

Constructing multimetric indices and testing ability of landscape metrics to assess condition of freshwater wetlands in the Northeastern US



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ARTICLE INFO

Article history:

Received 23 August 2015

Received in revised form 10 January 2016

Accepted 11 January 2016

Keywords:

Multimetric indices

Freshwater wetland condition

Landscape context

Wetland ecological integrity

National Wetland Condition Assessment

National Park Service Inventory and

Monitoring Program

ABSTRACT

Using data collected for the Environmental Protection Agency's (EPA) 2011 National Wetland Condition Assessment (NWCA), we developed separate multimetric indices (MMIs) for vegetation, soil, algae taxa, and water to assess condition of freshwater wetlands in the northeastern US. This study represents the first attempt at developing multiple biotic and abiotic MMIs of wetland condition over this large of an area, and is only possible because of the high quality data collected by the NWCA. We chose metrics that distinguished between reference and most disturbed sites, had a signal:noise ratio > 2, and were not strongly correlated with other metrics, latitude, or longitude. The vegetation and soil MMIs were the best performing indices, with good separation between reference and most disturbed sites, and included commonly used condition metrics (e.g., pH and P concentration for soil, and percent cover of exotic species for vegetation). The algae MMI was the weakest index, with considerable overlap between reference and most disturbed sites. For areas smaller than our study, algae taxa may be suitable for wetland MMIs. However, in our study area, many algae taxa followed strong latitudinal or longitudinal gradients, and could not be considered for the algae MMI. Small sample size and several metrics with a high signal:noise ratio were the major limitations of the water MMI. We also examined how well landscape (level 1) and rapid assessment (level 2) metrics predicted MMIs using random forest regression. Agricultural land use surrounding wetlands was an important predictor for all four MMIs, although the soil, algae and water MMI models performed best when intensive (level 3) vegetation metrics were also included in the random forest regression models. Based on these results, we recommend wetland assessment programs employ a combination of landscape and rapid assessment monitoring at many sites, along with level 3 monitoring at a subset of sites. We developed these MMIs to evaluate freshwater wetland condition for a long-term monitoring program in Acadia National Park. These MMIs are also applicable to a range of wetland types covering 11 states in the northeastern United States and can be calculated using a downloadable spreadsheet that calculates and rates each MMI using raw metric values.

Published by Elsevier Ltd.

1. Introduction

As transitional zones between terrestrial and aquatic habitats, wetlands provide many important ecosystem functions including

chemical uptake and nutrient cycling, groundwater recharge, carbon storage, and erosion and flood control (Keddy, 2000; Mitsch and Gosselink, 2000). Wetlands play vital roles in maintaining water quality in aquatic systems, including filtration of toxins and removal of excess nutrients and sediment (Verhoeven et al., 2006). With roughly half of the migratory bird species in the US and over 30% of plants and animals listed under the Endangered Species Act reliant on wetland communities, wetlands are also important sites of threatened biodiversity (U.S. Fish and Wildlife Service, 1996).

The major components that define a wetland are hydrology, soils, and vegetation, and perturbations to any of these components can impact wetland condition (Mitsch and Gosselink, 2007).

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Altered hydrology, such as ditching, filling, damming or draining, can dramatically impact wetland function, structure, and composition (Ritcher et al., 1996). Wetlands are particularly vulnerable to invasive plant species, which can form monotypic stands that reduce wetland structure and diversity (Zedler and Kercher, 2004). Sediment and nutrient inputs from run-off can increase wetland vulnerability to invasion of exotic species (Werner and Zedler, 2002). Disturbances and habitat alterations that originate in adjacent uplands can also greatly impact wetlands. For example, urban development increases impervious surfaces, resulting in greater peak flows, inputs of poor quality water, and increased erosion and sedimentation (Schueler, 1994). Adjacent agricultural land use often alters hydrological regimes and contributes to increased sediment and nutrient inputs to wetlands (Zedler, 2003). As wetlands are disturbed or degraded their capacity to provide habitat and ecosystem services is often compromised (Jansen and Healey, 2003; Zedler and Kercher, 2005).

Climate change projections for the Northeast and Great Lakes region suggest a shift toward higher intensity storms and greater variability in rainfall, along with overall increases in mean annual precipitation (Bates et al., 2008). Changes in precipitation have already been documented in New England where the ratio of snow to wet precipitation has decreased over the last half century and mean annual precipitation has increased by an average of 8.2 cm since the 1930s (Huntington et al., 2004, 2009). Combined with increased human development, climate change is expected to further exacerbate impacts and threats to wetlands (Tu, 2009; Pavri et al., 2013). Understanding the current status and threats to wetland condition is imperative for ensuring continued maintenance and protection of wetland resources (National Research Council, 2001).

Recognizing the importance of wetland monitoring, the U.S. Environmental Protection Agency (EPA) initiated a National Wetland Condition Assessment (NWCA) as part of the National Aquatic Resource Surveys program (NARS). The NWCA, which represents the first standardized, nationwide survey of wetlands in the U.S., was first implemented in 2011. The overall objectives of the NWCA are to provide regional and national estimates of wetland condition and extent, and to determine stressors most commonly associated with poor condition (EPA, 2011a).

Due to their importance for ecosystem function and diversity, and for their scenic quality and recreational opportunities (e.g. bird watching), wetlands are also a critical concern in US national parks. In 2011, the Northeast Temperate Network (NETN) of the National Park Service (NPS) began monitoring permanent freshwater wetlands in Acadia National Park (ACAD) using the protocols developed for the EPA NWCA, and following a three-tiered monitoring approach. Level 1 is GIS-based monitoring of landscape condition and does not require a field visit. Level 2 is a rapid field assessment in addition to level 1 monitoring. Level 3 is intensive field assessment plus level 1 and 2 monitoring. The overall goal of the NETN monitoring program is to monitor status and trends in wetland condition relative to vegetation, soil, hydrology, and water quality in ACAD.

