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Linking the diversity and abundance of stream biota to landscapes in the mid-Atlantic USA

Scott Goetz *, Gregory Fiske

Woods Hole Research Center, Falmouth MA 02540, United States

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ABSTRACT

The amount of human altered land surface within a watershed has long been known to influence the biota of receiving streams and waterways. In contrast, vegetation in riparian zones can filter pollutants and reduce flow velocities that incise stream channels. We examined the relationship between the built environment and water quality for streams (1st through 4th order) across three physiographic provinces of the State of Maryland, USA, including 59 watersheds with some 865 stream sampling locations. We used image data products capable of discriminating fine-scale information of the land surface, including proportional impervious, tree, grass and crop cover. Stepwise multiple linear regression and decision tree statistical approaches were used to assess the relationship between the land cover predictors and benthic indices of biological integrity (BIBI) and number of sensitive invertebrate taxa (NEPT), response variables derived from the Maryland Biological Stream Survey (MBSS). Impervious and tree cover were found to be the best predictors of stream biota, although this varied with physiographic province and the response variable of interest. The best multivariate models predicted 65% of variability in BIBI and 62% of NEPT ($p<0.001$). The configuration of tree cover across the landscape and the distance of land cover to the stream channel was found to be important in many, but not all cases for improving the predictive quality of statistical models estimating stream biota metrics. This work advances the estimation of stream health characteristics in areas where MBSS measurements do not exist but can be estimated using comparable land cover information, and informs guidelines for management and restoration.

1. Introduction

The altered composition and configuration of land use within a watershed, such as expansion of commercial and residential development, is widely known to disrupt the hydrology and ecology of stream ecosystems (Allan, 2004; Nilsson et al., 2003). Non-point source pollutants arise primarily from impervious surface areas (such as roads, parking lots, houses) and agricultural fields (pesticides, herbicides, excess nutrients). As impervious area increases, watershed base flows are lowered and flood discharge frequency and magnitude increase due to the combination of reduced infiltration into groundwater and the consequent increase in overland flows (Brun & Band, 2000, Jennings & Jarnagin, 2002). The connection of impervious surface areas across the landscape also produces flashier stream hydrographs that exhibit a decreased lag time between storm events and peak discharge (Moglen & Beighley, 2002). Stream channels are modified by these changes in flow, increasing bank and stream bed incision, exacerbating erosion and associated sediment loads (Palmer et al., 2002; Schueler, 1994).

Freshwater stream biota are vulnerable to land use disturbance and change, and associated pollutants, resulting in a high proportion of freshwater fishes, amphibians, and macroinvertebrates being classified as vulnerable, imperiled or extinct in the United States (U.S. EPA, 2002). Numerous studies in the Chesapeake Bay watershed alone have demonstrated the association between land use changes and the degradation of the biological, chemical and physical quality of streams (Liu et al., 2000; Paul et al., 2002). Further, the proportion of impervious cover in this region is expected to more than double over the next 30 years, assuming current trends continue (Jantz et al., 2003), and related trends are expected nationwide (Brown et al., 2005).

The adverse effects of these developed and agricultural areas on aquatic systems can be mitigated by riparian vegetation buffers, which reduce the force of overland flows, take up excess nutrients, maintain stream bank integrity, provide shade that reduces stream warming, and generally act to mitigate the physical and ecological impacts described above (Baker et al., 2006a; Reed & Carpenter, 2002; Groffman et al., 2003; Jordan et al., 1993; Snyder, et al., 2003; Weller et al., 1998).

Biological monitoring can help identify anthropogenic influences and degradation in streams, and stream health databases have been compiled (e.g., U.S. EPA, 2002; Strayer et al., 2003) allowing more

* Corresponding author. Tel.: +1 508 540 9900.
E-mail address: sgoetz@whrc.org (S. Goetz).

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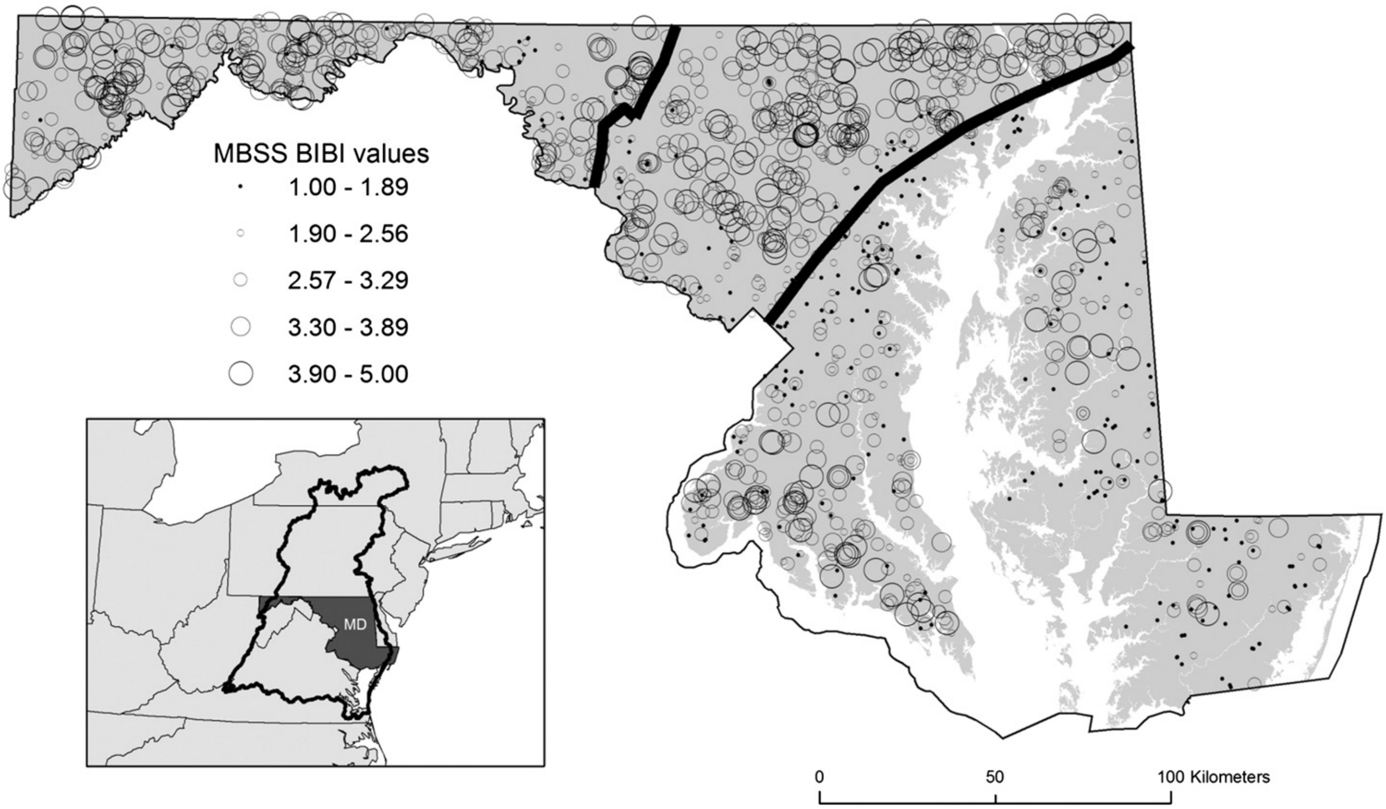

Fig. 1. Maryland Biological Stream Survey (MBSS) sampling point locations. Graduated symbols depict the value of the biological index of biotic integrity (BIBI), where higher values (larger symbols) indicate higher biotic indices and stream health.

comprehensive analyses in relation to land cover information (e.g., Basnyat et al., 2000; Meador & Goldstein, 2003; Potter et al., 2004; Roth et al., 1996; Urban et al., 2006). Similar advancements in monitoring land cover with satellite image data permit improved characterization of the links with stream biota (e.g.,Fisher et al., 2000; Goetz et al., 2003; Jones et al., 2001; Stewart et al., 2001; Snyder et al., 2005).

