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APPENDIX D

**METHODS AND RESULTS DETAILS FOR CASE STUDY 2: BIOLOGICAL
ASSESSMENT IN THE PRESENCE OF CLIMATE CHANGE**

D.1. DETAILED METHODS FOR CASE STUDY 2

D.1.1 Analysis Approach

The objective of this case study is to examine the potential vulnerability of biomonitoring programs and assessment methods to biological changes that result from climate change. The vulnerabilities we examine include 1) detection of reduced biological condition, and 2) the ability to assign cause to impaired condition. The case study uses existing data, and by examining the associations of biological attributes with proxy attributes of climate change, we evaluate the potential effects and vulnerabilities of aquatic biomonitoring programs to climate change.

This case study addresses the following questions:

- How do we detect impairment under climate change?
- How does climate change affect our ability to identify causes of biological impairment?
- Are there analytical or monitoring design approaches that will allow managers to effectively identify and manage stressors independently of climate change?

D.1.1.1. What is the sensitivity of stream systems to climate change?

Detectable biological responses to climate change effects in streams that are important in a bioassessment framework include the following:

- Southern taxa expanding their range northward.
- Habitat change from increased winter/spring scour.
- Loss of taxa sensitive to summer drought periods or higher temperatures (including higher water temperature associated with drought).
- Improved conditions for invasive species, including disturbance regimes favoring invasive species and warmer water temperatures allowing overwintering.
- Change in number of reproductive periods leading to changes in timing of peak abundance (possibly also tied to changes in phenology).

In addition to the direct effects of temperature change, streams are also subject to hydrologic changes from changed precipitation patterns and increased evapotranspiration (e.g.,

1 Moore et al. 1997). Extreme stream flows reshape the stream habitat, and summer low-flow
2 events represent bottlenecks of both warm temperature and reduced habitat (Moore et al. 1997).
3 We focus this analysis on changes that may occur in the Mid-Atlantic region, but results may be
4 generalized to similar changes occurring in other regions.

5 We examined biological responses of streams to various stressors, but with particular
6 emphasis on hydrologic parameters that may be influenced by climate change, and by
7 partitioning the data into subsets defined by wet and dry periods. After partitioning by climate
8 (normal, wet, dry), we examined biological indicators of reference and impaired sites, and we
9 examined several stressor-response relationships under the different climatic conditions.
10 Although we cannot project changes, we can estimate minimum and maximum changes.

11 *D.1.1.2. Datasets Evaluated*

12 The Maryland Biological Stream Survey (MBSS) dataset was used in this case study;
13 MBSS program approach and sampling methods are described in Appendix B.

14 *D.1.1.2.1. Metrics*

15 The Maryland 305(b) evaluation of the status of waters of the State, which uses the
16 MBSS data in addition to other data sources, uses benthic and fish Indices of Biotic Integrity
17 (IBIs) to determine impairment status and attainment of uses (Maryland Department of the
18 Environment, 2004; Appendix C [http://www.mde.state.md.us/assets/document/AppndxC2004-
19 303d_Final.pdf](http://www.mde.state.md.us/assets/document/AppndxC2004-303d_Final.pdf)). For a single stream reach assessment, Maryland takes into account population-
20 wide measurement error (for details see Appendix C, Maryland 303(d) report). The approximate
21 result is that if both indexes are ≥ 3.3 , the stream segment is considered unimpaired, and if either
22 index is ≤ 2.7 , the segment is impaired. Intermediate values are considered to be potentially
23 impaired but are still listed as supporting aquatic life uses.

24 Several invertebrate metrics were calculated in the Ecological Data Application System
25 (EDAS) database for the 1320 randomly located benthic samples that were collected over the 10
26 year period (1994-2004) and analyzed as response variables. These included total taxa (taxa
27 richness), number of taxa in the insect families of mayflies (Ephemeroptera), stoneflies
28 (Plecoptera) and caddisflies (Trichoptera) (“EPT taxa”), and the Maryland benthic index of
29 biotic integrity (IBI; 2005 version). For fish, response variables examined include the Maryland
30 fish IBI, total number (abundance) of fish, and number of species of fish (taxa richness).

1 *D.1.1.2.2. Data Partitions*

2 The MBSS data were partitioned based on Maryland’s classification into four ecoregions
3 (coastal plain, Eastern Piedmont, Cold Water Highlands, and Warm Water Highlands; Figure
4 D.1), to account for known sources of natural variation in both habitat (physical and chemical)
5 and biological data. The Eastern Piedmont region has been heavily developed, and the high level
6 of urbanization represents an existing source of impairment which we targeted for evaluation in
7 this case study. By the same token, the Eastern Piedmont has relatively few reference areas. In
8 the original MBSS index development, the Piedmont and Highlands were deemed to be
9 biologically similar (Roth et al., 1998; Stribling et al., 1998). Sampling of more reference sites
10 showed that the Piedmont can be separated from the highlands (Southerland et al., 2005). In
11 order to have sufficient reference locations to support our analyses, we reverted to the original
12 classification and recombined the Piedmont and Highlands sites for those analyses requiring
13 identified reference sites.

