

## An Index of Ecological Condition Based on Bird Assemblages in Great Lakes Coastal Wetlands

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**ABSTRACT.** We use bird distributions in non-forested coastal wetlands of the Great Lakes to illustrate a new, conceptually explicit method for developing biotic indicators. The procedure applies a probabilistic framework to derive an index that best “fits” an observed assemblage of species, based on preliminary information about species’ responses to human environmental disturbance. Among 215 coastal wetland complexes across the U.S. portion of the Great Lakes, 23 bird species were particularly sensitive (positively or negatively) to a multivariate environmental disturbance gradient ranging from 0 (maximally disturbed) to 10 (minimally disturbed). Species like Sandhill Crane (*Grus canadensis*) and Sedge Wren (*Cistothorus platensis*) showed strong negative relationships with human disturbance, while others like Common Grackle (*Quiscalus quiscula*), American Robin (*Turdus migratorius*), and European Starling (*Sturnus vulgaris*), showed strong positive relationships with disturbance. The functional shapes of these biotic responses were used to determine indices of ecological condition (IEC) for new sites. Values of IEC were highly correlated with the environmental gradient, but deviations from a 1:1 relationship reveal novel insights about local ecological conditions. For example, sites dominated by invasive plant species like *Phragmites australis* tended to yield IEC values that were lower than expected based on the environmental gradient. This framework for calculating ecological indicators holds significant potential for other applications because it is flexible, explicitly linked to a disturbance gradient, and easy to calculate once standardized biotic response functions are documented and made available for a region of interest.

**INDEX WORDS:** Coastal wetland, environmental assessment, indicator.

### INTRODUCTION

Coastal wetlands of the Laurentian Great Lakes provide important ecological links between the

lakes and surrounding watersheds. To a significant degree, the extent and health of these coastal wetlands reflect the overall ecological condition of the coastal zone (Krieger *et al.* 1992). Unfortunately, many of the Great Lakes coastal wetlands have

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been destroyed or degraded by human activities (Herdendorf *et al.* 1981, Chow-Fraser and Albert 1999), in some cases leaving only a small fraction of the original wetland area (Herdendorf 1987, Smith *et al.* 1991). Shoreline development and invasive species, among other factors, continue to threaten remnant wetlands in the Great Lakes coastal zone (Niemi *et al.* 2004).

To monitor ecosystem changes and facilitate conservation strategies, biologists and policy-makers have sought to develop quantitative indicators of ecosystem health for the Great Lakes coastal zone (Shear *et al.* 2005). The State of the Lakes Ecosystem Conference (SOLEC) was first convened in 1992 by U.S. and Canadian authorities to specifically address the reporting requirements of the Great Lakes Water Quality Agreement of 1972 (Bertram *et al.* 2003). Biannual meetings of SOLEC involving federal, state, provincial, and local government agencies; academic scientists; environmental groups; private industry; and the general public have led to the publication of approximately 80 indicators, ranging from direct measures of toxic chemicals in food webs to abundances of individual sensitive species (e.g., *Hexagenia*) or natural communities (e.g., area, quality, and protection of alvar) to multivariate measures like the diversity or abundance of wetland dependent bird species (Shear *et al.* 2005).

An ongoing challenge in the development of meaningful environmental indicators is an understanding of relationships between indicators (e.g., diversity of wetland-dependent species) and environmental stress (e.g., habitat degradation). Karr and Chu (1999), Jackson *et al.* (2000), and others (Niemi and MacDonald 2004) provide conceptual frameworks for designing and interpreting indicators of ecological health in relation to human activity. Those analyses are important because they help guide the development of cost-effective indicators and, most importantly, because they can be used to help guide remedial actions for improving environmental conditions.

In this paper we introduce the index of ecological condition (IEC), a new approach for developing ecological indicators. The general method (Howe *et al.* 2007) uses a probabilistic framework pioneered by Hilborn and Mangel (1997) to assess the occurrences of species (or any set of monotonic variables) in the context of an explicit gradient of environmental stress or disturbance. This flexible approach can use either simple biological variables like those used in the Hilsenhoff (1982) index and

its analogues or multimetric variables like those used in the index of biotic integrity (IBI) of Karr (1981) and others. Our approach is unique because of the way in which the final number (index) is generated.

The IEC approach, like the multimetric approach of Karr (1981), requires that users clearly identify an *a priori* environmental gradient, which ultimately helps determine what the ecological indicator truly “indicates.” As long as the same preliminary environmental gradient is applied, estimates from different taxonomic groups, different types of variables, and even different field methods can be compared and combined readily because information from different species or variables is not additive.

Application of our method requires that preliminary studies or expert opinion quantify the responses of species or other variables to an explicit environmental stress or disturbance gradient, which we will simply call the *environmental gradient*. Points along the environmental gradient will be defined as having an environmental condition of  $C_{env}$ . Once the responses of species to the environmental gradient have been documented, users provide data on the occurrences of species or values of the response variables at new places of interest. The IEC is calculated iteratively using widely available computer software (e.g., Microsoft Excel), leading to an estimate of ecological condition ranging from 0 (maximally degraded) to 10 (minimally degraded). Conceptually, we suggest that this approach measures ecological condition because it is predicated on biotic responses to environmental condition ( $C_{env}$ ) as defined by the original environmental gradient.

We illustrate the IEC by applying results from an extensive survey of birds in coastal wetlands of the U.S. portion of the Laurentian Great Lakes. Our purpose is not to seek the final word on bird-related indicators in this system. Instead, we use this information to demonstrate the method and to provide a foundation for later, more complete analyses of coastal wetland bird assemblages and their suitability as ecological indicators.