The EPA is currently developing Multimetric Indices (MMIs) to assess condition at the national level. MMIs are a common tool used to assess condition of aquatic resources, and in many cases they have been shown to be more responsive to disturbance and a better measure of condition than individual metrics (Stoddard et al., 2008; Schoolmaster et al., 2013). While the national EPA MMIs will be valuable for assessing condition across the diverse wetland systems in the US, the metrics may lack resolution at smaller regional or site-level scales (e.g., ACAD). The EPA approach also relies heavily on data collected as part of intensive (level 3) monitoring, while wetland scientists often only have metrics collected during level 1 (GIS-based) and 2 (rapid field assessment) monitoring. The primary

objective of this research is to develop metrics that can assess wetland condition for the northeastern US using the intensive (level 3) data collected by the NWCA. We first constructed separate MMIs of wetland condition for vegetation, soil chemistry, algae, and water chemistry. After completing the MMIs based on level 3 data, we then examined how well landscape metrics (level 1) and rapid assessment metrics (level 2) could predict wetland MMIs. Our study is the first to develop multiple biotic and abiotic MMIs of wetland condition over a large area of the eastern US, and is only possible due to the high quality data collected by the NWCA.

2. Methods

2.1. Field sampling

The NWCA uses a combination of many probability sites and a smaller set of hand-picked targeted sites, and collects information on a suite of vegetation, soil, water, hydrology, and site characteristics. The probability sites are randomly located and used to assess wetland condition and extent. The targeted sites are potential reference sites, based on best professional judgment to be least disturbed, and are used to characterize the natural range of variation of wetland attributes. The targeted sites go through an additional screening process to check for evidence of disturbance and/or poor condition before they are classified as reference. For more information on the EPA NWCA sample design, refer to Chapter 1 of the EPA Field Operation Manual (EPA, 2011a). EPA conducts the NWCA every 5 years, with the first assessment in 2011, and the next assessment scheduled for 2016. Data for this analysis were collected during the 2011 NWCA.

During the 2011 NWCA, 1138 sites were sampled across the conterminous U.S. representing every state except Hawaii and Alaska. Intensive sampling (level 3) methods for the 2011 NWCA are documented in the EPA Field Operations Manual (FOM), and consist of site-based sampling of vegetation, hydrology, soils, water chemistry, and algae typically within a 40-m radius assessment area (AA; EPA, 2011a). The FOM also includes multiple procedures to collect material for later lab analysis, including soil, water, and algae. The FOM procedures characterize the habitat and degree of stressors in the AA and a 100-m buffer around the AA using thirteen square 100-m² buffer plots. Buffer plots are oriented in the four cardinal directions and centered at 5, 50, and 95 m from the AA boundary, and one buffer plot is located at the center of the AA.

The USA-RAM, which was also implemented at every NWCA site, uses a 40-m radius AA, along with a 100-m buffer surrounding the AA (EPA, 2011b). The level 1 component in the USA-RAM quantifies the extent of natural habitat in the 100-m radius buffer surrounding the AA. The level 2 component in USA-RAM evaluates the overall condition and presence of stressors in the assessment area and buffer, and focuses on the hydrology, physical structure, and biological structure of the wetland (EPA, 2011b).

In NETN, we followed the FOM to implement intensive (level 3) and the USA-RAM for level 1 and 2 monitoring in 10 targeted sites in ACAD. The 10 targeted sites in ACAD are sampled every 5 years for the NWCA to serve as potential NWCA reference sites, and are also permanent sentinel sites for monitoring freshwater wetlands in ACAD. In the 4 years between the NWCA, we monitor 40 randomly selected sites in ACAD using the USA-RAM and a timed search for plant species in the AA (Miller and Mitchell, 2013).

2.2. Data analysis

We used multiple statistical techniques to analyze data in this study, including non-metric multi-dimensional scaling (NMDS) to select plots for the study, *t*-tests and Pearson correlations to select

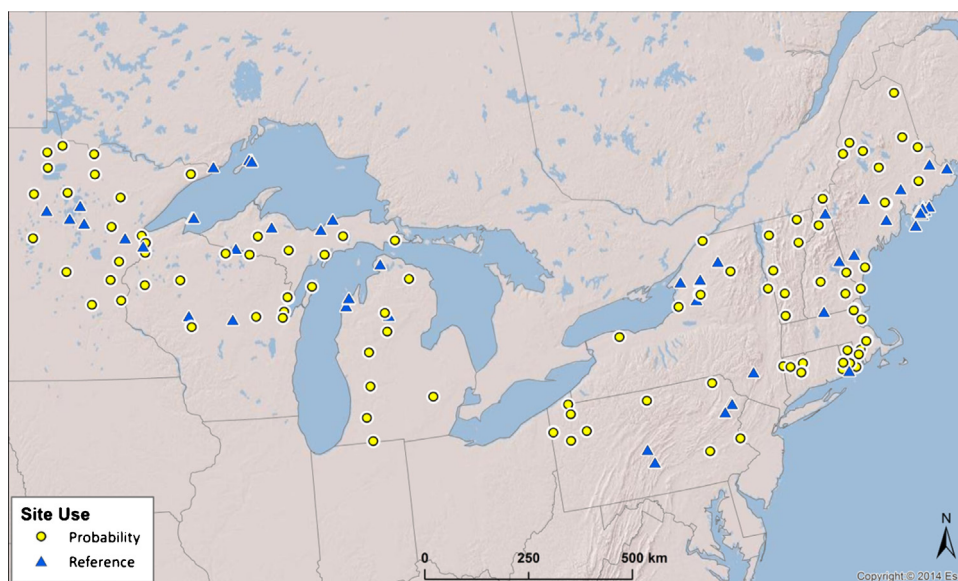


Fig. 1. Location of plots sampled during the 2011 NWCA that were included in this analysis.

