Chapter 4
On the Relationship Between Stream Biotic Diversity and Exurbanization in the Northeastern USA

Scott Goetz and Gregory J. Fiske

Abstract Stream macroinvertebrate diversity is a commonly used indicator of aquatic health, reflecting overall ecological integrity within a watershed. Our study made use of two metrics of stream biota, the Hilsenhoff Biotic Index (HBI) and the diversity of *Ephemeroptera*, *Plecoptera*, and *Tricoptera* (nEPT) species, to develop statistical models relating land cover information within watersheds to these stream biotic health indicators. The study area in southern New England included over 100 small streams, which make up a substantial portion of the region's largest catchments. General additive models (GAM) and step-wise multiple linear regression (MLR) models were used to explore the relationship between the land cover and the biotic indicators. Although the GAMs explained a greater amount of the variation in the stream biota metrics, the MLR models were also consistently reliable predictors of nEPT and HBI. This research indicates land cover can be used as a robust predictor of stream biological indicators of small catchments (HUC12) in the region, and help to target streams for restoration or protection.

Keywords Aquatic • Biodiversity • Habitat • Impervious • Land cover • Land use • Remote sensing • Species richness • Water quality • Stream • Watershed

4.1 Introduction

The links between land cover and water quality, including stream health, have long been known but not until recently have analyses over large areas been conducted (Mitsch et al. 2001; Nilsson et al. 2003; Carlisle and Meador 2007). This is partly a result of wider availability of land cover information from regional to national

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scales (Wickham et al. 2004; Homer et al. 2004). Impervious surface areas (the built environment, like buildings, roads, parking lots) increase the amount of pollutants within and the temperature of runoff reaching streams. Forested riparian buffers, on the other hand, preserve or increase stream quality by contributing leaf litter, regulating temperature and sunlight, deterring erosion and retaining nutrients (e.g. Jordan et al. 1997; Lowrance et al. 1997; Groffman et al. 2004). Despite a great deal of effort, much of the progress that has been made in restoring the health of the nation's waterways has been offset by continued urban, suburban, and exurban development (CBPO 1998; Wickham et al. 2005). The expansion of impervious surface areas associated with this urban growth disrupts aquatic biology and degrades water quality by inhibiting infiltration, increasing peak flows, reducing base flows, reducing lag time between storm events and peak discharge (i.e., increased flashiness), facilitating the overland transport of pollutants, and increasing sediment loads associated with stream channel incision and erosion (see updated review by Schueler et al. 2009).

Other impacts result from the associated loss of resource lands (forests, wetlands and riparian buffer areas), which serve ecological functions such as filtering water flows and buffering chemical pollutants (e.g. Goetz et al. 2004). Many of these pollutants arise from impervious surface areas, particularly the roads and parking lots built to accommodate increased vehicle use. The adverse effects of these changes can be mitigated by increased vegetation cover, landscape configuration, and low-impact development techniques, which together reduce the volume and velocity of overland flows, uptake excess nutrients and pollutants, maintain stream bank integrity, provide shade that reduces stream warming, and generally reduce the negative ecological and economic impacts of urbanization.

As a result of the processes described above, landscape configuration modifies the relationship between land use and in-stream biological metrics, such as the widely used index of biological integrity (IBI). Those elements that may have an effect on stream quality at the catchment scale, such as water chemistry (Sponseller et al. 2001) and non-point source pollution (Paul et al. 2002), may not retain their predictive power at more local (e.g. riparian or near-stream) scales, and vice versa (Jones et al. 2001). With particular reference to the relationship between stream macroinvertebrates and watershed scale land cover, distance to the stream channel appears to be a key variable that can influence the relative importance of specific land cover variables (Walsh et al. 2005; King et al. 2005; Goetz and Fiske 2008). Recent work also emphasizes the spatial arrangement of landscape patches (Strayer 2006), gradient/slope complexity (Snyder et al. 2003), and dominant substrate (Lammert and Allan 1999). Assessing the influence of riparian zone land cover over large areas has also increased in recent years as a result of more widely available high resolution sources of land cover data with relevance to riparian buffer mapping and monitoring (see review by Goetz 2006). It is thus now more feasible to use comparable metrics of riparian buffer properties, combined with those of stream hydrology, lithology, and other landscape metrics to more fully assess the influence of human land use on stream ecosystems at a variety of spatial scales (Allan 2004; Brabec et al. 2002; Grimm et al. 2008; Nilsson et al. 2003; Parsons et al. 2002).

In earlier work the statistical association between land cover variables mapped using high resolution satellite imagery (impervious cover, tree cover, and trees and crops in the riparian buffer zone) and stream ecology assessments was documented across 246 small watersheds within central Maryland (Goetz et al. 2003; Snyder et al. 2005). These watersheds spanned a wide range of land uses, from predominantly agricultural to mostly residential. Stream conditions assessed by state departments of natural resources and other groups made use of indices of biological integrity (IBI), and stream ecological health was ranked as excellent, good, fair, or poor, based on a combination of the IBI scores and physical stream properties such as dissolved oxygen, pH, and temperature (Van Ness et al. 1997; Yetman 2002). Related analysis of land cover variables and landscape configuration metrics, such as mean distance from impervious areas to the stream channel along a topographically defined flow path, and indices which define the dispersion or aggregation of land cover within the watershed, indicated the potential of these as independent predictors of stream biotic health (Snyder et al. 2005). Most recently, the research expanded that analysis to the state of Maryland, making use of the Maryland Biological Stream Survey (MBSS) data sets, and showed that both IBI and nEPT had a strong correlation to moderate resolution imagery (30 m Landsat imagery) (Goetz and Fiske 2008). Here the focus is on extending these earlier analyses to another geographic region with quite different geological substrate and a different set of biotic indicators, and testing the relative utility of landscape configuration in this context.