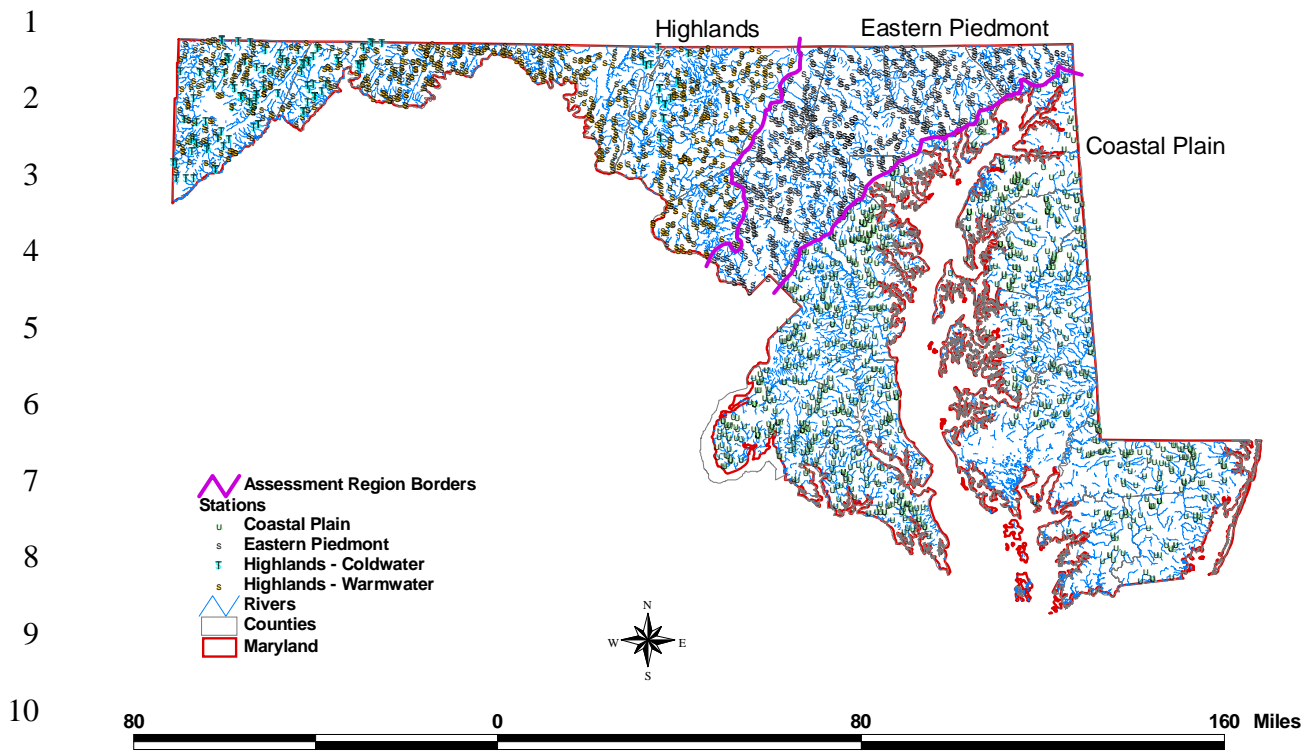


Figure D.1 – Maryland MBSS sampling stations showing regional divisions

D.1.1.2.3. Climate Data

The National Climatic Data Center (NCDC; www.ncdc.noaa.gov) makes available several average monthly parameters, organized by state climatic regions. Although we do not expect climate to follow state boundaries, it was convenient in this case because our biological data did follow the state boundaries. We used data from two NCDC regions of Maryland: the Northern Central Division (primarily Northern Piedmont ecoregion, and the Blue Ridge ecoregion within Maryland), and the Appalachian Mountain Division (Central Appalachian Ridge and Valley ecoregion). Maryland’s Piedmont and warm-water mountain streams occur primarily in these two climatic divisions. The Northern Central Division data were applied to the Eastern Piedmont streams, and the Appalachian Division data to Highlands streams.

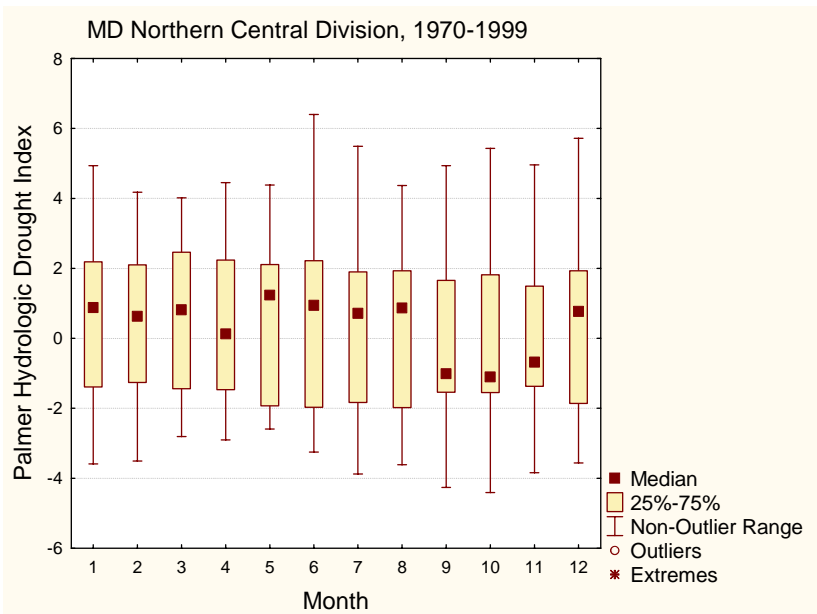
We estimated potential hydrologic effects of climate change by using the Palmer hydrologic drought index as a proxy for estimates of hydrologic changes as a result of climate change. The Palmer Hydrological Drought Index (PHDI) is a monthly hydrological drought

1 index used to assess long-term moisture supply to water bodies (Karl, 1986). The Palmer
2 Hydrological Drought Index (PHDI) is described by NCDC as:

3 “...the monthly value (index) that indicates the severity of a wet or dry spell. This index is based on the
4 principles of a balance between moisture supply and demand. Man-made changes such as increased
5 irrigation, new reservoirs, and added industrial water use were not included in the computation of this
6 index. The index generally ranges from - 6 to +6, with negative values denoting dry spells, and positive
7 values indicating wet spells. There are a few values in the magnitude of +7 or -7. PHDI values 0 to -0.5 =
8 normal; -0.5 to -1.0 = incipient drought; -1.0 to -2.0 = mild drought; -2.0 to -3.0 = moderate drought; -3.0
9 to -4.0 = severe drought; and greater than -4.0 = extreme drought. Similar adjectives are attached to
10 positive values of wet spells. This is a hydrological drought index used to assess long-term moisture
11 supply.” (<http://www.ncdc.noaa.gov/oa/climate/onlineprod/drought/readme.html>)

12 The PHDI takes into account water storage as soil and groundwater, and therefore is
13 more applicable to streamflow than the Palmer drought severity index, which uses only
14 temperature and rainfall information (Karl, 1986). The 30-year distribution of the PHDI for the
15 Maryland Northern Central Division, which includes the Piedmont, is shown in Figure D.2. The
16 range of the PHDI varies little from month to month, but the 30-year median value is positive
17 during the spring macroinvertebrate sampling index period (> 0 in March-April), and markedly
18 lower in late summer-early fall fish sampling index period (< -1 in September-October).

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21 **Figure D.2. Monthly Palmer HDI for the 30 year period 1970-1999 (Data source: NCDC;**
22 **<http://www.ncdc.noaa.gov>).**

1 *D.1.1.2.4. Hydrologic Attributes*

2 We estimated Baker’s flashiness index (Baker et al., 2004) for each stream. Flashiness is
3 a component of the hydrologic regime of streams, and in general is related to the frequency of
4 short-term changes in runoff associated with rainfall events, and how rapidly each event comes
5 and goes. Flashiness is generally considered to increase with increases in impervious cover
6 associated with urbanization and/or with land clearing for agriculture. It is both responsive to
7 urbanization as an existing stressor, and also is expected to change in the future in response to
8 climate change projections of increased frequency and intensity of storms within many regions
9 of the United States. Baker’s index is calculated as the average of absolute values of daily mean
10 flow change divided by mean flow for the 2-day period. The maximum range is from 0
11 (absolutely constant flow) to 2 (alternating days of flow and no flow).

12 Daily flows were simulated for each site using the Flow Time Series Estimation tool
13 (FTSE; Tetra Tech, 2005). The model estimates daily flows for ungauged streams, based on
14 multiple regressions using a smaller set of gauged streams. The main criterion for proper
15 functioning of the model is that there must be gauged stations relatively near to the ungauged
16 streams (e.g., within the same ecoregion) so that a standard is available for calibrating the model.
17 Estimates had been developed for a set of 764 streams in the Piedmont only (Barbour et al.,
18 2006); no set of appropriate gauged streams was available for the Appalachians.

19 **D.1.2. Specific Analyses**

20 *D.1.2.1. Sensitivity of the System to Climate Change*

21 As discussed earlier, the primary hydrologic stressors associated with climate change are
22 changes in precipitation patterns combined with changes in temperature regime, which will drive
23 changes in hydrologic regime. The projected extent of changes in temperature and precipitation
24 varies regionally in the United States; therefore, so too will changes in the magnitude, frequency,
25 flashiness, and other patterns of runoff. The National Assessment of climate change in the
26 United States provides regional summaries of projected changes in the temperature and
27 precipitation regimes of the major regions of the US (NAST, 2001). Table D.1 summarizes these
28 projections by region.

