Figure 4. Example of box plot used in cluster naming process.

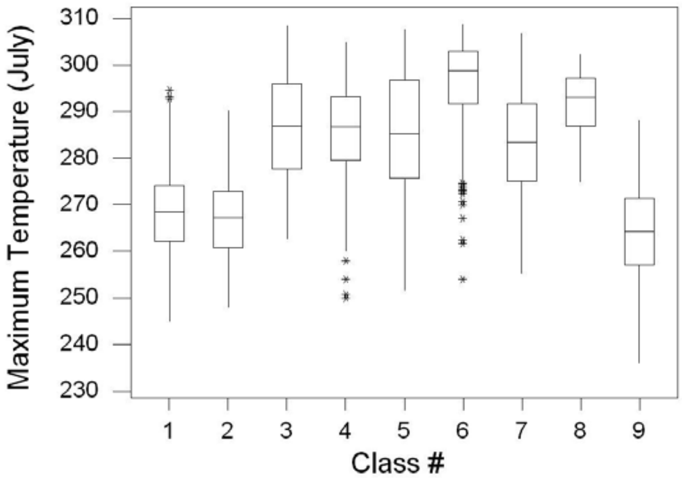


Table 2. Designated names and a brief description of each of the 9 cluster groups shown in Figure 3.

Class No	Name	Description
1	Cold Wet Flats	Climate cold and wet. Landform flat with low soil infiltration
2	Dry Glaciated Northeast	Glaciated. Soils low infiltration, high silt. Climate cold and dry
3	Floodplains	Pass-through watersheds with high percent area in floodplain
4	Moderate Mountains	Watersheds intermediate in all variables.
5	Canyon Lands	Steep, rugged landform with least erodible soils.
6	Fertile Plains	Fertile soils, warm climate, flat and low landform.
7	Steep Dry Mountains	Dry, high elevation range and high stream density.
8	Clay Hills Plateau	Basic, clayey soils and narrow elevation range.
9	High Wet Mountains	High, cold, wet, and steep.

CHARACTERIZATION OF STRESSORS

Our next task was to examine the pattern of stressors in the region. This would allow us, ultimately, to look at the relationship between stressor strength and watershed condition - that is, the "dose-response" relationship. The sensitivity of this relationship can be considered a measure of watershed vulnerability to stress. We compiled a list of potential watershed stressors in the study region, for which synoptic data layers could be formulated. Based on work by Adamus and Brandt (1990), we considered enrichment/eutrophication, biological oxygen demand, contaminants, acidification, sedimentation, turbidity, vegetation alteration, thermal alteration, hydrologic modification, and habitat fragmentation, among others. The goal was to interpret the magnitude of these stressors with existing remotely sensed data. Some were clearly incompatible with remote data, and are more appropriate for site-level investigations.

From this list of potential stressors, candidate stressors were chosen based on the collective expertise of the project team, taking into consideration the availability of suitable GIS layers and other data to describe that stressor. Most of the stressors were derived directly from land cover/ land use, with the exception of acidification and nutrient concentrations in streams, because the former encapsulate long-term and short-term impacts from earth disturbances and land cover conversions. The 1992 National Land Cover Dataset (NLCD, USGS 1999c) served as the primary source for computing values of the land cover-related metrics. Most stressors were developed at the spatial unit of the HUC-14 watershed; however, we also gave some attention to the spatial pattern of stressors within the watershed, comparing riparian zone land use with that of the watershed as a whole. Table 3 presents a list of the stressors examined. Details of GIS data set development and data sources can be found in Griscom et al. (in prep #2, in prep #3 - see Appendix B).

Table 3. List of candidate stressors. The spatial unit for all is the HUC-14 watershed (WS), unless otherwise noted.