metrics for the MMIs, and random forest regression to predict the MMIs based on data that are readily available (level 1) or easy to collect (level 2). The first step for this analysis was to determine which sites to consider for MMI development using NMDS. Our primary goal with the NMDS analysis was to find a large collection of NWCA sites that were comparable with wetlands in ACAD based on vegetation data, and we judged this by the lack of strong geographic (e.g., latitude and longitude) gradients in the NMDS. Because freshwater wetlands were our primary focus, estuarine sites were excluded. We used non-metric multidimensional scaling (NMDS) on plant species percent cover to determine the best collection of NWCA sites for MMI construction. NMDS ordinations were conducted using the *vegan* package (Oksanen et al., 2015) in R 3.1.1 (R Core Team, 2014) with Bray–Curtis distance, square root transformation, Wisconsin double standardization, and $k=2$ dimensions. We started with over 200 palustrine sites from the NWCA dataset from northern Maine, south to VA, and west to northern MN. Because the northeastern US was our primary focus, southern and western sites were excluded by level IV ecoregion (Omernik and Griffith, 2008) until latitude and longitude were not strong gradients in the first axis. Level IV ecoregions are mapped areas that have similar ecosystems and environmental resources. They serve as a spatial framework for ecosystem monitoring and management, and are the finest-scale units mapped by EPA (Omernik and Griffith, 2014). The final sample included 166 NWCA sites, with 112 probability and 54 targeted sites (Fig. 1). This sample included all of the palustrine sites in EPA's Northern Appalachians and Upper Midwest reporting regions and represented the following palustrine wetland habitats: emergent, farmed, forested, scrub/shrub, and unconsolidated bottom/aquatic bed. Stress for the final NMDS was 0.217. Given the large number of sites ($n=166$) and species ($n=431$) in the NMDS, the relatively high stress was expected, and the results were still useful and valid for exploring patterns in the dataset. Using the 166 sites, we began building metrics using level 3 data for vegetation, soils, water and algae. Vegetation metrics were averaged over the five 100 m² vegetation plots sampled at each site. Soil chemistry metrics were based on the upper-most soil sample collected in each site. Water chemistry metrics were based on surface water samples, and were only collected from about half of the sites due to lack of sufficient (30 cm deep) surface water in those sites. Counts were summed to the genus level for the algae metric.

We used the approach outlined by Stoddard et al. (2008) to construct MMIs. The first step classified sites as least disturbed (reference) and most disturbed using an independent set of metrics. Following procedures designed by the EPA NWCA analysis team, we used the number of stressors recorded in the buffer plots to classify the most disturbed sites and to check that the reference sites were minimally disturbed. Buffer plots were proximity-weighted by the distance from the center of the AA. Weights for the buffer plots were 1, 0.44, and 0.23 for the buffer plots that were 5 m, 50 m, and 95 m from the boundary of the AA. The buffer plot at the center of the AA was also weighted by 1. The number of stressors recorded in each buffer plot were counted and multiplied by the corresponding distance weight. Targeted sites (i.e., potential reference sites) were excluded from the reference group if a stressor was recorded in any of the buffer plots, which excluded 5 of the 10 targeted NWCA sites in ACAD. Sites were considered most disturbed if the weighted sum of the buffer stressors was ≥ 2 . This resulted in 35 reference and 50 most disturbed sites out of the original 166 sites, and represented five hydrogeomorphic classes and five modified Cowardin classes (Table 1). The remaining 81 sites, which included probability sites not considered most disturbed and targeted sites that were excluded from the reference category, were placed in an intermediate disturbance category. We included the intermediate disturbance category in figures and tables to check the range against the reference and most disturbed groups, but the intermediate group was not used for MMI construction.

Our approach deviated from the EPA NWCA analysis team's approach in a few ways. EPA screened probability sites for inclusion in the reference group, whereas we only considered targeted sites for the reference group. The EPA approach used more metrics for the screening process to determine which hand-picked sites and probability sites to include in the reference group. This method can increase the sample size for the reference group, but the trade-off is that the metrics used cannot be included in MMIs. Because we wanted to develop multiple MMIs, we chose not to include probability sites, which would have required a more thorough screening process for the reference group. We therefore had more metrics to consider for MMI construction, but were slightly limited by our reference group sample size. We also could not validate the MMIs with a holdout dataset, as suggested by Stoddard et al. (2008). Instead, we will validate the MMIs after new sites are sampled for the 2016 NWCA.

Table 1
Characteristics of sites included in MMI construction including hydrogeomorphic class (HGM) and modified Cowardin class (REF=reference, MOST=most disturbed, and INT=intermediate disturbance).

	Class	Code	REF	INT	MOST	Total
HGM	Unclassified	UNCL	1	1	0	2
	Depressional	DEPR	14	30	22	66
	Flats	FLAT	7	22	16	45
	Fringe	FRIN	3	8	2	13
	Riverine	RIVE	8	15	10	33
	Slope	SLOP	2	5	0	7
Cowardin	Palustrine Emergent	PEM	4	27	12	43
	Palustrine Farmed	PF	0	0	5	5
	Palustrine Forested	PFO	15	32	23	70
	Palustrine Scrub/Shrub	PSS	13	22	6	41
	Palustrine Unconsolidated Bottom/Aquatic Bed	PUBPAB	3	0	4	7
Total			35	81	50	166

We followed the methods described in Stoddard et al. (2008) to determine which metrics distinguished between reference and most disturbed sites. We started by examining box plots and performing *t*-statistics on metrics to determine how well metrics distinguished between reference and most disturbed sites (Stoddard et al., 2008). For metrics that distinguished well between reference and most disturbed (based on *t*-tests and box plots), we then examined their range, signal:noise ratio, and correlation with other metrics to further refine the list of candidate metrics. As suggested by Stoddard et al. (2008), metrics with a large range are often better than metrics with a very small range for assessing condition. The signal:noise ratio compares the variance among all sites (the signal), to the variance of multiple visits at the same site (the noise). Metrics with a low signal:noise ratio indicate high sampling error relative to the metric, and are less ideal than metrics with a high signal:noise ratio. We dropped metrics with a small range or a signal:noise ratio <2, although most metrics had a signal:noise ratio >4. We checked for redundancy (i.e., metrics that measure the same gradient or biological phenomenon) using correlations within reference sites. In cases where metrics were strongly correlated ($r \geq |0.7|$), preference was given to the metric with the highest *t*-statistic and that was available at the most sites. For example, soil percent total carbon and bulk density were highly correlated ($r = -0.89$) and were also different measures of a similar phenomenon. We selected percent total carbon over bulk density because it had a higher *t*-statistic (7.0 vs. -5.1) and was available at more sites (165 vs. 136). Candidate metrics were checked for correlations with latitude and longitude within reference sites to ensure that they were not describing a natural gradient that happened to follow a disturbance gradient. Our aim was to include at least four metrics in each MMI, but we were only able to find three for the water MMI (WMMI). After settling on metrics to include in each MMI, we converted each metric to a 10-point scale and summed those metrics for each site (Stoddard et al., 2008). The summed metrics were then converted to a 100-point scale for the final MMIs. We calculated thresholds based on distributions of the reference sites for each MMI to distinguish Good, Fair, and Poor categories, and rated each site. The lower 25th percentile of the reference sites was the threshold that distinguished between Good and Fair. The threshold between Fair and Poor was the lower 5th percentile distribution of the reference sites.

