Environmental indicators of macroinvertebrate and fish assemblage integrity in urbanizing watersheds

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ABSTRACT

Urbanization compromises the biotic integrity and health of streams, and indicators of integrity loss are needed to improve assessment programs and identify mechanisms of urban effects. We investigated linkages between landscapes and assemblages in 31 wadeable Piedmont streams in the Etowah River basin in northern Georgia (USA). Our objectives were to identify the indicators of macroinvertebrate and fish integrity from a large set of best land cover (n = 45), geomorphology (n = 115), and water quality (n = 12) variables, and to evaluate the potential for variables measured with minimal cost and effort to effectively predict biotic integrity. Macroinvertebrate descriptors were better predicted by land cover whereas fish descriptors were better predicted by geomorphology. Water quality variables demonstrated moderate levels of predictive power for biotic descriptors. Macroinvertebrate descriptors were best predicted by urban cover (-), conductivity (-), fines in riffles (-), and local relief (+). Fish descriptors were best predicted by embeddedness (-), turbidity (-), slope (+), and forest cover (+). We used multiple linear regression modeling to predict descriptors using three independent variable sets that varied in difficulty of data collection. "Full" models included a full range of geomorphic, water quality and landscape variables regardless of the intensity of data collection efforts. "Reduced" models included GIS-derived variables describing catchment morphometry and land use as well as variables easily collected in the field with minimal cost and effort. "Simple" models only included GIS-derived variables. Full models explained 63-81% of the variation among descriptors, indicating strong relationships between landscape properties and biotic assemblages across our sites. Reduced and simple models were weaker, explaining 48-79% and 42-79%, respectively, of the variance among descriptors. Considering the difference in predictive power among these model sets, we recommend a tiered approach to variable selection and model development depending upon management goals. GIS variables are simple and inexpensive to collect, and a GIS-based modeling approach would be appropriate for goals such as site-screening (e.g., identification of reference streams). As management goals become more complex (e.g., long-term monitoring programs), additional, easily-collected field variables (e.g., embeddedness) should be included. Finally, labor-intensive variables (e.g., nutrients, fines in sediments) could be added to meet complex management goals such as restoration of impaired streams or mechanistic studies of land use effects on stream ecosystems.

Key Words: land use, biotic indices, stressor gradient, urban syndrome, biotic integrity

1. Introduction

As natural landscapes are altered by human disturbances, the health of streams and rivers draining the land are increasingly at risk (Schlosser, 1991; Allan et al., 1997; Walters et al., 2003b; Allan, 2004). The global rise in human population is driving a continual conversion of land to anthropogenic uses (Cohen, 2003; Grimm, 2008), so there is a strong need for monitoring stream health. Indicators of stream health (e.g., biotic integrity) and stream stressors (e.g., geomorphology, water quality) are important tools not only for assessing stream condition, but also for determining the mechanisms of impacts and, accordingly, effective avenues for protecting and restoring stream ecosystems.

Increases in impervious cover and a concomitant reduction in forest cover in urbanizing landscapes alter stream biotic assemblages (see reviews, Paul and Meyer, 2001; Walsh et al., 2005). Typical responses of benthic macroinvertebrate assemblages include reduced richness and diversity, and increased abundances of tolerant organisms in urbanized streams (Jones and Clark, 1987; Lenat and Crawford, 1994; Kennen, 1999; Walsh et al., 2001; Morse et al., 2003; Roy et al., 2003; Cuffney et al., 2005, and others). Likewise, fish responses to urbanization include reduced biotic integrity (Klein, 1979; Steedman, 1988; Wang et al., 1997; Wang et al., 2000; Kennen et al., 2005; Morgan and Cushman, 2005) and increased homogenization of assemblages (Walters et al., 2003a; Marchetti et al., 2006; Scott, 2006). While these biota have been well-studied with respect to land cover change, few studies have assessed differences in the strength and mechanism of responses between fish and macroinvertebrates at the same sites (but see Lenat and Crawford, 1994; Lammert and Allan, 1999; Passy et al., 2004).

There are several mechanisms by which land use change alters stream biota, including: riparian clearing and loss of large wood, hydrologic alteration, excessive sedimentation, nutrient enrichment, and contaminant pollution (Allan, 2004). A primary mechanism of stream disturbance in urbanizing areas is stormwater runoff from impervious surfaces, which alters the magnitude, volume, frequency, and timing of high flow events (see reviews, Shuster et al., 2005; Walsh et al., 2005). The physical force of stormwater runoff causes stream bank erosion, sedimentation, bed scouring, and channel morphology alteration (Booth, 1990; Trimble, 1997; Finkenbine et al., 2000; Pizzuto et al., 2000; Fitzpatrick et al., 2005). Runoff also delivers contaminants to streams resulting in increased nutrients, metals, pharmaceuticals, and other toxins in urban streams (Wilber and Hunter, 1977; Herlihy et al., 1998; Ometo et al., 2000; Kolpin et al., 2002; Hatt et al., 2004). This extensive suite of stressors and ecosystem responses compose the symptoms of the "urban stream syndrome" (Paul and Meyer, 2001; Walsh et al., 2005) and may be used to assess the severity of stream disturbance.

Given the wide variety of stressors in urban streams, a key management goal is to identify key indicators and mechanisms of stream alteration, so managers can rapidly diagnose stream health and work toward treating the symptoms. Here we assess biotic responses to watershed and reach-scale stressors in the Etowah River basin near Atlanta, Georgia, in an effort to identify key indicators of disturbance. The objectives of this paper are to (1) determine which attributes of land cover, geomorphology, and water quality best predict biotic assemblage health, and (2) evaluate the potential for variables measured with low or minimal cost and effort to effectively predict biotic integrity. We compare the responses of macroinvertebrate and fish assemblages to disturbance, assessing whether there are different mechanisms by which biotic health declines. The results are placed in a management context and used to recommend a tiered approach to monitoring and assessment, based on management goals and resource availability.

2. Methods

2.1. Study Sites and Environmental Setting

The study area includes 31 catchments of the Etowah River Basin in north Georgia (Figure 1). All sample reaches are on the Piedmont, but a few of the catchments have headwaters in the Blue Ridge Mountains. Catchments varied in size from 11 to 126 km^2, with channel types ranging from low-gradient (0.1%), sand-bed streams to high-gradient (1.0%), cobble-bed streams. Detailed site characteristics are provided by Walters et al. (2003b) and Roy et al. (2003). Stream reaches were sampled in 1999 (n = 29) and 2000 (n = 2). Natural land cover was primarily forest which was cut and supplanted by various land uses including mining, agriculture, silvaculture, and urbanization. By the 1930s, agriculture was in steady decline and was being replaced by secondary growth forest. This conversion corresponded with population expansion associated with metropolitan Atlanta (Figure 1, inset). Urbanization was the main form of land cover conversion in the last decade, with human population growth rates among the highest in the U.S. (Walters et al. 2005). The catchments exhibit a steady gradation between urban and forested landscapes with land cover ranging from 6-37% urban, 7-38% agriculture (primarily pasture) and 40-87% forest.

