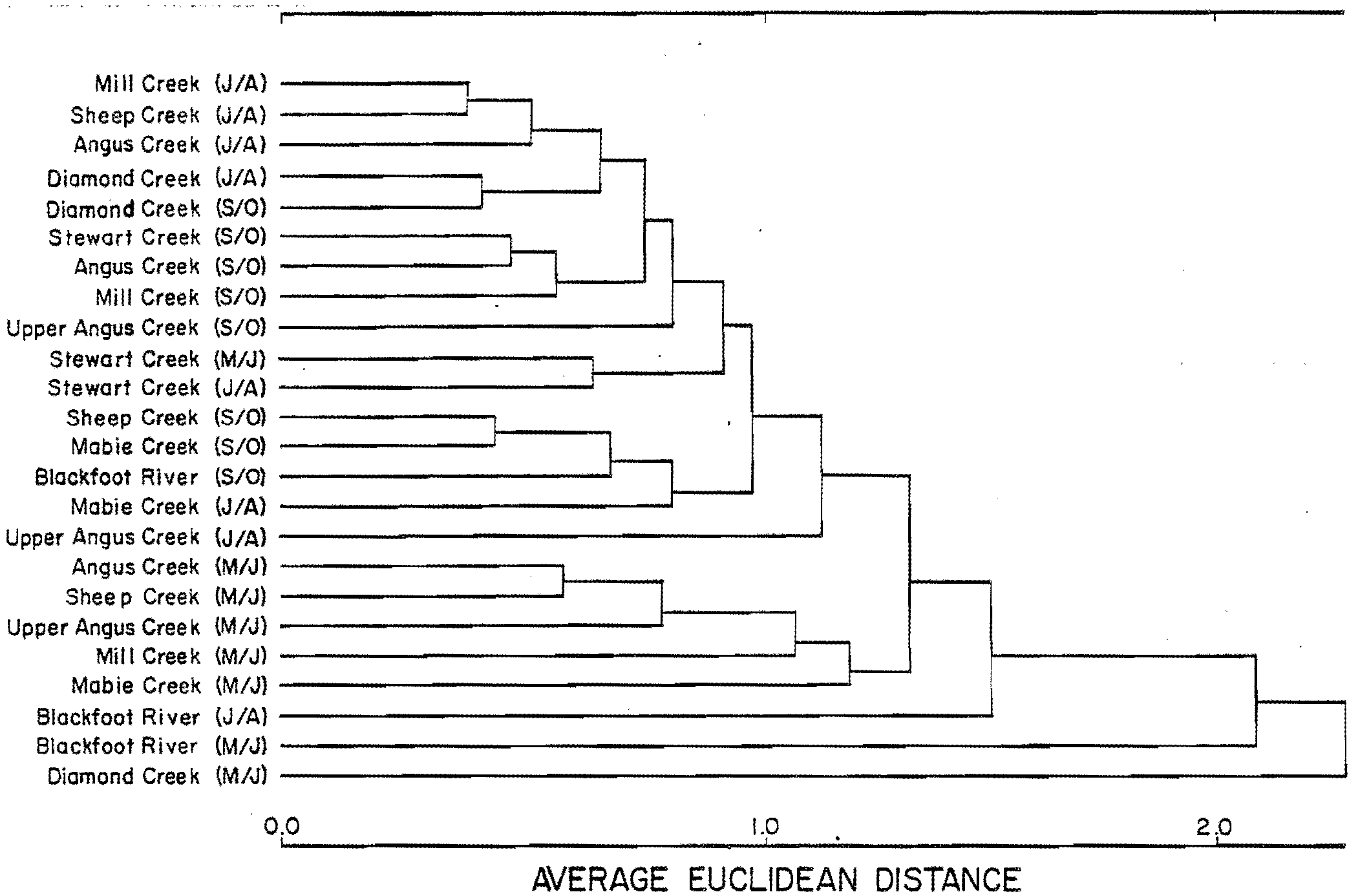

Figure 4.4. Dendrogram of bimonthly averages of water quality variables for all streams.

P-flow factor (subindex 2) shows the greatest decline with season in Mill Creek (3) and the Blackfoot River (8). The orthophosphate subindex (3) appears to be similar in most streams, although a seasonal trend toward an increasing value for this index appears in the Blackfoot River (8). While Diamond Creek (2) remains the "worst" stream, the Blackfoot River (8) replaces Upper Angus (6) and Mabie Creeks (10) to become the second poorest stream. More detailed data on the bimonthly and monthly models can be found in Mahmood (1981).

Application of Model Results

The work by Mahmood (1981) reported thus far produced two water quality indices (one based on annual and one on bimonthly data) that were composed of subindices that appear to have ecological significance. Water quality variables clustered in a satisfactory (logical) way, which allowed some redundant variables to be eliminated. Although the streams did not separate into groups with similar water quality, chaining of the stream dendrogram allowed ranking of the streams based on the decreasing similarity of their standardized variables. Finally, quantitative WQIs were produced that resulted in a wider spread of values than the NSF WQI produced, with Diamond Creek (2) generally having the highest (worst) water quality. An increasing WQI was generally associated with impacts (logging, phosphate mining, road impacts) that would be expected to degrade water quality (e.g., Table 3.2).

The problem then remained to determine how such an index might be applied in information transfer to the public or for comparing tradeoffs in a linear programming model.

One way to apply the WQI would be to define acceptable and unacceptable levels from criteria values for the variables. This could be done by calculating the resulting water quality index for a hypothetical stream with its variates set at the criteria values. Another possibility would be to try to relate empirical values of the WQI in the study streams to biological community variables, as outlined in Chapter 2. Acceptable levels of community biomass, diversity, or metabolism could then be used to constrain the maximum value of the WQI. We shall describe the results of these approaches in the following chapter.

Table 4.8. Bimonthly principal components for all streams.

Physical-Chemical Variable	Variability Explained 43.7% Factor 1	16.4% Factor 2	12.2% Factor 3
Temperature	-0.389 (-0.369)[1]	0.559 (0.158)	0.289 (0.621)
Flow	0.209 (-0.103)	0.813 (0.830)	-0.216 (0.228)
Turbidity	0.869 (0.812)	-0.063 (0.282)	0.072 (-0.157)
Conductivity	-0.732 (-0.745)	0.189 (-0.099)	-0.130 (0.150)
pH	-0.714 (-0.423)	-0.278 (-0.673)	0.353 (0.282)
Alkalinity	-0.849 (-0.844)	-0.185 (-0.297)	0.290 (-0.105)
Total Nitrogen	0.739 (0.831)	-0.168 (0.026)	0.344 (0.033)
Total Phosphorus	0.703 (0.389)	0.521 (0.824)	-0.263 (-0.073)
Dissolved Phosphorus	-0.149 (0.090)	0.406 (-0.093)	0.818 (0.916)
Suspended Solids	0.768 (0.778)	-0.276 (0.068)	0.076 (-0.249)

[1]Varimax Rotation

Table 4.9. WQIs and bimonthly subindices based on bimonthly averages for all streams.