After constructing the MMIs, we tested whether level 1 (GIS-based) and 2 (rapid field assessment) metrics could predict the MMI scores that were based on level 3 (intensive field survey) data, using random forest regression in R (Liaw and Wiener, 2002). Random forest regression is a machine-learning method for modeling and predicting data that offers many benefits over more common approaches, such as generalized linear models (GLM) and analysis of variance (ANOVA). For example, compared with

GLM and ANOVA, the random forest regression technique has few underlying assumptions, is more robust to outliers, can better handle complex interactions among predictor variables, and has high classification accuracy (Cutler et al., 2007). For each of the 166 sites we calculated the proportion of land cover types within a 500 m and 1 km buffer around the center of the AA using the 2011 National Land Cover Database (NLCD; Jin et al., 2013) and NLCD Percent Developed Imperviousness data (Xian et al., 2011). We calculated the proportion of area within 500 m and 1 km buffers that were in the following NLCD land cover categories: barren land, open water, deciduous forest, evergreen forest, mixed forest, developed-open space, developed-low intensity, developed-medium intensity, developed-high intensity, cultivated crops, pasture/hay, shrubland (upland), herbaceous (upland), woody wetlands, and emergent herbaceous wetlands. In addition we summed over several of the NLCD land cover categories within the 500 m and 1 km buffers to derive total percent forested, percent wetland, percent developed, and percent agriculture (cultivated crops + pasture/hay). We calculated the area of the 8-digit and 10-digit hydrologic unit that contained each site, and included the modified Cowardin and Hydrogeomorphic (HGM) classes for each site. In addition to the previously listed level 1 metrics, we included level 2 metrics collected by the USA-RAM in each site in the random forest regression models. We assessed how effective the random forest regression models were using the percent of variance explained by the random forest regression in the original training dataset, which is calculated as 1-Mean Squared Error of the out-of-bag data/Variance in Y (Liaw and Wiener, 2002). We used the variable importance output from the random forest regression to determine which variables were most important in predicting the MMI for each model, and ranked variable importance for each model to determine the variables that were consistently strong predictors across the MMIs. We used a 30% holdout dataset to cross-validate the random forest regression models, and generated linear models with the observed MMI versus the predicted MMI of the holdout data. We used the R^2 and slope from the linear models of the observed versus predicted values in the holdout data to assess how well the random forest regression models predicted the MMIs. A perfect, albeit unlikely, random forest regression model would have an R^2 of 1.0 and a slope of 1.0 for the linear model of observed versus predicted MMIs. After building random forest regression models that contained only level 1 and 2 metrics to predict the MMIs, we added metrics that were used in the vegetation MMI (VMMI) to see if they improved prediction of the other MMIs. Vegetation data can be collected quickly and relatively inexpensively in the field compared with data incorporated in the other MMIs, and we were interested in whether vegetation and landscape metrics alone could effectively assess wetland condition.

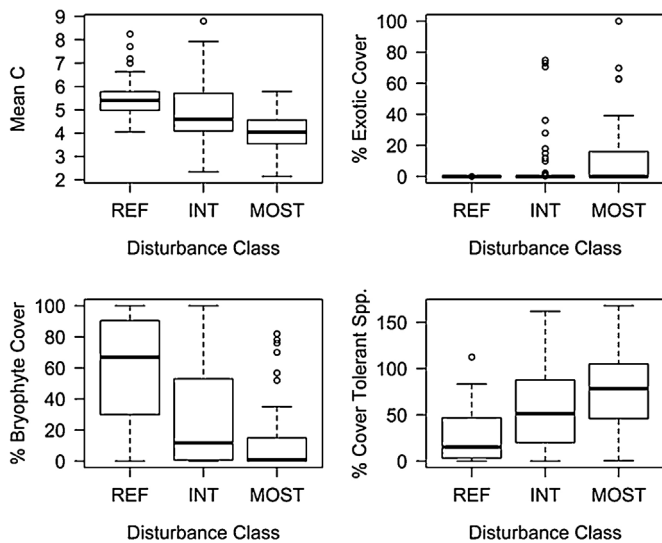


Fig. 2. Metrics included in the final VMMI by disturbance class (REF = reference, MOST = most disturbed, and INT = intermediate disturbance).

3. Results

3.1. Vegetation MMI

Over 50 metrics were considered for the VMMI, including species richness overall and by plant groups, index of wetness (Ervin et al., 2006), metrics derived from coefficients of conservatism (Taft et al., 1997; Miller et al., 2006), and percent cover by plant groups. Plant groups included all native species, all exotic species, graminoids, *Carex* species, and woody species. The exotic group included cryptic species which have native and non-native, often invasive genotypes in the eastern US (e.g., *Phalaris arundinacea*). We calculated proportion of total cover occupied by each plant group as potential metrics for the VMMI. Metrics derived from coefficients of conservatism included mean coefficient of conservatism (mean C), floristic quality index (FQI), cover-weighted mean C, and cover-weighted FQI (Taft et al., 1997; Bourdaghs et al., 2006). For both the mean C and FQI, we calculated metrics that only included native species and metrics that included all species. We also considered percent cover of tolerant species ($C \leq 4$) and cover of sensitive species ($C \geq 7$) for the VMMI. Finally, we examined percent cover of multiple groundlayers, including bryophytes, exposed soil, gravel, surface water, and algae.

Table 2

Thresholds used to distinguish between Good, Fair and Poor. The 25th % threshold is the lower 25th percentile of the MMI in REF sites and distinguishes between Good and Fair. The 5th % threshold is the lower 5th percentile of the MMI in REF sites and distinguishes between Fair and Poor.