2.2. Land Cover

We calculated numerous land cover variables and indices of land disturbance to characterize human alteration of catchments. Calculations for variables used in statistical analyses are provided in Supplementary Material (Table 1) and have been previously described (Roy et al., 2003; Walters et al., 2003b; Walters et al., 2005). Land cover data were derived from Landsat thematic mapper (TM) images from July 1997 (Lo and Yang, 2000). TM images were resampled to 25 m and classified using modified Level-I and Level-II Anderson schemes (Anderson, 1976) and summarized into 12 land cover classes within four major groups: urban (high-density, low-density, total), agriculture (cultivated/exposed, cropland/grassland, golf course, total), forest (deciduous, evergreen, mixed, total), and water. Land cover was calculated at three scales: 1) catchment-wide or "catchment"; 2) the stream network riparian scale or "network"; and 3) the stream-reach riparian scale or "riparian". Catchment scale included everything within the watershed boundary. Network scale included everything within a 100 m wide band on either side of the stream network (200 m wide band) as it is portrayed on 1:100,000 USGS topographic maps. Riparian scale included everything within a 100 m wide band on either side of the stream within a distance of 1000 m upstream from the downstream end of the sample locale. We also used a Landsat image from October 1998 to determine the extent of ponds (i.e., artificial impoundments) within catchments based on a 20-bin unsupervised classification scheme (Arc View 3.2, Esri, CA). Total impervious area (TIA) was estimated by multiplying low-density urban and high-density urban land cover by either the minimum (0.5 & 0.8) or median (0.65 & 0.9) impervious coverage estimates, respectively (Lo and Yang, 2000). Other measures of human disturbance included road density, a disturbed land index (median TIA + cultivated/exposed) and an erosive land index (urban + cultivated/exposed). The latter two indices were calculated separately for the catchment scale and for slopes >10% within catchments.

2.3. Geomorphology

Geomorphic variables were collected at the catchment and reach scales. Categories of variables included catchment morphometry (n = 17), stream channel morphology (n = 60), and sedimentology (n = 38). In most cases, we followed standard methods in reference manuals for collecting reach data (i.e., Harrelson et al., 1994; Fitzpatrick et al., 1998; Kaufmann et al., 1999). Detailed descriptions of collection methods are in Leigh et al (2002) and Walters et al. (2003b) and information on geomorphic variables analyzed in this study is provided in the Supplementary Material (Table 1).

Morphometry variables included the area, perimeter, shape (compactness), and drainage density of the study catchments. We also characterized length, slope, total relief, relative relief (total relief ÷ perimeter), and ruggedness (total relief × drainage density) for the catchment and trunk stream based on standard equations from Ritter et al. (1995). We included an innovative variable, local relief, measured as the elevation difference between the surveyed reach and the ridges confining the stream valley. Finally, we estimated soil erosion by applying the universal soil loss equation (USLE) to land cover and digital elevation maps (DEMs). All variables were derived in ArcView 3.2 using digital raster graphics (DRGs) of 1:24,000 USGS 7.5-minute quadrangles.

Stream channel morphology was measured in reaches 20 times the average baseflow water width and was surveyed with an electronic total station. Most of the channel dimensions were calculated as averages obtained from three cross sections arbitrarily located at the lower, upper, and midpoint of each reach. Percent geomorphic units (riffle, glide, and pool) were sampled along five longitudinal transects (i.e., "zig-zag" survey, Walters et al., 2003b) and summarized for the thalweg (the line connecting the deepest parts of the channel) and all points. Water depth was also sampled in the zig-zag survey and summarized as average, standard deviation, coefficient of variation, and 95th percentile for riffles, glides, pools, and the entire reach (thalweg and all points). Baseflow width, depth, and velocity were characterized and averaged along five equally-spaced cross-sections. Three cross-sections were mapped for bankfull conditions, and flow variables (area, width, depth, thalweg depth, hydraulic radius, velocity, discharge, tractive force, and stream power) were generated from models (Walters et al., 2003b). Entrenchment ratios and flood recurrence intervals at bankfull and valley-flat levels were also modeled using HEC-RAS. Other miscellaneous variables included stream slope, channel sinuosity, Manning's roughness coefficient (n), and the volume of large wood (>10 cm). It is important to note that we measured stream slope at three scales. At the reach-scale, slope was measured as the average gradient projected across the tops of riffles in the survey reach. We also calculated map slope as the height/distance of the two contours nearest the survey reach from 1:24000 topographic maps. Finally, we calculated trunk stream slope as the total gradient from the catchment divide to the surveyed reach as measured along the trunk (or main channel) of the stream.

Bed sediment variables were derived using three methods: 1) pebble counts from representative riffles (Wolman, 1954), 2) sieving of samples from three riffles and three pools, and 3) point counts from the zig-zag survey (Walters et al., 2003b). Point counts were based on the modal sediment size observed within a 50 cm diameter patch of the upper 5 cm of stream bed sediment at each sample point. Texture variables derived from these methods included mean particle size, percent composition of different size classes (<0.063, <2, 2-63, and 63-256 mm), and estimates of variance in particle size. Sediment transport variables were calculated to estimate bed mobility during the 0.5 year recurrence interval flood. Bed mobility ratios compare the force exerted on the streambed during the 0.5-year flood relative to the threshold force (stream power, tractive force, or velocity) needed to initiate motion of average size particles on the whole steam bed or in riffles. In addition, embeddedness of coarse particles was determined from a visual assessment by 2-4 observers (Bjorkland et al., 2001).

2.4. Water Quality

Baseflow water chemistry samples were collected during monthly synoptic surveys at 29 sites from May 1999 to June 2000, at least 72 hours after significant rainfall. Dissolved oxygen (DO), specific conductance (SC), and pH were measured with a Hydrolab® Datasonde 4 multi-probe (Hydrolab Corporation, Texas, USA). Grab samples for dissolved orthophosphate, nitrate, and ammonium analyses were collected from the thalweg at 0.6 water depth. Samples were filtered (Gelman A/E glass fiber filter, 0.47-µm pore size) in the field, placed on ice, frozen until analysis (< 2 weeks), and analyzed with an Alpkem® autoanalyzer following standard methods (American Public Health Association, 1989). We collected depth-integrated samples for turbidity and total suspended solids (TSS) from the thalweg using a DH-48 sampler. Turbidity samples were analyzed in the field on a portable turbidimeter (Hach 2100P). TSS samples were filtered through pre-weighed 0.7-µm glass fiber filter, dried, and weighed. At two sites, mean dissolved oxygen, pH, conductivity, nitrate, and turbidity were calculated using quarterly samples collected from March 1997 and December 2000 by the Cobb County Water Authority (CCWA, Marietta, GA).