### Probability Indicator Model

Consider a general framework where the probability of observing a particular species given a specific site's ecological condition ( $C$ ) is  $P_i(C)$ . For simplicity, we define a fixed scale of  $0 < C < 10$ , where 0 represents the most degraded condition and

10 represents the most pristine or desirable condition.  $C$  is related to  $C_{env}$ ; in fact it fundamentally “indicates”  $C_{env}$ , but  $C$  also incorporates biotic responses of multiple species or related variables. Here we use the term  $C_{env}$  only with reference to the *a priori* environmental gradient. The probability of observing species  $i$  can be described by a function of the site’s condition and  $p$  attributes  $\beta = \beta_{i,1}, \dots, \beta_{i,p}$ , which reflect the species’ response to variation in ecological condition. The height of the response curve along the gradient (i.e., its position on the y-axis) will reflect the species’ overall ubiquity in the region and its ease of detection. We call this quantitative relationship a *biotic response* (BR) function, identical to the *species-specific sensitivity/detectability* (SSD) functions described by Howe *et al.* (2007). The function is affected by a species’ response to the environmental gradient (the shape of the curve) as well as its overall ubiquity and detectability (the height of the curve), although it is not necessary to differentiate these factors as long as the species is equally detectable along the entire gradient. Each BR function must be linked to a specific sampling method used to collect field data at new sites of interest. We use a model with four parameters:

$$P_i(C) = \beta_{i,1} + \beta_{i,2} \frac{e^{\beta_{i,4}(C-\beta_{i,3})}}{1 + e^{\beta_{i,4}(C-\beta_{i,3})}} \quad (1)$$

where

- $\beta_{i,1}$  = the lowest probability of observing species  $i$  (across all values of  $C$ );
- $\beta_{i,2}$  = the difference between highest and lowest probabilities of observing species  $i$  (across all values of  $C$ );
- $\beta_{i,3}$  = the condition ( $C$ ) where  $P = \beta_{i,1} + \frac{1}{2}\beta_{i,2}$ ; and
- $\beta_{i,4}$  = a measure of the steepness of the function at  $\beta_{i,3}$ .

The  $\beta$  parameters can be estimated from observed species occurrences along an independent environmental gradient. Specifically, values for the parameters can be estimated iteratively from field data through maximum likelihood (Hilborn and Mangel 1997) or related goodness-of-fit criteria using a computer algorithm such as the “Solver” add-on in Microsoft Excel. A critical step is definition of the environmental gradient, which identifies levels of ecological stress or degradation at prospective sites. Once the species-specific  $\beta$  parameters have been

determined, IEC values can be calculated at new areas by observing which species are present or absent at the sites.

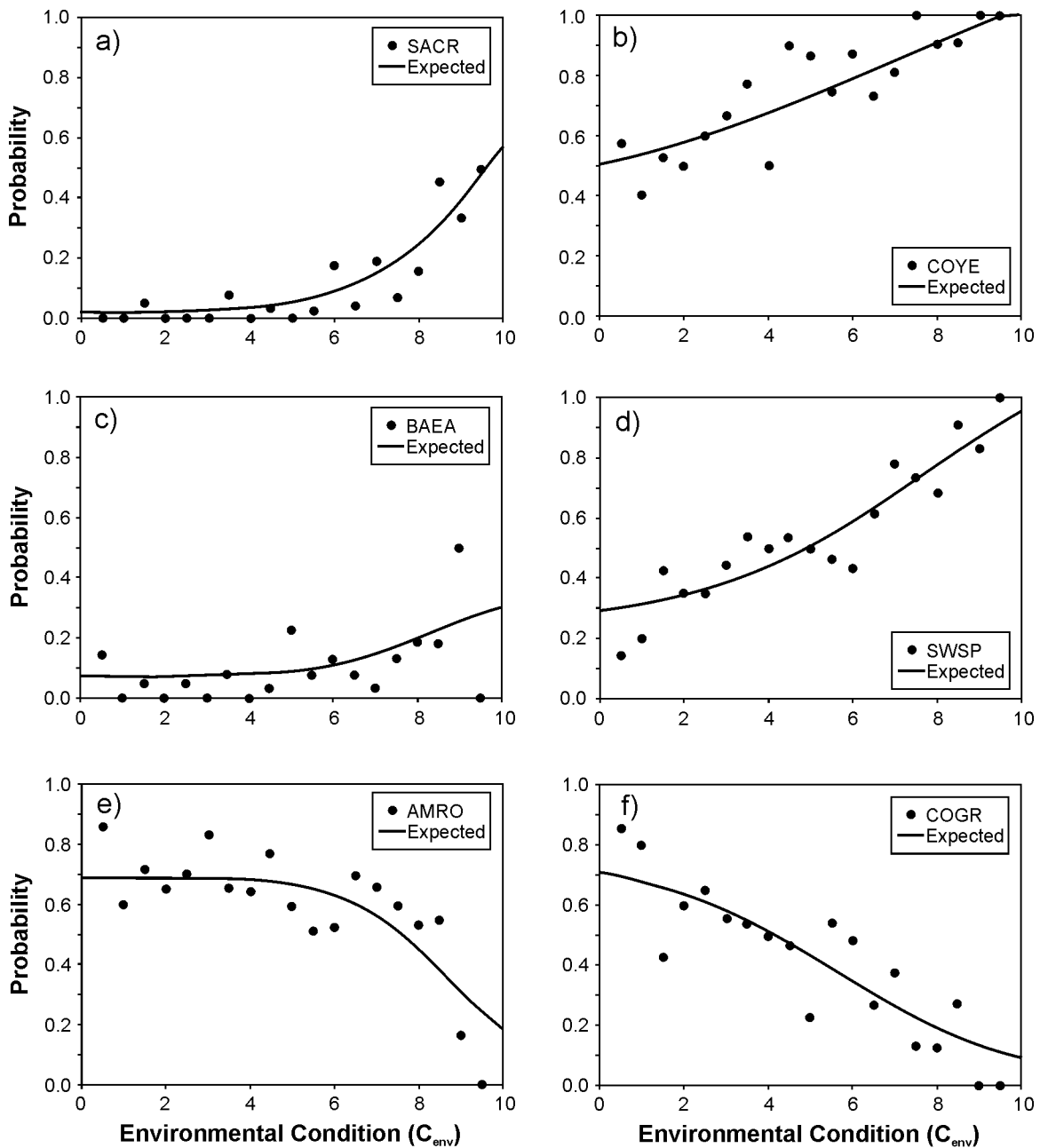
BR functions represent species-specific responses to the *a priori* environmental gradient ( $C_{env}$ ). Typically, these functions describe the probability of observing a species at different levels of environmental condition or, inversely, environmental stress. Some species may show negative responses to environmental stress (Figs. 1a–1d), while others may show a positive response (Figs. 1e and 1f). The height of the response curve (i.e., the probability of observing the species) is associated with the species’ overall relative abundance and ease of detection. The  $\beta$  parameters are fixed constants for an area or region of interest, although different species-specific functions might be applied for different habitat types, different field methods, or different climatic conditions (e.g., different water level regimes in the Great Lakes [Wilcox *et al.* 2002]). BR functions can be derived for species groups or even multivariate calculations as long as all dependent variables are scaled to the same range (e.g., 0–1).