29

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1 **Table D.1 – Summary of regional climate projections from NAST, 2001**
 2 **Averages and/or ranges for Hadley (H) and Canadian (C) model projections to 2100 compared to 1961-90.**

		Northeast ¹	Southeast ²	Midwest ³	Great Plains ⁴	West ⁵	Pacific Northwest ⁶
Temperature	ave annual	5-9 °F (2.6-5 °C) increase	4.1-10 °F (2.3-5.5 °C) increase	5-10 °F (2-6 °C) increase (mins increase more than max)	Increase >5 °F (3 °C) (both models)	8-11 °F (4.5-6 °C) increase	5 °F (3 °C) increase by 2050
	winter min	7 to 4-12 °F (4 to 2-7 °C)			9-14 °F (5-7 °C) (winter ave)	8.8-12.8 °F (4.9-7.1 °C) (winter ave)	8.5-10.6 °F (4.7-5.9 °C) (winter ave)
	winter max	3-5 to 5-12 °F					
	summer min	5 °F (3 °C)			7-9 °F (4-5 °C) (summer ave)	7.7-8.3 °F (4.3-4.6 °C) (summer ave)	7.3-8.3 °F (4.1-4.6 °C) (summer ave)
	summer max	2-3 to 7-11 °F (1.3 to 4-6 °C)					
Precipitation	ave annual	small increase to 5-10% decrease (C) ; up to 25% increase (H).	10% decrease (C) to 20% increase (H)	Increase 20-40% by 2100 in upper Midwest, decrease up to 20% Ohio Valley (C) ; ave precip increases everywhere, up to 20-40% (H).	13% increase (both models)	Double winter precip in CA, decrease in parts of Rockies (both models); summer precip no change (C) to decrease (H).	Increase of a few to 20% (ave 10%) (H); increase 0-50% (ave 30%) (C)
	extreme events	small increase in count and strength of storms (H); decrease in count for most of region except mid-Atlantic (C)		Increase in mean associated with increase in frequency and intensity of heavy events	Likely increase, esp. in southern GPs.	More extreme wet and dry years (both models).	winters wetter and warmer, increase in precip in heavy storms.
Droughts		less (H) to more (C) drought	slightly drier (C) to more precip in long term (H)	Small increase in soil moisture (H); small decrease (C).	Decrease in soil moisture in large part of region.		
Runoff	magnitude	northern areas under higher emissions). Lowest weekly flow projected to decrease ~10% by 2100. For a 2.5 °C increase in ave temp and 17.5% (17.5 cm) increase in precipitation, flow at the mouth of the Susquehanna will increase 24% ± 13% (11.8 ± 6.7 cm) (Najjar, 1999). Neff et al. (2000) projects decrease of 4% to increase of 24%. Moore et al (1997) estimates decrease of 21-31% by 2100.		overall decrease in river levels (i.e., decrease in runoff?)	Great Lakes area runoff decrease up to 32% (Magnuson et al. 2001).	Summer runoff less by 20% of annual total (Knowles and Cayan 2002)	
	timing	Peak (spring) flows advancing 10 to >14 days by 2100. Low summer flows extended almost 1-month under higher emissions.					

1 –Barron et al, 2001. NAST.
 2 - Burkett et al., 2001. NAST.
 3 – Easterling and Karl, 2001. NAST.
 4 – Joyce et al., 2001. NAST.
 5 – Smith et al., 2001. NAST.
 6 – Parson et al., 2001. NAST.

3

1 *D.1.2.2. Components of the System that are Vulnerable to Climate Change*

2 We established the ranges and variability of system response variables to climate change,
3 and described the response signatures to stressors.

4 *D.1.2.2.1. Stress-Response*

5 Due to the large number of parameters available in the MBSS database, correlation
6 analyses were used to identify stressor variables that were most strongly related to response
7 variables. Spearman Correlation coefficients were used for this analysis; as a non-parametric
8 test, there is no need to make assumptions about or test for normal distributions for each variable.
9 Graphs of key variables were used to illustrate the relationships defined by correlation analysis,
10 and to confirm that all relationships reflected consistent data with no errors or false trends
11 introduced by data entry errors, reporting unit errors, or other inconsistencies. The subset of
12 parameters showing the strongest relationships are used for further exploration of stressor-
13 response models.

14 We used a conditional probability approach (Paul and MacDonald, 2005) to examine
15 changes in the biological community along stressor gradients. A conditional probability
16 statement provides the likelihood (probability) of a predefined response, if the value of a
17 pollutant stressor (condition) is exceeded. Conditional probability is the probability of an event
18 when it is known that some other event has occurred. To estimate conditional probability of
19 impairment, we first define impairment as a specific value for a response variable (e.g., EPT < 11
20 genera). The analysis asks the question: for a given threshold of a stressor, what is the
21 cumulative probability of impairment? For example, if total phosphorous concentration is
22 greater than 0.2 mg/L, what is the probability of biological impairment for each site under
23 consideration? All observed stressor values (in this example, all observed values of total
24 phosphorous) are used to develop a curve of conditional probability (Paul and MacDonald,
25 2005).

26 *D.1.2.2.2. Effects of Climate Change*

27 We used proxy estimates of climate (in the existing data) that are representative of
28 projected climate change, and examined the ability to detect biological impairment and stressor-
29 response relationships. Our proxies of climate change were the estimates of wetter-than-normal
30 and drier-than-normal conditions in the PHDI for each sampling event. The MBSS data were
31 post-stratified into dry, normal, and wet conditions based on the index, and ability to detect

1 impairment and selected stressor-response relationships were reexamined under the wet and dry
2 scenarios.

3 This analysis assumes that future biological responses to altered hydrological conditions
4 will be similar to responses to current natural variability, and that future hydrologic changes will
5 be comparable to extremes observed in the past 10 years. The assumptions are probably
6 reasonable in the near-term (i.e., 50 years), but become less reasonable farther into the future.

D.2. RESULTS

D.2.1. Observed Responses

Establishing definitive stressor-response relationships is a critical step in the Stressor Identification process, and is fundamental to identifying probable causes of impairment (see Section 1.3.2). Appendix E summarizes the data examined, and associations between a variety of stressor and response variables from the MBSS data set. Numerous relationships were examined; only a subset of results that show some correlation and/or those that were considered potentially important but showed no significant relationship are presented in Appendix E.

Rather than examining all possible biological indicators, we selected 2 fish indicators and 2 benthic macroinvertebrate indicators: the Maryland Fish IBI score, and fish taxon richness; and the Maryland Benthic IBI score (B-IBI), and mayfly-stonefly-caddisfly (EPT) taxon richness. The selected indicators are all responsive general indicators of stress, but are not diagnostic of any particular stressor.

D.2.1.1. Physical habitat

Both fish and benthic macroinvertebrate measures were correlated with overall physical habitat, as measured by the Maryland Physical Habitat Index (Paul et al., 2002) (Figures A-2, A-5, A7). Fish taxa richness was not correlated with the habitat index, but the fish IBI and both invertebrate indicators were strongly correlated, increasing with improved habitat score. Among habitat components, the EPT taxa were also positively correlated with the embeddedness score, reflecting a component of habitat (interstitial spaces in cobble substrate) utilized by these organisms. Fish taxa richness was also very strongly correlated with total flow, but this was a reflection of the effect of stream size.

D.2.1.2. Hydrology

Both the fish and the benthic macroinvertebrate indicators were negatively associated with Baker's flashiness index (Figures A-3, A-6, A-7). Below a flashiness index value of 0.5, biological indicator values could be in the normal range, but above a flashiness of 0.6, most biological values indicated impairment. Flashiness is affected by impervious surface, which in the study area, indicates urban land use. The macroinvertebrate indicators declined with impervious surface in a catchment, but the fish indicators did not (Figures A-3 through A-6).

