VULNERABILITY OF WATERSHEDS TO HUMAN IMPACTS IN WEST VIRGINIA

Our objective in this component of the study was to illustrate the integration of the information developed earlier in this report - our classification system for watersheds based on inherent characteristics, and our characterization of stressors in the study area - to evaluate the vulnerability of watersheds to loss of stream biological integrity due to human impacts.

Differences in watershed vulnerability are defined here as differences in the response of watershed ecological integrity to increasing human impacts, manifested as different stressor levels within watersheds. For example, "type A" watersheds in Figure 9 demonstrate low vulnerability to human stress, while "type C" watersheds demonstrate high vulnerability.

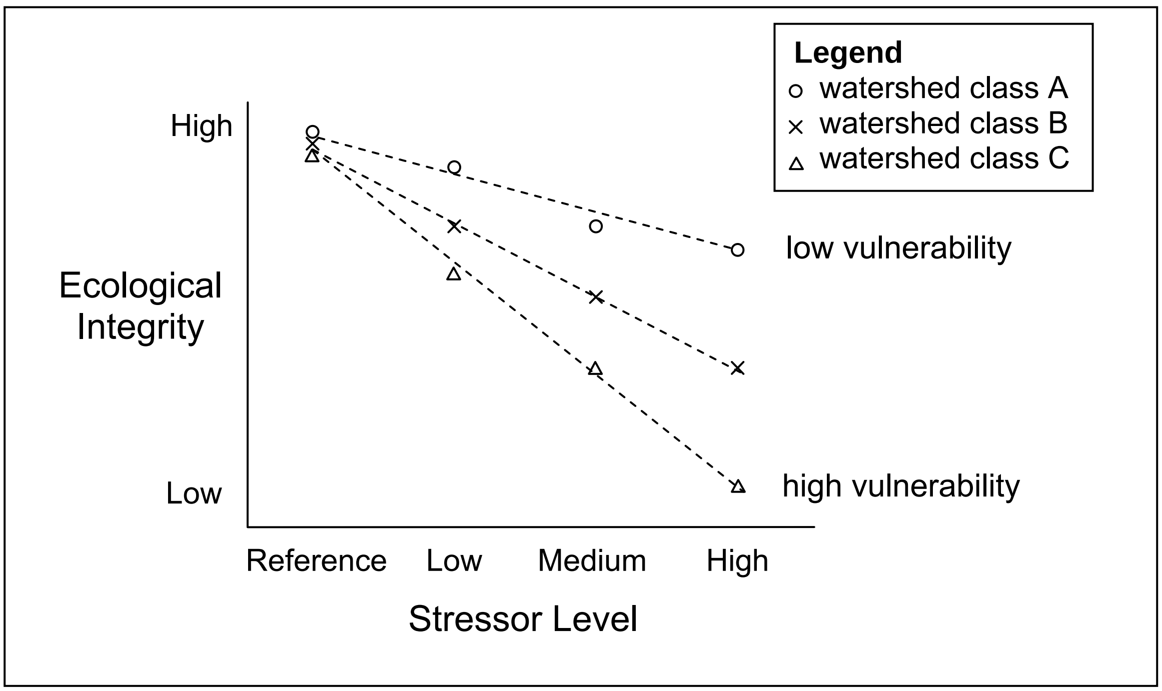


Figure 9. Conceptual diagram of watershed types demonstrating different response of ecological integrity to stressor levels, and thus different vulnerabilities in terms of ecological resistance. Watershed type A has the lowest vulnerability, while watershed type C has the highest vulnerability.

In order to classify watersheds with regard to vulnerability, it was necessary to identify or develop three parameters of the model in Figure 9:

(1) A watershed classification system that identifies classes of watersheds with different vulnerability levels. For this we examined our different inherent classifications described earlier in the report, to see which performed the best.

(2) One or more indices of stressor level. These are described earlier in this report, and some refinements are noted below.

(3) An index of watershed ecological integrity.