Station Name	Station #	Period	Subindex 1	Subindex 2	Subindex 3	WQI
Stewart Creek	1	May-June	12.72	7.94	9.38	17.69
		July-Aug.	9.31	8.25	9.86	15.87
		Sept.-Oct.	8.31	8.27	9.32	14.98
Diamond Creek	2	May-June	21.46	7.91	11.71	25.69
		July-Aug.	9.83	9.99	9.67	17.02
		Sept.-Oct.	9.13	9.43	9.58	16.25
Mill Creek	3	May-June	10.70	10.49	8.60	17.28
		July-Aug.	6.59	9.09	9.90	14.97
		Sept.-Oct.	6.16	7.84	10.08	14.18
Angus Creek	4	May-June	16.21	10.10	9.64	21.40
		July-Aug.	8.24	9.96	9.43	16.00
		Sept.-Oct.	7.47	9.04	8.91	14.73
Sheep Creek	5	May-June	14.04	9.24	9.52	19.32
		July-Aug.	5.73	9.66	9.97	15.02
		Sept.-Oct.	4.60	8.8S	8.91	13.37
Upper Angus Creek	6	May-June	14.43	10.22	11.45	21.07
		July-Aug.	9.13	10.67	10.18	17.34
		Sept.-Oct.	9.24	9.58	10.42	16.91
Blackfoot River	8	May-June	15.07	14.68	7.53	22.35
		July-Aug.	5.54	13.32	13.06	19.46
		Sept.-Oct.	4.87	11.42	10.41	16.21
Mabie Creek	10	May-June	13.53	9.15	9.60	18.94
		July-Aug.	5.09	10.01	9.91	14.98
		Sept.-Oct.	4.81	9.00	9.17	13.72

CHAPTER 5

TESTING AND APPLICATION OF THE WQI: RESULTS AND DISCUSSION

Introduction

The annual water quality index developed by Mahmood (1981), as described in the previous chapter, appears to have several useful attributes. It is reasonably robust, inasmuch as groupings were not especially sensitive to exclusion of stations. Also, high index values were associated with known impacts such as phosphate mining and logging (cf Table 3.2 and James et al. 1982). However, it remained to be seen whether the value of the WQI had ecological meaning in terms of a significant relationship to stream habitat. Establishment of a relationship between the 1) physico-chemical variables represented by the WQI and its subindices and 2) community variables such as benthic community biomass, diversity, and composition could in turn establish critical WQI values for use as constraints in a linear programming model.

The sampling program designed for this approach was to collect periphyton on diatometers and benthic invertebrates, both from natural habitats and artificial substrates. Diatometers were placed in Stewart (1), Diamond (2), Mill (3), Angus (4), Sheep (5), and Kendall (7) Creeks on July 15, 1981, but all but two were lost to natural causes or vandalism. Benthic invertebrates were collected from riffle areas in the streams listed above and from the Blackfoot River (8) between September 17 and 19, 1981, in order to provide community data. Upper Angus Creek (6) and Mabie Creek (10) could not be sampled because legal access could not be obtained. Although artificial substrates were to be placed during the fall of 1981, staff changes precluded this effort, and substrates will be placed at a future date to provide additional data on water quality effects on invertebrates that are not confounded by benthic substrate heterogeneity.

Following identification of the invertebrates, multivariate analysis was used to reduce the dimensionality of the data set, and the relationship between the WQI (including its subindex values) and the species assemblages was explored. Also, emergent properties such as biomass and species diversity were related to water quality variables. Because the data set used to develop the WQI did not correspond to the stations for which invertebrate data were collected, new WQI's were recalculated following Mahmood (1981). Also, several additional data manipulations were tested in order to increase the ecological meaning of the index. Finally, it was hoped that a criterion level for the WQI could be deduced from these relationships.

Rationale

It reasonable to expect the occurrence of species or assemblages of species to be meaningfully related to the physico-chemical variables used to construct the water quality index in the previous chapter. Even natural variations in streamwater chemistry within a single drainage basin can effect species distributions (e.g., Macan 1974), often regardless of food or substrate considerations (Minshall and Minshall 1978). However, the differences most often studied are between softwater tributaries and their more mineralized downstream reaches, rather than between streams of moderately different hardness. Also, there is no question that the amount of detritus and the degree to which it is processed is extremely important in the distribution of benthic invertebrates (e.g., Cummins and Lauff 1969, Cummins 1974, Cummins and Klug 1979). Of similar importance is the physical substrate as it interacts with stream hydraulics to trap the detritus for invertebrate consumption (Gore 1978, Gore and Judy 1981).

Nonetheless, given several streams of similar order draining roughly equal areas of similar aspect in the same drainage basin, similar habitats should contain similar benthic faunas. Alteration of chemical conditions alone, as opposed to spatially proximate perturbations such as bank erosion or removal of riparian cover, may be expected to produce some differentiation in the macroinvertebrate community. Such effects could include the impact of phosphorus (Meyer 1979) or nitrogen (Grimm et al. 1981) on autotrophs or detritus processing. Weathering products such as sodium, potassium, hardness, hydrogen ion, and alkalinity may not be particularly important in regulating community structure over their annual range in these streams (e.g., alkalinity = 100-220 mg/l as $CaCO_3$, pH = 7.1-8.5). However, these changes may be accompanied by other chemical factors (e.g., presence or availability of toxic metals) that could affect sensitive species or trophic relationships, perhaps even at the microbial level. Maximum monthly average summertime temperatures range from 8.3-14.4°C in these streams. While such temperature differences may directly impact sensitive species by altering oxygen availability, more subtle effects on detritus processing rates may have a more important impact.

The effects of the factors aggregated in the WQI on benthic invertebrate communities are determined by the complex interactions involving stream discharge, velocity distribution, bedload sorting and transport, and siltation (e.g., Rabeni and Minshall 1977). Nonetheless, extremely high or low discharge, or high suspended sediment concentrations, would _a priori_ suggest relatively poorer benthic invertebrate habitat.

A useful way of viewing the interaction of the physico-chemical variables in the WQI with benthic communities is through the concept of ecosystem stress. Because the WQI is most heavily loaded on those variables with the smallest coefficients of variation, only _unusually_ high values for a parameter (except pH) lead to a high value for the WQI. Odum et al. (1979) suggest that low levels of energy (often in the form of utilizable materials) input to a system act as a subsidy, thus increasing system output (e.g., productivity, organization, etc.). As these inputs increase beyond a certain threshold, however, the subsidy becomes a stress, system output decreases, and its variance increases. In a stream, this may take the form of replacement of a highly organized system containing many species with simpler, more tolerant communities.

Ecosystem subsidy or stress is most usually inferred from measurements of emergent community properties such as standing biomass, species diversity or community metabolism (e.g., Odum 1971). Unfortunately it is difficult to decide, _a priori_, where the optimum point on the subsidy stress curve occurs in nature, and extrapolation of classical mechanical models to complex, open ecosystems are fraught with difficulties (e.g., Ulanowicz 1978). Indeed, some stream ecologists deny the utility of an energetic approach to analyzing benthic ecosystems (O'Neill 1976). If the subsidy-stress approach is meaningful, however, some objective method must be available to reduce the dimensionality of the input variables to the ecosystem. The standardized multivariate WQI would seem to be a promising approach.

Description of the Benthic Invertebrate Community

A partial summary of the invertebrate data for the stations sampled is presented in Table 5.1. Although all invertebrates were classified, oligochaetes and most dipterans were not keyed to the genus level, and were not used in subsequent taxonomic calculations. Field data sheets are reproduced in Appendix A. The organisms in Table 5.1 represent three orders of insects, Ephemeroptera, Plecoptera, and Trichoptera, selected to provide sufficiently diverse food and habitat preferenda to reflect the diversity of their larger communities adequately. A similar approach has been taken in stream studies by Ulfstrand (1967) and Sheldon and Haick (1981). The 125 or more organisms sampled in each stream should provide a good data base.

As a first step toward exploring for relationships between the invertebrate data in Table 5.1 and the WQIs for the streams in the study area, cluster analysis was used to search for associations between invertebrates and index values. An initial analysis was run using nonstandardized population values for each of 34 species and with each sample treated separately. Not standardizing the population values places heavier emphasis on common species than on less numerous species. This is acceptable if the less common species are not important indicators of water quality (e.g., sensitive to pollutants, high temperature, etc.). The dendrogram should also suggest whether multiple samples from the same station are more similar than samples between stations. The dendogram is shown in Figure 5.1.

Two basic clusters are apparent, one containing samples from Stewart Creek (1), Diamond Creek (2), Angus Creek (4), and the Blackfoot River (8), and the other from Sheep Creek (5) and Kendall Creek (7). Samples 3-2 and 8-3 are extreme outliers, and do not cluster with either group. This results in the Mill Creek (3) samples not clustering at all. Closely associated clusters generally had two replicates associated with a third stream, rather than all three replicates clustered together.

