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LANDSCAPE INDICATORS OF WETLAND CONDITION IN THE NANTICOKE RIVER WATERSHED, MARYLAND AND DELAWARE, USA

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Abstract: We developed relationships for estimating wetland condition from remotely sensed data and digital maps. Assessment methods relying on maps rather than field sampling (level 1 assessment) are often expert systems summarizing the best professional judgments of wetland scientists. We instead developed level 1 assessment relationships by statistically analyzing results from field sampling. The field campaign applied the hydrogeomorphic (HGM) functional assessment approach to sample 143 freshwater flat and riverine wetlands in the Nanticoke River watershed, Maryland and Delaware, USA. Functional condition index (FCI) scores for five wetland functions were calculated from the field observations. We used geographic information system (GIS) analysis of digital maps to derive candidate landscape indicators for the sampled points. We tested which indicators correlated strongly with the field condition scores, and then we used stepwise multiple regression and regression tree analysis to identify the most effective combinations of landscape metrics for predicting the condition measurements. The best multiple regressions combined information from land-cover, road, and stream maps, especially a stream map resolving natural stream reaches from channelized or ditched reaches. For riverine wetlands, we obtained statistically significant regressions explaining 63%–85% of the variance of measured FCI scores for all five HGM functions (hydrology, biogeochemistry, habitat, plant community, and landscape). Comparable models for flat wetlands were also statistically significant but explained less (48%–54%) of the variance. Regression tree analysis produced more parsimonious models than did stepwise multiple regression. A tree model explained the same amount of variability as the multiple regression model for two flat and two riverine functions, but the tree model explained less variability for two flat and three riverine functions. Our level 1 relationships can be applied to estimate condition scores for unsampled wetlands and to provide confidence limits for those estimates. The uncertainty in predicting a condition scores for individual assessment points is high for most HGM functions, but the models can still help prioritize field visits to select sites for management action. Confidence limits are narrower for predicting mean scores across many wetlands, so the relationships are more powerful for predicting average wetland condition across an assessment area, such as a watershed.

Key Words: flat, HGM assessment, landscape assessment, riverine, wetland assessment

INTRODUCTION

Wetland or watershed management efforts often rely on assessments of wetland function to prioritize wetlands for protection or restoration (DNREC 2002, Brooks et al. 2004, Thomas and Lamb 2004, Tiner 2004). Available assessment methods have been categorized into three "levels" (Brooks et al. 2004, Fennessy et al. 2004). The most detailed (level 3) assessments collect intensive field observations at each assessment site, while rapid (level 2) methods require less field data that can be collected in briefer visits of more sites (Fennessy et al. 2004). Level 1 assessments use information from maps and remotely sensed data rather than field measurements, so level 1 methods can be used when there are no resources to support field data collection, or a preliminary level 1 analysis can help target field efforts on critical sites within the assessment area (Brooks et al. 2004). Level 1 assessments are typically expert systems based on review of the scientific literature and the best professional judgments of wetland scientists (Abbruzzese and Leibowitz 1997, Suter et al. 1999, CBP 2004, Tiner 2005) rather than on data from a specific set of wetlands. As such, most level 1 models include no objective estimate of model quality and cannot provide confidence limits for predicted assessment scores.

We used the Nanticoke River watershed of Maryland and Delaware, USA (Figure 1) as a model system to develop and test three methods for evaluating wetland function: the HGM field assessment method (Whigham et al. 2007), a level 1 assessment method (this paper), and a comparison of HGM results to direct measures of nitrogen processing (Jordan et al. 2007). The Nanticoke River is a tributary of Chesapeake Bay and has a 2211 km^2 watershed (USGS 2000, 2004a). Once mostly forested (Tiner 2005), the watershed is now 38% forest, 38% cropland, 18% grassland, 3% developed land, and 3% other (NLCD 2001 land cover, Homer et al. 2004). Wetland area has decreased from 45% of the presettlement watershed to 28% in 1998 (Tiner 2005). The remaining wetlands contain many rare and endangered species, and the watershed has been designated as a bioreserve by the Nature Conservancy (TNC 1998). The watershed is also a focus of state conservation efforts (DDA 2003, MD DNR 2003).

In this paper, we use data from HGM field assessments (Whigham et al. 2007) to identify and calibrate statistical models for level 1 relationships that predict wetland condition from landscape variables derived from land-cover, stream-disturbance, road, and wetland maps. Univariate correlation was used to identify the best landscape indicators for each HGM function of two wetland classes. Multiple regression and regression trees were applied to identify the best combinations of indicators. We tested the ability of multiple regression models to predict average wetland condition in a watershed by comparing level 1 assessment results with HGM field results for three subbasins of the Nanticoke watershed. We explored the advantages and disadvantages of our approach and its possible application within and beyond the Nanticoke River watershed.

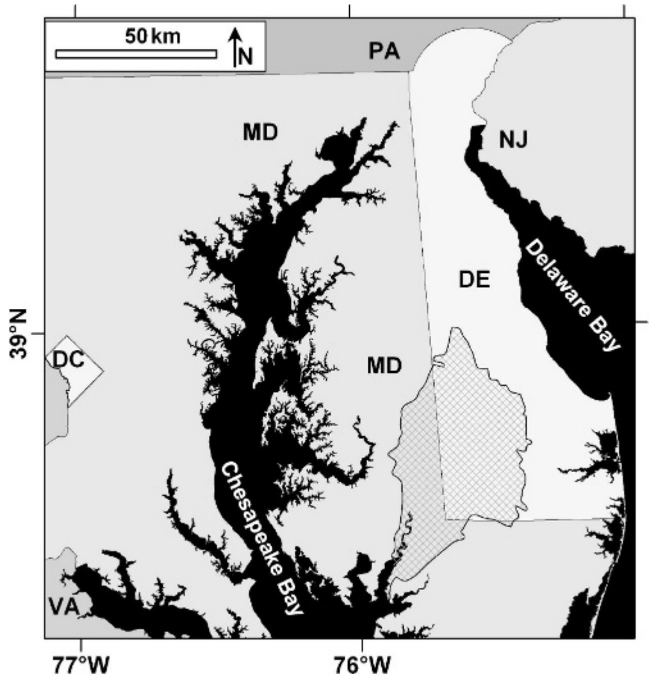

Figure 1. Location of the Nanticoke River watershed (hatched area) in the states of Maryland (MD) and Delaware (DE), USA, near the Chesapeake Bay.

METHODS

HGM Field Assessment

We calibrated our indicator models to results from a field assessment of freshwater non-tidal wetland condition in the Nanticoke watershed (Figure 1). The hydrogeomorphic (HGM) approach (e.g., Brinson et al. 1993, USACE 2005) was applied to assess two classes of wetlands, flat and riverine, which together comprise more than 99% of the non-tidal wetlands in the Nanticoke watershed (Tiner 2005). Consultations with local experts helped identify degraded wetlands and reference standard wetlands representing the best possible conditions currently achieved in the Nanticoke watershed. Field teams visited each wetland to measure likely indicators of wetland condition, and then expert workshops selected the subset of candidate variables most useful in resolving degraded from reference conditions. The experts also scaled each variable to range from 0 (completely degraded) to 1 (reference condition), and then developed scoring models to combine the scaled variables into Functional Capacity Index (FCI) scores, which were also scaled between 0 and 1. For flat wetlands, scoring models were developed for four functions: Hydrology, Biogeochemistry, Plant Community, and Habitat (abbreviated here HYDROL, BIOGEO, PLANT, and HABITAT). The same functions were developed for riverine wetlands, along with a Landscape function (LANDSC).

The scoring models were applied to field measurements from a representative sample of assessment points for each wetland class. Probability sampling (Stevens and Olsen 1999, 2000, Stevens and Hornsby 2007) was used to select a list of sampling points (post-stratified by class) from a wetland map combining information from the National Wetland Inventory (Tiner 1985, Tiner and Burke 1995, USGS 2005) and from the states of Maryland and Delaware (State of Delaware 1994, MD DNR 2005) Candidate sites that were not accessible or that were not actually in a riverine or flat wetland were eliminated, yielding a final sample of 89 flat and 54 riverine wetlands where field data were collected in 1999 and 2000. The field methods, the data collected during assessments, the calculation of FCI scores, and our interpretations of the results are detailed in Whigham et al. (2007).