MMI	25th%	5th%
Vegetation	65.23	52.79
Soil	71.39	46.90
Algae	65.12	30.59
Water	68.00	55.86

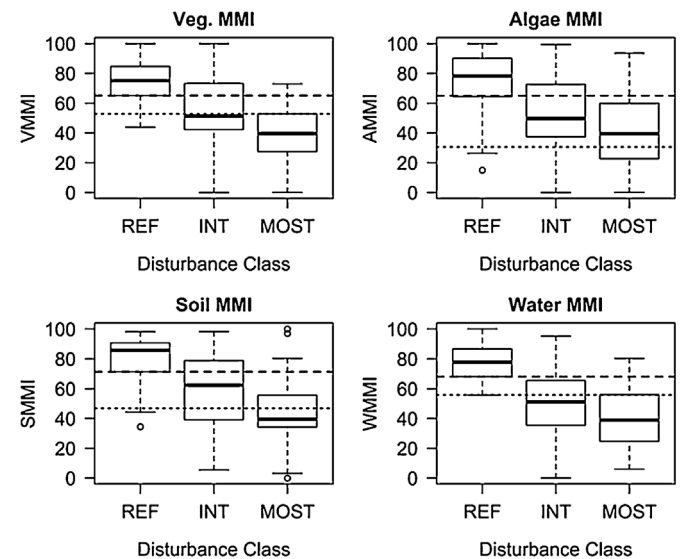


Fig. 3. MMI scores by disturbance class for vegetation, soil, algae and water. Gray dashed lines (---) represent the threshold between Good and Fair. Gray dotted lines (...) represent the threshold between Fair and Poor.

The metrics resulting in the best VMMI were mean C of all species, percent cover of bryophytes, percent cover of exotic species, and percent cover of tolerant native species. The mean C of all species and percent cover of bryophytes decreased with disturbance, and the percent cover of exotic species and of tolerant native species increased with disturbance (Fig. 2). Based on the lower 25th and 5th percentiles of the reference sites, the thresholds for the VMMI were 65.23 and 52.79 (Table 2). Using the VMMI thresholds, 74% of the most disturbed sites were classified as Poor, 20% as Fair and 6% as Good (Fig. 3). The mean VMMI in reference sites was 73.8, whereas the mean VMMI in the most disturbed sites was 39.0 (Table 3). Good, Fair and Poor ratings were relatively evenly

Table 3

Results of each MMI, including number of sites that were rated Good, Fair, and Poor, total number of sites, and mean and standard error (SE) of each MMI score by disturbance class.

MMI	Disturbance class	Good	Fair	Poor	Total	Mean MMI	SE MMI
Vegetation	REF	26	7	2	35	73.8	2.42
	INT	25	15	41	81	55.6	2.59
	MOST	3	10	37	50	39.0	2.64
Soil	REF	24	7	2	33	78.4	2.95
	INT	30	21	28	79	58.9	2.89
	MOST	5	14	31	50	43.5	3.10
Algae	REF	22	6	2	30	73.8	4.03
	INT	24	36	12	72	52.6	2.68
	MOST	9	21	19	49	41.2	3.51
Water	REF	12	4	1	17	78.40	3.35
	INT	9	8	25	42	49.46	3.63
	MOST	2	4	18	24	39.95	4.35

Table 4

Number of sites that were rated Good, Fair, and Poor in each of the HGM and modified Cowardin classes.

Class		VMMI ratings			SMMI ratings		
		Good	Fair	Poor	Good	Fair	Poor
HGM	UNCL	1	0	1	1	0	1
	DEPR	20	11	35	19	22	23
	FLAT	20	12	13	26	4	14
	FRIN	4	5	4	6	4	3
	RIVE	6	3	24	4	10	18
	SLOP	3	1	3	3	2	2
Cowardin	PEM	9	8	26	8	11	23
	PF	0	0	5	0	0	5
	PFO	23	14	33	30	18	20
	PSS	20	7	14	20	11	10
	PUBPAB	2	3	2	1	2	3
Class		AMMI ratings			WMMI ratings		
		Good	Fair	Poor	Good	Fair	Poor
HGM	UNCL	1	1	0	1	0	0
	DEPR	20	24	15	6	9	23
	FLAT	21	12	7	7	1	4
	FRIN	3	7	2	2	2	3
	RIVE	9	15	9	7	4	11
	SLOP	1	4	0	0	0	3
Cowardin	PEM	5	25	11	3	3	20
	PF	1	1	3	0	0	1
	PFO	31	20	12	6	5	10
	PSS	17	14	4	13	7	8
	PUBPAB	1	3	3	1	1	5

distributed within the HGM classes, with the exception of Riverine wetlands that tended to have more plots rated Poor by the VMMI (Table 4). Palustrine emergent and palustrine farmed also tended to have low VMMI scores, and remaining modified Cowardin classes were well distributed across the ratings (Table 4). The VMMI was strongly correlated with the SMMI, WMMI and AMMI, which were also strongly correlated with each other (Table 5). These results suggest that the MMIs are consistent in rating wetland condition.

3.2. Soil MMI

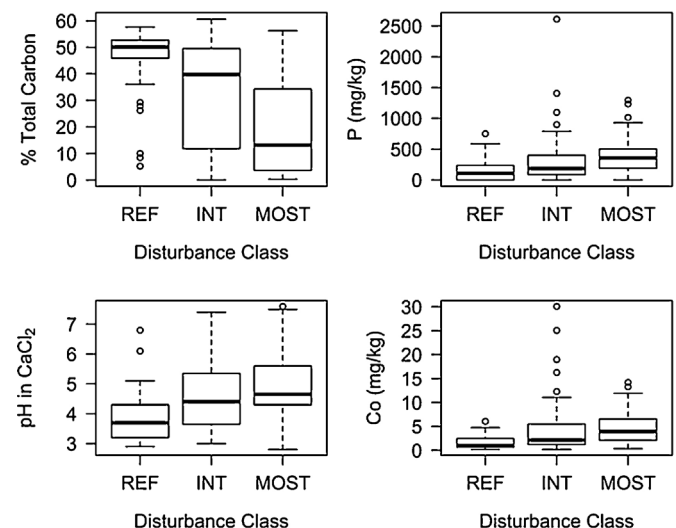
We examined 46 potential metrics of soil chemistry for the soil MMI (SMMI). These metrics included percent total carbon (TC), percent total nitrogen (TN), percent total sulfur (TS), trace element analysis of over 20 elements, ammonium oxalate extraction of Al, Fe, Mn, P and Si, pH measured with deionized water, and pH measured using a CaCl₂ solution (EPA, 2011c). The metrics that resulted in the best SMMI were TC, pH measured in a CaCl₂ solution, P (mg/kg), and Co (mg/kg). TC was highest in the reference sites, and remaining metrics increased with disturbance (Fig. 4).