4.2 Study Area and Data Sets

4.2.1 Study Area

The study area comprises the southern portion of New England, including the states of Massachusetts, Rhode Island, Connecticut, and southern Vermont (Fig. 4.1). Weather in the region is characterized by warm and humid summers, with rainfall generally around 90–150 cm annually. Daily winter low temperatures tend to remain below freezing from November through March, although winter temperatures and snowfall have both increased in the four decades preceding 2005 (Burakowski et al. 2008).

The watersheds we focused on cover approximately 7000 km^2 of formerly glaciated land underlain by mostly granite and metamorphic bedrock. These watersheds include most of the large drainage systems in the area including Narragansett and Buzzard's Bays, and the Connecticut and Taunton rivers. Land cover in this area is generally forested with small amounts of agriculture in the Connecticut River valley, cranberry growing in Southeastern Massachusetts, and steadily increasing exurbanization characterized by low density residential development scattered between large urban centers like Boston, Providence, and Worcester.

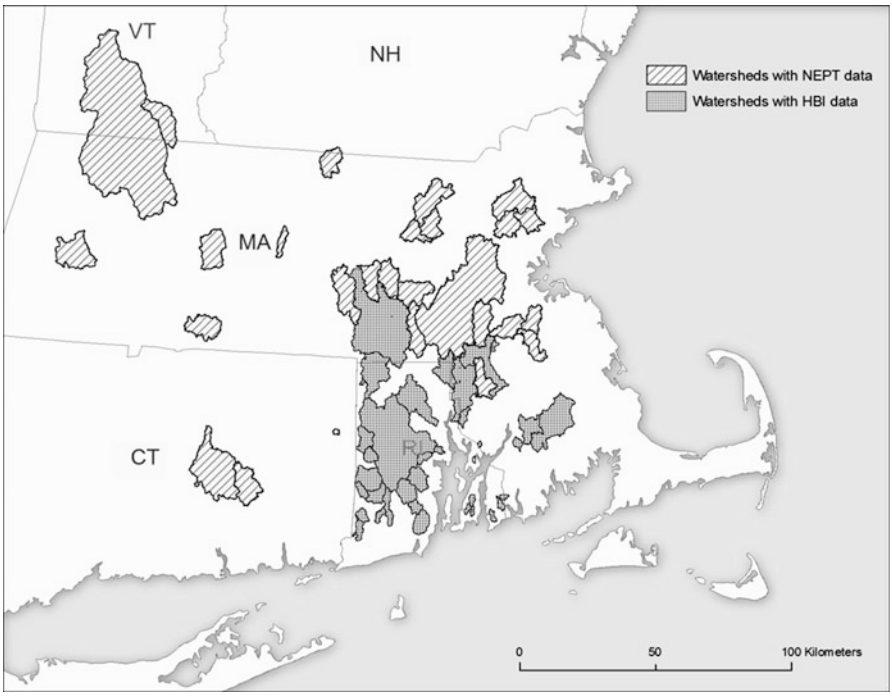

Fig. 4.1 Map of southern New England, USA, showing the extent of watersheds

4.2.2 Sensitive Taxa

This study developed models on both number of EPT individuals (abundance) and number of EPT taxa (genera). Total EPT abundance (NEPT) was defined as each individual within the Ephemeroptera order (mayflies), Plecoptera order (stoneflies), or Trichoptera order (caddisflies). The number of EPT taxa was simply a tally of the number of different genera represented by NEPT, which can also be considered as EPT taxa diversity or taxa richness.

These data were obtained from the U.S. Geological Survey's National Water Quality Assessment (NAWQA) program, which has collected chemical, biological, and physical water quality data from watersheds across the country since 1991. At the time of this study, data from over 7,000 surface sites could be found within the NAWQA archives, including biological data for over 2,500 stream reach segments. A search of the online NAWQA Data Warehouse (http://water.usgs.gov/nawqa/data) was restricted to the southern New England states of Connecticut, Rhode Island, and Massachusetts. The tabular results from the search included sample station ID and geographic coordinates, as well as the Order and Genus attributes necessary for calculating number of EPT individuals (abundance) and

number of EPT taxa (richness). After restricting dates of interest to those within the range of the land cover information, and filtering out repeated sampling at the same location (keeping the most recent), we had a sample of 32 sites with NAWQA data in southern New England (Fig. 4.1). No sampling locations for sensitive taxa were located within Rhode Island.

