INTRODUCTION

Rationale and Context

The US Environmental Protection Agency's (USEPA) expressed purpose for a watershed classification system is to "support the design of efficient monitoring strategies, diagnose the causes of biological impairment, and prioritize watersheds for restoration." Such a system should include conceptual models to explain and predict the relationships between land-use activities and the biological conditions within a watershed. Using Characterization and Prioritization models for the Mid-Atlantic Highlands, we developed a classification system that groups watersheds with similar physical characteristics and ecological stressors to provide scientifically defensible information for monitoring and management practices. This will provide managers with efficient tools to prioritize options and defend their decisions.

The degradation of surface waters has spawned responses to remediate both point and nonpoint pollution [e.g., Clean Water Act of 1972 (CWA), Chesapeake Bay Agreement]. Through implementation of the CWA and derivative state laws, "fishable and swimmable" conditions have been restored in some areas. The original intent of the CWA "to restore and maintain the chemical, physical, and biological integrity of the Nation's waters" [CWA 1972, Sec. 101(a)] is increasingly addressed as the USEPA encourages states to unify all three categories equally under a watershed umbrella. Threats to life, both human and other, continue to be major issues of concern. In this project, we assumed that the ultimate endpoints of management are to protect, maintain, and enhance both biological integrity and human quality of life in the study area.

The ecological health of a watershed reflects attributes of the transmission, storage, and release of water. The influences of climate, soils, and topography, for example, drive the channel's hydrologic and fluvial geomorphologic processes (Leopold et al. 1964, Lotspeich 1980). These processes in turn affect water quality, flow regime, physical habitat, food and energy sources, and biotic interactions (Karr and Chu 1998), which collectively affect biotic communities. The contributions of each of these factors will likely vary among ecoregions. For example, in the Southwest, groundwater and riparian vegetation may play larger roles in determining watershed condition than in the Adirondacks. To classify watersheds, we must identify the relative contributions of each attribute to the scale of interest which in turn will help managers understand the costs and benefits of management options (Claessen et al. 1994, Bradshaw 1998, Hawkins et al. 2000).

Based on indicators of biotic integrity, many Highlands streams are in poor condition (USEPA 2000a). Both the abiotic (Poff and Ward 1990, Johnson et al. 1997) and biotic (Harding et al. 1998) conditions of an aquatic community are affected by historic and current characteristics of its basin. Within the Highlands, some of the main stressors to local streams are excess sediment, riparian degradation, mine drainage, acid deposition, excess nutrients, and exotic species (USEPA 2000a). Region-wide stressors include loss of riparian habitat, farming in riparian areas and on steep slopes, road crossings, and forest fragmentation (Jones et al. 1997). Most streams are degraded by more than one stressor (Karr 1981, Minshall et al. 1983).

In light of multiple stressors, classification tools are useful to managers. These tools can be geographically dependent or independent, hierarchical or non-hierarchical, incorporate a fixed or sliding scale, and based on structure or function (Detenbeck et al. 2000). Examples of hierarchical, geographically dependent classifications include ecoregions (Omernik 1987, Bryce and Clarke 1996), aquatic regions (Maxwell et al. 1995), and functional groupings (Hawkins et al. 2000). Maxwell et al. (1995) grouped watersheds by indicators of watershed function, including geoclimate, zoogeographic pattern, watershed morphology, and disturbance history. To reveal function in a geographically dependent scheme, The Nature Conservancy developed a nested framework for biotic and abiotic aquatic classification based on two landscape-level regions and two levels of smaller-scale habitat characterization (Lammert et al. 1997).

Geographically independent, hierarchical classifications rely on stream hydrogeomorphic (HGM) structure (Rosgen 1996) and wetland HGM function (Brinson 1993). Imnof et al. (1996) developed a scheme based on physical processes that drive fish abundance. Other examples classify watersheds based on water chemistry and/or temperature (e.g., Richards 1990, Seelbach et al. 1997, Momen and Zehr 1998), and hydrology and geomorphology and/or sediment size (e.g., Whiting and Bradley 1993, Seelbach et al. 1997).

Several *a posteriori* classifications attempt to assess relative risks. For example, one scheme generates a risk index for watersheds based on aerial photos, topographic maps, and rapid bioassessment (Bryce et al. 1999). Another approach maps predicted risk of drought damage due to changes in water withdrawal and soil and groundwater conditions (Claessen et al. 1994).