Our objectives in this study were to analyze stream biota measurements routinely acquired across the state of Maryland in the context of the land cover and land use that comprise the watersheds (catchments), and to assess the influence of landscape configuration on statistical model predictions of stream biota metrics.

2. Study area and data sets

The ~26,000 km^2 state of Maryland was stratified into three general physiographic provinces; coastal plain, Piedmont, and highlands (Fig. 1). The coastal plain (13,500 km^2), surrounding the Chesapeake Bay estuary, is mostly flat lowlands with interspersed forest and agricultural cover. The Piedmont (7000 km^2), occupies the area between Washington DC and the Ridge and Valley region of central Maryland. The Highlands (5500 km^2), as defined for this study, are made up of the Ridge and Valley, Appalachian Plateau, and the Blue Ridge of western Maryland. The state has relatively steep climate gradients across these provinces, with warmer average temperatures and longer growing season lengths as one moves from the western highlands to the eastern coastal plain.

2.1. Stream survey data

Stream biota and associated water quality measurements were acquired from the Maryland Biological Stream Survey (MBSS) (Roth et al., 2005). The MBSS is a cooperative effort between several governmental and non-governmental agencies, professional biologists, students and volunteers designed to assess the biophysical integrity of a rotating selection of Maryland's streams on an annual basis (MD-DNR, 2007). Streams are sampled in a stratified random selection of segments, 75 m in length, within one third of the 18 major drainage basins of Maryland. The MBSS sampling points include 1st through 4th order streams, using the Strahler (1952) stream order method and USGS stream channel delineations, where 1st order streams are in the headwaters (most upstream). Approximately 300 stream segments are sampled each year, acquiring data on the chemical, biological, and physical characteristics of each stream reach (Roth et al., 2005).

The Maryland Department of Natural Resources provided us five years (2000 to 2004) of MBSS data covering 1360 stream samples; 544 for the coastal plain, 382 for the Piedmont, and 434 for the highlands (see Fig. 1). There were over three dozen attributes for each MBSS stream sample point, including information on site location and identification, physiographic province, number of vertebrate and invertebrate taxa, and rated metrics of biotic indexes. A complete list of the MBSS data set attributes is available online (www.dnr.state.md.us/streams/mbss/parameters.html).

We restricted the current analyses to a selection of attributes denoting geographic location, Benthic Index of Biological Integrity (BIBI), number of *Ephemeroptera, Plecoptera,* and *Trichoptera* individuals (NEPT), and physiographic province. The richness (total number) of NEPT macroinvertebrate taxa is a commonly and widely used measure of benthic community condition because these taxa are generally intolerant of poor water quality. The MBSS determined BIBI scores by comparing the benthic assemblage (i.e. the composition of invertebrate stream organisms) at each site to those found at minimally impacted reference sites, the latter of which are defined as those sites having minimal exposure to human activities and representative of the stream type and region of interest (seeRoth et al., 2005). Benthic macroinvertebrates were sampled in the spring and

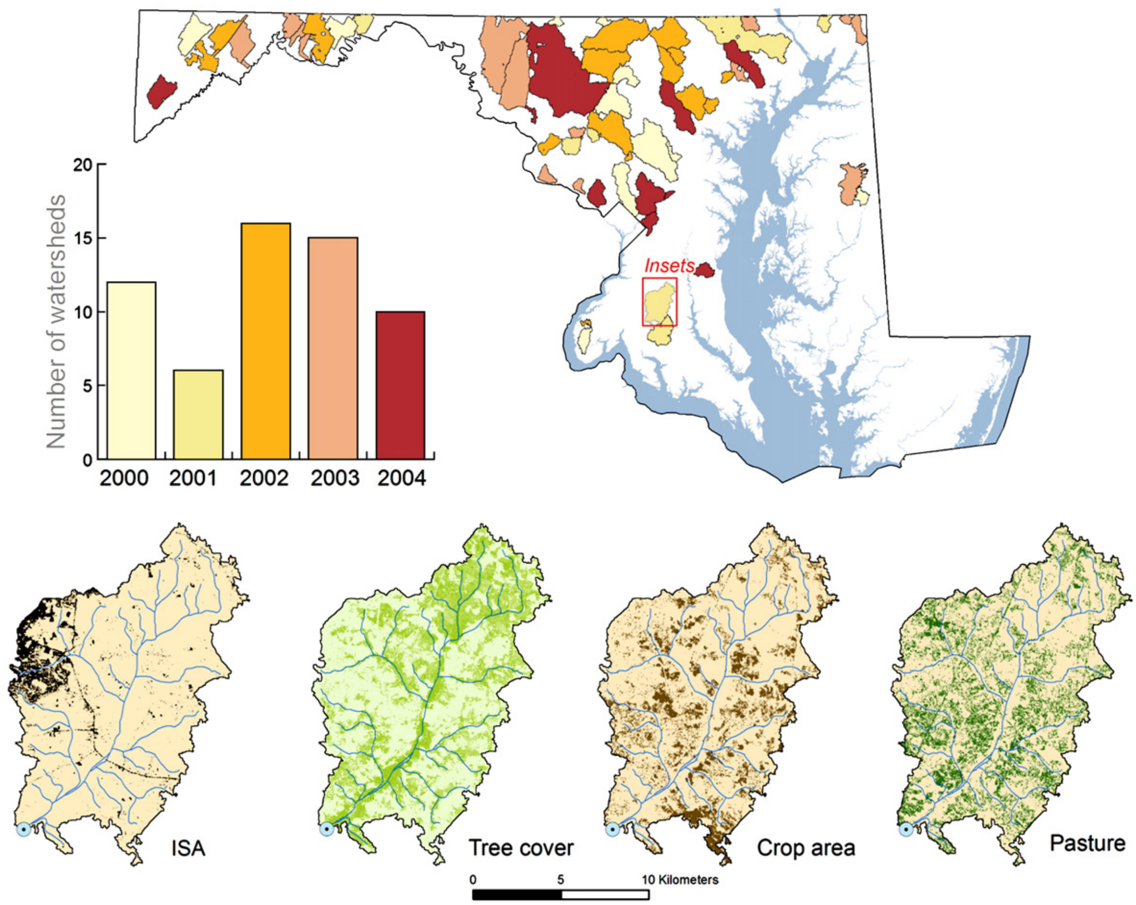

Fig. 2. Map of the state of Maryland showing MBSS watershed locations and year sampled, and land cover variables depicted for an example watershed in the Coastal Plain province. ISA is a per-pixel impervious surface area.

identified to genus or lowest practical taxon in 100-organism subsamples. Thus, the BIBI provides an index of the biological integrity of a stream reach relative to high quality undisturbed conditions (Stribling et al., 1998). The range of NEPT was 0 to 23 (unique taxa), and the range and distribution of the relative BIBI values are provided in Fig. 1.