Stressor	Abbreviation	Units
Land cover-based, Watershed Scale:		
Impervious Cover	WSIC	%
Disturbed Vegetation	WSDV	%
Disturbed Cover (= IC + DV)	WSDC	%
Landscape Development Index	LDI	Dimensionless
Percent Agriculture	WSAG	%
Percent Mining	WSMINE	%
Land cover-based, Sub-watershed Scale:		
Impervious Cover in Riparian Zone	RZIC	%
Disturbed Veg in Riparian Zone	RZDV	%
In-stream measurements or estimates:		
Acid Neutralizing Capacity	ANC	µeq/L
Nutrients and Total Suspended Solids	N, NO_3, NH_4, P, TSS	Various

Land Cover Stressors - Watershed Scale

Impervious Cover (WSIC)
Impervious cover was defined as anthropogenic land cover types that are not pervious to water (e.g., pavement, roofs). Percentages of impervious cover per watershed were generated using a combination of 1992 NLCD land use data and 2000 U.S. Census Road data. Details of computation are given in Griscom et al., in prep #3)

Disturbed Vegetation (WSDV)

Disturbed vegetation was defined as all other classes of anthropogenic land use that are presumed to be water pervious and, in most instances, are in some form of modified early serial plant regeneration (e.g., agriculture, transitional, lawns, barren).

Disturbed Cover (WSDC)
Disturbed cover includes both IC and DV. According to the literature, IC and DV have very distinct impacts on watershed condition, thus we separated the two for some analyses. However, for the purpose of quantifying the overall proportion of watersheds that has native cover vs. human-impacted cover, they were lumped into a single variable, DC.

Percent Agriculture (WSAG)
Percent agriculture was calculated as the percentage of the watershed in pasture or row crops (NLCD classes 81 (pasture/hay) and 82 (row crops)).

Percent Mining (WSMINE)
Percent mining is defined as the percentage of 1992 NLDC Class 32 (quarries/strip mines/gravel pits) in the watershed.

Land Development Index (LDI)
This index, developed by Brown (2005), is an expression of the intensity of landscape development. Values of LDI were computed using NLCD 1992 land cover data, and coefficients developed by Brown (2005).

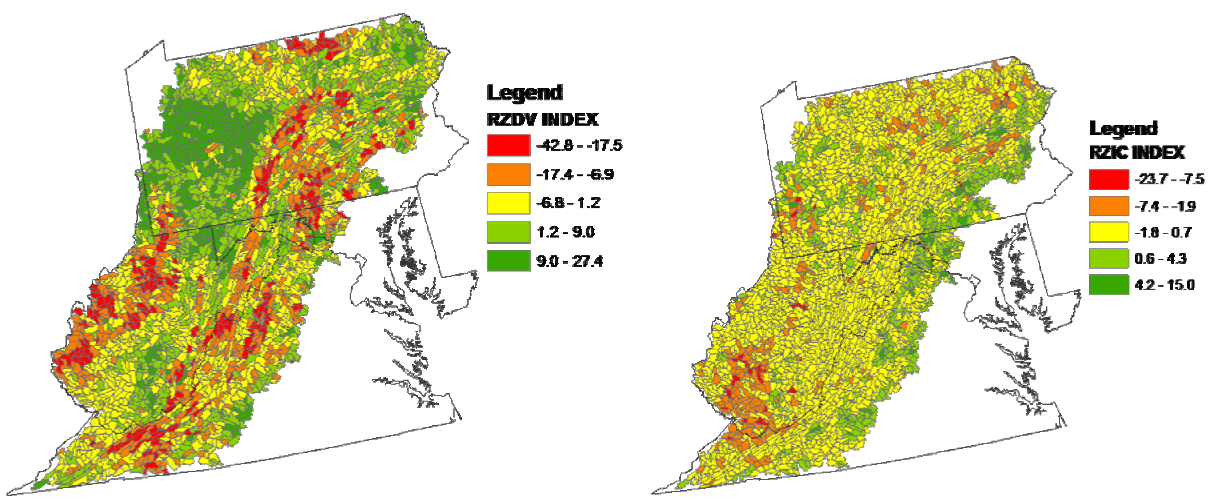
Land Cover Stressors – Sub-watershed Scale