Geographic Data and Spatial Analysis

We derived potential geographic indicators from digital maps of land-cover data, streams, roads, and wetlands (Table 1). We used the ArcGIS/ArcINFO geographic information system (GIS, Environmental Systems Research Institute, Inc., Redlands, CA) to summarize the digital geographic data into candidate independent variables describing areas near assessment points or distances from assessment points to landscape features. We used statistical analyses to identify the strongest predictors of wetland function.

Land Cover. The National Land Cover Database (NLCD 2001) provides land cover (Figure 2) at the resolution of 30 m^2 pixels classified from satellite imagery (Landsat 7 ETM+) and ancillary information (Homer et al. 2004). The satellite images used for the Nanticoke watershed were acquired in July 1999, September 1999, and April 2001 (USGS 2004). Thirteen NLCD land-cover types occurred in the Nanticoke watershed. There were four categories of developed land: developed open space (NLCD code 21) developed low intensity (code 22), developed medium intensity (23), and developed high intensity (24). These were combined into one category, total developed land, called DEVTOT here. Variable names (Table 1) were assigned to eight other NLCD categories as follows: BARE, barren land (NLCD code 31); FORDEC, deciduous forest (41); FOREVER, evergreen forest (42); FORMIX, mixed forest (43); GRASS, pasture/hay (81); CROP, cultivated crops (82); WOODWET, woody wetlands (90); and HERBWET, emergent herbaceous wetlands (95). Two additional measures were also derived: undeveloped, unforested land, CLEAR = GRASS + CROP and total forest, FOREST = FORDEC + FOREVER + FORMIX + WOODWET. The NLCD water category (code 11) was not used in our analyses. GIS analysis was used to quantify the percentages of the 11 land-cover categories in concentric circles (with 100-m and 1,000-m radii) around each assessment point.

The NLCD 2001 data set also provides estimated percentages of impervious surface and tree canopy coverage within each pixel (Huang et al. 2001, Yang et al. 2003, Homer et al. 2004). These data (see insets in Figure 2) were summarized for the whole watershed and for 100-m and 1,000-m-radius circles around assessment points to estimate four additional measures: IMPMEAN, the average percentage of impervious surface; TREEMEAN, the average percentage of tree canopy coverage; IMPZERO, the percentage of area with zero impervious surface; and TREEZERO, the percentage of area with zero tree canopy coverage.

Streams and Stream Condition. We analyzed digital stream maps (Figure 3, left) developed by the NWI for the Nanticoke watershed (Tiner et al. 2000, 2001) to derive variables describing the proximity of wetland assessment points to streams and the possible hydrologic disturbance of wetlands by channelizing streams and ditching. The NWI stream maps were based on USGS 1:24,000 topographic maps with additional stream lines, including man-made ditches, added from 1998 aerial photographs (Tiner et al. 2000, 2001). Each stream reach was assigned to one of 12 categories: natural tidal (data code R1UBV), excavated tidal (R1UBVx), natural perennial (R2UBH), excavated perennial (R2UBHx), natural intermittent (R4SBC), excavated intermittent (R4SBCx or R4SBEx), impounded, centerline, outline, natural polygon, and excavated polygon (Tiner et al. 2000, 2001). The last two types

Table 1. Potential landscape indicators of wetland condition. Asterisks denote variables describing the distance from an assessment point to a road or stream. The remaining variables are percentages or densities quantified for the areas in 100-m and 1,000-m-radius circles around assessment points and for the entire Nanticoke watershed.

Variable Name	Description
	Land-cover categories from NLCD 2001
FORDEC	Deciduous forest %
FOREVER	Evergreen forest %
FORMIX	Mixed forest %
WOODWET	Wooded wetland %
FOREST	Total forest %
DEVTOT	Total developed land %
CROP	Cropland %
GRASS	Grassland %
CLEAR	Cropland % + grassland %
HERBWET	Herbaceous wetland %
BARE	Barren land %
	Pixel percentages from NLCD 2001
IMPMEAN	Mean % impervious
IMPZERO	% with zero impervious
TREEMEAN	Mean % tree cover
TREEZERO	% with zero tree cover
	Nanticoke watershed stream and ditch map
XSTRDEN	Excavated stream density (km/km^2)
NSTRDEN	Natural stream density (km/km^2)
TSTRDEN	Total stream density (km/km^2)
STRCOND*	Condition of nearest stream (0 = excavated, 1 = natural)
STRDIS*	Distance (m) from assessment point to nearest stream
STRDISMIN*	Minimum of STRDIS and STRDISNHD
	1:24,000 National Hydrography Dataset (NHD)
TSTRDENNHD	Stream density (km/km^2)
ORDER*	Strahler order of nearest stream
STRDISNHD*	Distance (m) from assessment point to nearest stream
	Roads from census TIGER files
ROADDEN	Road density (km/km^2)
ROADDIS*	Distance (m) from assessment point to nearest road
	Wetlands from NWI and states of MD and DE
WETPERC	Wetland %

represented wide stream reaches that were mapped as polygons rather than lines (H. C. Bergquist, personal communication). Other wide reaches were mapped with both a centerline and outline representing the banks of the reach. These reaches were classified as natural reaches, and only the centerline was used in our spatial analyses to avoid multiple accounting for the same reach. Unclassified reaches were dropped. For analysis, the classification was simplified to two categories by lumping all the disturbed reaches (excavated, ditched, and impounded) into one category (here called ''excavated'') and all the natural reaches into another category, called ''natural'' (Figure 3, left). GIS software was used to find the straight line distance from each assessment point to the nearest stream (STRDIS), and the condition of the nearest stream was recorded in the variable STRCOND (0 = excavated, 1 = natural). We quantified stream density in 100-m and 1,000-m-radius circles around each assessment point to get three measures of stream density in km/km^2: TSTRDEN, total stream density; NSTRDEN, density of natural streams; and XSTRDEN, density of disturbed streams (excavated and impounded).

The high-resolution National Hydrography Dataset (1:24,000 scale; USGS 2000, 2004) lacks the NWI information on stream channel disturbances (Tiner et al. 2000, 2001) but provides detailed stream maps for the entire U.S. The high-resolution NHD