Stream temperature at 29 sites was recorded hourly from June 1999 to June 2000 with Onset Hobo temperature data loggers (Onset Corporation, Massachusetts, USA). Data were analyzed on an annual, summer (June 21 to September 21), and winter (December 21 to March 21) time scales. Stream temperature was also recorded with a thermometer during monthly surveys (April 1999 to June 2000) at 29 sites, and quarterly (March 1997 to June 2000) at two sites. These data were used to calculate mean annual baseflow temperature.

2.5. Biotic Assemblages

Sampling methods for macroinvertebrates and fishes are provided in Roy et al. (2003) and Walters et al. (2003b), respectively. Briefly, sites were sampled once during baseflow conditions. Three benthic macroinvertebrate samples were taken in each of three habitats within 100 m reaches. Macroinvertebrates were sampled in riffle, pool, and bank habitats using a Surber sampler, stove-pipe corer, and rectangular dipnet, respectively (500-µm mesh). Samples from all habitats were pooled to calculate assemblage descriptor variables. Fishes were collected in reaches approximately 40 times mean wetted width using a backpack electroshocker, seine, and dipnet. All samples were preserved in 10% formalin. Fishes were identified to species and invertebrates were identified to genus, where possible, using standard keys (e.g., Merrit and Cummins, 1996; Mettee et al., 1996).

Assemblages were characterized using sensitive taxa metrics, multi-metric indices, and ordination analyses. Macroinvertebrate assemblages were characterized using richness of Ephemeroptera, Plecoptera, and Trichoptera (EPT) orders and the Invertebrate Community Index (ICI; Ohio EPA 1989). The ICI is a tool for assessing invertebrate assemblage health based on 10 metrics of invertebrate richness and community structure (see Roy et al., 2003 for a full list of metrics). The ICI calculation excluded one metric, percent predatory Chironomidae composition, because it was non-normally distributed and added no useful information to ICI score. Fish assemblages were characterized using an index of homogenization (the ratio of endemic species to endemic + cosmopolitan species richness, E/E+C, Walters et al., 2003a) and an index of biotic integrity (IBI) for the Piedmont portion of the Coosa River system (including the Etowah basin, Georgia Department of Natural Resources, 2005). Low values for the homogenization index indicated dominance by cosmopolitan species and a high degree of homogenization. The IBI is a tool for assessing fish health based on 8 metrics of richness (e.g., number of native species), seven metrics of community structure (e.g., relative abundance of *Lepomis* species) and fish abundance.

Axis scores from non-metric multidimensional scaling (NMDS) analysis were used as objective measures of macroinvertebrate and fish assemblage structure. Analyses were performed with PC-ORD (Version 4.1, MjM Software Design, Glenden Beach, OR, USA). For macroinvertebrates, we used habitat-weighted densities, calculated by multiplying macroinvertebrate densities by the proportion of habitat present at each site (Roy et al., 2003). Density data were transformed ($\log_{10}(x+1)$) and rare species (i.e., present at one site or density <0.01 individuals m^{-2}) were excluded. NMDS analysis on fishes used transformed ($x^{0.25}$) abundance data and rare species (present at <10% of sites) were excluded (Walters et al., 2003b). We used the inverse of invertebrate axes 1 and 2 (Invert A1 & A2), which explained 78.1% and 10.6% of variation in assemblages across sites, respectively, and responded negatively to disturbance. We used fish axis 2 (Fish A2, 46% variance explained) and the inverse of fish axis 3 (Fish A3, 35% variance explained) as descriptors of fish integrity.

2.6. Statistical Analyses

All predictor (i.e., independent) and response (i.e., dependent) variables were tested for normality with the Komolgorov-Smirnov (KS) test using SigmaStat 2.03 (SPSS Inc., Chicago, IL, USA) and transformed, when necessary. In total, there were 45 land cover, 115 geomorphology, and 12 water quality variables. We used Pearson correlation analysis to screen the large sets of predictor variables and exclude correlated variables (i.e., Pearson's $|r| > 0.80$) within categories of land cover, geomorphology, and water quality (Supplementary Material, Table 2). If variables were correlated, we retained the variables that were identified in previous publications as important predictors of fish and macroinvertebrate assemblages (Parisi, 2001; Roy et al., 2003; Walters et al., 2003a; Walters et al., 2003b; Walters et al., 2005). To further reduce geomorphic variables to ≤ 30, we excluded variables that were 1) derived from other variables in the remaining list (e.g., ruggedness, which is a product of drainage density and total relief), 2) components of other variables (e.g., % silt plus clay in riffles, which is included within % fines in riffles), or 3) largely redundant with other variables (e.g., pool, riffle, and glide depth at baseflow were excluded while average depth at baseflow remained). The reduced sets of land cover (n = 27), geomorphology (n = 30), and water quality variables (n = 12) were then correlated against fish and macroinvertebrate response variables to determine the best predictors of assemblage attributes.

We used multiple linear regression (MLR) analysis with a forward, stepwise selection procedure to determine the best models for predicting each response variable, and compare the predictive ability of models which included the best variables ("full models"), relatively easy-to-collect variables ("reduced models"), and variables derived exclusively from GIS ("simple models"). First, we ran MLR for the separate variable sets (land cover, geomorphology, and water quality) to identify the most important variables in the models and select those variables for inclusion into the full model set (n = 30 variables). Variables that explained <6% of the variation in assemblage descriptors and were never in the top three variables in any model were excluded. Then, variables from the full set that were relatively intensive to collect (e.g., required more than one field visit) or analyze in the laboratory (e.g., water chemistry) were replaced by variables that were correlated with these and relatively easier to collect in order to construct the reduced model set (n = 24 variables). Finally, a simple model set was created that only included land cover and morphometry variables that were derived from digital topographic map data (n = 28 variables). For the simple model set, we again screened variables to ensure that variables were not highly correlated ($|r| < 0.80$), and we also excluded derivative, forest subcategories (deciduous, evergreen, and mixed) to obtain <30 variables for MLR. We compared the adjusted

R^2 values of the separate models (limited to 3 predictor variables) to determine whether variables with minimal cost and effort could effectively predict biotic integrity. Correlation and MLR analyses were performed using JMP Version 5 (SAS Institute Inc., Cary, NC, USA).