Reference to Table 5.1 indicates that Sheep Creek and Kendall Creek both have relatively high populations of the Chloroperlid stonefly *Utaperla*. Little is know about the trophic habits of this genus, although the family is characterized as ranging from predatory on mayfly nymphs and dipterans to gatherers, collectors, and scrapers; they are clingers and generally restricted to well oxygenated waters (Merritt and Cummins 1978, Pennak 1978). Although chironomids (Diptera) and mayflies were common in Sheep and Kendall Creeks, their numbers were also large in Stewart Creek and the Blackfoot River, where *Utaperla* was rare. The extreme outliers were caused by relatively high populations of two mayflies, *Paraleptophlebia* and *Baetis* in the Blackfoot River sample and two Baetid genera, *Baetis* and *Centroptilum* in the Mill Creek sample.

Several manipulations to the matrix were performed to test the robustness of the clusters in Figure 5.1. Elimination of the outlier stations and rare species (≤ 1 observation) failed to change the relationships. Standardization of the data to increase the importance of rare species was accomplished by applying the equation:

$$z_i = \frac{x_{i,j} - \bar{x}_i}{s_i} \quad . \; . \; . \; . \; (5.1)$$

where $\bar{x}_i$ is the mean population for the i'th species in all streams, $x_{i,j}$ is the number of individuals of the ith species in the jth stream, and s_i is the standard deviation about $\bar{x}_i$. This required eliminating all species with $x_i \leq 2$. For the standardized data, Mill Creek sample 3-3 replaced 3-2 as the outlier, and two of the Kendall

Table 5.1. Numbers of ephemeroptera, trichoptera, and plecoptera found in samples in the Upper Blackfoot River drainage on September 17-19, 1982.

	Stewart Creek (1)	Diamond Creek (2)	Mill Creek (3)	Angus Creek (4)	Sheep Creek (5)	Kendall Creek (7)	Blackfoot River (8)
Ephemeroptera							
Epeoris	9	7					
Cinygmula	7	3	135			67	28
Rhithrogena	6	15			42		
Baetis	310		177	5		89	94
Centroptilum		36	202			142	7
Siphlonurus							
Paraleptophlebia		24	5	29	31	2	174
Ephemerella							
doddsi	1		15		46	1	
coloradensis	6			3			23
grandis			10			126	4
other		4	4			6	25
Ameletus	1	3					
Trichoptera							
Rhyacophila A	58			3	21	19	
Chimarra			2				
Hydropsyche			1				
Arctopsyche					2		191
Hesperophylax						3	
Psychoglypha						2	
Other						30	
Leptocella						10	4
Lepidostoma			119	16		23	20
Brachycentrus			13				
Plecoptera							
Pteronarcys							10
Zapada	16	11	9	27	23	12	
Hesperoperla					13		
Skwala	1	14		27	12		
Isogenoides							
Diura						8	
Utaperla	5	36	74	23	213	156	6
Coenidae		11	19			5	24
Paeronella							3
Acronevria							2
Totals							
Ephemeroptera	340	92	548	37	119	433	355
Trichoptera	58	0	235	19	23	87	215
Plecoptera	22	81	102	77	261	181	45

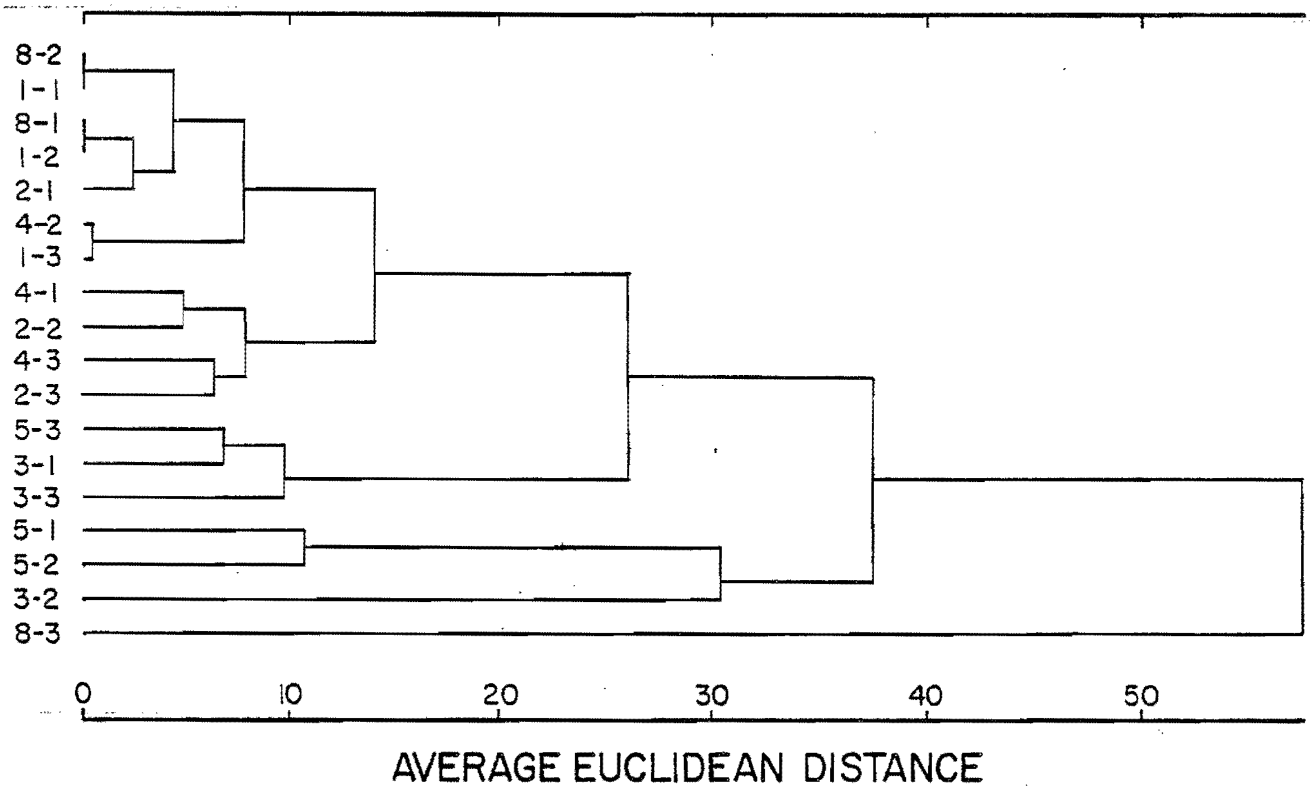

Figure 5.1. Dendrogram of nonstandardized invertebrate data from Stewart (1), Diamond (2), Mill (3), Angus (4), and Sheep (5) Creeks, and the Blackfoot River (8). The number following the dash is the replicate number.

Creek stations (7-1 and 7-2) formed a third cluster, separate from Sheep Creek and the remaining Kendall Creek station.

Because the water quality data set could not be used to produce a WQI for Kendall Creek, this station was eliminated from the cluster. Using nonstandardized population data the Blackfoot River station (8-3) remained an outlier, with Mill Creek (3) and Sheep Creek clustering together. The most closely clustered set of samples from the same stream is from Stewart Creek (1), and the Stewart (1), Diamond (2), and Angus (4) Creeks samples all clustered before Mill (3) and Sheep (5) Creeks. Overall standardization of the population values did not alter the basic dendrogram.

One issue that continued to cause concern was the inclusion of the Blackfoot River station (8) in the data base. The Blackfoot is a sixth order stream, compared to the third order streams higher in the watershed. A higher degree of detritus processing and other factors either not measured by the physico-chemical variables in the WQI data set might be expected to obscure WQI-invertebrate relationships (Vannote et al. 1980). Removing this station from the data set resulted in the dendrogram in Figure 5.2. Diamond Creek (2) and Angus Creek (4) samples clustered together, as did the Stewart Creek (1) samples, leaving the Sheep (5) samples strongly clustered alone. In either case Mill (3) and Stewart (1) Creeks emerge as being somewhat unusual.