Ecosystems are also classified by measures of ecological resistance, or the ability of the system to withstand perturbation (Forman and Godron 1986). Resistance, and resilience, which is the ability of a system to return to its original state after a disturbance (Gunderson 2000), are the primary determinants of ecosystem stability. Aquatic systems are dynamic, but if resistance is overwhelmed by disturbance, then its average long-term state changes (Reeves et al. 1995). Poff and Ward (1990) suggested that because stream communities reflect the history of disturbance they are resistant. Others have suggested that resistance is enhanced by material retention (Minshall et al. 1983) or storage capacity (Detenbeck et al. 2000). With these concepts and previous findings in mind, we developed the following objectives for this study.

Objectives and Approach

To develop a standardized process for assessment and restoration, we proposed to:

- develop a geographically-independent classification system that links watershed characterization and prioritization,
- compile synoptic data for a set of relevant anthropogenic stressors for the region,
- use existing ecological data to validate our watershed classification system, and
- compare the rankings from our models to those of other classification approaches.

Our approach was to construct a Characterization Model to classify watersheds based on their inherent natural physical features (climate, soils, topography and hydrology), which eventually resulted in the delineation of nine distinct clusters of watersheds for the region. Also, we had envisioned building a Prioritization Model to classify watersheds according to disturbance (primarily expressed through land cover) and their susceptibility to impairment from a variety of stressors, including land use, acidification, impervious coverage, and nutrients. Based on our research products and conversations with potential users, we discovered that the best way to "prioritize" watersheds was to produce maps showing the geographic distribution of those clusters throughout the region. Using those maps, managers can recognize where and how their specific watersheds of concern fit into a larger landscape context. We produced narrative descriptions of the watershed clusters that relate their characteristics to their vulnerability of being impacted by a suite of stressors. We also produced a Watershed Characterization and Prioritization Tool that helps users locate graphically watersheds of interest and to obtain relevant characterization data and an initial assessment of vulnerability.

This approach is preferred to one of where researchers impose a prioritization scheme on potential users. For example, some managers and users operate at the scale of a single watershed of a single type (e.g., municipalities, watershed associations), whereas others are responsible for larger regions encompassing many watershed types (e.g., regional natural resource managers and biologists, state agencies). Given this disparity of scale, the concerns and questions about vulnerability and restoration will be vastly different. By producing a synoptic classification involving both inherent characteristics and responses to stressors, potential users can apply the results to their best advantage.

To validate our classification system, our intent was to use data on multiple biological taxa to provide a diverse assessment of condition for each watershed. This proved more challenging than initially planned due to the use of disparate methods of both data collection and for the development of indices, and the lack of consistent variables across the entire region. So, as a test of concept, we applied our models to the data from the West Virginia portion of the Mid-Atlantic Highlands (Fig. 1) using a recently developed biological index; however, the process is applicable elsewhere.

Study Area

The USEPA's Request for Application encouraged applicants to develop classifications of understudied areas or well-studied areas that demonstrate a "proof of concept." Opting for a well-studied region, the Mid-Atlantic Highlands Area (MAHA), we proposed to develop a geographically independent system with potentially wider applicability.

The Highlands includes parts of 6 ecoregions and 4 states (Fig. 1), including the state of West Virginia, and the mountainous portions of Virginia, Maryland, and Pennsylvania. Ecoregions have been used to define the study area in terms of natural potential and variability, and response to stressors (Bryce et al. 1999) and are useful in characterizing spatial patterns of water quality (Griffith et al. 1999, Omernik 1995). The Highlands region supports some of the largest tracts and best examples of the Eastern Broadleaf Forest (Riitters et al. 2000). Trees, songbirds, land snails, salamanders, and freshwater mussels are highly diverse (Terwilliger 1991, Ricketts et al. 1999). The Highlands also support many unique natural features, as well as national parks and national forests.

In addition, the Highlands are changing. Population growth threatens natural resources along interstate highways and around urban centers. Mountaintop mining fragments interior forest in

West Virginia and Virginia, and surface and deep mining have led to chronic acid mine drainage in some areas. Invasive species and tree pathogens threaten oaks, beech, hemlock, and pines. Acid deposition, low-level ozone, and toxic ion deposition are also local stressors. Environmental stressors also affect the Highlands' socio-economic health through flooding, unplanned growth, lost economic development opportunities, and loss of farmlands.