3. Results

Land cover variables explained up to 66% of the variation in macroinvertebrates (urban vs. Invert A1, r = -0.81) and 46% of the variation in fishes (forest network riparian vs. E:E+C, r = 0.68, Table 1). Urban land cover at the catchment scale was consistently among the best predictors of macroinvertebrate descriptors, and was negatively correlated with ICI, EPT, and Invert A1. Pond and road density were also negatively correlated with macroinvertebrate descriptors whereas forest cover assessed at catchment and riparian scales was positively related to these descriptors. Fish descriptors generally showed weaker relationships with land cover compared with macroinvertebrate variables. Forest cover at the catchment and riparian scale was among the best predictors and was positively correlated with IBI, E:E+C, and Fish A2. The degree of pond construction (pond density, number, and open water in the riparian zone) was negatively correlated with fish descriptors. In contrast to macroinvertebrates, fish variables were largely uncorrelated with urban land cover (except E:E+C) at the $p < 0.001$ level. Agriculture land cover variables were not strongly related to macroinvertebrate or fish descriptors.

The strongest geomorphic predictors of macroinvertebrate descriptors were local relief (+) and sediment characteristics (fines in riffles (-) and embeddedness (-); Table 1). Compared with other macroinvertebrate descriptors, Invert A3 was strongly predicted by the highest number of geomorphic variables (8), including slope, bed texture, and bed mobility. Two fish variables were also strongly predicted by numerous geomorphic variables, E:E+C (8 correlations with $p < 0.001$) and Fish A2 (7 correlations). Embeddedness (-), bed mobility (-), riffle bed texture (-), stream power (+), and stream gradient (+) were among the strongest predictors of fish descriptors. Measures of stream size (e.g., drainage area, width, depth, and discharge) were generally poor predictors of macroinvertebrate and fish descriptors.

The strongest water quality predictor of macroinvertebrate descriptors was conductivity, which was negatively correlated with ICI, EPT, and Invert A1 (Table 1). Dissolved oxygen (DO, +), and NH_4^+ (-) were also consistent predictors of macroinvertebrates. Fishes were most strongly correlated with NH_4^+ (-) but were also consistently predicted by turbidity (-) and DO (+). Stream temperature variables were weak predictors except for baseflow temperature, which was negatively correlated with ICI, Invert A1, and Fish A2. Macroinvertebrates and fishes were uncorrelated with $NO_3^- + NO_2^-$, pH, annual temperature, and winter temperature at $p < 0.001$.

Multiple linear regression models using land cover, geomorphology, and water quality variable sets generally confirmed results of bivariate analysis in terms of key environmental predictors and their scale of measurement (Table 2). Land cover models explained 41 – 70% of the variance in descriptors, and were strongest for macroinvertebrate descriptors (ICI and Invert A1). The primary predictors for macroinvertebrates were urban land cover, pond density, and (to a lesser extent) forest and agriculture cover. Catchment-scale variables were more important than network- and riparian-scale variables among macroinvertebrate descriptors. Fish descriptors were primarily related to forest cover assessed at the catchment and riparian network spatial scales, with variables describing open water emerging as secondary predictors. The exception was Fish A3, which was best predicted by the disturbed land index.

Geomorphology models explained 51 – 79% of the variance in assemblage descriptors. Fines in riffles and local relief were the primary predictors of macroinvertebrate descriptors, with stream gradient, entrenchment ratio, large wood, and percent bedrock as secondary predictors.

The strongest macroinvertebrate model was for Invert A2, confirming the bivariate results that this ordination axis represents assemblage response to stream geomorphology, rather than land cover. Fish descriptors were most strongly predicted by embeddedness, variation in thalweg depth, and various measures of stream gradient. Secondary predictors included local relief, erosion index, bankfull discharge, percent of pool habitat, and large woody debris. Pool was negatively correlated with axes scores because low scores for both axes described sites dominated by pool-dwelling species with generalized habitat requirements whereas sites with high axis scores were dominated by benthic species specializing in riffle habitats. The strongest geomorphic models among fish descriptors were for E:E+C (R^2 = 0.74) and Fish A2 (R^2 = 0.74).

Water quality models explained 33 – 66% of the variance in assemblage descriptors. Conductivity and temperature were the primary predictors of macroinvertebrate descriptors, and DO, pH, and turbidity were secondary predictors. Fish descriptors were best predicted by turbidity and baseflow temperature, with DO as a secondary predictor. Water quality models for both macroinvertebrates and fish were typically weaker than land cover and geomorphic models (see ICI and E:E+C; Figure 2).

Full, three variable models explained a remarkably high percentage of the variation in assemblage descriptors (73–81%), except for fish IBI (R^2 = 0.63; Table 3). These models always equaled (2 cases) or exceeded the predictive power of the separate land cover, geomorphology, and water quality MLR models. The top three variables selected in the stepwise procedure always included variables across at least two categories (land cover, geomorphology, or water quality). Urban (-), fines in riffles (-), and large wood (+) were predictors in multiple macroinvertebrate models, with urban as the top predictor for ICI and Invert A2. Embeddedness

(-) was the top predictor in two fish models (E:E+C and Fish A2), with turbidity (-), map slope (+), and pool (-) also predictors in multiple models.

The reduced and simple models were weaker than full models in most cases but many were surprisingly robust, explaining 48-79% and 42-79% of the variance, respectively, among descriptors (Table 3). Among measures of biotic integrity, reduced models were substantially weaker than full models for EPT and IBI (Figure 3), and simple models generally had among the lowest predictive ability. We also repeated the stepwise procedure for reduced models including two easily collected (albeit requiring multiple visits) water quality variables, conductivity and turbidity (data not reported in tables). Conductivity entered the EPT model and increased the variance explained from 55% to 71%, similar to the variance explained by the full model (73%). Turbidity entered the IBI model, but only increased the variance explained from 48% to 49%.