Riparian Zone Indices
A central tenet of conservation biology is that the spatial distribution of land use has implications for landscape ecological integrity (Alberti 2000, Forman 1995). The riparian zone with native vegetation is a landscape element of particular concern as both a zone of high biological diversity and a zone of critical hydrologic function including water purification and flood attenuation, so we focused our pattern analysis on this proximal and essential feature of aquatic resources. We hypothesized that spatial patterns of land use are non-random with respect to the riparian zone, and developed indices that describe the extent to which a given land use type tends to either avoid the riparian zone or prefer the riparian zone. We investigated spatial patterns of two broad categories of human land use: impervious cover (IC) and disturbed vegetation (DV).

We chose to define the riparian zone based on the average width of the floodplain for each stream order (Strahler 1964). Available FEMA Q3 digital floodplain maps were combined with a synthetically generated stream network in GIS to calculate average 100 year floodplain widths. As expected, riparian zone or floodplain width generally increases with stream order.

We developed indices that express spatial distribution of the two land use categories (IC and DV) with respect to the riparian zone independent of the total intensity (proportion) of land use across a watershed. Best-fit curves were identified that explained the highest proportions of variation (highest r^2) in the relationship between percent land use (IC or DV) within whole watersheds (x-axis) vs. percent land use within the riparian zone of watersheds (y-axis). Indices were developed from the residuals of variation in riparian zone percent land use (IC and DV) that was not explained by variation in whole watershed land use. These two indices are termed the “Riparian Zone Impervious Cover (RZIC) Index”, and the “Riparian Zone Disturbed Vegetation (RZDV) Index”. Thus, the degree to which the indices are above or below zero represents the degree to which land use types (IC or DV) have a spatial distribution with respect to the riparian zone that is different than the central tendency for any given range of land use within watersheds.

On average across the Mid-Atlantic Highlands, we did not detect a tendency for disturbed vegetation to avoid or be concentrated in the riparian zone. In contrast, impervious surface land use classes (IC) tend to be concentrated in the riparian zone: percent IC in the riparian zone is on average about 1.5 times that for watersheds as a whole. Figures 4 a & b show the spatial distribution of these two indices. See Griscom et al. (in prep #3 – Appendix B) for a more complete description of the development of these indices, as well as some related analyses. For example, based on the data results from the above methods, we describe characteristic land use spatial patterns for each inherent class, and identify individual watersheds that represented examples of characteristic land use patterns.



Figures 5a & b. Maps of RZDV and RZIC indices for Mid-Atlantic Highlands Area.

In-stream Stressors: Direct Measurements or Predictions of Water Quality Parameters

Acidification/ ANC

Acidification has a direct and strong impact on the diversity and productivity of aquatic fauna in streams of the Mid-Atlantic Highlands. Atmospheric deposition is considered the largest cause of acidification in this region (Herlihy et al. 1993), followed by acid mine drainage. Although prior studies have made some estimates of the extent of acidification in the region (e.g., Herlihy et al. 1991, Herlihy et al. 1993, USEPA, 1994), we are not aware of any analysis that estimates acidification of stream networks due to both atmospheric deposition and/or acid mine drainage in a spatially explicit manner.

To address this data shortfall we developed regression models that predict stream acid neutralizing capacity (ANC), which indicates degree of stream acidification and vulnerability to further acidification. These predictions are based on watershed characteristics which can influence acidification, including: geology type, area, soil pH, soil texture, depth to bedrock, presence of acid mine drainage, acidity of atmospheric deposition, amount of agriculture, and amount of forest.

Stream ANC is predicted at the pour-point of watersheds 40 – 200 km^2 in size. This size range tends to be relevant to watershed groups in the region, and is at the higher end of the range of stream sizes affected by acidification (Kaufmann et al. 1991, Herlihy et al. 1993). A detailed description of the development of these regression models can be found in Griscom et al. (in prep #2 - Appendix B). Figure 6 presents a map of our estimates of ANC in the study area.