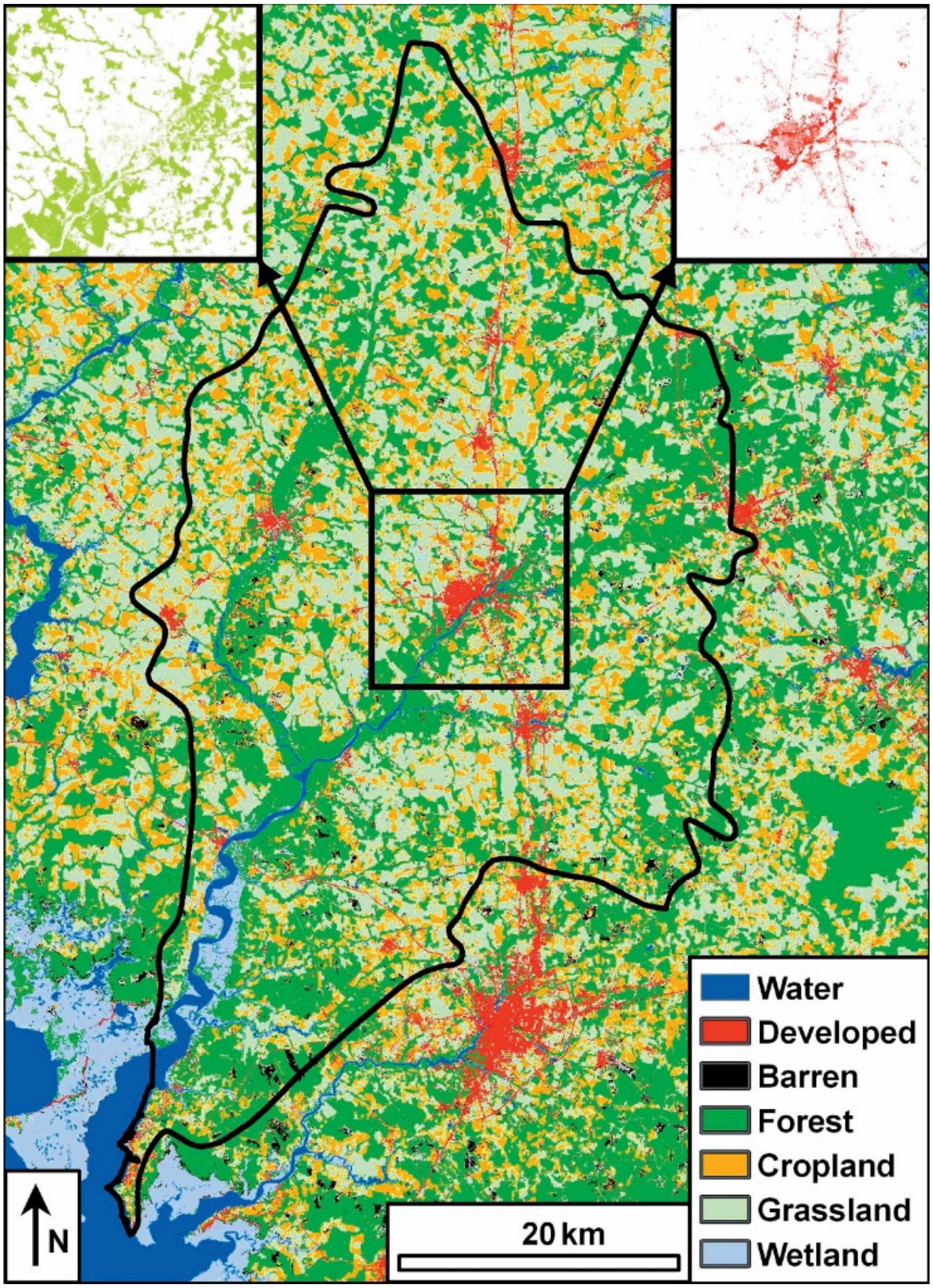

Figure 2. Land-cover map for the Nanticoke River watershed. Land-cover categories were aggregated from the NLCD 2001 data base (Homer 2004, USGS 2004b). For the area framed in the center of the map, the upper left inset shows the percentage of tree cover per pixel (Huang et al. 2001), with darker green indicating greater tree canopy cover. The upper right inset shows the percentage of impervious surface per pixel (Yang et al. 2003), with darker red indicating a higher percentage.

dataset also includes topological information for connecting stream reaches into a network. These "flow relations" were used to assign the Strahler stream order (Gordon et al. 1992) to each reach in the Nanticoke watershed (Figure 3, right). GIS analysis was used to calculate the density of streams (in km/km^2) within 100-m and 1,000-m-radius circles (TSTRDENNHD), the distance from each assessment point to the nearest stream (STRDISNHD), and the Strahler stream order of that stream (ORDER).

Roads and Wetlands. To represent the possible disturbance of wetlands by roads and associated

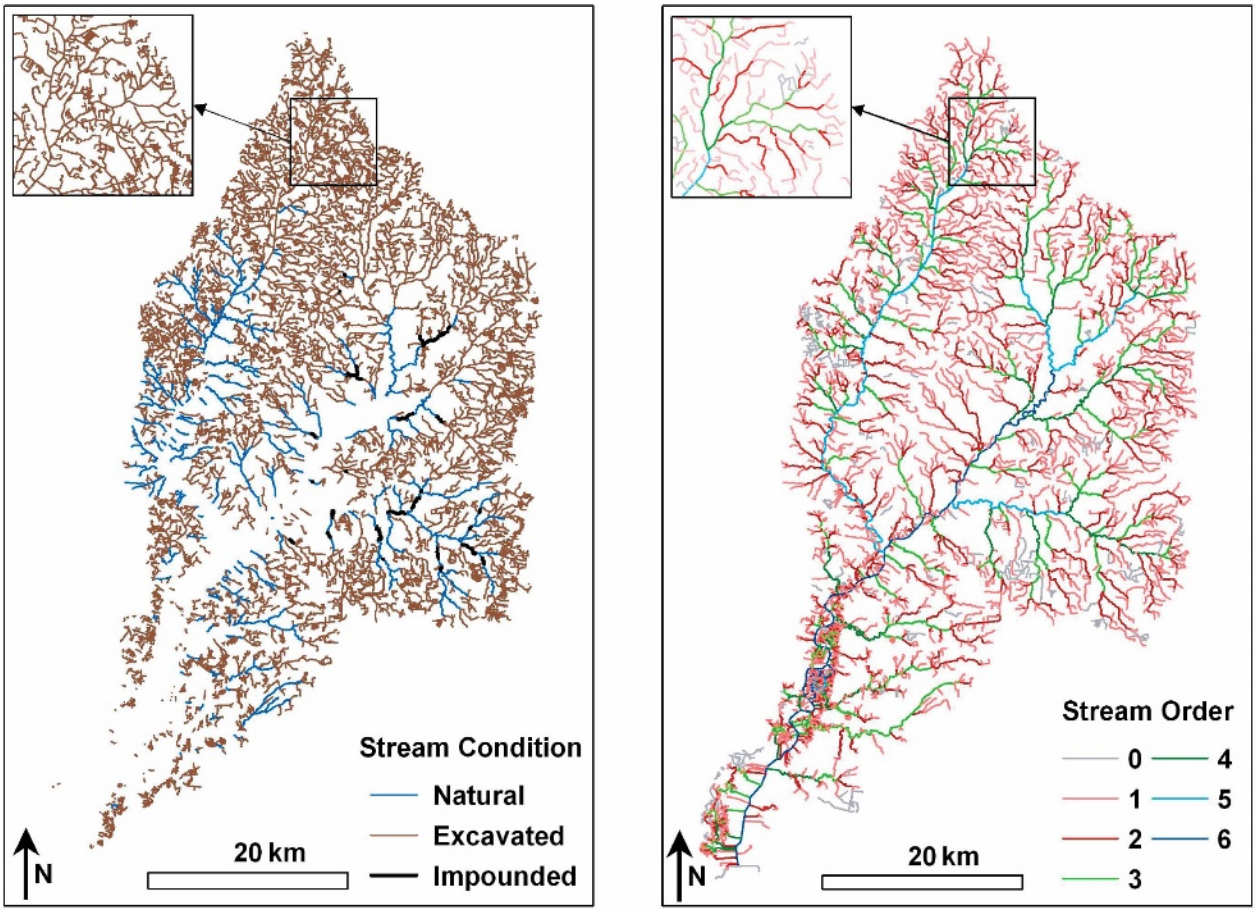

Figure 3. Stream maps of the Nanticoke River drainage network. The left panel shows stream reaches mapped and categorized by stream condition (natural, excavated, or impounded) by the NWI (Tiner et al. 2000, 2001). The right panel shows the NHD high-resolution (1:24,000) digital stream map (USGS 2000, 2004) with streams colored by Strahler stream order. In each panel, the corner inset shows an enlarged view of the framed area.

activities, we analyzed the U.S. Census Bureau's map of roads prepared for the 2000 census (USDC 2001, ESRI 2005). We calculated the distance from each assessment point to the nearest road (ROAD-DIS, in m) and the density of roads (ROADDEN, km/km^2) within 100-m and 1,000-m-radius circles around each point and for the entire watershed. We used the same wetlands map from which assessment points were chosen to estimate the prevalence of wetlands around sampling points. The map was simplified to a binary classification (wetland or upland) and analyzed to estimate the percentage of wetland (WETPERC) within 100-m and 1,000-m radii of each assessment point and for the entire watershed.

Statistical Analysis

Descriptive Statistics. For each wetland class, we summarized the geographic indicators to describe how landscape properties near wetlands (within 100-m and 1,000-m radii) differed from the properties of the whole watershed. Means and standard errors were tabulated by wetland class. Two sided *T*-tests were used to test for significant differences between the areas within 100 or 1,000 m of assessment points and the whole watershed, and ANOVA was used to test for differences between the 100-m and 1,000-m-radius circles.

Univariate Correlations. To test how landscape characteristics relate to wetland condition, we calculated the univariate correlations of the field-measured FCI scores with all of the landscape metrics for each wetland class. We report the squared correlations (R^2) to quantify amount of variation in an FCI score that can be explained by a landscape indicator, along with the sign of the original correlation to show the direction of association. We used the sequential Bonferroni correction (Holm 1979) to guard against false positives and ensure an overall significance level of

$P < 0.05$ when evaluating simultaneous tests for 48 independent variables.

Multiple Regression Models. We used multiple regression analysis to identify models that combine more than one landscape indicator to yield better (higher R^2) predictions of the field measured FCI scores for each wetland class. Stepwise multiple regression (Sokal and Rohlf 1981, SAS Institute Inc. 2004) was applied to decide how many independent variables (landscape indicators) to use. We chose a conservative value of $P = 0.05$ for the stepwise parameters "P to enter" and "P to remove" (SAS 2004) to favor parsimonious models with lower mean square errors (Sokal and Rohlf 1981). Stepwise regression may not identify the best model (highest R^2) for a given number of independent variables (Sokal and Rohlf 1981), so we subsequently applied the SAS RSQUARE model selection method (SAS 2004) to identify the best model (highest R^2) with that number of independent variables. We also developed a separate set of regression models omitting variables derived from the NWI stream maps (Tiner et al. 2000, 2001), which are only available for the Nanticoke basin.