2.2. Land cover metrics

2.2.1. Impervious cover

We made use of a 30 m continuous impervious surface area maps (%ISA) of the entire Chesapeake Bay watershed, derived from a multidate (1998–2002) series of Landsat7 Enhanced Thematic Mapper (ETM+) imagery (Goetz & Jantz, 2006). A total of 60 Landsat images were analyzed, including scenes capturing Spring, Summer and Fall differences under both leaf-on and leaf-off conditions (a list of scenes is available inGoetz et al., 2004). All scenes were radiometrically calibrated, orthographically rectified using USGS 30 m digital elevation data sets, corrected for topographic illumination effects, temporally normalized between scenes, and cloud and shadow masked (Goetz et al., 2004). The derived %ISA maps contains subpixel information on the proportion of each 30 m (900 m^2) pixel that is occupied by impervious cover, ranging from ca. 10% for low-density residential development to nearly 100% in intensively developed commercial and industrial areas (Fig. 2).

The extent of impervious cover represented in the map was validated using higher resolution imagery, with overall accuracy of ~90% (Jantz et al., 2005). The spatial detail in the subpixel maps is sufficient for delineating areas with even relatively little impervious cover, such as low-density residential housing, albeit at somewhat lower accuracy in these areas. This methodology was also recently used by the Multi-resolution Land Cover Consortium (MRLC) to produce similar maps across the nation, as part of the National Land Cover Database (NLCD) (Homer et al., 2004; Yang et al., 2003).

2.2.2. Tree Cover

Continuous tree cover maps (%Tree) were produced using the same approach as that for the %ISA maps, including use of fine-scale maps of tree cover derived from digital orthophotographs (0.5 m DOQs) and high-resolution (fused 1 m and 4 m) IKONOS satellite imagery for training the subpixel algorithms applied to the multitemporal Landsat imagery (Goetz, 2006). The latter were precision georeferenced image data sets acquired and processed over an 1800 km^2 area in central Maryland. The IKONOS images were classified into tree cover maps, making use of forest cover interpreted from the DOQs as training data, and the resulting accuracy of the tree cover classification, as assessed with an independent validation sample of some 600,000 point locations, was over 97% (Goetz et al., 2003). The tree cover maps derived from the Landsat imagery (Fig. 2) are, as with the impervious maps, expressed as a continuous value between 0 and 100%. Again, the NLCD now provides a similar %Tree cover product nationwide, by mapping zones loosely based on ecoregions.

2.2.3. Crop and grassland

Proportional crop and grassland cover were derived from the U.S. Department of Agriculture's *National Agricultural Statistics Service* (NASS)(USDA, 2002), based on analyses we helped them conduct using the same Landsat imagery as previously described (Goetz et al., 2004). NASS personnel derived over 60 categories of crop and anthropogenic

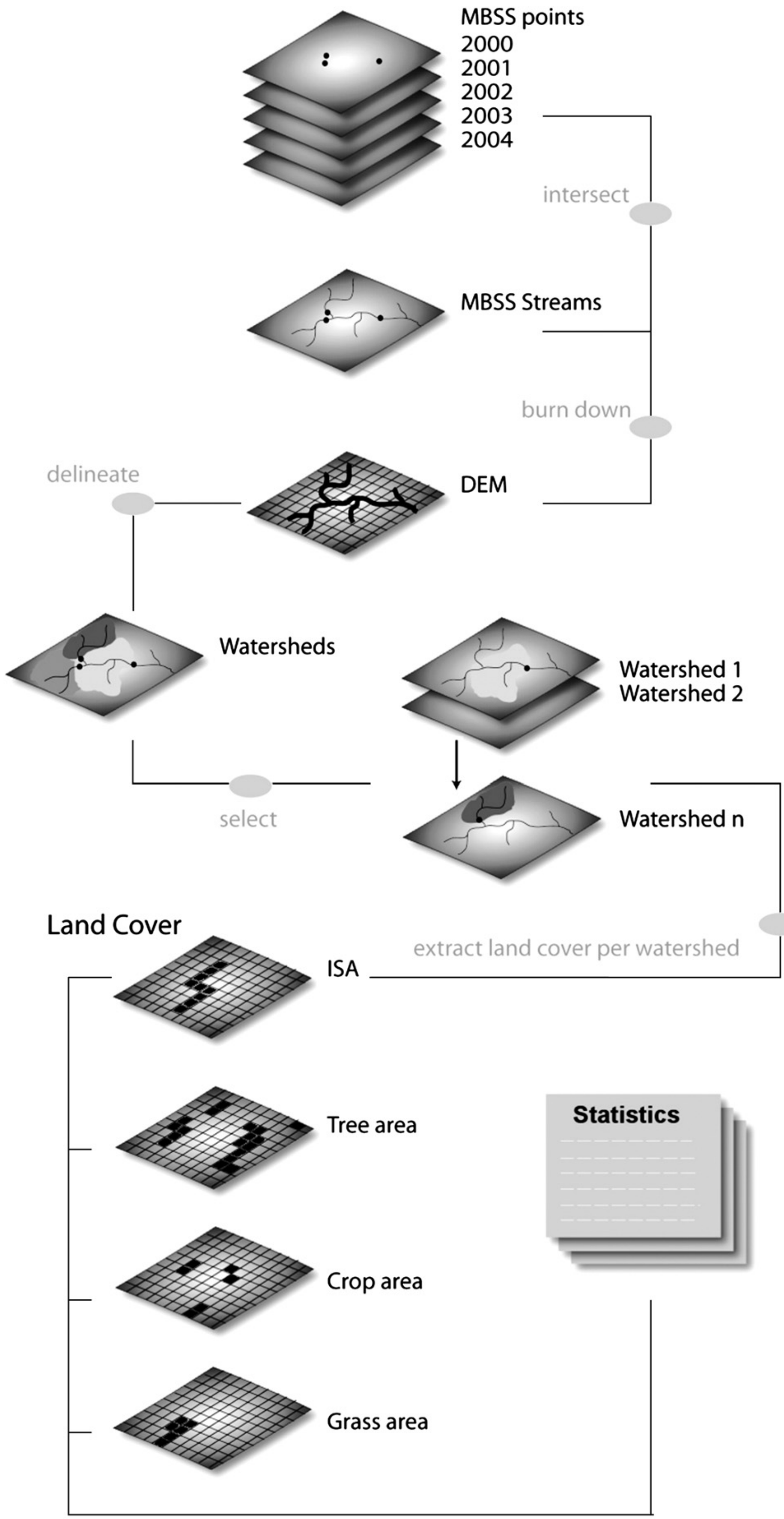

Fig. 3. Flow chart of the methodological approach used to assess the relevance of land cover to stream biota measurements. MBSS data from multiple years were extracted for associated watersheds delineated using a digital elevation model, and land cover information was summarized for the same watersheds to conduct comparisons with the MBSS metrics.