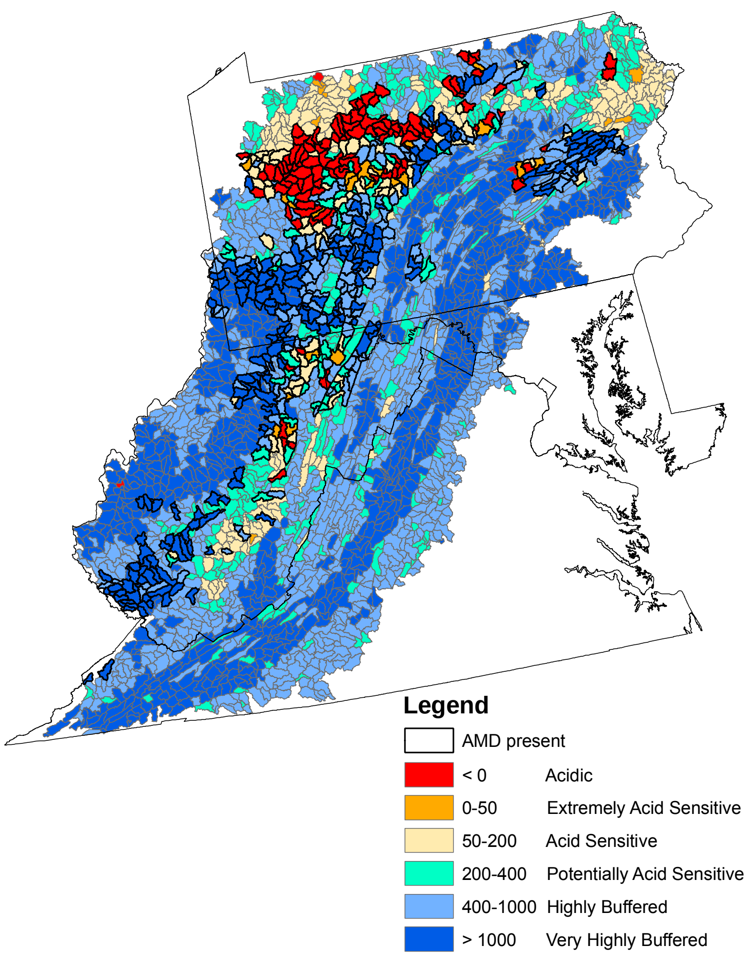


Figure 6. Predicted stream ANC classes (μeq/L) at the pour point of watersheds in the Mid-Atlantic Highlands region. One of the five regression models developed for this study was used for any given watershed, depending upon geology occurring in each watershed and presence/absence of acid mine drainage (AMD).

The predictability of our models is limited by the data limitations of regional datasets used in this analysis, and our estimates are conservative – actual conditions are likely to be more acidic. The map of watershed vulnerability to acidification presented here is intended as a first-cut reference for watershed stakeholders to assess relative condition and vulnerability of their watersheds to acidification. Use of this map should be followed-up with analysis of more detailed local datasets.

Nitrate and other Water Quality Parameters

Excessive nutrients and sediments in surface waters can become significant stressors to aquatic biota and pose risks to human health. Therefore, we considered these as candidates for inclusion in our vulnerability analysis.

Levels of nutrients (total nitrogen, total nitrate, total ammonia, dissolved phosphorus, total phosphorus) and sediments (suspended sediments) in true watersheds were predicted by application of multivariate regression models developed for the Mid-Atlantic Integrated Assessment region by Jones et al. (2001). In their study, models were developed from an initial set of 17 landscape metrics for watershed supporting areas at 148 USGS surface water sampling stations. Atmospheric deposition of nitrate was one of the factors considered in the regression models. Use of land cover models to predict nutrients was considered the preferred method because EMAP water chemistry data were available for only a portion of study watersheds (<600); classification of watersheds in this study was also anticipated to be coarse and broad-scaled.