Regression Tree Models. Regression tree analysis requires fewer assumptions than linear regression analysis and can work well with non-normal variables, non-linear responses, and non-continuous variables (De'Ath and Fabricius 2000). We used the RPART statistical library (Therneau and Atkinson 1997, Venables and Ripley 2002) with a minimum split of 5 to identify a regression tree for predicting each FCI score for each wetland class. Each tree was subjected to a 10-way cross validation, which was then used to prune superfluous nodes from the tree using the (1-SE) rule (Therneau and Atkinson 1997, Venables and Ripley 2002). This process yields the simplest tree in which all the branches produce an improvement in prediction (higher R^2) that is discernable against the background variability in the data (Therneau and Atkinson 1997).

RESULTS

Descriptive Analysis

The environmental indicators we summarized revealed extensive human modification of the Nanticoke watershed and also documented differences between the wetland classes and the entire watershed (Tables 2 and 3). There were differences in land-cover proportions between the areas near wetland sampling points and the entire landscape, between the two classes of wetlands, and between the two sizes of neighborhoods (100 m and 1,000 m) around sampling points (Table 2). Measures of forest cover showed significantly higher forest percentages near wetlands than throughout the watershed, and higher percentages of forest occurred nearer assessment points (within 100 m) than farther away (within 1,000 m). Measures of undeveloped cleared land (CLEAR, GRASS, CROP, and TREEZERO) showed opposite patterns. There was little developed land in the whole watershed and near assessment points, and the patterns with respect to assessment points were less clear. Impervious surface percentage was slightly but significantly lower near flat wetlands or within 100 m of riverine wetlands than throughout the watershed, while developed land within 1,000 m of riverine assessment points was slightly (but not significantly) higher than the entire watershed.

The NWI stream map documents the extensive alteration of the Nanticoke watershed drainage network that has occurred. Of the 4,014 km of non-tidal stream length mapped in the Nanticoke watershed, only 12.8% was characterized as natural stream channel, while 86.6% consisted of channelized streams or ditches added to the original drainage network. A small fraction of the stream length (0.6%) was characterized as impounded.

Not surprisingly, riverine assessment points were generally much closer to streams than were flat assessment points (Table 3). The difference was even greater when measured with the high-resolution NHD stream network because, compared to the NWI map, the NHD stream map includes fewer of the ditches that are often the drainage feature closest to flat wetlands. The average Strahler order of the nearest stream was higher for riverine points than for flat points. The nearest stream reach was in natural condition for 57% of the riverine assessment points, but the nearest reach was excavated for 94% of the flat assessment points. Total stream density was higher near riverine points than near flat points (Table 2). For riverine wetlands, stream density was higher within a 100-m-radius circle than within a 1,000-m circle, while the reverse was true for flat wetlands.

Riverine assessment points tended to be closer to roads than flat points (Table 3), and road density (ROADDEN) was higher near riverine points than near flat points (Table 2). For both classes, road density within 100 m of assessment points was lower than road density in a 1,000-m circle. Wetland percentage was higher for flat points than for riverine, and nearby wetland percentage (within 100 m) was higher than the percentage in a larger circle for both classes.

Table 2. Means and standard errors of potential wetland condition indicators for 100-m and 1,000-m-radius circles around assessment points and for the entire Nanticoke watershed. * indicates assessment point means that are significantly different from the watershed value (T-test, $P < 0.05$). § indicates that the mean for 100-m-radius circles is significantly different from the mean for 1,000-m circles (ANOVA, $P < 0.05$).

		Flat (n = 89)		Riverine (n = 54)	
	Wtsd.	100-m Circle	1,000-m Circle	100-m Circle	1,000-m Circle
Variable Name	Value	Mean ± SE	Mean ± SE	Mean ± SE	Mean ± SE
FORDEC	24.9	49.6 ± 3.7*§	35.2 ± 1.5*	62.3 ± 3.4*§	31.2 ± 1.6*
FOREVER	6.5	18.2 ± 3.1*	13.4 ± 1.5*	3.8 ± 1.3*§	8.1 ± 1.5
FORMIX	2.7	5.4 ± 1.1*	3.6 ± 0.3*	5.3 ± 1.3	3.4 ± 0.4*
WOODWET	4.2	9.7 ± 2.1*	7.6 ± 1*	13.2 ± 3.1*§	4.9 ± 0.7
FOREST	38.3	82.8 ± 2.7*§	59.8 ± 2.1*	84.6 ± 2.9*§	47.6 ± 2.9*
DEVTOT	2.8	1.0 ± 0.6*	1.8 ± 0.5	1.9 ± 1.3	5.5 ± 2
CROP	38.3	8.4 ± 1.6*§	23.9 ± 1.6*	8.8 ± 1.7§	31.5 ± 2.1*
GRASS	17.5	4.6 ± 1.4*§	11.4 ± 0.9*	2.9 ±1§	15.1 ± 1.1*
CLEAR	55.9	13 ± 2.1*§	35.3 ± 2.2*	11.7 ± 2.2*§	46.5 ± 2.6*
HERBWET	1.9	0.3 ± 0.3*	0.8 ± 0.2*	0.9 ± 0.6	1.2 ± 0.3*
BARE	1.2	3.2 ± 1.3	2.9 ± 0.5*	0.7 ± 0.6	1.0 ± 0.2
IMPMEAN	0.83	0.3 ± 0.2*	0.4 ± 0.1*	0.1 ± 0.1*§	1.0 ± 0.4
IMPZERO	97.3	99.3 ± 0.4*	98.8 ± 0.3	99 ± 0.8*	96.7 ± 1.2
TREEMEAN	28.3	67.2 ± 2.5*§	46.7 ± 1.8	64.3 ± 2.7*§	35.7 ± 2.3*
TREEZERO	61.3	15.2 ± 2.6*§	40 ± 2.1	14.5 ± 2.8*§	51.7 ± 2.7*
XSTRDEN	1.71	1.34 ± 0.28§	1.97 ± 0.12*	2.36 ± 0.43§	1.46 ± 0.13
NSTRDEN	0.25	0.06 ± 0.06*	0.06 ± 0.02	2.67 ± 0.46*§	0.72 ± 0.08*
TSTRDEN	1.96	1.4 ± 0.29§	2.04 ± 0.12	5.03 ± 0.44*§	2.18 ± 0.1*
TSTRDENNHD	1.47	1.04 ± 0.24	1.23 ± 0.09*	5.03 ± 0.44*§	2.18 ± 0.1
ROADDEN	1.82	0.5 ± 0.16*§	1.15 ± 0.08*	0.88 ± 0.29*§	1.63 ± 0.16
WETPERC	23.8	84.5 ± 2.1*§	48 ± 2.2*	53.8 ± 4.4*§	20.1 ± 1.7*

Univariate Correlations

FCI scores for each of the HGM functions in both wetland classes were significantly and strongly correlated with several landscape indicators (Tables 4 and 5). Between 20% and 60% of the variation among scores for any function was explained by the best single indicator, and more variation was explained for the riverine class (26% < R^2 < 60%) than for the flat class (20% < R^2 < 40%). Most of the top predictors for flat functions described the landscape very near the wetland (within 100 m), while more of the top riverine predictors were based on data from a larger neighborhood (within 1,000 m).

Variables describing stream density and stream disturbance were the top predictors for three riverine functions (HYDROL, BIOGEO, and HABITAT) and two flat functions (HYDROL and BIOGEO). In contrast, land-cover variables were the top predictors for the HABITAT and PLANT functions of flat wetlands and for the riverine LANDSC function. Stream variables and land-cover variables had similar explanatory powers for the riverine PLANT function. Predictors based on roads or

Table 3. Means and standard errors of potential wetland condition indicators for assessment points and means for the entire Nanticoke watershed. *indicates assessment point means that are significantly different from the watershed mean (T-test, $P < 0.05$). Distance measures are not defined for the entire watershed (NA).