Based on the lower 25th and 5th percentiles of the reference sites, the thresholds for the SMMI were 71.39 and 46.90 (Table 2). Using the SMMI thresholds, 62% of the most disturbed sites were classified as Poor, 28% as Fair and 10% as Good (Fig. 3). The mean SMMI in reference sites was 78.4, whereas the mean SMMI in the most disturbed sites was 43.5 (Table 3). As with the VMMI, Good, Fair and Poor ratings were relatively evenly distributed within HGM

classes, with the exception of Riverine wetlands that tended to have more plots rated Poor by the SMMI (Table 4). Palustrine emergent and palustrine farmed also tended to have low SMMI scores, and remaining modified Cowardin classes were evenly distributed across the ratings (Table 4).

3.3. Algae MMI

We examined counts of 193 genera and 6 major groups (e.g., diatoms, green algae, blue-green algae, etc.) for the algae MMI (AMMI). The genera that best distinguished between reference and disturbed sites, and that were not strongly correlated with latitude or longitude, were *Eunotia*, *Fragilaria*, *Gomphonema*, and *Nitzschia* (Fig. 5). *Eunotia* counts were higher in reference sites, and the remaining genera were higher in the most disturbed sites. The

**Fig. 4.** Metrics included in the final SMMI by disturbance class.**Table 5**

R² values for the vegetation, soil, algae and water MMIs based on all available plots. *p*-Values for all R² values were highly significant (*p* < 0.0001).

MMI	VMMI	SMMI	AMMI	WMMI
VMMI	1.0			
SMMI	0.72	1.0		
AMMI	0.54	0.61	1.0	
WMMI	0.73	0.48	0.58	1.0

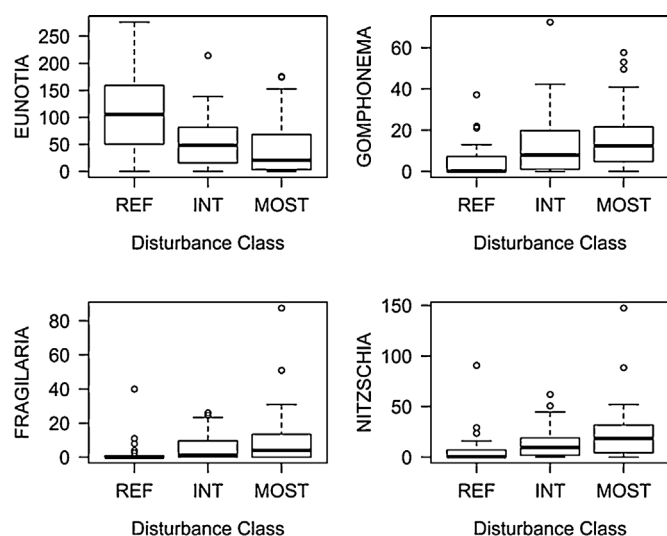


Fig. 5. Metrics included in the final AMMI by site type. The four metrics all represent the genus-level counts. See the caption for Fig. 2 for more detail.

rating thresholds for the AMMI were 65.12 to distinguish Good from Fair, and 30.59 to distinguish Fair from Poor (Table 2). Using these thresholds, 39% of the most disturbed sites were rated Poor, 43% as Fair, and 18% as Good (Fig. 3). The mean AMMI for reference sites was 73.8, and the mean AMMI for most disturbed sites was 41.2 (Table 3). AMMI ratings were distributed relatively evenly within HGM classes and modified Cowardin classes (Table 4).

3.4. Water MMI

We examined 8 potential metrics for the WMMI, including pH and conductivity ($\mu\text{S}/\text{cm}$), and concentrations of NH_3 ($\text{mg}/\text{N}/\text{L}$), nitrate-nitrite ($\text{mg}/\text{N}/\text{L}$), Total N (TN; $\text{mg}/\text{N}/\text{L}$), Total P (TP; $\mu\text{g}/\text{P}/\text{L}$), and chlorophyll *a* ($\mu\text{g}/\text{L}$). The metrics that best distinguished between reference and most disturbed sites were conductivity, pH, and TP, and all of these metrics were higher in the most disturbed sites (Fig. 6). Conductivity and TP were both log transformed to improve the distribution of the WMMI. Using the WMMI thresholds, 75% of the most disturbed sites were classified as Poor, 17% as Fair and 8% as Good (Fig. 3). The mean WMMI for reference sites was 78.4, and the mean WMMI for most disturbed sites was 39.95 (Table 3). Riverine wetlands were not rated as poorly as with the SMMI or VMMI, and depressional wetlands had considerably more sites that were rated Poor than with the other MMIs (Table 4). Palustrine emergent also tended to have low WMMI scores, and remaining modified Cowardin classes were well distributed across the ratings (Table 4).

3.5. MMI prediction

Results of random forest regression models varied considerably by MMI. The random forest regression models containing only level 1 and 2 metrics performed moderately well for the VMMI, SMMI

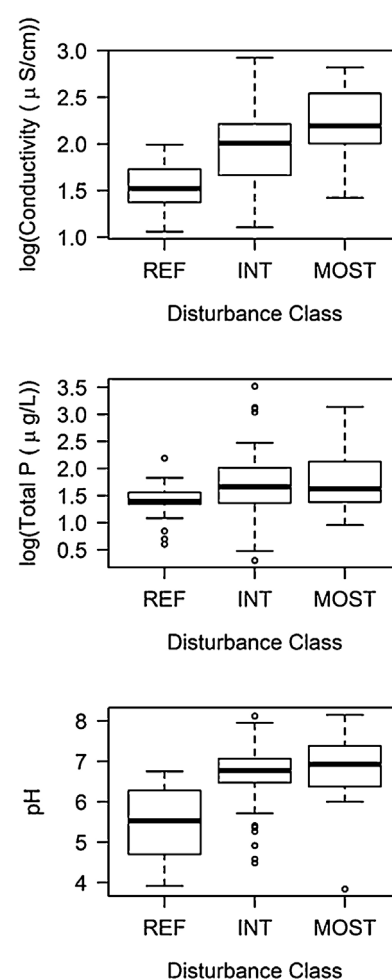


Fig. 6. Metrics included in the final WMMI by site type. See the caption for Fig. 2 for more detail.

and WMMI, but performance was very poor for the AMMI (Table 6). For the VMMI and SMMI, the level 1 and 2 models explained over 40% of the variance in the original data, and had R^2 values of 0.51 and 0.50, respectively, for the observed versus predicted values in the holdout dataset. Agricultural land uses in the wetland buffers had consistently high importance across the random forest regression models (Table 7). The only USA-RAM metric that was consistently important in the models was Metric 4. Metric 4 evaluates topographic complexity, such as hummocks, swales, and channels, and is a count of the number of indicators out of 20 possible indicators that were present within the 40-m radius assessment area.