We examined various regional and sub-regional datasets for the availability of stream-based indices of biotic integrity or "IBIs", commonly used as a measure of watershed condition. Regional datasets included those collected by the Environmental Monitoring and Assessment Program (EMAP) (US EPA 2000a); state-level datasets included the Maryland Biological Stream Survey (MBSS) (US EPA 1999), the West Virginia DEP's Stream Condition Index (WVSCI) (US EPA 2000b), and Pennsylvania's Surface Water Assessment Program (PA DEP 2004). We found that there were sufficient differences among these programs in their data collection and processing methods that the datasets could not be reliably combined to create a large regional dataset. Therefore, we selected the West Virginia dataset to illustrate our methods, due to the large number of sample sites (n = 4167), and the fact that this state occupies the core of our study area.

The West Virginia DEP's Stream Condition Index (WVSCI) (Gerritsen 2000) 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 – see Appendix B).

Evaluation of Classification Systems

To test the hypothesis that our nine cluster classification using all variables was indeed the most suitable one for assessing vulnerability, we compared eleven watershed classification systems for their ability to explain variability in vulnerability (as defined in Figure 9). Two of the classification systems compared are commonly used in our region: Physiographic Provinces (Fenneman 1946) and Ecoregions (Omernik 1987). The other nine classification systems were developed as part of this study as described in the next section. All classification systems are based on inherent characteristics of watersheds (e.g., landform, soils, climate), as opposed to human-derived characteristics (e.g., road network, agricultural systems). An exception occurs for Ecoregions, for which human land use patterns were used in addition to inherent characteristics.

To make this comparison we developed indices of vulnerability based on two general indicators of human land use impact intensity: (1) percent of watershed in predominantly anthropogenic land use (referred to as "disturbed cover" (DC)), (2) land development intensity index (LDI) (Brown 2005) within a watershed. Two vulnerability indices were calculated as the difference between actual WVSCI scores and WVSCI scores predicted from stressor levels with the following equation:

$$v_i = \mathrm{msci}_i - \mathrm{psci}_i$$

Where

- "v_i" is the vulnerability index calculated for watershed "i"
- "msci_i" is measured WVSCI score for watershed "i"
- "psci_i" is predicted WVSCI score for the stressor level occurring in watershed "i"

The variable "$psci_i$" was calculated for both LDI and DC (as dependent variables) using a robust (MM) regression model. Thus, "class A" watersheds in Figure 9 would generally have positive values for each vulnerability index, "class B" watersheds would generally have values near zero, and "class C" watersheds would generally have negative values.

A non-parametric ANOVA (Kruskal-Wallis rank test – Chi-square statistic) was used to quantify the amount of variability in our vulnerability indices explained by each of eleven classification system for West Virginia. The classification system with the highest Chi-square statistic was selected as the "best" system. We also compared classification systems for variability explained in other variables of interest: (1) land use intensity (DC and LDI), (2) stream condition (WVSCI) and (3) spatial patterns of land use with respect to the riparian zone (Griscom et al., in prep #2 – Appendix B). Ideally the classification system selected would also perform well in explaining differences in these other variables.

		Vulnerability						*Land Use Intensity*						*Spatial Patterns*						*Acidification*			*Condition*			
		WVSCI - LDI			**WVSCI-DC**			**DC**			**LDI**			**RZIC Index**			**RZDV Index**			**stream ANC**			**WVSCI**			
System	No. cat.	Chi-sq	P	Rank	Chi-sq	P	Rank	Chi-sq	P	Rank	Chi-sq	P	Rank	Chi-sq	P	Rank	Chi-sq	P	Rank	Chi-sq	P	Rank	Chi-sq	P	Rank	Mean Rank
All Met-9	8	81.5	**	1	87.8	**	1	285.9	**	1	200.8	**	1	229.1	**	1	192.7	**	4	316.2	**	2	78.1	**	1	1.5
All Met-6	6	76.5	**	2	81.4	**	2	254.2	**	2	171.9	**	2	191.6	**	2	188.1	**	5	285.0	**	4	65.4	**	2	2.6
Ecoregions	6	73.6	**	3	80.7	**	3	229.9	**	3	149.4	**	4	185.1	**	3	125.4	**	6	202.0	**	7	43.5	**	5	4.3
Climate	4	60.9	**	4	68.6	**	4	89.3	**	9	61.2	**	9	152.7	**	4	120.8	**	7	314.9	**	3	40.1	**	6	5.8
Climate-Soil	6	29.4	**	7	29.5	**	7	78.2	**	10	50.5	**	10	85.1	**	7	197.2	**	3	359.6	**	1	46.8	**	4	6.1
Soil	5	25.0	**	8	27.6	**	8	151.5	**	6	122.3	**	6	62.8	**	8	241.2	**	1	250.0	**	5	39.6	**	7	6.1
Phys-Soil	6	10.4		11	10.4		11	188.5	**	4	162.5	**	3	27.8	**	11	220.5	**	2	214.1	**	6	65.3	**	3	6.4
Hydro-Phys	5	34.3	**	6	38.2	**	6	143.8	**	8	98.4	**	8	85.7	**	6	44.8	**	10	85.5	**	9	29.7	**	8	7.6
Provinces	4	39.3	**	5	49.0	**	5	25.2	**	11	6.5		11	102.0	**	5	34.9	**	11	63.9	**	10	21.7	*	9	8.4
Phys	6	15.6	*	9	18.1	*	9	150.4	**	7	119.7	**	7	58.5	**	9	62.7	**	8	141.2	**	8	10.5	**	11	8.5
Hydro	6	15.1	*	10	15.9	*	10	163.3	**	5	127.4	**	5	57.8	**	10	46.6	**	9	26.5	*	11	10.7	**	10	8.8