To derive the species-specific BR functions, the environmental gradient must be defined *a priori*. Sites with ideal condition (i.e.,  $C_{env} = 10$ ) or maximally degraded condition (i.e.,  $C_{env} = 0$ ) might not exist in nature, but the investigator nevertheless must model the expected probabilities of occurrence under these conditions.

The IEC (an estimate of  $C$ ) is calculated by applying the BR functions to field data acquired using the same methods that generated the BR functions. An iterative computer program asks the mathematical question: “Given the *a priori* BR functions, what is the value of  $C$  that best fits the observed field data?” In our examples the BR functions describe probabilities of species’ occurrences (ranging between 0 and 1), but any variable that changes monotonically over the environmental gradient can be used.  $C$  can be estimated in two ways: 1) a *least squares method*, which finds an IEC that minimizes the sum of squared differences between expected probabilities of species presence,  $P_i(C_i)$ , and observed probabilities of presence,  $p_i$ , for  $i = 1, 2, \dots, n$  species; and 2) a *likelihood method*, which finds an IEC that maximizes

$$\sum_{observed} \log(P_i(C)) + \sum_{unobserved} \log(1 - P_i(C)) \quad (2)$$

where the term on the left is the sum of log-probabilities of species that were observed at the site and



**FIG. 1.** Biotic response (BR) functions for selected bird species from coastal wetlands of the Laurentian Great Lakes. Condition (x-axis) represents a gradient of human environmental disturbance derived from principal components (PCA) analysis (FIG. 2), where 0 = maximally disturbed condition and 10 = minimally disturbed condition. Y-axis gives the proportion of occurrence in coastal wetlands across 19 categories of condition (0–0.5, 0.5–1.0, 1.0–1.5, etc.): a) sandhill crane, b) common yellowthroat, c) bald eagle, d) swamp sparrow, e) American robin, and f) common grackle. Scientific names are given in Table 3.

the term on the right is the sum of log-probabilities of species that were not observed. In cases like ours, the observed probabilities ( $p_i$ ) are the proportions of field samples in which species  $i$  was de-

tected. The likelihood method is applicable where multiple samples are available for a given site or category of sites. If a targeted site has many species characteristic of high quality environmental condi-

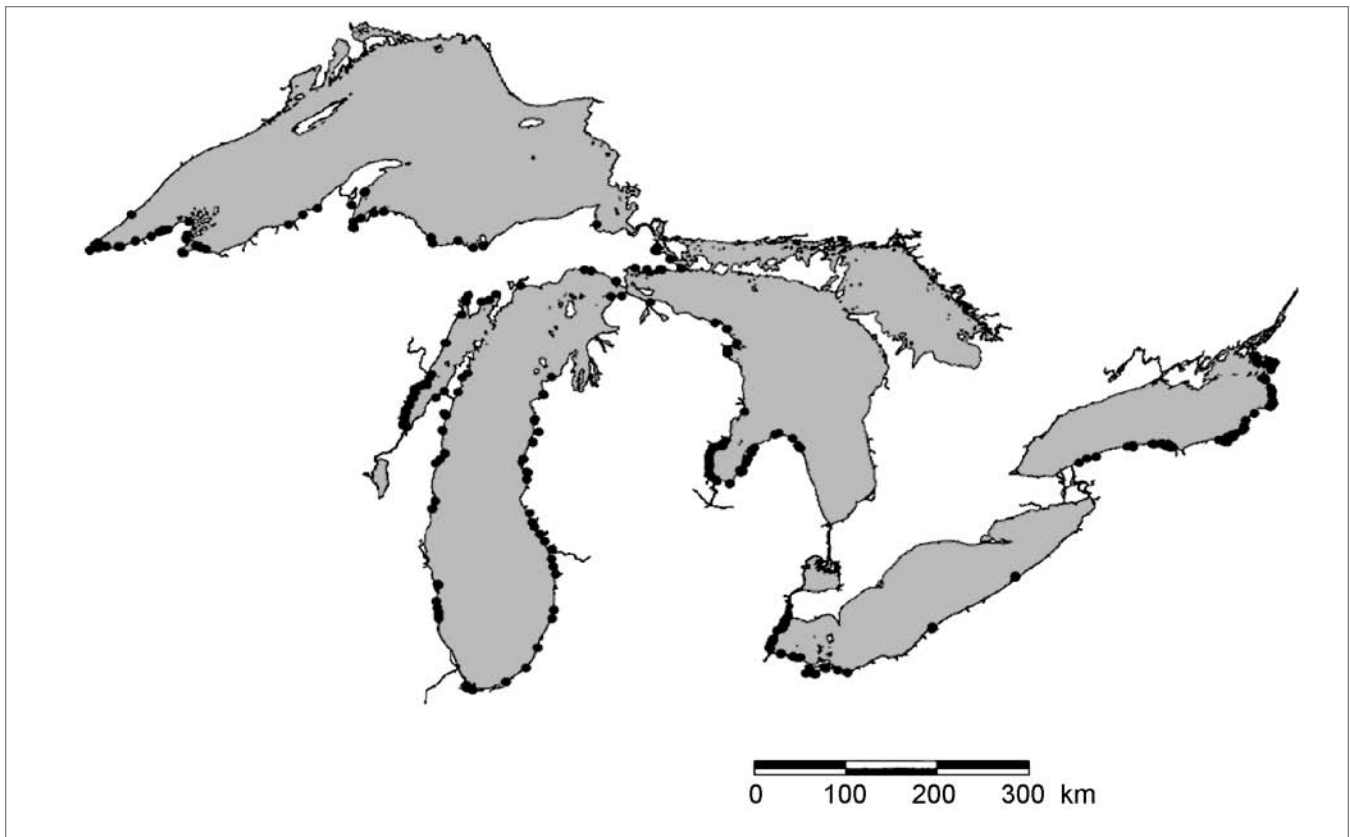


FIG. 2. Map of Laurentian Great Lakes showing locations of wetland sample sites (•).

tion (e.g.,  $C_{env} > 7$ ) and few species characteristic of poor conditions (e.g.,  $C_{env} < 3$ ), the site will yield a high estimate of  $C$ ; if the site has few species associated with quality environmental condition and many species associated with poor condition, the site will yield a low estimate of  $C$ . A computer algorithm like Microsoft Excel's "Solver" can be used to find the best-fit IEC (estimate of  $C$ ).