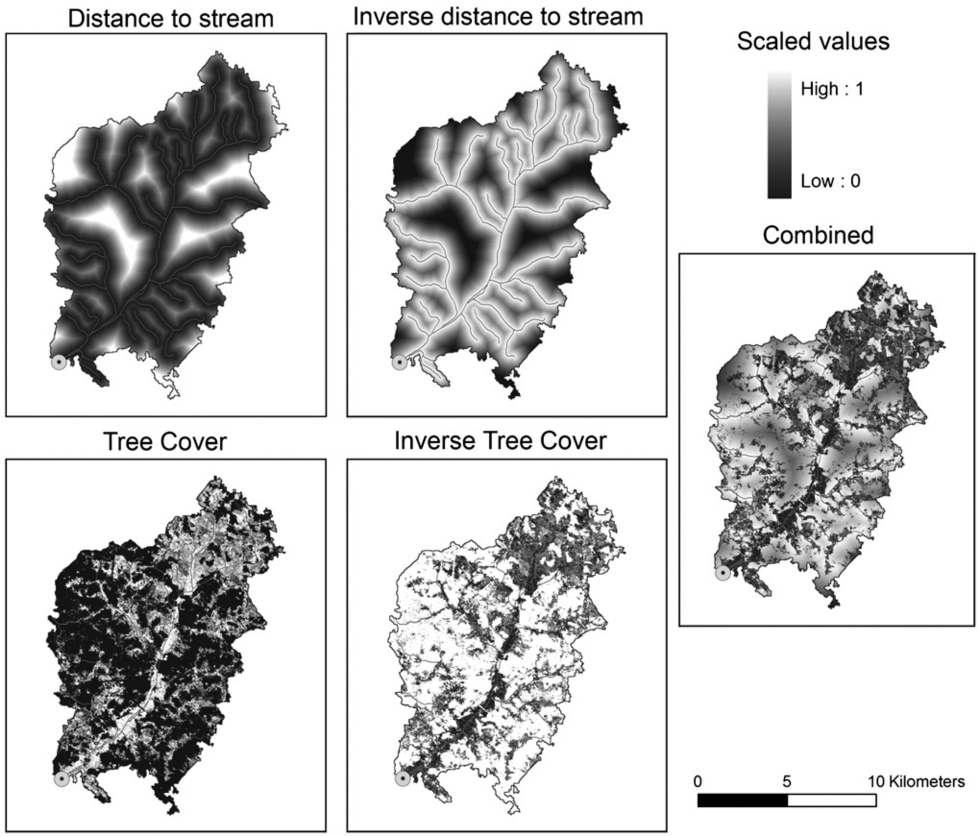

Fig. 4. Graphic depiction of example landscape weighting scheme used to assess the relevance of inverse distance to the stream channel (linear in this case) and land cover information (%Tree in this case). Combining these two weighted variables produces maps depicting the most heavily weighted areas as those that are closest to the stream but with little to no tree cover.

land cover using an iterative, supervised Bayesian cluster labeling approach, informed with a large database of randomly selected training sites, rotated and revisited on a 5-year basis, as part of their routine crop surveys (USDA, 2002). We used 44 of the crop categories in the NASS map, selecting only those that correspond to agricultural human use of the land that cannot easily be misinterpreted as "natural" land cover in order to be relatively conservative about what was considered agriculture. Grass areas were identified using the *Grass* and *Pasture* categories of the NASS map. An example of these map products is shown in Fig. 2.

3. Methods

Using the land cover data sets previously described we calculated the percentage of each cover type (%ISA, %tree, %crop, %grass) within each delineated catchment upstream of the MBSS sampling point (described below), and compared those statistics to the MBSS metrics collected at that point. Because these variables were all continuous, each point in the landscape may consist of some fraction of each of these cover types, and each variable therefore reflects this proportional cover when calculated across MBSS watersheds. In some cases, the proportional values can add up to slightly greater than 100%, particularly where tree cover overlies grass and other cover types. Various weighting schemes were used to explore the relative importance of landscape configuration, riparian buffer zones (to a minimum of 30 m), and upstream distance from the sampling point on predictions of stream biotic metrics. The general approach is outlined in Fig. 3, and the details are given below.

3.1. Watershed delineation

We used a statewide 30 m digital elevation model (DEM) to define catchment areas associated with the MBSS stream network and the sample point locations (Fig. 3). The limited vertical accuracy of the DEM data made it difficult to delineate catchments in the coastal plain, which has very little vertical relief and is dissected by trenches used to aid crop drainage on poorly drained soils. These areas were based upon use of the MBSS delineated catchments, which are known to be somewhat unreliable in this province (Baker et al., 2006b). In areas where the stream network derived from the DEM did not match the MBSS stream network, we reconciled the two by "burning" the MBSS streams into the DEM and locating the MBSS sample locations as "pour points." Any remaining sampling points that were located on an adjacent but incorrect tributary were omitted. We also used a flow accumulation map derived from the DEM which, together with the other checks, refined our delineation of the catchments while ensuring that the MBSS sampled stream reaches were properly located in the correct catchment. This also allowed us to have confidence in different delineations of catchment extent and associated area contributing to the MBSS sampling point. Very small catchments, less than 15 pixels (1.35 ha) in the DEM, were omitted from further analysis. We also removed repeat sample data where multi-year measurements were made at the same sampling point, keeping only the data closest to the time period of the land cover data set.

We explored definitions of catchment area contributing to the MBSS sampling point locations in three ways; 1) all the upstream land area (30 m grid cells) that contributes to any sampling point, 2) only the catchment area that contributes to a specific sampling location, excluding areas that contribute to sampling locations that may exist further upstream, 3) aggregated catchment areas that contribute to the highest order sampling locations, considering only the data from the point that subsumes all lower order streams. This last definition differs from the other two in that, for example, a 3rd order stream will subsume the catchment of any MBSS sample points on 2nd or 1st