4.2.3 HBI

Our research made use of the Hilsenhoff Biotic Index (HBI) for data collected across 83 stream reaches in Rhode Island and Southeastern Massachusetts. The HBI, developed in the late 1970s by William Hilsenhoff at the University of Wisconsin, rates stream biologic integrity on a scale of 0–10, with the lower values representing an excellent ranking and the higher values representing poorer conditions (Hilsenhoff 1987). The HBI scale incorporates the tolerance of each taxa identified during stream reach inspections to organic pollutants (Robinson 2004). The HBI is one of several metrics from the Wadeable Stream Condition Index used for stream health monitoring in Rhode Island, and a Rapid Biomonitoring Protocol (RBP) index used to rate stream health in Massachusetts. The Rhode Island portion of these data (n = 39) were part of an archive of 11 years of biomonitoring data, collected by Sara da Silva (University of Rhode Island) (2003), the Rhode Island Department of Environmental Management and Environmental Resource & Wetlands Assessment, and Nelson, Pope & Voorhis LLC of Melville, New York (da Silva, *personal communication*). The HBI metric information for Massachusetts (n = 44) was provided by the Massachusetts Department of Environmental Protection, Division of Watershed Management. These data were concentrated on the Taunton River watershed area of south-eastern Massachusetts, but also included samples from the Blackstone and 10-mile watersheds (see Fig. 4.1).

4.2.4 Land Cover Metrics

The land cover metrics used in this analysis included maps of percent impervious surface cover, percent tree cover, and categorical (presence/absence) of grassland and crop cover. These data sets were derived from National Land Cover Database 2001 (NLCD), available through the U.S. Geological Survey's EROS Data Center. The NLCD data set, produced using 30 m Landsat Thematic Mapper satellite imagery, covers watersheds across the nation (including our entire study area) using a consistent classification scheme (Homer et al. 2004). From this categorical map product, we extracted Grassland/Herbaceous and Pasture/Hay land cover information (NLCD classes numbered 71 and 81) to identify areas dominated by grass vegetation cover. Corresponding crop cover was derived using NLCD

class 82 (Cultivated Crops). The NLCD percent impervious surface cover map was used to identify areas of human development as a more continuous variable (ranging from 10 to 100 % for each 30 m image pixel), while the continuous percent tree cover reflected the comparable proportion of land cover in a more naturally forested state (again ranging from 10 to 100 %).

4.3 Approach

4.3.1 Watershed Delineation

Our research involved both local high-resolution elevation data sets and coarser nationwide data sets to delineate the catchment areas upstream of our sample points. Where high-resolution elevation data were available, including Rhode Island and southeastern MA, a digital elevation model of 5 m horizontal spatial resolution was built. Where these data were unavailable, we used the National Elevation Data set (http://ned.usgs.gov), which has a 30 m spatial resolution.

The areas upstream of each sample point in the HBI and EPT analyses were defined in two ways. One was to generate the area of contribution (catchment) to each sample point, with additional areas of contribution for sample point upstream along the same stream reach. The other was to combine (aggregate) those sample points along the same stream reach and link only the biological sample data to the lowest sample point (highest stream order) along the reach. These are referred to as the *catchment* and *aggregated* watershed sampling schemes throughout the remainder of the paper. Each of the watershed sampling schemes were generated using standard GIS hydrology functions/tools available in ESRI® GIS software. These tools derive watershed boundaries based on topographic variables (slope, aspect and elevation) derived from digital elevation data sets.

4.3.2 Landscape Distance Weighting

Weighting land cover metrics with some form of inverse distance weighting has been explored elsewhere in the context of land cover assessments of stream biota (e.g. King et al. 2005; Baker et al. 2006; Snyder et al. 2005). A landscape distance weighting methodology was designed to capture the relative importance of land cover information based on its proximity to the stream channel (after Goetz and Fiske 2008). For each watershed in the study area, a distance-weighted surface was developed, allowing us to use the distance from the stream channel and catchment "pour point" independent of adjacent watersheds. The first component of the

distance weighting scheme is a distance to stream channel, where for each 30 m cell within the watershed distance is calculated to the closest cell that defines the stream channel. These values are scaled between 0 and 1, with 1 representing the greatest possible distance. The second distance metric incorporates the amount of tree cover within each pixel (30 m grid cell) of the watershed.

Originally containing values of 0–100%, the tree cover layer was also scaled between 0 and 1. The inverse distance is then calculated for both of these components, providing two data layers, one depicting the inverse distance to stream, with values closest to the stream being the highest (at or near 1), and the values furthest from the stream being the lowest (at or near 0). These two data layers are combined (multiplied) to provide a scaled landscape weighted cost surface that reflects the potential buffering capacity of tree cover on both overland and, to a lesser extent depending on rooting depth, subsurface flow. Each of the other land cover classes (impervious, grass and crop cover) were then multiplied by the landscape weighting scheme. Results using this distance-weighting scheme for each watershed were compared to results without using distance weighting. Analyses was conducted using ESRI® GIS software, making use of Python and Arc Macro scripting languages to summarize the data for further statistical analysis.