This approach assumes that species respond in various ways to a common gradient of environmental condition. For a given location our IEC reflects the BR functions of all species simultaneously. To avoid spurious estimates of  $C$ , the analysis can be restricted to species showing strong statistical responses to stress (i.e., steep BR functions with minimal scatter) or to species characteristic of a particular habitat type.

#### METHODS

We applied our probabilistic indicator approach to samples of breeding birds from 215 wetland complexes in the U.S. portion of the Great Lakes (Fig. 2) during June and early July (the main avian

breeding period) of 2002 and 2003 (Table 1). Wetland complexes consisted of one or more non-forested coastal wetlands (marshes or shrub wetlands) located within the same local drainage area, ranging from 1 to 1,265 ha (average = 91 ha) and within 1 km of the Great Lakes shoreline. We sampled a variety of wetland types (Albert *et al.* 2003), including riparian wetlands, coastal marshes, and protected wetlands not directly connected to the lake. Wetland complexes were selected according to a stratified random method described by Danz *et al.*

TABLE 1. Distribution of sampling points among Great Lakes and coastal segments, defined as the drainage area associated with major rivers and streams (Danz *et al.* 2005).

Lake	Segments	Points
Erie	24	41
Huron	47	61
Michigan	73	113
Ontario	35	61
Superior	45	62
<b>Total</b>	<b>224</b>	<b>338</b>

**TABLE 2.** Variables used to define an environmental stress gradient associated with wetland bird survey sites. Principal components incorporate numerous variables derived from the drainage area of the shoreline segment (segment-shed) surrounding the wetland complex (Danz et al. 2007). Land cover classes were determined by Wolter and others at the University of Minnesota Duluth's Natural Resources Research Institute (Wolter et al. 2006) and combined into six general categories (industrial, roads, residential, cultivated, natural, wetland). Proportions of land cover in each category were determined by GIS analysis for areas within 100 m, 500 m, 1 km, and 5 km of the centroid of the wetland complex.

Variable #(s)	Variable(s)
1	Agricultural principal component 1 (Danz et al. 2007)
2	Atmospheric deposition principal component 1 (Danz et al. 2007)
3	Atmospheric deposition principal component 2 (Danz et al. 2007)
4	Point source pollution principal component 1 (Danz et al. 2007)
5	Point source pollution principal component 2 (Danz et al. 2007)
6	Soil type principal component 1 (Danz et al. 2007)
7	Soil type principal component 1 (Danz et al. 2007)
8	Urbanization principal component 1 (Danz et al. 2007)
9	Proportion industrial land use in wetland complex (excluding water)
10	Proportion road area in wetland complex
11	Proportion residential land use in wetland complex
12	Proportion cultivated land in wetland complex
13	Proportion natural land cover in wetland complex
14	Proportion wetland land cover in wetland complex
15–18	Proportion industrial land use within 100 m, 500 m, 1 km, 5 km (excluding water)
19–22	Proportion road area within 100 m, 500 m, 1 km, 5 km (excluding open water)
23–26	Proportion residential land use within 100 m, 500 m, 1 km, 5 km (excluding open water)
27–30	Proportion cultivated land within 100 m, 500 m, 1 km, 5 km (excluding open water)
31–34	Proportion natural land cover within 100 m, 500 m, 1 km, 5 km (excluding open water)
35–38	Proportion wetland land cover within 100 m, 500 m, 1 km, 5 km (excluding open water)
39	Total road length within 5 km

(2005). The number of bird sample points varied from only a single point in the smallest wetlands (65% of wetland complexes), two points in 47 moderately large complexes (22%), three points in 26 larger complexes (12%), and four and five points in the two largest complexes. Sampling was conducted during both 2002 and 2003 at 50 of the 321 sample points, giving a total of 371 point samples. Differences in overall bird distributions between the 2 years were minor, so we treated each point count as a separate sample.

From each bird survey point, field observers recorded all birds seen or heard within a 100 m radius half-circle extending from the edge into the wetland. This method and standardized data forms followed the standardized National Marsh Monitoring Protocol (Ribic et al. 1999, Weeber and Valianatos 2000). All point counts were conducted between first light (just before sunrise) and 0900 in benign weather conditions (rainless with winds < 20 km/h). Field samples were part of the multi-

disciplinary Great Lakes Environmental Indicators project (GLEI) funded by the U.S. Environmental Protection Agency (<http://glei.nrri.umn.edu>).

A large suite of independent environmental variables was acquired by GLEI collaborators for each of the wetland complexes (Table 2). One set of variables (1–8 in Table 2) applies to the drainage area of the shoreline segment (segment-shed) associated with the wetland complex. Danz et al. (2007) used principal components analysis (PCA) to summarize five groups of anthropogenic variables, including agricultural data, pesticide application records, point sources of chemical and air pollution, soil attributes, and human population density. A second set of variables (9–39 in Table 2) was derived from Landsat 5 and Landsat 7 satellite imagery (30 m × 30 m pixels) from the years 1992 and 2001 (Wolter et al. 2006). Land cover classes were combined into six general categories (Table 2). ArcGis 9.1 (ESRI 2005) was used to calculate the proportional area of each land cover category within 100 m, 500 m, 1

km, and 5 km of the centroid of the wetland complex. Principal components analysis (correlation matrix) was used to further summarize these 39 environmental variables (Table 2). Scores from the resulting principal components were combined into a single index of human impact ( $= C_{env}$ ), forming a standardized environmental gradient.  $C_{env}$  was calculated for each wetland complex by adding the scores for each principal component accounting for at least 5% of the overall variation, weighted according to the percent variation explained. This analysis allowed us to order the wetland complexes along a single environmental gradient, ranging from most impacted sites (e.g., sites with high levels of pesticide application, high air pollution emissions, high human population density, low proportion of natural vegetation or wetland land cover, many roads, etc.) to least impacted sites.