With the addition of VMMI metrics, the SMMI model performed especially well, with 66.55% of the variance explained and an R^2 of 0.71 for the observed versus predicted values in the holdout dataset. Adding VMMI metrics also improved prediction for the WMMI and AMMI. While agricultural land uses were important in all of the random forest regression models, the metrics that were used for

Table 6

Results of random forest regression. R^2 and slope values are based on predictions with a 30% holdout dataset. p -Value refers to the significance level of the slope of the observed versus predicted values in the 30% hold out dataset.

	Level 1 & 2 metrics				Level 1 & 2 & VMMI metrics			
	% Variance explained	R^2	Slope	p -Value	% Variance explained	R^2	Slope	p -Value
VMMI	43.61	0.51	0.46	<0.001	–	–	–	–
SMMI	45.05	0.50	0.36	<0.001	66.55	0.71	0.56	<0.001
AMMI	14.17	0.06	0.12	0.113	41.08	0.29	0.33	<0.001
WMMI	30.66	0.44	0.40	0.006	47.25	0.50	0.49	<0.001

Table 7

Category of variable importance based on the random forest regression models with level 1 and 2 metrics only. Importance categories are a 5-point range, such that category 1 includes variables that had the 1–5 highest importance ratings for predicting a given MMI, category 2 had the 5–10 highest importance, and so on. Only variables that were ranked in the top five most important for at least one MMI are included.

Variable	VMMI	SMMI	AMMI	WMMI
% Agriculture 1 km buffer	1	1	1	1
% Agriculture 500 m buffer	1	1	1	6
% Cultivated crops in 1 km buffer	1	1	3	4
USA-RAM Metric 4: Topographic Complexity	1	1	5	3
% Hayed/Pasture land 1 km buffer	1	2	1	1
% Forest 1 km buffer	3	5	2	1
% Wetland 1 km buffer	4	5	1	8
% Emergent wetland 1 km buffer	5	7	6	1
% Hayed/Pasture land 500 m buffer	9	1	1	6
% Herbaceous upland 1 km buffer	9	6	7	1

the VMMI and the overall VMMI tended to have higher importance than the land use metrics (Table 8). In every case, the slope of the observed versus the predicted MMIs in the holdout dataset was flatter than the expected slope of 1, indicating that lower MMI values are over-predicted and higher MMI values are under-predicted. However, the rank orders of site MMIs were maintained between the observed and predicted values in the holdout dataset.

4. Discussion

The SMMI and WMMI incorporated widely used metrics to assess soil and water quality, including pH, conductivity, and TP for the WMMI, and TC, pH, and P concentration for the SMMI (Lougheed et al., 2001; Danz et al., 2007; Trebitz et al., 2007; Little et al., 2010; Cabezas et al., 2014). In addition to the more obvious metrics, we included the concentration of the trace metal cobalt (Co) in the SMMI. Trace metals, which are often attached to suspended particles, are a potential indicator of sedimentation and runoff from urban areas (Faulkner, 2004). Several other trace elements were strong candidates for the SMMI, including beryllium (Be), chromium (Cr), and vanadium (V), but they were also strongly negatively correlated with TC and strongly correlated with each other. Organic matter and pH play an important role in metal mobility in wetland soils, and this may at least partially explain the correlation (LaBauve et al., 1988; Grybos et al., 2007). Release of Co into soil solution is not as strongly associated with organic matter and pH (Grybos et al., 2007), and was only weakly correlated with TC. Because TC was the strongest overall metric to include in the SMMI, we chose to include Co as the indicator for trace metals.

The % silicon (Si) variable, which was a measure of non-crystalline Si in the soil, was also a strong candidate for the SMMI, with consistently higher % Si in disturbed than reference sites. However the reasons behind this pattern were not entirely clear, and may be more an indication of the vegetation present than of soil condition. That is, invasive grasses like *P. arundinacea* and *Phragmites australis* that were more common in the most disturbed sites

are good fixers of Si, which may then build up in soils through dead plant material (Struyf and Conley, 2009). Given the uncertainty in the underlying reasons for higher % Si, it was not included in the final SMMI.

The WMMI and SMMI contain similar metrics and are somewhat redundant (e.g., pH, P). We had planned on constructing an overall abiotic MMI that included water and soil chemistry metrics. Had we gone in that direction, we would only have used unique metrics of soil and water chemistry for the MMI. We did not build an abiotic MMI because water samples were only collected for about half of the NWCA sites in our study. In future surveys, we recommend collecting water samples in as many sites as possible, even if the sample is of soil pore water. If the water chemistry sample size increases in future surveys, we will examine the potential for an overall abiotic MMI.

We tested multiple metrics that used coefficients of conservatism for the VMMI including the FQI, mean C and cover-weighted FQI and mean C. We calculated these four metrics using only native species and with all species. Mean C was a clear winner over FQI, regardless of whether the metrics were cover-weighted or which richness value was used (i.e., native-only or all species). Numerous studies have examined the use of FQI and mean C metrics to assess habitat condition (Taft et al., 1997; Lopez and Fennessy, 2002; Mushet et al., 2002), with some studies determining FQI, which includes species richness, as the better metric (Bourdagh et al., 2006), and others determining mean C, which is not a function of species richness, as the better metric (Rooney and Rogers, 2002; Cohen et al., 2004; Miller and Wardrop, 2006). Given the large area of our analysis and the different types of wetlands examined, species richness may vary for many reasons not related to condition. Therefore the superior performance of mean C in our study is no surprise. For studies examining a smaller region, and more homogenous wetlands, the FQI may be a better metric for assessing wetland condition. With the exception of the most disturbed sites, the majority of wetlands in our study, including all of the reference wetlands, were composed entirely of native species. Therefore, using richness of all species in the mean C calculation resulted in better separation between the reference and most disturbed sites, due to the presence of exotic species in most disturbed sites. In areas where exotic species are more widespread, calculating the mean C with only native species richness may distinguish better between sites.