4.3.3 Statistical Analyses and Predictions

A stepwise Multiple Linear Regression (MLR) and General Additive Model (GAM) was used to test the relationship between the biotic metrics (EPT and HBI) and the land cover variables. In addition to the NLCD land cover layers (percent impervious, tree cover, grassland, and cropland), predictor variables included watershed size and the landscape weighted transformations of the land cover variables. The response variables were the stream biotic metrics: HBI, EPT abundance and EPT richness (Fig. 4.2). The same predictor and response variables were used for both the landscape weighted and the non-weighted tests.

As in previous research, a forward stepwise MLR and GAM was used to predict stream biota indictors from the land cover metrics. These procedures allowed us to train a linear model on a portion of the data (90%) while withholding a selection of the data (10%) for cross validation. Predictor variables were iteratively selected based on their relative power in explaining variance within the response variable. Finally, the best fit models were used to create a map of predicted stream biotic quality for each HUC12 watershed, which were selected because they encompassed a comparable total watershed area (size) as those for which HBI and EPT metrics were derived and aggregated.

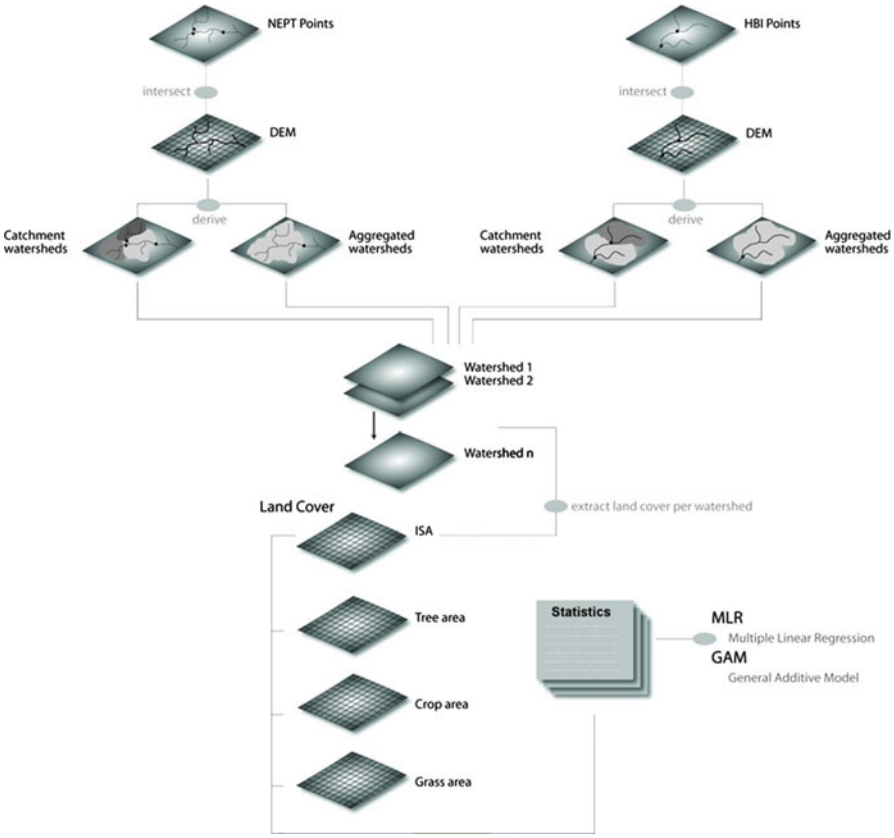

Fig. 4.2 A flow chart indicating the methodology used in comparing land cover metrics with stream reach biological indices data for southern New England

4.4 Results

4.4.1 Land Cover Predictors of Stream Biota Metrics

The relationships between the land cover metrics and the biotic indicators is shown in Fig. 4.3. In general, the amount of impervious surface and tree cover had the strongest correlation with the stream biotic metrics. These two metrics are inversely correlated to one another. The relationship between percent imperviousness within a watershed and nEPT produces an R^2 of 63 %, percent tree cover to nEPT, 41 % (p-value $\leq$ 0.001), while HBI to imperviousness produces an R^2 of 14 %, with percent tree cover, 34 % (p-value $\leq$ 0.001). The effectiveness of the landscape distance weighting was not consistent in terms of improving model predictions, despite generally higher simple correlations between the biotic indicators and land cover variables weighted

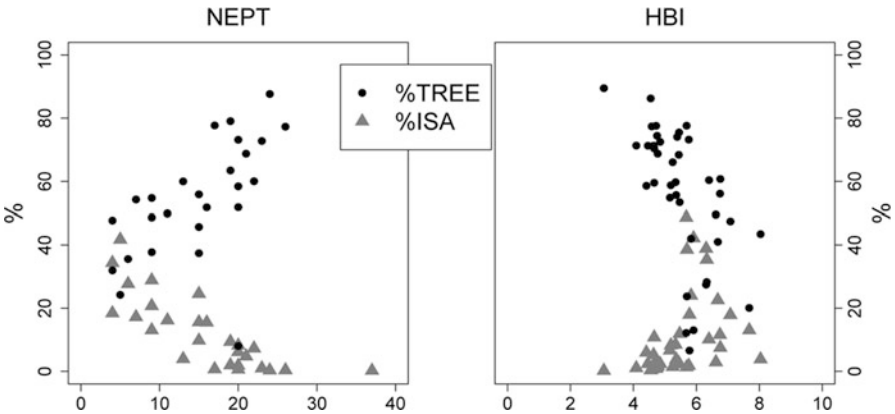

Fig. 4.3 Graph mosaic indicating the plotted values of percent impervious surfaces and percent tree cover land cover metrics versus the HBI and nEPT biotic indices. These values are further stratified by landscape weighted or non-weighted scenarios

for landscape configuration. The amount of crop and grassland showed little to moderate relationships with the stream biotic metrics, which may be a result of relatively low amounts of these land cover types in the study area.