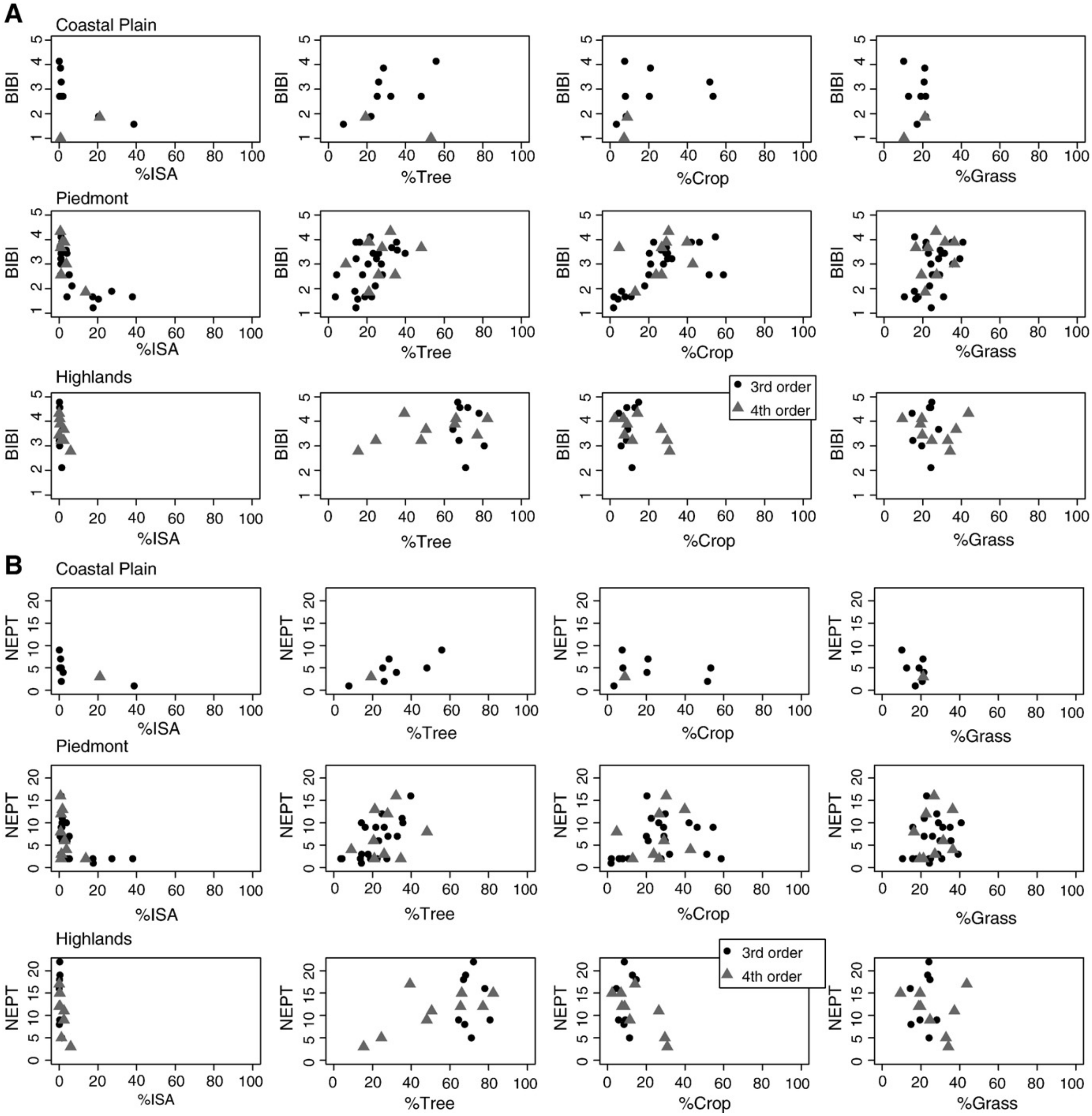

Fig. 5. Scatterplots showing the relation of each of the four land cover variables to (A) BIBI and (B) NEPT, stratified by physiographic province. The comparisons shown here are for the higher order (aggregated) watersheds, which subsume any upstream sampling points.

order headwater streams. In these cases, only the MBSS data from the higher order catchment (3rd over 2nd and 1st; 2nd over 1st) was utilized in the analyses. For catchments without upstream sampling points the various catchment definitions will be the same. We note that multiple sampling points occur only in the larger watersheds (those with more than 100 non-tidal stream miles), by design, in order to improve the metrics (BIBI, NEPT) estimated from the stream measurements.

3.2. Landscape weighting schemes

We tested several distance weighting schemes to scale the land cover contribution at each location (cell) within a watershed to the stream biota metrics at the sampling point. The first approach incorporated an inverse distance weighting (IDW) to the stream channel from each cell location, as well as an IDW upstream from the MBSS sample location (pour point) (Fig. 4). Both were calculated as simply 1 / distance (*D*). The combination of these two weightings, similar to that used by King et al. (2005) with land cover type classification, provides a relative contribution from each watershed location assuming both linear distance decay to the stream channel and downstream to the sample point, regardless of actual flow path or stream routing complexity. A variation of this approach incorporated negative exponential decay (−0.1 to −0.0001) weighting schemes applied to each location within the watershed. These weightings were again applied to both the distance from the stream channel and the along-stream distance to the MBSS sampling location (Fig. 4).

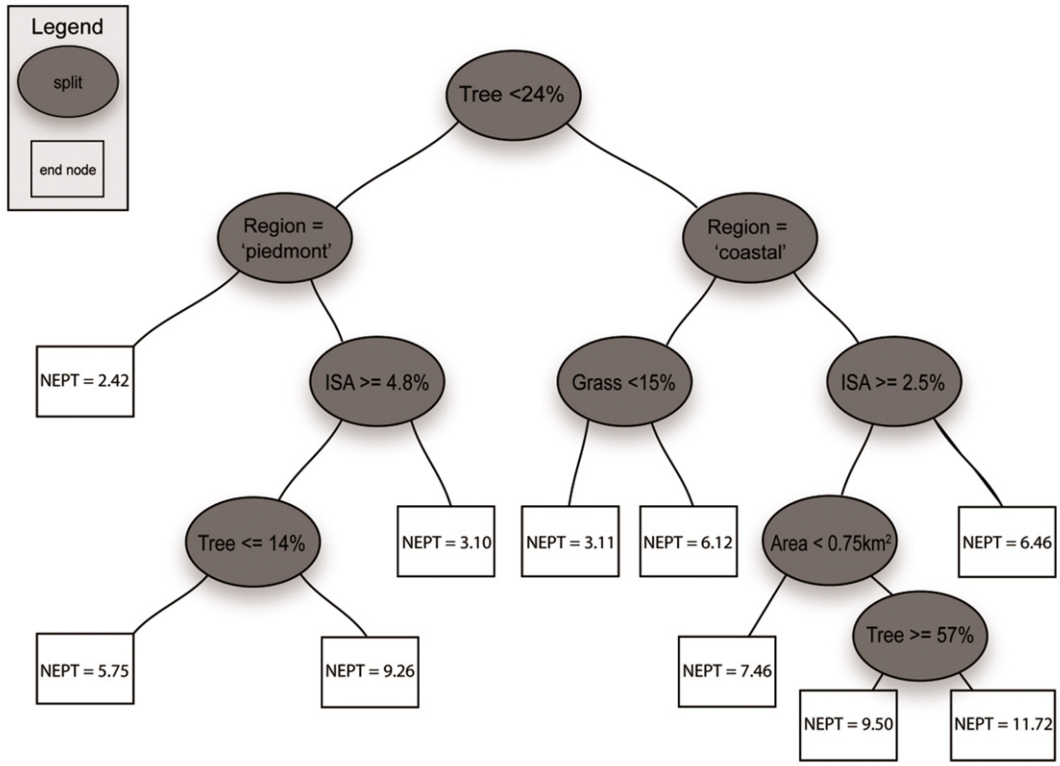

Fig. 6. An example of binary hierarchical splits produced by a decision tree algorithm, in this case trained to classify NEPT for all (1st through 4th order) stream catchments, across all physiographic provinces. Numbers in the terminal nodes (boxes) correspond to the mean value for that class.

Another weighting scheme made use of the flow accumulation grid, which we derived as part of the watershed delineation exercise in the ESRI ArcGIS environment, and a map derived from the per-pixel amount of tree cover. We used the flow accumulation grid to weigh cells within each watershed based on their relative ranking in flow accumulation across the landscape, summed for each grid cell, such that each cell has a value for the number of other cells within the catchment that drains into it. We used a log transformation of the flow accumulation values to deemphasize a large number of areas representing flow from just a few pixels, which form entirely self-contained small 'catchments'. This occurs almost entirely within areas of little or no topographic relief. Outputs of the flow accumulation map were scaled between 0 and 1. The tree cover surface was created by weighting the cells without tree cover higher than those with denser tree cover. By combining the tree cover surface with the scaled flow accumulation grid, a weighted surface was created that emphasized contributions from areas nearer the stream channel and without tree cover over those areas further away from the stream channel with dense tree cover. Our intent with this approach was to account for land cover contributions to streams from areas where forested riparian buffers were lacking, particularly in areas where flowpaths converged on the stream channel.