Table 6. Inherent classification systems are ranked based on explanatory power (as measured by chi-square statistic) for seven different landscape metrics expressing vulnerability, land use intensity, spatial patterns, and stream condition. Vulnerability indices were calculated with respect to disturbed cover (DC) and land development intensity index (LDI). Spatial pattern indices were calculated as tendency of impervious cover (RZIC) and disturbed vegetation (RZDV – dominated by agriculture) to avoid or be concentrated in the riparian zone. Chi-square and P-value results from Kruskall-Wallis Rank Sum test. Significant differences among classes for each variable were found at $P<0.05$ (*) and $P<0.0001$ (**) levels.

Our WVSCI-DC and WVSCI-LDI vulnerability indices generated the same ranking of 11 classification systems based on Kruskal-Wallis chi-square statistic (Table 6). Our "All Met-9" classification system ranked highest; that is, it explained the greatest amount of variability in both WVSCI-DC and WVSCI-LDI vulnerability indices according to chi-square values. Our "All Met-6" classification system ranked the second highest. Climate ranked the fourth highest, and ranked the highest among classification systems using only one category of inherent variables. Our "All Met-9" classification systems also ranked 1st and 2nd for the other variables tested with the exception of the riparian zone disturbed vegetation spatial pattern index (RZDV). Our "Soils" based classification system ranked the highest for RZDV, followed by "Phys-Soil", "Climate-Soil", and then "All Met-9" and "All Met-6" systems.

Ecoregions (Omernik, six subdivisions) was ranked just behind All Met-6 for all metrics with the exception of LDI and WVSCI for which Ecoregions had poorer performance. In particular, Ecoregions demonstrated medium-range prediction of stream condition (WVSCI), which is best predicted by All Met-9 and All Met-6 classification systems.

Comparison of Vulnerability among Inherent Classes

In order to statistically assess vulnerability levels, we used a non-parametric ANOVA (Kruskal-Wallis rank test) to compare median WVSCI score for specified stressor ranges among all inherent classes (All Met-9). We conducted these tests for three stressor parameters: IC, AG, and LDI. DC was not tested due to its low explanatory power for condition (low r2), and similarities to LDI. AG also had a weak relationship with condition, but was retained since it was the primary stressor for one inherent class (Class 6). Water quality variables (e.g., total nitrogen, nitrate) were considered for inclusion; however we found these to have only a weak relationship with condition, likely due to their correlation with other variables already included in the analyses.

Results from the analysis of dose-response curves conducted by Griscom et al. (stressor classification paper manuscript) were used to specify ranges of each stressor parameter as presented in Table 7. LDI ranges were selected based on ranges for IC and AG (Table 7).