1 *D.2.1.3. Water Quality*

2 The invertebrate indicator EPT was associated with dissolved organic carbon (DOC),
3 total phosphorus (TP), and conductivity, with the number of EPT taxa declining with increases of
4 all three stressors. The strongest association was with conductivity. No other chemical water
5 quality measures were associated with either fish or benthos (dissolved oxygen (DO) was
6 uniformly moderate to high in the dataset, and there were too few observation of low DO to
7 show any relationship).

8 *D.2.1.4. Temperature*

9 We examined the associations of both the fish and benthic macroinvertebrate
10 communities to water temperature. Fish observations in the data set had already been classified
11 according to expected warm-water and cold-water communities, using current and likely
12 sustainable distributions of brook trout to define cold-water streams in the region west of Evitts
13 Creek in western Maryland (Southerland et al., 2005). It is important to note that temperature
14 was measured in late summer and fall, at the same time that the fish assemblage was sampled.
15 Macroinvertebrates were sampled in spring, and temperature was not measured at that time.

16 Fish taxa richness increased with temperature in warm-water streams in both the
17 Piedmont and in the Appalachians (Figures 3-2, 3-3), but there was no detectable relationship in
18 the cold-water streams. There was no detectable relationship between temperature and benthic
19 macroinvertebrates in Piedmont streams (Figure D.3a), but in the Appalachian streams, EPT and
20 total taxa richness (measured in early spring) were reduced in streams where late summer
21 temperatures exceeded 18-20° C (Figure D.5).

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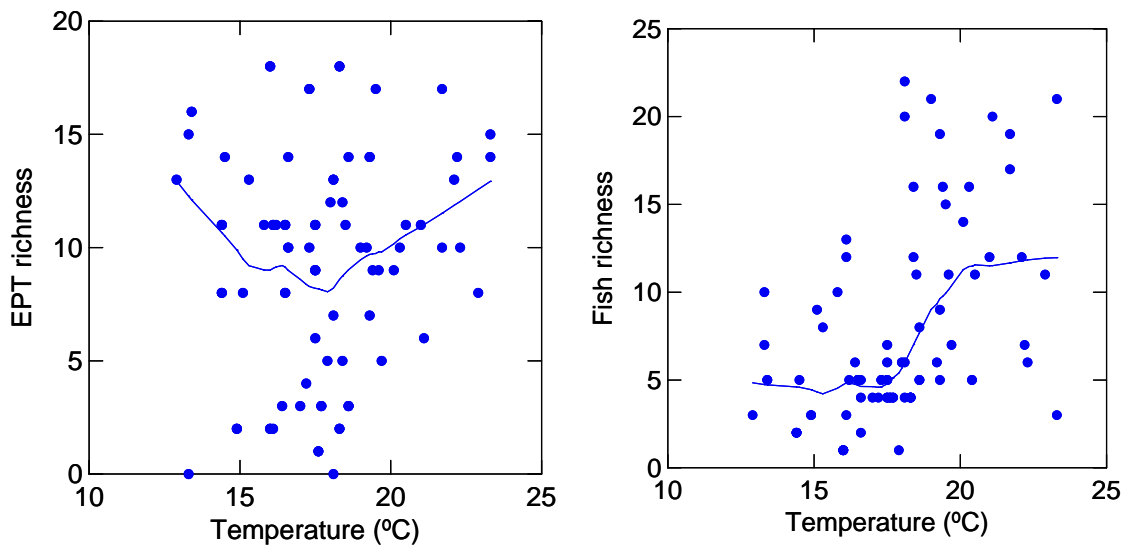


Figure D.D.3 – a). EPT vs. temperature relation; and b) fish richness vs. temperature relation in reference sites in Piedmont streams. Lines are LOWESS estimates.

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2 **D.2.2. Estimates of Climate Change Effects**

3 *D.2.2.1. Temperature*

4 Increase in average regional temperature may have the result that some fraction of cold-
5 or cool-water streams change to warm-water conditions and biota. Global average air
6 temperatures are expected to increase by at least 2 °C by 2100 (likely range 2 °C to 4.5 °C, likely
7 average 3 °C; Alley et al, 2007). On the average, summertime air temperature increases are
8 projected to be less than wintertime increases (MacCracken et al., 2001), and the late-summer
9 stream water temperature increase is expected to be less than the average increase (Mohseni et
10 al., 2003). Based on current observations of fish and invertebrate taxa in Mid-Atlantic streams
11 (Figures 3-3–3-5), we may expect a net increase in site-specific fish richness, as individual
12 streams change from cold- or cool-water conditions to warm-water. Fish taxon richness is higher
13 in warm-water habitats (Wehrly et al., 2003). Warm-water conditions are associated with
14 reduced invertebrate taxa richness in Highland streams, but not in Piedmont streams (Figure
15 D.4). Accordingly, invertebrate taxa per site may decrease in Appalachian streams that exceed
16 18 °C, but with no change in streams that remain well below 18 °C in late summer.

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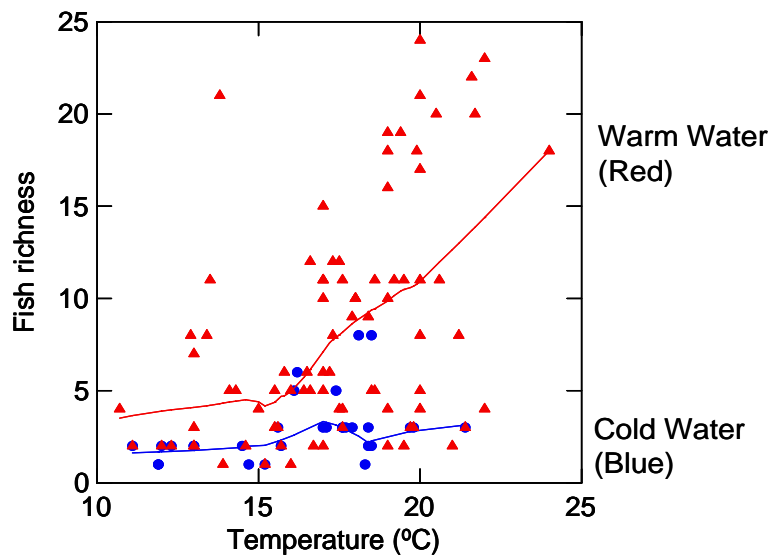


Figure D.4 – Fish richness vs. temperature in Highland reference streams. Lines are LOWESS estimates.