Principal components analysis was run on the invertebrate data in order to define certain genera or groups of genera that could later be correlated with the WQI subindices. Using non-

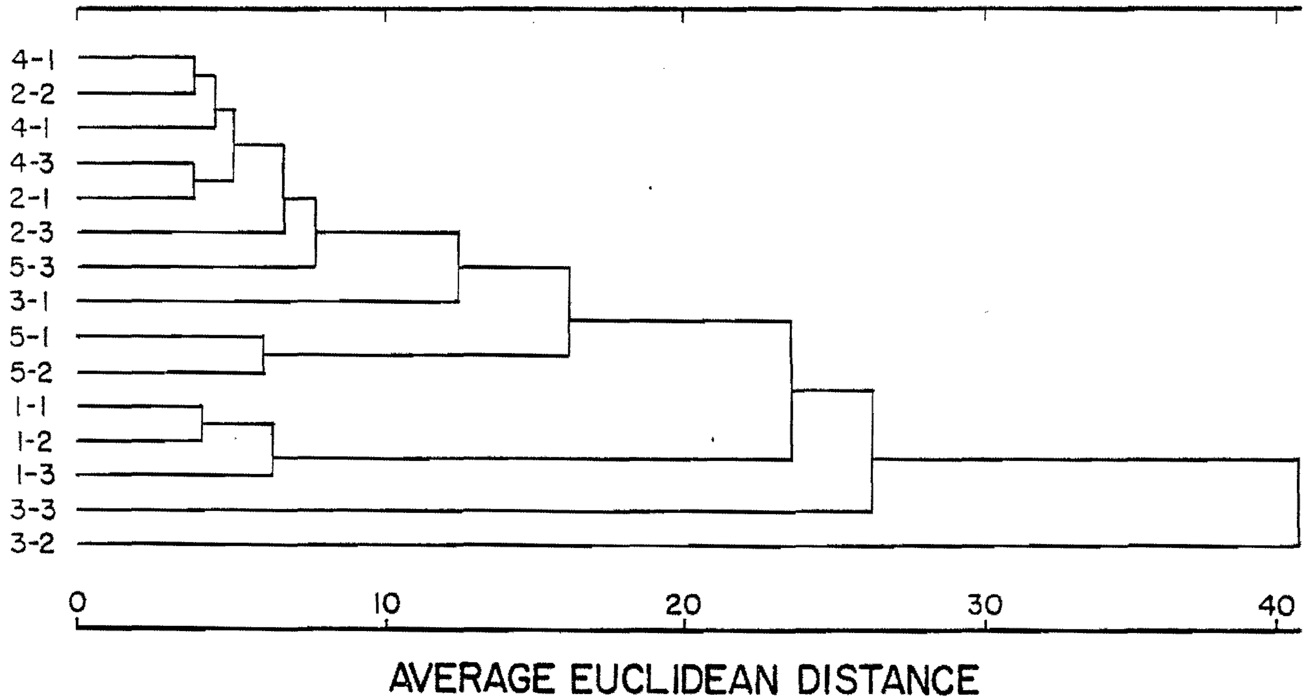

Figure 5.2. Dendrogram of nonstandardized invertebrate data from Stewart (1), Diamond (2), Mill (3), Angus (4), and Sheep (5) Creeks.

standardized data, Varimax rotation of four principal components produced eigenvalues greater than one (Table 5.2). The first PC was heavily weighted on Rhyacophilia (a rhyacophiloid caddisfly), Centroptilum, a baetid mayfly, and Cinygmula, an heptagenid mayfly. The latter two species are collector gatherer genera, feeding on detritus and diatoms, or scrapers, normally living in erosional habitats (Merritt and Cummins 1978). Rhyacophilia is also characteristic of erosional habitats, and is represented by predators (engulfers) as well as by collector-gathers (Merritt and Cummins 1978). This organism was not identified to species level, and thus its particular trophic habits are not known.

The remaining three PCs are dominated by single genera. Lepidostoma, a detritivorous caddisfly that may occupy either erosional or depositional habitats dominated PC 2. Zapada, an erosional, detritivorus nemourid stonefly, dominated PC 3, and Paraleptophlebia the detritivorus mayfly described above dominated by PC 4. There were no strong negative loadings on any of the four PCs which together accounted for 82% of the variation.

Several emergent properties of the invertebrate communities are displayed in Table 5.3. Standing stock biomass ranged from 2520 mg ash free dry weight in the Blackfoot River (8) to only 212 mg in Diamond Creek (2), based on all taxa collected. These numbers can be converted to areal densities by dividing by 0.3 m^2. Mill Creek had the highest biomass of the lower order streams, and Diamond and Angus, which were associated with higher WQI's, had the lowest biomass.

Two forms of diversity index were calculated, Shannon-Weaver (H'_G) and Brillouin (H_G) (footnote, Table 5.3). The Shannon-Weaver index has been popular as a measure of community diversity since it was first used by MacArthur (1955), and many data are available for comparison (e.g., Wilhm 1970). However, Kaesler et al. (1978)

Table 5.2. Principal components describing benthic invertebrate communities in Stewart, Diamond, Mill, Angus, and Sheep Creeks (1-5). Only PCs with eigenvalues > 1 are given.

Genus	Principal Component (% variation explained) 1 (42.9)	2 (15.7)	3 (13.0)	4 (10.3)
Paraleptophlebia	-0.12	-0.11	-0.05	0.96
Sweltsa/Triznaka/Naeviperla	0.29	0.66	-0.24	-0.26
Utaperla	0.08	-0.04	0.06	0.11
Zapada	-0.11	-0.08	0.98	-0.05
Lepidostoma	0.34	0.93	-0.03	-0.05
Rhyacophila	0.91	0.19	0.06	-0.02
Skwala	-0.25	-0.12	0.08	0.09
Baetis	0.29	-0.09	-0.03	-0.19
Centroptilum	0.93	0.1S	-0.18	-0.15
Cinygmula	0.86	0.41	-0.12	-0.10

have criticized its practical application to stream studies because it is based on the concept of N representing a conceptually infinite population of invertebrates in the ecosystem under study. They prefer Brillouin's (1962) equation, which is based only on the sample population. They also demonstrate that its value is nearly asymptotic with increasing sample sizes (N_i) greater than 100 organisms.

In either case, the diversity indices are highly correlated (r^2= 0.993), and show high values for Mill (3), Diamond (2) and Kendall (7) Creeks, and a decidedly low value for Stewart Creek (1). These indices are based on genera, rather than species, but Kaesler et al. (1978) have shown little contribution to diversity indices at the species level in benthic invertebrate communities from stream ecosystems

Table 5.3. Numbers, biomass and Shannon-Weaver (H') and Brillouin's diversity (H) of benthic invertebrate samples in the study watershed, based on genera in Table 5.1.

Stream #	n	Ash Free Dry Weight (mg)	H'_G [1]	H_G [2]
Stewart Creek (1)	420	706	1.42	0.94
Diamond Creek (2)	173	212	3.34	2.15
Mill Creek (3)	885	1262	3.71	2.43
Angus Creek (4)	133	433	2.64	1.77
Sheep Creek (5)	403	565	2.27	1.53
Kendall Creek (7)	701	-	3.06	2.07
Blackfoot River (8)	615	2520	2.90	1.86

[1] $H'_G = -\sum^{i} \frac{N_i}{N} \ln \frac{N_i}{N}$ (Shannon-Weaver genus diversity index)

[2] $H_G = \frac{1}{N} \ln \frac{N!}{N_i!\, N_{i+1}! \, \ldots \, N_s}$ (Brillouin's genus diversity index)

N = total number of individuals, N_i = number in ith species.

in a variety of geographic locations. Both indices fall within the range of relatively unstressed stream (river) communities (H' > 2, Wilhm 1970; H > 1.5, Kaesler et al. 1978) for all streams except Stewart Creek (1). Inclusion of invertebrate taxa other than those in Table 5.1 might alter the indices somewhat, but a check using the data in Appendix A indicate that Stewart Creek (1) still had the only H' below 1.5. The latter values are minima, because the taxa not included in Table 5.1 were not identified to genus level. The relationship between the invertebrate community data and the WQI will be discussed following a presentation of the revised WQIs.