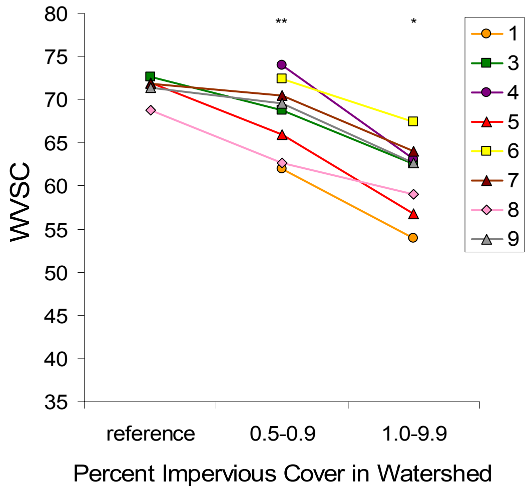
Selection of LDI range for each land use intensity class

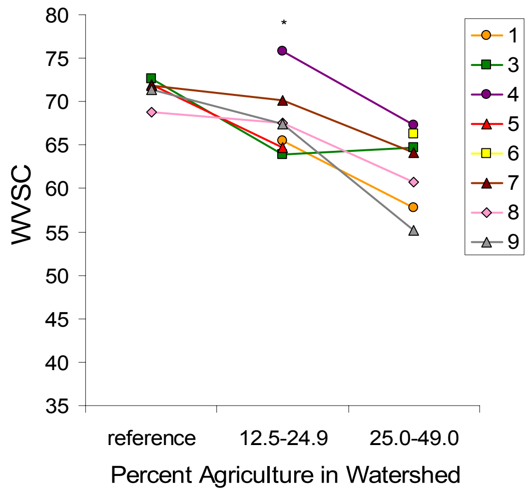
Land Use Intensity	*Reference*		***Low***		***Medium***		***High***	
Land Cover Type	WSIC	WSAG	WSIC	WSAG	WSIC	WSAG	WSIC	WSAG
Percent Land Cover	0.0-0.4	0.0-12.4	0.5-0.9	12.5-24.9	1.0-9.9	25.0-49.9	10.0-19.9	50.0-74.9
No. watersheds	162		196	140	197	71	6	15
LDI mean	117.3		**141.0**	**147.7**	**161.0**	**191.6**	**288.3**	**267.3**
LDI stdev	9.7		25.5	9.1	32.7	18.5	22.4	25.1
Selected LDI range	na		**130.0 - 154.9**		**155.0 - 224.9**		**225.0-299.9**	

Table 7. Selection of LDI range for each land use intensity class.

Median WVSCI scores were not significantly different for reference watersheds comparing among All Met-9 inherent classes. Median WVSCI scores were significantly different ($P < 0.05$) among inherent classes at low stressor levels for all three stressor parameters (IC, AG, and LDI). Median WVSCI scores were significantly different among inherent classes at medium stressor levels for IC and LDI, but not for AG. Median WVSCI scores were highly significantly different ($P < 0.001$) at both low and medium LDI stressor levels. Due to lack of adequate replication ($n < 3$), mean WVSCI scores were not presented for any inherent classes at high stressor levels, and were not presented (or included in Kruskal-Wallis test) for select inherent classes at medium, low, and reference stressor levels.

Inherent classes 6 and 4 (of All Met-9) were among the three highest mean WVSCI values for a given stressor level – stressor type combination. Inherent classes 5 and 1 had among the three lowest mean WVSCI values for a given stressor level – stressor type combination. Some inherent classes (e.g., 3 and 9) demonstrated variable relative WVSCI levels depending upon stressor parameter. LDI analysis produced results intermediate to that of AG and IC and, unlike AG and IC, had consistent results for low and medium stressor levels. Thus, LDI was selected as the best parameter for ranking vulnerability among inherent watershed classes as presented in Figure 10.





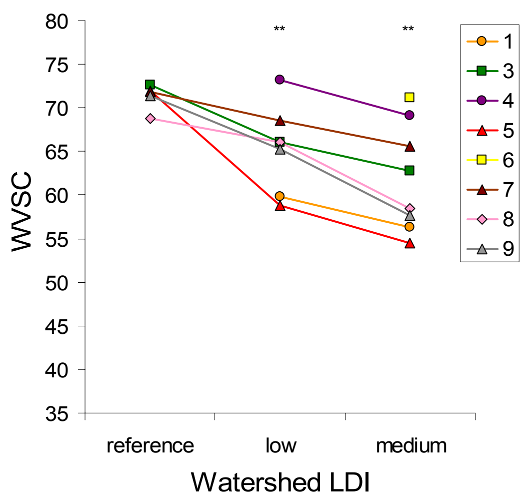


Figure 10. Significant differences were found at P<0.001 (**) and P<0.05 (*) for Kruskal Wallis Rank test comparing median WVSCI among inherent classes for levels of impervious cover (IC), agriculture (AG) and land development intensity index (LDI) as specified in Table 7. Categories with less than three watersheds were considered insufficient replication and were not included in graphs.