4. Discussion

4.1. Predictive power and limitation of Etowah models

A major goal of stream ecologists and resource managers is to predict the response of stream ecosystems to environmental factors and human disturbances such as land use change. The Etowah data showed relatively strong correlations between landscape components and assemblage descriptors (R^2 values of 0.63-0.81) compared with similar studies that generally demonstrated lower predictive capabilities (Richards et al., 1996; Roth et al., 1996; Allan et al., 1997; Wang et al., 1997). We believe there are several important reasons why our predictive capabilities are high. First, the Etowah data set is relatively large (n=31) considering the extensive suite of geomorphic variables considered (Walters et al. 2003b) and includes a wide range of physical and biological conditions, which allows a full spectrum of possibilities to be analyzed. Unlike studies that have been conducted in the intensive agricultural landscapes

(Richards et al., 1996; Roth et al., 1996; Allan et al., 1997; Wang et al., 1997), the Etowah basin contains fully forested to non-forested landscapes and a wide range of urban to rural land uses. The topographic setting of the Etowah basin also presents a wide range of variation, which broadens the spectrum of the physical template shaping stream ecosystems. Additionally, our variables were largely collected as continuous data, which maximizes numerical precision, as opposed to lumping observations into categories. Finally, some of the success of our indicator models must be attributed to the fact that the study was conducted within wadeable streams in a single river basin and physiographic province. This eliminated potentially confounding problems associated with scale, intra-basin, and regional differences in environmental setting and biotic assemblages, thus allowing more emphasis to be placed on variation among landscape components.

While the predictive power of many models was high, our dataset and statistical analyses are not without limitations. First, our sample size (n = 31 sites) is relatively large considering the suite of intensively collected geomorphic variables (Walters et al., 2003b), but it is small relative to the total number of predictor variables considered. This is an inherent problem for studies seeking to empirically link stream biological responses to landscape and stream environmental variables. For example, with advances in computing capabilities and increasing availability of digital spatial data, our ability to generate GIS-based variables can quickly outpace our ability to sample sites. One danger of having many more predictor variables than sites is developing overspecified models that “over-explain” biological descriptor variables. We took three steps to minimize this threat. First, we used Pearson correlation analysis to screen predictor variables and trim the dataset prior to modeling. This reduced the number of variables and minimized potential overspecification of models related to multicollinearity among predictor variables.

Second, we limited the limited the number of predictors in model sets so that *n* of predictors was less than *n* of sites (Draper and Smith, 1998). Third, we arbitrarily limited the number of variables in multiple linear regression models to three when reporting R^2 and F values to limit overspecification of models. Another drawback of our models is that they were not validated by comparing predicted values from environmental variables with observed values of biotic descriptors from sites not used to build the models. Thus, even though predictive power of some models was high, they must be tested with additional data prior to application. In spite of these shortcomings, the modeling approach we used was reasonable and conservative for achieving our main objectives of (1) identifying environmental indicators of stream assemblage integrity and (2) comparing the predictive power of variables that vary in their difficulty of collection.

4.2. Key Indicators and their Roles as Stressors to Stream Biota

The indicators that we identified represent broader landscape components that should be considered in the context of physical and chemical stressors on stream communities. Key landscape components (land cover, morphometry, channel morphometry, sedimentology, and water quality) identified in this study are expected to vary considerably in respect to their status as stressors to stream ecosystems. Many of these indicators were correlated with other environmental variables (Supplementary Material, Table 2), so we must be cautious in overemphasizing or interpreting the biotic response to individual variables. However, those variables that we highlight here were consistent predictors of biotic assemblages, and may have broader applicability to other river basins or ecoregions.

Land cover was a significant predictor of assemblage descriptors, as it is the source of a suite of reach-scale physical and chemical stressors which, in turn, affect biota. Urban land cover is a proxy for altered hydrology, habitat, and water quality (Paul and Meyer, 2001; Walsh et al., 2005) that affect stream assemblages at the reach-scale, leading to predictable changes in assemblage traits in Etowah River basin streams. Likewise, deforestation is a proxy for general disturbance (riparian forest loss, excessive sedimentation) in these naturally forested systems. In particular, deforestation and urban development are linked to higher turbidity and increasing fines on stream beds (Walters et al., 2003a; Price and Leigh, 2006a; b), both of which were strong predictors of biotic assemblages in this study. We also found that variables related to pond development were strong predictors of assemblage descriptors. We view these artificial impoundments as proxies for many sorts of stresses to aquatic ecosystems, because they represent signs of agricultural and urban development, they are typically associated with livestock within and close to the stream, and they directly affect water temperature, chemical conditions, and connectivity of stream systems (e.g., Maxted et al., 2005). Impoundments are also one of the easiest land cover indicators to measure because water has a very distinctive signature on Landsat images and thus exhibits high levels of accuracy and reproducibility.

Morphometry is a static variable over timescales of thousands to millions of years (Ritter et al., 1995), which cannot be significantly influenced by humans. Thus, we do not consider it as a stressor to biota, but rather as an inherent template of the landscape that influences biotic assemblages. For instance, catchment-wide geomorphic variables are important elements of the bedrock and topographic template that ultimately influence channel form and sedimentology (Montgomery, 1999). Morphometry variables typically resulted as secondary predictors in our models, but were particularly useful for improving the predictive capabilities of simple models that relied solely on remotely sensed and map data. We identified local relief and map slope as key indicators. Local relief and stream gradient exert strong influences on the localized morphology of the stream reach and physical processes operating within it. Rugged, high relief terrain is most conducive to a high frequency of riffles and shoals that tend to favor both high levels of habitat quality and habitat heterogeneity (Leigh et al., 2002; Walters et al., 2003a; Fitzpatrick et al., 2005; Walters et al., 2005). Biotic assemblages in such streams in the Etowah River basin tend to have high species richness as well as endemic fishes and sensitive macroinvertebrates that are positive indicators of biotic integrity (Roy et al., 2003; Walters et al., 2003a). Stream size generally was found to be a minor indicator compared with other variables (channel morphology, sedimentology, and land cover) that have little or no relationship with stream size, likely due to the narrow range in size among catchments in our study (11-126 km^2).

Channel morphology is an indicator category that may or may not be linked with human disturbance, depending upon the variable under consideration. Stream slope, depth variability, width, entrenchment ratio, stream power, discharge, and large wood were key indicators within the channel morphology category. Even though stream slope was not always among the strongest assemblage predictors, it is a critical channel morphology variable to consider because it establishes the template for velocity, stream power, and tractive forces that shape channel morphology and is the key determinant of the particle size composition on the stream bed (Walters et al., 2003b). It is not likely that land use has had much influence on channel slopes, because many of our sites have their slopes controlled by bedrock or they are in alluvial settings where no evidence for historical changes in slope can be observed (Leigh et al., 2002). In general, we do not view slope as a distinct stressor, but rather as a critical element of the physical template influencing both assemblages and habitats within these streams (Walters et al., 2003a; Walters et al., 2003b; Walters et al., 2005).