Relationships between the WQIs and the Ecological Data

The original WQIs computed by Mahmood (1980) and described in Chapter 4 indicated the hierarchies of stream water quality in Table 5.4 Diamond (2) and Upper Angus (6) Creeks generally showed the worst water quality, with the Blackfoot River (8) appearing in the worst bimonthly indices, primarily

Table 5.4. Hierarchical ranking of WQI's of worst streams based on Mahmood (1981). WQIs separated by a comma are within 1.0 point of each other. Rankings are based on Tables 4.8 and 4.9.

Index Period	Ranking Worst Best
Five year May-Oct. flow in m^3/sec	2,6 > 10 > 4,1
Five-year May-Oct. flow in $m^3/sec\text{-}m^2$ watershed	6 > 2 > 10 > 4
Bimonthly	
May-June	2 > 8,4,6
July-August	8 > 6,2 > 4
September-October	6 > 2,8 > 1,4

1 = Stewart Creek; 2 = Diamond Creek; 4 = Angus Creek;
6 = Upper Angus Creek, 8 = Blackfoot River; 10 = Mabie Creek.

because the ratio of Blackfoot River discharge to the standard deviation for all 35 discharge measurements increased in the bimonthly indices. Mabie (10) and Angus (4) Creeks appear in intermediate positions, and Stewart (1), Mill (3), and Sheep (5) Creeks (not shown) have the best indices. The latter groups of streams is associated with high standing stock invertebrate biomass (Table 5.3), but diversity indices of the three insect orders range from a high (H = 2.43) in Mill Creek to a low (H = 0.94) in Stewart Creek. Diamond Creek, the worst stream sampled in terms of invertebrates, had the lowest biomass, but a relatively high species diversity. These results suggest that invertebrate biomass is inversely correlated with the physico-chemical constituents constituting the WQI, but that diversity (H) has no clear relationship with water quality as expressed by the WQI. We shall explore possible explanations for these relationships below.

The purpose of ordination of the invertebrate data in Table 5.2 was to search relationships between the common factors (principal components) influencing the physico-chemical attributes of the ecosystem and the community composition. For this comparison, it was necessary to reformulate the WQI using only streams in which invertebrate data were collected. This change in the data base also provided a test of the robustness of the WQIs in the face of a reduction in the number of streams.

Upper Angus Creek (6) was removed from the data set because no invertebrates were collected. Blackfoot River was excluded because of its high order and the possible influence of stream order on the invertebrate community in ways not related to the WQI. Thus two of the "worst" streams were excluded, leaving only Diamond Creek (2) of those with a high WQI (Table 5.3).

Additional testing was also done to determine the effect of including temporal variation within streams when computing WQIs. Mahmood (1981) originally worked with May through October averages expressed as one data point encompassing five years of data for each stream. This temporal averaging resulted in a relatively low coefficient of variation for the variables, and thus maximized the contribution to the WQI of parameters with abnormally high values.

Because of this temporal averaging, the index is based on between stream variation. From an ecological standpoint, however, benthic invertebrate communities respond to within stream variability in energy subsidies or stresses. The influence of temporal variability depends in a complicated way on the relative degree of physiological versus genetic adaptation of the invertebrates to their ecosystem. On a genetic level, a population of insects may become adapted to the range of variability characteristic of the streams where they may oviposit. At the physiological level, however, individual streams may subsidize or stress their inhabitants during the period from hatching to emergence based more on their own variability than on their characteristics in comparison to other streams nearby.

Consequently, a new WQI was formulated using annual averages (May-October) parameter values for each of water years 1974, 1976, 1978, and 1979. Water year 1977 was excluded due to an extreme drought, which significantly affected water quality (Messer et al., in preparation). Inclusion of the drought year would increase the coefficients of variation of the variables in an unsatisfactory and unrealistic way. It should be noted that the variation between years should be less than that between months (or pairs of months) within a given year, a factor which caused undesirably large coefficients of variation in the bimonthly and monthly WQIs (Mahmood 1980).

The new data sets grouped upon Q-clustering (Figure 5.3) in a pattern similar to the one obtained previously (Figure 4.1). Conductivity, hardness, and alkalinity still clustered as in the original WQI (Figure 4.1), representing groundwater inputs. Flow and suspended solids also continued to cluster, as would be expected. A third cluster included nitrate, phosphorus, and turbidity. TKN was associated with this cluster when separate data were used for the 4 years, but had clustered with flow and suspended solids with the 5-year averages. The nitrate-phosphorus-turbidity cluster apparently represents a nutrient input term not closely associated with spring runoff when clastic materials contribute heavily to suspended soils loads. The association of TKN with the nutrient cluster may represent "pollution" rather than natural organic detritus moved about by spring runoff, as suggested in Chapter 4, although no definite conclusions can be drawn.

Principal components for the 5-year averages at the reduced number of stations are shown in Table 5.5. The three components shown account for 95.1 percent of the model variability. The first varimax rotated factor represents snowmelt, and the second represents phosphorus. The third factor appears to be a nutrient factor that explains little model variance. The first three factors obtained from the data set using four separate average annual values accounted for 91.1 percent of the model variation (Table 5.6). Unfortunately, however, none of the factors loaded heavily on any group of parameters. The resulting WQI's are shown in Table 5.7. The groups of parameters used to construct the WQIs in Tables 5.6 and 5.7 are slightly different because of the slightly different