No significant difference in stream condition (WVSCI) was identified among watersheds with predicted high (ANC < 50), medium (ANC 50-200) and low (ANC > 200) vulnerability to acidification. Inherent classes 5, 6, 7, and 8 had less than 3 percent of watersheds with predicted ANC < 200. Inherent classes 1, 3, and 4 had 10-15 percent of watersheds with predicted ANC < 200. Inherent class 9 had over 1/3 (37 percent) of watersheds with predicted ANC < 200.

Table 8. ANC vulnerability. Highly significant difference found (P<0.0001) among Allmet-9 classes in median predicted ANC.

All Met-9 Class	Percentage of WV Watersheds <200 ANC	Mean ANC
1	10.81%	1058.36
3	10.29%	996.09
4	14.29%	657.31
5	1.91%	1095.46
6	0.00%	3567.73
7	2.44%	848.16
8	0.46%	1247.65
9	37.06%	337.65

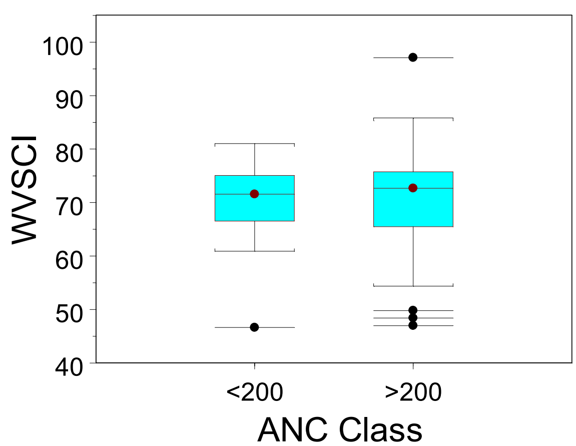


Figure 11. No significant difference (at P<0.05) found between median WVSCI scores of two ANC classes for "reference" watersheds. N=23 <200 ANC, N=132 >200 ANC.