A variation of the latter scheme excluded the flow accumulation information in order to attempt a simpler approach that still deemphasized contributions from sufficiently buffered riparian areas, but also eliminated issues with the contribution of flow paths in areas of little topographic relief. In this case, instead of flow accumulation combined with tree cover, we simply combined the inverse distance to the stream with the tree cover map. Thus the importance of tree cover decreased with distance from the stream channel (Fig. 4).

All of these analyses were done with ESRI® GIS scripts that were used to extract each watershed, calculate distance to the stream channel or other components of the particular weighting scheme, apply the resulting weighted surface to each of the proportional land cover maps (%ISA, %tree, %crop, %grass), and aggregate the values for all contributing cell locations. In all cases, outcomes of each landscape weighting schemes were compared to non-weighted results to assess the effectiveness of the approach.

3.3. Statistical analyses

To examine the relationships between response and predictor variables, we used simple correlation analysis, stepwise multiple linear regression (MLR), and binary hierarchical splitting (decision

Table 1
Best predictors selected in stepwise MLR models of BIBI and NEPT by physiographic region, with and without landscape weighting

	Region	Primary selected variables	r^2	Δr^2	p-value
BIBI	All regions	ISA, Tree, Crop	49%		***
	Coastal	ISA, Tree, Crop	35%		0.146
	Piedmont	ISA, Crop, Tree	65%		***
	Highlands	ISA, Grass, Area	28%		*
	Landscape weighted				
	All regions	ISA, Grass, Area	42%	−7%	***
	Coastal	Tree, Crop, Grass	55%	+20%	0.087
	Piedmont	ISA, Crop, Grass	55%	−10%	***
	Highlands	Tree, ISA, Grass	49%	+21%	**
NEPT	All regions	Tree, Grass, Crop	52%		***
	Coastal	ISA, Area, Crop	39%		0.158
	Piedmont	Tree, Crop, Grass	43%		**
	Highlands	ISA, Grass, Tree	44%		**
	Landscape weighted				
	All regions	ISA, Crop, Tree	35%	−17%	***
	Coastal	Tree, Area, Crop	62%	+24%	*
	Piedmont	ISA, Grass, Tree	29%	−14%	**
	Highlands	ISA, Tree, Area	52%	+8%	**

Sample sizes for the results shown here (aggregated catchments) were 10 (Coastal), 32 (Piedmont), 17 (Highlands) and 59 (all). p-values *, ** and *** correspond to $p<0.05$, $p<0.01$, $p<0.001$ respectively.

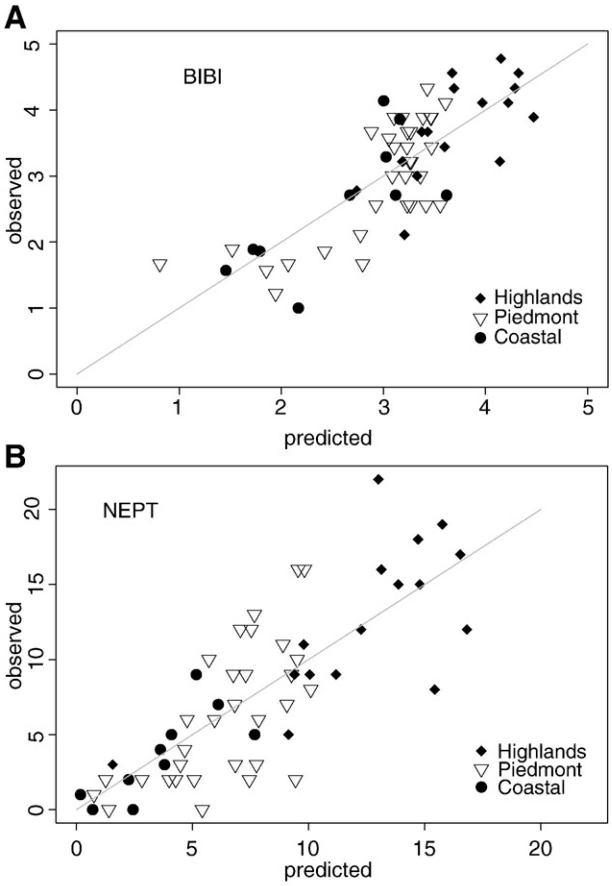

Fig. 7. Scatterplots of observed versus best multivariate-predicted values of (A) BIBI and (B) NEPT, with symbols indicating the physiographic province. The models are listed in Table 2. A one-to-one line, indicating perfect agreement, is shown. Note the distinction between regions, particularly in NEPT, with the highest values in the Highlands province and the lowest in the Coastal Plain.

tree) approaches. Using both MLR and decision trees, we tested models for 1st through 4th order MBSS stream samples and compared distance-weighted versus non distance-weighted schemes. The predictor variables included physiographic region (categorical) and the continuous variables stream length, stream order, watershed area, %ISA, %tree, % crop, and %grass. The response variables were the continuous variable metrics benthic IBI (BIBI) and the number of sensitive taxa (NEPT).

MBSS stream biota metrics were predicted from the weighted land cover information using *k*-fold forward stepwise MLR (Sokal & Rohlf, 1994). This procedure allowed us to train a linear model on a portion of the data (80%) while withholding a selection of the data (20%) for subsequent cross validation. This was done repeatedly (k=20 times) using randomly selected subsets of the data. Predictor variables were iteratively selected based on their relative power in explaining variance within the response variable, with at least a 2% increase in explained variance for entry.

The decision tree approach was also used to identify key land cover variables in relation to MBSS response variables. This technique builds a predictive model in a hierarchical fashion using binary splits of predictors that explain the most variance in the response variables, resulting in a 'tree' that identifies split values (sometimes referred to as decision rules) and a set of terminal or end nodes that identify the final set of response variable values that can be derived from the predictors (sometimes referred to as leaves). We used the decision tree implemented in the R statistical / graphical software package (http://www.r-project.org/), specifically the recursive partitioning and regression trees (rpart) function in R. Additional detail on decision trees is available in Breiman et al. (1984), and examples are further described by Goetz et al. (2004).

4. Results

4.1. Land cover predictors of stream biota metrics

When plotted against one another, the predictor and response variables, stratified by physiographic province and stream order, revealed differences in the variability of individual predictors relative to the response variables over this domain (Fig. 5). The highest correlations were between the land cover predictors and MBSS response variables in the Piedmont region, although other significant correlations were evident in other provinces as well. We do not present or discuss all the results here because of the large number of possible combinations of predictors derived from the various distance weighting schemes, and the lack of consistent predictors across provinces and catchment sizes, but we do provide a few inferences. The utility in presenting these single predictor variable correlations with the response variables is to convey how the data vary in terms of the land cover variables, the physiographic provinces, and the highest stream order present within the catchment. Generally the response variables increase with tree cover and decrease with impervious cover, but that was not always the case. Crop and grass cover were much more variable relative to the response variables, despite the potential effectiveness of grass as a buffer in riparian zones (Lyons et al., 2000), and not readily interpreted or consistent across the range of comparisons. Nonetheless, results for BIBI and NEPT were comparable in terms of direction of the correlations (positive or negative) with the individual predictors.