The gradient of environmental condition ( $C_{env}$ ) among sampled wetlands was used to develop biotic response (BR) functions for bird species. Wetland sites were grouped into 19 categories of 0.5 unit intervals (e.g., 0.0–0.5, 0.5–1.0, 1.0–1.5, etc.) ranging from maximally stressed or affected by human activities ( $C_{env} = 0$ ) to minimally impacted ( $C_{env} = 10$ ). For species  $i$  and category  $j$ , the proportion  $p_{ij}$  was defined as the proportion of bird sample points where the species was recorded. Parameters of the best-fit BR functions were estimated by iteration, minimizing the expression:

$$\sum_{j=1}^N (p_{ij} - P_i[C_j])^2 / (P_i[C_j] * [1 - P_i(C_j)]) \quad (3)$$

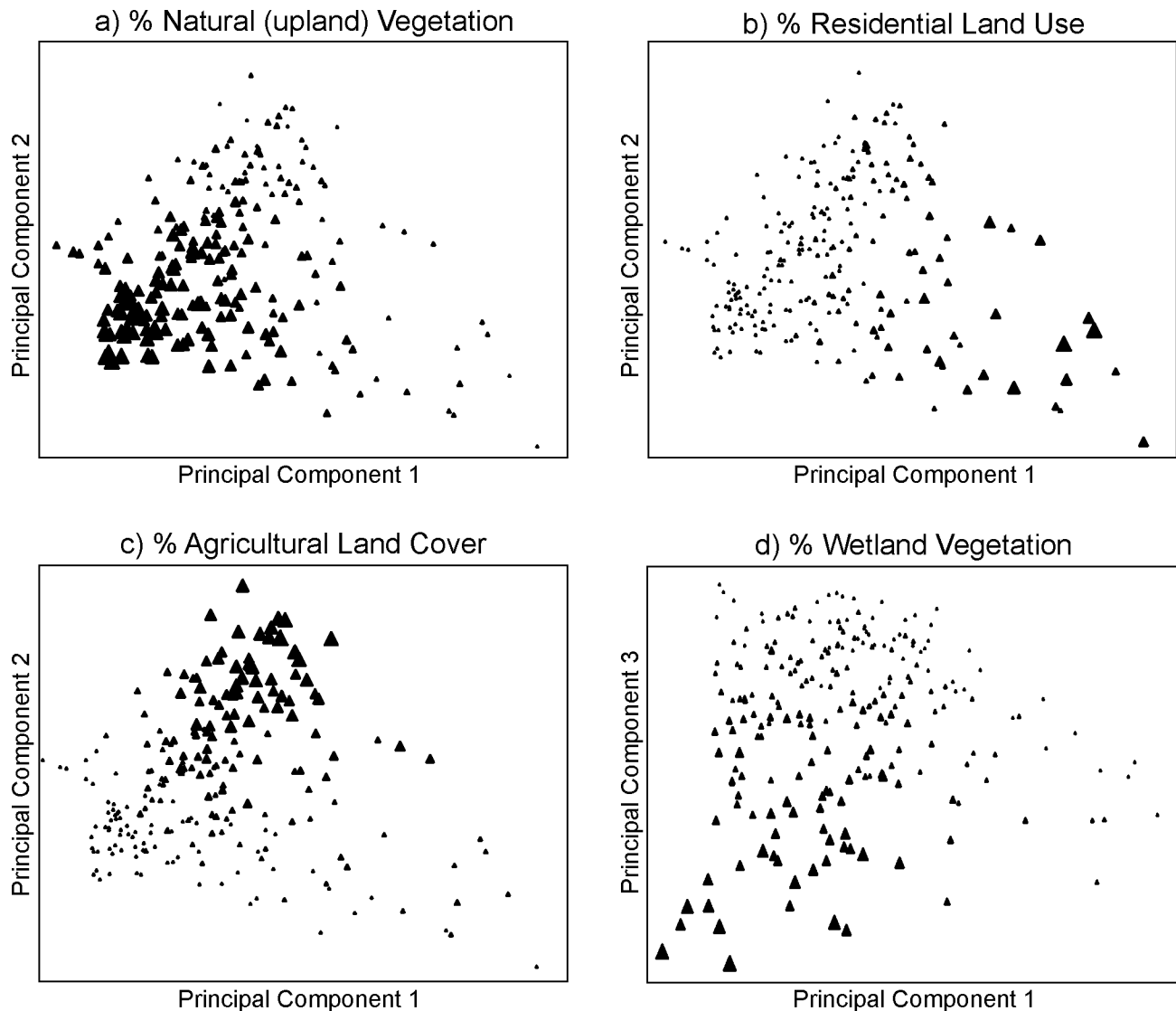
where  $N$ , equal to 19 here, is the total number of samples (in this case, categories),  $p_{ij}$  is the observed proportion of point counts in category  $j$  where observers detected species  $i$ ,  $C_j$  is the midpoint value of  $C_{env}$  in the  $j^{\text{th}}$  interval (e.g., 0.25 for the interval 0.0–0.59), and  $P_i(C_j)$  is the expected probability of occurrence from Equation 1 given a specific set of parameter values for the BR function. The “Solver” tool of Microsoft Excel was used to derive parameter estimates for  $\beta_{i,1}$ ,  $\beta_{i,2}$ ,  $\beta_{i,3}$ , and  $\beta_i$  by minimizing Equation 3, subject to the constraints that  $0 < \beta_{i,1} < 1$ ,  $0 < \beta_{i,2} < 1 - \beta_{i,1}$ , and  $0 < P_i(C_j) < 1$ . We also limited the steepness parameter ( $\beta_{i,4}$ ) to values between -1 and 1.

We tested this method by evaluating birds at 20 wetland complexes that were randomly excluded (“reserved”) from the development of BR functions. IEC values based on bird species composition were derived using the maximum likelihood

method of estimation. Bird species selected for the calculations had BR functions that met the following criteria: 1) the absolute difference between the predicted probability of occurrence at  $C_{env} = 10$  and  $C_{env} = 0$  was at least 0.2 (in other words, the species showed strong sensitivity to environmental condition, either positively or negatively); and 2) the lack-of-fit (LOF) expression (Equation 3) was less than 1.75, thereby excluding species that showed relatively high scatter around the BR function. We also excluded colonial species like great blue heron (*Ardea herodias*), forest specialists like red-eyed vireo (*Vireo olivaceus*), and aerial feeders like northern rough-winged swallow (*Stelgidopteryx serripennis*) and barn swallow (*Hirundo rustica*) because their presence in a coastal wetland is largely dependent on proximity to habitats or local nesting sites that are not part of the wetland complex. Results (IECs) were compared with the *a priori* values of environmental condition ( $C_{env}$ ) based on land cover and other environmental variables.