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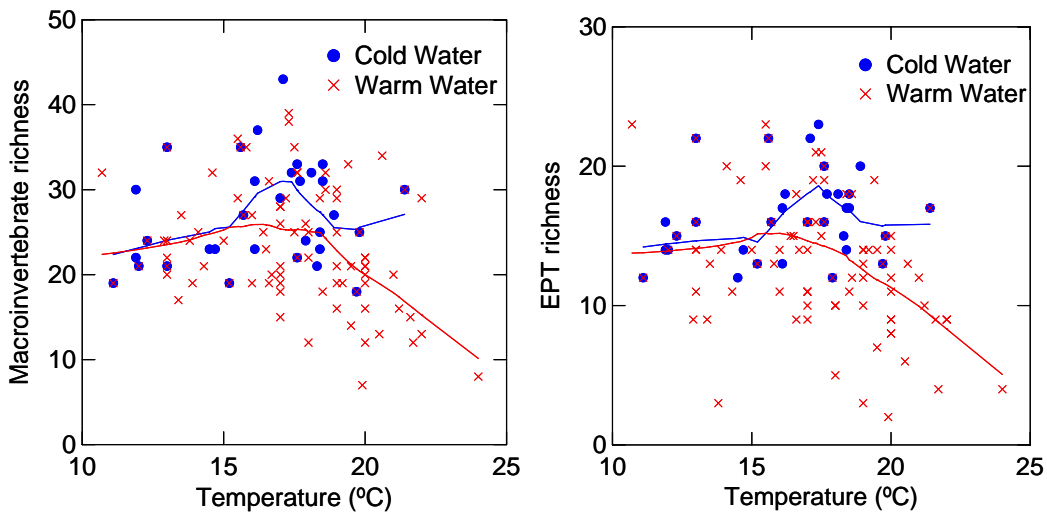


Figure D.5 – a) Macroinvertebrate richness vs. temperature; and b) EPT richness vs. temperature in Highland reference streams. Lines are LOWESS estimates.

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11 *D.2.2.2. Hydrology*

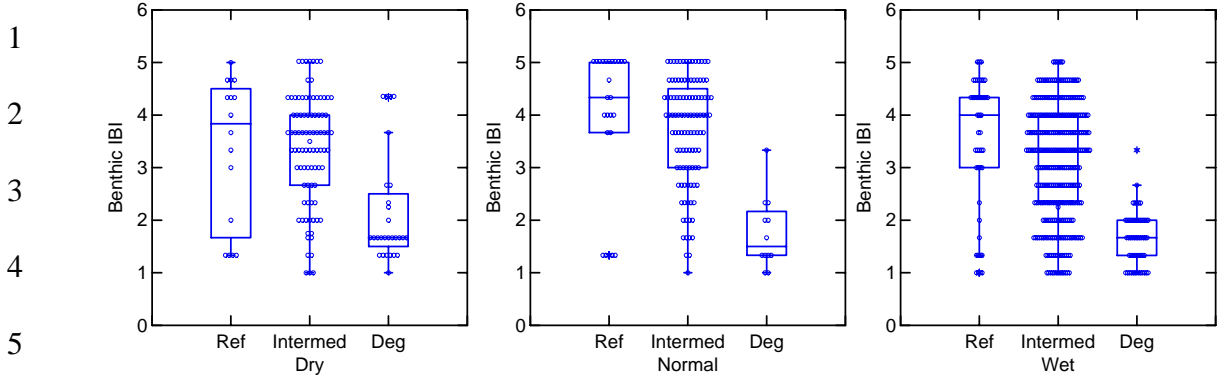
12 A variety of running averages for the Palmer hydrologic drought index (PHDI) were also
 13 calculated. Along with monthly PHDI, other parameters were also calculated, including the
 14 previous 6-month average, the previous 12-month average, and the previous summer PHDI, to
 15 account generally for possible lags in effects, and specifically for the time lag between when
 16 droughts occur and directly impact the biota (summer/early fall) and when the benthic
 17

1 community is sampled (the spring index period). We classified sampling sites into three groups:
2 reference (Maryland reference sites for the Eastern Piedmont and for warm-water mountain sites,
3 which were primarily in the Ridge and Valley ecoregion), impaired sites (Maryland impaired
4 sites and sites with 10% or more impervious surface), and intermediate sites (anything not
5 included in the impaired or reference groups). We evaluated two metrics: EPT taxa richness and
6 the benthic IBI.

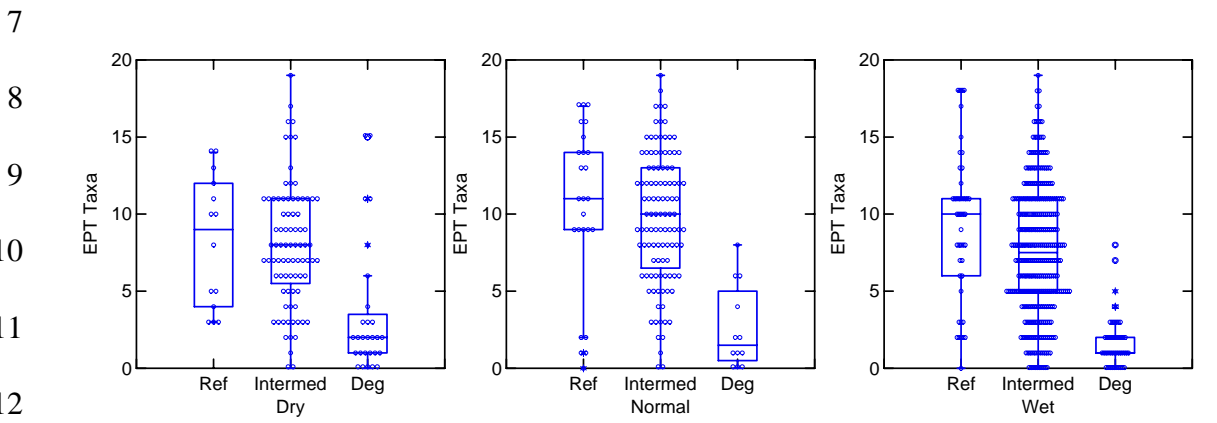
7 To examine the potential effects of changed rainfall and evapotranspiration patterns, we
8 divided the existing data into 3 groups: samples taken in relatively dry conditions; samples taken
9 in approximately normal conditions, and samples taken in relatively wet conditions. “Dry”,
10 “Normal” and “Wet” were defined according to the distribution of the PHDI in the data set, thus,
11 we used the range of conditions from the recent past (from the month of sampling to the
12 preceding year) to obtain some insight into consequences of climate change. The range of PHDI
13 was from -4.24 to +4.75, with a median of +1.8. Although the total range was symmetrical from
14 extreme drought (<-4) to extreme wetness ($> +4$), there were more wet months than dry months
15 in the 10 year period. We defined 3 climatic groupings: Dry: $\text{PHDI} < -2.5$ ($N=264$); Normal: $-$
16 $1.1 < \text{PHDI} < 1$ ($N=176$); and Wet: $\text{PHDI} > 3.5$ ($N=353$). These groupings were selected to get
17 substantial differences between wet and dry conditions, i.e., to eliminate confounding effects of
18 “moderately dry” and “moderately wet” conditions, and yet have sufficient sample size in each
19 of the hydrologic groups.

20 Figure D.6 shows the Benthic IBI (B-IBI) scores of the 3 stream classes under the 3
21 climatic conditions. Dry conditions are associated with greater variability of reference sites, and
22 a net degradation of median B-IBI score in both reference and intermediate sites. Wet conditions
23 are similarly associated with increased variability and a net decline in median B-IBI score, but
24 less so than in dry conditions. The EPT taxa metric showed the same overall pattern (Figure
25 D.7): a slight net loss of median number of taxa in reference and intermediate sites, and
26 increased variability in reference sites. The macroinvertebrate communities at degraded sites
27 were low in EPT taxa and IBI scores, so changes of hydrological condition did not affect them
28 much. The Fish IBI was also similar (Figure D.8), but showed slightly greater effects under wet
29 conditions than did macroinvertebrates: larger decline in median reference score, and larger
30 reference variability.