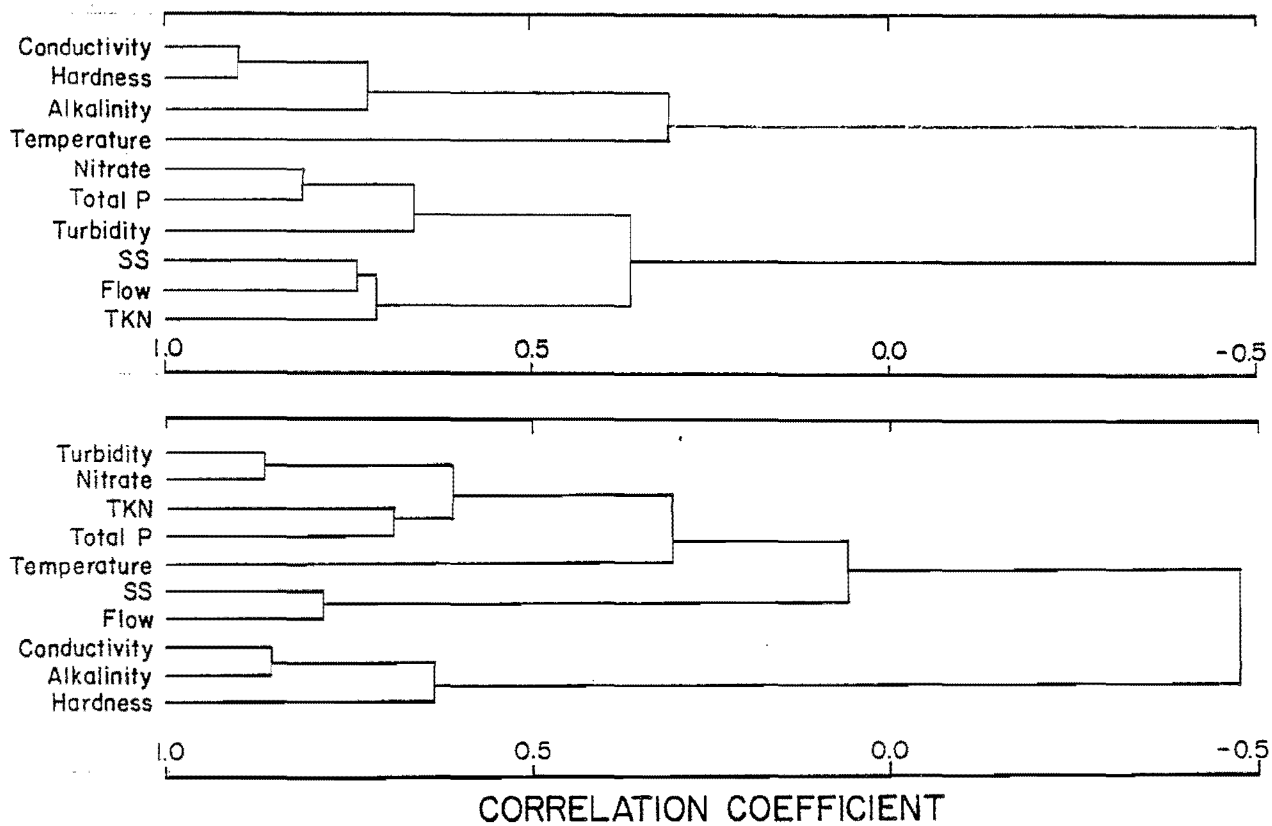

Figure 5.3. Dendrograms from Q-analysis of physico-chemical variables based on (a) 5-year averages and (b) annual averages for 1975, 1976, 1978, and 1979 water years.

Table 5.5. Principal components of physico-chemical variables based on 5-year May-October data for stations 1-5.

Variable	PC1 (59.1)[1]	PC2 (29.3)	PC3 (6.7)
Temperature	-0.321	0.106	0.180
Turbidity	0.150	0.341	0.910
Alkalinity	-0.521	-0.544	-0.655
TKN	0.714	0.570	0.380
Total P	0.094	0.942	0.314
Suspended Solids	0.875	0.022	0.331
Hardness	-0.931	-0.158	-0.020

[1]% of variation explained.

Table 5.6. Principal components of physico-chemical variables based on annual averages for water years 1975, 1978, and 1979, stations 1-5.

Variable	PC1 (43.5)[1]	PC2 (32.7)	PC3 (14.8)
Temperature	0.729	0.246	0.630
Turbidity	0.487	0.694	-0.204
Total P	0.556	0.595	-0.387
Flow	-0.602	0.702	0.380
Hardness	0.858	-0.496	0.010

Table 5.7. Multivariable WQIs based on 5-year and annual May-October means for Stewart, Diamond, Mill, Angus, and Sheep Creeks (1-5).

Stream (#)	5-year WQI	Annual WQI
Stewart Creek (1)	20.9	49.3
Diamond Creek (2)	28.4	51.2
Mill Creek (3)	19.3	51.3
Angus Creek (4)	22.6	54.0
Sheep Creek (5)	21.1	51.4

clustering of the parameters between the two data sets (Figure 5.3). Although this practice might appear to confound the comparison, it was necessary to eliminate redundant variables in order to invert the similarity matrices during PCA.

The rank order of the reduced number of streams with the 5-year WQI is the same as that in the original annual index (Table 4.8). Diamond Creek (2) appears to be significantly worse than the remaining streams, all of which have similar index values. The annual WQI has Angus Creek (4) replacing Diamond Creek as the worst stream, with Stewart Creek (1) being the best and the others intermediate.

Subindex values associated with the five-year WQI (Table 5.8) indicated that the Diamond Creek (2) WQI was heavily affected by all three factors. Angus Creek (4) was slightly affected by factor 1 (suspended sediment/ TKN/flow), but heavily impacted by phosphorus (factor 2). The remaining streams

Table 5.8. Subindex values for stations 1-5 based on 5-year mean WQI.

Station (#)	Subindex 1	Subindex 2	Subindex 3
Stewart Creek (1)	15.6	13.9	14.5
Diamond Creek (2)	20.9	19.2	18.9
Mill Creek (3)	13.0	14.4	13.4
Angus Creek (4)	14.6	17.5	17.7
Sheep Creek (5)	15.3	14.6	15.0

appear to be similar, with the greatest differences caused by factors 1 and 3 (nutrients).

The two sets of WQIs in Table 5.7 were compared with the biomass and diversity data in Table 5.3. The only correlation that appeared was between biomass and the 5-year WQI (Figure 5.4). The strong negative power function suggests that increasing suspended sediments, flow and TKN lead to a decreased standing crop. According to a subsidy-stress interpretation, the detritus input associated with high flows must be insufficient to subsidize the benthic invertebrate communities in amounts needed to overcome the stresses imposed by inputs of silt. In the case of Angus Creek, total phosphorus (or a related parameter), associated with some TKN, apparently replaces the suspended sediment factor in reducing invertebrate production.

There appears to be no relationship between species diversity and the WQI in the study streams. The reason for the low species diversity in Stewart Creek, relative to its good WQI value, is likely to be found in its physical substrate. Physical habitat characteristics for the five streams in Table 5.7 are shown in Table 5.9. Stewart Creek has a sandy bottom that is heavily silted, owing primarily to the absence of bank vegetation near the sampling site. The banks are soft, steep, and heavily eroded in this reach, rather than being trampled by cattle. Bank erosion in the absence of vegetation is known to cause changes in benthic invertebrate communities (Karr and Schlosser 1977). The relationship is not simple; however, as can be seen by the high diversity index in Diamond Creek (2) being associated with moderate bank erosion and heavily silted gravel. Rabini and Minshall (1977) have demonstrated that siltation interacts in a complex way with the microdistribution of current, oxygen, and detritus quality in controlling invertebrates.

It is important to restate the premise that benthic habitat quality should reflect WQI constituents such as suspended solids and flow. Indeed, the data in Table 4.1 indicate that the mean suspended solids concentration in Stewart Creek (1) is second only to Diamond Creek (2) in the study area. Apparently the failure of this variable (as well as flow) to contribute substantially to the overall WQI represents a serious shortcoming of this type of