4.4.2 Statistical Analyses

The GAM and MLR models identified the key predictor variables for all three stream biotic indices and allowed us to compare the effectiveness of landscape weighting, as well as the differences between different definitions of upstream area (catchment vs. aggregated watersheds) (see Tables 4.1 and 4.2). With few exceptions, the GAM and MLR models selected percent impervious area to be the key predictor variable for number and abundance of EPT, as well as the HBI. Percent tree cover was also a key predictor variable, being selected second for most of the MLR models, while the size of the watershed (area) was a significant predictor only in the GAM model results. Crop and grasslands were consistently poor predictor variables for all scenarios.

The GAM models produced the highest R^2 values, with 76 % reported for both EPT abundance and richness within the catchments watershed scenarios, which had slightly but systematically higher explained variance. There was no clear indication that catchment predictions were systematically better than the aggregated watershed predictions, as both scenarios produced R^2 values within a few percentage points of one another. The poorest R^2 values were generated from the models that predict HBI, and this was consistent for both the GAM and MLR approaches. To explore the effect of differing data collection methods used between states, we divided the two HBI data sets for Massachusetts and Rhode Island. The results presented in Tables 4.1 and 4.2 show the fit (R^2) values for

Table 4.1 Tabular results of 'multiple linear regression' statistical analysis for all scenarios

Multiple linear regression										
Watershed		Primary selected variables		R^2		ΔR^2		p-value		n	
NEPT		*Non-weighted*									
	Aggregated	ISA,Tree,Crop		65 %				***		27	
	Catchment	Tree,Grass,Area		74 %				***		32	
		Landscape weighted									
	Aggregated	ISA,Tree,Crop		61 %			−4 %	***		27	
	Catchment	ISA,Crop,Grass		70%			−4 %	***		32	
NEPT Taxa		*Non-weighted*									
	Aggregated	ISA,Crop,Grass		67 %				***		27	
	Catchment	Tree,Grass,Area		72 %				***		32	
		Landscape weighted									
	Aggregated	ISA,Tree,Grass		68 %			1 %	***		27	
	Catchment	ISA,Tree,Grass		69 %			−3 %	***		32	
HBI		*Non-weighted*									
	Aggregated	Tree,Grass,ISA$_{MA}$ Tree,Grass,Area$_{RI}$	68 %$_{MA}$	50 %$_{RI}$				***$_{MA}$	***$_{RI}$	11$_{MA}$	28$_{RI}$
	Catchment	ISA$_{MA}$ Tree,Grass,Area$_{RI}$	69 %$_{MA}$	48 %$_{RI}$				***$_{MA}$	***$_{RI}$	47$_{MA}$	36$_{RI}$
		Landscape weighted									
	Aggregated	ISA,Grass,Tree$_{MA}$Tree,Area,Grass$_{RI}$	68 %$_{MA}$	40 %$_{RI}$	0 %$_{MA}$		−10 %$_{RI}$	***$_{MA}$	***$_{RI}$	11$_{MA}$	28$_{RI}$
	Catchment	ISA,Crop,Tree$_{MA}$ Grass,ISA,Area$_{RI}$	51 %$_{MA}$	41 %$_{RI}$	−18 %$_{MA}$		−7 %$_{RI}$	***$_{MA}$	***$_{RI}$	47$_{MA}$	36$_{RI}$

*** $p < 0.001$

Table 4.2 Tabular results of 'general additive model' statistical analysis for all scenarios

General additive model

Watershed		Primary selected variables		R^2	ΔR^2		p-value		n	
NEPT		*Non-weighted*								
	Aggregated	ISA,Area		71 %			***		27	
	Catchment	ISA,Crop		74 %			***		32	
		Landscape weighted								
	Aggregated	ISA		76 %		5 %	***		27	
	Catchment	ISA,Area,Grass		76 %		2 %	***		32	
NEPT Taxa		*Non-weighted*								
	Aggregated	ISA,Grass		72 %			***		27	
	Catchment	ISA,Area,Tree		76 %			***		32	
		Landscape weighted								
	Aggregated	ISA,Grass,Crop		69 %		−3 %	***		27	
	Catchment	ISA,Area,Crop		76 %		0 %	***		32	
HBI		*Non-weighted*								
	Aggregated	n/a_{MA} ISA,$Crop_{RI}$	n/a_{MA}	60 $\%_{RI}$			$***_{MA}$	$***_{RI}$	11_{MA}	28_{RI}
	Catchment	ISA,$Crop_{MA}$ ISA,$Tree_{RI}$	51 $\%_{MA}$	47 $\%_{RI}$			$***_{MA}$	$***_{RI}$	47_{MA}	36_{RI}
		Landscape weighted								
	Aggregated	n/a_{MA} ISA,Crop,$Tree_{RI}$	n/a_{MA}	59 $\%_{RI}$	n/a_{MA}	−1 $\%_{RI}$	$***_{MA}$	$***_{RI}$	11_{MA}	28_{RI}
	Catchment	ISA,Crop,$Tree_{MA}$ ISA,$Crop_{RI}$	43 $\%_{MA}$	44 $\%_{RI}$	−8 $\%_{MA}$	−3 $\%_{RI}$	$***_{MA}$	$***_{RI}$	47_{MA}	36_{RI}