In the Mid-Atlantic Highlands, federal agencies such as the USEPA, Natural Resource Conservation Service, U.S. Geological Survey, U.S. Army Corps of Engineers, National Park Service, U.S. Fish and Wildlife Service, and others play regulatory, management, and funding roles that affect over 27 million people (USEPA 2000a). The Highlands' states also regulate, manage, and fund myriad watershed activities. Nearly 300 counties, thousands of local governments, and hundreds of citizens' watershed associations and related groups need a logical system to understand issues, establish ecological and human health goals, tailor management approaches, and target resources for protection and restoration.

The Mid-Atlantic region contains over 25,000 stream miles designated as impaired (USEPA 2000). As required by the Clean Water Act, over 4,000 TMDL restoration plans are needed. A classification system that groups watersheds with similar features and problems would provide a scientifically defensible scheme to develop "off-the-shelf" monitoring and management practices. These methods could then be deployed proactively, potentially improving a stream's condition before TMDL development. For streams that may not receive TMDL remediation due to fiscal constraints, the stream's class would point to best management practices.

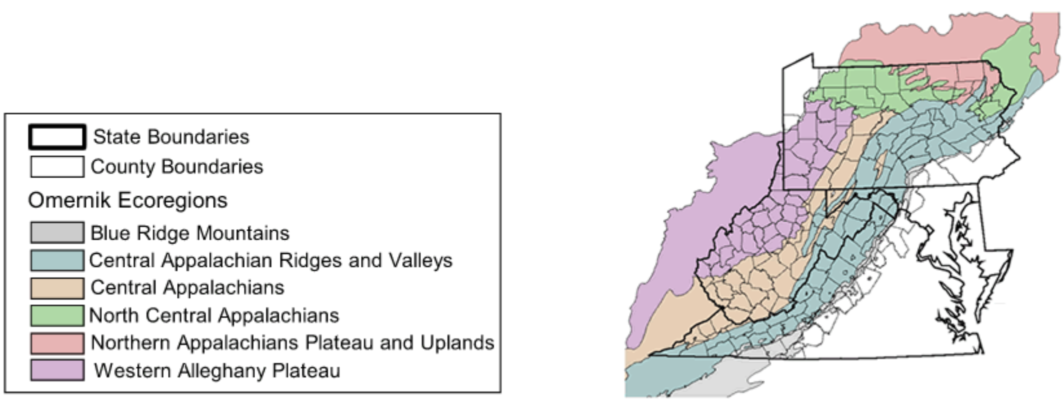


Figure 1a. The Mid-Atlantic Highlands study area includes the mountains and valleys of Pennsylvania, Virginia, Maryland, and West Virginia, plus areas of continuous watersheds.

The Highlands is a desirable region in which to develop watershed classification models because of its available landscape data and multiple, spatially explicit biological datasets. Potentially useful datasets are EMAP (USEPA 2000s) and landscape atlases (Jones et al. 1997), regional indicators of biological integrity (IBIs) such as the Bird Community Index (BCI) (O'Connell et al. 1998, 2000), an IBI for fish (McCormick et al. 2001), and other studies (Pan et al. 1999). Finally, the Mid-Atlantic Highlands Action Program (CVI 2002) has been formulated to encourage restoration activities in the region, including the development of technological and economic stimuli to promote a restoration industry. The availability of this type of tool should enhance the abilities of managers to address the many issues affecting aquatic resources in the region.

Our chosen scale of analysis for this study was that of a 14-digit Hydrologic Unit Code watershed, or "HUC-14" (Seaber et al. 1987). Prior studies and a review of the literature had indicated that this scale was the one at which management decisions are typically made (Brooks et al. 2006b). In the course of compiling a watershed GIS (Geographic Information Systems) layer for use in this project, we found that existing watershed delineations for each state varied widely in the average size of a given HUC unit. For example, watersheds in a HUC-14 delineation in Maryland averaged 3,155 hectares (ha), while in Virginia they averaged 21,749 ha; discontinuities across state boundaries presented additional challenges. We were concerned that computing watershed metrics on units of such disparate size would confound the results of our analyses. Therefore, we made the decision to generate "synthetic" watershed boundaries.