		Flat (n = 89)	Riverine (n = 54)
Variable Name	Wtsd. Mean	Mean ± SE	Mean ± SE
STRCOND	0.13	0.06 ± 0.02	0.57 ± 0.07
STRDIS	NA	289 ± 33	73 ± 12
STRDISNHD	NA	276 ± 32	71 ± 12
ORDER	1.84	1.34 ± 0.07*	3.19 ± 0.19*
STRDISMIN	NA	381 ± 39	77 ± 13
ROADDIS	NA	438 ± 34	321 ± 31

Table 4. Univariate correlations of flat wetland FCI scores with potential landscape indicators (only correlations significant after applying a sequential Bonferroni correction for 48 simultaneous tests). Values are squared correlations expressed as percentages and augmented with the sign of the correlation.

Variable	$\pm R^2$
BIOGEO	
TSTRDEN100	−19.6
XSTRDEN100	−18.8
STRDISNHD	16.0
TSTRDENNHD100	−13.8
STRDIS	13.5
HABITAT	
FOREST100	36.0
TREEMEAN100	29.9
TREEZERO100	−28.3
FORDEC100	25.1
CLEAR100	−21.7
BARE100	−20.3
CROP100	−14.7
FORDEC1000	14.5
HYDROL	
TSTRDEN100	−39.8
XSTRDEN100	−37.3
TSTRDENNHD100	−32.5
STRDISNHD	16.9
STRDIS	14.8
PLANT	
FORDEC100	21.8
FOREVER100	−16.6
FOREVER1000	−14.4

wetland percentage were not among the top indicators for any function.

For the flat class (Table 4), the HYDROL and BIOGEO function scores were most strongly related to stream density near the assessment point and to distance to the nearest stream. Being closer to the nearest stream or having greater drainage density within 100 m were both associated with lower condition scores. The flat HABITAT and PLANT scores were most strongly related to land-cover variables. For these two functions, variables reflecting less land-cover disturbance (greater FOREST or TREEMEAN) were associated with better condition scores. The percentage of evergreen forest was negatively associated with flat PLANT condition scores.

The riverine HYDROL, BIOGEO, and HABITAT functions were most strongly predicted by measures of stream disturbance (Table 5). The condition of the nearest stream was the best predictor for HYDROL and HABITAT and the

Table 5. Univariate correlations of riverine wetland FCI scores with potential landscape indicators (only correlations significant after applying a sequential Bonferroni correction for 48 simultaneous tests). Values are squared correlations expressed as percentages and augmented with the sign of the correlation.

Variable	$\pm R^2$
BIOGEO	
NSTRDEN1000	45.5
NSTREAM	43.3
XSTRDEN100	−41.9
XSTRDEN1000	−31.5
HABITAT	
NSTREAM	45.9
XSTRDEN1000	−41.6
NSTRDEN1000	40.6
XSTRDEN100	−36.7
NSTRDEN100	19.4
HYDROL	
NSTREAM	60.0
NSTRDEN1000	58.2
XSTRDEN100	−50.2
XSTRDEN1000	−39.5
NSTRDEN100	26.6
WOODWET1000	21.1
PLANT	
GRASS100	−26.0
XSTRDEN1000	−26.0
CLEAR100	−22.2
XSTRDEN100	−20.8
FOREST100	20.4
TREEMEAN100	20.1
LANDSC	
FOREST100	46.9
FOREST1000	37.5
TREEMEAN1000	37.2
XSTRDEN1000	−36.3
FORMIX1000	35.9
TREEMEAN100	35.3
CLEAR100	−34.4
TREEZERO1000	−34.1
TREEZERO100	−29.7
NSTRDEN1000	28.7
IMPMEAN1000	−28.5
NSTREAM	27.4
ROADDEN1000	−27.4
IMPZERO1000	25.8
XSTRDEN100	−25.6
FORDEC1000	25.6
DEVTOT1000	−25.4
CROP100	−24.0
WOODWET1000	22.7
GRASS100	−20.2

Table 6. Variance explained (R^2) by regression models predicting HGM FCI scores from landscape indicators. Models were fit with and without variables from the NWI stream disturbance maps (Tiner et al. 2000, 2001). Regression equations are in Appendix A.

	With NWI Stream Vars.		Without NWI Stream Vars.	
Function	No. Vars.	R^2	No. Vars.	R^2
Flat				
BIOGEO	5	47.5%	4	36.7%
HABITAT	4	54.4%	2	47.9%
HYDROL	4	50.0%	1	32.5%
PLANT	4	50.3%	4	50.3%
Riverine				
BIOGEO	4	66.5%	2	28.0%
HABITAT	5	72.8%	4	38.4%
HYDROL	6	80.2%	2	31.3%
PLANT	4	63.3%	6	58.8%
LANDSC	8	85.0%	5	71.4%

second best for BIOGEO. Measures of the density of disturbed streams were negatively associated with all riverine functions, while greater density of natural streams was positively associated with all five functions. Greater coverage by forest vegetation was associated with higher scores for all riverine functions, while more disturbed vegetation (e.g., higher CLEAR, CROP, or TREEZERO) was associated with lower scores.

Multiple Regression Models

Combining indicators in multiple regression models yielded better predictions (higher R^2) of FCI scores than could be achieved by any single indicator. Among the final models selected for all functions in both classes (Appendix A), all were highly significant ($P < 0.0001$), and all but one model (flat BIOGEO) explained at least 50% of the variability in field measured assessment scores when stream variables from the NWI stream maps were considered as possible predictors. Two of the regression models (riverine HYDROL and LANDSC) explained more than 80% of the variability (Table 6). The number of independent variables ranged from four to eight. Figure 4 illustrates the performance of the regression models for two of the weaker models (R^2 near 50%, flat BIOGEO and PLANT) and for two of the stronger models ($R^2 > 80\%$, riverine HYDROL and LANDSC). All four cases demonstrate a strong and significant (Table 6) correspondence between the field assessment scores (y axis) and the model predictions (x axis), and all predictions are centered on the solid 1:1 line representing equality of predicted and observed FCI scores. The outer dashed lines in each plot show the 95% confidence limits for predicting the FCI score of an individual assessment point. In contrast, the inner dashed lines show much narrower 95% confidence limits for predicting the mean condition across the set of assessment points ($n = 89$ for flat and $n = 54$ for riverine). Regression models omitting variables from the NWI stream maps were not as good (lower R^2) as those including NWI stream predictors, and the loss in predictive power was greater for riverine wetlands than for flat wetlands (Table 6). However, the regression equations for all HGM functions of both classes were still highly significant ($P \leq 0.0002$).

Regression Tree Models

For both wetland classes, regression tree analysis produced significant models for predicting FCI scores from landscape indicators (Figure 5). The final regression trees after cross validation and pruning to remove spurious branches all involved between one and four independent variables in 1-4 splits. All the trees, including those using only one independent variable, gave better predictions (higher R^2) than any single univariate correlation (Tables 3 and 4), except for the riverine HYDROL regression tree, which had the same R^2 value as the best single correlation. Figure 4 shows regression tree predictions (open squares) of field-measured FCI scores and contrasts them with the corresponding predictions from multiple regression models.

DISCUSSION

Calibrated Level 1 Assessment Models

We succeeded in our central objective to calibrate statistical models for level 1 assessment of wetland functional condition. Many of the landscape indicators derived from land-cover, stream, road, and wetland maps (Table 1) were strongly and significantly correlated with Functional Condition Index (FCI) scores derived from HGM field assessments (Tables 4 and 5). For all HGM functions in both wetland classes, multiple regression and regression tree models could explain much of the variability in field-based assessment scores. The multivariate models were better (higher R^2) for riverine than for flat wetlands (Table 6, Figure 5), so level 1 assessment based on the multivariate relationships will be more precise for riverine than for flat