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6 **Figure D.6 – Benthic IBI performance and climatic condition.**



13 **Figure D.7 – EPT performance and climatic condition.**

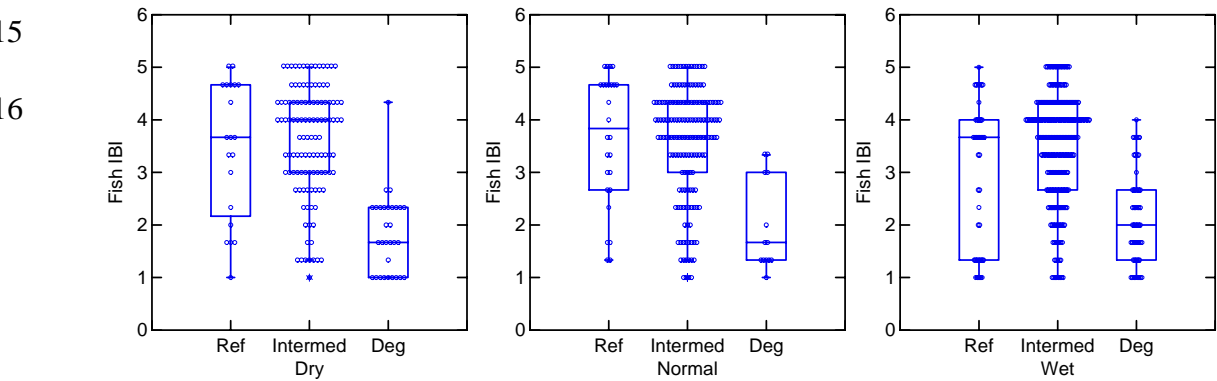


Figure D.8 – Fish IBI performance in three climatic conditions. The dry, normal and wet designations under each of the three graphs refers to categorizations based on the PHDI.

1 A quantitative measure of the efficacy of an index in discriminating between reference
 2 and stressed sites is the Discrimination Efficiency (DE), calculated as the percent of stressed
 3 sites with scores less than the 25th percentile of the reference sites (Barbour et al., 1999). DE is
 4 influenced both by the absolute difference between the reference and stressed site mean scores,
 5 and the variability or spread of the scores. DEs under the scenarios described above are given in
 6 Table D.2. From this analysis, it appears that increased drought degrades reference sites enough
 7 to reduce the ability to discriminate impaired from reference conditions for both the benthic IBI
 8 and EPT taxa richness. Interestingly, the median value under both dry and wet conditions was
 9 reduced compared to normal conditions in the intermediate sites, indicating a net impairment
 10 from normal conditions. Also, the overall spread or variability of reference IBI scores increased
 11 in both the wet and dry scenarios.

12 Benthic macroinvertebrates were sampled in spring, and fish were sampled in late
 13 summer and fall. In wet years, the fish IBI showed much higher variability in reference sites,
 14 reducing the discrimination efficiency (Figure D.8, Table D.2). Late summer and fall are slightly
 15 drier than other times of the year: the 30-year median of the PHDI during the fish sampling index
 16 period is less than -1 (Figure D.2). Thus, wet conditions during the fish sampling period may
 17 represent a greater departure from a median expectation than do dry conditions during the
 18 invertebrate sampling period. This may explain the increased variability of the reference site fish
 19 IBI values under wet conditions than under dry conditions, and the reduction of discrimination
 20 efficiency.

21 **Table D.2. Discrimination efficiencies of IBIs and EPT taxa under 3 climatic conditions.**

Climatic condition	Benthic IBI	EPT Taxa	Fish IBI
Base (current normal year)	100%	100%	69%
Dry year	64%	78%	60%
Wet year	98%	95%	16%

22
 23 Alternative methods to average PHDI (previous 6 months, previous summer, previous 12
 24 months) did not yield different results from the above (not shown). Therefore, we continued to
 25 use the simple monthly PHDI for further analyses.

26 Natural conductivities of streams in the region are generally low due to low buffering
 27 capacities of the parent rocks and soils, with the exception of limestone-influenced streams in the

1 Great Valley, in smaller limestone valleys of the Ridge and Valley ecoregion, and marble
2 formations in the Piedmont (Woods et al., 1999). Increased conductivity is consistently and
3 reliably associated with reduced stream biological condition throughout the Appalachian region
4 (Gerritsen and Zheng, unpublished data). One of the consequences of urbanization is an increase
5 in impervious area from roads, parking lots, and rooftops. Impervious surface increases the
6 “flashiness” of streams, as well as being a conduit for urban contaminants and pollutants.

7 We further examined the association of climatic condition on the relationships between
8 EPT taxa and two environmental stressors, conductivity and impervious surface, which had
9 shown good stressor-response relationships (Figures E.3 – E.6). The full dataset (both Piedmont
10 and Highland warm-water streams) was included for this analysis.

11 We overlaid the plots of the stressor-response relationships from all three climate
12 scenarios to ask whether changes in the response curves might be associated with the climate
13 change scenario, namely increasing drought or increasing storm events. Figure D.9 shows the
14 stress-response relationships (with linear regressions) between EPT taxa richness and
15 conductivity for the Piedmont region, and the conditional probability analysis. First, mean
16 number of EPT taxa is generally higher in the base condition, and reduced under wet conditions,
17 with little difference between base and dry conditions.

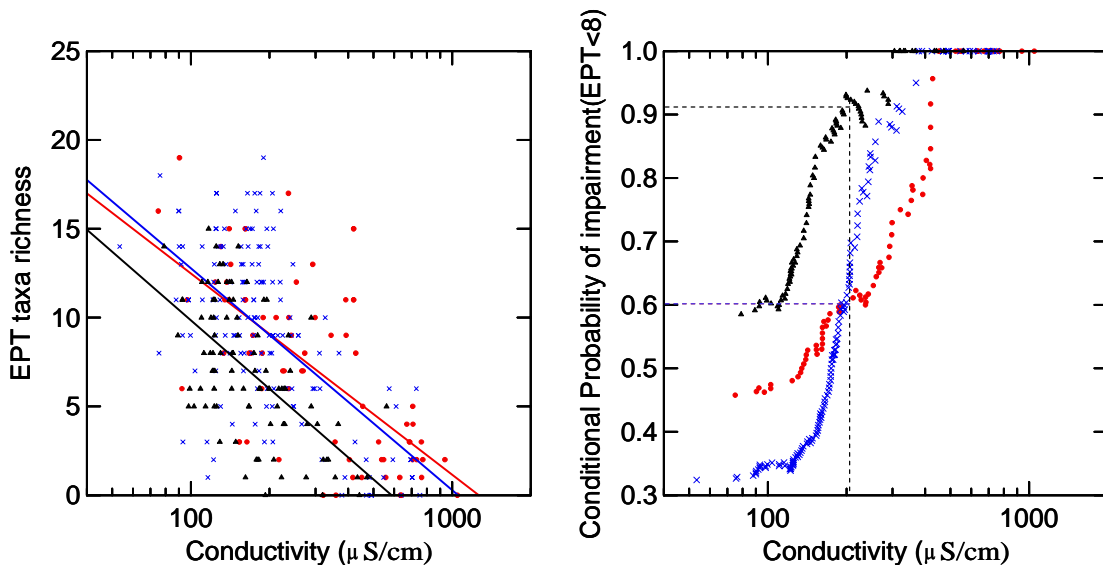


Figure D.9 – a) Relationship of EPT richness to conductivity under drought (red), base (blue), and wet (black) conditions; and b) conditional probability of impairment for the same three relationships.