Sedimentology, the particle size composition of the channel bed, is an influential variable group for stream assemblages. Finer, more embedded, and more mobile beds exhibited lower biotic integrity and altered assemblage structure. Excessive sedimentation is widely viewed as a key stressor in stream ecosystems, and the detrimental effects on macroinvertebrate and fish assemblages (e.g., altered assemblage structure, increased drift, reduced feeding, growth, and recruitment, and respiratory impairment) are well documented (Waters, 1997). We previously documented the strong effects of channel slope on particle size in Etowah streams (Walters et al., 2003a), suggesting that sedimentology is mostly determined by non-anthropogenic controls. Yet channel bed sediment can be considered a stressor, at least in part, because deforestation and urbanization are significantly related to finer bed texture (e.g., fines in riffles, mean particle size, and embeddedness) beyond the primary correlations with slope (Leigh et al., 2002; Walters et al., 2003a). This suggests that that land cover change has influenced the particle size composition of stream beds to some extent, with subsequent negative effects on stream biotic assemblages. Considering that bed texture indicators are both simple to collect (requiring one field visit and minimal laboratory processing) and are strong indicators of biotic condition, their value for predicting assemblage traits in Piedmont streams can not be overstated.

Declining water quality is an important stressor to stream ecosystems, and some water quality variables may be more directly linked to land use change than other stressor variables we considered (e.g., catchment morphometry and channel morphology). We found that specific conductivity was a strong predictor of macroinvertebrate descriptors and that turbidity was a strong indicator of fish descriptors. Elevated conductivity has been previously linked to increased urbanization and altered macroinvertebrate assemblages in other regions (Wang and Yin, 1997; Paul and Meyer, 2001; Kratzer et al., 2006) and in these Etowah streams (Roy et al., 2003). Likewise, elevated stream turbidity is linked to removal of native forest cover and other land disturbing activities (Allan, 2004) and altered fish assemblages in these streams (Walters et al., 2003a) and other systems in the southeastern highlands (Sutherland et al., 2002). Streams of the Etowah are naturally low in conductivity due to the underlying metamorphic geology and were reportedly clear during low flow prior to human alteration of the landscape (Burkhead et al., 1997). Since we detected elevated levels of conductivity and turbidity during baseflow conditions, we view them as indicators of chronic, long-term (i.e., press) disturbances resulting from landscape alteration as suggested by others (Bolstad and W.T., 1997; Price and Leigh, 2006a) for the nearby Blue Ridge Mountains province.

4.3. Differential response of macroinvertebrate and fish descriptors to environmental indicators

Macroinvertebrate and fish impairment were correlated with different watershed and reach-scale stressors. Macroinvertebrate descriptors were linked to changes in urban land cover, propagated through water quality (e.g., conductivity) and sedimentology (% fines in riffles). On the other hand, fish descriptors were more closely tied to reach-scale variables including embeddedness and turbidity, which were, in turn, related to reach-scale stream slope (largely a natural factor) and forest cover. The results also suggest that macroinvertebrates are more sensitive than fishes to urban effects in streams, at least in newly urbanizing systems. The predictive models were robust across the various descriptors for each assemblage, lending support to these causal pathways. Our results also coincide with previous studies of land use effect on multiple biotic assemblages that indicate that macroinvertebrates are more affected by chemical parameters (particularly sediment-related contaminants) and depositional sediment, whereas fish impairment is controlled by geomorphic and erosional (e.g., suspended sediment) alteration (Fitzpatrick et al., 2004; Burcher et al., 2007; Carlisle et al., 2008).

Considering that macroinvertebrates and fishes vary in morphological, behavioral, and life history traits, it is not surprising that they have different sensitivities to various stressors. Studies that sample multiple assemblages (e.g., fish, macroinvertebrates, and diatoms) in streams have repeatedly documented different responses to disturbances (Griffith et al., 2001; Triest et al., 2001; Fitzpatrick et al., 2004; Passy et al., 2004; Burcher et al., 2007; Feio et al., 2007; Carlisle et al., 2008). These patterns suggest that complete and accurate assessment stream ecosystem condition should include multiple assemblages. In fact, Carlisle et al. (2008) reported that only half of the sites would have been considered impaired if only one of the three assemblages (fish, macroinvertebrates, or diatoms) were sampled. Furthermore, primary sources of stream impairment may be missed by using a single assemblage indicator. While combining multiple assemblages into a single index has been recommended (Griffith et al., 2003), we argue that sampling multiple assemblages and separately examining causal pathways will lead to a better understanding of the multiple mechanisms by which land cover impacts stream ecosystems. The suite of stressors will, in combination, provide the best indicators of disturbance and, in turn, the most comprehensive management recommendations.

4.4. Implementing environmental indicators into a management framework: A tiered approach

One objective of this research was to compare the predictive capability of indicators collected with minimal cost and effort to those that are laborious or expensive to collect. To this end, we modeled assemblage descriptors using simple, reduced, and full model sets, that included variables progressively more laborious to collect (Gergel et al., 2002). Not surprisingly, the predictive power tended to be highest for full models, intermediate for reduced models, and least for simple models. However, many of the reduced and simple models were quite robust (8 of 14 models explaining >66% of the variance among descriptors), indicating that some ecosystem properties in urbanizing watersheds can be well predicted without the added expense of intensive measurements.

Given our results, we suggest a tiered approach to modeling stream response to land use change depending upon management or research goals (Table 4). For example, a relatively simple and inexpensive GIS-based modeling approach would be appropriate if the management goals are to identify the likely degree of impairment among sites or to identify at-risk populations of sensitive or endemic species (Tier 1). As goals increase in complexity or specificity (e.g., long term monitoring of sites, identifying incipient levels of biotic integrity loss), a minimal field effort is needed to augment the simple variable set (Tier 2). This would include biotic community sampling and collection of geomorphology and water quality variables (e.g., bed texture and turbidity) that could recorded in a single visit. Water quality sampling could be expanded to increase temporal resolution of baseflow conditions (monthly or quarterly site visits), but should still be limited to indicators like turbidity or conductivity that are easily measured in the field. More complex goals, such as restoring impaired streams, would require collecting the full suite of geomorphic and water quality variables considered in the full model set, particularly for studies focusing on both fish and macroinvertebrate endpoints (Tier 3). Tailoring study designs to meet these different goals would help managers maximize financial and labor resources, a critical element of aquatic resource management in an era of diminishing budgets.