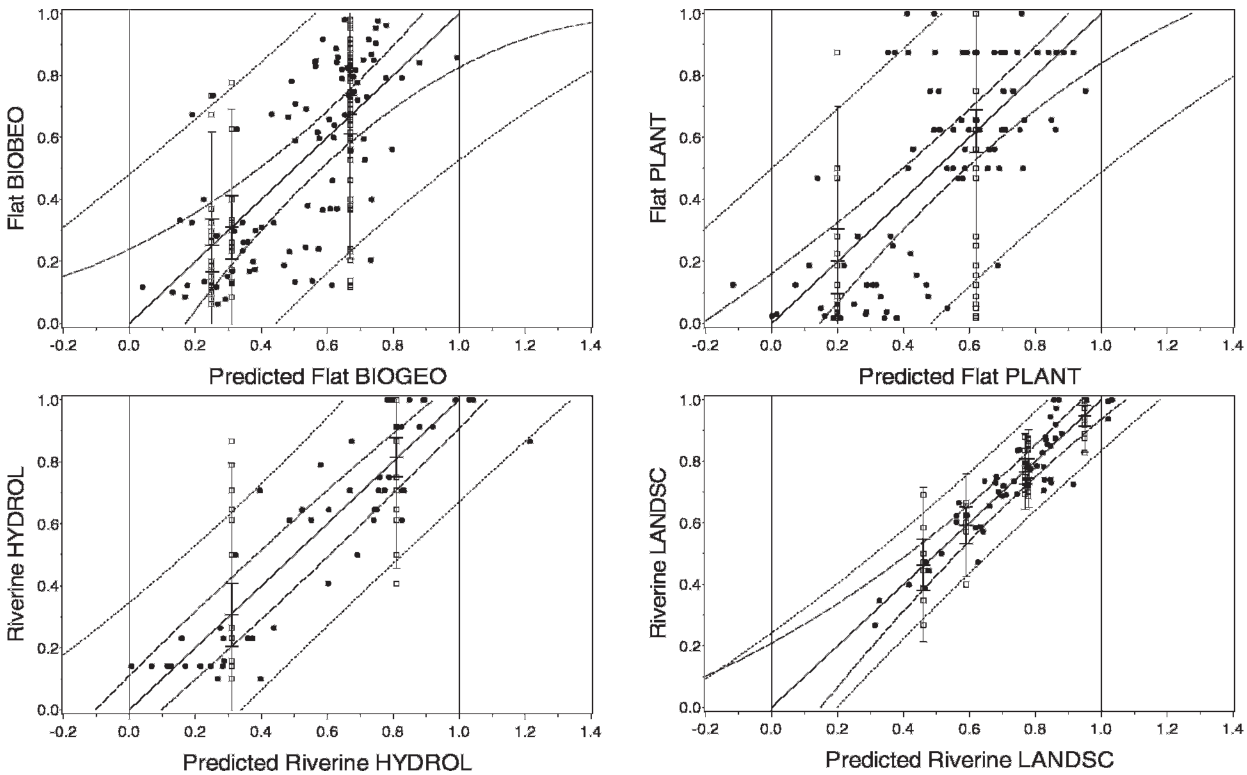

Figure 4. FCI scores predicted from landscape indicators by the fitted models. The solid dots and the lines show predictions from multiple regression models including variables from NWI stream maps (Table 6). The solid line is the 1:1 line (predicted FCI score = measured FCI score). Dashed lines are 95% confidence limits for regression predictions. The outer dashed lines are confidence limits for predictions of individual assessment points and the inner dashed lines are confidence limits for the predicting the mean given the sample sizes in the field assessment effort (89 for flat, 54 for riverine). Open squares are predictions from regression trees (Figure 5). Passing through the open squares, the thinner vertical line and whiskers show 95% confidence limits for predicting individual wetland condition, while the heavier line and whiskers show the mean and 95% confidence limits for predicting mean condition given the number of wetlands at each predicted value (see Figure 5).

wetlands, but even the poorest regression model explained almost 50% of the variability among field assessment points (Figure 5, Table 6).

Our analyses supported general expectations of how landscape factors affect wetland function (e.g., Brooks et al. 2004, Houlahan and Findlay 2004, Tiner 2004, 2005, Whigham et al. 2007). We found that greater drainage (higher density of all streams or excavated streams) is associated with lower wetland condition, while less drainage (higher density of natural streams or greater distance to a stream) is associated with higher condition (Tables 3 and 4). Similarly, wetland condition was negatively associated with land clearing (higher cropland, grassland, developed land, land with no trees, bare land, impervious surface) and positively related to forest variables (proportions of total, deciduous, or mixed forest; tree cover; zero impervious surface). Evergreen forest was negatively associated with the condition of flat wetlands, which are often disturbed by replacing native deciduous forest with pine plantations (Whigham et al. 2007). Measures of developed land and impervious surface were not as negatively associated with wetland condition as we expected, possibly because the rural Nanticoke watershed lacks major cities and industrial areas so that the primary disturbances are associated with agriculture (TNC 1998, Tiner 2004). Road variables were also only weakly related to wetland condition, possibly because of time lags in detecting road effects on biotic communities (Findlay and Bourdages 2000) or failure to account for some roads, which could be remedied by developing a more detailed road map. Also, the measurements we took during one-time visits to the assessment points (Whigham et al. 2007) may simply not provide good indicators of impervious surface effects.

Because they are all statistically significant, any of the level 1 regression models (Table 6, Appendix A)

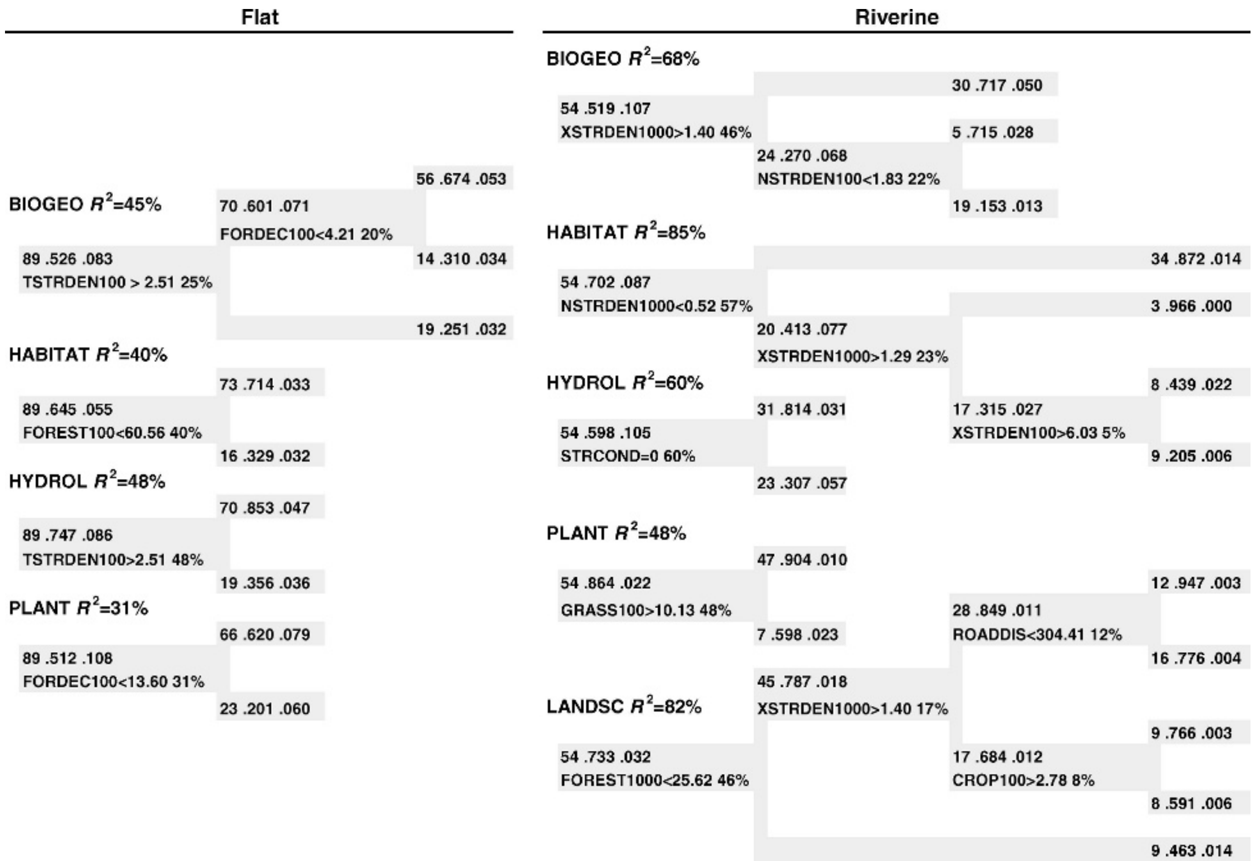

Figure 5. Regression trees predicting flat and riverine FCI scores from landscape indicators, along with the overall variance explained (R^2 in %) by each tree. For each branch of a tree, the number of assessment points, the mean FCI score, and the standard deviation of FCI score are given in that order. For each split, the splitting criterion and partial R^2 (%) are given. Sites that meet a splitting criterion follow the lower branch of the split, and sites that do not meet the criterion follow the upper branch.

can be used to make an interpretable FCI score prediction for a particular wetland assessment point. However, the confidence intervals for individual predictions are wide (Figure 4). Given that uncertainty, the level 1 predictions alone should not be used to make management decisions about particular wetlands. One would always want to verify and refine the level 1 predictions for a site with field observations. However, the level 1 predictions can target the fieldwork more effectively. For example, field visits to prioritize wetlands for preservation could be focused on wetlands that the level 1 models predict to be in good condition. Conversely, the level 1 models could identify wetlands likely to be degraded, helping to target field visits aimed at selecting restoration sites.