Watersheds were delineated with an automated ArcInfo AML program that used the National Elevation Dataset (USGS 1999a) and the National Hydrography Dataset (USGS 1999b) as inputs. The target size for watershed delineation was set at 17,000 acres, using stream intersections for defining watershed pour points. No watersheds were permitted to be smaller than 3,000 acres or exceed 50,000 acres. This program generated 2,830 watersheds with a mean size of 7,438 ha, a maximum size of 20,125 ha, and minimum size of 1,216 ha. Approximately half of the watersheds thus delineated were hydrologically self-contained (headwaters) while the other half import water from upstream watersheds ("pass-through" watersheds)(Figure 1b).

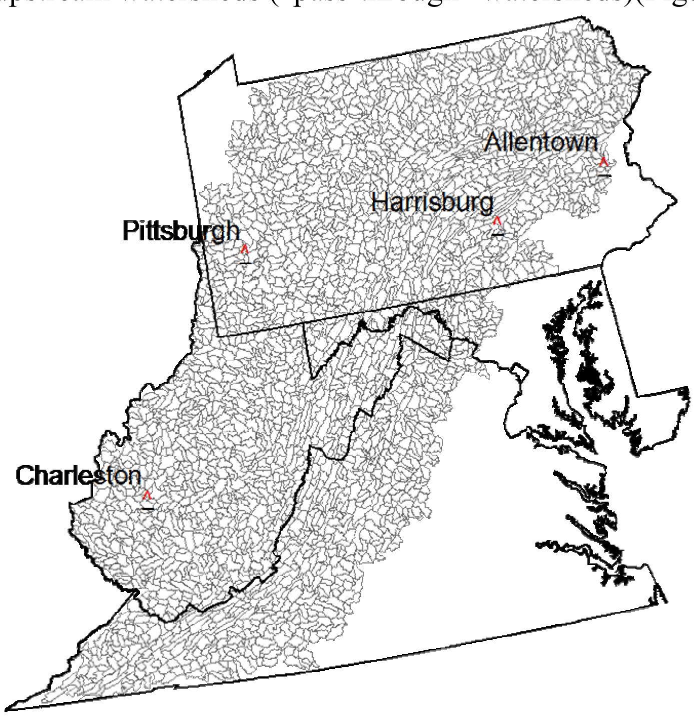


Figure 1b. The 2,830 watersheds we investigated for this study, delineated in grey.

CHARACTERIZATION BASED ON INHERENT ATTRIBUTES OF WATERSHEDS

Dataset Development and Exploratory Analyses

The project team used their combined expertise to develop an initial set of metrics based on expert judgment. These metrics were used to define "inherent" classes of watersheds - that is, watersheds that are expected to respond in a similar manner to anthropogenic stressors. Candidate metrics fell into four categories: landform, soils, climate, and hydrologic characteristics. The full set of potential metrics that was computed and considered is listed in Appendix A.

Cluster analysis (MINITAB 2000) was chosen as the statistical technique for stratifying watersheds into groups with similar characteristics. A detailed account of our clustering can be found in Myers et al. (2006 – see Appendix B, #7). Our initial analyses were conducted with the set of 1297 headwater watersheds alone on the premise that, since the source of water is fully contained within the watershed, the relationship between watershed characteristics and water quality should be more direct (Brooks et al. 2006a).

To prepare the data for cluster analysis we developed a set of "clean and screen" procedures (Myers et al. 2006). We eliminated outliers through examining the results of Principal Components Analysis (PCA) (MINITAB 2000). We also eliminated redundant variables in the dataset using guidance from the results of correlation analysis, parallel coordinate plots, and weighting coefficients for the principal component axes. We had three criteria for choosing among strongly related variables: (1) ease of interpretability, (2) inherent accuracy of the underlying information, and (3) computational tractability. Following the above clean and screen operations, 14 variables each were retained in the landform and soils datasets, 9 variables in the climatic set, and 11 variables in the hydrologic set. These variables are shown in Table 1.

We first performed cluster analyses using each variable set individually. The decision of how many cluster groups to recognize was made by examining both the dendrograms and cluster similarity values, to find the level at which the number of groups increased rapidly. We chose the number of groups just before the point of rapid increase, generally aiming for 5 to 10 groups. These groups were then mapped. We found that groups based on the soils and climate variables showed more highly regionalized spatial patterns than those based landform and hydrologic variables (see Figures 2a-d below).