## RESULTS

PCA of environmental variables yielded 5 interpretable axes of variation among wetland complexes, together accounting for 68% of the variance in the original 39 environmental variables. Principal component 1, associated with 24.3% of the variation, was most strongly correlated (negatively) with the proportion of natural vegetation within 500 m of the wetland complex centroid (Fig. 3a); other correlated variables included proportions of natural vegetation at 100 m, 1 km, and 5 km and proportions of wetland vegetation within 100 m and 5 km. Positive correlates with the first principal component included proportion of residential land cover within 500 m and 5 km (Fig. 3b) and total road length within 5 km. The second principal component, accounting for 17.4% of the overall variation, was strongly correlated with proportions of cultivated land at all distances (Fig. 3c) and the multivariate index (principal component) of agricultural activity defined by Danz *et al.* (2007). Proportions of natural vegetation (especially within 500 m and 1 km) were negatively associated with principal component 2. The third principal component, accounting for 13.3% of the variation, separated sites with extensive wetland area from sites with predominately upland vegetation (Fig. 3d); including residential, natural, and cultivated lands. The fourth principal component, accounting for 7.4% of the



**FIG. 3.** *Principal components analysis (PCA) of wetland complexes (triangles) based on environmental stress variables of Danz et al. (2007) and land cover variables in the wetland complex and within 100 m, 500 m, 1 km, 3 km, and 5 km of the wetland centroid. Size of the triangle is correlated with individual environmental variables: a) % natural (upland) vegetation such as forest, native grassland, or shrub land within 500 m; b) % residential land use within 500 m; c) % cultivated land within 500 m; and d) % wetland vegetation within 1,000 m.*

variation, was negatively correlated with industrial land cover types and positively correlated with residential land use. Finally, the fifth principal component, accounting for 5.7% of the variation, was negatively correlated with the proportion of natural vegetation within and near the wetland complex itself, and positively correlated with road length and proportion of road associated land cover in the vicinity (< 500 m) of the wetland complex. In all of

these cases, the principal components differentiated sites that were heavily influenced by human activities from sites that were less influenced.

The PCA scores were combined by 1) reversing the signs of axes 1,2,3, and 5 so that all scores correlated with a gradient from maximally degraded to minimally degraded sites; 2) converting the PCA scores to a standardized scale (0–10); and 3) weighting the standardized scores by the % total



**TABLE 3.** Bird species used to estimate ecological condition in Great Lakes coastal wetlands. List includes 23 species exhibiting the strongest association with a standard environmental gradient ( $C_{env}$ ) based on intensity of human activities. Values of  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ , and  $\beta_4$  correspond to estimates of the parameters in Equation 1. Species with negative  $\beta_4$  are more likely to occur in sites with poor condition. LOF is the lack-of-fit statistic described in Equation 2. The quantity  $|P(10)-P(0)|$  gives the absolute difference in probabilities of a species' occurring at poorest quality ( $C_{env} = 0$ ) vs. highest quality ( $C_{env} = 10$ ) sites. Scientific names are from AOU (1998) and recent supplements.

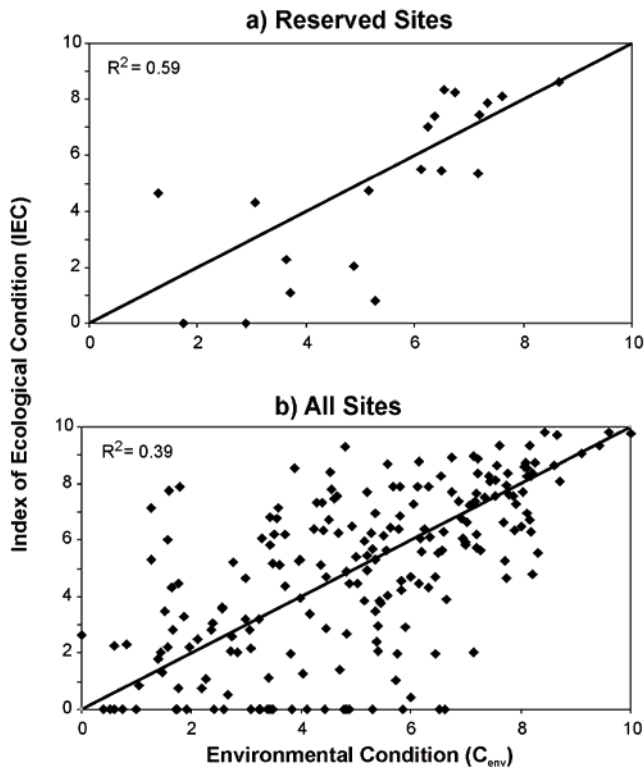
Common Name	Scientific Name	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	LOF	$ P(10)-P(0) $
Swamp sparrow	<i>Melospiza georgiana</i>	0.29	0.92	7.90	0.42	0.76	0.62
Common grackle	<i>Quiscalus quiscula</i>	0.00	0.76	5.61	-0.45	1.31	0.61
Common yellowthroat	<i>Geothlypis trichas</i>	0.27	1.00	5.54	0.25	0.88	0.55
Sandhill crane	<i>Grus canadensis</i>	0.02	1.00	9.71	0.72	0.76	0.55
American robin	<i>Turdus migratorius</i>	0.00	0.69	8.69	-1.00	1.07	0.54
European starling	<i>Sturnus vulgaris</i>	0.00	0.59	4.35	-0.56	1.15	0.52
Northern cardinal	<i>Cardinalis cardinalis</i>	0.00	0.49	5.89	-1.00	1.31	0.48
Sedge wren	<i>Cistothorus platensis</i>	0.04	1.00	10.12	0.36	1.71	0.46
Mallard	<i>Anas platyrhynchos</i>	0.00	0.45	7.34	-1.00	1.28	0.42
American goldfinch	<i>Carduelis tristis</i>	0.00	0.54	8.93	-1.00	1.11	0.40
Mourning dove	<i>Zenaidura macroura</i>	0.00	0.45	8.32	-1.00	0.96	0.38
Alder flycatcher	<i>Empidonax alnorum</i>	0.06	0.35	5.46	1.00	1.01	0.35
Marsh wren	<i>Cistothorus palustris</i>	0.00	0.36	6.77	-1.00	0.76	0.35
Gray catbird	<i>Dumetella carolinensis</i>	0.00	0.34	8.42	-1.00	1.18	0.28
Bobolink	<i>Dolichonyx oryzivorus</i>	0.02	1.00	11.06	1.00	0.60	0.26
Baltimore oriole	<i>Icterus galbula</i>	0.00	0.28	7.63	-1.00	1.10	0.25
American redstart	<i>Setophaga ruticilla</i>	0.11	0.25	5.18	0.99	1.53	0.25
Bald eagle	<i>Haliaeetus leucocephalus</i>	0.07	0.33	8.61	0.70	1.55	0.24
Northern harrier	<i>Circus cyaneus</i>	0.02	1.00	11.28	1.00	0.67	0.22
Brown-headed cowbird	<i>Molothrus ater</i>	0.00	0.23	7.81	-1.00	0.92	0.21
Brown thrasher	<i>Toxostoma rufum</i>	0.03	1.00	11.37	1.00	0.76	0.20
White-throated sparrow	<i>Zonotrichia albicollis</i>	0.02	0.20	6.70	1.00	1.27	0.20
Killdeer	<i>Charadrius vociferus</i>	0.00	0.21	7.56	-1.00	1.01	0.20