The decision tree models produced the strongest results in cases with the largest samples sizes (i.e. all watersheds and 1st order watersheds), which is consistent with observations that these algorithms are more robust with larger sample sizes. Initial splits in the decision trees typically included %ISA or %tree, followed by additional splits by physiographic region. This was true for both the non-weighted land cover values and the various landscape weighted schemes. An example is the decision tree model of NEPT generated for all watersheds, where the initial split on %tree cover was followed by splits on physiographic province, and then finer gradients in the other land cover variables (Fig. 6). The highest explained variance of all the decision tree models was for the case shown in Fig. 6 (r^2=60%) and decision rules (based on the binary splits on predictor variables), which can be used to apply the model to other watersheds, are included.

Using the stepwise MLR approach allowed a systematic selection of predictors across the range of scenarios considered. Unlike the decision tree models, the best results, in terms of predictive ability, were for the aggregated watersheds consisting of 4th order and stand-alone 3rd order stream catchments (n=59, Table 1). These aggregated catchments may incorporate contributions from areas upstream of additional sampling points, which were not included in this analysis of aggregated catchments in order to avoid issues associated with lack of statistical independence (i.e. catchment definition 3 above, for which only the MBSS data from the sampling point that subsumes all upstream area was considered). The total variance explained was comparable to the decision tree approach (>60%), but the decision tree results were a useful addendum to the MLR in terms of identifying the importance of physiographic province (a categorical variable more difficult to incorporate and interpret in MLR without log transformation). Based on the results of the decision trees, we first stratified the MLR modeling by physiographic province. The differences between provinces emphasized the considerable differences in both stream biota and land cover between these regions.

Within the MLR modeling, land cover variables were always selected as best predictors, whereas simple physical descriptors (e.g. area, stream length) were only occasionally selected, unlike in some

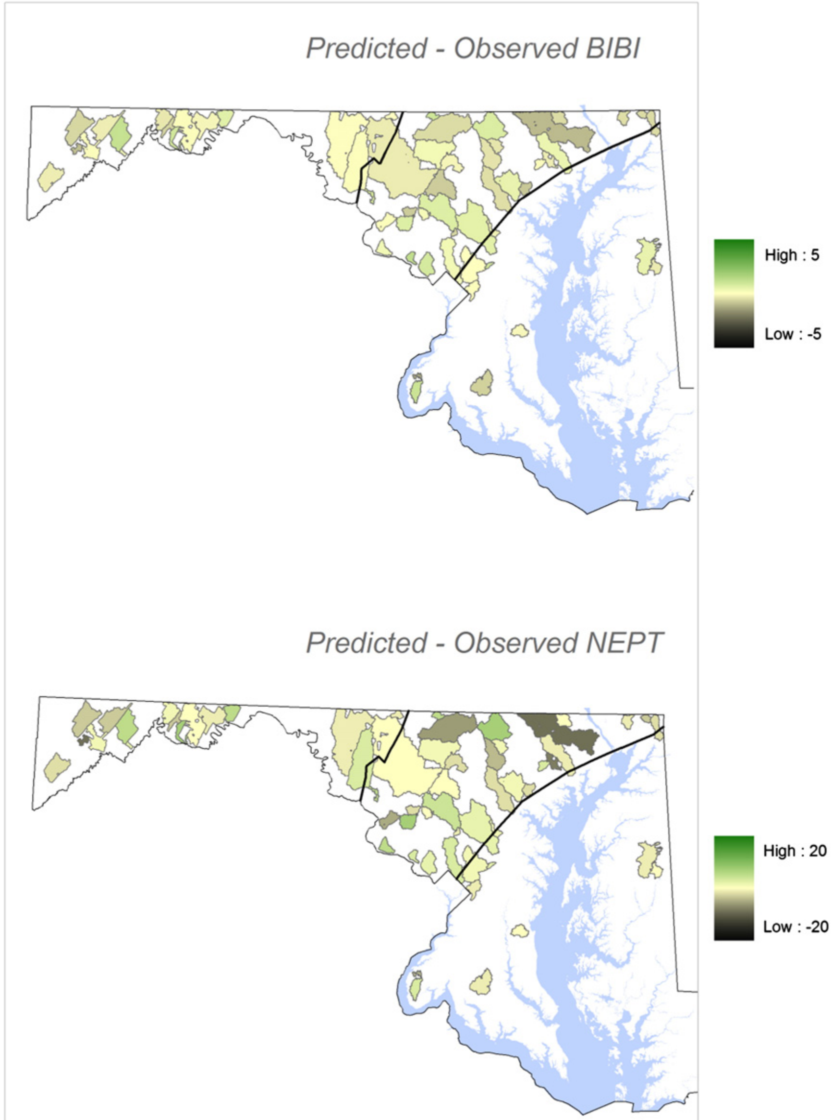

Fig. 8. Maps of the spatial distribution of differences between observed and predicted BIBI and NEPT values.

previous studies that are also stratified by physiographic province (e.g. Strayer et al., 2003). Percent ISA was the most commonly selected variable, and this was particularly true when landscape weighting schemes were not applied (Table 1). %Tree cover was the second most frequently selected variable, even accounting for the slight co-linearity of these variables (r=0.47), which further decreased with landscape weighting (r=0.35). Multivariate models of the Coastal Plain were sometime statistically insignificant ($p<0.05$) because of the relatively small sample sizes. %Tree was usually selected (3 of 4 cases) in the Coastal Plain, and this was particularly true when distance weighting was considered (Table 1). Further, %ISA was replaced in this case by %Crop as a predictor. %Crop was never selected in Highlands but usually (7 of 8 cases) in the Piedmont and Coastal Plain province models. The strongest multivariate models, with over 60% of variance explained, were for BIBI in the Piedmont (10% more variance explained if not weighted) and NEPT in the Coastal Plain (24% more variance explained when weighted).

The best multivariate models of BIBI and NEPT values for watersheds across each of the physiographic provinces compared well to the observed values, i.e., the models performed reasonably well both in terms of statistical correlation (Fig. 7) and consistency in the spatial distribution of the residuals (Fig. 8). These best-fit models are presented in Table 2, along with RMS error values.