Next, we explored different methods for combining the variable sets, including (1) simply combining all variable sets, and (2) joint classification of the landform and hydrologic variables, since these two sets of variables were the least regionalized, and had the potential of together providing information that would allow a finer delineation of the broader patterns defined by the climate and soils classifications.

Following the exploratory analyses using the group of headwater watersheds only, we turned to the group of "pass-through" watersheds to investigate their characteristics relative to the variable sets considered. We first conducted clustering using the set of

Table 1. Variables used with cluster analysis to define inherent watershed groups.

Data type	ID	Variable
Phys/topo	area	Watershed area
Phys/topo	elevmean	Mean elevation of watershed
Phys/topo	elevrange	Elevation range in watershed
Phys/topo	slopemean	Mean slope of watershed
Phys/topo	slopemax	Maximum slope in watershed
Phys/topo	mpar	Mean perimeter:area ratio
Phys/topo	mpfd	Mean patch fractal dimension
Phys/topo	ctimax	Maximum compound topographic index
Phys/topo	ctimin	Minimum compound topographic index
Phys/topo	curvemin	Minimum local curvature
Phys/topo	curvemax	Maximum local curvature
Phys/topo	curvemean	Mean local curvature
Phys/topo	flowmean	Mean flow accumulation
Phys/topo	mcnabmean	Mean of Mcnab topographic index
Soil	clay_dwa	Depth-weighted average % clay
Soil	silt_dwa	Depth-weighted average % silt
Soil	PH_dwa	Depth-weighted average pH
Soil	perm_dwa	Depth-weighted average permeability
Soil	awc_100aw	Area-weighted available water capacity
Soil	bd_dwa	Depth-weighted average bulk density
Soil	poros_dwa	Depth-weighted average porosity
Soil	kfacta	USLE erosion k-factor without rocks
Soil	kkfacta	USLE erosion k-factor with rocks
Soil	hsgaa	Area % in hydrologic soils group A
Soil	hsgba	Area % in hydrologic soils group B
Soil	hsgca	Area % in hydrologic soils group C
Soil	hsgda	Area % in hydrologic soils group D
Soil	hsgwa	Area % in hydrologic soils group W
Climate	annff	30-yr average annual frost-free period
Climate	anngdd	30-yr average growing degree days
Climate	jan_mar_pr	30-yr average Jan-Mar precipitation
Climate	apr_jun_pr	30-yr average Apr-Jun precipitation
Climate	jul_sep_pr	30-yr average Jul-Sep precipitation
Climate	oct_dec_pr	30-yr average Oct-Dec precipitation
Climate	tmax_jul	30-yr average max July temperature
Climate	tmin_jan	30-yr average min January temperature
Climate	annsnow	30-yr average annual snowfall
Hydro	sinuos_avg	Sinuosity
Hydro	chan_slp_avg	Mean channel slope
Hydro	sd_ch_slp	Standard deviation of channel slope
Hydro	node_dens	Density of stream network nodes
Hydro	strm1_pct	Stream length % first-order
Hydro	strm2_pct	Stream length % second-order
Hydro	strmlen_tot	Total stream length
Hydro	strmdens_tot	Total stream density
Hydro	strmdns1	Density of first-order streams
Hydro	strmdns2	Density of second-order streams
Hydro	seg_len_avg	Average stream segment length

mainstem" hydrologic variables that were relevant only to this group of watersheds. Our "clean and screen" procedures, described above, were applied to this variable set prior to clustering. The general spatial pattern of the clustering was fine-grained and not highly regionalized, similar to that seen for the headwater watershed group. One interesting pattern observed with the mainstem group of variables was the presence of a cluster group that appeared to represent large river watersheds.

Since, ultimately, we wanted a classification that included all watersheds in the study area, our next step was to re-combine the headwater and pass-through watershed groups. Furthermore, we also saw no compelling differences between the two subsets of watersheds in their classification, based on the analytical techniques and set of variables used in this study. (This is not to imply that these two types of watershed lack differences, but rather that these differences were not highlighted by the methods used in this study.)