variation associated with the corresponding PCA axis. The five adjusted scores then were summed to give a single gradient of environmental condition ( $C_{env}$ ), ranging from 0 (maximally degraded) to 10 (minimally degraded). Values along this environmental gradient were highest for wetland complexes with high proportions of natural and wetland vegetation surrounding the wetland, and lowest for complexes with a high proportion of urban/industrial lands and extensive roads within and near the wetland complex.

From 155 bird species observed at least once in our study sites, we selected 23 wetland, shrub/woodland, or open-country species (Table 3) that exhibited relatively strong sensitivity to the reference gradient ( $|P(C(10))-P(C(0))| > 0.20$ ) and relatively low deviation from the best-fit BR function ( $LOF < 1.75$ ). Swamp Sparrow, Common Yellowthroat (Fig. 1a), sandhill crane (Fig. 1b), and sedge wren showed strongest positive associations with the reference gradient ( $\beta_2 \gg \beta_1$  and  $\beta_4 > 0$ ),

while common grackle (Fig. 1e), American robin, European starling, northern cardinal, and mallard (Fig. 1f), showed strongest negative relationships ( $\beta_2 > \beta_1$  and  $\beta_4 < 0$ ). The shapes of the best-fit BR functions varied according to the ecology and overall abundance of different species. Bald eagle, for example, showed a rather low probability of occurrence even at pristine wetland complexes (Fig. 1c), whereas swamp sparrow exhibited a positive relationship with environmental condition but was present at even some highly degraded sites (Fig. 1d).

Given parameters from the best-fit biotic response (BR) functions (Table 3) and detection data for the 23 selected bird species, we used the "Solver" function of Microsoft Excel to calculate IECs (i.e., estimate ecological condition) for the 20 reserved sites. The resulting IECs (Fig. 4a) correspond closely to the independently derived  $C_{env}$  based on environmental variables ( $r = 0.77$ ,  $p < 0.01$ ), showing that bird species composition of coastal wetlands can meaningfully indicate ecologi-



**FIG. 4.** Correlation between environmental condition ( $C_{env}$ ) based on human disturbance (x-axis) and indices of ecological condition (IEC) based on bird species assemblages for: a) reserved sites, which were not used in calculations of biotic response (BR) functions, and b) all sites. Solid line represents points where  $C_{env} = IEC$ .

cal condition. Deviations from a 1:1 relationship between the IEC and  $C_{env}$  are especially meaningful. In at least two cases (Point au Sauble on Lake Michigan/Green Bay and near the mouth of the Calumet River in Indiana), the IEC was substantially lower than  $C_{env}$  (e.g.) at wetlands with extensive cover of invasive species, especially common reed, *Phragmites australis*, and purple loosestrife, *Lythrum salicaria*.

## DISCUSSION

The advantages of using species as environmental indicators have been articulated extensively by Karr (1981), McGeoch and Chown (1998), Yoder and Rankin (1998), Karr and Chu (1999), O'Connor *et al.* (2000), Niemi and McDonald (2004) and others. (But see Landres *et al.* (1988) for an alternative perspective.) Species assemblages integrate the ef-

fects of environmental stress over space and time and populations of sensitive species represent biologically meaningful signals from many interacting and complex variables.

Results of our analysis show that birds of coastal wetlands are differentially sensitive to environmental condition. Some species are associated positively with human impacts, others are associated negatively, while others show no consistent, monotonic relationship. The first two groups (sensitive species) can be used as indicators of a site's ecological condition.

The relationship between our empirically-derived ecological condition (IEC) and environmental condition ( $C_{env}$ ), however, is not 1:1. For example, a wetland near Green Bay, Wisconsin (Point au Sauble) showed an environmental condition ( $C_{env}$ ) of 4.87, but the bird-based IEC was only 2.05 (Fig. 4a). This wetland was dominated by the invasive plant *Phragmites australis*, which was not reflected in the land cover and land use variables used to calculate  $C_{env}$ . Consequently, the observed bird species composition indicated a lower level of ecological condition than predicted by the environmental variables. In this and other cases, the IEC provided more information about the site's condition than environmental variables alone. This finding also suggests that a more detailed environmental gradient that takes into account invasive species should be used in the derivation of biotic response (BR) functions. As more information is acquired about Great Lakes coastal wetlands and their biota, improvements in the BR functions and in IEC values for individual wetlands will be desirable.

With two exceptions (both from Lake Ontario), wetlands with low values of environmental condition ( $C_{env} < 0.6$ ) tended to yield even lower values of ecological condition (IEC), suggesting that a threshold effect might apply to bird species composition (Fig. 4a). In other words, highly sensitive bird species occur especially infrequently (or highly tolerant species occur especially frequently) below a certain level of environmental degradation (e.g.,  $C_{env} < 0.6$ ). The nonlinear forms of many BR functions further illustrate this view (Fig. 1). If verified by further analyses, this finding has important implications for conservation of Great Lakes environmental quality and possibly for wetlands in other geographic areas. To sustain environmentally sensitive bird species, natural vegetation, and other aspects of landscape quality must be maintained at or above threshold levels, in our case corresponding to

$C_{env}$  values higher than 6.0. In general, species like sandhill crane, bald eagle, and sedge wren were absent from sites with environmental condition below this threshold level, even though they would have been expected to occur at least occasionally.