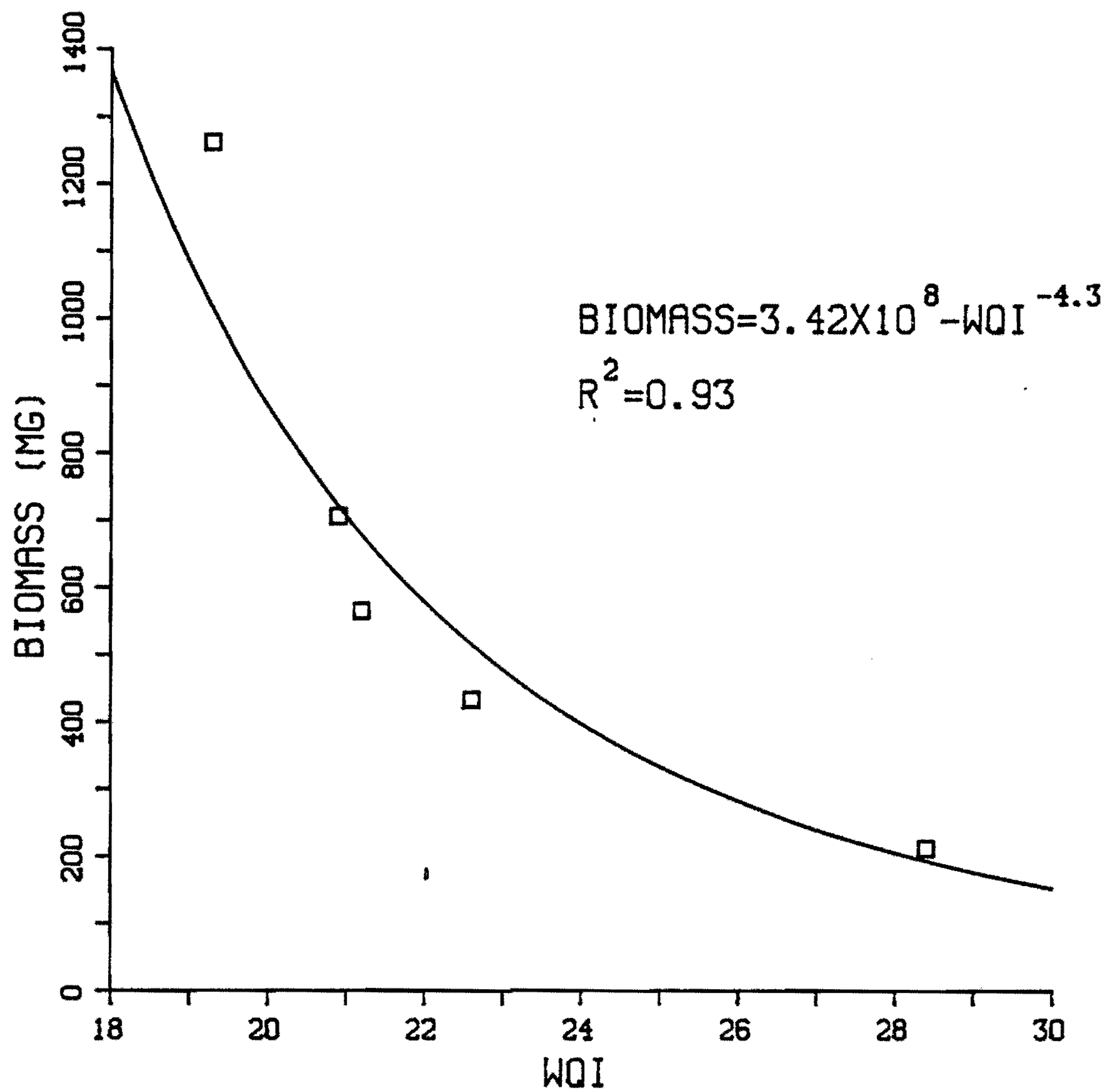

Figure 5.4. Relationships between benthic invertebrate biomass in three replicate samples (total = 0.9 m^2) and the 5-year WQI based on physico-chemical parameters.

index in a group of streams with a wide range (11-47 mg/l 5-year average, Table 4.1) of suspended solids loads.

Even though community structure as expressed by diversity indices failed to reflect the ranking of WQI values, it was hoped that certain components (taxa) of the benthic community might reflect either the WQI or subindex rankings. Table 5.10 indicates low correlation coefficients between most invertebrate principal components (PC's) and WQI subindex values. Only the asterisked correlations were significant at the α = 0.2 level, and none was significant at $\alpha \leq 0.1$, although the small number of samples (n = 5) certainly contributed to the wide confidence limits. Occurrence of the invertebrates represented by PC 1 (Lepidostoma, Centroptium, Cinygmula) and PC 2 (Zapala) were negatively correlated with all WQI subindices, especially the nutrient (3) subindex. Invertebrate PC 3 (Utaperla) showed no strong correlations, while PC 4

Table 5.9. Some physical habitat characteristics of the invertebrate sampling stations.

Stream (#)	Substrate[1]	Silt[2]	Bank Erosion[2]	Cover Type	% Bank Cover	Pool:Riffle Upstream
Stewart Creek (1)	2	3	3	Willow	20	1:4
Diamond Creek (2)	3	3	2	Willow	50	1:1
Mill Creek (3)	3	1	0	Grass	95	1:10
Angus Creek (4)	1	3	0	Willow	70	20:1
Sheep Creek (5)	3	2	0	Grass/ Willow	90	3:1

[1] 1 = silt; 2 = sand; 3 = gravel

[2] 0 = none; 1 = low; 2 = medium; 3 = high

Table 5.10. Correlation coefficient (r) for WQI subindices of 5-year May-October physico-chemical variables (Table 5.8) and principal components of three orders of benthic invertebrate genera (based on Table 5.7) for Stations 1-5.

WQI Subindex	Invertebrate PC			
	PC1	PC2	PC3	PC4
Subindex 1	-0.51*	-0.41	-0.02	0.34
Subindex 2	-0.44	-0.28	0.12	0.50*
Subindex 3	-0.67*	-0.53*	0.35	0.64

*$\alpha \leq 0.20$

(Paraleptophlebia) was positively correlated with the Total P (2) and nutrient (3) subindices. The last organism thus may be considered to be a eutrophic (or eulichthophilous) species in the study area, whereas the assemblages represented by PCs 1 and 2 may be considered oligotrophic (or oligolichthophilous). The association between high biomass and low WQIs (Figure 5.4) suggests that the absence of sediments may be a more important determinant than the absence of nutrients.

The genus level taxonomic assemblages listed above are insufficiently characterized in terms of ecological information to bear out the generalized conclusions regarding their water quality preferences. It is frequently necessary to identify aquatic invertebrates to the species level in order to gain much useful habitat information (Merritt and Cummins 1978). However, calculation of invertebrate PC's for Kendall Creek (7) resulted in a high score on PC 1, and slightly lower on PC 2, thus indicating an oligotrophic stream. This is consistent with the water quality data available (Table 4.1), even though a WQI could not be calculated for the stream. The high biomass in Kendall Creek, as inferred from the number of Trichoptera, Plecoptera, and Ephemeroptera collected (Table 5.3) is also consistent with this interpretation.

Application of the WQI

It was originally hoped that invertebrate community analysis would provide relationships between attributes of the benthic invertebrate community and the WQI that would suggest critical value of the WQI appropriate for use in an LP model for forest management. The only apparent dependent value that could be used to constrain the WQI was benthic invertebrate standing stock biomass, as expressed by the formula:

$$\text{Biomass} = 86.8\ \text{WQI}^{-0.216} \quad . \quad . \quad (5.2)$$

where biomass is expressed in mg ash-free dry weight/0.3 m^2 and the WQI is based on five-year average values for low order streams (stations 1-5). To the extent that invertebrate secondary productivity influences fishery yields, some minimal acceptable biomass may be used as a critical level, although it is important to note that standing crop and productivity of invertebrate communities are not necessarily proportional (e.g.,