Predicted values for watersheds containing one or more EMAP stream sampling points were examined to evaluate the correspondence between predicted and observed values (n=896). Efforts were made to compensate for differences between datasets when making the comparisons. We found that our predictions of total nitrogen and total nitrate (Figure 7) were the most highly correlated to EMAP values, while total ammonia correlated the most poorly. The total phosphorus model generally underestimated values. A more detailed description of methods used to estimate water quality parameters for the study region can be found in Rocco et al. (unpublished – see Appendix B).

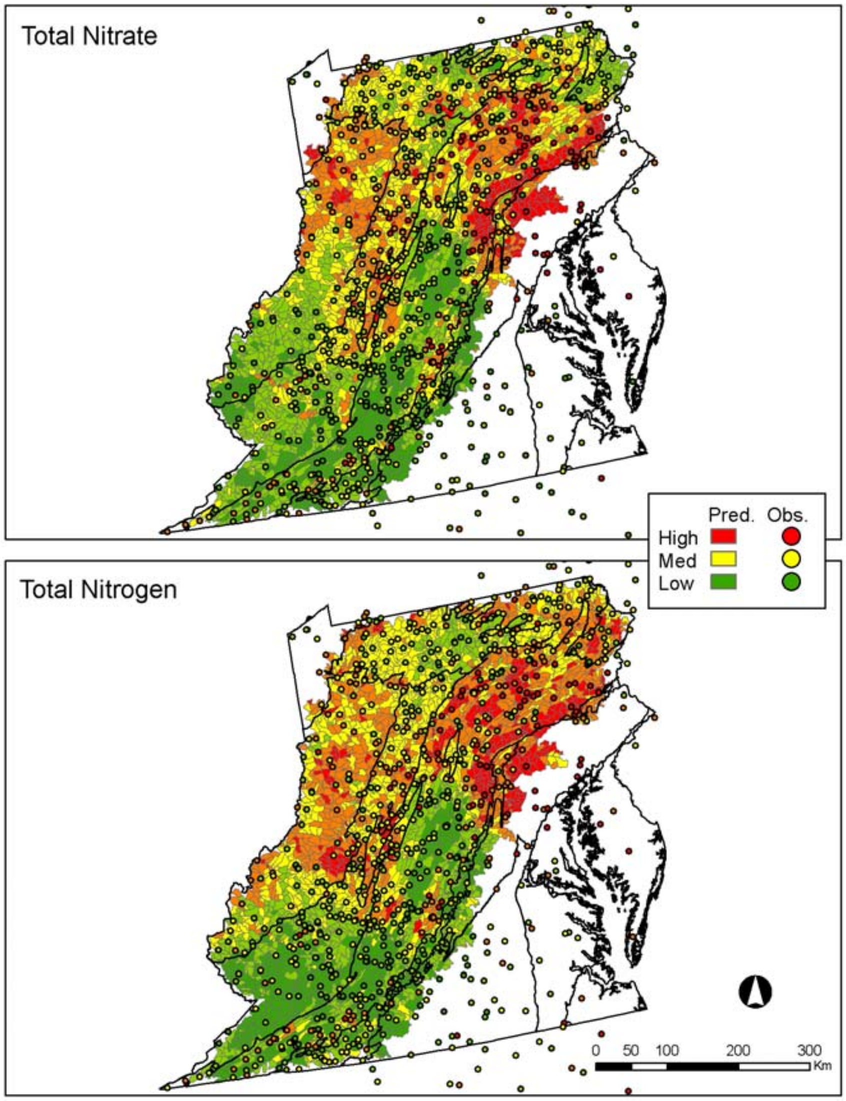


Figure 7. Map showing correspondence between total nitrogen and nitrate predicted from regression models (Predicted Ln Total nitrate (or Total nitrogen) kg/ha/yr) vs. values measured at EMAP sampling points (Observed Ln Total nitrate (or Total nitrogen) μg/L).