*** $p < 0.001$

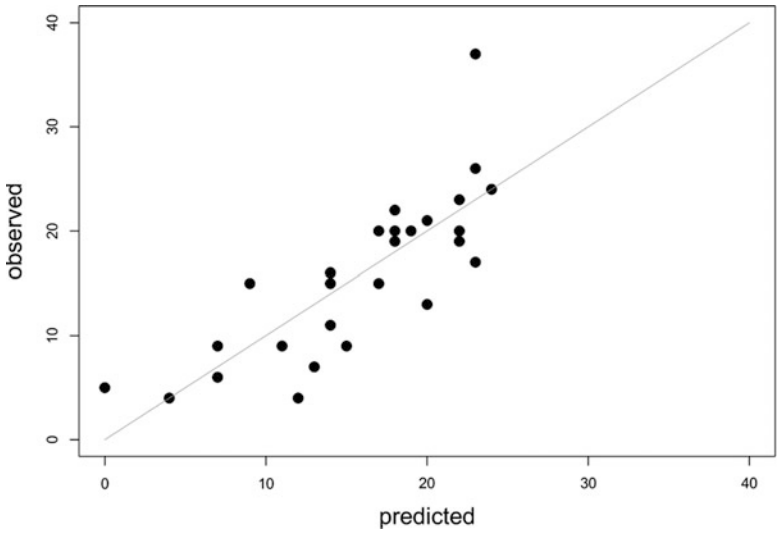

Fig. 4.4 A graph showing the output predicted vs. observed number of EPT for the aggregated training watersheds in southern New England. These results are from an MLR model that did not utilize landscape weighting of the land cover variables

Table 4.3 Tabular results comparing general statistics for predicted vs. modeled watersheds for nEPT scenario

		Land cover variables			
		% ISA	% Tree	% Crop	% Grass
Predicted	Min	0.01	10.42	0.00	0.10
	Max	53.75	91.15	31.03	52.21
	Mean	6.16	64.44	1.66	7.86
	Std dev	8.82	16.69	3.23	6.84
Modeled	Min	0.24	8.04	0.00	1.59
	Max	41.75	87.66	1.60	10.75
	Mean	12.25	55.50	0.51	4.98
	Std dev	11.53	19.01	0.43	2.88

each state individually. Splitting the HBI data this way limited the number of samples needed for robust GAM or MLR models of the landscape weighted watersheds in Massachusetts. Furthermore, low sample sizes for each of the tested scenarios precluded the use of other data intensive approaches, such as decision-tree models, which have performed well in other studies of this nature (e.g. Goetz and Fiske 2008) (Fig. 4.4).

Although the GAM results produced higher R^2 values overall, they also were less consistent. The models were run several times for each scenario, to iterate on variable selection and generate a different data subset for testing and validating the models. The MLR results, on the other hand, were consistently more robust. Considering these findings, we used the MLR models, and watersheds of southern New England (with land cover relative to those we used to build the models – Table 4.3), to produce a map of predicted nEPT (e.g. Fig. 4.5). This same model