Development of Candidate Classifications

Based on our previous results we conducted the clustering in several different ways: (1) separate clusterings for each variable set, (2) separate clusterings for different pairs of variable sets, including the regional variables (soils and climate), the more localized variables (physical and hydrologic), and the soils and physical variables, and (3) with all variable sets combined. (The hydrologic variables used in these analyses were those that were common to both headwater and pass-through watersheds – i.e., the set of "tributary" variables.) The results of these cluster analyses are shown in Figures 2a – h and Figure 3.

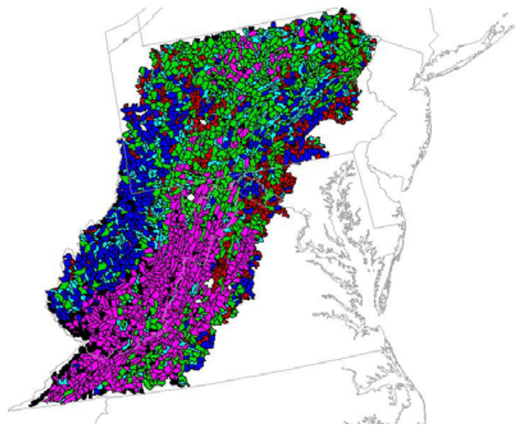
We made the assumption that the cluster groupings with all variables sets considered would yield the best representation of watershed vulnerability to stress. We describe a test of this hypothesis in the Vulnerability section of this report. Ultimately, we chose the nine-cluster version ("AllMet9") to carry forward in our analyses.

Naming of the Nine Clusters

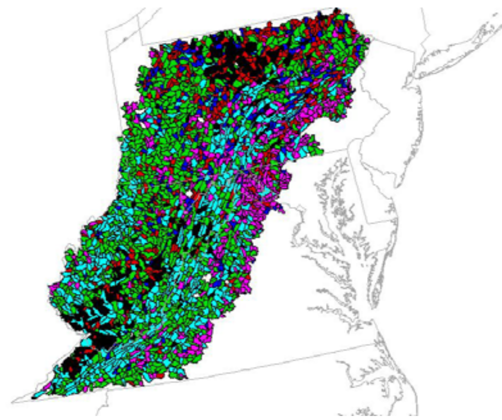
Once watersheds were classified into groups and mapped, descriptive names were assigned to each group (Table 2). Although the groups were delineated based on 48 variables, a smaller subset of variables was chosen to name the groups. The variables chosen are common watershed descriptors that can be related to land use and vulnerability of watersheds, including temperature, precipitation, soil infiltration, soil erosion, soil texture, soil pH, elevation, slope, and stream density. Additionally, the location of each group of watersheds within the Mid-Atlantic Highlands and the geologic processes that contributed to the formation of each group was also considered in the naming process (e.g., Dry Glaciated Northeast).

In order to identify which of the previously listed variables differentiated one group from another group, box plots summarizing each variable by cluster were analyzed and named/described accordingly. For example in Figure 4, class numbers 1, 2, and 9 appear to have lower temperatures and class number 6 appears to have higher temperatures compared to the other classes. These low temperatures for classes 1, 2, and 9 and high temperatures for class 6 are reflected in their names and/or descriptions (Table 2). A detailed description of each watershed class is presented later in this report.

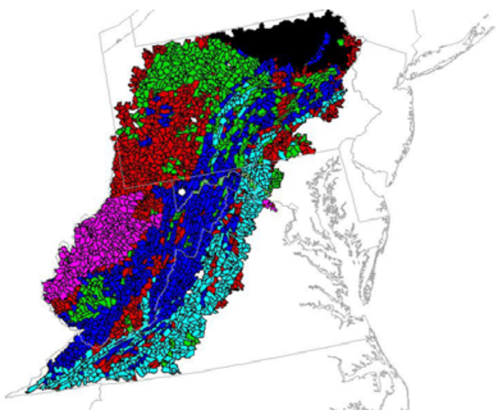
Figures 2a-h. Alternative watershed classifications for the Mid-Atlantic Highlands Area. Labels refer to the types of variables included in the cluster analysis.