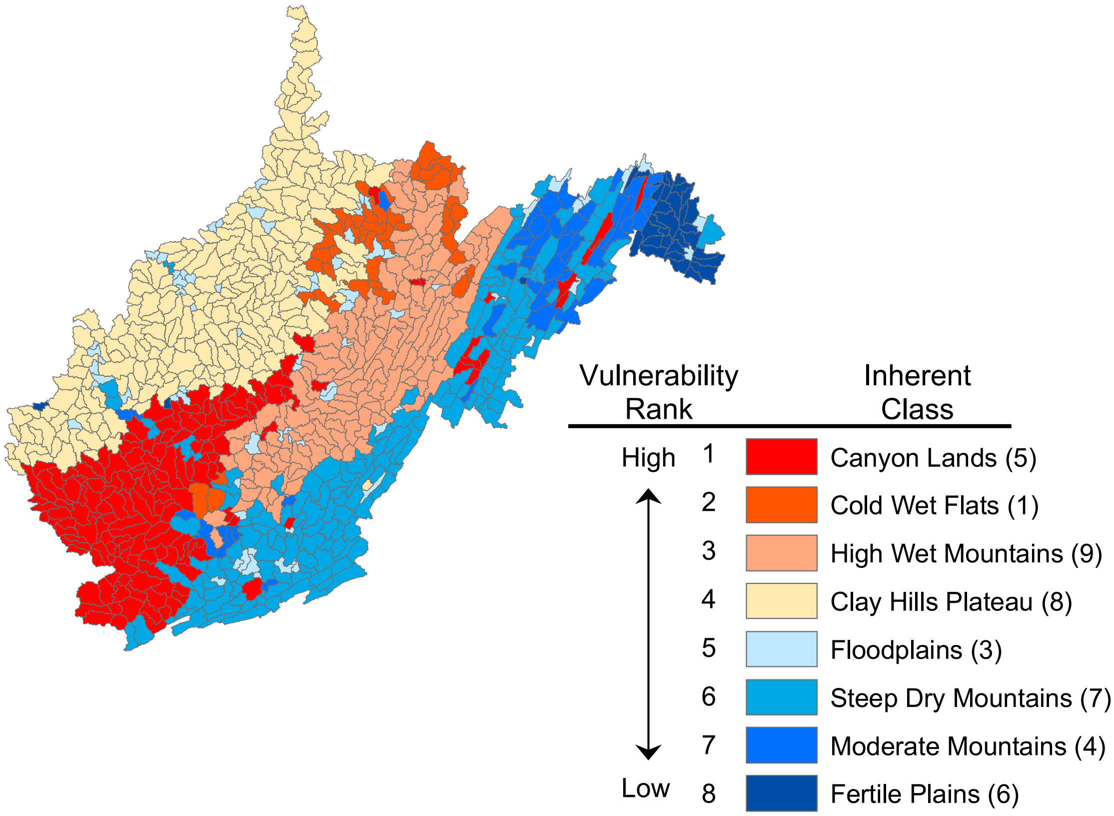


Figure 12. Map of vulnerability to land use impacts for watersheds of the West Virginia.

DISCUSSION & CONCLUSIONS

The "All Met-9" system that takes into account multiple types of inherent landscape characteristics (soils, climate, landform, hydrology) was the best predictor of our vulnerability indices, land use intensity variables, stream condition (WVSCI), and an index of spatial patterns of impervious cover with respect to riparian zone. The "All Met-9" classification system also performed well in predicting the other two stressors tested: ANC, and spatial patterns of disturbed vegetation. Since all the watershed parameters tested (land use vulnerability indices, land use intensity indices, spatial pattern indices, condition index, acidification vulnerability index) were expected to influence our analysis of watershed vulnerability, the "All Met-9" classification was the best system for characterizing watershed vulnerability in West Virginia, and presumably the other states, although only 8 of the 9 watershed types are found in West Virginia. Thus, we projected vulnerability rankings from the analysis in West Virginia to the remainder of the MAHA watersheds for the Watershed Characterization and Prioritization Tool.

Of the three stressor variables used to characterize "dose" in the construction of dose-response graphs (percent impervious cover, percent agriculture, and LDI), we selected LDI for ranking overall vulnerability of watershed classes. LDI generated results intermediate between those for agriculture and impervious cover, as expected since LDI accounts for all anthropogenic land use classes. LDI analysis generated the strongest statistical results (lowest P-values and highest chi-square) for differences between median WVSCI scores among inherent classes at both low and medium stressor levels. LDI also had higher replication since watersheds with multiple primary stressors (e.g., medium agriculture and impervious cover) did not need to be excluded, thus generating a ranking for all eight inherent classes at the medium stressor level. Finally, LDI ranking was consistent at both low and high stressor levels, thus avoiding the need for complicated ranking systems.

Overall, watershed classes of the central wet Appalachian mountains and westward were more vulnerable, while watershed classes of the drier central mountain ranges and east were less vulnerable. Vulnerability (ecological resistance) tended to have an inverse relationship with likelihood of land use impacts: high vulnerability watershed classes tended to have relatively low land use impacts, while low vulnerability watershed classes tended to have relatively high land use impacts. A notable exception to this trend occurred for mining: higher vulnerability watershed classes (e.g., *Canyon Lands* and *High Wet Mountains*) tend to have high levels of mining impacts.

Inherent classes 5 and 1 (Canyon Lands and Cold Wet Flats) were consistently high vulnerability, regardless of the stressor variable used. They also showed the steepest drop in condition between reference and low LDI stressor range, suggesting that thresholds of response to impacts occur at surprisingly low levels of land use impacts for these watershed classes (less than 25% agriculture, and less than 1% impervious cover). Inherent classes 4, 6, and 7 (Moderate Mountains, Fertile Plains, and Steep Dry Mountains), were consistently low vulnerability, regardless of stressor variable used. The remaining inherent classes 3, 8, and 9 (Floodplains, Clay Hills Plateau, and High Wet Mountains), showed more variable results depending upon stressor level and stressor variable; however, the overall pattern as expressed by LDI was that inherent classes 8 and 9 are higher vulnerability, while inherent class 3 is lower vulnerability.