5. Conclusions

In conclusion, it is appropriate to recall our two general research questions concerning (1) how well stream biota can be predicted from land cover, geomorphic, and water quality conditions, and (2) how well variables collected with minimal cost and effort predict assemblage integrity compared with variables that are more difficult and expensive to collect. Our results clearly indicate that strong predictions (R^2 = 0.50 – 0.79 in most cases) of stream assemblages can be made with separate multivariate models of either land cover, geomorphic or water quality variables, but that the best models (R^2 = 0.63 – 0.81) involve a combination of these variables in order to capture the full range of natural conditions and stressors structuring stream assemblages. We were encouraged to find that predictive power of our models remained high when using variables that were relatively simple and inexpensive to collect. The Etowah River basin was selected for this study because it contained a wide range of land cover characteristics and a wide range of topographic variation; thus, a reasonable level of regional applicability should exist. However, tests of these models in other regions are necessary to validate their general applicability. Even if the indicators we identified lack applicability to certain regions, our general approach of using multiple landscape components for modeling efforts and adjusting the complexity and intensity of data collection efforts to suit management goals provides a structured framework for managing land use effects on stream ecosystems.

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Table 1. Best bivariate predictors of invertebrate and fish assemblage descriptors. Only Pearson's correlation coefficients (r) with $p < 0.001$ are shown. n = 31 sites except n = 29 sites for water quality variables in italics. Sed. = suspended sediment. Land cover variables were assessed at the catchment (C), network (N), and riparian (R) scale (see methods). Descriptions of predictor variables are provided in Supplementary Material, Table 1.

		Invertebrate descriptors				Fish descriptors			
	Predictors	ICI	EPT	Invert A1	Invert A2	IBI	E:E+C	Fish A2	Fish A3
Land Cover									
Urban	urban (C)	-0.73	-0.64	-0.81	-	-	-0.58	-	-
	high-density urban (R)	-	-	-	-	-	-	-	-
	low-density urban (R)	-	-	-	-	-	-	-	-
Forest	forest (C)	0.61	0.56	0.63	-	0.59	0.66	0.60	-
	forest (R)	-	-	-	-	-	-	0.56	-
	forest (N)	0.64	0.61	0.65	-	-	0.68	0.61	-
	deciduous forest (C)	-	-	-	-	-	-	-	-
	deciduous forest (R)	-	-	-	-	-	-	-	-
	evergreen forest (C)	-	-	-	-	-	-	-	-
	evergreen forest (R)	-	-	-	-	-	-	-	-
	mixed forest (C)	-	-	-	-	-	-	-	-
	mixed forest (R)	-	-	-	0.60	-	-	-	-
Agriculture	agriculture (C)	-	-	-	-	-	-	-	-
	cultivated (C)	-	-	-	-	-	-	-	-
	cultivated (R)	-	-	-	-	-	-	-	-
	cultivated (N)	-	-	-	-	-	-	-	-
	cropland (R)	-	-	-	-	-	-	-	-
	golf course (C)	-	-	-	-	-	-	-	-
	golf course (R)	-	-	-	-	-	-	-	-
Water	water (C)	-	-	-	-	-	-	-	-
	water (R)	-	-	-	-	-	-	-	-
	water (N)	-	-	-	-	-	-0.66	-	-
	ponds (C)	-	-	-	-	-	-	-	-0.56
	pond density (C)	-0.67	-0.65	-	-	-	-0.57	-	-
	pond density (>1ha), (C)	-	-	-	-	-	-0.56	-	-
Index	road density (C)	-	-0.59	-0.60	-	-	-	-	-
	disturbed land index (C)	-	-	-	-	-	-	-	-0.56

Geomorphology									
Morphometry (GIS)	drainage area	-	-	-	-	-	-	-	-
	compactness	-	-	-	-	-	-	-	-
	drainage density	-	-	-	-	-	-	-	-
	total relief	-	-	-	-	-	-	-	-
	local relief	0.60	0.61	0.72	-	-	-	-	-
	trunk stream slope	-	-	-	-	-	0.64	-	-
	map slope	-	-	-	0.67	-	0.63	-	0.70
	erosion index	-	-	-	-	-	-	-	-
Channel morphology	slope	-	-	-	0.71	-	0.71	0.61	-
	sinuosity	-	-	-	-	-	-	-	-
	riffle	-	-	-	-	-	-	-	-
	pool	-	-	-	-	-	-	-	-
	glide	-	-	-	-	-	-0.56	-	-
	entrenchment ratio	-	-	-	-	-	-	-	-
	baseflow width	-	-	-	-	0.57	-	-	-
	baseflow depth	-	-	-	-	-	-	-	-
	baseflow width:depth	-	-	-	-	-	-	-	-
	bankfull width:depth	-	-	-	-	-	-	-	-
	depth variability (t)[1]	-	-	-	-	0.65	-	0.64	-
	depth variability (c)[1]	-	-	-	-	-	-	-	-
	baseflow Q	-	0.56	-	-	-	-	-	-
	bankfull Q	-	-	-	-	0.56	-	-	-
	stream power	-	-	-	-	-	-	0.71	-
	large wood	-	-	-	-	-	-	-	-
Sedimentology	bedrock	-	-	-	0.56	-	-	-	-
	bed texture variability	-	-	-	0.58	-	-	-	-
	riffle bed texture	-	-	-	-0.60	-	-0.67	-0.72	-
	fines in riffles	-0.70	-0.56	-	-0.81	-	-0.69	-0.65	-
	embeddedness	-0.65	-0.56	-0.56	-0.67	-	-0.79	-0.75	-
	bed mobility	-	-	-	-0.63	-	-0.78	-0.63	-
Water Quality									
Chemistry	*SRP*	-0.59	-	-	-	-	-	-	-
	NH_4^+	-	-0.59	-0.68	-	-0.73	-0.73	-0.82	-
	$NO_3^- + NO_2^-$	-	-	-	-	-	-	-	-
	DO	0.60	0.56	-	-	-	0.67	0.68	-
	conductivity	-0.70	-0.71	-0.64	-	-	-	-	-
	pH	-	-	-	-	-	-	-	-

Sed.	turbidity	-	-	-	-	-0.66	-0.74	-0.69	-
	TSS	-	-	-	-	-	-0.61	-	-
Temperature	baseflow temp	-0.64	-	-	-0.60	-	-	-	-0.59
	annual temp	-	-	-	-	-	-	-	-
	summer temp	-	-	-	-	-	-	-	-0.60
	winter temp	-	-	-	-	-	-	-	-

[1.] Depth variability was assessed for the thalweg (t) and entire channel (c).

Table 2. Multiple linear regression analysis models (stepwise procedure, forward selection, $p < 0.05$) for invertebrate and fish assemblage descriptors for land cover, geomorphology, and water quality. Adjusted R^2 and F values are reported for ≤ 3-variable models (i.e., predictors in italics excluded). Land cover variables were assessed at the catchment (C), network (N), and riparian (R) scale (see methods).