The level 1 models are even more useful for predicting average wetland condition across broader regions, such as a county or a watershed. This application uses the mean condition score for many assessment points rather than the score for a single point. The confidence limits for the mean score of many points are much narrower than the confidence limits for individual point predictions (Figure 4). Therefore, the level 1 models can provide fairly precise estimates of average condition within an area. Further field verification would always be desirable, but one could reasonably use the level 1 predictions alone to identify areas, perhaps watersheds, where restoration, preservation, or other management efforts should be focused.

Our method unites two assessment levels by ‘‘scaling up’’ field results with relationships that can estimate wetland condition across broad regions. Applications of our level 1 models at the individual point scale and the watershed scale are consistent with other visions of how level 1 tools can be used (Brooks et al. 2004, Fennessy et al. 2004), but both applications are enhanced by the information on model quality and prediction uncertainty that our approach provides. Also, many other level 1 methods only provide a very general estimate of ability to perform a function (Whigham et al. 2007), but like the underlying field assessments, our level 1 models index functional capacity relative to that of a reference, undisturbed wetland of the same class. Tools that objectively scale up field results to provide cost-effective predictions for whole watersheds are needed to meet the current strong emphasis on planning and managing resources at the watershed scale (e.g., USEPA 2001).

A Sample Watershed Assessment

We used our multiple regression equations (Table 6, Appendix A) to predict riverine FCI scores for three subwatersheds of the Nanticoke River basin. Analysis of the HGM field scores had already shown that FCI scores for the PLANT function were significantly higher in the Broad Creek basin than in the two other basins, while the Nanticoke River subwatershed (upstream from the confluence with Broad Creek) had significantly lower average FCI scores for the other four HGM functions than did wetlands in the Broad or Marshyhope drainages (see Figure 2 and Table 5 in Whigham et al. 2007).

Predictions from the level 1 regression models including stream variables mapped by NWI (Table 6) correctly represented the observed differences among subbasins (Figure 6). For the BIOGEO, HABITAT, and HYDROL functions in the Broad Creek basin, the mean predicted FCI scores were slightly lower than observed, but all the other comparisons (LANDSC and PLANT for Broad Creek, and all five functions in both the Marshyhope Creek and Nanticoke River basins), the mean predicted FCI scores were very close to the observed means. For all 15 comparisons (5 functions $\times$ 3 subbasins), the 95% confidence limits for the mean from regression predictions were similar in width to the 95% confidence limits for the mean of field observations. Most important, the level 1 predictions clearly match the HGM field results in representing the lower FCI scores for four functions in the Nanticoke River subbasin and the higher scores in the Broad Creek basin for the PLANT function. The agreement between the level 1 models and field-based results would have been even closer if we had adjusted regression predictions exceeding one back to one and predictions less than zero up to zero (Figures 4 and 6). Because the FCI scores are defined to range from zero to one (Whigham et al. 2007), we recommend this adjustment in any real application of the level 1 regression models.

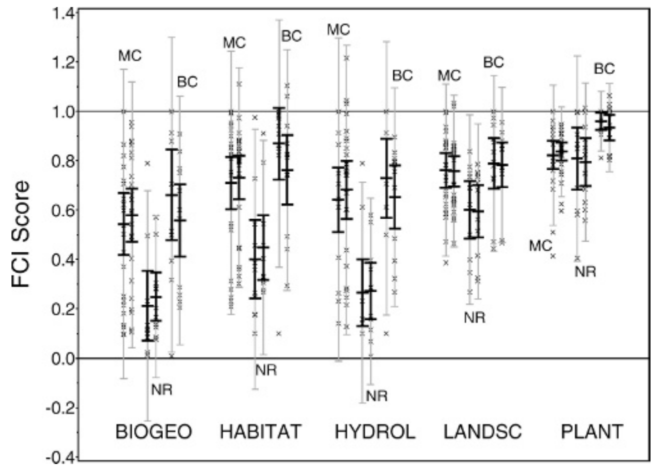

Figure 6. A test of the multiple regression models predicting FCI scores for riverine wetlands. Results for five HGM functions are shown for assessment points in three subbasins of the Nanticoke drainage: Marshyhope Creek (MC), Broad Creek (BC), and the Nanticoke River upstream from Broad Creek (NR). Each pair of bars represents an HGM function in a subbasin, and the pair contrasts field-based FCI scores (left bar) with level 1 FCI predictions (right bar) from a multiple regression model including variables from NWI stream maps (Table 6, Appendix A). Each bar shows individual FCI scores (X), the mean FCI score $\pm$ 2 standard errors of the mean (heavy black lines), and $\pm$ 2 standard deviations (gray lines).

Generality of Our Models and Methods

Our level 1 models (Table 6, Figure 5) have been developed for flat and riverine wetlands in the Nanticoke River watershed and can certainly be applied to assess additional wetlands or groups of wetlands in that watershed. The models could also be useful elsewhere on the Chesapeake Bay's eastern shore where the predominant wetland groups and settings are similar to those in the Nanticoke basin. However, the NWI stream disturbance variables were only available for Nanticoke streams, so applications outside the Nanticoke basin would have to rely on the somewhat weaker, but still highly significant models that omitted the NWI variables (Table 6, Appendix A). Because information on stream disturbance mapped by NWI (Tiner et al. 2000, 2001) provided some of the most useful predictors of wetland condition, we recommend that similar information should be collected elsewhere. Stream disturbance maps may also inform other assessment needs, such as understanding the factors affecting biotic integrity in streams.

The need for field assessment results to calibrate the level 1 models may sometimes limit the use of our method. Level 1 models are sometimes needed because there are *no* resources available to do field assessments (Brooks et al. 2004). In such cases, relationships derived from literature review and expert judgment may be the only choice, but our results on which landscape variables are most important (e.g., Tables 3 and 4) can help inform the design of those models. We do not advocate doing costly field assessments for the sole purpose of developing models like ours. However, we strongly advocate that understanding of wetland condition should ultimately rest on a sound base of field observations from appropriate samples of sites. By providing objective, statistically based tools for extrapolating field observations to new sites and broader areas, our method of calibrating level 1 models provides a strong, value-added component to the field assessments. Our method could be applied wherever a large group of field assessments (say 50 or more) can be matched with appropriate digital geographic data (e.g., Table 1). When new assessment efforts are planned, considering a modeling component like ours up front could help to maximize the value and use of the field assessment data.

Improvements in Calibrating Level 1 Models

The regression relationships for predicting FCI scores (Table 6) are better (higher R^2) than preliminary results that we reported earlier (Whigham et al. 2003). Some errors in analyzing the field data were corrected, and the HGM models used to calculate FCI scores from the field data were improved (Whigham et al. 2007). Our present analysis also added landscape indicators not available in our earlier efforts, including percentages of tree cover and impervious surface (Huang et al. 2001, Yang et al. 2003) and stream metrics derived from the high-resolution national hydrography dataset (USGS 2000, 2004a). The current analysis also used circa 2000 land-cover data from NLCD 2001 (Homer et al. 2004), while our previous analysis relied on circa 1990 land cover (EPA-EMAP 1994, Vogelmann et al. 1998). The newer land-cover map more closely matches the time of the 1999–2000 field-assessment campaign and is based on improved methods for classifying land-cover data from satellite imagery (Homer et al. 2004).

All the digital data we used to derive landscape metrics (Table 1) still have inaccuracies as described in their metadata files (e.g., USDC 2001, USGS 2004a,b, USGS 2005). For example, cross-validation analysis of the NLCD 2001 land cover suggests an overall classification accuracy of 77% across the zone that includes Delaware, most of Maryland, and parts of four other states (USGS 2004b). Positional and classification errors contribute to the "noise" in analyses relating field-condition measurements to landscape variables, so that the analyses detect fewer significant relationships with lower explained variance than might be achieved with more accurate landscape data. The results we report are robust relationships that emerge above that noise. Still better relationships might be achievable by incorporating higher resolution spatial data, such as land cover derived from high-resolution imagery (Goetz et al. 2003) or topographic variables derived from precision LIDAR instruments (Lefsky et al. 2002).