4.2. Assessing the various weighting schemes

The landscape distance weighting schemes had the most improvement on predictions of NEPT or BIBI when applied to the aggregated (4th and stand-alone 3rd order) catchments. For higher (1st and 2nd) order stream catchments, i.e. headwaters, there was generally no more than a 2% increase in explained variance (r^2) for the weighted versus

Table 2
Best fit stepwise multiple linear regression models of BIBI and NEPT by physiographic region, with root mean squared errors (RMSE)

	Region	Multivariate model	RMSE
BIBI	All regions	2.01+(−0.03·ISA)+(0.02·Tree)+(0.02·Crop)	0.47
	Piedmont	0.74+(0.01·ISA)+(0.04·Crop)+(0.05·Tree)	0.30
	Coastal*	0.59+(0.27·Tree)+(0.04·Crop)+(0.02·Grass)	0.14
	Highlands*	2.74+(0.34·Tree)+(−0.18·ISA)+(0.01·Grass)	0.14
NEPT	All Regions	−4.33+(0.17·Tree)+(0.23·Grass)+(−0.03·Crop)	3.75
	Piedmont	−6.72+(0.33·Tree)+(0.17·Crop)+(0.11·Grass)	1.95
	Coastal*	−0.38+(0.65·Tree)+(0.02·Area)+(−0.03·Crop)	0.74
	Highland*	8.47+(−1.47·ISA)+(1.88·Tree)+(−0.008·Area)	1.60

An * next to the region category (physiographic province) indicates that the land cover variables are landscape weighted values (as described in methods). Watershed area values are in km^2.

the non-weighted model results. The distance weighting scheme that accounted for both the amount of tree cover and the distance from the stream channel (Fig. 4) proved to be the most effective at capturing contributions from the landscape that accounted for the variability of the stream biotic measurements at the sampling point. This was true for both BIBI and NEPT. The increase in variance explained using this approach ranged from 20% in both the Coastal Plain and the Highlands, to negligible or negative influence in the Piedmont. As noted above, landscape weighting sometimes changed the variables selected, e.g., deemphasizing the relevance importance of %Grass for predicting NEPT in the Highlands (Table 1).

5. Discussion and conclusions

The primary objectives of this analysis were to assess the extent to which land cover variables, including maps of proportion land cover (%ISA, %tree, etc.), can be used as predictors of the biotic health of streams, and the extent to which configuration of the landscape influences these predictions. The land cover and stream biota data sets were well quantified and documented (e.g.Goetz et al., 2004; Jantz et al., 2005; Roth et al., 2005), and thus provided a good basis for addressing these objectives.

The statistical analyses identified %ISA and %Tree within a watershed as the best predictors of stream biotic metrics, as well as the proximity of tree cover in the landscape relative to the stream channel. There were no cases with either the decision tree or MLR models where less than 3 variables were selected, and physical variables (e.g. area) were selected second or third if at all, emphasizing the importance of land cover information to stream health. These results are consistent with recent findings across a similar gradient of physiographic provinces in North Carolina (Potter et al., 2004), an urban-rural gradient in Connecticut (Urban et al., 2006), across the Highlands of West Virginia (Snyder et al., 2003) and, most recently, the eastern U.S. (Carlisle & Meador, 2007). They also refine earlier findings relating the amount of different land cover types to stream biota in the mid-Atlantic region (e.g., King et al., 2005; Roth et al., 1996; Snyder et al., 2005; Strayer et al., 2003) by focusing on continuous land cover variables and metrics of landscape connectivity to the stream network. Each of these studies, ours included, builds substantially upon previous work (see for example Table 2 in Schueler, 1994) by utilizing improved information on land cover, landscape configuration, and stream biota.

The %ISA maps, in particular, provided unique information relevant to stream health assessments. These maps are not only more useful than traditional land cover type approaches (see alsoDougherty et al., 2004), but also provide information on the spatial configuration of developed areas across the landscape, which has advantages for assessing proximity to streams and for mapping changes in land use intensity (Goetz et al., 2004; Jantz et al., 2005). The results presented here further support management goals for reducing the impacts of urbanization, particularly those associated with impervious cover in new residential and commercial development. For example, the pollutants and hydrological effects of urbanization associated with impervious cover, discussed in the Introduction section, can be partially offset through measures such as low impact development techniques (retention ponds, green roofs, rain gardens) which capture some pollutants and reduce overland flow, thereby benefiting stream water quality and associated biotic health.

The results also indicate that consideration of landscape configuration (our weighting schemes) often improved predictions of stream biota metrics at the catchment sampling points. This was particularly true for the aggregated catchments, where the most downstream MBSS sampling point integrated those from further upstream. Weighting the landscape by distance to stream and the amount (and location) of tree cover improved stream biota predictions in some provinces better than others. Predictions of BIBI and NEPT in the Coastal Plain and Highland provinces were significantly improved, whereas those in the Piedmont province were not improved. We note that the Piedmont is the most intensively developed region of Maryland, and also the most extensively connected by storm drainage systems to the stream network, which may diminish the buffering effects of the landscape. The consistent selection of %ISA as a primary predictor in this region supports the view that buffer zones may often be bypassed by the storm drain system, effectively connecting the developed landscape with the stream system. Additional research in this area, particularly using paired watersheds, may be useful for testing this hypothesis.

Subsurface flow may also modify the influence of landscape configuration on stream measurements (Weller et al., 1998), however we were unable to generalize how these would likely vary among the physiographic provinces we considered. One might expect that the sandy loams of the coastal plain would facilitate subsurface flow more readily than in the Piedmont, but the former has less variable topography than the latter or the Highland provinces. If groundwater flow was an overriding factor that connects land cover to streams, topography (and catchments defined by topography) would be less important than landscape configuration. In this case we would expect the landscape weighting to have little significance in improving model fits in the coastal plain province, which was not the case.

We further note that the distance along stream appeared to be less relevant to stream biota predictions than the distance from a given point on the landscape to the stream channel. This suggests that in-stream processes may be less critical in buffering upstream inputs as the buffering processes across the landscape (e.g. vegetation cover density and proximity to the stream network), although this is beyond what we can address in the current study. If true, it is at least partly due to the more efficient transport of a vector of degradation once it reaches the stream channel. Notably, the landscape weighting scheme that incorporated both the influence of distance to stream and the presence and density of tree cover (Fig. 4) was more effective than just the distance weighting alone, indicating that both of these factors are important to consider in assessments of land cover (and use) with stream properties.

As with previous studies summarized in the Introduction, these results have practical implications. Maryland is one of the signatories of the Chesapeake Bay Restoration Agreement (Chesapeake Bay Program, 2000), which sets water quality improvement and increased riparian buffer goals for the year 2010. Information on stream health is used in a range of land use planning and resource management activities (Roth et al., 2005). More broadly, the information contained within the land cover maps we have produced, which are also now nationally available as NLCD products, has utility for incorporating landscape configuration information into large-area hydrological models and for improving a range of watershed management efforts (e.g.Wickham et al., 2005). It is important to keep in mind, however, that we have developed statistical models capturing variability in steam biota, broadly associated with stream ecosystem integrity and aquatic health, not the causal mechanisms that underline these observations. Impervious cover is treated here as a surrogate for a series of physical and biological properties and processes that impact streams and water quality. As such, it may act as an integrator of multiple interacting variables, and thus provide a relatively simple indicator with wide applicability, but the link is not directly causal and can be masked in areas where, for example, point sources dominate stream degradation. Thus, while percent impervious cover is a useful index of urbanization extent in-stream catchments, our results do not imply that reductions in impervious cover alone are sufficient for protecting water quality. Many water quality degradation pathways are associated with urbanization. Thus, management efforts that focus on reducing impervious cover without addressing the overall rate and pattern of urbanization might mitigate only a portion of the water quality effects of urbanization. We are currently conducting similar analyses using NLCD data sets in other regions in the eastern United

States where stream biota data are available to assess this further, and encourage additional studies on this topic. Regional and national mapping efforts, and associated products, can uniquely inform environmental policy related to human modification of the landscape, and thus assessments of impacts on water quality and aquatic ecosystems.

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