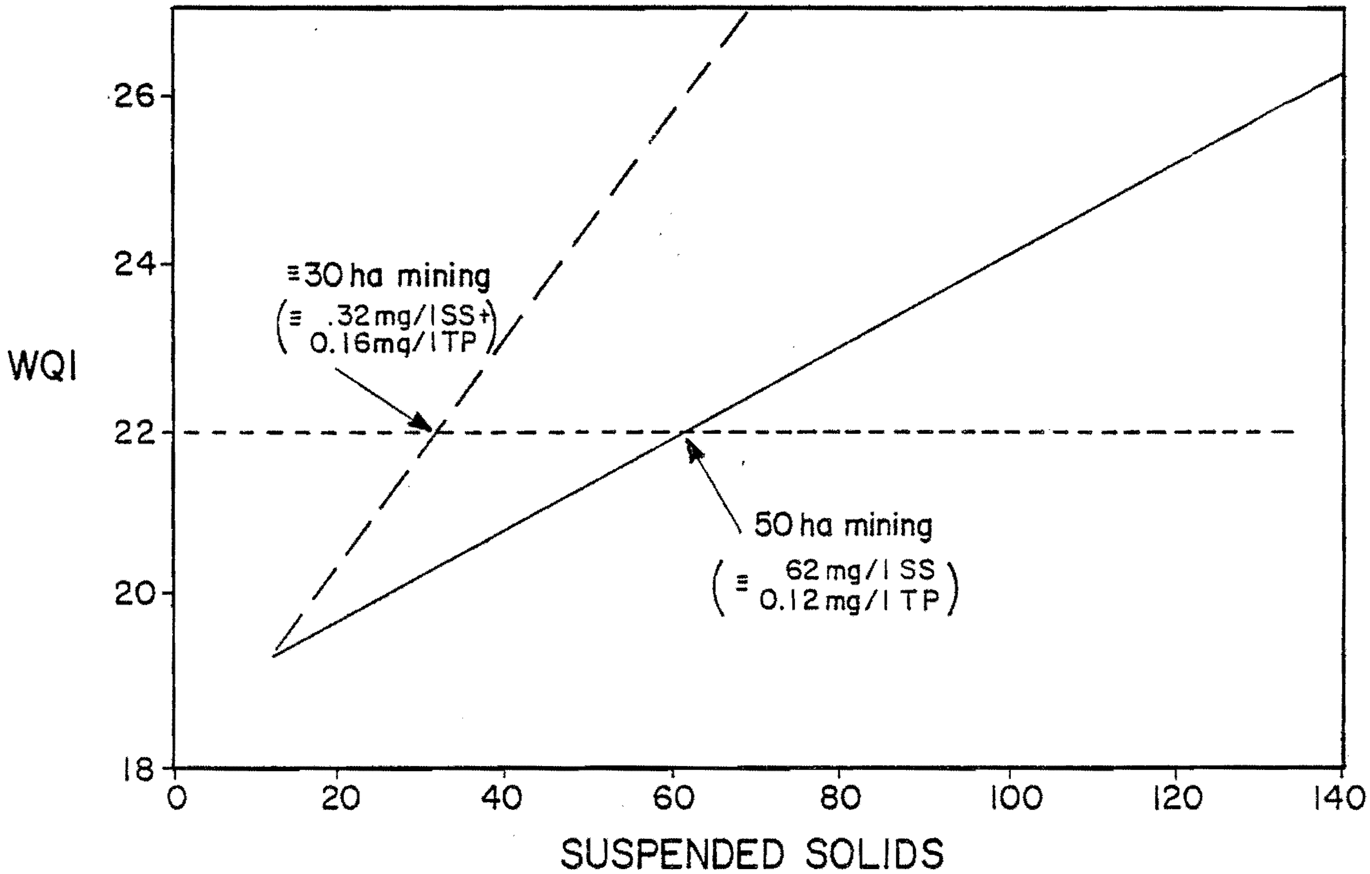

Figure 5.5. Effect of increments of 10 mg/l increases of suspended solids on the WQI for Mill Creek, with (---) and without (-) additional increments of 0.02 mg/l total P. Amounts of land mined for phosphate constrained by a WQI of 22, along with the resulting SS and total P values) are indicated by arrows.

Hynes 1970). Because Equation 5.2 is relatively insensitive to changes in the WQI value above approximately 26, this value may be a suitable constraint, Alternatively, trout spawning in Angus and Upper Diamond Creeks is thought to have declined due to phosphate mining and inadequate grazing management, respectively (Thurow 1980). This might suggest that the cluster of points from 20-23 might already represent habitat impairment, and thus a value of 19 or 20 might be more appropriate (see Figure 5.4).

As an application test exercise, assume that Mill Creek (WQI = 19.3, Table 5.7) was subjected to phosphate mining in its headwaters. If each hectare of land disturbed by mining resulted in an average increase of suspended solids of 10 mg/l, both with and without an additional increase in total P of 0.02 mg/l during May through October, the resulting change in the WQI value is shown in Figure 5.5. Without the phosphorus increment, approximately 50 ha of disturbance could be tolerated, based on a critical WQI of 22. If the phosphate increase occurs as well, the additional disturbance must be limited to 30 ha. For a constraint value of 26, either 50 or 130 ha could be disturbed, with and without a phosphorus increment respectively. Of course phosphate mining could alter other variables contributing to the WQI. These impacts should be quantified and included in the WQI calculations in addition to suspended solids and total P.

The above mining example shows that an activity that produces an increase in suspended sediments alone (without increasing P) could increase suspended solids values to >60 mg/l before exceeding the WQI constraint level of 22. If the total P also increased only 32 mg/l suspended solids and a relatively modest increase in TP concentration from 0.12 to 0.16 mg P/l would be allowed. This would result in the permissible mining level to decrease from 50 to 30 ha in the watershed. The insensitivity of the WQI to suspended sediment results from its relatively high coefficient of variation (46%), compared to that for total P (16%). Thus, we have a specific example of how absolute contributions to water quality degradation contribute significantly to the WQIs only if they are large relative to the background stream to stream variability.

Consequently, multivariate WQIs produced for groups of streams which contain a significant proportion of already impacted streams will tend to have larger coefficients of variation for their constituent variables. This will reduce the apparent impact of perturbations, relative to what would be seen if the WQI were based on a data set containing only pristine streams subject to natural biogeochemical variations. In the case of the data set from the Upper Blackfoot drainage, however, many of the streams already show some effects of disturbance.

This effect suggests that the WQI index user should explicitly decide whether to create a sensitive WQI, based only on pristine streams characteristic of the watershed area, or a more tolerant WQI based on streams draining watersheds some of which are already impacted, but not seriously degraded. In the former case, however, it is unlikely whether useful data could be gathered regarding the effects of changes in the WQI values on invertebrate communities or other instream habitat quality indices, and raises the issue of transferability of WQI from one location to another. Indeed, if Upper Angus Creek (6) could have been sampled for invertebrates, it is likely that its high WQI value would be juxtaposed against both quite low community diversity and biomass. The high total P concentration for this station (Table 4.1), however, would decrease the apparent sensitivity of the WQI to phosphate mining in other streams in the area, based upon the type of example described above. The lack of sensitivity to suspended solids has already raised some questions about the expected relationship between the WQI and invertebrate diversity for Stewart Creek, as explained above.

As always, a significant caution in applying any statistical model is the failure of correlation to imply causality. As an example, the multivariate WQI produced by Snyder (1980) to describe the trophic state of wilderness mountain lakes was based on the first principal component, consisting of heavy factor loadings on specific conductance, pH, suspended solids, and potassium concentration. This factor is an excellent descriptor of the causes of natural "eutrophy," most likely indicating broad biogeochemical differences in the ionic input to the lakes and hence their natural trophic state. However, anthropogenic inputs resulting from dispersed recreation (animal and human wastes) are not likely to alter the variables listed above, thus leading to poor predictive capacity to use in monitoring trophic changes in wilderness lakes. Similarly, it is not known whether changes in certain water quality variables in the Blackfoot streams will result in the changes described by the model, or whether the observed effects were caused by an unanticipated common factor.

It is recognized that the relationships inferred between the WQIs and invertebrate community data are based on a single sampling trip. The timing of insect emergence as signaled by water temperature or other variables may produce different patterns of invertebrate abundance earlier or later in the year. Also, invertebrate data were correlated with water quality data measured two to seven years earlier. Sampling error may be large in that there were a small number of replicate samples. However, the invertebrate data presented here are in qualitative agreement with at least one previous study (Platts and Andrews 1980), no large management changes are thought to have occurred between 1979 and 1981 (James et al. 1982), and the three subsamples of invertebrates taken at the same stream station had similar species diversities and overall compositions. Additional work with 1980-1982 water chemistry data and artificial substrates during fall of 1982 may serve to strengthen or refine the relationships reported here.

Prospectus

The experience gained from this study suggests that the multivariate approach to water quality indexing for high mountain watersheds may be useful, but it is still an unproven technique. The indexing process focuses attention on the important water quality variables in a large and what would otherwise be a confusing data set. Multivariate analysis can be useful in eliminating redundancy, and it may suggest subtle environmental impacts not obvious to those managers equipped only with a book of water quality standards. Multivariate community analysis, used in conjunction with water quality indexing, may suggest useful invertebrate taxa, or assemblages of taxa, that can act as indicators of some types of low level system stress, or may suggest appropriate critical numerical WQI values. Analysis of emergent community variables in the streams studied here suggest a (possibly) counterintuitive relationship between nutrient concentrations and invertebrate productivity, at least as indicated by standing stock biomass.

The use of essentially descriptive WQIs in the predictive setting of an LP model remains dubious. Standing stock invertebrate biomass was shown to correlate well with WQI values, and this function may serve to provide constraint values for the water quality function. However, more study is needed to explain and verify the causal link between the variables that most affect the index, and invertebrate community structure. Furthermore, some means must be found of resolving the degree of variability expected in a variable as determined by the choice of pristine versus mixed impact groups of streams. Owing to the lack of good water quality data bases for streams not subjected to pollution or environmental disturbance, extension of such studies will not be an easy task.

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