Multivariate Modeling Methods

We explored stepwise multiple regression and regression tree analysis as alternate ways to fit level 1 prediction models. Neither method was clearly better than the other. In four cases of the nine functions considered across both wetland classes, the regression tree models had similar R^2 values to the multiple regression models, even though the regression trees required fewer independent variables (Table 6, Figure 5). However, regression trees for the remaining five cases had much lower R^2 values than the multiple regressions. In all cases, the variables used for splits in the regression trees were among the variables that have strong univariate correlations with condition (Tables 3 and 4), and the directions of the splits agreed with expected effects of landscape disturbances. In contrast, some of the independent variables in the stepwise multiple regressions (Table 6) are not among the top univariate predictors (e.g., ROADDIS in the riverine LANDSC equation), and some of the multiple regression coefficients differ in direction of association from the univariate correlations and from expected effects of landscape disturbances (e.g., FORDEC100 in the riverine BIOGEO function). Thus, the regression trees have the advantages of parsimony and interpretability, but at some cost of predictive power for the majority of functions considered across both classes. Regression trees have been recommended for responses that are non-linear, non-normal, and not continuous (Therneau and Atkinson 1997, De'Ath and Fabricius 2000). Such advantages may be less important for predicting HGM FCI scores because HGM models are typically normalized to provide relatively monotonic responses in FCI scores across reference wetlands ranked from degraded to pristine condition (Brinson 1993, Whigham et al. 2007).

CONCLUSIONS

Field assessment results can be used to calibrate statistical models that predict wetland condition by using landscape indicators derived from digital maps. Unlike level 1 relationships based only on best professional judgment, the statistically calibrated models provide an objective measure of the quality of the model, and the statistical method allows the estimation of confidence limits on condition predictions. For flat and riverine wetlands of the Nanticoke River basin, the most useful landscape indicators came from maps of land cover and stream condition (natural or excavated). The correlations of the landscape indicators with wetland condition agreed with expectations based on scientific literature on the processes leading to wetland degradation. The statistical models for predicting wetland condition worked better (higher R^2) for riverine wetlands than for flat wetlands. The confidence limits on predicted functional condition index (FCI) scores for individual wetlands were broad, but the models could still be used to prioritize field visits needed to select sites for preservation, restoration, or other management actions. The confidence limits for predictions of average condition in a group of wetlands were much narrower, so the level 1 models can provide fairly precise predictions of mean condition in an assessment area, such as a watershed or subwatershed.

Our level 1 models could be applied for further assessment of wetlands within the Nanticoke watershed, but our best models use information from stream maps that have only been developed for that watershed. We also developed models that are less predictive but use landscape indicators from maps available for broader areas. These latter models could be applied to other areas on the Coastal Plain that have flat and riverine wetlands in settings like those in the Nanticoke River watershed. Our approach to developing level 1 models could be implemented wherever a reasonable number of field assessments can be matched with relevant landscape data. Level 1 modeling should be considered when new field assessment programs are planned.

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Appendix A. Multiple regression equations for predicting HGM FCI scores from landscape indicators. Models were fit with and without variables from the NWI stream disturbance maps (Tiner et al. 2000, 2001). Regression summary information is in Table 6.

Including stream variables from NWI stream disturbance maps

Flat

$\mathit{BIOGEO} = 0.38 + 0.000588 \cdot \mathit{STRDISMIN} - 0.0465 \cdot \mathit{TSTRDENNHD100} - 0.00667 \cdot \mathit{FOREVER1000} + 0.00347 \cdot \mathit{TREEMEAN100} - 0.000294 \cdot \mathit{STRDISNHD}$

$\mathit{HABITAT} = 0.28 + 0.00380 \cdot \mathit{FOREST100} + 0.00272 \cdot \mathit{FORDEC100} - 0.0558 \cdot \mathit{TSTRDEN1000} + 0.00522 \cdot \mathit{FORMIX100}$

$\mathit{HYDROL} = 1.04 - 0.0616 \cdot \mathit{TSTRDEN100} + 0.000251 \cdot \mathit{STRDISMIN} - 0.00626 \cdot \mathit{WOODWET1000} - 0.00274 \cdot \mathit{WETPERC100}$

$\mathit{PLANT} = -1.04 + 0.00597 \cdot \mathit{FORDEC100} + 0.0147 \cdot \mathit{TREEMEAN100} + 0.0142 \cdot \mathit{TREEZERO100} + 0.00998 \cdot \mathit{FORMIX100}$

Riverine

$\mathit{BIOGEO} = 0.06 + 0.431 \cdot \mathit{STRCOND} + 0.00107 \cdot \mathit{STRDISNHD} + 0.00535 \cdot \mathit{TREEMEAN100} - 0.00347 \cdot \mathit{FORDEC100}$

$\mathit{HABITAT} = 0.27 + 0.00149 \cdot \mathit{STRDISNHD} + 0.321 \cdot \mathit{STRCOND} + 0.0101 \cdot \mathit{FOREVER100} + 0.0169 \cdot \mathit{HERBWET100} + 0.0308 \cdot \mathit{NSTRDEN100}$

$\mathit{HYDROL} = 0.26 + 0.188 \cdot \mathit{NSTRDEN1000} + 0.328 \cdot \mathit{STRCOND} + 0.000850 \cdot \mathit{STRDISNHD} - 0.0301 \cdot \mathit{HERBWET1000} + 0.00500 \cdot \mathit{FOREVER100} - 0.00366 \cdot \mathit{CROP100}$

$\mathit{PLANT} = 1.04 - 0.0270 \cdot \mathit{XSTRDEN100} - 0.00524 \cdot \mathit{WETPERC1000} - 0.00397 \cdot \mathit{CLEAR100} + 0.00436 \cdot \mathit{FOREVER1000}$

$\mathit{LANDSC} = 1.57 + 0.156 \cdot \mathit{STRCOND} - 0.00512 \cdot \mathit{CLEAR100} - 0.00536 \cdot \mathit{DEVTOT1000} + 0.0160 \cdot \mathit{FORMIX1000} + 0.000361 \cdot \mathit{STRDISNHD} - 0.00925 \cdot \mathit{IMPZERO100} + 0.000138 \cdot \mathit{ROADDIS} - 0.000855 \cdot \mathit{WETPERC100}$

Without stream variables from NWI stream disturbance maps

Flat

$\mathit{BIOGEO} = 0.487 - 0.0570 \cdot \mathit{TSTRDENNHD100} + 0.00438 \cdot \mathit{FOREST100} - 0.00344 \cdot \mathit{FOREVER100} - 0.00238 \cdot \mathit{WETPERC100}$

$\mathit{HABITAT} = 0.196 + 0.00605 \cdot \mathit{FOREST100} - 0.00284 \cdot \mathit{FOREVER100}$

$\mathit{HYDROL} = 0.824 - 0.0742 \cdot \mathit{TSTRDENNHD100}$

$\mathit{PLANT} = -1.039 + 0.00597 \cdot \mathit{FORDEC100} + 0.0147 \cdot \mathit{TREEMEAN100} + 0.0142\ \mathit{TREEZERO100} + 0.0100 \cdot \mathit{FORMIX100}$

Riverine

$\mathit{BIOGEO} = 0.337 + 0.00649 \cdot \mathit{WOODWET100} + 0.00124 \cdot \mathit{STRDISNHD}$

$\mathit{HABITAT} = 0.954 + 0.0441 \cdot \mathit{WOODWET1000} - 0.0101 \cdot \mathit{WETPERC1000} - 0.0663 \cdot \mathit{ORDER} - 0.0048 \cdot \mathit{CLEAR100}$

$\mathit{HYDROL} = 0.522 + 0.0283 \cdot \mathit{WOODWET1000} - 0.0539 \cdot \mathit{HERBWET1000}$

$\mathit{PLANT} = -2.796 - 0.00586 \cdot \mathit{WETPERC1000} + 0.0394 \cdot \mathit{FOREST1000} - 0.00765 \cdot \mathit{GRASS100} + 0.0224 \cdot \mathit{HERBWET100} + 0.0373 \cdot \mathit{TREEZERO1000} - 0.0205 \cdot \mathit{HERBWET1000}$

$\mathit{LANDSC} = 0.299 + 0.0039 \cdot \mathit{FOREST100} + 0.0198 \cdot \mathit{FORMIX1000} + 0.0116 \cdot \mathit{WOODWET1000} - 0.00144 \cdot \mathit{WETPERC100} + 0.000168 \cdot \mathit{ROADDIS}$