The AMMI was our worst-performing MMI. While the mean AMMI score in reference sites was higher than the mean AMMI score, there was considerable variability in the AMMI across reference and most disturbed sites. AMMIs have been successfully developed and used to assess wetland condition in multiple regions in the US, including in isolated wetlands in FL (Lane and Brown, 2007), wetlands in western KY (Pan and Stevenson, 1996), and the Casco Bay watershed in Maine (Wang et al., 2006). Genera documented as tolerant of eutrophic conditions in previous studies, including *Planthodium*, *Amphora*, and *Stauroneis*, also tended to be higher in the most disturbed sites in our study. However, there was a strong latitudinal and/or longitudinal gradient in the abundance of these genera that was not related to condition. Finding genera for the AMMI that did not follow a geographic gradient proved challenging. We therefore conclude that AMMIs are most appropriate for state-level or small regional scales. Algae samples are also costly and time-consuming to have identified. Where possible, we recommend sampling vegetation instead of algae to assess biotic condition of wetlands. Vegetation at a site can typically be sampled by a botanical expert in under a day, and the results of our random forest regression models indicate that vegetation condition is a strong predictor of soil and water condition in wetlands. Given that wetland vegetation is strongly influenced by, and can influence soil and water chemistry and hydrologic regime (Bedford et al.,

Table 8

Category of variable importance based on the random forest models with level 1 and 2 metrics and level 3 VMMI metrics.

Variable	SMMI	AMMI	WMMI
VMMI score	1	1	1
VMMI: % Bryophyte Cover	1	1	1
VMMI: % Exotic Plant Cover	1	1	1
VMMI: Mean C	1	1	2
% Agriculture 500 m buffer	1	2	13
% Hayed/Pasture land 1 km buffer	3	1	3
% Forest 1 km buffer	5	3	1
% Herbaceous upland 1 km buffer	7	9	1

1999; Mitsch and Gosselink, 2007), these results are not surprising. For example, nutrient enrichment in wetlands commonly results in a shift in vegetation from native plant communities to monotypic stands of invasive species (Craft et al., 2007), which in turn may contribute to enriched wetland soils (Tuchman et al., 2009).

There may be a bias in our MMIs against certain wetland types for reasons other than condition. Several of the metrics in the MMIs, including soil pH, water pH, and soil TC, will rate wetlands that naturally have low TC or high pH as being in poor condition. For example, riverine wetlands tended to have lower MMI ratings than depressional wetlands or flats, and this may be due to the differences in water inputs. Sites in riverine wetlands tended to have more stressors in the surrounding buffer, which somewhat justifies the low MMI scores. However, there are too few riverine sites in the reference group to determine their natural range of variation. Wetlands that have naturally high pH and conductivity because of underlying calcareous bedrock will also be rated low, and the MMIs may not reflect the actual condition in those areas. Therefore, the MMIs we developed are most applicable to wetlands classified as depressional, flats, or slope, where precipitation and poorly-buffered groundwater are the primary water sources. Fortunately, the vast majority of wetlands analyzed in this study and many of the freshwater wetlands in the northeast (U.S. Army Corps of Engineers, 2012) fit this description and are appropriate for our MMIs.

The results of the random forest regression models indicate that surrounding agricultural land use is an important predictor of wetland condition (Table 7), although the models perform best when level 3 vegetation data are also included (Table 8). This suggests that land use metrics can provide a decent estimation of which wetlands are likely in the poorest condition, and the addition of a site visit to collect vegetation data will greatly improve the ability to accurately assess the condition of wetland soils and surface water. These are useful results, as vegetation data are relatively easy to collect, and less costly than having soil and water samples analyzed chemically. Vegetation sampling is also less intrusive than digging soil pits, and as our study showed, vegetation can predict water chemistry in the absence of sampleable surface water.

While the random forest regression models were strong, they did tend to over-predict low MMI values and under-predict high MMI values. This is a common feature of random forest regression, particularly with small datasets (e.g., the 30% holdout). However, the rank-order of site condition was preserved by the random forest regression, which is more important than the ability to predict the full range of MMI scores. After the 2016 NWCA, we will further refine and test the ability of land use and vegetation metrics to predict the MMIs using data from new sites.

Based on these results, we recommend monitoring programs employ a combination of rapid assessment and intensive monitoring. GIS-based assessments of surrounding land uses can help determine which wetlands are likely most impacted, and can be completed with minimal effort on many sites. Where possible, we recommend rapid field assessments, several of which can be completed in a day, to collect vegetation and stressor information. While the level of effort and cost is much greater, intensive monitoring should occur in a subset of rapid assessment sites to validate and further refine procedures. Intensive, level 3 monitoring will also contribute most to our understanding of how vegetation, soil and water respond to and interact with different stressors over time.

5. Conclusions

The EPA NWCA in 2011 represented the first standardized, nationwide survey of wetlands in the US. The high-quality and extensive data collected by the NWCA provided a unique

opportunity to assess and develop metrics of wetland condition over a large area. In this study we developed MMIs that measure condition of vegetation, soils, water and algae that are applicable to a range of wetland types covering 11 states in the northeastern US. We will use these MMIs to assess wetland condition in for a long-term monitoring program in Acadia National Park, and we encourage other wetland scientists in the northeast to test and apply these MMIs in their sites. To ensure the MMIs we developed are useful for wetland scientists across the study area, we provide example R code for VMMI metric development as supplemental material, and a spreadsheet available from the NETN website (go.nps.gov/MMI) that can calculate MMIs for new sites. The 2016 NWCA will allow us to validate and further refine the MMIs using new sites, and will also allow us to examine trends in wetland condition using these MMIs.

Acknowledgements

We are grateful to the many people who were involved with the 2011 National Wetland Condition Assessment, and are especially thankful for the support and input from Gregg Serenbetz, EPA Wetlands Division. Thanks also to Teresa Magee, EPA for supplying the plant species list, and to Annie Rossi, EPA for input on the soils MMI. Finally, we thank two anonymous reviewers for their valuable feedback.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.ecolind.2016.01.017>.

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