1 The conditional probability analysis (Figure D.9a) examined the probability of
2 impairment along the stressor gradient. We defined EPT taxa <8 as the threshold of impairment,
3 consistent with the threshold used by Maryland DNR in the Piedmont (Southerland et al., 2005).
4 Conditional probabilities of EPT impairment under base, wet and dry conditions, show that the
5 probability of impairment is higher under the wet scenario than under baseline conditions. This is
6 not merely the result of reduced conductivity in wet years, because the overall distribution of
7 conductivity in wet and normal years is almost identical (Figure D.10; CDF of conductivity).
8 Under dry conditions, the probability of impairment was greater at low conductivities, and less at
9 high conductivities, though the actual difference in numbers of EPT taxa were small.

10 Figure D.11 shows the relationship with impervious surface for the climate scenarios.
11 Overall, the base group (i.e., average hydrologic conditions) had higher levels of EPT taxa than
12 either the drought or the storm groups, but the differences were subtle, a difference of
13 approximately 1-2 taxa, and the differences were not consistent. Drought conditions yield a
14 higher risk of impairment with impervious surface, but the change is marginal.

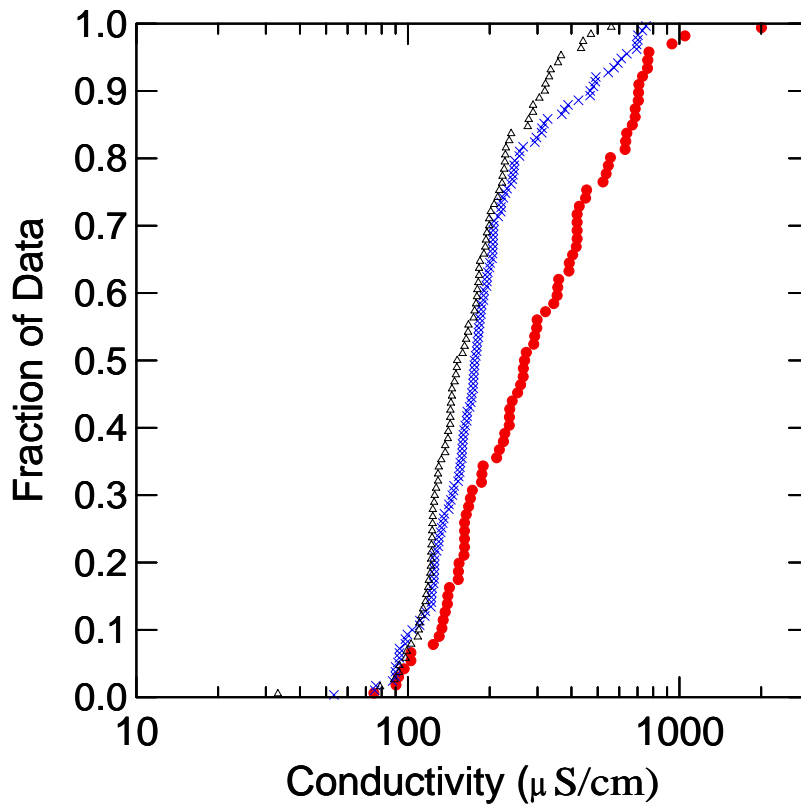


Figure D.10 – Conductivity CDFs - Piedmont

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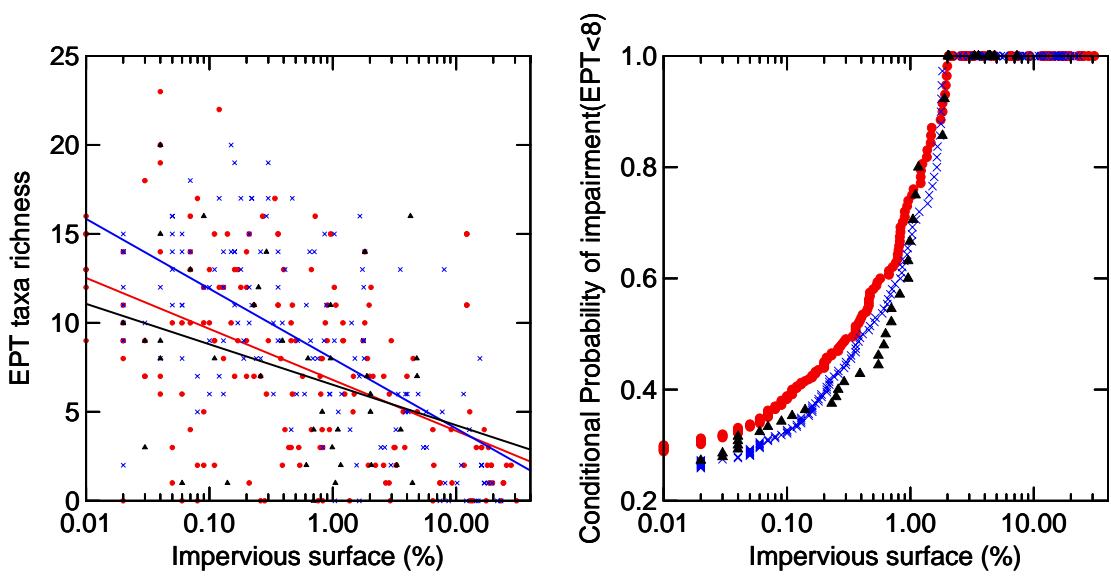


Figure D.11 – a) Relationship of EPT richness to impervious surface under drought (red), base (blue), and wet (black) conditions; and b) conditional probability of impairment for the same three relationships.

D.3. DISCUSSION

We have examined several biological indicators and their associations with stressors, under scenarios of normal, relatively dry, and relatively wet conditions. The scenarios were derived by partitioning a long-term dataset from the Mid-Atlantic Piedmont and Appalachians by moisture conditions estimated by the Palmer Hydrologic Drought Index. Some caveats regarding the sampling design and the partitioning:

- Temperature and water chemistry measurements did not coincide with the benthic macroinvertebrate samples. Macroinvertebrates were sampled in spring (March- early May), coincident with the spring freshet; fish and water quality (temperature, DO, conductivity, habitat, nutrients, etc.) were sampled in late summer (July-Sept), coincident with annual low water. Different index periods for the organisms would have resulted in different drought index estimates
- The PHDI applied to the month and year a site was visited; all sites sampled in the same month (e.g., March 1999) and NCDC district (e.g., Piedmont) would have the same PHDI value.
- The climatic conditions we examined are all recent, from the period 1995-2005. Future climate is expected to show a greater frequency of extreme conditions, but we have not linked our analysis to frequency and magnitude of climate projections and models.

We observed differences in median values and distributions of several biological indicators associated with dry, normal, or wet conditions; however, we cannot rule out that the associations may have been due to an “unlucky” random sample, especially at the basin level. All samples from a particular basin-year sampling would fall in the same dry-normal-wet category, and there is no assurance that basins sampled in any one year are representative of the range of stressor conditions throughout the region, especially with respect to urbanization.

In spite of these caveats, the results give an indication of the potential consequences of climate change on bioassessment indicators. In dry and wet years, indicator variability increased markedly in reference sites and there were slight reductions in median indicator values. Consequently, there was reduced ability to discriminate between reference and stressed sites under dry conditions (macroinvertebrates), and under wet conditions (fish) (Table D.2). These trends were slightly more pronounced in the macroinvertebrate indicators under dry conditions,

1 and in the fish indicators under wet conditions (Figures 3-6 – 3-8). Associations of the indicators
2 with stressors, which are used to develop stress-response relationships for Stressor Identification
3 (Suter et al., 2002; Norton et al., 2002), may also change. In our analysis, we saw a marked
4 change in apparent response to conductivity (increased probability of impairment at all
5 conductivities in wet conditions, Figure D.9), but very little change in response to impervious
6 surface (Figure D.11).