STRESSOR CLASS IDENTIFICATION AND CONDITION RANKING

In addition to assessing the vulnerability of watersheds to stress, our conceptual model of prioritization requires an estimate of watershed condition. To that end, this component of the study subdivides the nine inherent watershed classes into stressor subclasses, and ranks those subclasses according to the condition of their aquatic ecosystems.

We used the West Virginia DEP's Stream Condition Index (WVSCI) (Gerritsen 2000) as an index of watershed ecological integrity, or condition. This index is based on diversity and composition of stream invertebrate community, with particular attention to disturbance-sensitive taxa. Prior to analyses, we corrected WVSCI scores for changes due to elevation (Griscom et. al., in prep #1 – Appendix B).

For defining the stressor subclasses, four variables were considered:

(1) The percent cover of impervious cover in a watershed (WSIC).
(2) The percent cover of agriculture in a watershed (WSAG).
(3) The percent cover of mining in a watershed (WSMINE).
(4) Acid Neutralizing Capacity (ANC).

The above variables were selected through exploratory analyses: we first broke down watersheds by impervious cover (IC) and disturbed vegetation (DV), since these were very different types of land cover (different dose-response curves). We next tested for subdivisions of DV (including agriculture and mining) to see if we needed to further refine these subclasses when looking at vulnerability. We found very different dose-response relationship for mining vs. agriculture dominated watersheds. This distinction between mining, and agriculture and impervious cover was also found by Detenbeck et al. (2004).

We also evaluated the water quality variables (e.g., total nitrogen, nitrate) for inclusion in our analysis. However exploratory analyses suggested that these were redundant with other variables (e.g., the land cover-related stressors, and the inherent classes themselves) and there was little additional information gained by their inclusion. Therefore, we did not include these variables in defining the stressor subcategories.

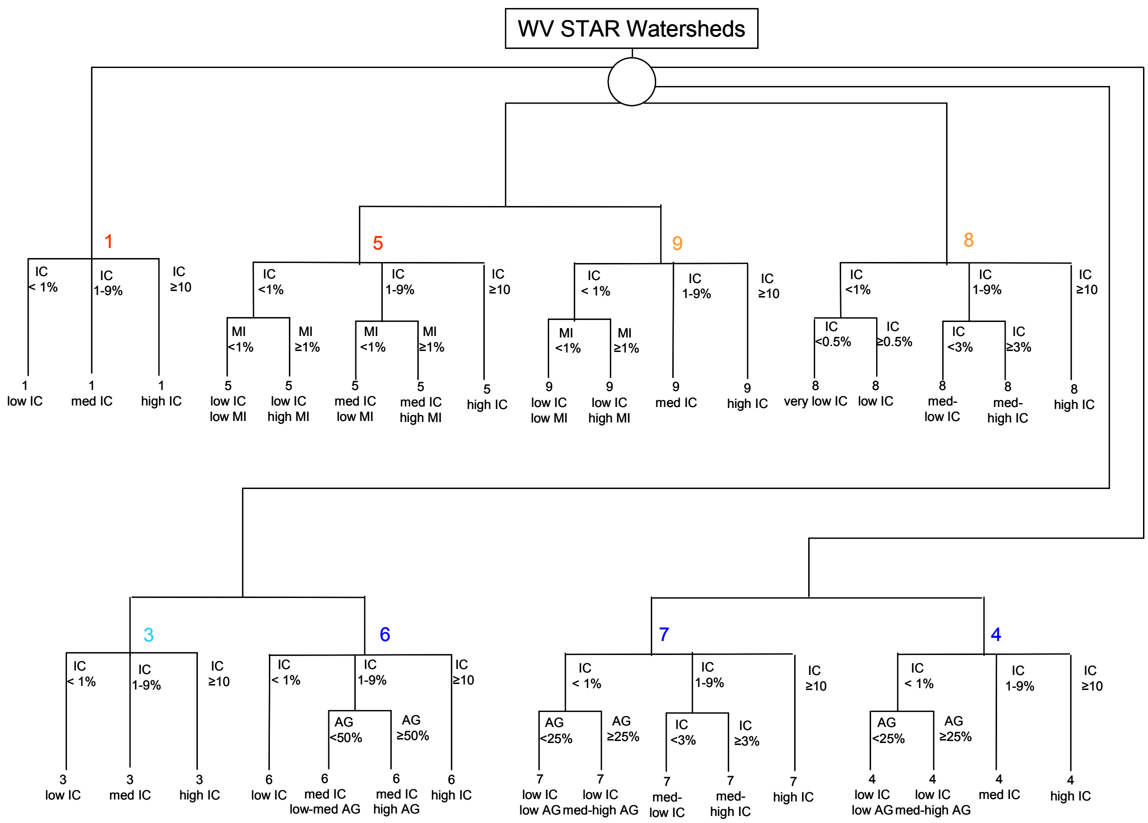
For each of the four variables noted above, tiers or categories were developed based on an extensive analysis of dose-response relationships for each land use type. (One exception is that tiers for ANC are based primarily on literature review, and confirmed by looking at dose-response). One notable finding was a drop-off (e.g., a “threshold” in dose-response curve) in condition (WVSCI score) at much lower levels of both WSIC and WSMINE than expected from review of the literature. Most studies discuss thresholds around 10 or 20 percent IC. We found that although 10 percent was appropriate, the most dramatic drop-off in condition occurred around 0.5 and 1 percent IC, and 1 percent Mining. Table 4 shows tiers for each of the four variables.