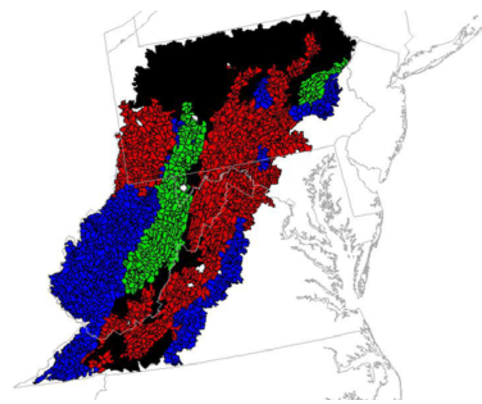
2a - Physical/ topographic variables.



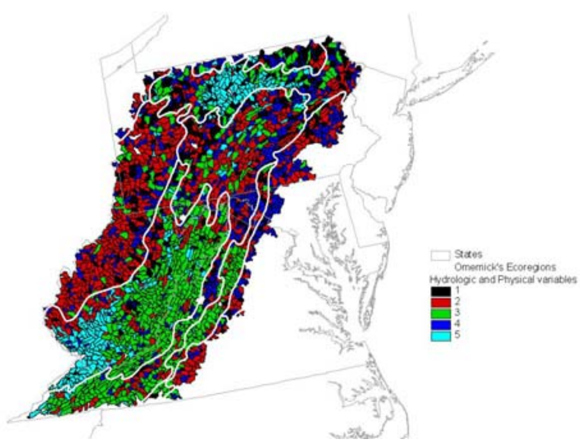
2b - Hydrologic variables.



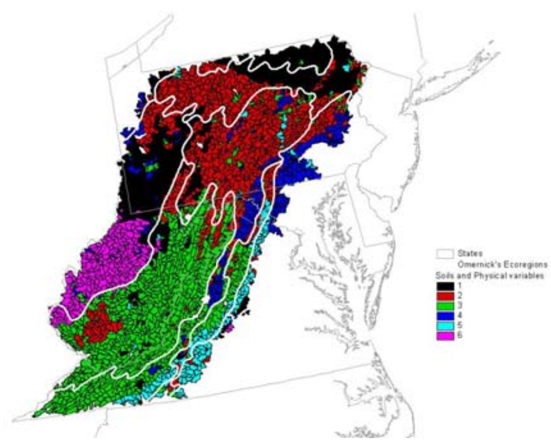
2c - Soils variables.



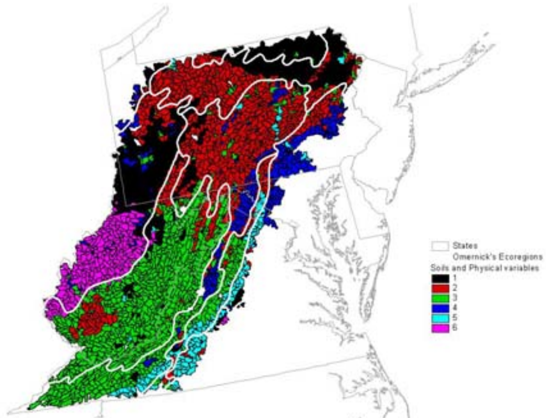
2d - Climate variables.



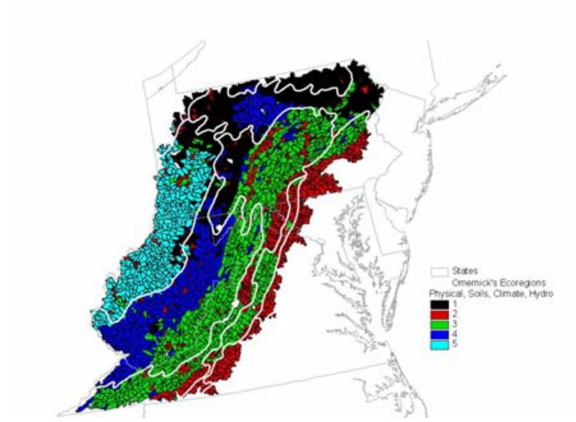
2e - Physical/ topo and hydrologic variables.



2f - Climate and soils variables.



2g - Physical/ topo and soils variables.



2h - Physical/ topo, soils, climate, and hydrol. variables: 5 clusters

Figure 3. Watershed classification using all variable sets (physical/ topographic, soils, climate, and hydrologic), with 9 clusters defined (= "All Met9"). This, ultimately, was selected as the classification that best captured patterns of vulnerability in the Mid-Atlantic Highlands Area. The associated dendrogram is also shown.