The most successful classification system for differentiating based on predicted ANC was “climate-soil” system. This stands to reason, given that (1) soils influence stream ANC, and are our best proxy for geology, considered the primary driver of stream ANC, and (2) climate classification is the best proxy for atmospheric contributions, another driver of acidification. All met-9 was second best system at differentiating based on predicted stream ANC – primarily identifying class 9 as highly susceptible to acidification. Mean (and median) WVSCI scores were slightly lower for reference watersheds with predicted ANC < 200; however, this difference was not significant. We suspect that this is due, at least in part, to scale issues. Acidification problems tend to occur in small streams, and probably need to measure many streams within each of our study watersheds to address appropriate scale of relationship.

Another method for prioritizing watershed developed, in part, during this project, used partially ordered sets (posets) (Myers et al. 2006). They demonstrated the patterns of partial ordering on watershed ranking, using vertebrate data vs. environmental data. The resultant “rank range runs” allow comparisons among watersheds (or other units) characterized by multiple factors. If unit A is equal or superior to another in its best rank and its worst rank, then it is considered superior (i.e., higher rank order or higher priority rank). A range of ranks produced over a set of multiple factors or indicators yields an objective ranking sequence. Although we did not implement this method over the entire set of MAHA watersheds, we believe that it offers an alternative means to prioritize watersheds, regardless of the criteria selected by managers.

Vulnerability of Watershed Classes

Cold Wet Flats

Watersheds of the *Cold Wet Flats* were ranked second highest vulnerability to loss of stream biotic integrity due to watershed land use impacts. The cold climate and low soil infiltration characteristic of *Cold Wet Flats* may be associated with high vulnerability status identified for this watershed class. Watersheds of the *Cold Wet Flats* are characterized by avoidance of the riparian zone for disturbed vegetation land uses (primarily agriculture) and neutral spatial patterns for impervious cover (Griscom et. al, in prep #3). Thus, disproportionate riparian impacts are not expected to account for elevated vulnerability within watersheds of the *Cold Wet Flats*. Acidification is expected to impact some watersheds: 10 percent of West Virginia’s *Cold Wet Flats* watersheds had predicted stream water ANC < 200. Medium and low intensity land use levels are most common in these watersheds.

Floodplains

Watersheds of the *Floodplains* were ranked intermediate-low vulnerability (fourth lowest) to loss of stream biotic integrity due to watershed land use impacts. *Floodplains* watersheds are scattered throughout the West Virginia due to the scattered occurrence of river floodplain systems. Thus, this class includes watersheds with a broad range of climate conditions and biotic communities. These watersheds are, however, expected to have biotic communities adapted to the chronic natural disturbance of flooding. This natural disturbance regime may pre-adapt biotic communities to be relatively tolerant of human impacts. *Floodplains* watersheds have soils with high available water capacity, which may allow water to infiltrate, thus reducing overland flow. Watersheds of the *Floodplains* show a substantial range of land use spatial patterns and no strong overall tendencies of riparian zone concentration or avoidance. While these watersheds tend to be tolerant of land use impacts, they have the highest proportion of watersheds subjected to heavy urbanization, and tend to have relatively high agricultural land use.

Moderate Mountains

Watersheds of the *Moderate Mountains* were ranked second lowest vulnerability to loss of stream biotic integrity due to watershed land use impacts. These watersheds are moderate in most inherent characteristics, but tend to be drier and lower in elevation than most West Virginian watersheds. Other classes tending to have drier climates and/or lower elevations are also low in vulnerability: "steep dry mountains" and "fertile plains."

Watersheds of the moderate mountains class show a moderate tendency for concentrated disturbed vegetation land use in the riparian zone, yet on average are neutral on impervious surface distribution. While this class is tolerant of human land use impacts, it is subjected to high agricultural land use impacts, second only to the *Fertile Plains* class (Griscom et. al, in prep #3). Acidification is expected to cause problems in some watersheds of the *Moderate Mountains*: 14% of watersheds were predicted to have stream ANC < 200.