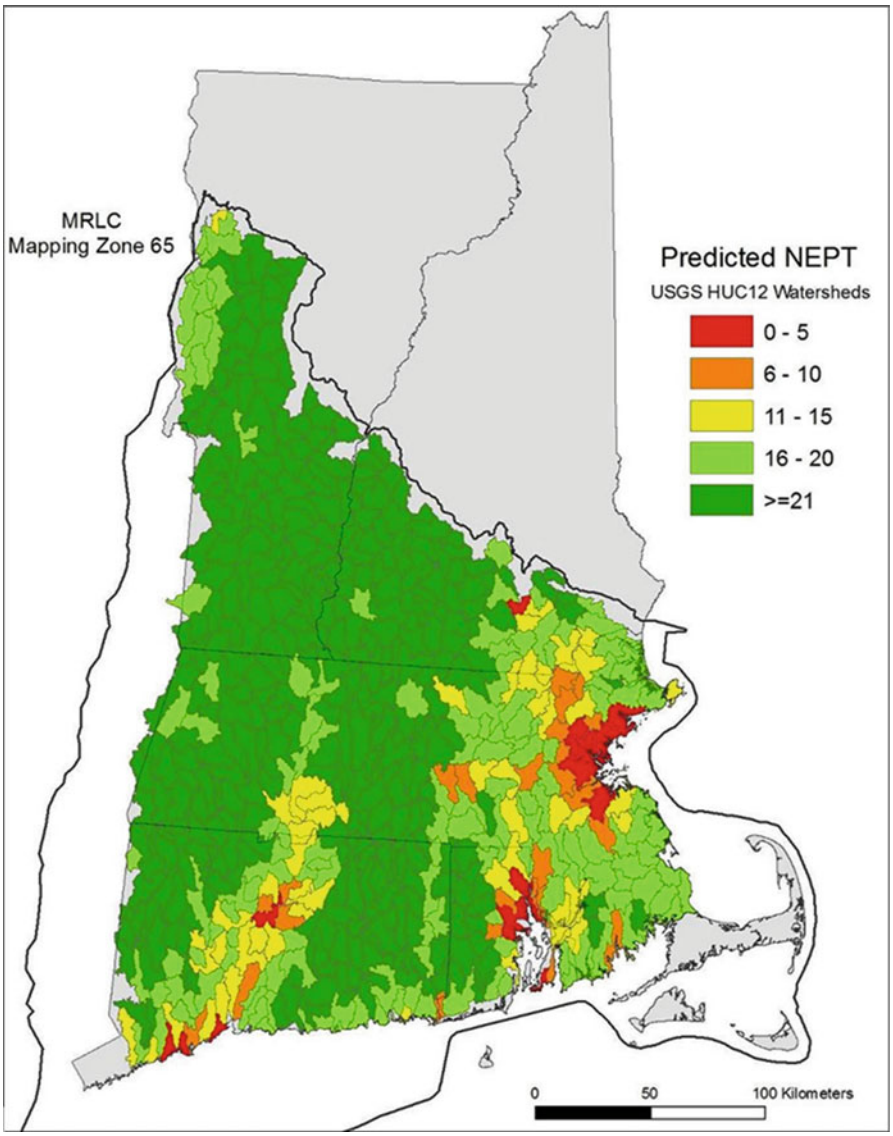

Fig. 4.5 A map showing the predicted number of EPT individuals for HUC12 watersheds in southern New England (MRLC mapping zone 65). The area within this region has a relatively uniform lithology. These results are from an MLR model that did not utilize landscape weighting of the land cover variables (see Fig. 4.4)

was used to predict nEPT in catchments of the Upper Delaware (UPDE) scenic river watershed to the west of the New England study area described in this chapter (Fig. 4.6).

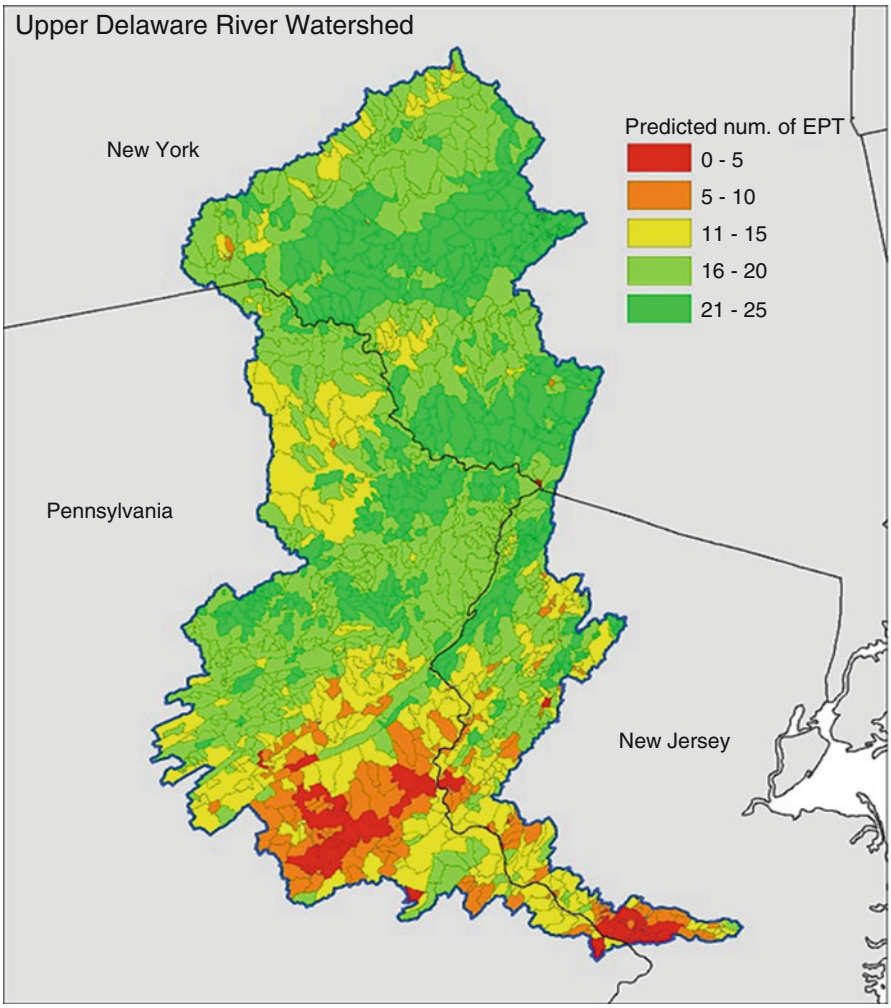

Fig. 4.6 A map showing the predicted number of EPT individuals for watersheds in the Upper Delaware river basin, using the same model as that noted in Fig. 4.5