7 **D.3.1. Sensitive and Vulnerable Components of Biological Assessments**

8 Our results illustrate the potential sensitivity of reference site scores to climate change.
9 Reference sites in many regions of the country are not pristine, but are merely the “best
10 available” in the region. This is especially true for the eastern Piedmont, which has been settled,
11 farmed, and industrialized since Colonial times. It is unlikely that there are any sampled
12 watersheds in the Piedmont of Maryland that are free of suburban development; the average
13 population density of HUC-8 accounting units in the Maryland Piedmont ranges from 111 to
14 >400 persons per square kilometer (1990 census; Jones et al., 1997).

15 Moderately stressed reference sites may be more sensitive to slight increases in additional
16 stress due to climate change than truly minimally stressed reference sites (Stoddard et al., 2006).
17 Therefore, it would be important to identify minimally stressed reference sites if they exist, to
18 document reference site selection criteria, whether minimally stressed or not, and to monitor
19 reference sites to document changes over time.

20 **D.3.2. Consequences of Changes on Bioassessment Programs**

21 *D.3.2.1. Biocriteria*

22 Increased variability of reference sites as a consequence of climate change could decrease
23 the ability of states to detect impairment, if impairment thresholds are determined by a statistical
24 percentile of the indicator distribution in reference sites. Many states use a lower percentile of
25 the reference distribution as a numerical biocriterion for 305(b) assessment, for example, the 25th
26 percentile (Ohio EPA), or the 10th percentile (Maryland), or the 5th percentile (West Virginia). If
27 climate change causes the percentiles to drift downward, and the state reevaluates its water
28 quality criteria with new data, then the new criteria may set a lower bar, i.e., permit more
29 degradation to take place, before any kind of management is implemented (e.g., TMDL). The
30 potential drift of reference site condition due to climate change illustrates the importance of

1 establishing a universal measurement scale of biological condition so that reference site drift can
2 be identified as such (see 3.5.3.1).

3 *D.3.2.2. Stressor Identification*

4 Stressor Identification may be similarly hampered by pervasive degradation and
5 increased variability of all sites. If we consider Figure D.9, the conductivity stress-response in
6 the wet condition, as a typical scenario, then conductivity is implicated in a smaller fraction of
7 impairment (because the baseline frequency of impairment is higher), yet the threshold water
8 quality criterion for conductivity would also be lower. That is, protection from degradation by
9 conductivity may need to be tighter and set at a lower conductivity than before the climate
10 changed.

11 **D.3.3. Dealing with the Consequences**

12 *D.3.3.1. Universal Scale to Measure Biological Condition*

13 As was described above, acceptable biological condition is determined in many states
14 from statistical properties of a numerical index. Index values and criteria vary widely from state
15 to state because of differences among data sets used to develop the respective indexes.
16 Furthermore, the criteria “action level” often reflects substantial biological degradation from
17 relatively undisturbed conditions, such that the highest quality waters are not adequately
18 protected (e.g., Figures 3-6 – 3-8). Our results here also demonstrate that biological responses to
19 climate change may further confound assessment and criteria for water management. To resolve
20 these issues, panels of state and academic aquatic biologists have proposed a conceptual model
21 for a universal measurement scale of aquatic biological condition, called the Biological
22 Condition Gradient (BCG) (Davies and Jackson, 2006).

23 The conceptual BCG model describes ecological changes that take place in flowing
24 waters with increased anthropogenic degradation, from pristine to degraded (Davies and Jackson,
25 2006). The model is intended to be broadly applicable to any kind of stream; the tiers are
26 independent of actual monitoring methods. The model promotes conceptual unification while
27 recognizing regional natural variability: it is not a one-size-fits-all approach. The BCG promotes
28 consistency among agencies in the application of the Clean Water Act by identifying tiers, or
29 condition classes, that can be operationally defined in a consistent manner. The BCG is a
30 general description of change in aquatic communities, is consistent with ecological theory, and

1 the approach has been verified by aquatic biologists throughout the US (Davies and Jackson,
2 2006).

3 Calibration of the BCG to local conditions, and on a nationwide basis, would help
4 establish two baselines that will reduce the effects of confounding by climate change. The first
5 baseline is the description of pristine or nearly pristine conditions, Tier 1 of the BCG. In many
6 regions, the description of Tier 1 must rely on historical descriptions of fauna and historical
7 ranges of organisms. The second baseline is the description of the present-day reference, or least
8 stressed condition, before large-scale effects of climate change have occurred.

9 *D.3.3.2. Importance of monitoring*

10 To be able to account for the effects of climate change on biological indicators and on
11 stress-response relationships, it will be necessary to monitor a set of sentinel sites over time, such
12 that the same sites are revisited. Systematic changes in biological attributes can only be
13 attributed to climate change if other potential causes are eliminated or accounted for, hence the
14 need to have sentinel sites that span a wide range of other potential stressors, and not just least-
15 stressed reference sites.

16 Because climate change effects are pervasive, components of trends that are common to
17 all sentinel sites can be assumed to reflect climate change effects. If no other degradation was
18 occurring at reference sites, then the magnitude and variation in trends at reference sites could be
19 used directly to characterize the climate change component and account for that component
20 within trends observed at non-reference sites. However, assumptions of continued “pristine”
21 conditions at reference sites are unlikely over time, given population growth, expected
22 encroachment of suburban and other land uses, increased water withdrawals for human use, and
23 other landscape-scale effects. Even if recommendations to protect reference sites are adopted,
24 lack of contribution from landscape-scale stressors would have to be verified in the process of
25 estimating climate change-associated trends.

26 Once trends common to all sentinel monitoring sites are defined, differential components
27 of trends at non-reference sites can be considered potentially due to other stressors and evaluated
28 through the familiar stressor identification approach.

29 *D.3.3.3. Analytical methods*

1 A question that arises is whether there are more robust or more powerful analytical
2 methods that can overcome the projected degradation in signal quality and discrimination ability.
3 Unfortunately, it is the quality of the information (signal to noise) that will degrade, and not the
4 analytical methods. If the information is degraded, then no amount of statistics can recover
5 something that no longer exists. Nevertheless, tracking of time trends at both reference and non-
6 reference “sentinel” locations over time provides a framework for defining climate change-
7 associated trends and differentiating these from the effects of conventional stressors that are of
8 regulatory interest.

9 In view of the likelihood of universal biological degradation due to climate change, it
10 becomes increasingly important to protect reference sites from degradation. Application of the
11 Biological Condition Gradient (universal measurement yardstick) and Tiered Aquatic Life Uses
12 (TALU) would establish a framework for such protection (EPA, 2005). For example, one
13 expected outcome of defining TALUs is that states would adopt “high” and “exceptional” quality
14 use classes along the BCG, which would be above their current action threshold for
15 “fishable/swimmable”. Each use class would have biological criteria associated with it, which
16 would allow detection of degradation at reference sites at a stage substantially before the
17 reference site would be “impaired” under current definitions. Such a formalized process also
18 provides for implementation of particular management actions, such as identification of the
19 cause of impairment and implementation of corrective actions.