Descriptors	Predictors	Adj. R^2	F value
	Land cover		
ICI	- urban (C), - pond density (C), - deciduous forest (C), + *agriculture* (C), + *water* (R)	0.69	22.8
EPT	- pond density (C), - urban (C)	0.52	17.0
Invert A1	- urban (C), + mixed forest (R)	0.70	35.2
Invert A2	+ mixed forest (R), - ponds (C)	0.47	14.0
IBI	+ forest (C), - ponds (C)	0.41	11.2
E:E+C	+ forest (N), + road density (C), - water (N), + *water* (C)	0.58	15.1
Fish A2	+ forest (N), + mixed forest (R), - ponds (C)	0.50	11.2
Fish A3	- disturbed land index (C), - ponds (C), - deciduous forest (R)	0.58	14.7
	Geomorphology		
ICI	- fines in riffles, + local relief, + large wood, + *bedrock*	0.66	20.1
EPT	+ local relief, + entrenchment ratio	0.56	20.3
Invert A1	+ local relief	0.51	31.9
Invert A2	- fines in riffles, + map slope, - trunk stream slope	0.79	37.8
IBI	+ depth variability (t), + bankfull Q, + local relief	0.58	14.9
E:E+C	- embeddedness, + map slope, + local relief, + *slope*	0.74	29.2
Fish A2	- embeddedness, + baseflow Q, - pool	0.74	28.8
Fish A3	+ map slope, - erosion index, - pool, + *trunk stream slope*, + large wood	0.60	16.1
	Water quality		
ICI	- SC, + DO	0.52	17.5
EPT	- SC, + pH	0.56	20.3
Invert A1	- SC, - turbidity	0.50	16.2
Invert A2	- baseflow temp	0.34	16.5
IBI	- turbidity	0.41	22.2
E:E+C	- turbidity, - baseflow temp	0.66	30.0
Fish A2	- turbidity, + DO	0.60	23.6

Fish A3	- baseflow temp	0.33	15.5

Table 3. Multiple linear regression models (stepwise procedure, forward selection, $p < 0.05$) for invertebrate and fish descriptors based on full, reduced (minimal cost and effort), and simple (least cost and effort) model sets. Land cover variables were assessed at the catchment (C), network (N), and riparian (R) scale (see methods).

Full				Reduced				Simple			
Predictors	Partial r^2	Adj. R^2	F value	Predictors	Partial r^2	Adj. R^2	F value	Predictors	Partial r^2	Adj. R^2	F value
ICI											
- urban (C)	0.54	0.77	34.0	- urban (C)	0.54	0.71	25.1	- urban (C)	0.54	0.68	22.6
- fines in riffles	0.19			+ embeddedness	0.12			- pond density (C)	0.11		
+ large wood	0.07			- decid. forest (C)	0.08			+ map slope	0.07		
EPT											
- conductivity	0.51	0.73	28.6	- pond density (C)	0.43	0.55	19.3	- pond density (C)	0.43	0.63	17.7
+ local relief	0.18			+ local relief	0.15			+ local relief	0.15		
+ bankfull Q	0.07							+ agriculture (C)	0.08		
Invert A1											
- urban (C)	0.66	0.78	36.5	- urban (C)	0.66	0.79	38.6	- urban (C)	0.66	0.79	38.6
+ large wood	0.07			+ map slope	0.07			+ map slope	0.07		
+ map slope	0.07			+ baseflow Q	0.09			+ drainage area	0.09		
Invert A2											
- fines in riffles	0.66	0.79	39.6	- embeddedness	0.46	0.66	20.3	+ map slope	0.45	0.43	23.6
+ map slope	0.12			+ map slope	0.16						
- pH	0.04			+ mixed forest (R)	0.08						
IBI											
- turbidity	0.43	0.63	18.4	+ forest (C)	0.35	0.48	10.4	+ forest (C)	0.35	0.49	10.5
+ bankfull Q	0.18			+ baseflow Q	0.10			+ drainage area	0.11		
+ depth variability (t)	0.06			- embeddedness	0.08			+ map slope	0.08		

E:E+C											
- embeddedness	0.62	0.78	36.8	- embeddedness	0.62	0.77	35.3	+ forest (N)	0.46	0.70	23.9
- turbidity	0.10			+ map slope	0.09			+ map slope	0.22		
+ map slope	0.09			+ forest (C)	0.09			+ road density (C)	0.04		
Fish A2											
- embeddedness	0.57	0.74	28.8	- embeddedness	0.57	0.73	27.4	+ forest (N)	0.37	0.42	11.9
+ baseflow Q	0.14			+ baseflow Q	0.14			+ total relief	0.09		
- pool	0.05			+ mixed forest (R)	0.04						
Fish A3											
+ map slope	0.49	0.81	43.1	+ map slope	0.49	0.73	42.2	+ map slope	0.49	0.73	42.2
- disturbed land index (C)	0.26			- disturbed land index (C)	0.26			- disturbed land index (C)	0.26		
- pool	0.08										

Table 4. Application of a tiered approach for assessing stream responses to land use change based on management goals. As management goals become more complex or specific (Tier 1 – 3), variables that are more intensive, laborious, and relatively expensive to collect may be required for modeling efforts.

Tier	Datasets required	Management goals
1	Land cover	Identify areas where biotic integrity is severely compromised
	Morphometry	Identify intact or minimally impaired systems (i.e., "reference" sites)
	Species distributions[1]	Identify at-risk populations of sensitive, protected or endemic species
		Guide development plans for local or regional planning commissions
2	Land cover	Monitoring
	Morphometry	Identification of incipient levels of decline for specific regions or watersheds
	Easily collected geomorphology (e.g., bed texture) and water quality variables (e.g., turbidity)	Assessment of temporal changes in stream habitat, water quality, or biotic assemblages
	Biotic community data	
3	Land cover	Regional assessment or condition studies
	Morphometry	Restoration of impaired streams
	Full geomorphic survey	Evaluation of best management practice (BMP) implementation programs
	Full water quality survey including field measures and laboratory analytical chemistry (e.g., nutrients)	Mechanistic or experimental studies of land use effects on stream ecosystems
	Hydrology[2]	Development of Habitat Conservation Plans[3]
	Biotic community data	

[1] Spatial data not used in this study, but often readily available through state agencies.

[2] Can be expanded to include a broader set of hydrologic variables than those considered in this study.

[3] Formal plans submitted to the U.S. Fish and Wildlife Service by private landowners, corporations, states, or local governments who wish to conduct activities on their land that might incidentally harm (or "take") Endangered or Threatened species protected under the Endangered Species Act.

Figure List