4.5 Discussion

The GAM and MLR model results were similar in terms of the selection of predictor variables, although the GAMS tended to select fewer variables and performed consistently better in terms of variance explained. This finding may reflect the relative advantage of GAMs over linear models in that GAMs require fewer assumptions of data distributions and error structures, assuming only that functions are additive and components can be smoothed by local fitting to subsets of the data. Smoothing parameters were automatically selected based on the effective degrees of

freedom and generalized cross validation based on use of default criteria. As such, the GAMs may have effectively already accounted for much of the variance explained and inclusion of additional variables added little in terms of additional model significance. Moreover, differences between the GAMs and MLR models, although not large, typically added some 5–15 % in terms of variance explained, which was a statistically significant improvement over the MLR models ($0.01 > p < 0.05$). In one case with landscape weighted variables, 76 % of variation in EPT abundance was explained by a GAM using just a single predictor variable - the amount of impervious cover within watersheds (Tables 4.1 and 4.2).

Watershed size was not often selected as a significant predictor of the biotic metrics in any of the model formulations, despite the area encompassed by the watersheds ranging substantially (from 2 to 146,000 ha). Related, although there were not many more cases in the catchment than in the aggregated watershed scenarios, predictions at the catchment scale were consistently better than those based on aggregating the watersheds. This finding suggests that the greater number of smaller watersheds in the case of the catchment scenarios reflected greater sensitivity of the biotic metrics to the land cover variables, even though the sample sizes were only slightly greater (32 versus 27 cases).

Models of EPT abundance and richness performed consistently better than those of the HBI metric, which is consistent with EPT representing sensitive taxa that are better indicators of watershed impacts associated with urbanization than HBI or other integrated indices of biotic integrity. Perhaps surprisingly, landscape weighting did not consistently improve model predictions, and in some cases actually reduced the variance explained by the different models. This finding is consistent with the results of some of our previous analyses in the mid-Atlantic region and may be due, in part, to the fact that impervious cover, which is consistently selected as the most important predictor variable, is often directly connected to the stream channel via storm drainage networks. In such cases, deep-rooted forest cover, or other vegetation cover (grasslands or shrublands), may be bypassed and landscape influences, in terms of buffering runoff volume and pollutant contents, effectively minimized or obviated. Nonetheless, the MLR models of EPT for the catchment scenarios selected tree cover as the primarily predictor variable, despite impervious cover being consistently selected as the primary predictor in nearly every other model formulation.

Only after landscape weighting did the amount of impervious cover get selected as a significant predictor in these cases, which indicates that the weighting did in fact effectively capture the buffering capacity of the landscape. Less variance was explained in the models with landscape weighting, but this is because tree cover was used in the weighting scheme and thus the relative importance of tree cover as a predictor variable dropped out since its effects were already accounted for in the landscape weighting scheme. Related, the HBI metrics showed some sensitivity to landscape weighting in terms of changes in the selection of predictor variables, although impervious cover remained the most important predictor. These findings are consistent with EPT taxa richness and abundance being sensitive indicators of urbanization impacts associated with impervious cover.

The basis of our comparison relies on date-matching the stream IBI and land cover data and that all of our samples were part of one homogenous physiographic province. The reality is that a mismatch in time is possible between our land cover data and stream biotic samples, thus these typs of analysis (given adequate data) should be stratified by state or, even better, well defined physiographic region. Likewise, sample timing and seasonality can also decouple the connection between invertebrate health/activity and land cover metrics.

The predictions of nEPT for an entirely different watershed, the upper Delaware (Fig. 4.6), appear consistent with our results for the New England watersheds, despite differences in topography and, to a lesser extent, in geological substrate. This watershed is experiencing rapid changes in land use via expanding residential development and associated exurbanization, which implications for stream biota. The streams of this watershed are just beginning to be systematically monitored for aquatic biota, including nEPT, by the National Park Service. Predicted maps of this sort, based on land cover variables, provide a baseline against which in situ stream measurements can be compared and assessed as the program develops.

It is known from previous work (e.g. Bolstad and Swank 1997; Booth and Jackson 1997), that management practices, storm water routing, point source pollution (sewage treatment plants, poultry plants, etc.), and other factors, can influence the relationships between land cover and stream biota. Moreover, impacts on stream health and water quality are not threshold responses, but more closely approximate a gradient in which even rural areas with reduced tree cover may display impairments comparable to more urbanized reaches (Booth et al. 2002; Moglen et al. 2004; Goetz and Fiske 2008). Nonetheless, the results presented here indicate that land cover metrics explain the majority or variation in stream biotic metrics in southern New England watersheds, and as such can be used as helpful indicators of stream impairment that can, in turn, be used to focus monitoring, restoration and protection management objectives. Moreover, these results support increasing evidence that reducing impervious cover in new residential and commercial development, or reducing the impacts of impervious areas through mitigation measures such as riparian buffers and overall tree cover within a watershed, is beneficial to stream water quality and associated biotic health.

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