Canyon Lands

Watersheds of the *Canyon Lands* were ranked as the highest vulnerability to loss of stream biotic integrity due to watershed land use impacts. This class of watersheds is characterized by extreme inherent characteristics: the steepest slopes, the steepest channel gradient, and the least erodible soils among inherent watershed classes of the Mid-Atlantic Highlands. Stream invertebrate communities are reported to be distinctive and sensitive in *Canyon Lands* watersheds.

Watersheds of the Canyon Lands had the strongest tendency for impervious surface concentrated in the riparian zone. Thus, high vulnerability of these watersheds may be due in part to disproportionate impacts within the riparian zone. Consistent with the challenges to land use, Canyon Lands have the highest proportion of watersheds with low intensity land use (88%). When disturbed vegetation land uses do occur, the highest proportion of that land use category is composed of barren, quarry, and transitional land use classes (28%), generally indicators of mining and logging activities.

Fertile Plains

Watersheds of the *Fertile Plains* were ranked as the lowest vulnerability to loss of stream biotic integrity due to watershed land use impacts; however, the *Fertile Plains* are also subject to the highest level of agricultural impacts, and the second highest level of urbanization (Griscom et. al, in prep #3).

The Fertile Plains class is characterized by fertile soils, warm climate, and relatively flat topography. Fertile Plains watersheds have the highest tendency for impervious surface land uses to avoid the riparian zone, a spatial pattern of land use that may contribute to the relatively low biotic response to land uses quantified at the watershed scale. On the other hand, watersheds of the Fertile Plains tend to have disturbed vegetation land use impacts concentrated in the riparian zone; however, there is high variability in disturbed vegetation land use patterns, and a substantial number of watersheds show avoidance of the riparian zone for all land use types.

Steep Dry Mountains

Watersheds of the *Steep Dry Mountains* were ranked as the third lowest vulnerability to loss of stream biotic integrity due to watershed land use impacts. We were surprised by this result, given (1) the steep slopes and high elevations of watersheds in this class, and (2) the tendency for "disturbed vegetation" land uses to be concentrated in the riparian zone. Like other low vulnerability classes (e.g. Moderate Mountains, Fertile Plains), climate tends to be drier in the *Steep Dry Mountains* than in watersheds to the west. *Steep Dry Mountains* also are not subjected to substantial levels of mining (Griscom et. al, in prep #3). Low and medium land use intensities are common among watersheds of the Steep Dry Mountains, suggesting that topography and other inherent characteristics restrict intensive land use, although not to the same extent as for Canyon Lands and High Wet Mountains.

Clay Hills Plateau

Watersheds of the *Clay Hills Plateau* were ranked as intermediate-high vulnerability (fourth highest) to loss of stream biotic integrity due to watershed land use impacts. There is a tendency towards concentration of land use in the riparian zone (particularly in the West Virginian portion of the *Clay Hills Plateau* region) and this may contribute to higher vulnerability.

High Wet Mountains

Watersheds of the *High Wet Mountains* were ranked as the third highest vulnerability to loss of stream biotic integrity due to watershed land use impacts. Also, the *High Wet Mountains* are the most vulnerable watershed class to acidification*:* over 1/3 of watersheds were predicted to have stream water ANC < 200. Aside from being steep and rugged, watersheds of the *High Wet Mountains* on average have the highest elevation, coldest climate, and highest precipitation of all inherent classes. Like Canyon Lands, the High Wet Mountains generally have low overall land use intensity, and a substantial proportion of disturbed vegetation is comprised of mining and logging related land uses (17%). This land use similarity is consistent with the similarity of inherent characteristics: Canyon Lands and High Wet Mountains are sibling classes according to the cluster analysis dendrogram; however, unlike Canyon Lands, impervious cover land uses do not show a strong tendency towards concentration in the riparian zone (RZIC index was close to zero). Also, unlike Canyon Lands, disturbed vegetation shows a tendency to avoid the riparian zone in the *High Wet Mountains*. This is apparently due at least in part to a shift in landform and other inherent factors that allows mountain tops to be more amenable to land use in the *High Wet Mountains* than in *Canyon Lands*.