Calculation of the IEC requires three steps: 1) definition of a standard environmental gradient ranging from 0 (poorest condition) to 10 (best condition), 2) development of BR functions describing species' responses (or responses of some other variable) to the environmental gradient, and 3) iterative calculation of the best-fit IEC given field data for a site of interest. Steps 1 and 2 are data intensive and typically require large-scale analyses such as our comprehensive surveys of birds in the Great Lakes basin. As new information is accumulated, the environmental gradient and BR functions can be improved and applied to both new and old data sets. Ideally, managers and scientists will establish standard gradients and BR functions, enabling widespread comparisons among sites over time and space. Note that different BR functions can be developed for different sampling methods or for different habitat types. As long as the same environmental gradient is used as a baseline the resulting indices of ecological condition (ranging from 0 to 10) will be comparable. The key consideration is that methods used to acquire field data at the target sites are identical to the methods used to derive the applicable BR functions. Field data for animal or plant species may consist of either probabilities of occurrence (e.g., frequency of presence in multiple samples) or presence/absence in single samples. If probabilities of occurrence are available, then the least squares method is used to estimate IECs; if only presence/absence data are available, then the maximum likelihood method is used. A Microsoft Excel spreadsheet is available from the authors with instructions and framework for calculating both BR functions and IECs.

The pre-defined environmental gradient represents a first attempt to characterize ecological condition at specific sites, but a species-based index (IEC) provides additional information about environmental quality and in most cases provides a less expensive and conceptually simpler method of site assessment. Although the IEC is useful as a stand-alone measure of ecological condition, comparison of a site's IEC and  $C_{env}$  may provide additional insights into the locality's condition. Sites with higher than expected IEC might possess favorable attributes that are worth emulating elsewhere; sites with lower than expected IEC might harbor unrecog-

nized environmental problems that deserve attention.

We have provided a preliminary set of BR functions (Table 3) that can be used by land managers and others to characterize the ecological condition of coastal wetlands in the U.S. portion of the Great Lakes. Our primary goal in this paper, however, is to introduce the IEC approach with a specific example. Further research and analysis of existing data should refine the BR parameters for broader use. In particular, we encourage the addition of multi-species variables that will take into account rarer species like rails, raptors, and other water birds. For example, a useful variable might be the probability of observing *any one* of several rare species. A biotic response (BR) function can be fitted for such multi-species variables just as we have done here for individual species.

The IEC achieves similar objectives as the IBI introduced by Karr (1981) and applied by Harris and Silveira (1999), Butcher *et al.* (2003), Crewe and Timmermans (2005), and many others. In the example presented here we use only single-species variables rather than multispecies or community level variables, but IEC calculations can employ both single-species and multispecies variables. The major difference between the IEC and IBI approaches is the way in which variables are combined. In the IEC an iterative, probabilistic framework articulated by Hilborn and Mangel (1997) is used to estimate the IEC value which best fits an observed data set. All applications of the IEC approach use a standard range between 0 (poorest condition) to 10 (best condition). In the IBI approach, variables are converted to a standardized range of values (e.g., 1, 3, or 5) and summed, leading to different scale of IBI values depending on the number of variables used in the analysis. Other approaches such as the floristic quality index (Wilhelm and Ladd 1988) and RIVPACS methods (Wright *et al.* 1993) use species richness or taxonomic richness (ratio of observed / expected taxa). Both of these methods are sensitive to sampling area or sampling effort, and neither method documents the relationship between species occurrences or taxonomic richness variables and an explicit environmental gradient. In the IEC approach, users are required to identify BR functions (perhaps generated by previous investigators) that clearly document the sensitivity of species or variables to an environmental gradient. This requirement insures that species or variables with different responses to disturbance are not treated identically. The IEC ap-

proach also provides a more transparent understanding of exactly what the indicator is meant to indicate.

Because it uses a standard 0 to 10 scale, the IEC method can incorporate data from different taxonomic groups or even different sampling methods as long as standardized BR functions are based on the same environmental gradient. Walsh (2006) argued that assessment of indicators against a standard disturbance gradient is critical for application of management objectives. Our approach requires that such an environmental gradient is pre-defined and built into the IEC process. Calculation of IEC values for sites of interest is straightforward and flexible once users have agreed on an underlying gradient.

Our method can be applied to any habitat or geographic area of interest. In order for IEC values to be valid, of course, different biotic response (BR) functions need to be calculated for different habitats, different sampling methods, and perhaps different regions. Variation in biotic responses of a single species among different geographic areas is poorly known and represents an interesting subject in its own right. We envision the development of standard BR functions to be completed by large-scale studies involving scientists from government agencies, universities, industry, and organizations. Once these functions have been standardized, managers can apply the IEC method at individual localities within the appropriate region.

#### ACKNOWLEDGMENTS

This research was supported by a grant from the U.S. EPA's Science to Achieve Results Estuarine and Great Lakes program through funding to the Great Lakes Environmental Indicators project, U.S. EPA Agreement EPA/R-8286750 and a grant from the National Aeronautics and Space Administration (NAG5-11262). This document has not been subjected to U.S. EPA required peer and policy review and therefore does not necessarily reflect the views of the agency, and no official endorsement should be inferred. We are grateful for contributions by other scientists involved with the GLEI project, especially John Kelly, whose editorial comments helped improve the manuscript significantly. Other important contributions came from T. Hollenhorst, P. Wolter, V. Brady, T. Brown, J. Brazner, S. Price, D. Marks, and others, including more than 20 student field investigators. Important ideas underlying this analysis were communicated by J. Karr, D. Simberloff, P. Bertram, A. Tyre, and H. Possing-

ham. This is contribution number 467 of the Center for Water and the Environment, Natural Resources Research Institute, University of Minnesota Duluth.

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Submitted: 18 September 2006

Accepted: 24 August 2007

Editorial handling: John R. Kelly