Table 4. Tiers used to assign watersheds to stressor subclasses.

	WSIC	WSAG	WSMINE	ANC
Very low	0.0-0.49%	-		
Low	0.49-0.9%	0-24.9%	0.0-0.9%	<50.0
Medium	1.0-9.9%	25-49.9%		
High	10.0-24.9%	≥ 50.0%	≥1.0%	≥ 50.0
Very High	≥ 25%			

West Virginia watersheds with one or more WVSCI scores were used for this analysis. Watersheds were first grouped according to their inherent class. Within this grouping, each watershed was assigned to a stressor subclass based on its values for these four variables. Variables were considered in the following order: WSIC, WSAG, WSMINE, ANC. Pairwise differences in mean watershed WVSCI scores among subclasses were then tested using a Kruskall-Wallis rank sum test (non-parametric). If the differences were not significant, the subclasses were lumped together. The resulting subclasses are shown in Figure 8. Mean WVSCI scores were computed for each of these subclasses, and they were ranked accordingly (see Table 5).

Figure 8. Stressor subclasses for nine inherent watershed classes.



All Met-9	Class	Avg WVSCI	WVSCI Biol. Impairment
4	Low IC Low AG	73.96	Unimpaired
9	Low IC Low MI	71.27	Unimpaired
7	Low IC Low AG	69.70	Unimpaired
8	Very Low IC	69.29	Unimpaired
7	Low IC Med-High AG	67.57	Gray Zone
5	Low IC Low MI	66.23	Gray Zone
3	Low IC	65.56	Gray Zone
9	Low IC High MI	64.14	Gray Zone
4	Low IC Med-High AG	63.98	Gray Zone
8	Low IC	63.37	Gray Zone
7	Med IC	63.23	Gray Zone
4	Med IC	63.09	Gray Zone
9	Med IC	62.44	Gray Zone
5	Med IC Low MI	61.46	Gray Zone
1	Low IC	61.42	Gray Zone
5	Low IC High MI	61.34	Gray Zone
8	Med IC Low MI	61.06	Gray Zone
3	Med IC	59.62	Impaired
1	Med IC	55.60	Impaired
5	Med IC High MI	50.44	Impaired
8	Med IC High MI	48.79	Impaired
6	Med IC High AG	46.99	Impaired

Table 5. Stressor subclasses ranked according to average IBI (WVSCI) score. Note: the “impairment” column below is based on cutoffs used in the WVSCI system.